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1 Billio Monica, Caporin Massimiliano, Panzica Roberto and Pelizzon Loriana (2017): "The impact of network connectivity on factor exposures, asset pricing and portfolio diversificaton", *SAFE Working Paper No.166*

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3 Billio, M.; M. Costola, R. Panzica, and L. Pelizzon (2016) Systemic risk and financial interconnectedness: network measures and the impact of the indirect effect, in Billio M., Pelizzon L., Savona R., (Eds) *Systemic Risk Tomography Signals, Measurements And Transmission Channels, Iste - Elsevier*

4 Panzica Roberto (2017): "Idiosyncratic volatility puzzle: the role of assets' interconnections", *SAFE Working Paper (forthcoming)*

5 Bellia Mario, Panzica Roberto, Peltonen Tuomas and Pelizzon Loriana (2017): "The Demand for Central Clearing: To Clear or Not to Clear, That is the Question", *SAFE Working Paper (forthcoming), ESRB Working Paper, N.62, December 2017*

Abstract

The financial crisis in 2007-2009 outlined the importance of systemic risk as the threat to financial system stability. Although it could be confused as the well known systematic risk, they have different nature. At the root of systemic risk, there is an endogenous risk component, i.e., risks that are generated and amplified within the financial system, initial shocks that in relation to the way which institutions are linked each other (topology or interconnections), increases its magnitude endogenously through the system. This thesis analyses the role of assets network interconnections as a variable that cannot be neglected for different perspectives: firstly in the standard asset pricing model as shocks amplification mechanism that differs from systematic risk; secondly as risk factor per se, as systemic risk measure; and finally by looking on whether counterparties prefer to be (i) directly connected or (ii) indirectly through Central Counterparty Clearing House (CCP) in the CDS market and which are the incentives that drive these different types of interconnections.

The first chapter extends the classic factor-based asset pricing model by including network linkages, leading to network-augmented linear factor models. Assuming that the network linkages are exogenously provided. This extension of the model allows a better understanding of the determinants of systematic risk in terms to (i) direct exposure to common risk factors and (ii) indirect exposures to common risk factors though systematic and idiosyncratic exposure to the other institutions in the system. We show that (i) network exposures act as an inflating factor for systematic exposure to common factors, (ii) the power of diversification is reduced by the presence of network connections and, (iii) risk premiums can be estimated more precisely. Moreover, we highlight that the presence of network links induces a misspecified traditional linear factor model to present residuals that are correlated and heteroskedastic. Extensive simulation experiment supports the analysis.

The second chapter is a generalization of the model used in the first chapter by considering different sources of asset interconnections, i.e., it presents a multi-network asset pricing model. In particular, the analysis shows how to use a linear factor model as a device for estimating a combination of several networks that monitor the links across variables from different viewpoints; and demonstrates that Granger causality should be combined with quantile-based causality when the focus is on risk propagation. The empirical evidence supports the latter claim.

The third chapter investigates the determinants of the idiosyncratic volatility puzzle by allowing network linkages across asset returns. The first contribution of the paper is to show that portfolios

sorted by increasing indegree computed on the network based on Granger causality test have lower expected returns, not related to IVOL. Secondly, empirical evidence indicates that stocks with higher idiosyncratic volatility have lower exposition to the Indegree risk factor.

The fourth chapter considers several network measures of connectedness applied to the network extracted using pairwise quantile regressions, i.e., it proposes the use of quantile-based network measures to estimate the importance of Globally Systemically Important Financial Institutions. The purpose is to assert the different informative content between quantile-based network measures and quantile-based loss measures such as ΔCoVaR. Globally Systemically Important Banks and Insurers and several Hedge Fund indices are considered. The work investigates whether systemic risk indicators based on network measures are similar to those based on ΔCoVaR and shows that they are capturing different features. In particular, network measures based on quantile regression capture the indirect effect of risk spillovers that is instead ignored by quantile-based loss measures. Finally, the comparison between quantile-based network measures and quantile-based losses measures highlights the predicting power of the former during the global systemic crisis of 2007/2008.

The global crisis induced G20 to develop procedures in order to increase the transparency in Over-The-Counter (OTC) market derivatives and mitigate the endogenous risk spillover effects and therefore systemic risk. The clearance is one of them, clearing a contract means that both counterparties decide to introduce a third subject in the agreement which becomes the counterparty to the buyer and the seller: the CPC and in this way breaking down the direct connection in terms of counterparties exposure between buyer and seller of an OTC contract. The clearance is compulsory for some class of derivatives for other instead is still voluntary. For these reasons, the fifth chapter analyses whether the post-crisis regulatory reforms developed by global-standard-setting bodies have created appropriate incentives for different types of market participants to centrally clear Over-The-Counter (OTC) derivative contracts and break down the direct counterparty connections between traders. Beyond documenting the observed facts, four main drivers have been selected for the decision to clear: 1) the liquidity and riskiness of the reference entity; 2) the credit risk of the counterparty; 3) the clearing member's portfolio net exposure with the Central Counterparty Clearing House (CCP) and 4) post-trade transparency. Empirical finding on confidential European trade repository data on single-name Sovereign Credit Derivative Swap (CDS) transactions show that for all the transactions reported in 2016 on Italian, German and French Sovereign CDS 48% were centrally cleared, 42% were not cleared despite being eligible for central clearing, while 9% of the contracts were not clearable because they did not satisfy certain CCP clearing criteria. However, there is a large difference between CCP clearing members that clear about 53% of their transactions and non-clearing members, even those that are subject to counterparty risk capital requirements, that almost never clear their trades. Moreover, diverse factors explain clearing members' decision to clear different CDS contracts: for Italian CDS, counterparty credit risk exposures matter most for the decision to clear, while for French and German CDS, margin costs are the most important factor for the decision. Clearing members use clearing to reduce their exposures to the CCP and largely clear contracts when at least one of the traders has a high counterparty credit risk.

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Summary

"A map is not the territory it represents, but, if correct, it has a similar structure to the territory, which accounts for its usefulness."

– Alfred Korzybski, *Science and Sanity, page 58, ch. I*

Introduction

Since the global financial crisis[1] outbreak, many studies have been profoundly redefining systemic risk concept. This meaning variation gives the idea of the complexity of the financial crisis and on its different interpretations. At the beginning of 2000, the systemic risk referred to bank runs or currency crisis. De Bandt and Hartmann (2000) define systemic risk as "systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system." Allen and Gale (2000) Freixas et al. (2000a) in their pioneer work show as a more balanced and symmetric distribution of interbank claims correspond to a less severe contagion across institutions. They are the first papers to relate interconnections to contagion. When Lehman Brothers demise compromised the stability of the financial system, the scale of the effect outlined the importance to revise the underlying assumptions for building a safer architecture. In 2008 Lehman Brothers bankruptcy infected in a domino effect other institutions especially the more exposed ones.

Banks, insurances and other financial institutions have a different kind of relations among each, e.g., loans, sales, derivative exposures, etc., that can be defined through interconnections. Before elaborating further on the different aspects, it is necessary a more formal definition of "Connectivity," "Network," "Interconnections," words often used in this literature.[2] The network is a complex system, which is formed by nodes and edges, nodes have relationships among each other defined by links or edges. Each network can be defined univocally through a matrix called adjacency matrix, binary (weighted), where each element can assume the value equal to 1 (> 0) when there is a link between two nodes, 0 otherwise. Therefore, interconnection is the synthetic way to collocate several relationships across institutions, to understand who are the most active in

[1] The term global financial crisis refers to the period 2007-2009

[2] In this thesis can be used indifferently.

term of links and finally to estimate the possible number of involved institutions when organizations default.

The underlying assumption is that the distress moves through the link between institutions to its neighbors',[3] Acemoglu et al. (2012) and Gabaix (2011) show that this risk can aggregate and therefore becomes systemic in "suitable conditions". Mainly, Gabaix (2011) imputes these "conditions" when the distribution of firm sizes is fat-tailed, Acemoglu et al. (2012) focuses on the structure of the network capturing such linkages. Both contributions are significant because they show, subject to the appropriate circumstances, the weakness of the central limit theorem and consequently the shortcoming of Lucas (1977) statement, that is, microeconomics shocks[4] have no global impact, the final safeguard against the aggregations of microeconomics shocks in aggregate fluctuations.

Once demonstrated the origin of the aggregate fluctuations from local initial conditions, fields of research on systemic risk exponentially enhanced. The reason is apparent, to understand the mechanism of aggregating the risk, to define asset pricing model (general or partial), to put early warning system, to collocate it in the financial regulation. A strand of literature, for example, investigated the network structure having higher resilience; in physic or engineering, for example, resilience is the maximum quantity of energy provided to a material before the fracture. In this direction researchers, classified the topology more resilient related to the stability (the number of defaulted firms) of the financial system. For example, Acemoglu et al. (2012) accredit the instability to an asymmetric structure of the interconnections, Gai and Kapadia (2010) define the financial system as robust-yet-fragile, they show by using simulated interbank exposures that the contagion magnitude is related to the location in the network where the initial shock occurs. In contrast to this view, Vivier-Lirimont (2006) and Blume et al. (2011) state that the connectivity of interbank exposure network increases the probability of the collapse of the system. Albeit there are different opinions on which structure of network are more resilient for the financial system, it necessary highlight that it could depend on the type of economic interconnections (interbank, sales, input-output, production) among the institutions. However, the most important consideration reached is that the interconnections affect the financial stability.

Financial Stability Board introduced interconnectedness as one of the drivers for detecting the Systemic Important Financial Institutions (SIFI). Successively Billio et al. (2012) observed that financial institutions were more interconnected during the global financial crisis than other periods. They define systemic risk as "any set of circumstances that threatens the stability of or public confidence in the financial system", i.e., something more relevant than a pure contagion among banks because systemic risk spreads from financial system to the real economics. Billio et al. (2012), for the first time, introduce a methodology for estimating the interconnections among institutions returns based on the Granger causality. They infer interconnections among organizations through

[3] Other institutions having a relationship with the organization concerned

[4] Specific for each firm

econometric measures rather than real data (interbank or derivatives exposure). Even though interconnections can be inferred or measured, both types mentioned consider that a microeconomic shock uses the link through the two institutions are related as the channel of spreading. The aggregation of microeconomic shocks can be relevant and became systematic. On this direction, theoretical models on asset pricing study whether interconnection can affect the state price density of investors. Herskovic (2015), study the problem theoretically showing as network production changes, in concentration and sparsity, are sources of systematic risk. Ahern (2013) finds positive relations between centrality and stocks returns, the more central is a firm in an Input-Output network the higher are the expected returns because firms are more exposed to sectoral shocks. The link between systemic and systematic risk is still more narrow.

Sytemic vs. Systematic risk: In order to understand the difference between systemic risk and systematic risk, I use the example of Benoit et al. (2017) presented in their survey on systemic risk. The environment proposed by the authors is the following:

Let consider N financial institution, each institution i has a risk exposure x_i. A part of x_i derives from the systematic risk $y_i^S = \alpha_i x_i$, the rest is idiosyncratic risk $y_i^I = (1 - \alpha_i)x_i$. The aggregate exposure on sistematic risk for all istitutions is $y^S = \sum_i^N y_i^S$. Each institution i has a return $\rho^S + \epsilon^S$ on the systematic factor and a return $\rho^i + \epsilon^i$ on the idiosyncratic factor. ρ^S and ρ^I are constant while ϵ^S and ϵ^i are random. The payoff of the firm i is function $\hat{\pi}(y_i^S, y_i^I, \epsilon^S, \epsilon^i)$

$$\hat{\pi} = (\rho^S + \epsilon^S) \times y_i^S + (\rho^i + \epsilon^i) \times y_i^I \tag{1}$$

Since all the ϵ^S have exposure on the systematic factor trough α_i, when a systematic shock occurs (negative or positive) it affects all the other institutions simultaneously. This framework corresponds to the standard theory, for example, the CAPM or the one-risk factor model, also known as the market model of stock returns.

Let assume now that the institutions have some relations with each other, i.e., derivatives, sales, input-output, etc. Then a matrix of interconnections W of dimension $(N \times N)$ exists, where each w_{ij} can be binary or weighted. Since each institution belongs to the system through links with the others, there is systemic risk when the payoff $\hat{\pi}$ of each organization depends on the exposures of the others. The idiosyncratic risk spreads through the exposures and affects the payoff. Defined π the actual payoff, function of $\pi(Y^S, Y^I, \epsilon^S, \xi^I, W)$, where Y^S, Y^I, ξ^I are respectively the vectors $N \times 1$ of systematic exposures, idiosyncratic exposure and the vector of idiosyncratic shocks. There is systemic risk when

$$\pi(Y^S, Y^I, \epsilon^S, \xi^I, W) \neq \hat{\pi}(y_i^S, y_i^I, \epsilon^S, \epsilon^i) \tag{2}$$

The vector of exposures: (i) systematic exposures, (ii) idiosyncratic exposure and (ii) the vector of idiosyncratic shocks influence the π through W. The disequality (2) shows as interconnections W influences the difference between systematic and systemic risk. The disequilibrium between two terms generates risk misperception, for this reasons the role of the interconnections should be not neglected.

In summary this dissertation focuses on interconnections as variable useful to understand how the idiosyncratic risk contribute endogenously to generate systemic risk. The thesis analyzes the role of interconnections from different perspectives, in other words, to provide the instruments to bridge the gap in disequality (2), chapter 1 investigates the role of interconnections in the multifactor model framework on the factor exposure, the pricing and the power of diversification. Chapter 2 provides a methodology to measure the network contribution when we have disposal several sources of interconnections. Chapter 3 analyzes if the centrality measured based on the Granger causality can be considered a factor per se and attempts to shed light on the idiosyncratic volatility puzzle. Chapter 4 examines whether systemic risk indicators based on network measures are similar to those based on Δ CoVaR or capture different aspects of systemic risk. Finally, chapter 5 studies which drivers influence the decision to build connections in the OTC derivative market. The following sections summarize the contribution of each chapter.

Chapter 1

The first chapter investigates the effects of the interconnections in the multifactor model framework. The network creates an endogenous factor that influences the pricing. The chapter extends the standard multifactor model by allowing interconnections (network) among assets returns. In this framework, interconnections coexist among the endogenous variables, and it is exogenous. The chapter investigates whether the connectivity has an impact on the common factor exposure, the expected returns, and the power of diversifications. Simulations experiments prove the obtained results. It is worth to notice that if a neglected latent linkage across assets returns exists, then this "endogenous" omitted factor would induce cross-correlations among residuals and consequently violate one of the standard multifactor model assumptions. The model augmented by the linkages is a spatial autoregressive (SAR) model where factors are the covariates see LeSage and Pace (2009). In the spatial econometrics framework, the matrix of the contemporaneous relationship among assets returns is a function of the interconnections provided exogenously and the spatial parameter to estimate. The work also considers further generalizations. When linkages across assets returns exist the multifactor model is the reduced model of the spatial augmented model, developed in this chapter (the structural one). The structural model assumes that the residuals are not cross-correlated. The contribution of this work is to disentangle the factor loading in two components: (i) the structural one (pure one) on the factor, and (ii) the network impact on the common factor. The higher is the spatial parameter; the higher is the effect coming from the network on the common factor. In the same fashion, the network connectivity influences also the variance decomposition. In particular, it is possible to distinguish four components: the two standard components systematic and idiosyncratic and the relative effects coming from the network.

The results show that, as soon as the spatial parameter increases, the power of diversification reduces. The connectivity also influences the expected returns, particularly the spatial parameter if positive inflates the expected returns. I want to outline that the network effect is estimated, the spatial parameter, by full information maximum likelihood method. The simulations also show that the standard multifactor model is as much as misspecified the stronger is the effect coming from the network. The distortions among the estimated coefficients with the true parameters and the cross-correlations across residuals show that. Finally, the model is flexible to different generalizations: (i) spatial parameters asset specific and (ii) network time-varying (with the condition of a lower frequency concerning the assets returns). The paper shows that when the network is time-varying, and the network impact is heterogeneous, there is a consistent reduction in the risk premium's standard errors.

Chapter 2

The second chapter extends the model of the first chapter by increasing the sources of interconnections (networks). The set up of the model provides more degree of freedom in term of interconnections and at the contrary of chapter one, the matrix of the contemporaneous relations among the assets returns is a function of spatial parameters and finite sources of interconnections. All the interconnections sources contribute to the matrix of the contemporaneous relations; the contribution of each network is measured by a coefficient (weight) estimated. The first contribution of the paper is to implement a methodology able to compare different networks among asset returns in a multifactor model framework, as outlined by Puliga et al. (2014) "Moreover, our findings show that reconstructing networks from time series poses some challenges. [...]. It is not clear how (and maybe it is not even possible) to compare the values of the link weights across the various methods." In other words, the paper offers a complementary methodology to detect the contribution of each network according to the data.

We consider three different networks estimated using the (i) Billio et al. (2012) Granger causality approach, (ii) quantile methodologies based on Koenker and Bassett (1978), (iii) quantile methodology proposed by Sim and Zhou (2015) and Jeong et al. (2012).

Comparing different causalities methods is useful to understand the way the risk spreads across institutions. In fact, causality in the mean, as estimated using Billio et al. (2012) could be largely different than the one we estimate on the tails using quantile regression. To give an example, two series having no causality relationship at the mean of the distribution could have connections at the tails. The paper empirically confronts different datasets, during and after the crisis, by looking at three types of institutions: the 25 most capitalized Banks; the 25 most capitalized Insurances and the 48 industry sectors portfolios. The results show as the network structure change when we move from the causality in the mean (Granger) to the causality in the quantile. The analysis shows that the different networks based on various methodologies jointly contribute to explain stock returns and their relevance changes through time because in some circumstances one can be more appropriate of others and vice-versa.

Chapter 3

The network estimation based on the causality methodology is used, as seen in chapter two, to understand how the risk spreads across assets returns. Assuming that the idiosyncratic shocks move according to the channel defined by the network based on the Granger causality, the chapter investigates if a relation by indegree centrality and stocks returns exists and if the risk factor based on the indegree explains the idiosyncratic volatility puzzle. The puzzle consists of observing empirically a negative relation between portfolios sorted by idiosyncratic volatility with respect to Fama and French (1993) at the previous month and the expected stock returns. This association does not agree with the standard theory because the idiosyncratic risk can be diversified away and therefore should not be priced; moreover, it is not clear why the market should treat stocks having high idiosyncratic volatility as insurance. The basic idea of the paper is that interconnections can interfere with the aggregation mechanisms of idiosyncratic shocks as seen in chapter one. In this case, the network does not affect endogenously assets returns as previously. The work analyzes if indegree associated with the Granger causality could be seen as an exogenous factor.[5]

The analysis starts by replicating the results of Ang et al. (2006) and by using the same data and the same data period I investigate whether portfolio sorted by the indegree measure shows any relationship with stock returns. The study shows that there is a negative relationship between portfolios sorted by increasing indegree at previous month and stocks returns. This factor is largely negatively correlated with the momentum factor. Although the work does not explain the idiosyncratic volatility puzzle, i.e., the omitted factor that makes the alphas significant concerning Fama and French (1993) is not imputable to indegree. The second question I investigate is if portfolios having stocks with higher idiosyncratic volatility have lower or negative exposures on the factor based on indegree. Other centrality measures do not reveal the negative relation between stocks returns as indegree does.

Chapter 4

The chapter four investigates whether systemic risk indicators based on network measures are similar to those based on Δ CoVaR. The work analyzes the systemically important banks, insurances and hedge funds returns. In particular, the work compares two different scenarios: the first one computes for each institution the Δ CoVaR; the second one calculates for each organization centrality measures associated to the network based on the quantile regression estimated by using the methodology of Billio et al. (2012). Although Adrian and Brunnermeier (2016) take into account the directionality of their measure, that is, the CoVaR of the system conditional on insti-

[5] Other centrality measures have been analyzed in the robustness checks.

tution i does not equal the CoVaR of institution i conditional on the system, the "indirect effect" is still missing. It is worth to notice that the term "indirect effect" is used in spatial econometrics to capture the spatial or the spillover impacts that arise in these models in response to neighbors changes in the explanatory variables see LeSage and Pace (2009).

This effect is useful to understand the indirect impacts of connections, i.e., in which way the neighbors, and the neighbors of neighbors, affect the nodes centrality, and consequently the externalities indirect among institutions. Network measures based on quantile regression captures the indirect effect of risk spillovers that is instead ignored by quantile-based loss measures. The contribution is to show that measures based on interconnections increment the informative content of the based loss measures because they capture different features. In addition, the former have the predicting power during the global systemic crisis of 2007/2008 in the out-of-sample test better than the $\Delta CoVaR$.

Chapter 5

The fifth chapter investigates whether counterparties prefer to be directly connected or indirectly through Central Counterparty Clearing House (CCP) in the CDS market and which are the incentives that drive these different types of interconnections. The selected drivers to test are: 1) the liquidity and riskiness of the reference entity; 2) the credit risk of the counterparty, and 3) the clearing members portfolio net exposure with the CCP. The analysis focuses on the single name CDS on sovereign bonds on Italian, French and German reference entities, for which clearance is still voluntary in 2016. The reasons driving clearing members to clear a transaction are unknown because the process is a trade-off between contrasting forces. For example, by looking at the driver 1 (the liquidity and riskiness of the reference entity), the riskiness of the reference entity could be negatively related with the decision to clear because the margin and the maintenance level would increase for clearing a reference entity riskier. At the same time, counterparty capital requirement would increase the incentive to clear the contract because clearance would lower the Counterparty capital requirements.

The analysis shows that the large majority of the transaction cleared are between CCP clearing members, while in the dataset there is almost no evidence of clearance of transactions by non-clearing members, independently whether they are subject to capital requirements or not. The first contribution is to find that both capital costs and margin costs are relevant for the decision to clear with some differences among the three sovereign CDS contracts. For the Italian sovereign CDS, the counterparty credit risk exposure is more relevant than margin costs in the decision to clear, while for the German sovereign CDS contracts margin costs are the most important. Instead, for the French sovereign CDS contract, it is difficult to disentangle which of the two main drivers prevails. The second contribution is to find that if a clearing member is a net seller of a specific sovereign CDS, then an additional contract bought increases its propensity to clear. Finally, the third contribution is to show that the counterparty credit risk alone, proxied by the CDS value of the traders, is an important incentive to clear a contract, as this factor is significant for the analyzed reference entities.

Concluding Remarks

Korzybski argued that we cannot put in the same dimension the reality and the models to represent it. The map is just an instrument. The financial system territory is full of shadows, moreover, the financial crisis showed that the preexisting maps are obsolete because the territory to explore is changed. In this thesis, I analyze how the connectivity among assets returns influences the pricing, goes beyond the standard systematic risk measures and affects the idiosyncratic risk. The analysis I proposed in this thesis is just an additional map to enlighten a complex environment as the financial system.

Chapter 1

The impact of network connectivity on factor exposures, asset pricing and portfolio diversification

1.1 Introduction

The term "systematic risk" is a well-established concept that derives from the seminal work on portfolio choice proposed by Markowitz (1952) and extended in a general equilibrium framework by Sharpe (1964), Lintner (1965a), Lintner (1965b) and Mossin (1966), and in the Arbitrage Price Theory model by Ross (1976). It refers to the risk to which an investor in a well-diversified portfolio is exposed, which stems from the dependence of the returns on common factors. However, as stressed by Cochrane (2011), there is a need for a better understanding of the determinants of systematic risk.

In this paper we provide a unique framework for systematic risk and network connectivity, and estimate the feedback between network exposures and common factors and their impact on the factor risk exposures and risk premia of stock returns.

A growing literature investigates the role of interconnections between different firms and sectors as a potential mechanism for the propagation of shocks throughout the economy. Acemoglu et al. (2012) use network structure to show the possibility that aggregate fluctuations may originate from microeconomic shocks to firms. Kelly et al. (2013) show how stock firm volatility is related to customer-supplier connectedness. Billio et al. (2014) use contingent claim analysis and network measures to highlight interconnections between sovereigns, banks and insurance. There are several other contributions to the literature on network analysis: see Billio et al. (2012), Diebold and Yilmaz (2015), Hautsch et al. (2012), Hautsch et al. (2013), Barigozzi and Brownlees (2014), Ozdagli and Weber (2015), Fernandez (2011), Kou et al. (2017), Buraschi and Tebaldi (2017). Network interconnections and the effects called network externalities that arise from small and local shocks that can become big and global are a possibility discarded in standard asset pricing and macroeconomic models due to a "diversification argument". As argued by Lucas (1977), among others, microeconomic shocks will average out and thus have only negligible aggregate effects. Similarly, they will have little impact on asset prices. However, there is also a growing literature on the role of sectorial shocks in macro fluctuations. Examples include Horvath (1998), Dupor (1999), Shea (2002) and Acemoglu et al. (2012). Moreover, Ang et al. (2006), among others, show that idiosyncratic volatility risk is priced in the cross-section of expected stock returns, a regularity that is not subsumed by size, book-to-market, momentum or liquidity effects. From a theoretical point of view, Wagner (2010), Ozsoylev and Walden (2011), Buraschi and Porchia (2012) and Branger et al. (2014) arrive at similar conclusions. Ahern (2013) empirically documents a positive market price of centrality, i.e., that more central assets earn higher expected returns. Buraschi and Tebaldi (2017) focus on vulnerability to network risk and show that it is associated with a risk factor impacting on the cross-section of expected returns.

The contribution of this paper is to propose a modelling framework in which network connectivity and common factor risks co-exist. The proposed model is a variation on the traditional Capital Asset Pricing Model (CAPM) or Arbitrage Pricing Theory (APT) framework in which networks are used to infer the exogenous and contemporaneous links across assets. By using our network-augmented linear factor model, we are able to disentangle direct exposures of a single stock to common factors from the indirect exposure to the common factors that arise from network interconnections. We also provide a number of generalizations to our approach to make it more flexible and coherent with the empirical evidence, for instance allowing for asset-specific reaction to network links and introducing time variation into networks.

Building on the network-augmented linear factor model, we provide a number of theoretical elements and pieces of empirical evidence based on a simulation framework. First, focusing on the dynamics of returns and the exposure to common factors, we show that the presence of asset interconnection acts to inflate the exposure to common risk sources. Moreover, we are able to disentangle the exposure to common factors that is structural, which is present even in the case of no network connections, from the exposure associated with network links. A similar argument applies to the shocks impacting on an asset return, whereby network relations expose assets to other assets' shocks. From a risk perspective, our approach allows us to decompose the risk of a single asset (or a portfolio) into four components: (i) the systematic component, (ii) the idiosyncratic component, (iii) the impact of the asset interconnections on the systematic risk component, that is, the contribution of network exposure to the systematic risk component, and (iv) the effect of interconnections between the idiosyncratic risks on the systematic risk component, that is, the amplification of idiosyncratic risks that generates systematic/non-diversifiable risk. Building on this result, we show how diversification benefits are reduced in the presence of network connectivity. Moreover, by combining the return dynamics with the variance decomposition, we can verify that our model is consistent with the presence of correlation and heteroskedasticity among traditional linear-factor-model residuals, thus providing a rationale for the empirical evidence found in the literature.

The simulation analysis allows us to disentangle the error estimation of linear factor models that ignore the presence of network connections. In particular we show that, when asset returns are significantly related to network interconnections, the factor loading estimation of common factors is largely misspecified if the estimation is based on a traditional linear factor model. Moreover, the residuals' correlations start drifting away from zero if network connections are ignored in the model estimation.

Finally, we also evaluate the impact of networks on the estimation of risk premiums and show that the premiums estimated by our approach and by a traditional linear factor model are equivalent in the long run (under some assumptions on the evolution of the network over time). However, our approach allows local (conditional) expected returns to change, according to changes in the network structure, and thus leads to price changes even if the risk premiums are time-invariant. The remainder of the paper is organized as follows. Section 1.2 describes network models. Section 1.3 presents our model combining network links and factor exposure, while Section 1.4 introduces a set of generalizations making the model more flexible. Section 1.5 describes the estimation methodology for the model augmented with the network links. Section 1.6 presents the simulation analysis and finally Section 1.7 concludes.

1.2 Network Models in Finance

1.2.1 Review of the literature

Network models have featured in an extremely diverse array of applications: in social sciences with studies related to social networking, in natural sciences with application to protein interactions, in government intelligence for analysing terrorist networks, in politics with application to bill co-authorship, in economics with the potential to be used in labour market analysis, and many other areas. In finance, network models have most frequently been used to assess financial stability as in Acemoglu et al. (2012). In fact, interconnections between financial institutions create potential channels for contagion and the amplification of shocks to the financial system that can also propagate into the "real economy". Theoretical and empirical studies in this area have garnered considerable interest in the aftermath of the 2007-2009 financial crisis. Network representation of interconnections ranges from linkages extracted from balance-sheet information to connections estimated by means of econometric approaches based on market, accounting or macroeconomic data.

In order to evaluate the relevance and the price of interconnections in the financial system it is fundamental to understand all of the channels by which small and local shocks can become big and global.

Empirical network modelling has been conducted to assess asset pricing linkages via contagion

(Allen and Gale (2000); Dasgupta (2004); Leitner (2005); Billio et al. (2012); Bianchi et al. (2015); Diebold and Yilmaz (2014); Hautsch et al. (2012), Hautsch et al. (2013)), linkages via balance sheets (Cifuentes et al. (2005); Lagunoff and Schreft (2001)) and how failures of institutions result from mutual claims on each other (Furfine (2003); Upper and Worms (2004); Wells (2004); Billio et al. (2014); Ozdagli and Weber (2015). Allen and A. (2009) provide a review of network models in finance.

Much of the empirical finance literature has focused on "direct"contagion arising from firms' contractual obligations. Direct contagion occurs if one firm's default on its contractual obligations triggers distress (such as insolvency) at a counterparty firm. Researchers' simulations using actual interbank loan data suggest that "domino defaults" arising from contractual violations are very unlikely (see Furfine (2003); Elsinger et al. (2005); Upper and Worms (2004); Mistrulli (2011); Degryse and Nguyen (2004); Lelyveld and Liedorp (2006); Alves et al. (2013)), though they can be highly destructive in the event that they do materialize.

As described above, there are various approaches for estimating networks among financial institutions. However, as far as we know, none of the approaches seems to prevail or to be more appropriate. Our purpose is not to clarify this ambiguity but to show how linkages existing among asset impact on returns and risk of assets and portfolios, and on the pricing of factor's risk premia.

1.2.2 Formal representation of networks

Formally, we could represent networks as nodes that are connected (in general) to a subset of the total number of nodes in the network, in which connections represent links across nodes. A financial system could be represented as a network structure in which nodes represent assets or the value of financial or non-financial institutions, and shocks on one asset/institution are transmitted to those connected to it.

Networks are, in general, graphically represented. Nevertheless, networks have an equivalent (square) matrix representation. Let us call W the K-dimensional square matrix representing a network composed of K financial assets/companies. Each entry $w_{i,j}$ represents the possible connection between assets i and j. A zero entry indicates that the two assets are not connected, while a non-null entry indicates the existence of a connection. Depending on the approach adopted to estimate the network, non-null entries might differ from one another, tracking the strength/intensity of the connection, or be equal to one another, simply indicating the existence of a connection. An example of the latter case is the following matrix:

$$W = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}, \tag{1.1}$$

where it should be noted that the diagonal contains only null elements (no asset influences itself) and that the network is not symmetric as the first asset is connected to the fourth, but the opposite is not true. In general, networks also convey a further element, the direction of the link. If links are all bidirectional, the network is symmetric. By convention, in the present paper we assume that a non-null element $w_{i,j}$ indicates the existence of a link between assets i and j with an effect from j to i.

Interestingly, matrices similar to that given in equation (1.1) are very common in other economic and statistical applications, those concerning research and studies associated with spatial econometrics and spatial statistics. In these fields, subjects (such as towns, buildings or regions) are neighbours of each other in a physical way, and the matrix W represents the neighbouring relations, with entries possibly associated with the physical distance existing between two subjects; such matrices are normally called *spatial matrices*, and are commonly row-normalized.

Matrix representation of financial networks might thus be seen as the financial parallel of spacial matrices. Clearly, neighbouring relations are no longer physical, but are the outcome of a specific model, measurement or estimation approach. Going back to the graphical representation of networks, in which nodes are connected to one another, we might state that connected nodes (assets/firms) are thus neighbours. Finally, we stress that, if we consider matrices to monitor only the existence of connections across assets, we adhere to the concept of “first-order contiguity” whereby a unit entry denotes the existence of a connection and the fact that two assets are neighbours (see LeSage (1999)). In addition, by convention in spatial statistics/econometrics, the main diagonal of the matrix W contains zero elements.

In the following, we will clarify how network connections, as monitored by the matrix W, will convey relevant information on the evolution of asset returns. In doing so, we do not restrict ourselves to a specific structure of W, that is, a W that monitors the existence of a connection and/or the intensity of the link, but propose a model that can be used with any form of W. Moreover, following Elhorst (2003), we normalize W so that, if we are monitoring only the existence of the connection, we equalize the impact of each unit on all other units. We discuss the normalization of W further in a later section. In the empirical part of the paper, we also briefly discuss alternative methods that can be used to estimate the existence of a connection between two assets.

1.3 The Systematic Effects of Network Exposure

1.3.1 The classic framework

Ever since the publication of the seminal works of Sharpe (1964), Lintner (1965a), Lintner (1965b), and Mossin (1966), linear returns models have attracted huge interest in the financial economics literature, and have had an extraordinary impact on both research and practice. In the last few decades, multifactor generalizations of the CAPM model have been proposed and are now as widespread as the single-factor model. The first multifactor model stems from the work of Ross (1976) on the APT, and the most commonly used approaches to pricing now take into account the developments of Fama and French (1993), Fama and French (1995) and Carhart (1997), leading to the so-called three-factor and four-factor CAPM models, respectively.

Our starting point is a multifactor model, within which all the previous cases are nested, and which we take as a general case into which network exposures can be introduced. We thus consider a linear specification in which a K-dimensional set of time-t risk asset returns, which we denote by R_t, depends on a set of M *observable* zero-mean risk factors F_t:

$$R_t = \alpha + \beta F_t + \varepsilon_t. \tag{1.2}$$

In equation (1.2), α is a K-dimensional vector of intercepts, β is a $K \times M$ matrix of parameters monitoring the exposure of the risky assets to the common factors included in the M-dimensional vector F_t, and ε_t is the vector of idiosyncratic shocks.

If we take a pricing perspective, and assume that the market is in equilibrium, then the model intercept can be replaced by the vector of expected returns

$$R_t = \mathbb{E}\left[R_t\right] + \beta F_t + \varepsilon_t. \tag{1.3}$$

Moreover, expected returns depend on the factor risk premiums Λ satisfying

$$\mathbb{E}\left[R_t\right] = r_f + \beta\Lambda. \tag{1.4}$$

The multifactor model allows for the decomposition of the total risk of the assets into the sum of two components:[1]

$$\mathbb{V}\left[R_t\right] = \beta\Sigma_F\beta' + \Omega_\varepsilon, \tag{1.5}$$

where $\mathbb{V}\left[\cdot\right]$ is the variance operator, $\mathbb{V}\left[F_t\right] = \Sigma_F$ is the covariance matrix of the common factors, and $\mathbb{V}\left[\varepsilon_t\right] = \Omega$ is the covariance matrix of the idiosyncratic shocks. The first term on the right represents the systematic contribution to the total risk, while the second term is the idiosyncratic

[1] This holds for any multifactor model.

risk contribution. The same decomposition of the total asset risk also applies to a generic portfolio formed using the K assets. If we take a vector of portfolio weights ω,[2] the portfolio returns satisfy the following equalities:

$$\begin{aligned} r_{p,t} &= \omega' R_t \\ &= \omega' \mathbb{E}\left[R_t\right] + \omega' \beta F_t + \omega' \varepsilon_t \\ &= \mathbb{E}\left[r_{p,t}\right] + \beta_p F_t + \varsigma_t, \end{aligned} \tag{1.6}$$

where $\mathbb{E}\left[r_{p,t}\right] = r_f + \beta_p \Lambda$. Moreover, we know that the total risk of the portfolio is given by

$$\begin{aligned} \mathbb{V}\left[r_{p,t}\right] &= \omega' \beta \Sigma_F \beta' \omega + \omega' \Omega_\varepsilon \omega \\ &= \beta_p \Sigma_F \beta_p' + \sigma_\varsigma^2. \end{aligned} \tag{1.7}$$

This framework has relevant implications for portfolio risk and diversification. If we take a diversification point of view, the final purpose is to control or sterilize the impact of idiosyncratic asset risks on the total portfolio risk. This corresponds to the willingness of achieving the following limiting condition:

$$lim_{K \to \infty} \omega' \Omega_\varepsilon \omega = \tilde{\sigma}^2 > 0, \tag{1.8}$$

where $\tilde{\sigma}^2$ is a small quantity depending on the idiosyncratic shock variances and correlations, as well as on the portfolio composition. In a simplified setting, assuming that idiosyncratic shocks are uncorrelated, that their variances are set to an average value $\bar{\sigma}^2$ and taking an equally weighted portfolio, we have the following well-known result:

$$lim_{K \to \infty} \omega' \Omega_\varepsilon \omega = \frac{1}{K} \bar{\sigma}^2 = 0, \tag{1.9}$$

showing that diversification allows the idiosyncratic shocks to be sterilized.

In this framework, the focus is on the shocks' impact, since we know that the systematic risk component cannot be diversified out, as it is driven by common factors. Therefore, in the multifactor model, the introduction of new assets allows a contraction of the contribution of the idiosyncratic component to the total risk of the portfolio but has, on average, no effects on the systematic components.

1.3.2 A network-augmented linear factor model

Our paper aims at introducing into a multifactor asset pricing model the impact of contemporaneous links that exist across assets, when those links are captured by a network. As discussed in

[2] We assume that the portfolio weights sum to 1 but we do not exclude short selling.

the previous section, networks provide information on the existence of links and might also convey details of the intensity of the links existing between assets. Therefore, we aim to couple the systematic and idiosyncratic risks with a sort of network risk that would introduce into the pricing model the assets' cross-dependence, beyond that captured by common factors. By doing so, we exclude the possibility that the network effects are driven by what Manski (1993) calls *correlated effects*, i.e. common factors. Given this further element, we then evaluate the effects on traditional uses of the multifactor model.

Let us assume that the risky assets are interconnected and that those links can be represented by a network. The network relations, as observed in the previous section, can be, in some sense, forward looking or represent the actual state of the connections across assets. Following Manski (1993), we could interpret network connections in different ways. They could correspond to correlated network effects associated with missing factors. Alternatively, they might relate to common characteristics, which have not been included in the analysis, but make nodes similar and therefore connected. Furthermore, network effects could stem from the so-called peer effects. We do not have a clear answer to this competing explanations, similarly to the current literature that provides evidences supporting the existence of networks from different viewpoints; see Cohen et al. (2008), Pool et al. (2015), Kou et al. (2017), among others.

We are tempted to say, that various network effects might co-exist. Our aim is to extend asset pricing model in order to take in consideration network effects on top of common factor exposure, as in Kou et al. (2017). Similarly to the latter paper, we allow for network effects and analyze their impact on asset pricing. However, we also introduce a number of additional elements: i) a detailed analysis on the role of network exposure on assets returns and risk; ii) a discussion on the impact of network effects on the assets exposure to common risk factors; iii) the evaluation of network exposures on diversification; iv) the introduction of asset-specific reactions to networks; v) the introduction of time-changes in the network structure; vi) the evaluation of iv) and v) on risk premium estimation both by proposing an ad-hoc estimation approach and evaluating its performance by means of simulation analyses.

From this point onward, we assume that a single network exists, that it is known, that it consists of elements going beyond a set of common factors, and that the network will impact on the contemporaneous relations across assets. We will show that the presence of interconnections implies that risky assets are exposed to the movements (both systematic and idiosyncratic) of other risky assets. Moreover, we will highlight how risky assets might differ in terms of interconnections with other assets. This creates an additional form of heterogeneity, going beyond those associated with the different exposures to common risk factors and with the different degrees of relevance of idiosyncratic shocks. Starting from this assumption, we reconsider the interpretation of a general multifactor model. If we postulate about the existence of contemporaneous relations across risky assets, we must acknowledge that such relations are not explicitly accounted for in equation (1.2). As a consequence, the beta matrix with respect to common factors that can be recovered from a traditional linear factor model, i.e. that of equation (1.2), cannot be directly linked to both the interconnections and the source of *network* heterogeneity across risky assets.

One possible way of reconciling the model in equation (1.2) with the network exposure is to interpret the model as a reduced-form model whose reduced-form parameters (the betas and the error covariance) are functions of structural parameters' network exposure and structural factors such as macro factors etc. The latter thus include the *true* exposure to common structural factors, the exposure to other assets due to the interconnections (or network exposure) and the *structural* idiosyncratic shock's variance.

To shed some light on the previous points we rewrite the model in equation (1.3) as a structural simultaneous equation system (later on called a structural model),

$$A\left(R_t - \mathbb{E}\left[R_t\right]\right) = \bar{\beta} F_t + \eta_t, \tag{1.10}$$

where the matrix A captures the contemporaneous relations across assets and coexists with the common factors, which are here considered as exogenous variables. In equation (2.2) the covariance of η_t represents the structural idiosyncratic risk while the parameter matrix A is associated with assets' interconnections, and thus with a network. Further details on the latter aspect will be given in a few paragraphs' time. If we translate the model in equation (2.2) into a reduced form, we have

$$\begin{aligned} R_t &= \mathbb{E}\left[R_t\right] + A^{-1}\bar{\beta} F_t + A^{-1}\eta_t \\ &= \mathbb{E}\left[R_t\right] + \beta^\star F_t + \epsilon_t^\star, \end{aligned} \tag{1.11}$$

where $\beta^\star$ is the matrix of reduced-form betas, equal to $\beta^\star = A^{-1}\bar{\beta}$ and $\epsilon_t^\star$ is the vector of reduced-form errors.[3] We stress two relevant elements. Firstly, we observe that the reduced-form parameters $\beta^\star$ are *non-linear* functions of the interconnections between assets (the matrix A) and of the structural exposure to common structural factors (the matrix $\bar{\beta}$). Secondly, the covariance matrix of the errors $\epsilon_t^\star$ is influenced by the presence of interconnections between assets.

We postulate that a network structure exists, thus assets are interconnected and at the same time the assets depend on a common set of risk factors. If on these assets we estimate the linear factor model in equation (1.2) without taking the network into account, we have, by construction, that the shocks are correlated.[4] This is a consequence of the fact that the reduced-form betas can be estimated consistently in equation (2.3) anyway by standard linear regression models, but the residuals' covariance is not coherent with the theoretical expectation, that is, idiosyncratic shocks are uncorrelated. Therefore, the empirical evidence of idiosyncratic shock correlation found in the residuals of multifactor models might be due to the exclusion of contemporaneous relations.

[3] We include the star as a suffix to distinguish the reduced-form errors implied by our model from the errors of the traditional multifactor model.

[4] This holds if we assume that A is not diagonal. However, this is an inconsequential restriction as, if A is diagonal, we do not have contemporaneous relations between assets.

This is also coherent with the following finding of Ang et al. (2006): idiosyncratic volatility risk is priced in the cross-section of expected stock returns, a regularity that is not subsumed by size, book-to-market, momentum or liquidity effects. In addition, if we assume that the network links affect the matrix A, and estimate the model in equation (2.3), the residuals' covariance will be a function of the network links.[5] So far our analysis concerns only observable factors. If the common factors are estimated by means of statistical approaches rather than being observed variables, the network exposure, if present, will be totally destroyed. In fact, *statistical* factors are generally estimated from a reduced-form model. Therefore, if we adopt principal component analysis, or fit a latent factor model, it might happen that one of the identified factors represents a sort of proxy or biased estimate of the network exposure, with possible further biases on the estimated factor loadings. Such a problem might be overcome by estimating a latent factor model accounting for contemporaneous links across assets. Examples can be found in the studies of Barigozzi and Brownlees (2014) and Bianchi et al. (2015), who show that, if network links are not known, they might be estimated by looking at the covariance of $A^{-1}\eta_t$. However, in such a case, the economic interpretation of network links might be difficult to recover and could be exposed to estimation error. In addition, the common factors we choose in the model must be exogenous. Our approach aims at reintroducing contemporaneous relations into the multifactor model, thus allowing both the impact of network exposure and the direct exposure to common structural factors to be recovered. Note that the two elements coexist, and network exposure can be seen as an additional *common* risk source going beyond that of common factors. We might even define the exposure to common factors as the exogenous systematic risk exposure, while the network exposure can be labelled as an endogenous systematic risk exposure. Further, we stress that we label the η_t in equation (2.2) as structural idiosyncratic shock to distinguish it from the vector $\varepsilon_t^\star$ in equation (2.3) that represents the reduced-form idiosyncratic shock. The simultaneous equation system in equation (2.2) poses serious challenges for the estimation of the matrix A. We overcome this potential problem by resorting to network links. If we postulate the existence of network connections, which we assume are exogenously provided, we can easily recast the network into an adjacency matrix W as mentioned in Section 1.2. The adjacency matrix can be used to impose a structure on the matrix A. Given the matrix W, as extracted from a network, we can easily specify a spatial autoregressive (SAR) model (see Anselin (1988); LeSage and Pace (2009)):[6]

$$R_t - \mathbb{E}\left[R_t\right] = \rho W \left(R_t - \mathbb{E}\left[R_t\right]\right) + \bar{\beta} F_t + \eta_t, \tag{1.12}$$

where the (scalar) coefficient ρ captures the response of each asset to the returns of other assets, as weighted by the corresponding row of W. In the spatial econometrics literature, the matrix W is also called spatial proximity matrix as it represents *physical* distances between a set of subjects.

[5] Assuming normality for the model innovations η_t, such that $\eta_t \sim N\left(0, \Omega\right)$, we have that the reduced-form residuals follow the distribution $N(0, A(W)^{-1}\Omega_n A(W)^{-1})$, where the reduced residuals are $\epsilon_t^\star = A(W)^{-1}\eta_t$.

[6] Anselin (1988) calls the model mixed-regressive spatial-autoregressive. We stick here to the simpler acronym adopted in LeSage and Pace (2009).

In the following we use *spatial proximity matrix* as a synonym for *adjacency matrix*. Moreover, we assume that the error term η_t has a diagonal covariance matrix, that is, $\mathbb{V}[\eta_t] = \Omega_\eta$ is diagonal. Such an assumption is required for identification purposes, as we will discuss in the model estimation section. If we assume, as we will do in the following, that the matrix W is known, the expected returns are conditional upon the (known) W.[7]

We suggest calling the model in (1.12) as network-augmented linear factor model. At the single asset level, the model reads as follows:

$$R_{i,t} = \mathbb{E}[R_{i,t}] + \rho \sum_{j=1}^{k} w_{i,j} \left(R_{j,t} - \mathbb{E}[R_{j,t}]\right) + \bar{\beta}_i F_t + \eta_{i,t}, \tag{1.13}$$

where $w_{i,i} = 0$, $w_{i,j} \geq 0$ and $\sum_{j=1}^{k} w_{i,j} = 1$. Taking a financial point of view, the coefficients in the vector $\bar{\beta}_i$ represent the exposure to the common factors, or *exogenous* exposure, while the coefficient ρ tracks the *endogenous* risk exposure, which is influenced by the network structure and is thus called network exposure. Further insights on the interpretation of the model coefficients will be given in the following subsections.

The model network-augmented linear factor model of equation (1.12) can be rewritten in a more compact form as follows:

$$(I - \rho W)(R_t - \mathbb{E}[R_t]) = \bar{\beta} F_t + \eta_t, \tag{1.14}$$

thus highlighting the fact that spatial proximity and the associated SAR model give a structure to the contemporaneous relation matrix, which is now parametrized as

$$A = I - \rho W. \tag{1.15}$$

The structural model now includes contemporaneous relations, driven by links or connections across assets, systematic components and asset-specific shocks. In this model, despite the presence of linkages among the companies, for instance those associated with the supply chain, it might be the case that the linkages have no impact on the contemporaneous relationships among the companies' equity returns. Such a case can be easily identifies by a null ρ coefficient. We now elaborate on the relation between returns, risk, networks and risk factors.

[7] To maintain a simplified notation, we do not report the conditioning with respect to W in the returns expectations.

1.3.3 Returns, networks and risk factors

The reaction of one asset to common factors and network exposure becomes clearer once we rewrite the model in a reduced-form representation. In this way, we highlight the impact of the network connections included in W on the reduced-form parameters (the reduced-form betas and the reduced-form shock's covariance). The reduced-form representation of the network-augmented linear factor model reads as in equation (2.3) with $A = I - \rho W$ now:

$$\begin{aligned} R_t &= \mathbb{E}\left[R_t\right] + \left(I - \rho W\right)^{-1} \bar{\beta} F_t + \left(I - \rho W\right)^{-1} \eta_t && (1.16) \\ &= \mathbb{E}\left[R_t\right] + \beta^{\star} F_t + \epsilon_t^{\star}, && (1.17) \end{aligned}$$

where the factor loadings equal $\beta^{\star} = \left(I - \rho W\right)^{-1} \bar{\beta}$ and for the moment we assume that $A = I - \rho W$ is non-singular.[8] For simplicity, we focus on the case in which the network exposure is driven by a single parameter, ρ. However, all derivations and comments also apply to the more general parametrizations of the matrix A that we will introduce in Section 1.4.

From LeSage and Pace (2009) we take the following relation:

$$\left(I - \rho W\right)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 \ldots, \tag{1.18}$$

where the term ρW monitors the effect of linked assets (in spatial econometrics, the neighbours). For instance, if asset j is linked to asset i we have a non-null entry in W_{ij}. Differently, $\rho^2 W^2$ is associated with the effect on asset j induced by the assets linked to asset i (in spatial econometrics called the second-order neighbours). The latter relation can be further generalized to higher orders. Notably, the matrices W^j might also include a so-called *feedback loop* as, following the previous example, asset i can be linked to asset j (making the relation bidirectional), causing the matrix W^j to have non-null elements on the main diagonal. We stress that, despite the fact that the summation has an infinite number of terms, by imposing that $|\rho| < 1$ we can easily ensure that the effect of linked assets converges to a finite number. On the contrary, if $|\rho| > 1$ we might have explosive patterns. In general, the coefficient ρ takes values in the range $\left(\lambda_{min}^{-1}, \lambda_{max}^{-1}\right)$, with λ_{min} and λ_{max} respectively the minimum and maximum eigenvalues of W. In the case of row-normalization of the W matrix, in spatial econometrics a commonly adopted range is $[0, 1)$.

Using equation (1.18), we can rearrange the network-augmented linear factor model of equation (1.17) as

$$R_t = \mathbb{E}\left[R_t\right] + \bar{\beta} F_t + \sum_{j=1}^{\infty} \rho^j W^j \bar{\beta} F_t + \eta_t + \sum_{j=1}^{\infty} \rho^j W^j \eta_t. \tag{1.19}$$

Such a representation highlights that the impact of the common factors as well as that of

[8] See the model estimation section for details on the constraints that ensure non-singularity of A.

the idiosyncratic shocks on the risky asset returns can be decomposed into two parts. For both elements, the first component is the traditional, or direct, or structural impact of the structural common factor, while the second component is the impact associated with the network exposure. We can thus define the following four elements:

a) $\bar{\beta}$: the structural exposure to the structural common factor;

b) $\sum_{j=1}^{\infty} \rho^j W^j \bar{\beta}$: the network exposure to the structural common factor;

c) η_t: the idiosyncratic shocks;

d) $\sum_{j=1}^{\infty} \rho^j W^j$: the network impact of idiosyncratic shocks.

Note that the network-related exposures depend on the structure of the matrix W as well as on the parameter monitoring the network impact, ρ. A relevant remark can be made in relation to the network impact of common factors. Let us take, for simplicity, a specific common factor. That is, we focus on a single column of F_t and consider the impact of the m-th factor on the risky asset returns:

$$\beta_m^{\star} = \bar{\beta}_m + \sum_{j=1}^{\infty} \rho^j W^j \bar{\beta}_m. \tag{1.20}$$

Starting from the observation that the reduced-form betas equal the sum of two elements, equation (1.20) provides two relevant insights.

First, we note that the network exposure to common factors acts as a multiplier of the structural exposure if the coefficient ρ is positive (W's elements are positive anyway). Therefore, shocks to the common factors will be amplified by (i) the presence of connections across assets, that is, when, for asset i, the i-th row of W contains at least one non-null element, (ii) the change in the impact of network connections, that is, when the coefficient ρ increases, and (iii) by changes in the network structure, that is, when the matrix W changes. Note that, if asset i is not connected to other assets, all products $\rho^j W^j \bar{\beta}_i$ are equal to zero.

From a different viewpoint, the presence of network exposure allows us to decompose the reduced-form betas into two components, a structural one and a multiplier depending on the network structure, the matrix W. The estimation of a standard factor model, where the data-generating process includes network dependence across returns, will provide partial information, returning only the combination of the two components, that is, only the reduced-form betas. Furthermore, by using this model we can disentangle the presence of network effects-induced exposure to common factors from the structural exposure to common factors. If network effects do not play a role, we expect the ρ coefficient to be zero, that is the network among the companies has no impact on the contemporaneous relations between the equity returns of the companies.

Now assume that, for the risky asset i, the m-th common factor is not relevant (that is, $\bar{\beta}_{i,m} = 0$). In this case, in the standard linear factor models, the common factor will have no role in explaining the asset returns. However, when assets are linked and network exposures are taken into account, a common factor to which a risky asset has zero structural exposure might still be relevant for explaining the evolution of the risky asset return. Such an effect is not direct but induced from the network exposure and is associated with the existence of non-null elements in the i-th row of the matrix W. Take, for instance, the following case:

$$W = \begin{bmatrix} & \vdots & \\ \mathbf{0}_i & 1 & \mathbf{0}_{K-i-1} \\ & \vdots & \end{bmatrix}, \tag{1.21}$$

where asset i is connected only to asset $i+1$ and the subscripts denote the lengths of the row vectors of zeros. Moreover, assume the following factor exposure for both assets:

$$\bar{\beta} = \begin{bmatrix} & \vdots & & \\ \bar{\beta}_{1,i} & 0 & 0 & 0 \\ \bar{\beta}_{1,i+1} & \bar{\beta}_{2,i+1} & 0 & 0 \\ & \vdots & & \end{bmatrix}, \tag{1.22}$$

where, in a multifactor model, asset i is not exposed to factor 2, while asset $i+1$ is affected by the same risk factor, and both assets are exposed to factor 1. Asset i's dependence on risk factors can thus be represented as

$$\bar{\beta}_{1,i}F_{1,t} + \rho\bar{\beta}_{1,i+1}F_{1,t} + \rho\bar{\beta}_{2,i+1}F_{2,t} + \sum_{j=2}^{\infty}\left(\rho^j W^j \bar{\beta} F_t\right)|_i, \tag{1.23}$$

where $|_i$ identifies the i-th element of a vector. Note that equation (1.23) shows that, because of the network effect, asset i increases the exposure to factor 1 of $\rho\bar{\beta}_{1,i+1}$ and is indirectly exposed to factor 2 of $\rho\bar{\beta}_{2,i+1}$, and the last term on the right represents further elements that can be specified only through the knowledge of the entire matrix W. Therefore, even if risky asset i is not (structurally) exposed to a common factor (in the previous example, factor 2), the common factor will still play a role if it impacts on the returns of the assets to which i is linked.

Such a result can be further generalized by focusing, for instance, on sector-specific risk factors. Those factors, in the presence of a network exposure, despite being sector-specific, will have a systematic impact on all connected assets. Moreover, if we disregard the network exposure, we might also incur the risk of misinterpreting the impact of risk factors. In fact, by estimating the reduced-form model, we might label as *common* a factor that in reality is structurally related just to a subset of the investment universe and that impacts on other assets only through network connections.

A similar property exists for the idiosyncratic shocks. In fact, if we assume they are uncorrelated, the existence of network connections implies that the structural shocks of one asset impact on the returns of all the assets connected to it. Therefore, shocks on single assets can have effects on many other risky assets.[9] This evidence on the impact of a given asset's factor exposures and the shocks of linked assets resembles the decompositions typically adopted in spatial econometrics; see, among many others, LeSage and Pace (2009), as well as Ozdagli and Weber (2015) for a recent application. We note that the latter decompositions are appropriate in a framework where, for given dependent-variable measures across subjects, we have a number of covariates, each of which is available with variable-specific observations. In our case, we do have common factors (not asset-specific variables) and therefore these decompositions cannot be applied.

From a pricing perspective, starting from the reduced-form representation of the network-augmented linear factor model, it is possible to show that the expected returns equal

$$\mathbb{E}\left[R_t\right] = r_f + \bar{\beta}\Lambda + \sum_{j=1}^{\infty} \rho^j W^j \bar{\beta}\Lambda, \tag{1.24}$$

see Kou et al. (2017) for a formal proof. Expected returns are thus influenced by network links that amplify the compensation for being exposed to the common factors. Further, we note that the pricing result depends on, and is thus conditional upon, the network structure, as summarized by W, which we assume to be known and time invariant. In fact, if we postulate that the coefficient ρ is positive and that the elements of W are all positive, the existence of links across assets induces higher expected returns than in the case of links being absent. Moreover, bearing in mind the previous discussion, the expected returns might depend on risk premiums associated with factors to which a given asset is not directly (structurally) exposed. The model estimation section discusses further elaborations on the risk premiums that emerge as consequences of the risk premium estimation.

In addition, we stress that the use of a network that is very dense, thus implying a matrix W that is almost full, will have further impacts. In fact, a full W implies that all idiosyncratic shocks are correlated. However, from our viewpoint, this corresponds to indirect evidence of model misspecification as an additional common factor is now present but not taken into account. As a consequence, such common structural factor risk must be priced, and could generate the empirical evidence shown by Ang et al. (2006). The latter case could also correspond to empirical evidence challenging the validity of the APT approach. From a different viewpoint, our modelling framework still satisfies the assumptions required for APT. As we show in the next section, the presence of a network exposure, despite inducing correlation across the idiosyncratic shocks, does not exclude the existence of diversification benefits. In line with the network literature, we can also establish a link

[9] Summary measures of the exposure to common factors and idiosyncratic shocks can be obtained by mimicking the approaches used in spatial econometrics. A discussion on this topic is included in LeSage and Pace (2009); see their Section 2.7. These measures have been used in a financial framework by Asgharian et al. (2013). We also note that the decomposition of asset returns into four elements is equivalent to that proposed by Abreu et al. (2005) for separating the standard impact of covariates from the impact that is due to the spatial links, and is thus an alternative to the impact measures of LeSage and Pace (2009).

between our model and a measure of network centrality. In fact, Katz (1953) uses the expression in equation (1.18) to introduce his centrality measures. If we denote by $\mathbf{x}$ the score vector of the centrality, while W is the adjacency matrix, $\mathbf{1}$ a vector of ones, and α and C arbitrary constants, then Katz (1953) shows that the centrality vector equals

$$\mathbf{x} = (I - \psi W)^{-1}\mathbf{1}, \tag{1.25}$$

with ψ being a free parameter. Note that the ψ manages the relationship between the centrality vector $\mathbf{x}$ and a limiting constant value for all centrality scores. In other words, if ψ is zero all the nodes have the same centrality value. Otherwise, if ψ assumes increasing values,[10] then W plays an increasing role.

1.3.4 Risk decomposition and portfolio diversification

The network-augmented linear factor model of equation (2.2) allows us to recover a risk decomposition similar to that available for the standard linear factor model in equation (1.2). The starting point is the reduced form introduced in equation (1.17). In fact, equation (1.17) highlights that the estimation output of standard multifactor models can be consistent with the presence of contemporaneous links across assets, and this allows us to elaborate on the returns covariance structure. In fact, we can redefine $\mathcal{A} = (I - \rho W)^{-1}$, and then write the total variance of the risky assets as follows:

$$\mathbb{V}\left[R_t\right] = \mathcal{A}\bar{\beta}\bar{\beta}'\mathcal{A}'\sigma_m^2 + \mathcal{A}\Omega_\eta\mathcal{A}'. \tag{1.26}$$

Despite being equivalent to the traditional risk decomposition of a multifactor model, equation (1.26) provides a relevant insight. In fact, both the systematic and idiosyncratic risk components are influenced by the presence of interconnections across assets, as the matrix $\mathcal{A}$ appears in both terms on the right hand side. This also shows that, if we estimate the reduced-form model using standard linear methods, our evaluations of the systematic and idiosyncratic risk components are in reality a blend between the structural loadings and idiosyncratic risks, and the network relations. Keiler and Eder (2013) suggest that the presence of spatial links could be interpreted as a systemic risk contribution. However, the previous decomposition provides an alternative view, in which spatial dependence is not an additive source of risk but rather a multiplicative one. In that case, the impact of the spatial dependence of a single asset cannot easily be recovered. In fact, the contribution to the asset risk due to the spatial dependence depends on both the structure of the network W and the spatial parameter ρ. The two elements impact on the systematic contribution and on the idiosyncratic structural shock variances in a non-linear way. Obviously, the same structure appears at the portfolio level, where we have

[10] With an upper limit at $1/\lambda_{max}$, λ_{max} being the maximum eigenvalue of W, the value for which $(I - \psi W)^{-1}$ is non-singular.

$$\mathbb{V}\left[r_{p,t}\right] \quad = \quad \omega'\mathcal{A}\bar{\beta}\Sigma_F\bar{\beta}'\mathcal{A}'\omega + \omega'\mathcal{A}\Omega_\eta\mathcal{A}'\omega. \tag{1.27}$$

We first note that, if asset interconnections are not present (that is, when $\mathcal{A} = I$), the idiosyncratic risk equals Ω_η while the systematic risk component is $\bar{\beta}\Sigma_F\bar{\beta}'$. We rewrite the portfolio variance decomposition in equation (1.27) by adding and subtracting the portfolio idiosyncratic and systematic variance components when they are not influenced by asset interconnections:

$$\mathbb{V}\left[r_{p,t}\right] \quad = \quad \omega'\mathcal{A}\bar{\beta}\Sigma_F\bar{\beta}'\mathcal{A}'\omega + \omega'\mathcal{A}\Omega_\eta\mathcal{A}'\omega \pm \omega'\bar{\beta}\Sigma_F\bar{\beta}'\omega \pm \omega'\Omega_\eta\omega. \tag{1.28}$$

With some rearrangement, the total portfolio variance can be recast into a decomposition comprising four different terms:

$$\mathbb{V}\left[r_{p,t}\right] \quad = \quad \underbrace{\omega'\bar{\beta}\Sigma_F\bar{\beta}'\omega}_{I} + \underbrace{\left(\omega'\mathcal{A}\bar{\beta}\Sigma_F\bar{\beta}'\mathcal{A}'\omega - \omega'\bar{\beta}\Sigma_F\bar{\beta}'\omega\right)}_{II} \tag{1.29}$$

$$+ \quad \underbrace{\omega'\Omega_\eta\omega}_{III} + \underbrace{\left(\omega'\mathcal{A}\Omega_\eta\mathcal{A}'\omega - \omega'\Omega_\eta\omega\right)}_{IV}. \tag{1.30}$$

We make the following interpretations of the four risk components derived from our network-augmented linear factor model:

I the structural systematic risk component that depends on the structural loadings from the common factors and from the covariance of the common factors; this is the *exogenous* systematic effect;

II the effect of asset interconnections on the systematic risk component, or the first contribution of network exposure to the total risk; this is the *endogenous* systematic effect;

III the structural idiosyncratic component that depends only on the covariance of the structural shocks;

IV the effect of interconnections on the idiosyncratic risk, or the second contribution of network exposure to the total risk; this might be interpreted as an *endogenous* amplification of idiosyncratic risks.

Note that by adding the second and fourth terms we obtain the total contribution of network exposure to the total portfolio risk. We finally note that the model with asset interconnections is the standard multifactor model if there are no interconnections, that is if W is a null matrix or if the coefficient ρ is *zero*.

In addition, the network exposure impacts on the idiosyncratic part of the variance. This implies that the diversification benefits might be endangered, depending on the network structure. In fact, despite the fact that the fourth term decreases with an increase in these cross-sectional dimensions, the speed of decrease is smaller than in the case without network effects.

Similarly to the standard linear factor model, we can recover analytical elements in a simplified setting. The covariance matrix Ω_η is diagonal; we further assume that the diagonal elements are set to an average value, $\bar{\sigma}^2 = 1$. In addition, we take an equally weighted portfolio and focus on the limiting case in which all assets are connected (thus W has zeros only over the main diagonal, while off-diagonal terms equal $\frac{1}{K-1}$ after row normalization). In this case, we have that

$$\begin{aligned} \omega' \mathcal{A} \Omega_\eta \mathcal{A}' \omega &= \bar{\sigma}^2 \omega' \mathcal{A}\mathcal{A}' \omega \\ &= \frac{\bar{\sigma}^2}{K^2} \mathbf{i}_K' \mathcal{A}\mathcal{A}' \mathbf{i}_K \\ &= \frac{K+\rho^2}{(K+\rho)^2 (\rho-1)^2} \bar{\sigma}^2, \end{aligned} \tag{1.31}$$

where K is the number of assets and $\mathbf{i}_K$ is a K-dimensional vector of ones.[11] Moreover, we have that

$$lim_{K\to\infty} \frac{K+\rho^2}{(K+\rho)^2 (\rho-1)^2} \bar{\sigma}^2 = 0, \tag{1.32}$$

thus preserving the diversification benefit. However, the idiosyncratic risk contribution is higher than in the case without spatial dependence (i.e. with $\rho = 0$). In fact, we can show that the above-reported portfolio idiosyncratic risk is higher than $\frac{1}{K}\bar{\sigma}^2$, thus confirming that term IV is positive.

The previous model thus gives a framework in which we can analyse the impact at the portfolio level of the interconnections we might observe across assets, and how those interconnections can endanger/limit the benefits of portfolio diversification.

1.4 Model Generalizations

In this section we provide two generalizations of the network-augmented linear factor model by allowing asset-specific reaction to the network and introducing a time change into the network structure. We also add further discussion on the model's interpretation, in particular on the sign of the network-related parameters.

[11] In the special case considered, the diagonal elements of $\mathcal{A}$ equal $\frac{(K-1)\rho-K}{\rho^2+(K-1)\rho-K}$ and the off-diagonal elements are $\frac{-\rho}{\rho^2+(K-1)\rho-K}$. Moreover, the diagonal elements of $\mathcal{A}\mathcal{A}$ equal $\frac{K\rho^2+[(K-1)\rho-K]^2}{[\rho^2+(K-1)\rho-K]^2}$ and the off-diagonal are $\frac{(K-1)\rho^2-2\rho[(K-1)\rho-K]}{[\rho^2+(K-1)\rho-K]^2}$. Summing up the elements in $\mathcal{A}\mathcal{A}$ and simplifying, we obtain the above-reported result.

1.4.1 Heterogeneous network reaction

The model in equation (1.14), despite being coherent with the presence of network links, has a very restricted structure. There is a single parameter, ρ, driving the network exposure. This can easily be generalized by allowing asset-specific responses to the network structure. We can thus modify the contemporaneous relation matrix of equation (1.15) into

$$A = I - \mathcal{R}W, \tag{1.33}$$

where $\mathcal{R} = diag(\rho_1, \rho_2, \ldots, \rho_K)$ is a diagonal matrix. This model is similar to the fixed coefficient specifications for spatial panels discussed in Elhorst (2003). A clear advantage of such a structure is given by the possibility that assets have different network exposures, as for each asset the model becomes

$$R_{i,t} = \mathbb{E}\left[R_{i,t}\right] + \rho_i \sum_{j=1}^{k} w_{i,j}\left(R_{j,t} - \mathbb{E}\left[R_{j,t}\right]\right) + \bar{\beta}_i F_t + \eta_{i,t}. \tag{1.34}$$

To estimate the asset-specific parameters, the network must satisfy an identification condition: each asset must be connected to at least one other asset. If this is not the case, the diagonal of matrix $\mathcal{R}$ must be restricted in such a way that unconnected assets will not have a network exposure. Further details will be discussed in the estimation section.

1.4.2 On the sign of the coefficient ρ

Up to this point, we have not discussed the sign of the coefficient ρ. Intuitively, we expect the assets to be positively related to one another, as the links come from a network. We thus imagine that shocks are transmitted to connected assets with their signs preserved. If we take a simplified model with a single coefficient ρ, it is highly improbable that we will ever observe negative coefficients. In fact, a single coefficient represents a sort of average reaction of the asset to the shocks coming from its neighbours.

However, in a model accounting for the heterogeneity of the reaction to the network exposure, negative asset-specific coefficients might appear. In other words, we cannot exclude a priori that a shock to one asset will lead to an opposite movement of a linked asset. We explain such a finding by making a parallel with negative correlations. If two assets are negatively correlated, their joint introduction to a portfolio will lead to a decrease of the overall variance. In a factor model, negative correlations across asset returns can be interpreted by loadings on the (same) common factors having different signs. In our framework, negative correlations across asset returns can emerge both in response to different signs in the factor loadings but also due to the presence of a negative asset-specific reaction to the network exposure.

Consider the reduced form of our model as represented in equation (1.30). In this case, the innovation term has a non-diagonal covariance. If we estimate the reduced-form model, the innovations could show evidence of non-null correlations, some of them being negative. They can be due both to the presence of opposite exposure to the common structural factors, whose coefficients have been estimated by a biased estimator (due to model misspecification), but also due to the presence of negative coefficients ρ_i.

In a general model with heteregeneous asset reactions to the network exposure, the components II and IV in the risk decomposition presented in equation (1.30) can become negative. In such a case, the network exposure reduces risk, and this could also be seen as a kind of flight-to-safety effect: if shocks hit financial assets and are then transmitted to industrial pro-cyclical sectors, we cannot exclude the possibility that the anti-cyclical sectors have an opposite network exposure.

Within our model, negative ρ might thus exist, but how can we interpret them from a pricing perspective? We read them as evidence of risk absorption due to the network exposure. In fact, a negative ρ_i allows a reduction of the exposure of one asset to the common factors, since the i-th component of the second term in equation (1.20) becomes negative. Risk absorption also has consequences for expected returns, leading to a reduction of the contribution of network exposure. In fact, the i-th component of the third term in equation (1.37) also becomes negative.

1.4.3 Time change in the network structure

The spatial econometrics literature generally assumes that the spatial proximity matrix is time invariant. In fact, if the matrix W depends on physical measures, such as those is the spatial distance, they can safely be assumed to be constant over time. However, in a financial framework, the connections between assets might change over time for a number of reasons, such as, for instance, the occurrence of an unexpected market shock, or a merger or acquisition. Similar approaches have been adopted by Asgharian et al. (2013) and Keiler and Eder (2013). We are still assuming that the network is exogenous with respect to the linear structural model,[12] and the contemporaneous matrix can be further rewritten as

$$A_t = I - \mathcal{R}W_t, \tag{1.35}$$

where we highlight that the network changes over time, and thus leads to a time-varying matrix W. In turn, this induces time-dependence on the matrix A, as well as on the reduced-form parameter matrices, both on the betas and on the covariance of idiosyncratic shocks. That is, we also have heteroskedasticity. Nevertheless, we might postulate that the dynamic of W_t is smooth, and operates at lower time scales than those monitoring the evolution of returns (for instance, we can assume the matrices W change over the years, or after specific events such as crises). Therefore, the heteroskedasticity is mild, and the betas are evolving slowly. The use of time-varying matrices

[12] We might relax the exogeneity assumption by stating that the network is known conditional upon the past.

W thus leads to a time change in the spatial dependence, differing from the approach of Blasques et al. (2016) who obtain the same result by letting the parameters $\mathcal{R}$ be time-varying. We note that, if the network exposure exists and the structural parameters in the matrix $\bar{\beta}$ are constant, the estimation of the reduced-form model over different samples might suggest changes in the factor exposure. However, those changes are not present but are due to the misspecification of the network relations. The expected returns are conditional upon the matrix W. If the network exposure is time-varying, the expected returns, conditional on W_t, are also time-varying.

A further issue associated with the change in W_t over time is the normalization. In fact, if we let each single W_t be row normalized, we could reduce the impact of changes in the network density: an increase in the number of assets linked to asset j would lead to a decrease in the impact arising from a single asset, since the corresponding element of W_t would diminish. As a consequence, with the introduction of the dynamic W_t we also suggest considering a different normalization, which we refer to as a *max row normalization*. Formally, a non-normalized W_t^U will be normalized as

$$W_{i,j,t} = W_{i,j,t}^U \left(max_t \sum_{i=1}^{N} W_{i,j,t}^U \right)^{-1}. \tag{1.36}$$

We stress that, when conditioning on the network structure, the pricing equation changes with respect to that in Kou et al. (2017). In fact, the pricing equation, for the most general network-augmented linear factor model, assumes the following form (in which we have also introduced asset-specific coefficients for network exposure):

$$\mathbb{E}\left[R_t|W_t\right] = r_f + \bar{\beta}\Lambda + \sum_{j=1}^{\infty} \left(\mathcal{R}W_t\right)^j \bar{\beta}\Lambda. \tag{1.37}$$

The heterogeneity with respect to connections creates reactions to shocks on the common factors that differ across assets due to the different exposures of assets to the factors, but also due to the differing impacts of feedback loops coming from the underlying network structure. The change over time of the matrix W_t, or the presence of a structural break on the coefficients $\mathcal{R}$ (that we might find located close to the time of a crisis or extreme event), creates abrupt changes in the expected returns, and relevant movements in stock prices as a consequence. Therefore, the pricing, conditional upon the network structure, becomes a function of the network structure: if the network changes, the *local equilibrium* expected returns change. When we introduce a time variation into the matrices W, or into the elements $\mathcal{R}$, we must estimate risk premiums in the cross-sectional dimension. However, differently from standard approaches, we should use reduced-form model parameters and account for their time variation, as we will show in Section 1.5.1. We stress that, if we focus on a standard pricing model, we neglect the potential time variation in the expected returns, with a possible impact on the estimation of the risk premiums. As an alternative approach, we could estimate the risk premium by taking the evolution of the network structure into account. However, this requires an assumption of the stochastic process that governs the network evolution.

The latter is well beyond the task of this paper and is left to upcoming research. In Section 6 we focus on a special case for the network evolution, and we show how correctly accounting for the time-variation of the network structure provide an improvement in the efficiency of risk premium estimators.

1.5 Model Estimation

In Sections 3 and 4 we formally introduced the theoretical framework of this paper, we described the network-augmented linear factor model and provided a number of model generalizations. In this Section, we first discuss the approach we propose to estimate model parameters, i.e. the factor structural loadings $\bar{\beta}$, the network impact parameters ρ_i, $i = 1, 2, \ldots k$ included in the matrix $\mathcal{R}$, the error covariance Ω_η, and the expected returns. Second, we move to the estimation of the risk premiums following a two-step approach, which is conditionally to the availability of the estimates of the model parameters. Both approaches pose various challenges that are related to the model structure, in particular from the existence of contemporaneous dependence driven by the network.

For estimating parameters let us consider the simultaneous equations model

$$AR_t = \alpha + \bar{\beta} F_t + \eta_t. \tag{1.38}$$

Identification conditions are required to estimate the parameters of A, α, $\bar{\beta}$ and the (diagonal) covariance matrix of η_t. The simple order condition of identification requires that the model parameters must be less than the parameters we can recover from the reduced-form specification. In fact, the latter can be estimated by least squares methods, and the structural parameters can be recovered thanks to their relation to the reduced-form parameters. The reduced-form model is

$$\begin{aligned} R_t &= A^{-1}\alpha + A^{-1}\bar{\beta} F_t + A^{-1}\eta_t & (1.39) \\ &= \alpha^\star + \beta^\star F_t + \varepsilon_t^\star, & (1.40) \end{aligned}$$

suggesting we can consistently estimate $K(M+1)$ mean parameters plus $\frac{1}{2}K(K+1)$ covariance parameters, where M is the number of factors and K the number of assets. However, an unrestricted structural specification, despite having the same number of parameters in the covariance, has $MK + K$ mean parameters.

The presence of asset interconnections, summarized into a network, allows a sensible reduction of the number of parameters included in the matrix A. In fact, if we have asset-specific network exposures and a single network, we have only K parameters in A. However, this is not sufficient to provide identification of the model's remaining parameters, since the order condition is still not satisfied. Identification is obtained by imposing the diagonality of the covariance matrix of η_t. Such a choice, which is economically motivated, allows the standard order condition for identification to be satisfied.

Nevertheless, further constraints on the model parameters are generally required. Starting from the spatial econometrics literature, which takes a scalar time-invariant coefficient ρ and a time-invariant row-normalized matrix W, we must impose $\frac{1}{\lambda_{min}} < \rho < \frac{1}{\lambda_{max}}$, where λ_{min} and λ_{max} are, respectively, the minimum and maximum eigenvalues of W. This constraint ensures the non-singularity of $A = I - \rho W$.

In our framework, we deviate from traditional approaches in several ways. We first consider the case of a time-varying adjacency matrix, that is, W_t. A sufficient condition for the invertibility of $I - \rho W_t$ for all t is stated in the following assumption:

Assumption 1.5.1 *The coefficient ρ satisfies the following condition:*

$$\bar{\lambda}_{min}^{-1} < \rho < \bar{\lambda}_{max}^{-1}, \tag{1.41}$$

where

$$\bar{\lambda}_{max} = \mathtt{min}\left\{\lambda_{t,max}\right\}_{t=1}^{T} \tag{1.42}$$

$$\bar{\lambda}_{min} = \mathtt{max}\left\{\lambda_{t,min}\right\}_{t=1}^{T} \tag{1.43}$$

and $\lambda_{t,max}$ and $\lambda_{t,min}$ are, respectively, the minimum and maximum eigenvalues of a matrix W_t.

If we have a diagonal matrix $\mathcal{R}$ containing the asset-specific reaction to the spatial links, we assume the non-singularity, which is then validated in the estimation step of the model:

Assumption 1.5.2 *The diagonal coefficient matrix $\mathcal{R}$ is such that*

$$I - \mathcal{R}W_t \tag{1.44}$$

is non-singular for each matrix W_t.

Note that the previous assumption covers both the case of a time-invariant and that of a time-varying adjacency matrix. We further note that, when we consider a model with $\mathcal{R}$, we must impose an additional identification condition:

Assumption 1.5.3 *The diagonal coefficient matrix $\mathcal{R} = diag\left(\rho_1, \rho_2, \ldots, \rho_K\right)$ is such that $\rho_j = 0$ if the matrix $W_j = \left[W'_{j,1} W'_{j,2} \ldots W'_{j,T}\right]$, with $W_{j,t}$ being the j-th row of W_t, has non-null rank.*

The previous assumption requires, irrespective of the number of matrices W_t, that if the j-th rows of all the matrices W_t contain only zeros (that is, the asset j is not linked to any other asset in the varying evolution of the network), then the asset j's network impact coefficient is restricted to zero as it cannot be identified. This condition ensures that the asset-specific impact on the network links is estimated only if such links exist for at least one point in time.

The use of covariance restrictions has a consequence for the estimation of the model parameters. In fact, they must be jointly evaluated, despite the fact that the linear model structure might allow for single-equation (single-asset) parameter estimation.

Under the two strong parametric restrictions we impose (the structure on A and the absence of correlation across the idiosyncratic shocks), a viable approach is the Full Information Maximum Likelihood (FIML) method. However, if K is even moderately large, the total number of parameters to be estimated in the restricted structural model, MK, might be quite large. Fortunately, we can follow the approaches commonly used in spatial econometrics, namely the use of concentrated likelihoods. As in Elhorst (2003), and LeSage and Pace (2009), we start by writing the full model's log-likelihood assuming Guassianity:[13]

$$
\begin{aligned}
L(\Theta) &= \sum_{j=1}^{T} l_t(\Theta), & (1.45)\\
l_t(\Theta) &\propto -\frac{1}{2}log|\Omega| - \frac{1}{2}e_t'\Omega^{-1}e_t, & (1.46)\\
e_t &= R_t - \bar{\alpha} - \mathcal{R}WR_t - \bar{\beta}F_t, & (1.47)
\end{aligned}
$$

where Ω is a diagonal matrix. If the parameters in $\mathcal{R}$ are known, we can write

$$R_t - \mathcal{R}WR_t = Z_t = \bar{\alpha} + \bar{\beta}F_t + \varepsilon_t. \quad (1.48)$$

Therefore, with a known network exposure parameter matrix $\mathcal{R}$, with a unique (and even time-variant) network structure, we can estimate the parameters in $\bar{\alpha}$ and in $\bar{\beta}$ by least squares methods, obtaining the well-known expressions. In addition, we can even recover standard estimators for the innovation variance. This suggests that the network exposure parameters can easily be obtained by maximizing the concentrated likelihood obtained by replacing the other parameters with their least squares estimators.[14]

We thus define $Z = [Z_1', Z_2', \ldots Z_T']$, $X_t = [1, F_t]$, $X = [X_1', X_2', \ldots X_T']$ and the least squares estimators of $\bar{\alpha}$ and $\bar{\beta}$ from (1.48) equal

$$\begin{bmatrix} \widehat{\bar{\alpha}}(\mathcal{R}) \\ \widehat{\bar{\beta}}(\mathcal{R}) \end{bmatrix} = \left(X'X\right)^{-1} X'Z \quad (1.49)$$

highlighting that the least squares estimates are functions of the network-related parameters included in $\mathcal{R}$. Similarly, the, variance parameters of ε_t correspond to the variance of $\widehat{\varepsilon}_t(\mathcal{R}) = Z_t -$

[13] We use a Normality hypothesis only for simplicity. More general distributions might be used or, alternatively, we might resort to Quasi-Maximum-Likelihood approaches which are anyway based on a Normal likelihood.

[14] This is of relevant computational importance as it allows us to reduce the parameters to be jointly estimated to $2K$ if we concentrate the likelihood with respect to $\bar{\alpha}$ and $\bar{\beta}$, and to K if we also concentrate with respect to the innovation variance. Standard errors can be recovered from the full-model likelihood by making numerical evaluations of the Hessian (and of the gradient if we take a robust-parameters covariance matrix).

$\widehat{\widehat{\alpha}}(\mathcal{R}) - \widehat{\widehat{\beta}}(\mathcal{R}) F_t$. If we use those least-squares estimators to replace the corresponding parameters within the likelihood function, we obtain a concentrated likelihood function depending only on the network-related parameters.

Using concentrated likelihood allows us, at no cost, to deal with zero restrictions added to specific parameters of $\mathcal{R}$, and to easily ensure model identifications. Furthermore, the estimation approach outlined above is also valid when a time-varying adjacency matrix W_t is given. In fact, we postulate that the sequence of W_t is known. Therefore we estimate the model parameters conditional to the sequence of adjacency matrices. In that case, we just have to define Z_t as

$$Z_t = R_t - \mathcal{R} W_t R_t. \tag{1.50}$$

Note that the only difference between (1.48) and (1.50) is in the time-varying nature of the network. Further, we point out that our framework accounts for cross-sectional dependence among the variables through the network, i.e. the time-varying adjacency matrices W_t. However, we cannot exclude a-priori that the networks might be affected by measurement errors. In fact, from an economic viewpoint, the networks might be estimated rather than observed. In a cross-sectional framework Conley (1999) discusses the estimation of a liner model where subjects are cross-sectionally correlated by means of an economic notion of distance and the distance might be measured with error. His work focuses on the estimation of the covariance matrix, which is contaminated by such an economic driven spatial correlation. We differ from his approach in both the presence of a dynamic network as well as for the specific heterogeneous impact that the network has over the asset returns. In the simulation section we have a closer look on the evaluation of the effects due to the time-varying networks on the asymptotics of the network effects measured by the parameters included in $\mathcal{R}$.

1.5.1 Risk premium estimation

We now tackle the crucial issue of risk premium estimation in our framework. The literature generally follows two approaches, the Fama and French (1993) or the Fama and MacBeth (1973) method. Similarly to Ahern (2013), for the network factors, we follow the Fama and MacBeth (1973) two-pass method. Therefore, we plan to estimate the risk premiums starting from the time-series estimate of the betas and then taking a cross-sectional regression. We thus stress that the risk premiums estimations comes after the estimation of the model parameters.

To highlight the links existing between the traditional multifactor model and our proposal, we first rewrite the two models, the linear factor model and the factor model augmented with network-driven contemporaneous relations, respectively, reporting the second in its reduced-form representation:

$$\begin{aligned} R_t &= \alpha + \beta F_t + \varepsilon_t \\ R_t &= \alpha^\star + \beta^\star F_t + \varepsilon_t^\star. \end{aligned} \tag{1.51}$$

Under the traditional factor model, in which the M factors do have a zero mean, the Fama-McBeth procedure corresponds to a collection of K time-series regressions of the form

$$R_{i,t} = \alpha_i + \beta_i F_t + \varepsilon_{i,t}, \tag{1.52}$$

followed by a cross-sectional regression

$$R^e = \hat{\beta}\Lambda + \nu, \tag{1.53}$$

where R^e is the K-dimensional vector of the sample averages of excess returns, $\hat{\beta}$ is the K-by-M matrix of (least squares) factor loadings estimates and Λ is the unknown vector of risk premiums. The estimates suffer from the error-in-variable issue. In the empirical part we manage the error-in-variable issue by working on industry portfolios. Further, we introduce the Shanken (1992) correction into the estimation of the standard errors.

We start by focusing on the case with heterogeneous network impact and time-invariant W. In that case, the risk premiums and the expected asset returns satisfy the following equilibrium condition:

$$\mathbb{E}\left[R_t\right] = r_f + \bar{\beta}\Lambda + \sum_{j=1}^{\infty} \mathcal{R}^j W^j \bar{\beta}\Lambda = r_f + \beta^\star\Lambda. \tag{1.54}$$

Therefore, in our model, the estimation of the risk premium using the Fama-McBeth approach points at using the reduced-form factor loadings $\beta^\star$. Consequently, we first estimate the model and then run the cross-sectional regression

$$\bar{R}^e = \widehat{\beta^\star}\Lambda + \nu^\star, \tag{1.55}$$

where we have replaced the reduced-form betas with their estimates. By simple comparison of the two second-stage (cross-sectional) regressions, we can state the following proposition:

Proposition 1.5.1 *If the true model includes a contemporaneous relation driven by a time-invariant network with heterogeneous asset impact, the Fama-McBeth approach based on ordinary least squares (OLS) leads to a consistent estimation of the risk premiums even if we estimate the factor loadings using the misspecified traditional factor model. In other words, the OLS estimates of Λ based on $\hat{\beta}$ and $\hat{\beta}^\star$ do coincide.*

Proof. This is a consequence of the fact that, if W is time-invariant, the least squares estimator applied to the model in equation (1.52) provides a consistent estimate of our model's reduced-form betas, $\beta^\star$. In other words, $\beta \equiv \beta^\star$, and thus the risk premiums also coincide. The same result will arise when noticing that the expected returns are functions of the reduced form betas. An alternative proof might be obtained by generalizing the framework of Kou et al. (2017) by introducing heterogeneous network impact and adapting their proof. ■

Few remarks are then needed. First, the previous result holds in the special case of scalar or heterogeneous network impact with time invariant networks. Second, the result holds only for the point estimates of the risk premiums and only if we estimate the premiums by standard least squares. This is due to the fact that, under our model, the covariance of $\varepsilon_t^\star$ has a known structure that depends on the network, i.e. the matrix W, and on the parameters included in $\mathcal{R}$. This covariance differs from the estimated covariance of ε_t under the multifactor model. Consequently, inference provides, potentially, different outcomes, that is different standard errors. Furthermore, if we adopt generalized least squares, even the (small-sample) point estimates differ. Finally, the innovations in (1.55) are likely affected by cross-sectional dependence due to spatial, i.e. network driven, interactions. In a time-invariant network case, one might use instead the covariance matrix estimator proposed by Conley (1999).

The previous proposition allows us to highlight that, when the network is time-invariant, the risk premium estimation is unaffected by the model misspecification, i.e. the absence of network-driver interdependence among assets. Consequently, our model's main contributions are as follows: (i) the ability to disentangle the structural and the network-induced factor exposure; (ii) the possibility of capturing correlation in the residuals of traditional linear factor models; (iii) the possibility of showing that diversification benefits are weaker than expected.

When the network is dynamic, the expected returns are characterized by

$$\mathbb{E}\left[R_t|W_t\right] = r_f + \bar{\beta}\Lambda + \sum_{j=1}^{\infty} \mathcal{R}^j W_t^j \bar{\beta}\Lambda = r_f + \beta_t^\star \Lambda. \tag{1.56}$$

We first point out that the reduced-form betas are time-varying, being equal to $\beta_t^\star = (1 - RW_t)^{-1}\bar{\beta}$, while we have time-invariant risk premiums.

From the previous expected return relation we have that, under our model with time-varying networks, the **classical** Fama-McBeth approach for risk-premium estimation involves a second-stage cross-sectional regression in which, if we still focus on reduced-form betas, we must account for the fact that those betas are time-varying. Despite this, the model structure allows to apply the classical Fama-McBeth approach after a filtering step. In fact, instead of working with reduced form betas, we might account for the network dependence on the left hand side of the pricing equation (1.56), and the structural betas on the right hand side, as follows:

$$\left(I - \mathcal{R}W_t\right)\left(\mathbb{E}\left[R_t|W_t\right] - r_f\right) = \bar{\beta}\Lambda. \tag{1.57}$$

Note that

$$(I - \mathcal{R}W_t)\left(\mathbb{E}\left[R_t|W_t\right] - r_f\right) = \mathbb{E}\left[(I - \mathcal{R}W_t)\left(R_t - r_f\right)|W_t\right], \tag{1.58}$$

since we are evaluating expected returns, conditionally to the knowledge of the network dynamic. Consequently, based on the first pass estimates, where we evaluate our returns model augmented with network dependence, we can filter out the network-driven cross-sectional dependence from the left hand side of the pricing equation computing the quantities

$$Z_t = (I - \mathcal{R}W_t)\left(R_t - r_f\right) \tag{1.59}$$

and then perform the Fama-McBeth approach on

$$Z^e = \hat{\bar{\beta}}\Lambda + \nu, \tag{1.60}$$

where Z^e are time averages of Z_t and $\hat{\bar{\beta}}$ denotes the estimated structural betas obtained from the model.

We can highlight the impact of our methodology by comparing the estimation of the risk premiums including time-invariant reduced form betas estimated from a misspecified linear factor model, with the risk premiums obtained following our procedure. In principle, the two approaches should lead to different estimates of the risk premiums.

However, the evolution of the network also plays a role. In fact, the time-varying network structure lies between two extreme cases, the full connection case where $W_t = \frac{1}{K-1}\left(\mathbf{ii}' - I\right)$ and the absence of connections, i.e. $W_t = 0$. This is a consequence of the spatial interpretation of the matrices W_t and of normalization rule we adopted.[15] Further, the time evolution of the reduced form betas, for a given vector of structural betas, is bounded, and oscillates around the, given, structural betas values. The latter is a consequence of

$$\beta_t = \bar{\beta} + \sum_{j=1}^{\infty} \mathcal{R}^j W_t^j \bar{\beta} \tag{1.61}$$

combined with the bounded structure of W_t and with the constraints that the parameters in $\mathcal{R}$ must satisfy. Therefore, for an increasing sample size, we postulate that the betas estimated from a classical linear factor model converge to the average of the time-varying reduced form betas. In turn, the average is also close to the structural beta vector due to the standardization that provides W_t matrices with elements, on average, relatively small. Consequently, we expect that the estimation of the risk premium from a misspecified linear factor model and from our methodology, based on network-filtered returns Z_t, will be close. In addition, given that our approach accounts for the time-varying nature of reduced form betas in the computation of Z_t, we expect differences in terms of the estimators efficiency. We verify these elements by means of simulations.

[15] We also remind that the networks and the parameters in $\mathcal{R}$ are such that $I - \mathcal{R}W_t$ is always non-singular.

1.6 Simulation Analysis

To show the capabilities of the proposed framework and to underline the effect due to model misspecification, that is, neglecting the network links across assets, we include in this section a set of simulations.

1.6.1 Scalar network impact

First, we concentrate on the simplest network-augmented linear factor model, with time-invariant W and scalar ρ. Such a baseline design will provide some expected results, as we will point out in a few lines. The first data-generating process we consider is a linear factor model with a unique risk factor, a scalar network impact and a fixed (and known a priori) network matrix W:

$$(I - \rho W)(R_t - \mathbb{E}[R_t]) = \bar{\beta} F_t + \eta_t, \tag{1.62}$$

with the following specification for parameters, shocks and asset interconnections:

- We consider $K = 100$ assets, thus focusing on a somewhat large cross-sectional dimension, and assume we simulate monthly returns.
- The coefficient ρ assumes fixed values $\rho \in \{0, 0.25, 0.5, 0.75\}$, allowing us to compare the case of no network impact with different and increasing levels of network impact; note that, when $\rho = 0$, our model collapses to the traditional linear factor model.
- The factor loading coefficients are randomly generated from $\beta_i \sim \mathcal{U}(0.8, 1.2)$, $i = 1, 2, \ldots, K$, giving positive factor loadings with an average value of 1.
- We simulate the factor returns from a Gaussian density, $F_t \sim \mathcal{N}\left(\mu_F, \sigma_F^2\right)$ with $\mu_F = 0$ and $\sigma_F = 15\%$, on a yearly basis.
- The risky asset's expected return equals $\mathbb{E}[R_t] = r_f + (I - \rho W)^{-1} \beta\Lambda$, β being the K-dimensional vector of betas simulated above, while the factor risk premium equals 5% on a yearly basis, and the risk-free rate is set to 1% on a yearly basis.
- The matrix W comes from a simple and naive design: each of its off-diagonal elements is extracted from a Bernoulli density $w_{i,j} \sim \mathcal{B}(p_B)$ with $p_B = 0.3$; the simulated W is then row-normalized.
- The shocks are extracted from a Gaussian $\eta_t \sim \mathcal{N}(0, \Omega)$, with Ω being a diagonal matrix with diagonal elements extracted from a uniform, $\omega_{i,i}^{\frac{1}{2}} \sim \mathcal{U}(10\%, 25\%)$ with limits referring to a yearly horizon.
- We simulate 500 sequences of monthly returns with three different sample sizes, $T = 200, 500$ and 1000.

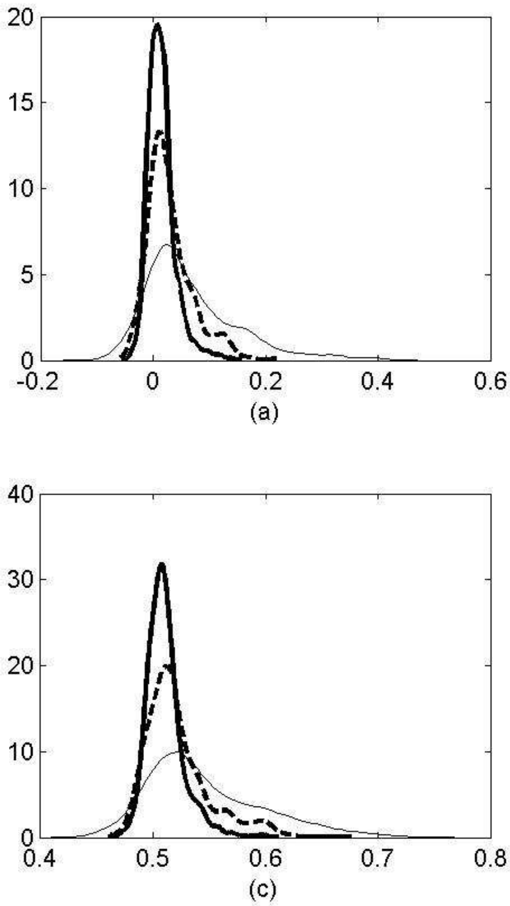


Figure 1.1: Distortions of the coefficients ρ under the correctly specified model. True values: (a) $\rho = 0$, (b) $\rho = 0.25$, (c) $\rho = 0.5$ and (d) $\rho = 0.75$. Lines refer to different sample sizes, $T = 200$ thin grey line, $T = 500$ dashed line and $T = 1000$ thick black line.

We proceed to the estimation of the model parameters by Concentrated Maximum Likelihood methods. The baseline simulation provides expected results. Firstly, the estimators of the coefficients ρ and of the (structural) vector β have an asymptotically normal density with dispersion decreasing with the sample size (see Table 1.1). Figure 1.1 reports a kernel estimate of the distortion $\hat{\rho} - \rho$ across different values of ρ, while Figure 1.2 provides a kernel density for the cross-sectional average (over the assets) of the distortions $\hat{\beta}_i - \beta_i$, $i = 1, 2, \ldots, K$; all graphs show the plots for the three different sample sizes. We note that the coefficients converge to the true values and that their dispersion decreases with the sample size, as expected.

If we estimate a standard linear factor model on the series simulated from equation (1.62), that is, we fit

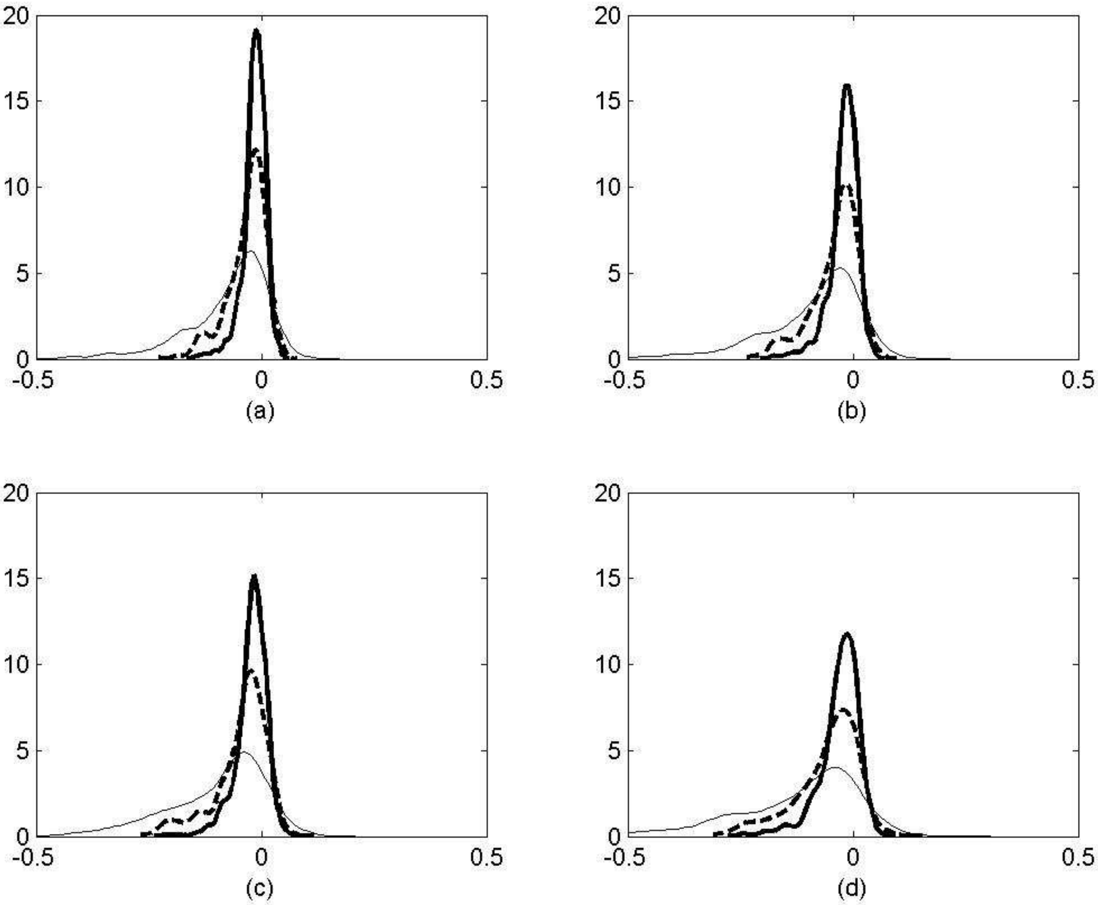


Figure 1.2: Cross-sectional average of the distortions for the coefficients β under the correctly specified model across different values of ρ. True values: (a) $\rho = 0$, (b) $\rho = 0.25$, (c) $\rho = 0.5$ and (d) $\rho = 0.75$. Lines refer to different sample sizes, $T = 200$ thin grey line, $T = 500$ dashed line and $T = 1000$ thick black line.

T	$\rho = 0$		$\rho = 0.25$		$\rho = 0.5$		$\rho = 0.75$	
	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev
				Distortions for ρ				
200	0.067	0.084	0.062	0.075	0.050	0.058	0.028	0.032
500	0.029	0.040	0.028	0.037	0.024	0.030	0.014	0.017
1000	0.015	0.024	0.014	0.023	0.012	0.019	0.007	0.011
				Cross-sectional average of the distortions β				
200	-0.072	0.091	-0.088	0.107	-0.096	0.107	-0.119	0.133
500	-0.032	0.043	-0.040	0.053	-0.045	0.061	-0.059	0.072
1000	-0.016	0.026	-0.020	0.032	-0.022	0.034	-0.031	0.045

Table 1.1: Mean and standard deviation for the distortions ρ and β under a correct model specification across different values of the network impact and different sample sizes. Values computed across 500 replications.

$$R_t = \gamma_0 + \gamma_1 F_t + \varepsilon_t, \tag{1.63}$$

we have that $\gamma_0 = \mathbb{E}[R_t]$, $\gamma_1 = (I - \rho W)\beta$, and $\mathbb{V}[\varepsilon_t] = (I - \rho W)^{-1}\Omega(I - \rho W')^{-1}$. Therefore, estimating the linear factor model by least squares, we estimate the reduced-form representation of our network-augmented linear factor model. The γ_1 coefficients, by construction, will be larger than the structural coefficients β when we simulate from a data-generating process with positive ρ. This is confirmed by Figure 1.3 and Table 1.2 in which we report the kernel density for the cross-sectional average of $\hat{\gamma}_{1,i} - \beta_i$, $i = 1, 2, \ldots K$ and some descriptive statistics. Moreover, the residuals of the linear factor model will be correlated, with average correlation increasing with ρ (see Table 1.2).

Figure 1.3 and Table 1.2 confirm that, by fitting a linear factor model, we estimate a beta much larger than the structural value, with distortion increasing with the impact from the network connections. As a consequence, the value of the true and structural factor loading might sensibly differ from the one that is empirically observed, being doubled for values of ρ equal to 0.5, and thus not particularly elevated.

When analysing the residual correlations, we can see that they are zero when the linear factor model is correctly specified, that is, when $\rho = 0$. However, in the presence of a network impact, the residual correlations start drifting away from zero, their values increasing with ρ. On the contrary, under the correct model specification, the residual correlations are almost zero, as expected.

Next, we move to the estimation of the factor risk premium. We adopt the widely used two-pass regression approach of Jensen et al. (1972) and Fama and MacBeth (1973). In linear factor models the first stage corresponds to the estimation of the factor loadings, that is, the betas. Differently, in our model the first stage is the estimation of reduced-form betas starting from the estimated coefficient ρ and corresponds to a by-product of the concentrated maximum likelihood estimation approach adopted. We stress that, under scalar ρ and with a static W, the reduced-form betas

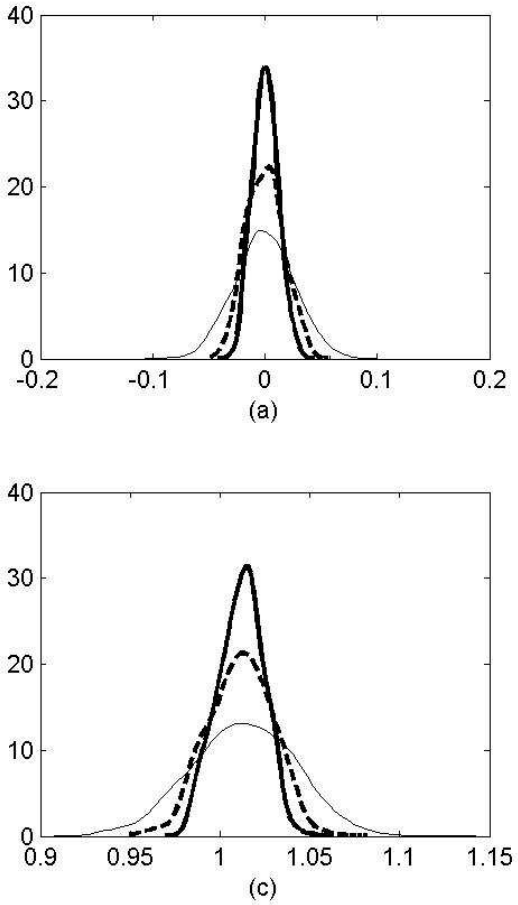


Figure 1.3: Cross-sectional average of the distortions $\hat{\gamma}_1 - \beta$ under the misspecified linear factor model across different values of ρ for the data-generating process. True values: (a) $\rho = 0$, (b) $\rho = 0.25$, (c) $\rho = 0.5$ and (d) $\rho = 0.75$. Lines refer to different sample sizes, $T = 200$ thin grey line, $T = 500$ dashed line and $T = 1000$ thick black line.

T	$\rho = 0$		$\rho = 0.25$		$\rho = 0.5$		$\rho = 0.75$	
	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev
Cross-sectional average of the distortions $\hat{\gamma}_1 - \beta$								
200	0.000	0.026	0.337	0.027	1.013	0.028	3.033	0.043
500	0.000	0.016	0.337	0.017	1.011	0.018	3.034	0.027
1000	0.000	0.011	0.337	0.012	1.012	0.012	3.035	0.019
Average residual correlations under the linear factor model								
200	0.000	0.003	0.009	0.007	0.034	0.014	0.149	0.035
500	0.000	0.002	0.009	0.007	0.033	0.013	0.149	0.035
1000	0.000	0.001	0.009	0.006	0.033	0.013	0.149	0.035
Average residual correlations under the network-augmented linear factor model								
200	-0.001	0.004	-0.002	0.003	-0.002	0.003	-0.002	0.003
500	-0.001	0.002	-0.001	0.002	-0.001	0.002	-0.001	0.002
1000	0.000	0.001	0.000	0.001	0.000	0.001	-0.001	0.001

Table 1.2: Mean and standard deviation for the cross-sectional average of the distortions $\hat{\gamma}_1 - \beta$ under model misspecification, upper panel; average residual correlation under model misspecification, central panel, and under correct model specification, lower panel. Statistics computed across different values of the network impact and different sample sizes. Values computed across 500 replications.

and the linear factor model betas are asymptotically equivalent. The second regression is a cross-sectional one, which takes as dependent the average risky asset returns and regresses them on the estimated betas (reduced-form betas in our model). As pointed out by Jensen et al. (1972), the estimated risk premium suffers from an error-in-variable problem and is thus inconsistent. Standard solutions include grouping assets into portfolios, increasing the sample size and increasing the cross-sectional dimension. We apply the second one, since we are working in a purely simulated setting in which we do not control for the risky asset's *market value*. As a consequence, we expect distortions in the estimation of the risk premiums for small sample sizes, and, given the asymptotic equivalence of the betas, no difference between our model and the misspecified linear factor model. However, an expected result like this does not impact on the purpose of our simulation design, as our final objective is not the correct estimation of the risk premiums but rather to highlight the differences in the estimated risk premiums obtained from either a network-augmented linear factor model or a (misspecified) linear factor model. We finally point out that the cross-sectional estimation of the risk premium could come from either a standard OLS or a GLS estimator. For the latter, we note that the correct model specification allows for a more precise design of the residuals' covariance (in the reduced-form representation of our model).

In Table 1.3 we report the estimated risk premiums. As expected, the premiums are very close to the true value, with a dispersion decreasing in T. The limited distortions depend on the large sample sizes we consider.[16] No difference emerges when we compare the correctly and

[16]Similar results have been obtained with smaller samples of 60 and 120 observations.

T	$\rho = 0$		$\rho = 0.25$		$\rho = 0.5$		$\rho = 0.75$	
	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev
	Estimated risk premiums from a linear factor model							
200	0.415	0.317	0.417	0.318	0.418	0.318	0.419	0.319
500	0.417	0.198	0.418	0.199	0.418	0.199	0.418	0.199
1000	0.423	0.137	0.423	0.138	0.423	0.138	0.423	0.138
	Estimated risk premiums from a network-augmented linear factor model							
200	0.418	0.322	0.419	0.323	0.420	0.324	0.421	0.325
500	0.418	0.200	0.419	0.200	0.419	0.200	0.419	0.200
1000	0.423	0.138	0.423	0.138	0.424	0.138	0.424	0.138

Table 1.3: Mean and standard deviation of the estimated risk premiums across the 500 replications. The cross-sectional regression adopts an OLS estimator. The true risk premium corresponds to 0.4167 at the monthly frequency.

incorrectly specified models. Finally, we should point out that the OLS and GLS estimators provide substantially equivalent results, and thus we report only the OLS case.

As a further example, we consider the portfolio variance, $1/N$, concentrating on the role played by the idiosyncratic risks. We order assets on the basis of their idiosyncratic risk and decompose the portfolio idiosyncratic risk into the structural component and the network effect. We consider portfolios with N varying from 5 to 100. Figure 1.4 reports the decomposition in both absolute and relative terms. Notably, network exposure induces a decrease in the idiosyncratic risks that is much smaller than that associated solely with the structural risks, and with a relative weight increasing over time. Such a result leads to diversification benefits that are reduced compared to the ideal case of independent idiosyncratic shocks (associated with the reduced-form model representation).

To evaluate the impact of the various settings of the data-generating process, we run a number of robustness checks: we simulate the vector β from a Gaussian with mean 1 so that the betas are more concentrated around the mean but also characterized by a larger variance; we increase the volatility of the common factor to a yearly value of 25%; we change the network density by setting $p_B = 0.15$ and $p_B = 0.45$, or, maintaining the same density, we simulate different networks; we modify the factor risk premium to $\Lambda = 3\%$ or $\Lambda = 10\%$; we increase the relevance of the idiosyncratic shocks by sampling elements of Ω as $\omega_{i,i}^{\frac{1}{2}} \sim \mathcal{U}(20\%, 50\%)$.

None of these changes affects the previously reported results.[17]

1.6.2 Heterogeneous network impact

The second simulation design we consider adds the heterogeneity to the network impact. We thus move from the coefficient ρ to the diagonal matrix $\mathcal{R}$. The asset-specific network impact comes from a normal density, $\rho_i \sim \mathcal{N}(0.5, 0.01)$, such that with probability close to 99% ρ takes values between 0.25 and 0.75. In order to control the computational time, we reduce the cross-sectional

[17] Additional figures and tables are available upon request.

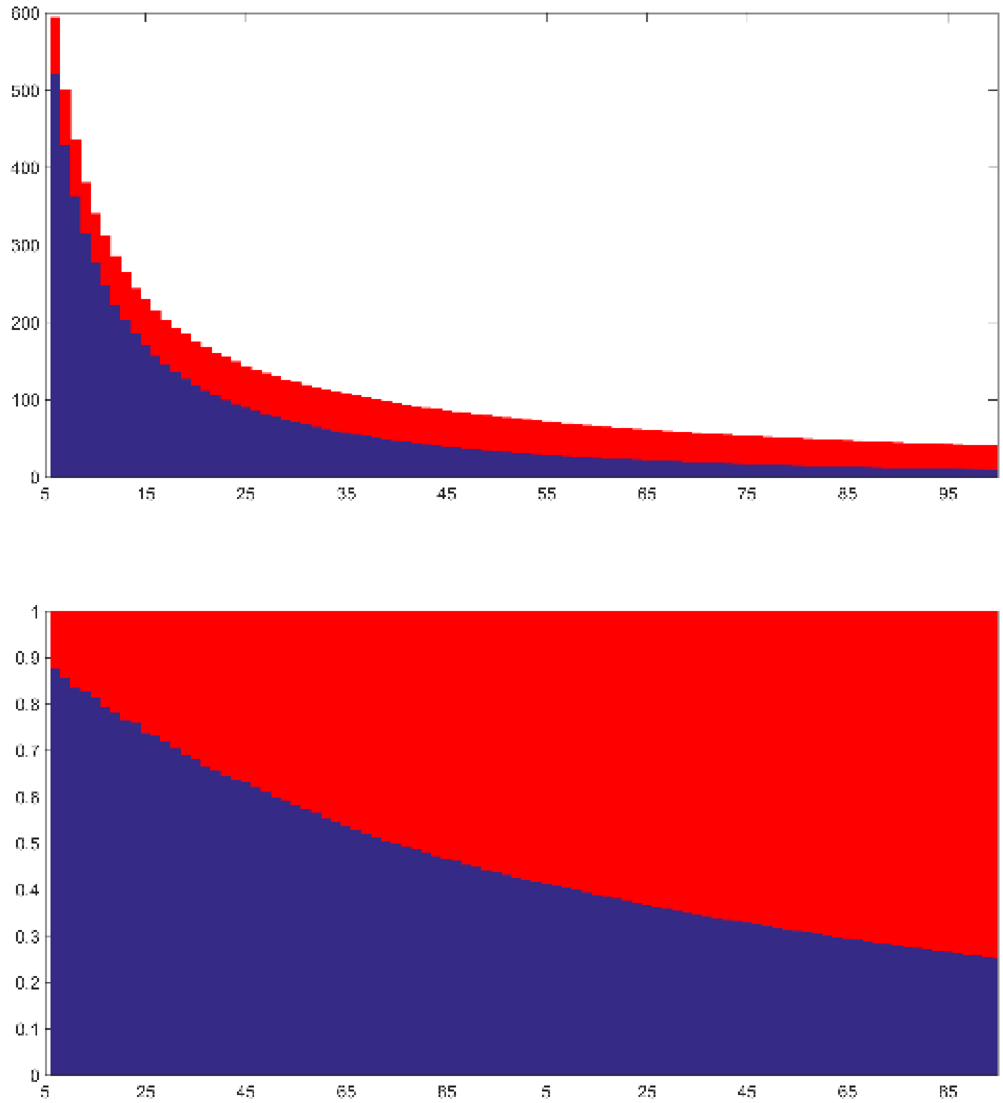


Figure 1.4: $1/N$ portfolio idiosyncratic risk components: structural risk (blue) and network-related risk (red) across different portfolio sizes using the same assets adopted in the simulations and with $\rho = 0.5$. Absolute decomposition (upper) and relative decomposition (lower).

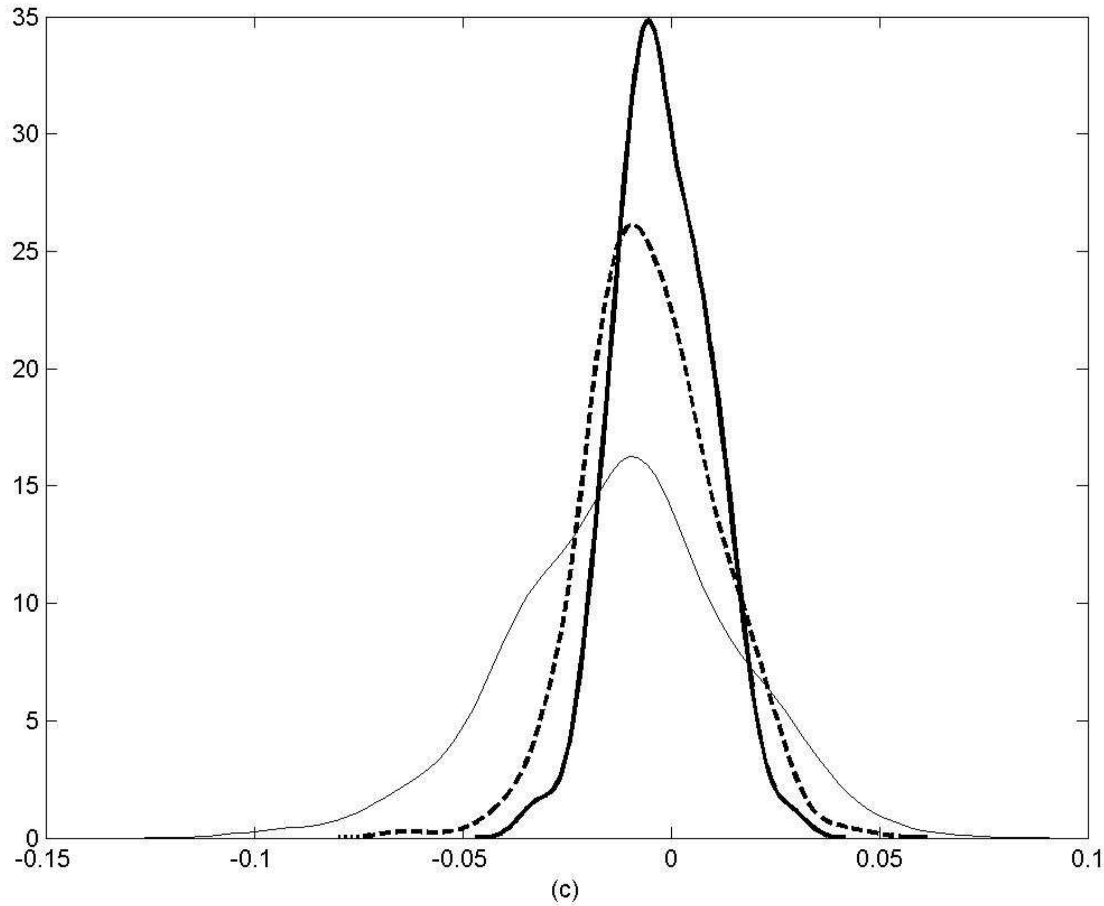


Figure 1.5: Distortions of the cross-sectional average of $diag\,(\mathcal{R})$ under the network-augmented linear factor model. Lines refer to different sample sizes, $T = 200$ thin grey line, $T = 500$ dashed line and $T = 1000$ thick black line.

dimension for this simulation and set $K = 20$.

For that case, we provide in Figure 1.5 a kernel density for the cross-sectional average of $\hat{\rho}_i - \rho_i$, $i = 1, 2, \ldots, K$ for different sample sizes.

We do not present further results for the estimated factor loadings and residual correlations associated with the fit of the standard linear factor model as they provide the same evidence as in the first simulation design: the betas are larger than the structural values and the residuals are correlated. We only point out that, in the presence of heterogeneity in the network impact, the residual correlations are even higher than in the case of scalar ρ.[18]

Instead, we provide in Table 1.4 further evidence from the risk premium estimation. Notably, the estimated risk premiums present a slight distortion (overestimation) in relation to the previous

[18] Additional tables and figures are available upon request.

	Linear factor model				Network-augmented linear factor model			
T	OLS		GLS		OLS		GLS	
	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev
200	0.440	0.326	0.440	0.324	0.443	0.331	0.442	0.328
500	0.443	0.201	0.443	0.200	0.444	0.202	0.444	0.201
1000	0.429	0.149	0.429	0.148	0.429	0.149	0.430	0.147

Table 1.4: Mean and standard deviation of the estimated risk premiums across the 500 replications. The cross-sectional regression adopts an OLS or GLS estimator. The true risk premium corresponds to 0.4167 at the monthly frequency.

simulation design. We link them to the introduction of the asset-heterogeneous impact of the network, which intuitively amplifies the impact of the error-in-variable problem. Increasing the sample size, the distortions tend to decrease as well as the dispersion of the estimated risk premiums. There are no differences found between the two estimation approaches, as in the previous case. Finally, as expected, the correctly and misspecified models provide comparable results. We stress that this is a consequence of the data-generating process we follow, in which the risk premium is estimated by looking at the reduced-form betas. In the current data-generating process, with heterogeneous network impacts, the linear factor model provides consistent estimates of the reduced-form betas, but does not allow separation of the network and structural elements that affect the betas.

For the first design we provided an example associated with the decomposition of the equally weighted portfolio's idiosyncratic risk, with weights equal to $1/N$, into the standard component and the network-related component. Here, we repeat the same exercise with two different $\mathcal{R}$ matrices: the first is the one used above, while the second also allows for the presence of negative ρ_i coefficients in half of the simulated assets. This second example allows us to highlight the *risk absorption* effect of the network exposure. While for the first case the results are qualitatively similar to those of the scalar ρ case, when we introduce negative ρ_i values, and order assets in descending order of their ρ_i values, we note that the introduction of assets with negative ρ_is leads to a moderate decrease of the interconnection impact on the idiosyncratic risk (the fourth component of the variance decomposition). Such an effect could even become negative, thus leading to the absorption of risk by the linked assets, or, in other words, to the amplification of the diversification benefits. This is evident in Figure 1.6, where we report the contribution of the fourth component, the network effect on, the idiosyncratic component to the equally weighted portfolio variance, with weights equal to $1/N$, where the portfolio size increases from 5 to 100 assets, and assets are ranked in descending order of ρ_i. The last 50 assets have negative network impacts, and the contribution of the interconnections to the idiosyncratic risk becomes negative around asset 80.

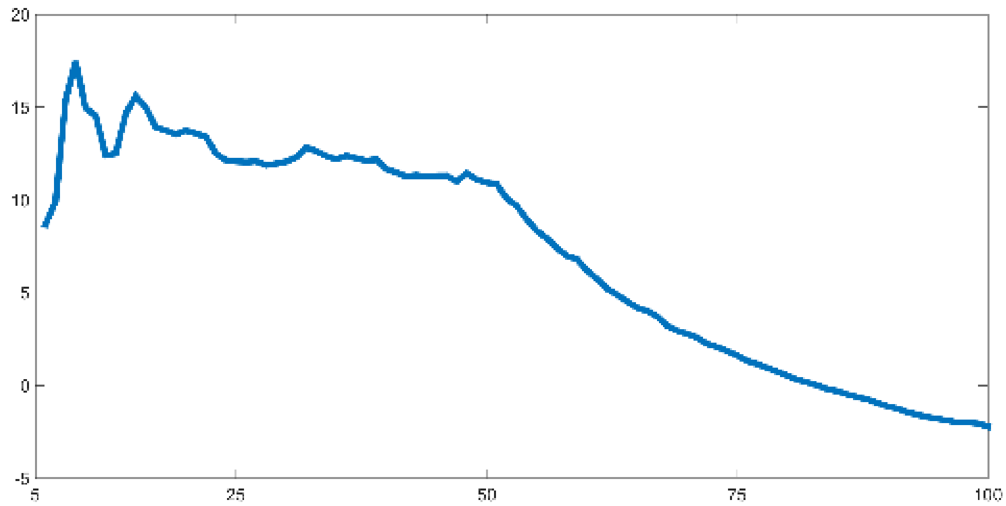


Figure 1.6: Fourth component of the equally weighted portfolio variance with weights equal to $1/N$ - impact of interconnections on idiosyncratic risk. Assets in descending order of ρ_i values.

1.6.3 Dynamic W and heterogeneous network impact

In the third simulation design, we combine the heterogeneity in the asset network impact with the time change in the network connections across assets. Now the data-generating process is

$$(I - \mathcal{R}W_t)(R_t - \mathbb{E}[R_t]) = \bar{\beta}F_t + \eta_t, \tag{1.64}$$

Note that, unlike in the previous designs, here the expected returns, conditional on W_t, are dynamic. To generate a time change in the W_t we chose a simple approach, starting from the empirical evidence that the links between assets are persistent; that is, we do not have networks that are completely different at times t and $t+1$. Moreover, as commented in the previous section, we do not allow for a change in W_t at every t but rather modify W_t every $m = 20$ observations.

We change W_t according to the following scheme: at time 1 we sample W_1 as in the first design, that is the off-diagonal elements $w_{i,j} \sim \mathcal{B}(p_B)$ with $p_B = 0.3$; every m observations, each off-diagonal $w_{i,j}$ can take one of only two values, 0 or 1, and is driven by a Markov chain, with diagonal elements of the transition matrix set as $p_{00} = p_{11} = 0.9$. Such a choice ensures persistence in the W_t with possibly long-lasting increases/decreases in the associated network density. Finally, we point out that the W_t matrices have been normalized with the maximum row normalization.

We now present a number of results obtained from this simulation design. First, we focus on the coefficients ρ_i. As in the previous case, Figure 1.7 reports the kernel density for the average of $diag\left(\hat{\mathcal{R}}\right) - diag(\mathcal{R})$ for different sample sizes. We observe a convergence (on average) of the

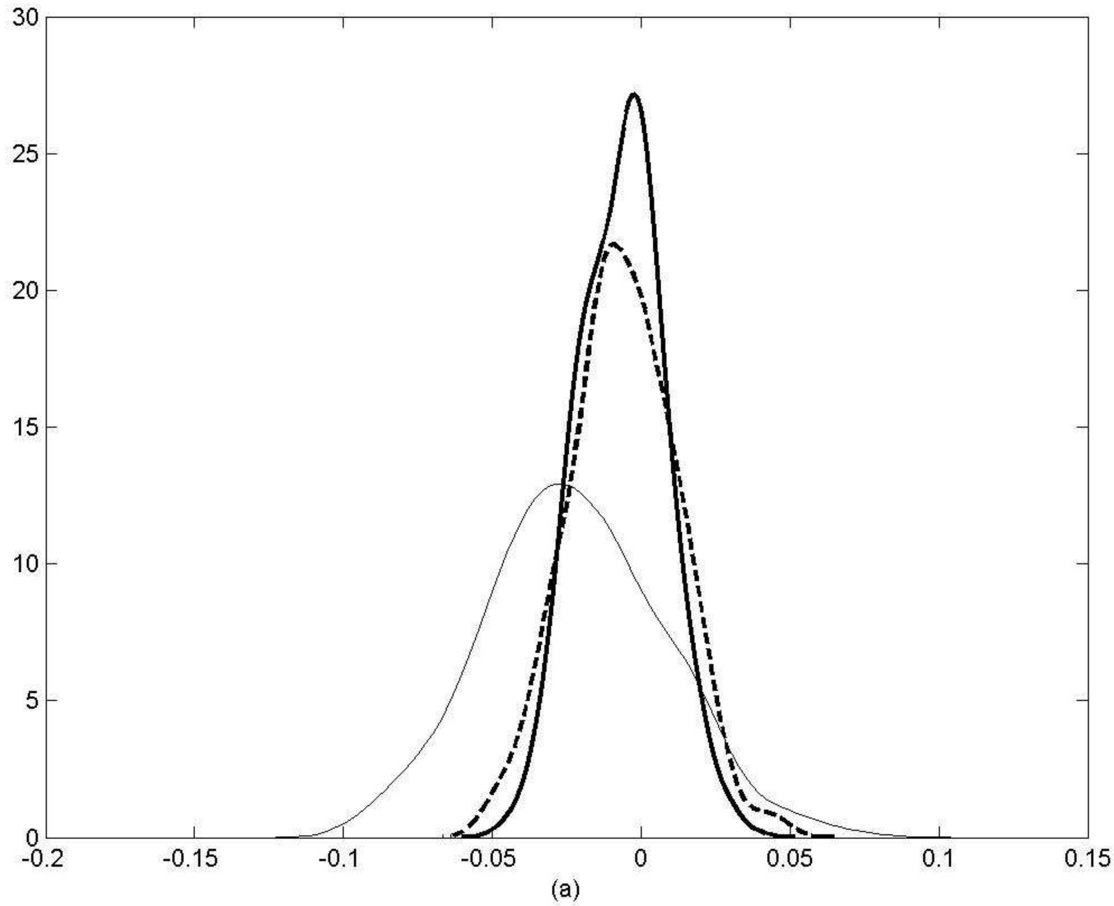


Figure 1.7: Distortions of the cross-sectional average of $diag\,(\mathcal{R})$ under the network-augmented linear factor model. Lines refer to different sample sizes, $T = 200$ thin grey line, $T = 500$ dashed line and $T = 1000$ thick black line.

concentrated estimates to the true values with increasing sample sizes, as expected.[19]

Secondly, we note that, with the data-generating process shown in equation (1.64), the linear factor model does not estimate the reduced-form betas as, by construction, they are time-varying: $\gamma_1 \neq (I - \mathcal{R}W_t)^{-1}\,\beta$. Therefore, to evaluate the distance between those two values, we compute the distortions $\hat{\gamma}_1 - (I - \mathcal{R}W_t)^{-1}\,\beta$ and compare them to the distortions under the correctly specified model $\left(I - \hat{\mathcal{R}}W_t\right)^{-1}\hat{\beta} - (I - \mathcal{R}W_t)^{-1}\,\beta$; in both cases, we focus on the cross-sectional averages of the distortions. We collect the results in Table 1.5. The table shows that the correctly specified model captures the evolution of the reduced-form betas which, we recall, are conditional on the knowledge of the network links. Moreover, the distortions decrease in both mean and dispersion. In contrast, for the misspecified model the distortions do not clearly converge towards the true

[19]Detailed tables with coefficient-specific results are available upon request.

T	Linear factor model		Network-augmented linear factor model	
	Mean	Std.dev	Mean	Std.dev
200	0.153	0.008	0.082	0.014
500	0.205	0.003	0.055	0.008
1000	0.194	0.002	0.040	0.006

Table 1.5: Mean and standard deviation of the cross-sectional averages for the distortions between the estimated betas under the misspecified linear factor model and the reduced-form betas induced by the true model (left-side columns), and between estimated and true reduced-form betas under the correctly specified model (right-side columns).

values but seem to be characterized by an average overestimation of the factor impact.

Finally, we move on to the risk premium estimation and report the results in Table 1.6. In this case, the GLS estimator we adopt for the correctly specified model takes into account the known time-varying nature of the reduced form betas. The risk premium estimation is carried out by focusing on the excess returns filtered from the network dependence, and on the structural betas. We first highlight that the OLS and GLS estimates are substantially equivalent. Thus, there is no effect associated with the estimator adopted. Then, we come to the most interesting finding: the risk premiums are very close to the true values for both the correctly and incorrectly specified models, and similarly the risk premium dispersions are very close together under the two estimated models. Distortions were somewhat expected but they have been cancelled out by two elements. The first is the introduction of an averaging across the different matrices W_t. In fact, under the linear factor model we estimate the betas using the entire sample, which is implicitly affected by the various networks. The reduced-form model estimators are implicitly averaging across the W_t. The second element is the pattern characterizing the matrix W_t, which is not exploding. Nevertheless, this second element plays a minor role. Further simulations with different dynamics for the W_t, introducing a linear or exponential increase in the network density, or a level shift in the network density, confirm the finding.[20]

As we anticipated in the previous section, the most striking result, is the reduction in the risk premium's standard errors. Given the relevant temporal dimension we adopt, the risk premium estimation on a misspecified linear factor model is equivalent to the one obtained from our approach, but the two models lead to completely different dispersions of the estimates. Taking the network dependence into account, the standard errors reduce, on average, by more than 75%. Such an evidence, might have a significant impact on the evaluation of the statistical significance of the risk premiums recovered from real data.

[20] Additional results are available upon request.

	Linear factor model				Network-augmented linear factor model			
T	OLS		GLS		OLS		GLS	
	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev	Mean	Std.dev
200	0.418	0.065	0.418	0.062	0.414	0.018	0.415	0.016
500	0.419	0.044	0.419	0.045	0.416	0.010	0.416	0.010
1000	0.418	0.030	0.418	0.030	0.416	0.005	0.416	0.005

Table 1.6: Mean and standard deviation of the estimated risk premiums across the 500 replications. The cross-sectional regression adopts an OLS or GLS estimator. The true risk premium corresponds to 0.4167 at the monthly frequency.

1.7 Conclusions

In this paper we propose a variation of the linear factor model in which networks are used to infer the exogenous and contemporaneous links across assets; we call the model the network-augmented linear factor model.

Building on the model structure, we first show how the presence of network links allows to decompose the single assets (or portfolio) returns highlighting the impact of interconnected assets in explaining the exposure to common factors. Further, we show how to decompose the risk for assets or portfolios into four components: (i) the systematic component, (ii) the idiosyncratic component, (iii) the impact of the asset interconnections on the systematic risk component, that is, the contribution of network exposure to the systematic risk component, and (iv) the effect of interconnections on the effect of idiosyncratic risk on the systematic risk component, that is, the amplification of idiosyncratic risks that generates systematic/non-diversifiable risk. Starting from this decomposition, we demonstrate the impact of network links on diversification benefits.

Our network-augmented linear factor model allows for heterogeneous impact of network links on the assets, and for the presence of time-variation in the networks. Using the most general model representation we discuss estimation approaches for recovering model parameters and, more interestingly, we show how to estimate the factor risk premiums.

We complement our analyses with a simulation study that shows how the misspecification of the network structure, and the consequent estimation of a classical linear factor model, leads to correlated model residuals and does not allow to recover the true, or structural, exposure to common factors. Moreover, in the misspecified linear factor model, the estimation of the risk premiums, despite being unbiased (in simulations), is much less efficient compared to the estimates obtained from our methodology.

The network-augmented linear factor model is relevant for policy makers and regulators, since they need to be aware of the implications of the different possible policy choices on network connections and their effects on equilibrium stock returns and volatilities, as well as for investors and other market participants, since they need to understand whether and to what degree network connectivity has an impact on risk premiums, volatilities and spillovers between markets. The model could be analysed not only through simulations but also using real data. We plan to work on this in our future research.

Chapter 2

Estimation and model-based combination of causality networks

2.1 Introduction

A growing strand of the financial economics literature has investigated the role of links between financial institutions, which serve as channels along which shocks spread through the financial system, so this strand of the financial economics literature is related to studies on financial contagion. The relationships between financial institutions may vary in nature and, as a consequence, the way in which we interpret these links may differ, depending on which type of relations are of interest to us, or which type of link we are monitoring or measuring. As examples, we cite the input-output relationship (where firms use the output of other companies as input, in their own production function), the ownership relationship (companies that hold assets of other companies), or the links measured on the grounds of stock market prices, such as causality-based connections.

The early literature on financial networks focused first on ascertaining the channel through which financial contagion was spreading within the financial system. The main objective was therefore to identify the networks by using appropriate criteria to detect the links between institutions. Following such an approach meant that the networks were, by definition, unique. Acemoglu et al. (2012) used a network structure based on input-output relationships to show that aggregate fluctuations may originate from microeconomic shocks to firms. Kelly et al. (2013), on the other hand, showed how stock firm volatility relates to customer-supplier connectedness. Billio et al. (2014) used contingent claim analysis and network measures to underscore the links between sovereign, banks and insurances. There is a constantly growing number of works proposing competing or alternative approaches for estimating the networks existing between groups of financial institutions, markets, countries and (not necessarily financial) assets. Among the many contributions in this area, we refer to Billio et al. (2012), Diebold and Yilmaz (2014, 2015), Hautsch et al. (2012, 2013, 2014, 2015), Barigozzi and Brownlees (2014), Ozdagli and Weber (2015), and Corsi et al. (2015), which have in common that they all refer to a financial or economic playground.

Despite the growing interest in the financial network topic, and the increasing understanding that there might be different channels over which financial contagion spreads, the literature on combinations of financial or economic networks is still very limited. In fact, the different approaches taken to estimating networks enable different potential channels for the spread of contagion or risk to come to light that might co-exist within the same financial system. It is therefore fundamentally important to allow for the possibility of combining them to obtain a more complete picture of risk spreading within a financial system.

This paper provides a possible solution based on a multiplex network, or a collection of networks (called layers) existing between a set of subjects, that we formally define in Section 2.2. Ideally, the constituents of the multiplex network represent the outcomes of different approaches to the estimation or identification of links between the subjects analyzed. Postulating the existence of a multiplex network, we take a step forward and consider the combination of the information contained in the various layers of the network for the purpose of analyzing their impact within a financial economic model. In this case, we focus on the linear factor model augmented with network dependence introduced by Billio et al. (2017). We show how the model can be generalized to accommodate the presence of a multiplex network, and we provide a model parametrization that offers two useful interpretations of the models estimation output. First, the model parameters will enable the statistical significance of the information contained in each multiplex network layer to emerge. This will highlight the relevance of the various approaches to network measurement/identification within the model, with consequences on the financial interpretation associated with the model. These analyses might be relevant for policy purposes and market monitoring, as they may identify the main risk-spreading channel.

Second, the estimated model parameters will reveal a composite network obtained by combining the multiplex network layers. The model-based combination will thus provide an overall picture of the links existing between the variables analyzed, as measured using the different approaches (i.e. those behind the various layers of the network), as well as accounting for their respective relevance.

The model-based combination of networks is the first main contribution provided by the present paper. The second contribution that we make to the financial network literature concerns the estimation of networks. As previously mentioned, several authors have already discussed possible ways to obtain a network of financial assets. Among the various methods, the Granger causality approach of Billio et al. (2012) is taken as our starting point: Granger causality is used within a collection of bivariate Vector Auto Regressive (VAR) models to identify the statistically significant links across the modelled variables; then the network is used to identify the shock propagation channels and establish the systemic relevance of financial companies.

When focusing on the risk dimension, Granger causality within a VAR model detects mean causality whether it is on the financial contagion, or on the diffusion of systemic shocks, whereas we normally focus on variances or, more generally, on systemic and/or systematic risk measures.

We consequently do not believe that using Granger causality will produce the most appropriate picture for interpreting the risk of the estimated financial networks. This prompts us to discuss a set of alternative approaches to estimating financial networks based on causality relationships that go beyond the classical Granger causality. We survey a collection of methods that have a common denominator: they all resort to the quantile regression approach of Koenker and Bassett (1978), in either a parametric or a non-parametric representation. Using these methods, we will show how we can identify causality among quantiles of the modelled variables. These quantile-based causality detection methods will lead to the estimation of causality networks mimicking the approach of Billio et al. (2012) but oriented towards a risk dimension. This is immediate when focusing on left quantiles of a random variable. As a further approach, we will also show that the non-parametric quantile causality test of Jeong et al. (2012) represents a further alternative to traditional Granger causality for building causality networks.

We stress that, by focusing on the quantiles of the modelled variables, we attach a clear risk interpretation to the estimated networks: on the one hand, the left quantiles are closely related to traditional risk measures such as the Value-at-Risk and the Expected Shortfall; on the other, the networks will monitor the spreading of shocks or the links between the modelled variables when they are in a high-risk state, and not when they are in a mean (or median) state, as captured by Granger causality. Our purpose is consistent with two other recent contributions, from Hong et al. (2009) and Corsi et al. (2015), that focus on causality among tail events. The Granger causality in risk in Hong et al. (2009), and also used by Corsi et al. (2015), is based on the occurrence of tail events and detects the possible causality among such events. We might associate the tail with a conditional quantile and estimate it with quantile regressions. We differ from the previous papers in that we focus on the causality within the assessment of the conditional quantiles, not on the occurrence of tail events. We thus consider the causality on the risk measures rather than the causality on the occurrence of extreme events.

We suggest different approaches to constructing causality networks, which involve monitoring the links across assets with views that might complement the (mean-based) Granger causality. These competing networks will represent the input for our model-based network combination. Using our model, we will be able to identify the relevance and the role of the various causality networks.

We empirically validate our two main proposals concerning the use of quantile causality to infer the network structure across a set of (financial) variables, and the model-based combination of causality networks. By using different datasets (US industrial portfolio returns, and a set of large banks and insurance companies), we first provide evidence of the different network structures that we can estimate from Granger causality and quantile causality. We show how the networks differ across methods and over two different samples relating to the global financial crisis (2006-2008) and to the years 2011-2015. Our results suggest that quantile causality networks are denser than Granger causality networks, a finding of relevance to systemic risk interpretation because a denser network is indicative of a much larger set of links, and thus a possibly greater systemic effect of shocks. The networks based on the non-parametric quantile causality test of Jeong et al. (2012) also have a clear core-periphery structure, which might help us to identify the more systemically relevant companies or sectors. Moreover, by resorting to the model-based combination approach, we show how different networks have a different impact and relevance on the various datasets, and we estimate a composite network. The model parameters indicate that quantile causality networks are much more relevant than Granger causality. In addition, the linear factor model augmented with a plurality of networks provides residuals that are much less correlated (on average) than traditional linear factor models, or the network augmented linear factor model of Billio et al. (2017), which is based on the Granger causality network alone. This latter finding might be implicated in explaining why the idiosyncratic risk is priced in the cross section. Since the quantile-based networks are the more relevant, it comes as no surprise that the composite network has a structure much closer to that of the quantile causality networks.

The paper proceeds as follows. Section 2 discusses the approach for obtaining a model-based composite network, extending the model of Billio et al. (2017). Section 3 presents the various approaches for estimating a causality network starting from the Granger causality method and then moving to quantile-based causality detection. Section 4 provides the empirical evidence with respect to both the estimation of quantile causality networks and the model-based combination of networks. This section also includes some robustness checks. Section 5 concludes. A Web Appendix accompanies the paper, which contains further tables and graphs, and some methodological notes.

2.2 Model-based network combination

In this section, we introduce how we obtain a model-based combination of a collection of networks. At this stage, we assume that all the networks are available. We therefore do not estimate the structure of the various networks, but concentrate only on their optimal combination. We start with a formal definition of a simple network and of a multiplex or multilayer network.

A network or graph $G = (V, E)$ is a collection of vertexes V and edges E, where the edges represent the links between the vertexes,[1] with $E \subseteq (V \times V)$. Networks are generally represented by using the adjacency matrix W, a binary matrix where each element $w_{i,j}$ can take only two values, 1 and 0. When $w_{i,j}$ is 1, the node j is linked to node i, with an information flow from i to j. A value of zero identifies the absence of a link. We do not consider self-loops, so the diagonal of the W matrix is identically equal to zero. If W is symmetric, we associate with each node a measure called *degree*, that counts the number of edges for the node concerned. Note that, when focusing on K assets, W has a dimension $K \times K$.

The W matrix might not be symmetric because we can have a link from i to j, but the opposite

[1] The terms *vertex* and *nodes* are equivalent, and both are used interchangeably in this work. In the same way, *edges* and *links* take on the same meaning.

might not hold. If the matrix W is symmetric, the associated network is *undirected* as the information contained in the direction of the links becomes redundant; in this case, edges represent mutual relationships between nodes. If W is not symmetric, the network is *directed* and there may be two edges between a pair of nodes; in this case, unlike the *undirected* case, we distinguish between *indegree* and *outdegree*. In particular, *outdegree* is the number of outgoing links starting from a given node, while *indegree* is the sum of the ingoing links on that node. If we relax the assumption of only two possible values for $w_{i,j}$ and allow for values within the (positive) real axis, the network becomes *weighted* (as opposed to *unweighted*) because the connection also has a *size/relevance*. In unweighted networks, each edge simply represents the presence of a connection, while in weighted networks edges also contain information on the strength of the relation between nodes.

As an example, the matrix in (2.1) represents the directed and unweighted network existing between a set of 5 nodes. Figure 2.1 provides a graphical representation of the network.

$$W = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}. \tag{2.1}$$

It is worth noting the parallelism between the adjacency matrix and the spatial (proximity) matrix used in spatial econometrics. The latter describes how the subjects of an analysis are spatially related. In such a different framework, the distance between subjects is (generally) measured on a physical (natural) playground, and connections correspond to neighborhood relationships. Therefore, if the element $w_{i,j}$ equals 1, the element j is a neighbor of the element i, following the spatial econometric nomenclature. The spatial matrices in the standard application are symmetric because neighboring relationships are symmetric. It is also common practice to focus on proximity matrices that are row-normalized. These matrices can therefore be interpreted as directed weighted networks, given that the symmetrical relations might become asymmetrical after normalization.

Within a financial framework, networks are generally directed and weighted when they are measured by means of balance sheet quantities. Billio et al. (2016) used BIS cross-holdings, Diebold and Yilmaz (2014) developed an approach based on variance decompositions of target series, Acemoglu et al. (2012) used the Input-Output matrix. The network might also be directed and unweighted like those obtained using Granger causality in Billio et al. (2012), or Granger Causality in the tails Corsi et al. (2015), or it might even be unweighted and undirected as in the economic sector case of Caporin and Paruolo (2015).

In the following, we assume that the strength of the edges is normalized at each node, as in a row normalization of the adjacency matrix W. We also assume that we are dealing with directed networks (the most general case that we could consider).

Assuming that we have d different networks, the multiplex (or multilayer) network is a collection

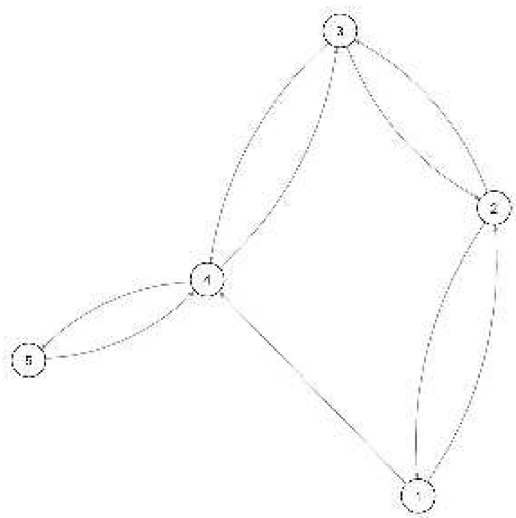


Figure 2.1: Network associated to the Matrix W

of the d networks organized into d different planes, or layers. In principle, the number of nodes needs not be the same across networks, so the total number of nodes in a multilayer network equals $\sum_{i=1}^{d} V_i$, where V_i is the number of nodes or vertexes in the $i-$th layer.

Assuming that the graphs (associated with the networks) are simple (there are no loops), the maximum number of edges (connections between nodes) equals $\prod_{i=1}^{d} \frac{V_i(V_i-1)}{2}$, since connections across layers are also allowed.

In a financial framework, the multilayer network has an even simpler structure: the nodes are the same across layers because we have measures of connections over, say, the same financial institutions, but we use different approaches to estimate the networks. We also assume that there are no connections between layers, leaving us a collection of networks that are unrelated, but all referring to the same nodes.

The literature on multiplex networks is relatively recent and, to the best of our knowledge, only a few papers combine networks in finance, focusing particularly on contagion and topological properties. Since institutions are linked in very different ways, it is useful to find a way to process all this information. Bargigli et al. (2015) analyzed the Italian interbank market using a multiplex network, distinguishing between five layers: unsecured overnight transactions, unsecured short-term transactions (up to 12 months), unsecured long-term transactions, secured short-term transactions and secured long-term transactions; they also considered the aggregated network, computed as the accumulation of all the layers.According to the authors, each layer had a different topological property and persistence over time and, among all the layers, only the overnight market was representative of the aggregate network.

Léon et al. (2014) studied the Colombian sovereign security market and built a multiplex network with three different layers corresponding to the three Colombian environments trading and registering sovereign securities. They found a strong nonlinear effect for the aggregate network value, attributable to the fact that the principal layer did not transfer its properties to the aggregate network or multiplex.

Montagna and Kok (2013) developed an agent-based multi-layered interbank network model using a sample of large EU banks, highlighting that there were non-negligible non-linearity effects influencing shock propagation to the individual banks. In other words, when different layers were considered simultaneously, the contagion effect was larger than the sum of the contagion-induced losses when the network layers were analyzed separately.

Molina-Balboa et al. (2014) analyze the multiplex structure of the bank exposures within the Mexican banking system. By associating layers with different financial instruments and the authors provides insight on the interdependence among banks with relevant implications from a systemic risk perspective.

The present contribution aims to combine financial networks by building on a variant of a financial economic model, the linear factor model augmented with a spatial link following the approach of Billio et al. (2017).

The advantage of our model lies in that the combination of the various layers of the multiplex network is weighted with a set of coefficients appearing in the models parametrization. As well as representing the elements for a convex linear combination of the layers, the coefficients would consequently enable the significance and relevance of each layer to be assessed.

In the next subsection we briefly review the model of Billio et al. (2017), and introduce the models generalization in the presence of a multilayer network. Then we discuss the approach used to derive a composite network from the models estimates.

2.2.1 A linear factor model with multilayer spatial dependence

To obtain a composite network, we generalize the model of Billio et al. (2017), a *revisited* multifactor model capable of taking into account the contemporaneous links between the assets (as measured by a network) together with the presence of common factors. In this model, the returns equation equals

$$A\left(R_t - \mathbb{E}\left[R_t\right]\right) = \bar{\beta} F_t + \eta_t \tag{2.2}$$

where A is the matrix of the contemporaneous relationships between endogenous variables, i.e. the returns, coexisting with the exposure to a set of common factors F_t; R_t, $\mathbb{E}\left[R_t\right]$ are, respectively, the asset returns and the expected asset returns, $\bar{\beta}$ is the structural asset exposure to the common factor and η_t are the structural idiosyncratic residuals with a diagonal covariance matrix Σ_η.

The standard multifactor model can be seen as the reduced form of equation (2.2). Under the invertibility of matrix A, the model has the following reduced-form representation

$$
\begin{aligned}
R_t &= \mathbb{E}\left[R_t\right] + A^{-1}\bar{\beta}F_t + A^{-1}\eta_t \\
&= \mathbb{E}\left[R_t\right] + \beta^{\star}F_t + \epsilon_t^{\star}
\end{aligned} \tag{2.3}
$$

Starting from the reduced form, and in the presence of contemporaneous links across assets, Billio et al. (2017) make the point that: i) the reduced-form residuals $\epsilon_t^{\star} = A^{-1}\eta_t$ are cross-correlated; and ii) the reduced-form betas, $\beta^{\star} = A^{-1}\bar{\beta}$, are a nonlinear function of the structural betas and of the contemporaneous relation matrix A.

The intuition of Billio et al. (2017) is to provide a structure for A driven by the existence of a network representing the (contemporaneous) links across the assets. They therefore propose to make the matrix A an affine function of a network, $A = (I - \rho W)$, where ρ is a scalar parameter indicating the spatial dependence of the returns on the network, while W is an exogenous spatial matrix, or adjacency matrix of a network. Such a choice also enables us to cope with the identification issues of the simultaneous equation system in (2.2).

Following Anselin (1988) and LeSage and Pace (2009), the model thus includes a spatial autoregressive component. The estimation of the spatial parameter ρ follows from concentrated likelihood methods.

Billio et al. (2017) also allow for a more flexible parametrization of the A matrix. In particular, they consider two relevant extensions:

- the use of asset-specific impacts from the network, which corresponds to a contemporaneous parameter matrix A with equation-specific network impacts, namely $A = I - \mathcal{R}W$, where $\mathcal{R} = diag(\rho_1, \rho_2, \ldots, \rho_K)$ is a diagonal matrix, and the coefficient ρ_i represents the impact of the network on each asset; and

- the possibility of the spatial matrix, or network, varying in time, thus leading to W_t; this is particularly relevant in finance because W is not related to a *physical* distance between subjects, but measures proximity or connections starting from variables liable to temporal differences.

We refer the reader to the paper by Billio et al. (2017) for further details on the models interpretation.

In the present paper, for the sake of simplicity, we assume the networks are time-invariant, though the approach that we introduce can easily be extended to the case of dynamic networks. In the presence of a multilayer network, we generalize the model of Billio et al. (2017) to accommodate the presence of several adjacency matrices.

In the spatial econometrics literature, we have some examples associated with the existence of richer spatial dynamics. In particular, Brandsma and Ketellapper (1979) propose a higher-order spatial autoregressive model, introducing two spatial matrices and consequently two spatial autocorrelation parameters: the first matrix based on the first-order neighbors, the second derived from the higher-order neighboring relations.

In the framework of Billio et al. (2017), the matrix of simultaneous relations A, in the presence of many networks, is easily generalized to

$$A = I - \sum_{j=1}^{d} \rho_j W_j. \tag{2.4}$$

In equation (2.4), we have d different scalar coefficients, ρ_j, capturing the impact of the network W_j on the contemporaneous links across the assets.

Such a parametrization would give rise to a common impact of each network on the whole collection of modelled asset returns, so we propose to combine the existence of many networks with a restricted parametrization, accommodating the presence of the various networks, while also allowing for heterogeneous impacts of the networks on the assets. In detail, we suggest the following model specification:

$$\left[I - \mathcal{R}\left(\sum_{j=1}^{d} \delta_j W_j\right)\right] R_t = AR_t = \mathbb{E}\left[R_t\right] + \beta F_t + \eta_t \tag{2.5}$$

where d is the number of layers or networks, $\mathcal{R}$ is a diagonal matrix, and the δ_j coefficients satisfy the following constraints:

$$\sum_{j=1}^{m} \delta_j = 1, \quad \delta_j \geq 0, j = 1, 2, \dots m. \tag{2.6}$$

The parameter δ_j controls the impact and role of each layer of the multiplex network, while the parameters in $\mathcal{R}$ determine the heterogeneous impact of the networks on the asset returns.

We suggest estimating the model using concentrated maximum likelihood, according to standard practice in spatial econometrics. If matrix A is known, the factor loadings β and the innovation covariance matrix Σ_η can be obtained with traditional least square estimators. We can thus concentrate out the latter parameters and use concentrated maximum likelihood to estimate the parameters entering A. The maximization must account for the constraints that we impose on the δ_j parameters.

The model contains a sort of spatial autoregression, the structure of which is driven by several spatial proximity matrices. A standard requirement for estimations of spatial econometric models is the invertibility of matrix A. When the number of networks is restricted to one, or $d = 1$, the non-singularity of A^{-1} is ensured when $\lambda_{min}^{-1} < \rho < \lambda_{max}^{-1}$, where λ_{max} and λ_{min} are, respectively, the maximum and minimum eigenvalues of the spatial/adjacency matrix W.

In the presence of numerous proximity matrices, the non-singularity of A might be addressed with analytical tools, but only in specific cases. For instance, Lee and Liu (2010) and Elhorst et al. (2012) discuss the case of two matrices W, referring to the estimation of a second-order spatial autoregressive model. These results are not easy to extend to our specification, however, we control for the invertibility of A within the estimation step.

The coexistence of many networks in the augmented linear factor model of Billio et al. (2017) has consequences on the identification of the models parameters too, particularly for those in $\mathcal{R}$.

The identification of the parameters entering the matrix A is guaranteed by the constraints on the δ_j parameters, the row normalization in the W_j matrices, and a further set of necessary (but simple and intuitive) conditions on the adjacency matrices:

i. $W_j \neq 0, \quad j = 1, 2, \ldots, d$;

ii. $W_i \neq W_j, \quad i, j = 1, 2, \ldots, d, \quad i \neq j$;

iii. $\rho\left(W_{i,.}\right) > 0$ where $\rho\left(\mathcal{A}\right)$ is the rank of matrix $\mathcal{A}$, $W_{i,.} = [W_1'|_{.,i} \quad W_2'|_{.,i} \quad \ldots \quad W_d'|_{.,i}]$ and $W_j'|_{.,i}$ denotes the $i-$th row of W_j.

Condition [i] simply rules out the case of absence of edges between a collection of nodes. Condition [ii] excludes the case where two networks, measured by two different approaches are identical. If the latter case realize, we loose identification as the two networks are indistinguishable, and one of the two must be excluded from the analysis. The first two conditions are relevant for the identification of the δ_j parameters. Condition [iii] refers to the parameters in $\mathcal{R}$, and ensures that in each row of the combined network

$$W^\star = \sum_{j=1}^{d} \delta_j W_j. \tag{2.7}$$

we do have at least a non-null element. The parameter $\rho_{i,i}$ of the diagonal matrix $\mathcal{R}$ is identified if the $i-$th row of $W^\star$ has at least one non-null element. In fact, if a given row of $W^\star$ contains only null elements, the corresponding parameter in $\mathcal{R}$ is not identified. Such a case corresponds to asset i having no spatial dependence on the other assets in the model, so we set the corresponding parameters in $\mathcal{R}$ to zero in the case of null rows in $W^\star$.

Finally, we note that the model is overidentified, given that the covariance matrix of the innovation, Σ_η, is diagonal, thus leaving space for any richer parametrizations in (2.5), with heterogeneous impacts on returns from groups of layers, for instance.

2.2.2 Relevance and combination of networks

The model offers two important insights. The first, and most relevant, concerns the feasibility of interpreting the summation of the adjacency matrices, matrix $W^\star$, as a new adjacency matrix representing a composite network. This is a direct consequence of the constraints on the coefficients leading to a convex linear combination of adjacency matrices, which are all row-normalized. The composite matrix will therefore also be a row-normalized matrix representing a combination of a collection of networks. The combination will also be directed and weighted because the initial networks are directed and weighted. The coefficients δ_j measure the relevance of each network layer in obtaining the composite network. The model thus generates both a composite network and an insight on the impact of each approach used to construct the various layers.

Secondly, the parameters included in $\mathcal{R}$ represent the heterogeneous reaction of the assets to the composite network, thus making the multiple-network model comparable, in terms of its economic interpretation, to the network of Billio et al. (2017), but with the important difference that its underlying network is composite.

2.3 Causality testing and estimating causality networks

The concept of causality and the tools used to test for its existence date back to the seminal contributions of Granger (1969, 1980, 1988). The purpose of his original contribution was to identify causal relationships in mean across economic variables, and his work attracted considerable interest in the econometrics literature, see Geweke (1984) and Hoover (2001). The concept was later extended to the analysis of causality among variances: Granger et al. (1986) provided a first definition of variance causality, while Comte and Lieberman (2000) extended and generalized the concept. On the testing side, Cheung and Ng (1996) proposed a test based on cross-correlations, Hafner (2003) introduced a procedure based on the likelihood of competing models, and Hafner and Herwartz (2008) presented a Wald-type approach.

More recently, there have been contributions on causality between two random variables that go well beyond the first- and second-order moments. We refer in particular to causality among quantiles such as the non-parametric test of Jeong et al. (2012) and the work of Lee and Yang (2014), and to the work of Candelon and Topkavi (2016) on causality in distributions.

Within a financial framework, the interest in causality and the use of Granger causality tests to estimate a network stems from the work done by Billio et al. (2012). The authors associated the statistical evidence of Granger causality in the mean with the existence of an edge connecting two assets (two nodes) of a financial network. In times of market turmoil, however, or when our interest lies in estimating systemic risk spreading after local or specific shocks, the causality in the mean might not be enough, and should be combined with a causality testing that covers the risk dimension.

In this section we provide a brief review of the Granger causality approach adopted by Billio et al. (2012), then suggest a number of competing methods we might consider for testing the existence of causality among quantiles of return distributions. As discussed in the introduction, the lower quantiles of returns acquire a more relevant role within a financial framework, because they correspond to Value-at-Risk levels. The availability of a number of competing methods for estimating causality networks enables the construction of a multiplex network, in which each layer is associated with a specific network. The multiplex network based on causality links can then be used for the model-based construction of composite networks, as discussed in the previous section.

The same criteria apply to the estimation of a single causality network, irrespective of the approach used to identify causality links. It is also important to note that we estimate a causality network starting from historical information on K assets, generally focusing on asset returns.

The K assets thus represent the nodes in the networks, and our purpose is to identify edges connecting each pair of nodes. If all assets are connected, and we exclude self-loops, we will have a total number of $K^2 - K$ edges in which case the associated adjacency matrix is symmetric if the network is unweighted.

In all the cases we discuss below, for any pair of assets i and j, the existence of an edge connecting the nodes i and j with a specific direction (say, from i to j) is established from a statistical test. The null hypothesis of the various tests corresponds to the absence of a causality link, while the null hypothesis is rejected in the presence of some form of causality. The type of causality detected clearly depends on the hypothesis tested.

For a given test statistic $\mathcal{M}$, and for any pair of assets i and j, we define the edge from i to j as

$$w_{i,j} = \begin{cases} 0 & \mathcal{M} \text{ null hypothesis rejected} \\ 1 & \mathcal{M} \text{ null hypothesis accepted} \end{cases} \tag{2.8}$$

where $w_{i,j}$ is the element in position i, j within an adjacency matrix. Given the use of the test statistic $\mathcal{M}$, we denote the corresponding adjacency matrix as $W_{\mathcal{M}}$. The outcome of the test statistic, either rejecting or accepting the null, thus identifies the edges of a directed and unweighted network. We do not discuss here the possible generalization to a more flexible form of network construction that accounts for the strength of the causal relation too: such an extension is clearly possible but is left to future research. It should be noted that the networks will be row-normalized before they are used in the model presented in the previous section.

2.3.1 Granger causality networks

We start from the discussion of Granger causality testing, and the estimation of a Granger causality network in which case the framework for testing the presence of causality in mean between two variables x_t and y_t is the Vector Auto Regressive (VAR). We focus on the simplest VAR model with a single lag, that is

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{x,t} \end{bmatrix} \tag{2.9}$$

where we assume, for the sake of simplicity, that the innovation term is identically and independently distributed.

Testing for causality from x_t to y_t is tantamount to testing for the significance of the coefficient

a_{12}, while the significance of a_{21} provides information on the causality from y_t to x_t. The framework can easily be generalized to the presence of more than one lag, in which case causality is associated with the null hypothesis of zero restrictions on a subset of the model parameters. Being obtained within a likelihood ratio framework, the test statistics have the usual Chi-square density.

The testing equation can also be extended by introducing further lagged or contemporaneous explanatory variables that affect both the dependent variables. This would bring to light a form of common behavior that might hide or distort the identification of causal relations. Notably, by replacing the series levels with their squares, or by focusing on realized volatility sequences, the Granger causality framework also enables us to test for causality between *risk* measures.

Billio et al. (2012) were the first to adopt Granger causality to estimate a relationship-based network among financial assets. The connections between nodes in their network denote the presence of a causality relation in the Granger sense.

The approach used by Billio et al. (2012) starts from a collection of series of K asset returns over a daily sample of size T, which we denote by $R_{i,t}$, with $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots T$. Returns are first filtered by means of a GARCH(1,1) model to eliminate the well-known heteroskedastic behavior. The authors thus estimate

$$R_{i,t} = \mu_i + \eta_{i,t} \quad i = 1, 2, \ldots N \tag{2.10}$$

where μ_i is the unconditional mean and $\eta_{i,t}$ is the innovation for asset i. Following the standard literature, $\eta_{it} = \sigma_{it}\epsilon_{it}$, where σ_t is the conditional standard deviation. The conditional variance follows a simple GARCH(1,1) process

$$\sigma^2_{i,t} = \omega_i + \alpha_i \eta^2_{i,t-1} + \beta_i \sigma^2_{i,t-1} \quad i = 1, 2, \ldots N \tag{2.11}$$

with $\omega_i \geq 0$, $\alpha_{i,1} \geq 0$, $\beta_i \geq 0$, and $\alpha_i + \beta_i < 1$. As usual in the GARCH literature, $\varepsilon_{i,t}$ is assumed to be a sequence of i.i.d random variables with zero mean and unit variance. After the model estimation, we can therefore obtain the so-called standardized residuals $\varepsilon_{i,t} = \dfrac{\eta_{i,t}}{\sigma_{i,t}}$.

The next step develops Granger's causality test on each pair of standardized asset residuals, but the simple framework of equation (2.9) might lead to the detection of *spurious causality*. In fact, if we take three assets, i, j and z, and we have $i \rightarrow_G j$ (the series i causes the series j in the sense of Granger causality) and $j \rightarrow_G z$, then by using the standard Granger causality test we might also find that $i \rightarrow_G z$, but such a causality could be a by-product of the presence of j, and not a real direct causality impact. To control for such effects, Billio et al. (2012) augment the model in (2.9) with a so-called *background* series and/or a set of common factors, leading to the following model

$$\begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t-1} \\ \varepsilon_{j,t-1} \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \varepsilon_{z,t-1} + \beta F_{t-1} + \begin{bmatrix} \varphi_{i,t} \\ \varphi_{j,t} \end{bmatrix} \tag{2.12}$$

where F_t might contain common factors, and with $i, j, z = 1, 2, \ldots N$, and $i \neq j \neq z$. Obviously, we have $N - 2$ possible background series for each pair of GARCH standardized residuals i, j.

The Granger causality test must therefore discriminate between the various choices of z, conditional to the possible presence of common factors F_t. The approach of Billio et al. (2012) made use of information criteria to specify the VAR lag structure and select the background series. Once the background series had been selected, the authors ran a set of Granger causality tests including/excluding the background series and/or the common factors, and selected the test outcome with the highest p-value (of the Granger's causality test) to produce more robust results.

We point out that the approach is computationally intensive because detecting the causality from i to j, for a specific choice of i and j, involves estimating $N - 2$ bivariate systems to select the background series, and then further estimates to perform the causality testing.

For each pair of GARCH standardized residuals i and j, the test enables us to check for the presence of causality from i to j, with a decision rule associated with the above-described procedure. The decision rule provides for just two outcomes, a 0 or a 1: if causality is present, the approach of Billio et al. (2012) leads to the creation of a connection from node i to node j. The adjacency matrix gives rise to a directed and unweighted network. Note that, in the empirical analyses, we obtain the network following the approach of Billio et al. (2012) and, before estimating our model, we proceed with a row normalization of the network.

2.3.2 Quantile causality: a baseline case

Granger causality tests focus on the possible presence of causality relations affecting the mean dynamic evolution of x_t and y_t. As noted earlier, this approach might easily be extended to testing causality among higher-order moments.

Despite the usefulness and simplicity of this approach, focusing on the moments alone might prove too restrictive, since it could preclude or limit the possibility of studying the causal relations between x_t and y_t in specific regions of their distributions, or the risk measures associated with the distributions of the two variables, such as quantiles or conditional moments.

For instance, there might be situations where x_t and y_t are not linked by causal relations in the center of their distributions, or in the mean, but they might still be strongly dependent on one another in the tails of their distributions. This phenomenon could be crucial in the context of financial returns (given that their distributions are typically characterized by fat tails, Cont (2001)), or when we are interested in the existence of causal relations during periods of market turmoil (when both the variables analyzed take values in their tails), or during a negative period for the target variable (when only the dependent variable takes values in its tail). There might also be more interesting cases in which the causal relations are asymmetrical between the left and right tails. The classical Granger's test and its baseline variants are obviously unable to detect such structural features.

This shortcoming can be overcome by building causality tests based on the quantile regression method introduced by Koenker and Bassett (1978). In such a framework, we postulate the existence of a linear relationship between the quantile of a target variable and the values taken by an explanatory variable. If we deal with two variables, we thus have two equations, and the bivariate system becomes:

$$\begin{aligned} Q_{y_t}(\tau) &= \beta_{0,1}(\tau) + \beta_{1,1}(\tau)y_{t-1} + \beta_{2,1}(\tau)x_{t-1} \\ Q_{x_t}(\theta) &= \beta_{0,2}(\theta) + \beta_{1,2}(\theta)y_{t-1} + \beta_{2,2}(\theta)x_{t-1} \end{aligned} \tag{2.13}$$

where $Q_{y_t}(\tau)$ and $Q_{x_t}(\theta)$ denote the τ-th and θ-th conditional quantiles of y_t and x_t, respectively. As in the idea behind Granger causality, testing for causality from x_t to the τ-th conditional quantile of y_t involves testing the significance of the coefficient $\beta_{2,1}(\tau)$. Likewise, testing for causality from y_t to the θ-th conditional quantile of x_t involves testing the significance of $\beta_{1,2}(\theta)$.

Unlike the Granger causality testing approach, the estimation of the conditional quantiles is based on the marginal model for each target variable. We therefore test for causality from x_t to y_t, and from y_t to x_t using two different models (i.e. two different conditional quantile linear models, one for each target variables). A recently-developed system approach is also viable, as discussed later on.

Financial variables are often highly correlated, due mainly to their sensitivity to market trends and shocks. The influence of these common factors can be isolated by including one or more control variables reproducing the market movements in the bivariate system (2.13). If we let $\mathbf{F}_t$ be the vector of these common factor variables observed in t, we rewrite the (2.13) as

$$\begin{aligned} Q_{y_t}(\tau) &= \beta_{0,1}(\tau) + \beta_{1,1}(\tau)y_{t-1} + \beta_{2,1}(\tau)x_{t-1} + \gamma_1 F'_{t-1} \\ Q_{x_t}(\theta) &= \beta_{0,2}(\theta) + \beta_{1,2}(\theta)y_{t-1} + \beta_{2,2}(\theta)x_{t-1} + \gamma_2 F'_{t-1} \end{aligned} \tag{2.14}$$

The latter conditional quantiles thus mimic the presence of common factors used in the Billio et al. (2012) approach. Similarly, we can introduce a further background variable, and increase the lag structure within the conditional quantile specification. Note that we could introduce lags for both the conditioning and the modelled variables.

If we focus on the conditional quantile for x_t (similarly for y_t), with or without additional control or background variables, the detection of causality is associated with the presence of a significant impact of y_{t-1} (or all lags if the models structure is more complex) on the conditional quantile of x_t.

Within a quantile regression framework, we can also assess the causality impact of x_t by comparing the first equation in (2.13) with its restricted version:

$$Q^{(r)}_{y_t}(\tau) = \beta^{(r)}_{0,1}(\tau) + \beta^{(r)}_{1,1}(\tau)y_{t-1}, \tag{2.15}$$

on the basis of the testing procedure proposed by Koenker and Bassett (1982). The test verifies the null hypothesis that the additional variable in the first equation belonging to the system (2.13), i.e. x_{t-1}, does not improve on the goodness-of-fit achieved with the restricted model given in (2.15). If the null hypothesis of the test, which reads like the F-test, is rejected at a given significance level, then there is evidence of causality from x_t to the τ-th conditional quantile of y_t. The same method could likewise be applied to test the causality relations from y_t to the θ-th conditional quantile of x_t.

Finally, we note that the quantile causality network is specific to the τ quantile used to test the link between x_t and y_t. The above-outlined method might therefore generate a collection of quantile causality networks. When the focus is on the risk, however, our interest lies in the left tail of the distribution, and therefore on small values of τ, ideally between 1% and 10%.

Using conditional quantile causality testing based on an assessment of the significance of the coefficients, we thus obtain the quantile causality network at quantile τ. We stress that the estimated network depends on the chosen quantile, so we can estimate a collection of quantile-based causality networks.

2.3.3 Quantile-on-quantile causality

So far, we have considered the causal impact of one variable on another, focusing either on moments (within a Granger causality framework) or on conditional quantiles. We can take the analysis further by directly linking the quantiles of both the causal and the dependent variables. In other words, our aim is to check whether the θ-th quantile of x_t causes the τ-th quantile of y_t, and vice versa, for θ equaling or differing from τ. In this way, we can test whether the power of x_t in causing the τ-th quantile of y_t changes over $\theta \in (0, 1)$.

From a different viewpoint, while in traditional quantile regression we analyze the possible impact of the values taken by x_{t-1} (across its whole density) on the conditional quantile of y_t, for instance, we are interested here in testing the existence of causality when we restrict our attention to a neighborhood of a quantile of x_{t-1}. This would enable us to seek causal relations when both the analyzed variables take values in the respective tails, for example.

Two different approaches can be used for this purpose. The first is based on the method introduced by Sim and Zhou (2015), who proposed a modified version of quantile regression in which observations (and then the corresponding loss function) are weighted using a kernel function. In particular, Sim and Zhou (2015) use kernel-based weights to estimate the relations in quantiles between oil prices and stock returns. In our framework, following Sim and Zhou (2015), the conditional quantiles in (2.13) are rewritten, respectively, as follows:

$$
\begin{aligned}
Q_{y_t}(\tau, \theta) &= \beta_{0,1}(\tau, \theta) + \beta_{1,1}(\tau, \theta) y_{t-1} + \beta_{2,1}(\tau, \theta) x_{t-1} \\
Q_{x_t}(\theta, \tau) &= \beta_{0,2}(\theta, \tau) + \beta_{1,2}(\theta, \tau) y_{t-1} + \beta_{2,2}(\theta, \tau) x_{t-1}
\end{aligned}
\tag{2.16}
$$

where the only difference lies in the fact that the parameters have both τ and θ subscripts. In fact, the estimated parameters depend on the quantile levels of both y_t and x_t. Despite the similarities in the form, the equations in system (2.16) differ from those in (2.13) in the manner in which the unknown parameters are estimated. Notably, the coefficients belonging to the first equation of the system (2.16) come from the following minimization problem:

$$\min_{\beta_{0,1}(\tau,\theta),\beta_{1,1}(\tau,\theta),\beta_{2,1}(\tau,\theta)} \sum_{t=1}^{T} \rho_\tau \left[y_t - \beta_{0,1}(\tau,\theta) - \beta_{1,1}(\tau,\theta)y_{t-1} - \beta_{2,1}(\tau,\theta)x_{t-1}\right] * \\ *K\left(\frac{F_T(x_t) - \theta}{h}\right), \tag{2.17}$$

where $\rho_\tau(e) = e(\tau - \mathbf{I}_{\{e<0\}})$ is the asymmetric loss function on the basis of the quantile regression method introduced by Koenker and Bassett (1978), and $\mathbf{I}_{\{\cdot\}}$ is the indicator function, taking a value of 1 if the condition in $\{\cdot\}$ is true, and a value of 0 otherwise. The difference with respect to the classical quantile regression of Koenker and Bassett (1978) lies in $K(\cdot)$, i.e. the kernel function, with bandwidth h, where $F_T(x_t) = T^{-1}\sum_{k=1}^{T} \mathbf{I}_{\{x_k<x_t\}}$, to focus on the impact of x_t in the neighborhood of its θ-th quantile. The parameters in the second equation of the system (2.16) are likewise estimated from

$$\min_{\beta_{0,2}(\theta,\tau),\beta_{1,2}(\theta,\tau),\beta_{2,2}(\theta,\tau)} \sum_{t=1}^{T} \rho_\theta \left[x_t - \beta_{0,2}(\theta,\tau) - \beta_{1,2}(\theta,\tau)y_{t-1} - \beta_{2,2}(\theta,\tau)x_{t-1}\right] * \\ *K\left(\frac{F_T(y_t) - \tau}{h}\right). \tag{2.18}$$

If we remove the kernel function, the parameters no longer depend on θ, and we return to the traditional quantile regression estimator. As discussed in the previous section, we can generalize the conditional quantiles in (2.16) by adding common factors and background variables. Notably, what Sim and Zhou (2015) call the *quantile-on-quantile* approach corresponds to a non-parametric quantile regression where the knots used to obtain the local quantiles are fixed at specific quantiles of the dependent variable, Koenker (2005).

The construction of a quantile-causality network by following the quantile-on-quantile approach of Sim and Zhou (2015) builds on the significance of the coefficients associated with the impact of the covariates quantiles. In particular, focusing on x_t, the existence of causality from the θ quantile of y_t to the τ quantile of x_t depends on the coefficient $\beta_{1,2}(\theta,\tau)$. If the conditional quantiles have a more complex structure, including several lags, the number of coefficients to be tested naturally increases. When accounting for the presence of common factors and background variables, we can again follow a procedure similar to that of Billio et al. (2012).

When estimating the quantile causality network by means of the quantile-on-quantile method, the estimated network depends on two quantile levels: one referring to the dependent variable and the other to the explanatory variable. As in the previous section, if we are interested in monitoring the causality networks during periods of financial turmoil, both quantiles would be placed in the range of $1\% - 10\%$.

We note that such an approach has some similarities with the *VAR for VaR* model introduced by

White et al. (2015), which, in a multivariate framework, estimates the dependence across quantiles for a collection of series, also accounting for the possible presence of an auto-regressive structure, in the spirit of the CAViaR by Engle and Manganelli (2004). Clearly, the quantile-on-quantile dependence might be seen as a special case.

2.3.4 Quantile causality: a nonparametric test

The previous quantile regression-based approaches for detecting causality have a relevant feature in common, that is their parametric nature. In this section, we refer to another approach that is non-parametric. Non-parametric techniques offer the important advantage of requiring no particular assumption concerning the distributions for the processes underlying the variables of interest. We refer here to the nonparametric testing procedure proposed by Jeong et al. (2012).

First, we assume that the conditional variable is x_t, and we define the following vectors: $\mathcal{Y}_{t-1} \equiv (y_{t-1}, ..., y_{t-p})$, $\mathcal{X}_{t-1} \equiv (x_{t-1}, ..., x_{t-q})$, $\mathcal{Z}_{t-1} \equiv (y_{t-1}, ..., y_{t-p}, x_{t-1}, ..., x_{t-q})$, for $(p, q) > 1$. Note that the vectors refer to the lags of one or both the variables of interest. Further, $F_{y_t|\mathcal{Z}_{t-1}}(y_t|\mathcal{Z}_{t-1})$ and $F_{y_t|\mathcal{Y}_{t-1}}(y_t|\mathcal{Y}_{t-1})$ denote the distributions of y_t, conditional on $\mathcal{Z}_{t-1}$ and $\mathcal{Y}_{t-1}$, respectively; the distribution of y_t is assumed to be absolutely continuous in y for almost all $\nu = (\mathcal{Y}, \mathcal{Z})$. For the sake of simplicity, we denote the τ-th quantile of y_t conditional on $\mathcal{Z}_{t-1}$ as $Q_\tau(\mathcal{Z}_{t-1})$ and the τ-th quantile of y_t conditional on $\mathcal{Y}_{t-1}$ as $Q_\tau(\mathcal{Y}_{t-1})$.

The definition of causality in quantiles in Jeong et al. (2012) focuses on the conditional quantiles of the series densities: x_t does not cause y_t in its τ-th quantile, with respect to $\mathcal{Z}_{t-1}$, if $Q_\tau(\mathcal{Z}_{t-1}) = Q_\tau(\mathcal{Y}_{t-1})$; conversely, x_t causes y_t in its τ-th quantile, with respect to $\mathcal{Z}_{t-1}$, if $Q_\tau(\mathcal{Z}_{t-1}) \neq Q_\tau(\mathcal{Y}_{t-1})$. From the previous definition, the hypotheses to be tested read as follows:

$$\begin{cases} H_0: \; P[F_{y_t|\mathcal{Z}_{t-1}}(Q_\tau(\mathcal{Y}_{t-1})|\mathcal{Z}_{t-1}) = \tau] = 1 \\ H_1: \; P[F_{y_t|\mathcal{Z}_{t-1}}(Q_\tau(\mathcal{Y}_{t-1})|\mathcal{Z}_{t-1}) = \tau] < 1 \end{cases} \tag{2.19}$$

The non-parametric test developed by Jeong et al. (2012) is based on a measure of distance defined as:

$$J_T = \mathbb{E}\left[[F_{y_t|\mathcal{Z}_{t-1}}(Q_\tau(\mathcal{Y}_{t-1})|\mathcal{Z}_{t-1}) - \tau]^2 g_{\mathcal{Z}_{t-1}}(\mathcal{Z}_{t-1}) \right], \tag{2.20}$$

where $g_{\mathcal{Z}_{t-1}}(\mathcal{Z}_{t-1})$ is the marginal density function of $\mathcal{Z}_{t-1}$. J_T is estimated using the feasible kernel-based estimator:

$$\widehat{J}_T = \frac{1}{T(T-1)h^m} \sum_{t=1}^{T} \sum_{s \neq t} K\left(\frac{\mathcal{Z}_{t-1} - \mathcal{Z}_{s-1}}{h} \right) \tilde{\epsilon}_t \tilde{\epsilon}_s, \tag{2.21}$$

where $m = p + q$, $K(\cdot)$ is the kernel function with bandwidth h, $\tilde{\epsilon}_t = \mathbf{I}_{\{y_t \leq \widetilde{Q}_\tau(\mathcal{Y}_{t-1})\}} - \tau$, $\mathbf{I}_{\{\cdot\}}$ being the indicator function that takes a value of 1 if the condition in $\{\cdot\}$ is true, and zero otherwise. In

Jeong et al. (2012), $\widetilde{Q}_\tau(\mathcal{Y}_{t-1}) \equiv \widetilde{F}^{-1}_{y_t|\mathcal{Y}_{t-1}}(\tau|\mathcal{Y}_{t-1})$, where

$$\widetilde{F}_{y_t|\mathcal{Y}_{t-1}}(y_t|\mathcal{Y}_{t-1}) = \frac{\sum_{s\neq t} C_{t-1,s-1}\mathbf{1}_{\{y_s\leq y_t\}}}{\sum_{s\neq t} C_{t-1,s-1}} \tag{2.22}$$

is the Nadaraya-Watson kernel estimator of $F_{y_t|\mathcal{Y}_{t-1}}(y_t|\mathcal{Y}_{t-1})$, with the kernel function $C_{t-1,s-1} = C(\mathcal{Y}_{t-1} - \mathcal{Y}_{s-1})/a$, and a is the bandwidth.

Under a set of precise assumptions, Jeong et al. (2012) derived the limiting distribution for the test statistic

$$Th^{m/2}\widehat{J}_T \xrightarrow{L} \mathcal{N}(0, \sigma_0^2), \tag{2.23}$$

where

$$\sigma_0^2 = 2\mathbb{E}\left[\sigma_\epsilon^4(\mathcal{Z}_{t-1})g_{\mathcal{Z}_{t-1}}(\mathcal{Z}_{t-1})\right]\left(\int K^2(u)du\right), \tag{2.24}$$

and $\sigma_\epsilon^2(\mathcal{Z}_{t-1}) = \tau(1-\tau)$.

The unknown parameter σ_0^2 is estimated as

$$\widehat{\sigma}_0^2 = \frac{2\tau^2(1-\tau)^2}{T(T-1)h^m}\sum_{s\neq t} K^2\left(\frac{\mathcal{Z}_{t-1} - \mathcal{Z}_{s-1}}{h}\right). \tag{2.25}$$

Then, after estimating all the quantities of interest, the standardized statistic can be computed:

$$\widehat{J}_T^* = \frac{Th^{m/2}\widehat{J}_T}{\widehat{\sigma}_0}. \tag{2.26}$$

The above-described method could likewise be applied to test the causality impact of y_t on the quantiles of x_t, simply by inverting the roles of x_t and y_t.

If we detect quantile causality using the non-parametric test of Jeong et al. (2012), then we have a dependence on the chosen quantile, as in the previous quantile-based causality cases. To keep the focus on the risk side, we suggest using quantile levels in the range 1%-10%.

2.4 Empirical examples

2.4.1 Data description

The empirical analyses are conducted on three different datasets: the first concerns the 48 industry portfolios on the Kenneth R. French website; the second includes the 25 US banks with the greatest market value; the third the 25 US insurance firms with the highest market value.[2] Using the three datasets, we can test for the presence of causality links from a general economic

[2]The series of industry portfolios are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/, the data on the banks and insurance firms were obtained from Thomson Reuters Datastream.

standpoint, or by looking at the companies that were mostly affected by the recent financial crisis.

For the three datasets, we use the daily returns over two different samples. The first spans the open-market business days between 3 January 2006 and 31 December 2008. The second covers the period between 3 January 2011 and 31 December 2015. The former is characterized by 755 daily returns for each time series, while the latter records 1258 observations for each industry portfolio or firm. The two samples behave very differently, since the first includes the years of the global financial crisis, while the second covers a period of upward trend in the financial market, excluding the initial recovery period after the crisis. Our purpose is to test whether there is a different dependence structure among the variables during periods of market distress vis-à-vis periods with a positive market trend. We proceed with our estimation of causality networks by focusing on the daily returns.

Just as we selected the 25 US banks and the 25 US insurance firms with the highest market value as at the beginning of 2006, for the first time interval considered, the choice of banks and insurance companies to consider in the second period was based on their market value as at the beginning of 2011. This means that most, but not all of these financial institutions are included in both of the samples. Appendix 2.6.1 contains a list of the selected banks and insurance companies. We stress that our objective is to obtain an overview of the changes occurring in the links across nodes (banks, insurance companies, or economic sectors) when we change the approach used to ascertain the existence of nodes, switching from Granger causality to quantile-based causality, to arrive at the optimal combination of competing available networks.

Tables 2.9-2.10 in Appendix 2.6.2 show the main descriptive statistics computed for the banks in the first and second time intervals, respectively; Tables 2.11-2.12 concern the insurance companies and the statistics for the 48 industry portfolios are given in Tables 2.13-2.14. In all cases, the average returns are lower in 2006-2008 than in 2011-2015. This was expected and is due to the effects of the global financial crisis. The first time interval is also characterized by a greater uncertainty, averaging higher standard deviations and interquartile ranges; this was also expected. The risk affecting the years 2006-2008 is also apparent from the corresponding minimum and maximum returns. The distributions of these returns are fat-tailed (especially in the first period), consistently with the stylized facts highlighted by Cont (2001). The distributions are also highly skewed. Finally, we used the Ljung-Box test for mean serial dependence on both the returns and the squared returns, using 1, 5 and 10 lags. As expected, the outcomes show no serial dependence on returns, while squared returns (a proxy of variances) are highly correlated, suggesting the presence of heteroskedasticity. In short, the descriptive analysis shows significant differences between the years 2006-2008 and 2011-2015, that are clearly a consequence of the turmoil affecting the US economy during the former period. We now take a closer look at the dependence across companies or economic sectors by focusing on causality analyses.

2.4.2 Granger and quantile causality networks

In building the causality networks, we extend the existing literature by combining the classic Granger testing approach with methods based on analyses of dependence across quantiles, as described in Section 2.3.1.

The methods based on quantile regression and quantile causality depend on the quantile at which the analysis is performed, so we must first specify which quantiles we use to conduct the dependence or causality analysis. Our analysis illustrates the changes occurring in the causality networks when we switch from Granger causality to quantile causality, without identifying the optimal quantile over which to measure quantile causality. We therefore decided to fix the quantiles of interest a priori: we chose three quantiles, 0.1, 0.5 and 0.9, corresponding to the tails and the center of the distributions of the returns. Note that, when considering the approach of Sim and Zhou (2015), where we have quantile causality depending on two different quantiles, we set both quantiles at the same level.

In the evaluation of quantile regression parameters, we estimate the standard errors with the xy-pair bootstrap method, Efron and Tibshirani (1993), with 5000 replications. This approach provides accurate results without assuming any particular distribution for the error term. When a kernel function is involved, we set it always to the Gaussian one. In the Jeong et al. (2012) test, we need to specify lag orders for both the dependent and the explanatory variables. To limit the computational burden, we fix a-priori both lag orders to be 1. For the bandwidths in the Jeong et al. (2012) test, we adopt the least squares cross-validation method of Rudemo (1982) and Bowman (1984). Differently, in the case of quantile-on-quantile, we fix a-priori the bandwidth at 0.1. We remind that the bandwidth applies to a quantile level. Our choice allows avoiding estimating the parameters with a small number of data points (as it is the case with smaller bandwidths) and, at the same time, to maintain the focus around the quantiles of interest. We set the confidence level at 5% for judging the significance of the coefficients and testing the null hypothesis behind the tests for Granger or quantile causality.

To control for the possible impact of the common dependence on the market, we test for Granger causality as well as for the various forms of quantile causality, also including the supercomposite US market index within the corresponding models.[3]

In the remainder of this paper, we identify the various networks that we estimate by means of acronyms. For networks estimated using quantile regression approaches (the baseline case, the quantile-on-quantile, and the non-parametric test), the acronym consists of four or five characters. The first and second identify the method: QR for baseline quantile regression; Qo for quantile-on-quantile; QN for non-parametric quantile. The third and fourth characters identify the quantile: for instance, QR10 refers to the network estimated by baseline quantile regression at the 10% quantile. For the quantile-on-quantile cases, the reported quantile is used for both the dependent and the

[3]We obtain the market return from the Fama/French 3 Factors dataset provided by Kenneth R. French and available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

explanatory variables. For standard Granger causality networks we use GR. Then we add a final letter F to the acronym if we allow for the presence of a common factor in our estimation of the causality networks.

Figures 2.2-2.4 graphically represent selected networks. Appendix 2.6.3 includes graphs for all the estimated causality networks.

Figure 2.2 includes four different networks among the largest US banks: the Granger causality network and three different quantile causality networks estimated by focusing on the 10% quantile. We indicate the baseline quantile network, the quantile-on-quantile network and the non-parametric quantile causality network. All the networks refer to the financial crisis period (2006 to 2008), and are estimated without any common factors. Figures 2.3 and 2.4 show similar networks estimated for the 25 largest US insurance companies and the US industry portfolios, respectively. We stress that we report results for the 10% quantile because we wish to shed some light on the possible differences between Granger causality (which focuses on the mean) and quantile causality (which places more emphasis on the tails). Networks that are based on quantile causality in the mean and also pay attention to the upper tail are available in Appendix 2.6.3.

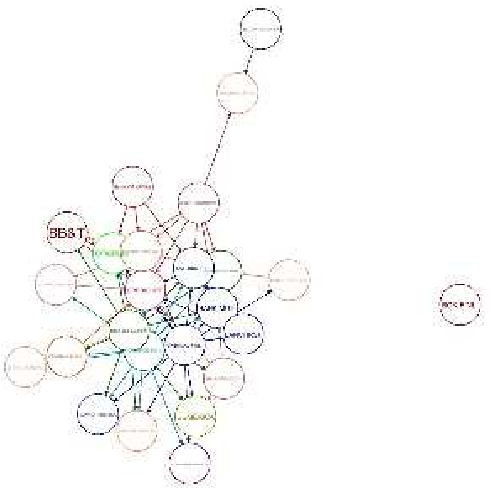
Figure 2.2 shows that the quantile causality network extracted using the baseline quantile regression method has a majority of isolated nodes, whereas the network extracted with a non-parametric quantile causality test suggests the presence of a much greater density. The comparison between the networks of the banks and those of the insurance companies and industry portfolios shows that the former are less connected whatever methods is used. The non-parametric quantile causality test also generates networks characterized by a similar topology for all institutions and portfolios; in particular, it is easy to distinguish between a kernel and a periphery.[4]

Figure 2.5 shows the dataset of 25 banks over time, comparing the networks estimated for $2006-2008$ with those obtained for $2011-2015$, using two specific causality network estimation methods: Granger causality and non-parametric quantile causality (10% quantile). We can see some changes in the Granger network structure when moving from the earlier to the later period. These changes are less clear when we consider non-parametric quantile causality, in which case the network still presents a kernel-periphery structure.

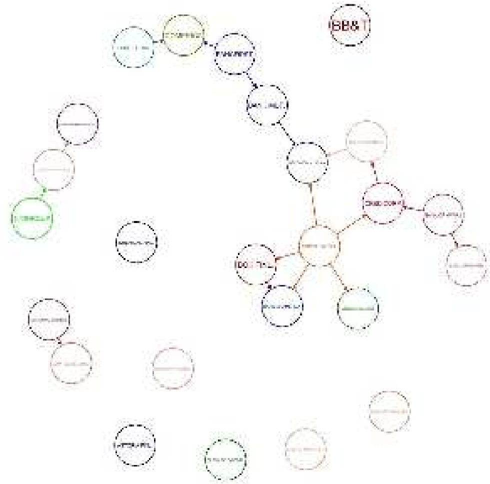
These preliminary graphical analyses suggest that there are potentially relevant differences between the networks estimated using Granger causality as opposed to quantile-based causality approaches. The latter have a more clear focus on risk than the former. Before moving on to the combination of the estimated networks, we run a comparison of the estimated networks using summary measures.

We consider four different indicators: *Density*, *Assortativity*, and two versions of *Eigenvector centrality*. Density monitors the number of connections between nodes. A higher density is the sign of a large number of connections between nodes, which are consequently more closely related to one another. Assortativity captures the nodes' tendency to connect with other nodes having

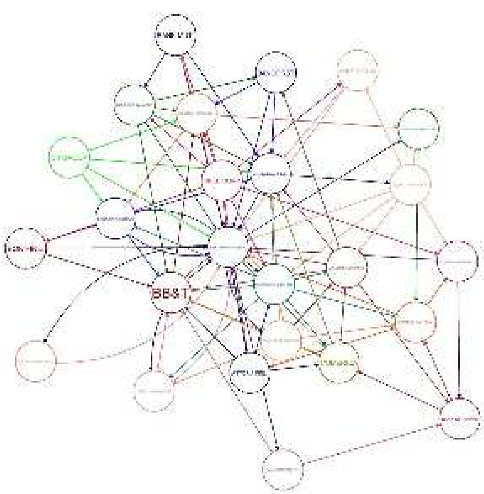
[4]We use the Fruchterman & Reingold algorithm for network visualization, Fruchterman and Reingold (1991).



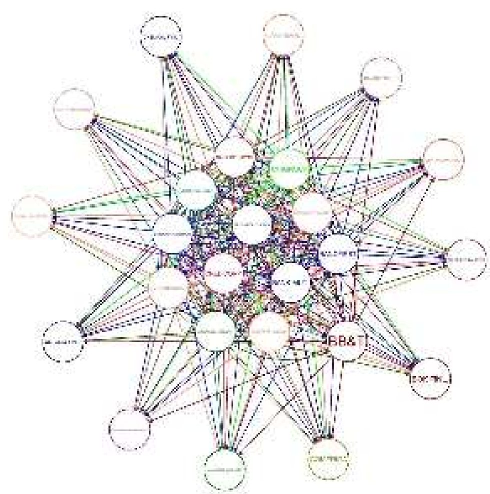
(a) Granger



(b) Baseline Quantile

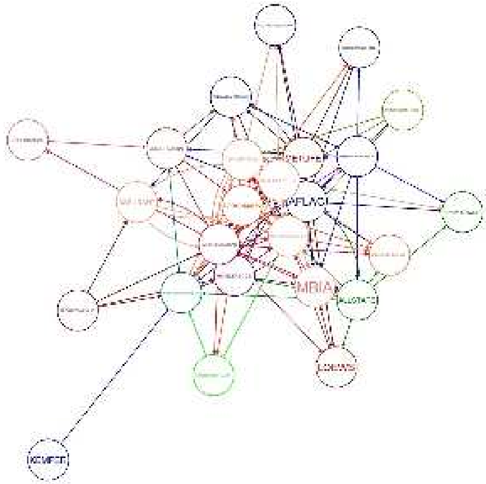


(c) Quantile on Quantile

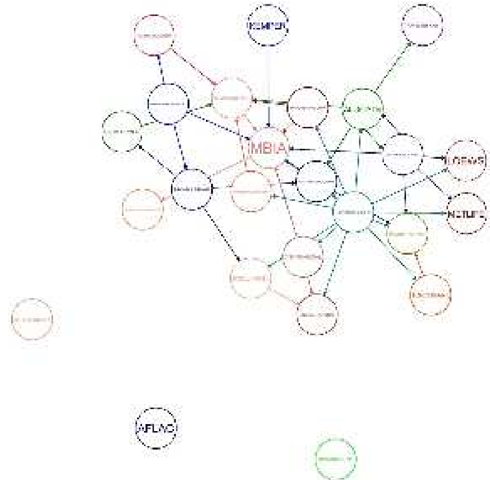


(d) Non-parametric Quantile

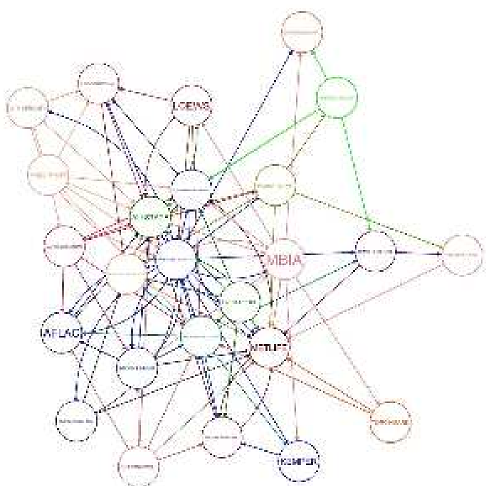
Figure 2.2: The figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 banks ordered for market capitalization and listed in Appendix 2.6.1. Panel a) reports the network extracted by the standard Granger causality approach of Billio et al. (2012). Panel b) reports the Network extracted from a baseline quantile regression methodology, at the 10% quantile. Panel c) plots the network extracted from a quantile-on-quantile methodology at the 10% quantile. Panel d) graphs the network estimated by a non-parametric quantile causality methodology at the 10% quantile. All the estimates exclude the presence of common factors. We use the Fruchterman & Reingold algorithm for network visualization.



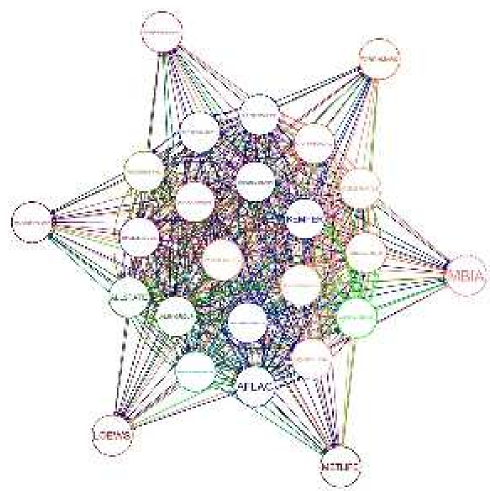
(a) Granger



(b) Baseline Quantile

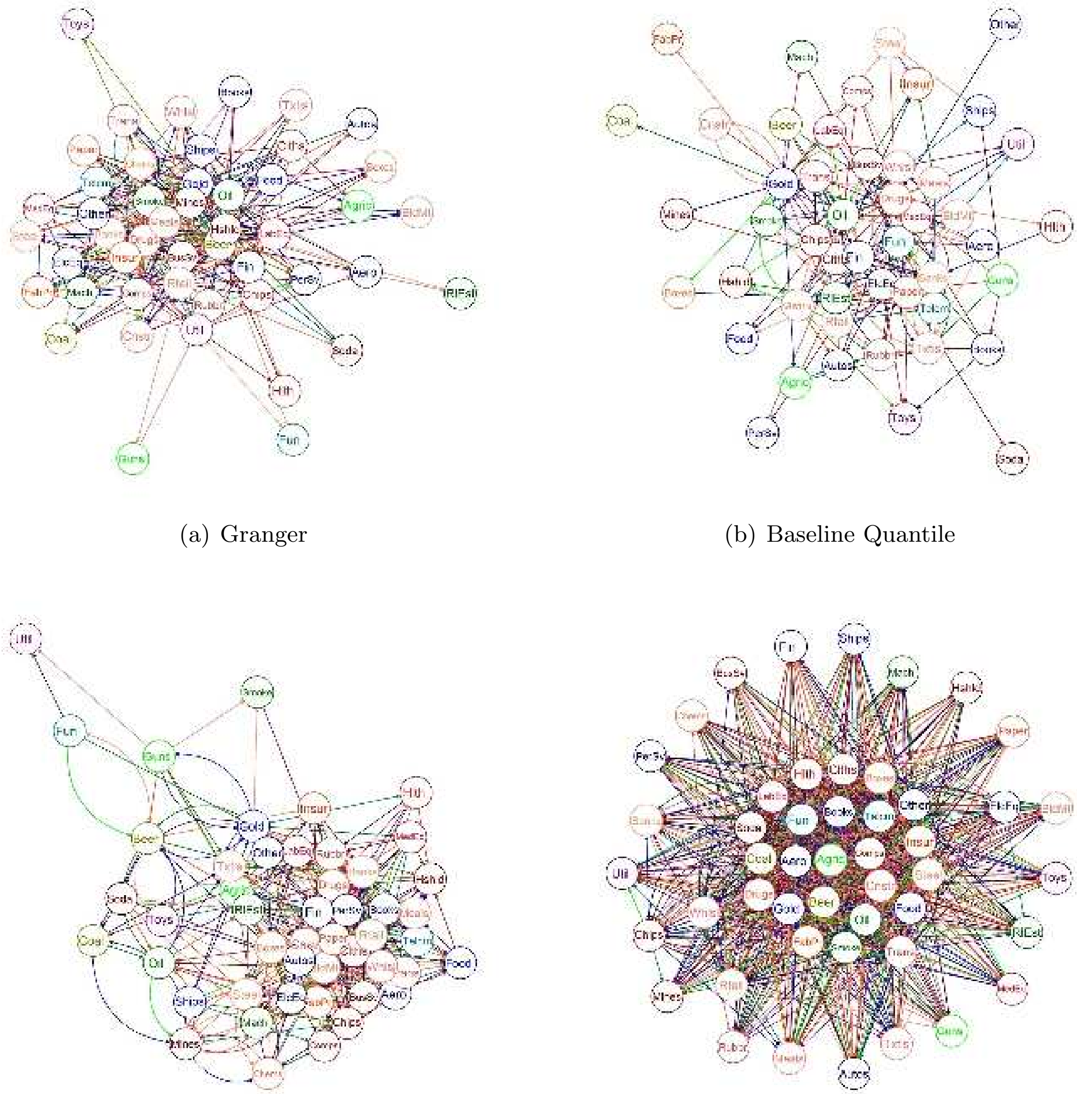


(c) Quantile on Quantile



(d) Non-parametric Quantile

Figure 2.3: The figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 insurances ordered for market capitalization and listed in Appendix 2.6.1. Panel a) reports the network extracted by the standard Granger causality approach of Billio et al. (2012). Panel b) reports the Network extracted from a baseline quantile regression methodology, at the 10% quantile. Panel c) plots the network extracted from a quantile-on-quantile methodology at the 10% quantile. Panel d) graphs the network estimated by a non-parametric quantile causality methodology at the 10% quantile. All the estimates exclude the presence of common factors. We use the Fruchterman & Reingold algorithm for network visualization.



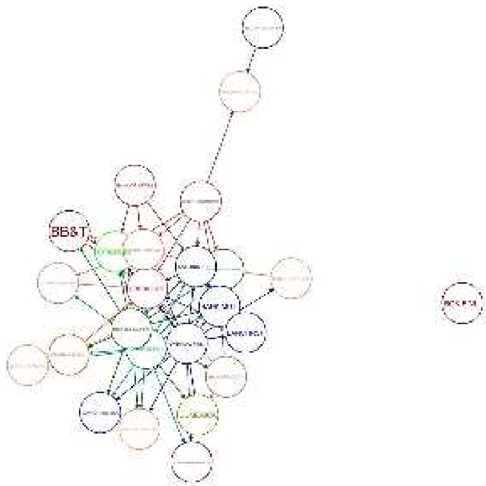
(a) Granger

(b) Baseline Quantile

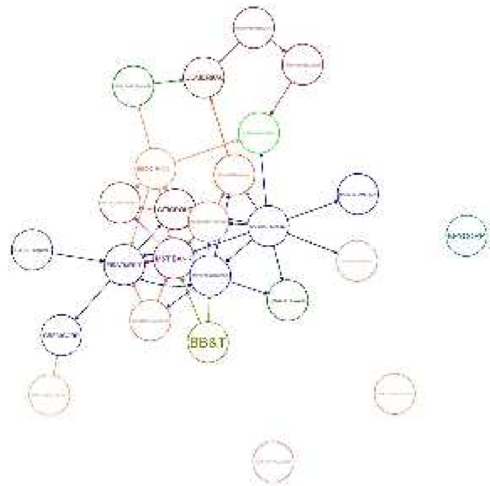
(c) Quantile on Quantile

(d) Non-parametric Quantile

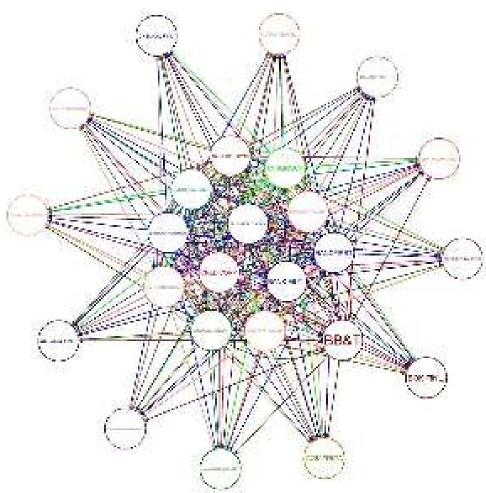
Figure 2.4: The figure visualizes 4 different networks for the period 2006-2008 relative to the 48 Industry portfolios obtained from the Kenneth French website. Panel a) reports the network extracted by the standard Granger causality approach of Billio et al. (2012). Panel b) reports the Network extracted from a baseline quantile regression methodology, at the 10% quantile. Panel c) plots the network extracted from a quantile-on-quantile methodology at the 10% quantile. Panel d) graphs the network estimated by a non-parametric quantile causality methodology at the 10% quantile. All the estimates exclude the presence of common factors. We use the Fruchterman & Reingold algorithm for network visualization.



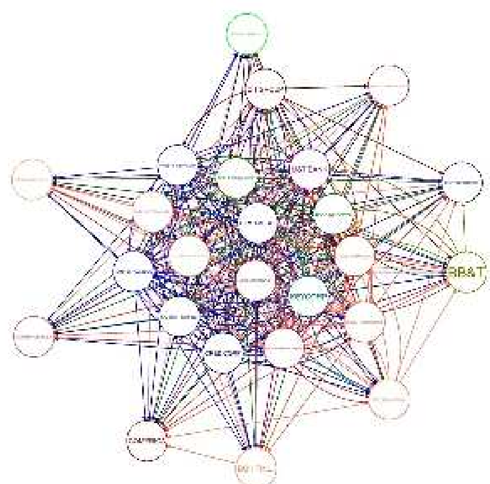
(a) Granger 2006-2008



(b) Granger 2011-2015



(c) Non-parametric quantile 2006-2008



(d) Non-parametric quantile 2011-2015

Figure 2.5: The figure displays the network of the 25 banks ordered for market capitalization (see Appendix 2.6.1 by contrasting methods and samples. Panels a) and b) report the networks extracted by using the standard Granger causality methodology for the $2006-2008$ and $2011-2015$ samples, respectively. Panels c) and d) report the networks extracted by using the the non-parametric quantile causality test at the 10% quantile for samples $2006-2008$ and $2011-2015$, respectively. All the estimates exclude the presence of common factors. We use the Fruchterman & Reingold algorithm for network visualization.

similar properties; it can take values in the range of $(-1, 1)$. For values close to 1, the network has an assortative behavior, with nodes being connected to other nodes that have similar degrees; for values nearing zero, the network becomes similar to a random graph. A disassortative behavior, when high-degree nodes point to low-degree nodes, corresponds to assortativity values close to -1.[5] Eigenvector centrality monitors the relevance of each node as a function of the relevance of neighboring nodes. We consider two versions: one based on the non-normalized adjacency matrix, and one based on the row-normalized adjacency matrix. We also normalize the eigenvector centrality of each node to the maximum score obtained by the most connected node. The eigenvector centrality value thus ranges from zero to one, and can easily be compared across networks. In the summary tables, we focus on the average eigenvector centrality across nodes. Changes in the eigenvector centrality are a sign of changes in the network structure. Appendix 2.6.4 provides additional details on the network measures considered. Tables from 2.1 to 2.3 contain the summary measures.

Table 2.1 contains the network measures for the banks dataset. We can see that, on average, the density is slightly smaller during the crisis, while the disassortative behavior (seen in both periods) is higher. Granger's causality networks (with/without the common factor) have small densities that remain almost constant in the two samples, and a disassortative behavior, and the average eigenvector centrality increases in the most recent period. The values for the quantile-based networks are quite different, as the previous graphical analysis suggests. In particular, the networks derived by means of the non-parametric quantile causality test have the highest density, combined with a disassortative pattern. These two elements could explain the kernel-periphery structure exhibited in the Figure 2.2.

A high density combined with a disassortative pattern is also associated with very high eigenvector centrality averages, which indicate that the nodes' relevance is quite evenly distributed, a somewhat expected result given that we focus on the largest banks. Notably, the picture is quite different in the Granger causality networks, which are characterized by a lower average eigenvector centrality. From a systemic risk perspective, this finding suggests that, while the Granger causality analysis provides evidence of few relevant nodes that are more central to the network structure, a non-parametric quantile causality test leads to the construction of a denser network where the risk is more evenly distributed across nodes, and many nodes (more than those emerging from Granger causality) are systemically relevant. As the graphs suggest, the non-parametric quantile causality networks also differ from those based on other quantile-based approaches. In particular, the baseline quantile case provides summary measures more closely resembling those of Granger causality, while the quantile-on-quantile cases have density measures higher than with Granger causality but lower than with non-parametric quantile causality, and they show the most disassortative behaviors. We note some interesting differences across quantiles, with higher densities on the

[5] The few blank spaces appearing in the following tables of network summary measures correspond to indeterminate forms. The indeterminate forms of the assortativity and eigenvector centrality measures are discussed in the Appendix 2.6.4.

Table 2.1: This table reports summary measures for the networks estimated from competing causality methodologies over the 25 Banks listed in Appendix 2.6.1. QB stands for baseline quantile, Qo for quantile-on-quantile, QN for non-parametric quantile causality, GR for Granger causality. Numbers identify the reference quantile for quantile-based causality networks, 10 for 10%, 50 for the median and 90 for 90%. An F at the end of the acronyms specifies that the underlying models included the market index as a common factor.

	Density		**Assortativity**		**Eigenvector Centrality**	
	06-08	**11-15**	**06-08**	**11-15**	**06-08**	**11-15**
GR	0.12	0.07	-0.37	-0.22	0.12	0.26
QB10	0.03	0.04	0.05	-0.13		
QB50	0.05	0.07	0.03	-0.06	0.16	
QB90	0.12	0.13	-0.44	-0.22	0.25	0.11
Qo10	0.16	0.36	-0.37	-0.28	0.23	0.45
Qo50	0.06	0.03	-0.43	0.00	0.34	
Qo90	0.17	0.35	-0.53	-0.07	0.25	0.44
QN10	0.51	0.63	-0.11	-0.20	0.93	0.83
QN50	0.29	0.33	-0.30	-0.28	0.75	0.72
QN90	0.57	0.52	-0.15	-0.13	0.90	0.83
GRF	0.07	0.07	-0.01	-0.24	0.22	0.31
QB10F	0.04	0.04	-0.26	0.13	0.08	
QB50F	0.04	0.09	-0.23	-0.12	0.14	0.29
QB90F	0.10	0.09	-0.37	-0.34	0.21	0.26
Qo10F	0.22	0.50	-0.29	-0.24	0.24	0.50
Qo50F	0.06	0.03	-0.07	-0.25	0.18	
Qo90F	0.10	0.51	-0.50	-0.20	0.18	0.57
QN10F	0.52	0.70	-0.14	-0.23	0.88	0.84
QN50F	0.34	0.38	-0.22	-0.21	0.80	0.81
QN90F	0.64	0.64	-0.09	-0.14	0.96	0.89
Average	**0.21**	**0.28**	**-0.24**	**-0.17**	**0.41**	**0.54**
Standard Deviation	**0.20**	**0.24**	**0.17**	**0.11**	**0.33**	**0.26**

extreme quantiles (10% and 90%) than on the median case, which comes the closest to the Granger causality. Notably, this would mean that the network structure changes if we move away from the mean (median), an important aspect to bear in mind if our purpose is to analyze the spread of risk in times of market turmoil. Finally, the introduction of a common market factor seems to have a limited impact.

Table 2.2 indicates that the insurance companies dataset behaves in much the same way as the banks dataset (thus confirming our previous comments), with a marked change in the network structure when moving from Granger causality to quantile causality. The most relevant difference concerns network density, which is much higher in the tails than in the mean (which coincides with Granger causality). We also find the highest average eigenvector centrality coinciding with non-parametric quantile causality.

Table 2.3 shows the summary measures for the causality network estimated from the 48 industry portfolios. Here again, we find relevant differences between the summary measures for the Granger and quantile causality networks. This holds particularly for network density and average eigenvector centrality. We note, however, that the structure of the non-parametric quantile causality networks differs considerably from the other quantile causality networks in all three datasets.

The graphical analysis and summary measures confirm that, changing our approach to estimating a causality network, coincides with important changes in the network structure. To examine the possible relevance of either the Granger causality network or the quantile causality networks, we therefore proceed, in the following section, with the estimation of a composite network.

2.4.3 The composite causality network

Starting from the availability of causality networks estimated using four different methods (Granger, Quantile Regression, Quantile-on-Quantile and Non-parametric Quantile causality), and over different quantiles (10%, the median and 90%) for three of them, we now proceed to estimate composite networks.

We estimate the model in equation (5), accounting for the presence of common factors, for which we follow the usual practice and introduce the market factor, the size factor, the book-to-market factor, and the momentum factor, following Fama and French (1993), Fama and French (1995), and Carhart (1997). We have no information a priori to suggest a possible preference for particular network, so we estimate the composite network starting from four different layers, where the quantile-based networks are associated with the same reference quantile. We provide a sensitivity analysis on the effect of excluding a single network in the robustness checks section.

Then we estimate the linear factor model, focusing on weekly returns. While it is more common to consider the monthly frequency when estimating factor models, this would leave us with only 36 observations in the first sample, while we have 60 monthly returns in the second. Hence our decision to focus on the weekly frequency, which enables us to increase the number of returns for the factor model (augmented with network dependence) to 108 in the first sample and 316 in the

Table 2.2: This table reports summary measures for the networks estimated from competing causality methodologies over the 25 Insurance companies listed in Appendix 2.6.1. QB stands for baseline quantile, Qo for quantile-on-quantile, QN for non-parametric quantile causality, GR for Granger causality. Numbers identify the reference quantile for quantile-based causality networks, 10 for 10%, 50 for the median and 90 for 90%. An F at the end of the acronyms specifies that the underlying models included the market index as a common factor.

	Density		**Assortativity**		**Eigenvector Centrality**	
	06-08	**11-15**	**06-08**	**11-15**	**06-08**	**11-15**
GR	0.20	0.03	-0.29	-0.37	0.34	
QB10	0.07	0.06	-0.36	0.15	0.15	0.22
QB50	0.07	0.14	-0.17	-0.15	0.32	0.36
QB90	0.04	0.07	-0.44	-0.03		
Qo10	0.17	0.25	-0.31	-0.29	0.29	0.33
Qo50	0.03	0.05	0.00	-0.10		
Qo90	0.22	0.21	-0.42	-0.08	0.38	0.30
QN10	0.76	0.56		-0.23	0.96	0.90
QN50	0.41	0.50	-0.35	-0.18	0.70	0.85
QN90	0.76	0.59	-0.02	-0.20	0.96	0.82
GRF	0.15	0.04	-0.31	-0.40	0.26	
QB10F	0.04	0.08	-0.49	-0.12		0.22
QB50F	0.05	0.12	-0.06	-0.05		0.27
QB90F	0.04	0.10	-0.44	-0.08		0.37
Qo10F	0.08	0.43	-0.06	-0.28	0.18	0.44
Qo50F	0.04	0.05	0.13	0.21		0.21
Qo90F	0.10	0.45	-0.43	-0.31	0.24	0.46
QN10F	0.76	0.66		-0.11	0.96	0.93
QN50F	0.54	0.55	-0.13	-0.11	0.92	0.93
QN90F	0.76	0.62		-0.18	0.96	0.86
Average	**0.26**	**0.28**	**-0.24**	**-0.14**	**0.54**	**0.53**
Standard Deviation	**0.29**	**0.23**	**0.19**	**0.15**	**0.34**	**0.29**

Table 2.3: This table reports summary measures for the networks estimated from competing causality methodologies over the 48 Industry portfolios recovered from the Kenneth French website. QB stands for baseline quantile, Qo for quantile-on-quantile, QN for non-parametric quantile causality, GR for Granger causality. Numbers identify the reference quantile for quantile-based causality networks, 10 for 10%, 50 for the median and 90 for 90%. An F at the end of the acronyms specifies that the underlying models included the market index as a common factor.

	Density		**Assortativity**		**Eigenvector Centrality**	
	06-08	**11-15**	**06-08**	**11-15**	**06-08**	**11-15**
GR	0.14	0.02	-0.49	-0.74	0.15	0.36
QB10	0.09	0.06	-0.39	-0.20	0.24	0.24
QB50	0.16	0.06	-0.27	-0.13	0.21	0.27
QB90	0.14	0.07	-0.24	-0.37	0.29	0.29
Qo10	0.20	0.52	-0.06	-0.10	0.29	0.60
Qo50	0.08	0.06	0.09	-0.13	0.25	0.13
Qo90	0.14	0.48	-0.29	-0.15	0.26	0.56
QN10	0.52	0.42	-0.25	-0.14	0.88	0.90
QN50	0.32	0.28	-0.22	-0.23	0.82	0.83
QN90	0.57	0.48	-0.14	-0.18	0.93	0.90
GRF	0.15	0.02	-0.33	-0.71	0.18	0.16
QB10F	0.14	0.04	-0.11	-0.11	0.17	0.18
QB50F	0.15	0.06	-0.17	-0.21	0.20	0.16
QB90F	0.09	0.08	-0.12	0.02	0.17	0.18
Qo10F	0.39	0.79	-0.28	-0.12	0.43	0.79
Qo50F	0.09	0.07	-0.19	-0.10	0.13	0.10
Qo90F	0.35	0.82	-0.27	-0.09	0.39	0.82
QN10F	0.59	0.47	-0.12	-0.18	0.95	0.88
QN50F	0.33	0.33	-0.18	-0.22	0.85	0.81
QN90F	0.59	0.51	-0.15	-0.11	0.93	0.93
Average	**0.26**	**0.28**	**-0.21**	**-0.21**	**0.44**	**0.51**
Standard Deviation	**0.18**	**0.26**	**0.12**	**0.19**	**0.32**	**0.32**

second. This choice has advantages in terms of model estimation and parameter inference. We do not consider daily data as they would be bound to require the introduction of heteroskedastic dynamics in the variance of the residuals, adding to the complexity of the estimation due to the well-known curse of dimensionality. Estimates of the network combination on monthly returns are nonetheless provided in the robustness checks sections.

The estimates of the linear factor model with network dependence generate different outputs. First, there are the model parameters: the weight of each network, as measured by the δ_i parameters, and the impact of the composite network on the asset returns, the parameters included in $\mathcal{R}$. Second, comes the composite network, obtained by combining the primitive networks weighted with the δ_i coefficients. Finally, there are the model residuals, which contain information useful for assessing the advantages of moving to a composite network as opposed to the benchmark cases of no network dependence (where the contemporaneous link matrix A is an identity), or a network dependence captured by Granger causality. The latter is a valuable benchmark as we would like to underscore the potential improvement associated with measuring asset links going beyond the mean (i.e. on the quantiles). To compare models, we use the residuals average correlation: if we see improvements, we expect to have residuals characterized by a smaller correlation level, i.e. more whitened residuals.

Table 2.4 shows the parameters estimated for the combined network in the three datasets and over sample periods. Bearing in mind that the sum of these parameters is 1 and they are all positive, a higher value of a parameter indicates a greater relevance of the associated network. We also assess the significance of the estimated parameters. Within the banks dataset, we note that the non-parametric quantile causality network is the most relevant during the financial crisis period and across all quantiles. Notably, the estimated δ parameter for this network ranges between 0.736 and 0.883, and it is always statistically significant when the estimation of the networks takes the presence of a common market factor into account.

We stress that, from a systemic risk perspective, this result suggests that the risk is more widespread across banks, as the non-parametric quantile network is much denser than the other causality networks. This greater relevance of the non-parametric quantile causality network also emerges for the median and for the lower and upper tails. In all cases, the Granger causality network has a very small weight (which is non-significant in five cases out of six). Switching to the more recent period considered, both the non-parametric quantile causality network and the quantile-on-quantile causality network are relevant, with and without the introduction of common market factors. Here again, although it is more statistically significant, the Granger causality network has smaller weights than the quantile-based causality networks. Overall, in both samples, the baseline quantile regression network has the least relevant role. Finally, in the second sample, we see a clear change in the combined network parameters when moving from median networks to the use of networks estimated on either the lower or upper tails. In particular, the impact of the quantile-on-quantile networks increases, thus supporting the importance of looking at quantile causality

Table 2.4: The table reports the δ of model (2.5) that represent the weights for networks combination. The top panel focused on the banks dataset, the middle panel on the insurance companies dataset and the bottom panel on the industry portfolios dataset. The first column identifies the quantiles used to estimate the quantile-based network, and the second column indicates if a common factor was used (Y) or not used (N) in the estimation of the causality networks. Columns 3 to 6 refer to the crisis sample while columns 7 to 10 to the most recent sample. The second row identifies the four different networks which are optimally combined: baseline quantile causality - QB; quantile-on-quantile causality Qo; non-parametric quantile causality - QN; Granger causality. Parameters are, by construction, positive and sum up to one (within each row and within each period). A star identifies parameters significant at the 5% confidence level.

		2006-2008				**2010-2015**			
Quantile	Factor	**QB**	**Qo**	**QN**	**GR**	**QB**	**Qo**	**QN**	**GR**
					25 Banks				
10%	N	0.061	0.055	0.875	0.010	0.000	0.630*	0.354*	0.017*
50%	N	0.146	0.108	0.736*	0.010	0.091*	0.065*	0.773*	0.071
90%	N	0.005	0.008	0.883	0.104	0.000	0.706*	0.243	0.051*
10%	Y	0.022	0.073	0.827*	0.077	0.000	0.538*	0.428*	0.034*
50%	Y	0.052	0.057	0.842*	0.050	0.107	0.072*	0.649*	0.173*
90%	Y	0.134	0.000*	0.762*	0.104*	0.000	0.876*	0.121	0.003*
					25 Insurance Companies				
10%	N	0.000	0.022*	0.951*	0.027	0.058	0.831	0.111	0.000
50%	N	0.865*	0.000	0.032*	0.103	0.059	0.045	0.886*	0.010
90%	N	0.000	0.028	0.972*	0.000	0.000	0.364*	0.436*	0.201
10%	Y	0.001	0.006	0.948*	0.045	0.000	0.488	0.512	0.000
50%	Y	0.731*	0.054	0.188*	0.027*	0.051	0.040	0.837*	0.072
90%	Y	0.000	0.046	0.954*	0.000	0.000	0.554	0.446	0.000
					48 Industry Portfolios				
10%	N	0.000	1.000*	0.000	0.000	0.032	0.968*	0.000	0.000
50%	N	0.212	0.000	0.478	0.310	0.021	0.031*	0.848*	0.100
90%	N	0.108	0.892*	0.000	0.000	0.000	1.000*	0.000	0.000
10%	Y	0.178	0.471	0.000	0.351	0.036	0.695*	0.228	0.041
50%	Y	0.123	0.000	0.000	0.877*	0.092	0.007*	0.836*	0.064
90%	Y	0.000	0.810	0.000	0.190	0.107	0.808	0.030	0.055

too when accounting for interdependence across assets in a linear factor model, and showing that a double conditioning (on both the dependent and the explanatory variables) is important when estimating causality at quantile level.

The insurance companies dataset produces somewhat similar results. In both periods, Granger causality networks are the least relevant, being associated with small coefficients (and only one in twelve is statistically significant). In the first period considered, non-parametric quantile causality

Table 2.5: The table reports summary measures of the composite networks estimated from model (2.5) over the different datasets, sample periods, and reference quantiles. In all cases the composite networks is formed by the combination of four networks: the baseline quantile causality network, the quantile-on-quantile causality network, the non-parametric quantile causality network, the Granger causality network. The top panel focused on the banks dataset, the middle panel on the insurance companies dataset and the bottom panel on the industry portfolios dataset. The first column identifies the quantiles used to estimate the quantile-based networks, and the second column indicates if a common factor was used (Y) or not used (N) in the estimation of the causality networks.

Measures		**Density**		**Assortativity**		**Eigenvector Centrality**		**Eigenvector Centrality Adj Weighted**	
Quantile	Factor	**06-08**	**11-15**	**06-08**	**11-15**	**06-08**	**11-15**	**06-08**	**11-15**
					25 Banks				
10%	N	0.63	0.79	-0.30	-0.23	0.70	0.83	0.35	0.47
50%	N	0.45	0.43	-0.28	-0.28	0.62	0.61	0.24	0.43
90%	N	0.69	0.76	-0.32	-0.25	0.70	0.77	0.32	0.57
10%	Y	0.65	0.87	-0.36	-0.25	0.67	0.87	0.39	0.64
50%	Y	0.45	0.48	-0.31	-0.36	0.65	0.69	0.31	0.41
90%	Y	0.72	0.85	-0.28	-0.25	0.75	0.85	0.39	0.64
					25 Insurance Companies				
10%	N	0.88	0.72	-0.17	-0.29	0.88	0.74	0.66	0.45
50%	N	0.59	0.61	-0.22	-0.21	0.72	0.85	0.37	0.60
90%	N	0.87	0.72	-0.15	-0.24	0.91	0.77	0.66	0.50
10%	Y	0.82	0.82	-0.22	-0.30	0.85	0.82	0.55	0.59
50%	Y	0.66	0.64	-0.25	-0.23	0.79	0.84	0.55	0.51
90%	Y	0.83	0.83	-0.22	-0.26	0.83	0.83	0.60	0.59
					48 Industry Portfolios				
10%	N	0.71	0.74	-0.22	-0.26	0.77	0.78	0.46	0.62
50%	N	0.50	0.37	-0.30	-0.29	0.58	0.51	0.29	0.19
90%	N	0.71	0.74	-0.21	-0.24	0.76	0.76	0.38	0.62
10%	Y	0.83	0.89	-0.24	-0.24	0.83	0.90	0.51	0.69
50%	Y	0.53	0.42	-0.35	-0.37	0.56	0.55	0.24	0.23
90%	Y	0.80	0.92	-0.29	-0.15	0.80	0.92	0.47	0.70

is the most relevant, although baseline quantile causality network receives a much larger weight in the median case (unlike the picture emerging from the banks dataset). In the second sample, both non-parametric quantile causality and quantile-on-quantile causality are relevant, with a change in the estimated parameters when moving from networks estimated on the median to networks estimated on the 10% or 90% quantiles.

Finally, for the industry portfolio dataset, the results are more heterogeneous in the first sample, while in the second they are consistent with the two previous cases. In the first period, the significance is limited in many cases, particularly for the quantile-based causality networks estimated at the median. In the second period, there is a marked difference between the quantile-based causality estimated at the median and those estimated on the tails. Be that as it may, Granger causality networks receive the smallest weight (and are never statistically significant).

Table 2.5 shows the summary measures for the combined networks. The various composite networks are similar in all the quantities we report (for a given sample period, and a given dataset). The heterogeneity identified is much smaller than was seen for the primitive networks. Figures 2.6 to 2.8 show the combined networks for the period $2006 - 2008$.

We link this finding to the use of a linear factor model augmented with network dependence. The contemporaneous relation across the modelled variables captures the correlation across these variables and goes beyond what we associate with common factors. It might be that the various composite networks capture the dependence across the returns (beyond common factors in a similar way. The differences we find depend partly on the heterogeneity across networks and partly on the different weights assigned to the primitive networks.

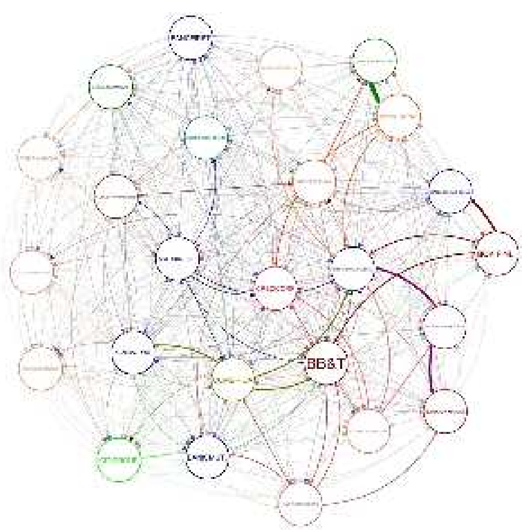


Figure 2.6: The figure visualizes the network for the Banks companies dataset. The network is extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method, during the period 2006-2008. In this case we do not allow the presence of the common factor for network estimations.

To shed further light on the differences between the composite networks and generate some evidence of the improvement gained by the linear factor model augmented with network combination, we provide descriptive analyses -in Tables 2.6 to 2.8- of the correlations between the model residuals (2.5). The tables include two benchmarks: a standard linear factor model, the Carhart (1997) 4-factors CAPM; and a linear factor augmented with network dependence where the latter is the Granger causality network (with or without the inclusion of a common factor in estimating

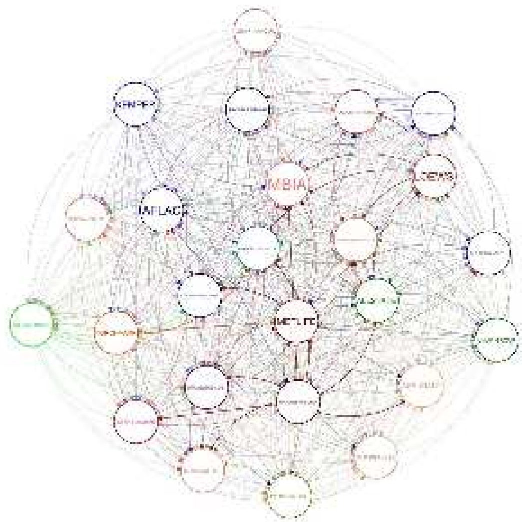


Figure 2.7: The figure visualizes the network for the Insurers companies dataset. The network is extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method, during the period 2006-2008. In this case we do not allow the presence of the common factor for network estimations.

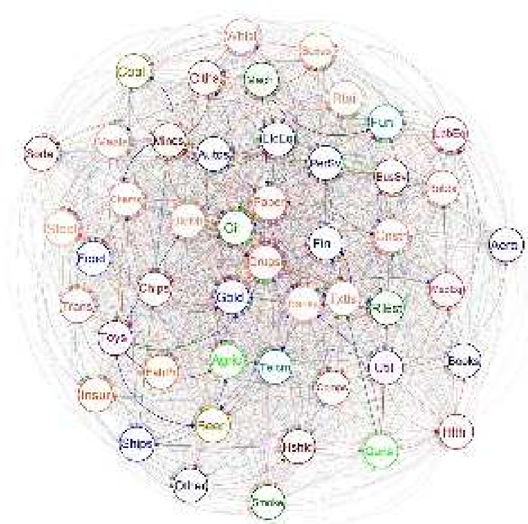


Figure 2.8: The figure visualizes the network for the Industry portfolios dataset. The network is extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method, during the period 2006-2008. In this case we do not allow the presence of the common factor for network estimations.

causal relationships). For the datasets concerning the banks and insurance companies, the results are much the same. The residuals of the 4-factors CAPM have the largest median correlations, and a distribution of these correlations shifted to the right, with a clear prevalence of positive values. The introduction of network dependence, when measured by Granger causality, improves the model fit, but the predominance of positive values in the correlation remains (see the small fraction of correlations below -0.1), and the median correlation remains above 0.1. With the introduction of a plurality of networks, the model fit improves considerably: the residual correlations are centered at zero, with a higher fraction of correlations below -0.1, and a marked reduction in the presence of large positive residual correlations. We thus conclude that our approach based on combining several networks within a network augmented linear factor model constitutes an improvement over the use of simple Granger causality. The improvement achieved by the latter, over the multifactor model, was already documented in Billio et al. (2017).

Table 2.6: The table reports residual correlation descriptive analyses for the Banks dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements** ≤ -0.1
				2006-2008				
Q(10%)	4	N	-0.279	0.584	-0.106	0.071	0.282	11.7%
Q(50%)	4	N	-0.345	0.596	-0.109	0.062	0.311	10.7%
Q(90%)	4	N	-0.269	0.600	-0.146	0.050	0.276	16.0%
Q(10%)	4	Y	-0.297	0.566	-0.135	0.035	0.238	17.7%
Q(50%)	4	Y	-0.349	0.503	-0.119	0.047	0.242	14.7%
Q(90%)	4	Y	-0.297	0.455	-0.161	0.020	0.218	18.3%
G	1	N	-0.381	0.670	-0.128	0.111	0.372	13.3%
G	1	Y	-0.394	0.641	-0.128	0.089	0.378	11.7%
4-F-CAPM	—	—	-0.358	0.678	-0.108	0.257	0.502	10.7%
				2011-2015				
Q(10%)	4	N	-0.263	0.422	-0.122	-0.013	0.135	15.3%
Q(50%)	4	N	-0.397	0.537	-0.129	0.055	0.224	13.7%
Q(90%)	4	N	-0.253	0.431	-0.127	0.010	0.138	15.7%
Q(10%)	4	Y	-0.283	0.503	-0.132	-0.008	0.140	19.0%
Q(50%)	4	Y	-0.330	0.505	-0.126	0.041	0.197	14.7%
Q(90%)	4	Y	-0.304	0.508	-0.140	0.001	0.132	17.7%
Granger	1	N	-0.211	0.598	-0.027	0.151	0.362	3.0%
Granger	1	Y	-0.211	0.598	-0.027	0.146	0.361	3.3%
Multifactor	—	—	-0.122	0.669	0.054	0.266	0.487	0.3%

Table 2.7: The table reports residual correlation descriptive analyses for the Insurance Companies dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
				2006-2008				
Q(10%)	4	N	-0.437	0.686	-0.205	0.003	0.250	27.7%
Q(50%)	4	N	-0.429	0.669	-0.167	0.039	0.258	15.3%
Q(90%)	4	N	-0.448	0.676	-0.207	0.009	0.255	25.7%
Q(10%)	4	Y	-0.436	0.684	-0.203	0.004	0.246	28.0%
Q(50%)	4	Y	-0.417	0.473	-0.176	0.023	0.226	19.3%
Q(90%)	4	Y	-0.464	0.671	-0.214	0.001	0.253	27.0%
G	1	N	-0.466	0.831	-0.166	0.044	0.316	17.7%
G	1	Y	-0.460	0.714	-0.166	0.048	0.323	15.0%
4-F-CAPM	—	—	-0.370	0.847	-0.149	0.089	0.422	14.0%
				2011-2015				
Q(10%)	4	N	-0.290	0.504	-0.121	0.009	0.157	14.7%
Q(50%)	4	N	-0.258	0.548	-0.149	0.019	0.202	16.7%
Q(90%)	4	N	-0.289	0.348	-0.137	-0.006	0.167	19.3%
Q(10%)	4	Y	-0.333	0.503	-0.153	-0.012	0.189	20.7%
Q(50%)	4	Y	-0.267	0.592	-0.156	0.016	0.192	18.3%
Q(90%)	4	Y	-0.299	0.398	-0.152	-0.001	0.199	21.3%
G	1	N	-0.136	0.658	-0.005	0.121	0.317	1.7%
G	1	Y	-0.136	0.658	-0.014	0.116	0.315	1.7%
4-F-CAPM	—	—	-0.103	0.658	0.017	0.138	0.332	0.3%

For the industry portfolio dataset, the results are less clear, since the various approaches produced very similar findings. This is in line with the heterogeneous results seen for the weights of the various networks, where we were unable to identify a clear preference. We interpret this as evidence to suggest that network augmented linear factor models might usefully improve on traditional linear factor models when we fit the model over single assets and not over portfolios. The aggregation of assets into portfolios probably distorts the dependence structure across assets and limits its impact. There might be a different reason linking the datasets of the banks and insurance companies to the potential presence of a sector-specific factor in the analysis - but if that were the case, we should have seen no such clear improvement in the residual correlations of the composite network cases. We consequently believe that the idea of a missing factor is inconsistent with our

Table 2.8: The table reports residual correlation descriptive analyses for the Industry portfolios dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
				2006-2008				
Q(10%)	4	N	-0.465	0.611	-0.191	-0.001	0.201	25.6%
Q(50%)	4	N	-0.369	0.663	-0.161	0.018	0.249	20.6%
Q(90%)	4	N	-0.443	0.608	-0.195	-0.006	0.206	25.9%
Q(10%)	4	Y	-0.417	0.625	-0.187	0.006	0.220	24.1%
Q(50%)	4	Y	-0.454	0.627	-0.159	0.011	0.233	20.4%
Q(90%)	4	Y	-0.508	0.592	-0.187	-0.007	0.215	23.8%
G	1	N	-0.384	0.687	-0.146	0.025	0.257	18.6%
G	1	Y	-0.401	0.687	-0.157	0.011	0.239	19.8%
4-F-CAPM	—	—	-0.486	0.733	-0.219	0.003	0.267	27.1%
				2011-2015				
Q(10%)	4	N	-0.463	0.567	-0.140	-0.008	0.135	19.7%
Q(50%)	4	N	-0.454	0.518	-0.136	0.005	0.169	16.7%
Q(90%)	4	N	-0.471	0.572	-0.144	-0.013	0.139	19.9%
Q(10%)	4	Y	-0.432	0.497	-0.147	-0.004	0.148	18.9%
Q(50%)	4	Y	-0.470	0.511	-0.135	0.001	0.155	16.6%
Q(90%)	4	Y	-0.438	0.565	-0.143	-0.006	0.154	17.9%
G	1	N	-0.470	0.577	-0.140	0.007	0.199	18.0%
G	1	Y	-0.503	0.577	-0.139	0.006	0.177	17.7%
4-F-CAPM	—	—	-0.456	0.592	-0.147	0.007	0.208	18.4%

findings. Further analyses are needed on this topic, but we leave them to future research.

We close this section with a few comments on the coefficients for monitoring the impact of the composite networks on the various assets, as included in the diagonal of matrix $\mathcal{R}$ in equation (2.5). Appendix 2.6.9 shows the plots of the coefficients for each bank, insurance company and industrial portfolio, across the various combined networks. Overall, we note that the coefficients are usually positive and significant for banks and insurance companies, while the networks impact is more heterogeneous and of limited significance for industrial portfolios. These results deserve a more thorough analysis, but this goes beyond the scope of the present paper.

2.4.4 Robustness checks

The previously-reported results focus on the combination of all four different networks, where the model providing the optimal combination makes use of weekly data and allows for a heterogeneous impact of the composite network on the assets. Here we provide some additional comments on variations to the model-based combination design. In particular, we estimate the model on monthly data, we consider combining just three networks, and we control for the optimal combination when the network's impact is homogeneous across assets.

Section 2.6.6 contains tables assessing the model-based network combination when we exclude a network. We consider two specific cases: the first excludes the network estimated from Granger causality in order to highlight the relevance of competing quantile causality networks; the second disregards the less relevant quantile causality network (the so-called baseline quantile causality). All the analyses are based on weekly data. The results confirm the relevance of the non-parametric approach for the purpose of obtaining a quantile causality that, in several cases, generates the largest and statistically most significant coefficients. The baseline quantile causality is the least relevant, even when the Granger causality network is excluded from the layers. The results for the industry portfolios are the most heterogeneous in terms of network relevance, and they show little improvement with respect to the contraction of the residual correlations. For the banks and insurance companies, there is a marked gain in moving from linear factor models, or Granger causality augmented factor models, to a model that accounts for the presence of quantile causality; the average residual correlation decreases considerably.

Section 2.6.7 contains estimates of the network combination modelled on monthly data (as opposed to the weekly data considered in the previous section).[6] We confirmed the importance of non-parametric quantile causality and the limited impact of Granger causality. Once again, the outcome is clearer for the datasets concerning banks and insurance companies than the industry portfolio dataset. In addition, contrary to the evidence emerging from the weekly data, the contraction on the residual correlations for the insurance company dataset is less evident during the financial crisis, while it is striking in the second period.

Given the heterogeneity of the network's impact on returns, as mentioned at the end of the previous section, we check the model's performance when we impose a common reaction of the returns to exposure to the network. Section 2.6.8 illustrates the outcomes for the composite network and the impact of the network on returns in the three datasets and two sample periods, when the model is estimated on weekly data. The only notable changes concern the composite network parameters: we now find a larger number of statistically significant coefficients. In addition, Granger causality seems to become more relevant, in the insurance companies dataset at least. The non-parametric quantile causality network nonetheless retains its role and receives the highest coefficients. Moving to the model-based combination confirms the previous results and enables a reduction in the

[6]In this case too, we ran a sensitivity analysis on the effects of excluding a network. The results are available on request.

average residual correlations in the banks and insurance companies datasets.

2.5 Concluding remarks

Causality networks have attracted some attention in the financial economics literature in recent years for the purposes of systemic risk interpretation. We show that the structure of causality networks changes considerably if we move from the mean, commonly associated with traditional Granger causality, to the quantiles. In the latter case, the causality across assets can be measured by means of quantile regression-based approaches. Here we illustrate three different possibilities: the simple quantile regression, its generalization to the quantile-on-quantile approach of Sim and Zhou (2015) and the non-parametric test due to Jeong et al. (2012). We show that changing the approach to network estimation gives rise to networks in which a systemic risk interpretation points to the existence of dense networks with a broader systemic relevance. By focusing on a linear factor model augmented with a multi-layer network dependence, we also demonstrate that causality networks are useful for capturing this dependence across financial returns, going beyond what can be explained by a market factor. This paves the way to further analyses, and has an associated impact on diversification analyses and portfolio construction, as well as on asset pricing.

2.6 Appendix

2.6.1 Banks and Insurance companies

In the empirical analyses we use the bank or the insurance companies as in the following lists. Within parentheses we report the ticker. A single star ⋆ identifies companies included only in the first sample - 2006 to 2008 - while a double star identifies companies included only in the second sample - 2011-2015. When stars are not present, the companies are included in both samples.

Banks:

Astoria Financial Corporation (AF⋆), Associated Banc-Corp (ASB), Bank of America (BAC), Bancfirst Corporation (BANF⋆), Credicorp (BAP), BB&T (BBT), Bbx Capital Corporation (BBX⋆), Bank Mutual Corporation (BKMU⋆), Bank of Hawaii (BOH), Bok Financial Corporation (BOKF), Boston Private Financial Holdings (BPFH⋆), Brookline Bancorp (BRKL⋆), Bancorpsouth (BXS⋆), Citigroup (C), Cathay General Bancorp (CATY⋆), Commerce Bancshares (CBSH), Capitol Federal Financial (CFFN), Cullen/Frost Bankers (CFR), Chemical Financial Corporation (CHFC⋆), Comerica (CMA), City National (CN), Central Pacific Financial Corporation (CPF⋆), CVB Financial Corporation (CVBF⋆), Doral Financial Corporation (DRLCQ⋆), East West Bancorp (EWBC), First Horizon National (FHN⋆⋆), Fifth Third Bancorp (FITB⋆⋆), Firstmerit (FMER⋆⋆), First Niagara Financial Group (FNFG⋆⋆), First Republic Bank (FRC⋆⋆), Fulton Financial Corporation

(FULT**), Huntington Bancshares Incorporated (HBAN**), Hudson City Bancorp (HCB**), Investors Bancorp (ISBC**), Jp Morgan Chase & Co. (JPM**), Keycorp (KEY**), M&T Bank (MTB**).

Insurances:

American Financial Group (AFG**), Aflac (AFL), American International Group (AIG), Assurant (AIZ), The Allstate Corporation (ALL), Berkshire Hathaway (BRKA), Brown & Brown (BRO), Cincinnati Financial Corporation (CINF), Cna Financial Corporation (CNA), Cno Financial Group (CNO*), Erie Indemnity Company (ERIE**), Genworth Financial (GNW), The Hartford Financial Services Group (HIG), Kemper (KMPR*), Loews (L), Lincoln National (LNC), Mbia (MBI*), Metlife (MET), Markel (MKL**), Marsh & Mclennan (MMC), Old Republic International Corporation (ORI*), Principal Financial Group (PFG), Progressive Ohio (PGR), Prudential Financial (PRU), Reinsurance Group of America (RGA**), Torchmark (TMK), The Travelers Companies (TRV), Unum Group (UNM), W.R. Berkley Corporation (WRB).

2.6.2 Descriptive statistics

STOCK	MEAN	MED	ST DEV	MIN	MAX	1^{st} Q	3^{rd} Q	SKEW	KURT	LB_1	LB_5	LB_{10}	SLB_1	SLB_5	SLB_{10}	MV
C	-0.262	-0.127	4.296	-30.661	45.632	-1.113	0.711	0.673	30.033	5.716	0.000	0.002	0.000	0.000	0.000	236630.90
BAC	-0.157	-0.039	3.765	-30.416	24.060	-0.977	0.688	-0.468	19.555	72.686	0.295	0.126	0.000	0.000	0.000	212543.10
BBT	-0.056	-0.070	3.108	-26.608	21.198	-1.167	0.849	-0.094	18.219	0.326	1.159	0.000	0.000	0.000	0.000	21015.19
CMA	-0.139	-0.102	3.361	-20.720	18.805	-1.266	0.885	0.049	10.555	23.288	6.167	0.032	0.000	0.000	0.000	9392.46
ASB	-0.058	-0.030	2.905	-18.999	19.354	-0.916	0.705	0.076	14.517	94.558	0.339	0.009	0.107	0.000	0.000	4619.78
CN	-0.053	0.000	2.730	-17.379	20.213	-0.964	0.827	0.048	13.119	0.080	0.035	0.003	0.000	0.000	0.000	3763.18
CBSH	-0.003	-0.040	2.113	-12.894	15.113	-0.808	0.651	0.696	13.581	0.000	0.000	0.000	0.000	0.000	0.000	3428.85
AF	-0.077	-0.096	2.676	-18.972	13.698	-1.172	0.820	-0.251	11.170	0.054	0.032	0.011	0.000	0.000	0.000	3162.41
BOKF	-0.016	-0.018	2.228	-13.426	12.315	-0.848	0.764	0.055	12.242	63.004	0.283	0.052	0.000	0.000	0.000	3135.55
CFR	-0.008	-0.051	2.302	-13.183	16.306	-0.915	0.852	0.539	13.505	0.007	0.000	0.000	0.000	0.000	0.000	2853.67
BOH	-0.017	-0.019	2.458	-25.508	12.946	-0.859	0.834	-1.279	23.778	0.009	0.002	0.006	0.000	0.000	0.000	2695.89
BAP	0.104	0.089	2.572	-17.439	11.226	-1.017	1.368	-0.507	8.735	76.155	6.593	1.739	0.000	0.000	0.000	2572.86
CFFN	0.043	0.052	1.636	-7.664	6.606	-0.619	0.755	-0.127	6.254	10.379	14.081	0.059	0.000	0.000	0.000	2366.73
EWBC	-0.109	-0.155	3.730	-23.669	24.166	-1.255	0.869	0.263	12.930	47.310	11.160	19.360	0.000	0.000	0.000	2089.00
BXS	0.008	-0.077	2.854	-15.116	19.711	-1.165	1.088	0.592	11.463	6.615	0.065	0.173	0.000	0.000	0.000	1895.44
CATY	-0.055	-0.121	3.631	-23.886	21.314	-1.504	1.227	0.167	11.957	39.151	1.648	1.971	0.000	0.000	0.000	1865.30
CVBF	-0.029	-0.145	3.257	-18.965	20.210	-1.419	1.101	0.702	10.139	1.833	1.097	3.680	0.000	0.000	0.000	1241.16
BPFH	-0.198	-0.138	3.671	-30.902	17.640	-1.403	1.161	-1.226	17.170	13.155	2.258	2.606	0.007	0.001	0.000	1171.49
DRLCQ	-0.443	-0.522	6.085	-36.564	36.891	-2.885	1.968	-0.166	9.962	84.586	85.266	69.825	1.543	0.144	0.000	1097.65
CPF	-0.169	-0.199	3.925	-22.119	29.376	-1.668	1.259	0.553	12.079	99.950	0.257	1.170	0.000	0.000	0.000	1042.41
BRKL	-0.038	-0.076	2.461	-14.973	11.878	-1.119	0.990	0.158	7.816	0.088	0.175	0.259	0.000	0.000	0.000	918.22
BBX	-0.330	-0.235	6.086	-48.290	35.188	-2.062	1.308	-0.797	16.628	15.046	30.970	3.020	0.000	0.000	0.000	828.74
CHFC	-0.017	-0.034	2.904	-19.297	17.823	-1.368	1.131	0.267	10.009	0.173	1.038	6.583	0.035	0.000	0.000	775.59
BKMU	0.011	-0.080	1.970	-14.235	9.307	-0.844	0.917	-0.048	9.507	0.000	0.000	0.000	0.076	0.000	0.000	718.23
BANF	0.039	0.000	2.709	-24.878	21.243	-1.325	1.233	0.039	19.231	0.158	0.044	0.667	0.000	0.000	0.000	675.88

Table 2.9: Descriptive statistics of the daily returns generated by the 25 U.S. banks with the largest market value, as recorded at the beginning of 2006, in the period between January 3, 2006 and December 31, 2008. From left to right the table reports, for each stock, the mean (%), the median (%), the standard deviation (%), the minimum (%), the maximum (%), the first and the third quartiles (%), the skewness, the kurtosis, the p-value of the Ljung-Box test (%), at the significance level of the 5%, applied for both the returns (LB) and the squared returns (SLB) with lags equal to 1, 5 and 10, respectively, and the market value recorded in January 2006.

STOCK	MEAN	MED	ST DEV	MIN	MAX	1^{st} Q	3^{rd} Q	SKEW	KURT	LB_1	LB_5	LB_{10}	SLB_1	SLB_5	SLB_{10}	MV
JPM	0.035	0.048	1.698	-9.888	8.101	-0.789	0.901	-0.206	7.043	0.338	0.628	0.272	0.000	0.000	0.000	186018.60
BAC	0.018	0.000	2.295	-22.713	15.481	-1.050	1.103	-0.508	14.427	1.340	0.000	0.000	0.000	0.000	0.000	136331.90
C	0.007	0.000	2.129	-17.934	12.968	-0.944	0.981	-0.533	10.310	8.722	0.001	0.001	0.000	0.000	0.000	132889.30
BBT	0.029	0.065	1.497	-11.274	6.693	-0.716	0.890	-0.685	8.638	0.001	0.000	0.000	0.000	0.000	0.000	18978.31
FITB	0.025	0.106	1.736	-12.067	8.709	-0.817	0.908	-0.430	8.619	0.001	0.000	0.000	0.000	0.000	0.000	12549.82
MTB	0.026	0.034	1.355	-8.059	6.554	-0.624	0.732	-0.222	6.892	0.008	0.000	0.001	0.000	0.000	0.000	10488.55
KEY	0.032	0.074	1.807	-10.987	8.319	-0.906	1.031	-0.228	7.187	0.000	0.000	0.000	0.000	0.000	0.000	8339.36
BAP	-0.016	-0.009	1.711	-20.843	6.231	-0.918	0.894	-1.487	21.228	41.290	15.174	10.460	9.994	0.071	1.654	7814.11
CMA	-0.001	0.041	1.772	-11.118	6.100	-0.879	0.942	-0.701	7.149	18.082	0.247	0.554	0.000	0.000	0.000	6795.13
HBAN	0.038	0.102	1.794	-10.472	8.542	-0.931	1.059	-0.301	6.869	0.000	0.000	0.000	0.000	0.000	0.000	5750.23
HCB	-0.018	0.000	1.805	-11.304	14.569	-0.748	0.793	-0.325	11.772	0.010	0.178	1.702	0.001	0.000	0.000	5161.57
FRC	0.065	0.064	1.546	-16.359	8.376	-0.715	0.921	-0.901	15.518	0.004	0.016	0.081	0.064	0.013	0.047	3821.80
CFR	-0.001	0.066	1.396	-8.121	7.493	-0.677	0.758	-0.102	6.964	0.004	0.000	0.001	0.000	0.000	0.000	3667.12
BOKF	0.009	0.059	1.403	-9.594	6.062	-0.709	0.720	-0.390	7.708	0.005	0.003	0.097	0.000	0.000	0.000	3553.32
CBSH	0.025	0.090	1.316	-6.635	6.047	-0.697	0.776	-0.307	5.971	0.002	0.001	0.004	0.000	0.000	0.000	3552.96
EWBC	0.060	0.091	1.747	-9.353	8.752	-0.867	0.992	-0.158	6.443	0.412	0.009	0.000	0.000	0.000	0.000	3321.22
CN	0.030	0.000	1.577	-8.200	17.330	-0.687	0.821	0.850	17.467	6.143	0.012	0.009	8.723	0.002	0.000	3083.03
FHN	0.017	0.032	1.884	-11.185	7.559	-1.003	1.034	-0.415	6.255	6.398	0.799	2.454	0.000	0.000	0.000	2999.39
FNFG	-0.020	0.017	1.708	-14.511	13.548	-0.878	0.922	-0.556	13.534	3.662	2.318	0.807	4.568	2.718	1.949	2907.62
ASB	0.017	0.059	1.666	-12.420	7.165	-0.858	1.005	-0.669	8.529	0.003	0.000	0.000	0.000	0.000	0.000	2538.15
BOH	0.023	0.085	1.323	-8.229	5.795	-0.671	0.799	-0.296	6.328	0.027	0.005	0.031	0.000	0.000	0.000	2272.40
FULT	0.018	0.085	1.678	-10.064	8.031	-0.806	0.913	-0.389	7.399	0.006	0.000	0.001	0.000	0.000	0.000	2216.42
CFFN	0.004	0.000	0.915	-5.721	5.001	-0.504	0.498	-0.252	7.127	0.000	0.000	0.001	0.000	0.000	0.000	1880.95
FMER	-0.005	0.058	1.765	-11.931	9.523	-0.951	0.999	-0.422	8.063	2.032	0.284	0.080	0.000	0.000	0.000	1855.60
ISBC	0.070	0.056	1.326	-8.360	7.474	-0.570	0.734	0.004	7.640	0.000	0.000	0.000	0.000	0.000	0.000	1645.87

Table 2.10: Descriptive statistics of the daily returns generated by the 25 U.S. banks with the largest market value, as recorded at the beginning of 2011, in the period between January 3, 2011 and December 31, 2015. From left to right the table reports, for each stock, the mean (%), the median (%), the standard deviation (%), the minimum (%), the maximum (%), the first and the third quartiles (%), the skewness, the kurtosis, the p-value of the Ljung-Box test (%), at the significance level of the 5%, applied for both the returns (LB) and the squared returns (SLB) with lags equal to 1, 5 and 10, respectively, and the market value recorded in January 2011.

STOCK	MEAN	MED	ST DEV	MIN	MAX	1^{st} Q	3^{rd} Q	SKEW	KURT	LB_1	LB_5	LB_{10}	SLB_1	SLB_5	SLB_{10}	MV
AIG	-0.500	-0.055	6.469	-93.626	35.853	-0.853	0.681	-5.387	75.716	0.000	0.000	0.000	0.000	0.000	0.000	164653.50
BRKA	0.011	-0.001	1.717	-12.883	14.953	-0.523	0.536	0.622	24.924	93.137	0.610	0.965	0.000	0.000	0.000	110164.70
MET	-0.045	0.000	3.687	-31.156	24.686	-0.991	0.915	-0.396	23.343	40.365	1.162	3.180	0.000	0.000	0.000	37890.41
PRU	-0.117	-0.055	3.973	-26.327	32.390	-0.989	0.964	0.207	22.244	20.640	0.081	0.203	0.000	0.000	0.000	36860.64
ALL	-0.066	0.000	2.761	-23.799	19.628	-0.735	0.621	-0.579	28.043	93.526	0.017	0.000	0.000	0.000	0.000	32610.33
TRV	0.002	0.000	2.655	-20.067	22.758	-0.917	0.850	0.438	20.729	0.000	0.000	0.000	0.000	0.000	0.000	28563.55
HIG	-0.219	-0.034	6.060	-72.486	70.487	-1.020	0.935	-0.386	64.131	15.143	0.000	0.000	36.736	0.000	0.000	24387.18
AFL	-0.002	0.021	2.601	-18.902	14.961	-0.801	0.700	-0.530	18.381	0.100	0.001	0.000	0.000	0.000	0.000	22472.57
PGR	-0.090	-0.082	2.382	-13.947	21.490	-1.010	0.888	0.536	17.712	6.330	0.000	0.000	0.006	0.000	0.000	20556.40
L	-0.015	0.091	2.745	-19.939	21.220	-0.906	0.946	-0.820	20.944	0.010	0.001	0.011	0.000	0.000	0.000	18655.31
LNC	-0.137	0.018	4.884	-50.891	36.235	-0.981	0.931	-1.672	39.635	3.661	0.073	0.093	0.000	0.000	0.000	16040.52
MMC	-0.036	-0.038	2.033	-13.075	11.690	-0.924	0.829	0.078	10.357	0.000	0.000	0.000	0.000	0.000	0.000	15753.62
PFG	-0.098	0.000	4.252	-31.978	34.190	-0.938	1.053	0.098	20.411	61.640	0.000	0.001	0.000	0.000	0.000	13717.85
GNW	-0.332	-0.088	7.528	-78.552	63.599	-1.295	0.939	-0.014	44.676	0.255	0.000	0.000	0.000	0.000	0.000	13158.24
CNA	-0.091	0.000	3.326	-39.476	24.106	-1.058	0.935	-2.559	39.779	97.177	5.119	0.584	0.000	0.000	0.000	7953.97
MBI	-0.357	-0.087	6.493	-41.264	38.219	-1.786	1.198	-0.076	12.808	4.703	0.584	5.430	0.000	0.000	0.000	7842.20
WRB	-0.003	-0.095	2.284	-11.607	15.049	-1.062	0.903	0.931	12.003	0.007	0.003	0.008	0.000	0.000	0.000	7607.63
CINF	-0.057	-0.022	2.653	-22.399	16.765	-0.836	0.729	-0.559	18.647	0.001	0.000	0.000	0.000	0.000	0.000	7239.32
AIZ	-0.049	0.034	3.069	-28.679	19.721	-0.869	0.903	-0.962	24.650	29.164	0.012	0.000	0.000	0.000	0.000	6239.33
TMK	-0.029	0.017	2.208	-15.228	13.967	-0.633	0.691	-0.495	17.199	54.298	0.005	0.079	0.000	0.000	0.000	5853.66
UNM	-0.027	-0.049	3.428	-35.145	20.010	-1.051	0.984	-1.268	28.910	0.282	0.000	0.005	0.000	0.000	0.000	5751.81
ORI	-0.075	0.000	3.340	-29.214	31.979	-0.932	0.792	0.115	28.746	1.547	0.000	0.000	0.000	0.000	0.000	5033.62
BRO	-0.050	0.000	2.077	-17.218	11.196	-0.867	0.835	-0.630	13.710	18.359	15.353	23.086	0.378	0.001	0.000	4632.19
CNO	-0.198	0.000	6.043	-55.048	59.157	-1.009	0.851	-0.891	36.127	0.000	0.000	0.000	0.000	0.000	0.000	3741.03
KMPR	-0.138	-0.045	2.827	-16.981	20.799	-1.066	0.871	-0.261	16.077	36.300	0.347	0.002	0.000	0.000	0.000	3326.30

Table 2.11: Descriptive statistics of the daily returns generated by the 25 U.S. insurance companies with the largest market value, as recorded at the beginning of 2006, in the period between January 3, 2006 and December 31, 2008. From left to right the table reports, for each stock, the mean (%), the median (%), the standard deviation (%), the minimum (%), the maximum (%), the first and the third quartiles (%), the skewness, the kurtosis, the p-value of the Ljung-Box test (%), at the significance level of the 5%, applied for both the returns (LB) and the squared returns (SLB) with lags equal to 1, 5 and 10, respectively, and the market value recorded in January 2006.

STOCK	MEAN	MED	ST DEV	MIN	MAX	1^{st} Q	3^{rd} Q	SKEW	KURT	LB_1	LB_5	LB_{10}	SLB_1	SLB_5	SLB_{10}	MV
BRKA	0.039	0.004	1.089	-6.289	7.791	-0.558	0.601	0.454	9.381	0.000	0.000	0.000	0.000	0.000	0.000	115505.80
AIG	0.020	0.071	1.892	-10.580	9.819	-0.831	0.962	-0.272	6.851	18.211	0.000	0.001	0.000	0.000	0.000	61232.09
MET	0.006	0.018	1.897	-10.460	8.551	-0.923	1.067	-0.299	5.819	21.753	0.372	0.823	0.000	0.000	0.000	47239.25
PRU	0.026	0.037	1.864	-11.469	8.822	-0.929	1.134	-0.386	6.904	2.498	0.004	0.002	0.000	0.000	0.000	29888.47
TRV	0.056	0.085	1.154	-7.893	6.205	-0.554	0.685	-0.181	7.791	0.017	0.346	0.141	0.000	0.000	0.000	25156.82
AFL	0.005	0.037	1.588	-10.758	8.334	-0.751	0.772	-0.288	8.789	11.965	0.421	0.745	0.000	0.000	0.000	24977.64
L	-0.001	0.021	1.130	-6.089	5.547	-0.598	0.620	-0.177	6.179	0.485	0.062	0.182	0.000	0.000	0.000	17509.66
ALL	0.053	0.045	1.294	-10.700	7.294	-0.602	0.725	-0.297	10.258	0.013	0.000	0.000	0.022	0.000	0.000	16607.85
MMC	0.056	0.034	1.166	-8.679	8.926	-0.561	0.706	0.128	9.663	0.001	0.000	0.002	0.000	0.000	0.000	16043.64
PGR	0.037	0.051	1.215	-7.178	6.798	-0.601	0.702	-0.294	7.486	0.147	0.173	1.376	0.000	0.000	0.000	14019.72
HIG	0.039	0.104	2.068	-15.366	14.438	-0.912	1.020	-0.071	10.936	0.031	0.000	0.000	0.000	0.000	0.000	11897.86
PFG	0.026	0.136	1.835	-12.159	8.351	-0.849	1.004	-0.422	7.102	0.107	0.000	0.001	0.000	0.000	0.000	10108.24
LNC	0.047	0.096	2.169	-13.056	9.641	-1.007	1.132	-0.329	6.844	8.444	0.014	0.004	0.000	0.000	0.000	9350.80
UNM	0.025	0.057	1.527	-11.128	9.625	-0.762	0.945	-0.285	7.207	0.013	0.000	0.000	0.000	0.000	0.000	8137.82
CNA	0.021	0.035	1.348	-9.850	8.464	-0.648	0.666	-0.188	9.603	0.004	0.004	0.120	0.000	0.000	0.000	7966.17
GNW	-0.100	0.077	3.460	-48.533	15.461	-1.468	1.431	-2.801	39.098	20.702	0.816	8.069	46.063	83.411	99.480	6219.79
CINF	0.050	0.086	1.188	-7.681	6.446	-0.590	0.706	-0.183	7.535	0.000	0.000	0.000	0.000	0.000	0.000	5292.70
TMK	0.061	0.115	1.216	-9.837	8.233	-0.548	0.706	-0.303	10.318	0.000	0.000	0.000	0.000	0.000	0.000	5184.13
WRB	0.055	0.080	1.095	-6.691	5.396	-0.540	0.651	-0.018	6.488	0.140	0.853	0.484	0.000	0.000	0.000	4491.24
RGA	0.037	0.086	1.461	-11.464	10.052	-0.613	0.779	-0.880	12.999	0.024	0.000	0.004	0.000	0.000	0.000	4464.94
MKL	0.067	0.057	1.125	-10.812	6.529	-0.509	0.598	-0.560	14.716	0.004	0.008	0.093	0.000	0.000	0.000	4084.38
AIZ	0.059	0.097	1.395	-7.794	6.927	-0.736	0.884	-0.279	6.412	0.076	0.000	0.014	0.001	0.000	0.000	3730.86
BRO	0.023	0.030	1.271	-9.392	9.262	-0.624	0.688	-0.253	11.251	95.429	0.122	0.010	0.000	0.000	0.000	3726.44
AFG	0.064	0.102	1.092	-7.551	6.529	-0.529	0.659	-0.219	7.525	0.008	0.004	0.030	0.000	0.000	0.000	3648.48
ERIE	0.030	0.042	1.275	-9.423	8.906	-0.616	0.667	-0.089	10.218	0.014	0.272	1.656	0.000	0.000	0.000	3541.31

Table 2.12: Descriptive statistics of the daily returns generated by the 25 U.S. insurance companies with the largest market value, as recorded at the beginning of 2011, in the period between January 3, 2011 and December 31, 2015. From left to right the table reports, for each stock, the mean (%), the median (%), the standard deviation (%), the minimum (%), the maximum (%), the first and the third quartiles (%), the skewness, the kurtosis, the p-value of the Ljung-Box test (%), at the significance level of the 5%, applied for both the returns (LB) and the squared returns (SLB) with lags equal to 1, 5 and 10, respectively, and the market value recorded in January 2011.

POR	MEA	MED	STD	MIN	MAX	1^{st} Q	3^{rd} Q	SKE	KUR	LB_1	LB_5	LB_{10}	SLB_1	SLB_5	SLB_{10}
Agric	0.096	0.050	2.701	-15.270	18.240	-0.930	1.140	0.078	10.597	35.606	0.424	0.016	0.268	0.000	0.000
Food	0.010	0.030	1.165	-7.250	7.400	-0.485	0.580	-0.076	12.281	1.713	0.000	0.000	0.000	0.000	0.000
Soda	-0.012	0.070	1.629	-8.020	11.140	-0.675	0.715	0.054	10.820	93.185	3.668	0.045	0.000	0.000	0.000
Beer	0.031	0.040	1.187	-7.700	10.120	-0.480	0.530	0.811	18.398	0.018	0.000	0.000	0.000	0.000	0.000
Smoke	0.030	0.070	1.479	-7.400	13.310	-0.600	0.725	0.338	16.033	12.642	0.000	0.000	0.665	0.000	0.000
Toys	-0.040	0.010	1.791	-9.630	9.250	-0.855	0.780	-0.140	8.508	37.202	2.289	0.544	0.000	0.000	0.000
Fun	-0.083	0.050	2.423	-12.170	16.580	-0.900	0.830	0.023	11.578	0.003	0.000	0.002	0.000	0.000	0.000
Books	-0.124	-0.060	1.953	-11.240	11.180	-0.785	0.590	0.004	11.861	42.319	0.069	0.341	0.000	0.000	0.000
Hshld	0.010	0.030	1.260	-7.250	9.440	-0.455	0.520	0.077	13.616	0.002	0.000	0.000	0.000	0.000	0.000
Clths	-0.023	-0.010	2.012	-11.520	12.690	-0.905	0.895	0.099	8.974	48.150	0.212	0.680	0.000	0.000	0.000
Hlth	-0.038	0.020	1.348	-9.020	8.290	-0.610	0.545	-1.041	15.622	19.523	0.002	0.000	0.000	0.000	0.000
MedEq	-0.026	0.030	1.349	-7.210	11.690	-0.560	0.560	0.153	15.334	55.714	0.057	0.319	0.000	0.000	0.000
Drugs	0.004	0.020	1.258	-6.530	11.140	-0.485	0.580	0.459	16.120	0.017	0.000	0.000	0.000	0.000	0.000
Chems	-0.010	0.110	2.039	-11.380	13.060	-0.720	0.880	-0.416	11.100	4.333	0.002	0.010	0.000	0.000	0.000
Rubbr	-0.015	0.000	1.701	-10.140	7.800	-0.740	0.840	-0.384	7.555	0.178	1.160	11.422	0.000	0.000	0.000
Txtls	-0.052	-0.010	2.114	-12.230	10.030	-1.010	0.820	-0.143	8.827	14.373	2.701	0.045	0.002	0.000	0.000
BldMt	-0.050	0.020	1.889	-10.670	8.540	-0.835	0.795	-0.365	8.230	61.661	2.884	4.807	0.000	0.000	0.000
Cnstr	-0.057	-0.050	2.767	-12.400	15.560	-1.355	1.280	0.091	7.184	28.169	3.002	9.516	0.000	0.000	0.000
Steel	0.011	0.160	3.015	-15.930	20.060	-1.190	1.430	-0.033	10.453	54.236	0.540	0.193	0.000	0.000	0.000
FabPr	-0.023	0.100	2.126	-11.830	10.520	-0.965	0.900	-0.702	8.651	15.807	0.124	0.381	0.000	0.000	0.000
Mach	-0.016	0.150	2.144	-12.250	13.910	-0.895	1.025	-0.315	11.089	18.366	0.000	0.000	0.000	0.000	0.000
ElcEq	0.000	0.100	2.006	-13.100	14.080	-0.740	0.875	-0.039	12.589	0.492	0.000	0.000	0.000	0.000	0.000
Autos	-0.080	0.070	2.349	-11.230	11.700	-0.995	1.010	-0.062	8.630	99.063	1.838	3.530	0.000	0.000	0.000
Aero	-0.009	0.070	1.777	-7.650	13.570	-0.725	0.805	0.497	12.728	2.192	0.000	0.000	0.000	0.000	0.000
Ships	0.004	0.030	1.715	-9.400	10.620	-0.810	0.815	-0.110	9.046	0.011	0.001	0.001	0.000	0.000	0.000
Guns	0.050	0.040	1.669	-9.000	10.220	-0.670	0.855	-0.316	9.248	0.000	0.000	0.000	0.000	0.000	0.000
Gold	0.017	-0.050	3.120	-14.160	25.560	-1.505	1.530	1.087	14.187	3.891	0.245	0.399	0.000	0.000	0.000
Mines	0.059	0.210	3.299	-16.990	19.850	-1.425	1.690	0.090	8.463	63.781	4.439	19.951	0.000	0.000	0.000
Coal	0.014	0.000	4.170	-19.340	21.360	-1.805	1.885	-0.204	7.777	37.757	0.120	0.013	0.000	0.000	0.000
Oil	0.039	0.120	2.417	-15.380	19.270	-1.030	1.230	0.181	14.674	0.004	0.000	0.000	0.000	0.000	0.000
Util	0.016	0.100	1.608	-8.920	14.430	-0.545	0.660	0.934	18.802	0.001	0.000	0.000	0.000	0.000	0.000
Telcm	-0.001	0.070	1.748	-9.670	14.510	-0.645	0.665	0.698	17.768	3.763	0.000	0.000	0.007	0.000	0.000
PerSv	-0.004	0.000	1.749	-8.690	8.950	-0.740	0.795	-0.139	7.585	9.509	0.008	0.003	0.000	0.000	0.000
BusSv	-0.022	0.040	1.616	-7.890	11.940	-0.670	0.660	0.301	11.959	0.398	0.000	0.000	0.000	0.000	0.000
Comps	-0.011	0.040	1.830	-9.890	11.870	-0.830	0.795	0.166	9.166	0.426	0.011	0.110	0.000	0.000	0.000
Chips	-0.051	0.020	1.841	-8.900	10.700	-0.905	0.860	0.002	8.591	0.486	0.001	0.004	0.000	0.000	0.000
LabEq	-0.014	0.070	1.655	-9.000	12.700	-0.700	0.760	-0.023	11.949	60.608	0.006	0.020	0.000	0.000	0.000
Paper	-0.043	0.050	1.535	-9.610	8.630	-0.610	0.630	-0.275	10.620	0.123	0.000	0.000	0.002	0.000	0.000
Boxes	0.028	0.110	1.881	-9.040	10.920	-0.855	0.800	-0.016	7.738	78.496	4.496	8.536	0.000	0.000	0.000
Trans	-0.006	0.020	1.785	-8.760	9.330	-0.870	0.890	-0.229	7.122	5.101	0.082	0.289	0.003	0.000	0.000

Whlsl	-0.028	0.030	1.476	-8.500	9.740	-0.585	0.650	-0.210	11.386	6.327	0.135	0.228	0.000	0.000	0.000
Rtail	-0.016	-0.040	1.612	-8.310	11.750	-0.745	0.710	0.375	9.746	7.334	0.006	0.011	0.000	0.000	0.000
Meals	0.015	0.060	1.580	-8.290	8.910	-0.805	0.800	0.048	7.214	92.449	0.753	0.790	0.000	0.000	0.000
Banks	-0.060	-0.040	2.735	-16.280	16.750	-0.860	0.665	0.314	12.215	1.838	0.093	0.102	0.000	0.000	0.000
Insur	-0.062	0.000	2.124	-11.530	17.840	-0.650	0.600	0.362	16.953	18.539	0.000	0.001	0.000	0.000	0.000
RlEst	-0.119	-0.080	2.740	-15.500	18.650	-1.180	1.065	0.125	10.400	45.850	0.253	1.581	0.000	0.000	0.000
Fin	-0.046	0.030	2.824	-16.270	17.940	-1.035	1.045	0.232	11.047	33.562	0.005	0.046	0.000	0.000	0.000
Other	-0.033	0.020	1.570	-9.880	9.990	-0.540	0.550	-0.270	12.982	44.794	1.394	0.069	0.000	0.000	0.000

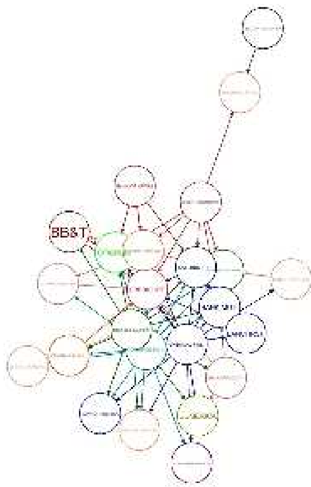
Table 2.13: Descriptive statistics of the daily returns generated by the 48 industry portfolios in the period between January 3, 2006 and December 31, 2008. From left to right the table reports, for each stock, the mean (%), the median (%), the standard deviation (%), the minimum (%), the maximum (%), the first and the third quartiles (%), the skewness, the kurtosis, and the p-value of the Ljung-Box test (%), at the significance level of the 5%, applied for both the returns (LB) and the squared returns (SLB) with lags equal to 1, 5 and 10, respectively.

POR	MEA	MED	STD	MIN	MAX	1^{st} Q	3^{rd} Q	SKE	KUR	LB_1	LB_5	LB_{10}	SLB_1	SLB_5	SLB_{10}
Agric	0.045	0.050	1.399	-6.940	7.650	-0.700	0.840	0.175	6.106	74.914	11.260	12.269	0.000	0.000	0.000
Food	0.063	0.100	0.855	-4.620	3.670	-0.420	0.550	-0.274	5.070	8.731	0.316	0.581	0.000	0.000	0.000
Soda	0.062	0.060	1.066	-6.570	5.150	-0.490	0.650	-0.202	6.850	0.007	0.000	0.000	0.000	0.000	0.000
Beer	0.064	0.075	0.833	-4.280	4.020	-0.430	0.520	-0.139	4.934	14.505	0.010	0.023	0.000	0.000	0.000
Smoke	0.075	0.090	0.966	-4.780	4.390	-0.488	0.640	-0.165	4.698	35.988	17.203	21.629	0.000	0.000	0.000
Toys	0.043	0.070	1.300	-8.290	6.680	-0.600	0.790	-0.270	6.759	34.771	50.545	67.397	0.000	0.000	0.000
Fun	0.060	0.120	1.624	-8.960	6.410	-0.840	0.968	-0.127	5.209	26.336	1.394	3.720	0.000	0.000	0.000
Books	0.055	0.090	1.332	-8.720	6.910	-0.650	0.820	-0.567	7.973	94.914	0.490	1.377	0.000	0.000	0.000
Hshld	0.039	0.050	0.851	-4.090	4.010	-0.430	0.540	-0.300	5.228	39.275	1.251	6.061	0.000	0.000	0.000
Clths	0.066	0.070	1.332	-8.330	6.790	-0.610	0.818	-0.286	6.471	81.731	0.000	0.000	0.000	0.000	0.000
Hlth	0.058	0.130	1.264	-10.100	5.040	-0.580	0.770	-0.971	9.741	91.847	9.331	0.267	0.001	0.000	0.000
MedEq	0.062	0.100	1.075	-6.910	4.780	-0.480	0.708	-0.528	6.520	17.852	1.430	0.098	0.000	0.000	0.000
Drugs	0.083	0.110	1.034	-4.720	4.550	-0.430	0.670	-0.312	5.204	68.920	7.524	1.500	0.000	0.000	0.000
Chems	0.044	0.080	1.299	-8.210	6.620	-0.600	0.748	-0.383	7.219	40.159	0.001	0.001	0.000	0.000	0.000
Rubbr	0.069	0.100	1.204	-5.960	6.710	-0.620	0.730	-0.177	5.742	34.775	0.009	0.137	0.000	0.000	0.000
Txtls	0.107	0.130	1.534	-8.130	6.830	-0.700	0.988	-0.262	5.268	94.660	0.008	0.048	0.000	0.000	0.000
BldMt	0.055	0.100	1.434	-8.410	6.330	-0.720	0.850	-0.204	5.708	49.169	0.003	0.017	0.000	0.000	0.000
Cnstr	0.039	0.080	1.646	-10.030	6.020	-0.860	0.978	-0.398	5.522	98.631	0.011	0.139	0.000	0.000	0.000
Steel	-0.016	0.000	1.730	-10.760	8.600	-0.945	0.960	-0.163	6.304	88.503	0.044	0.281	0.000	0.000	0.000
FabPr	-0.009	0.060	2.007	-15.450	8.170	-1.108	1.070	-0.266	7.224	94.000	0.034	0.211	0.000	0.000	0.000
Mach	0.022	0.060	1.392	-8.790	6.790	-0.690	0.750	-0.169	6.720	42.870	0.001	0.003	0.000	0.000	0.000
ElcEq	0.025	0.040	1.351	-7.740	7.560	-0.718	0.740	-0.069	6.608	57.250	0.049	0.335	0.000	0.000	0.000
Autos	0.034	0.080	1.456	-8.530	6.380	-0.660	0.850	-0.374	6.056	12.214	0.070	0.295	0.000	0.000	0.000
Aero	0.059	0.095	1.167	-7.030	5.050	-0.568	0.740	-0.457	6.455	85.949	0.328	3.428	0.000	0.000	0.000
Ships	0.091	0.195	1.733	-8.900	7.180	-0.880	1.070	-0.173	5.049	25.610	2.883	11.182	0.000	0.000	0.000
Guns	0.106	0.120	1.069	-5.730	3.740	-0.488	0.770	-0.345	4.931	32.729	6.839	18.811	0.000	0.000	0.000
Gold	-0.079	-0.150	2.375	-11.760	8.760	-1.480	1.298	0.074	4.495	33.125	70.504	68.383	0.586	0.000	0.000
Mines	-0.043	-0.045	1.882	-8.500	10.040	-1.010	0.970	0.060	5.541	6.054	0.108	0.554	0.000	0.000	0.000
Coal	-0.206	-0.135	2.886	-18.440	18.080	-1.795	1.288	-0.012	7.057	20.566	0.015	0.176	0.001	0.000	0.000
Oil	0.009	0.020	1.422	-8.350	5.480	-0.720	0.780	-0.342	6.057	54.006	0.005	0.001	0.003	0.000	0.000
Util	0.039	0.070	0.886	-6.050	4.550	-0.470	0.558	-0.311	6.626	8.517	0.007	0.020	0.000	0.000	0.000
Telcm	0.058	0.110	0.960	-6.600	4.650	-0.440	0.628	-0.521	6.756	52.461	0.002	0.013	0.000	0.000	0.000
PerSv	0.033	0.080	1.345	-8.650	4.810	-0.700	0.888	-0.457	5.261	25.112	29.973	29.929	0.000	0.000	0.000
BusSv	0.060	0.090	1.106	-6.310	4.870	-0.490	0.678	-0.290	5.843	91.176	0.049	0.141	0.000	0.000	0.000
Comps	0.027	0.100	1.251	-6.260	5.500	-0.660	0.770	-0.190	5.481	74.150	10.162	7.555	0.001	0.000	0.000
Chips	0.057	0.090	1.245	-5.760	5.070	-0.600	0.760	-0.117	4.863	99.802	1.614	0.298	0.000	0.000	0.000
LabEq	0.062	0.100	1.318	-7.460	5.740	-0.620	0.780	-0.283	6.327	73.759	0.251	0.216	0.000	0.000	0.000
Paper	0.056	0.100	1.084	-6.330	5.170	-0.460	0.630	-0.356	6.220	5.275	0.090	0.533	0.000	0.000	0.000
Boxes	0.045	0.090	1.218	-8.280	7.420	-0.570	0.720	-0.340	6.851	11.874	0.035	0.526	0.000	0.000	0.000
Trans	0.053	0.130	1.187	-6.010	4.760	-0.588	0.720	-0.321	5.009	90.781	0.800	1.182	0.000	0.000	0.000

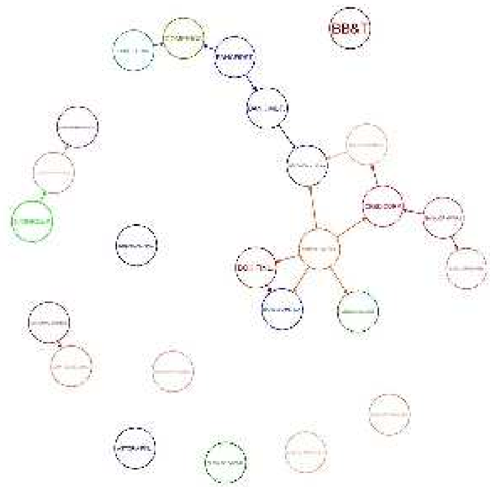
Whlsl	0.057	0.090	1.039	-6.710	5.440	-0.470	0.650	-0.239	6.954	42.801	0.029	0.089	0.000	0.000	0.000
Rtail	0.067	0.095	0.936	-5.990	4.790	-0.428	0.620	-0.369	6.227	11.008	0.213	0.118	0.000	0.000	0.000
Meals	0.063	0.090	0.982	-5.440	4.870	-0.468	0.638	-0.313	6.208	4.122	0.084	0.000	0.000	0.000	0.000
Banks	0.055	0.070	1.384	-10.670	7.950	-0.638	0.770	-0.316	9.177	0.001	0.000	0.000	0.000	0.000	0.000
Insur	0.066	0.115	1.149	-8.520	6.940	-0.510	0.690	-0.342	9.017	0.021	0.000	0.000	0.000	0.000	0.000
RlEst	0.048	0.070	1.427	-10.310	6.600	-0.680	0.820	-0.367	7.586	54.196	0.036	0.024	0.000	0.000	0.000
Fin	0.044	0.100	1.421	-8.930	8.900	-0.668	0.790	-0.207	7.838	0.456	0.000	0.000	0.000	0.000	0.000
Other	0.049	0.050	1.070	-6.750	5.890	-0.510	0.618	-0.078	7.505	0.098	0.000	0.000	0.000	0.000	0.000

Table 2.14: Descriptive statistics of the daily returns generated by the 48 industry portfolios in the period between January 3, 2011 and December 31, 2015. From left to right the table reports, for each stock, the mean (%), the median (%), the standard deviation (%), the minimum (%), the maximum (%), the first and the third quartiles (%), the skewness, the kurtosis, and the p-value of the Ljung-Box test (%), at the significance level of the 5%, applied for both the returns (LB) and the squared returns (SLB) with lags equal to 1, 5 and 10, respectively.

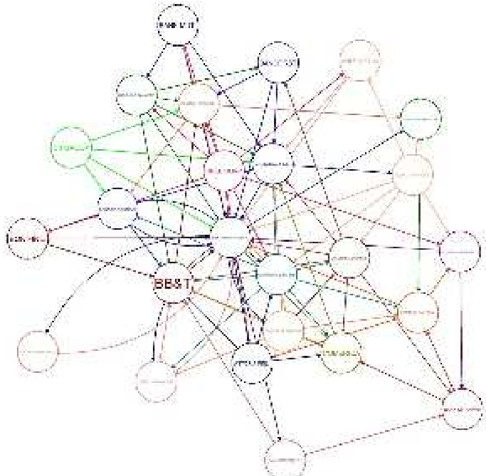
2.6.3 Figures of primitive causality networks



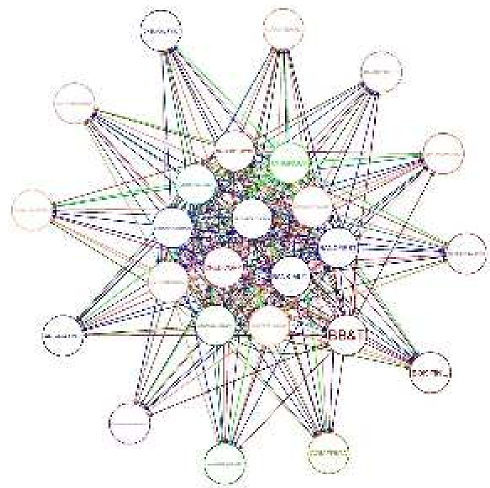
(a) Granger



(b) Q_{10} Base Quantile

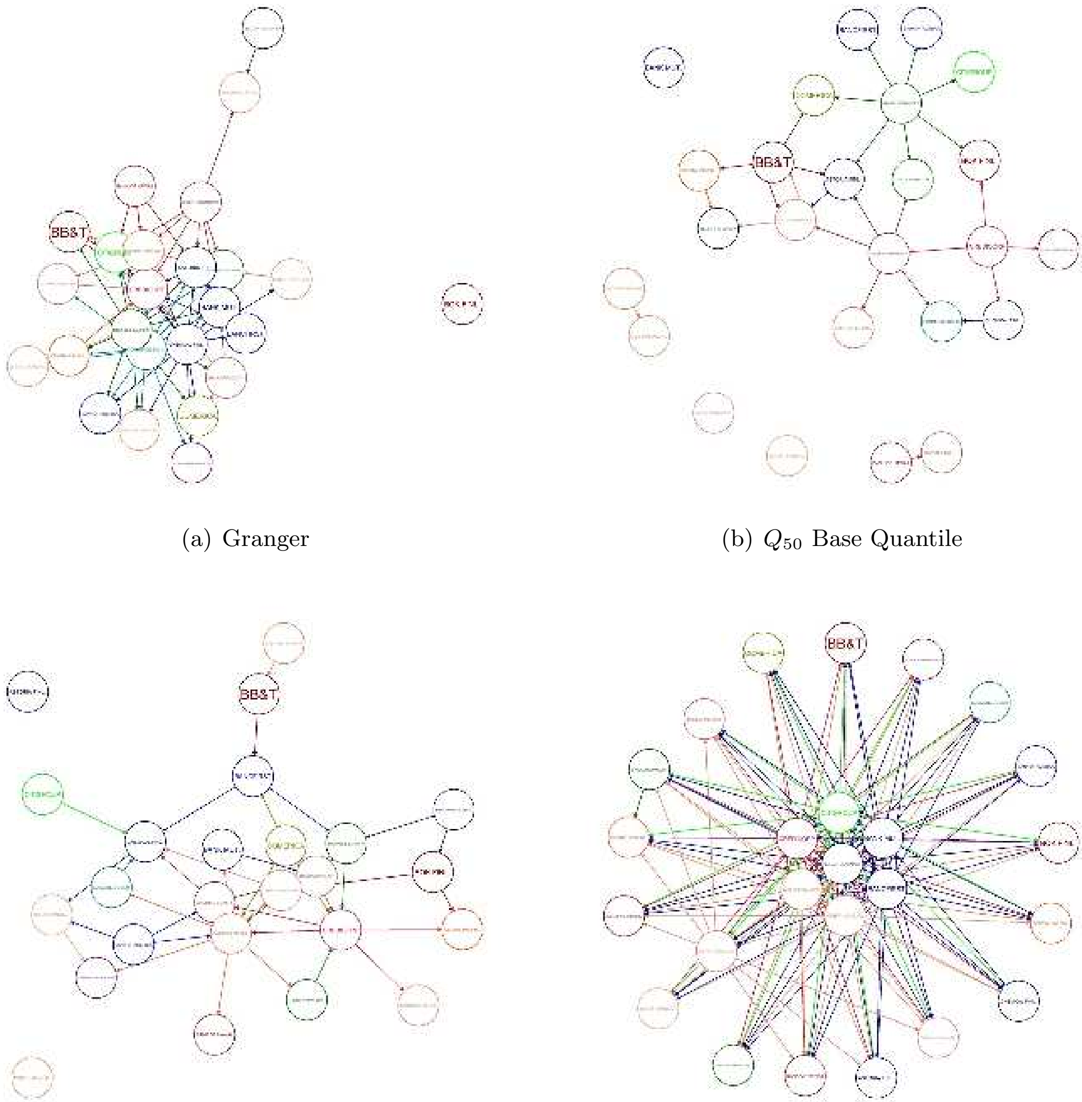


(c) Q_{10} Quantile on Quantile



(d) Q_{10} Not Parametric

Figure 2.9: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 banks ordered for market capitalization. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 10% quantile q_{10}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 10% quantile q_{10}. Panel d) reports the network extracted by a not parametric methodologie on the 10% quantile q_{10}. All the causality regression are computed without the market factor.



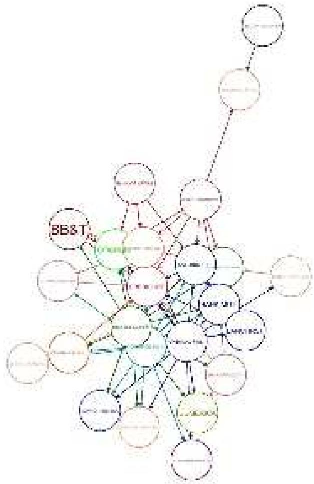
(a) Granger

(b) Q_{50} Base Quantile

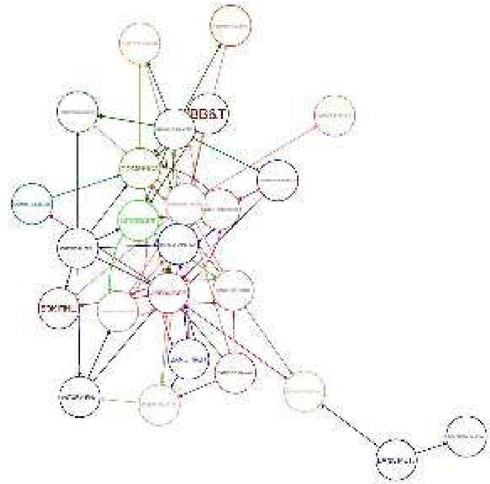
(c) Q_{50} Quantile on Quantile

(d) Q_{50} Not Parametric

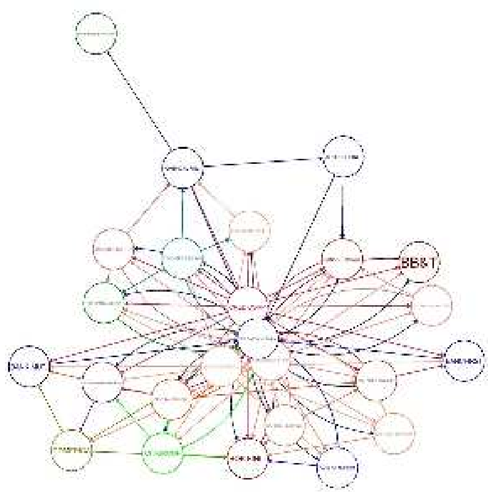
Figure 2.10: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 banks ordered for market capitalization. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 50% quantile q_{50}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 50% quantile q_{50}. Panel d) reports the network extracted by a not parametric methodology on the 50% quantile q_{50}. All the causality regression are computed without the market factor.



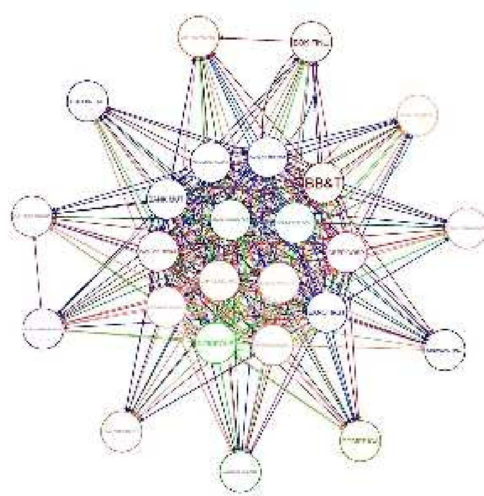
(a) Granger



(b) Q_{90} Base Quantile

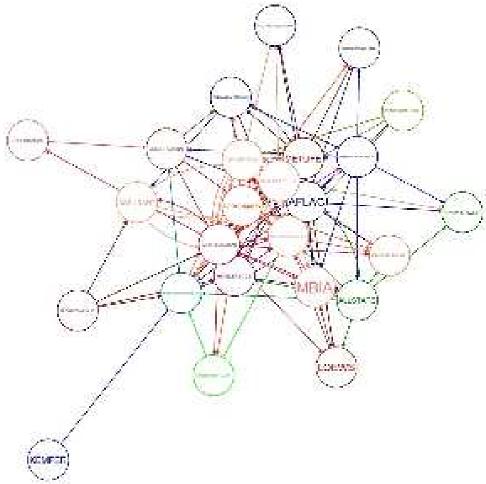


(c) Q_{90} Quantile on Quantile

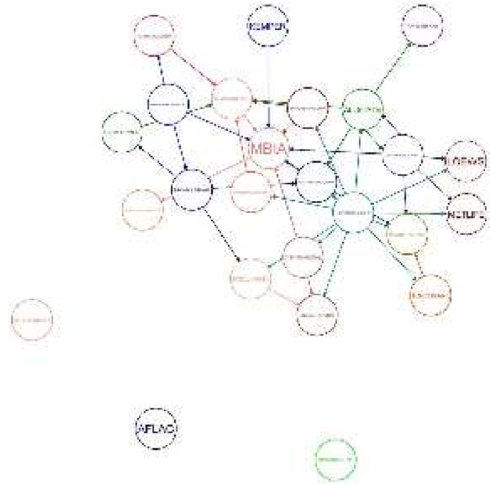


(d) Q_{90} Not Parametric

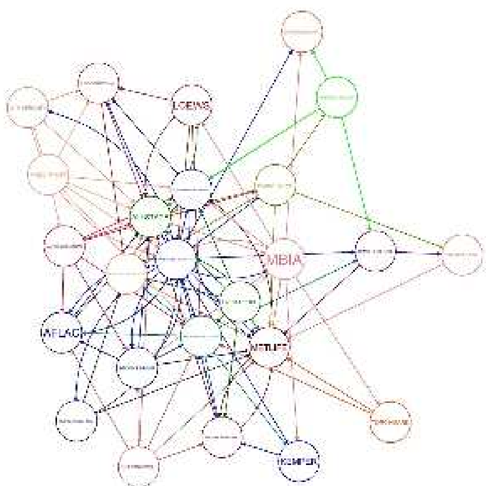
Figure 2.11: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 banks ordered for market capitalization. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 90% quantile q_{90}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 90% quantile q_{90}. Panel d) reports the network extracted by a not parametric methodology on the 90% quantile q_{90}. All the causality regression are computed without the market factor.



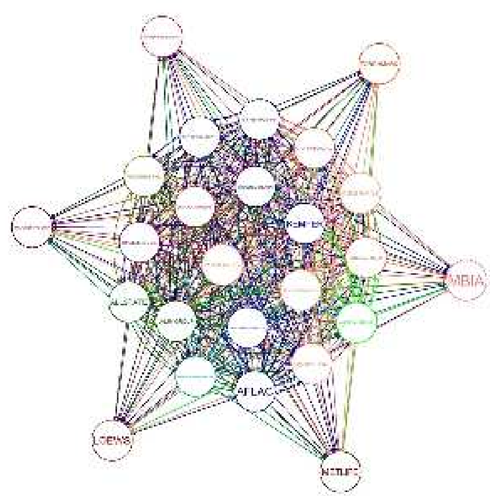
(a) Granger



(b) Q_{10} Base Quantile

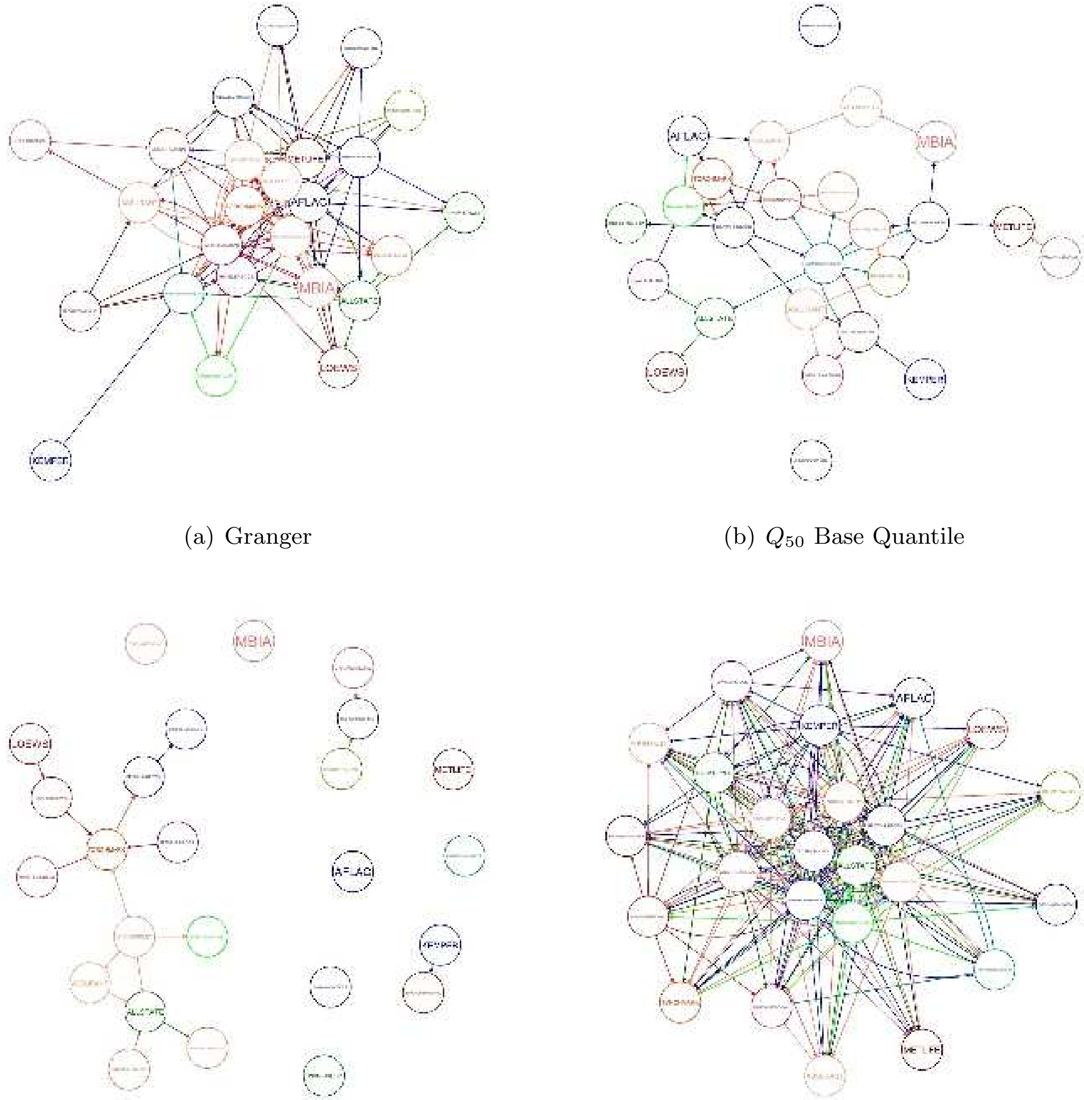


(c) Q_{10} Quantile on Quantile



(d) Q_{10} Not Parametric

Figure 2.12: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 Insurers ordered for market capitalization. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 10% quantile q_{10}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 10% quantile q_{10}. Panel d) reports the network extracted by a not parametric methodologie on the 10% quantile q_{10}. All the causality regression are computed without the market factor.



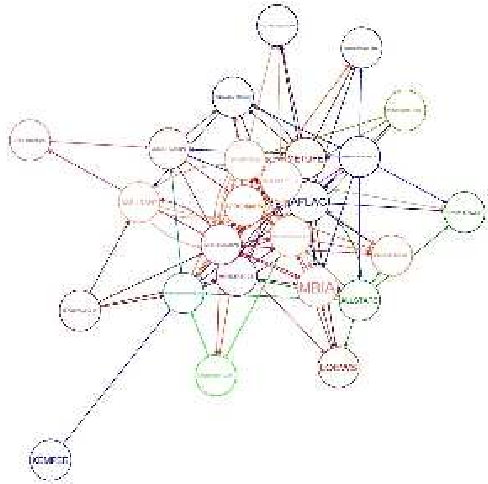
(a) Granger

(b) Q_{50} Base Quantile

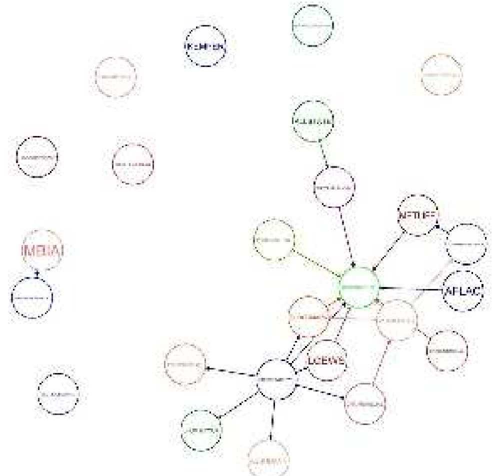
(c) Q_{50} Quantile on Quantile

(d) Q_{50} Not Parametric

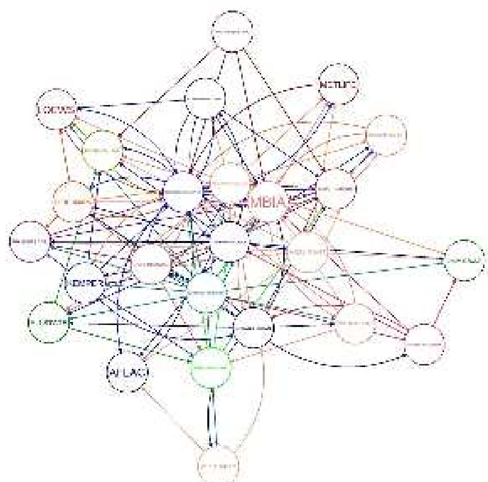
Figure 2.13: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 Insurers ordered for market capitalization. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 50% quantile q_{50}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 50% quantile q_{50}. Panel d) reports the network extracted by a not parametric methodology on the 50% quantile q_{50}. All the causality regression are computed without the market factor.



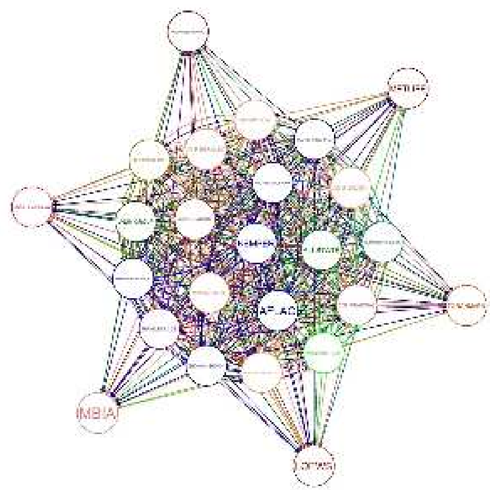
(a) Granger



(b) Q_{90} Base Quantile

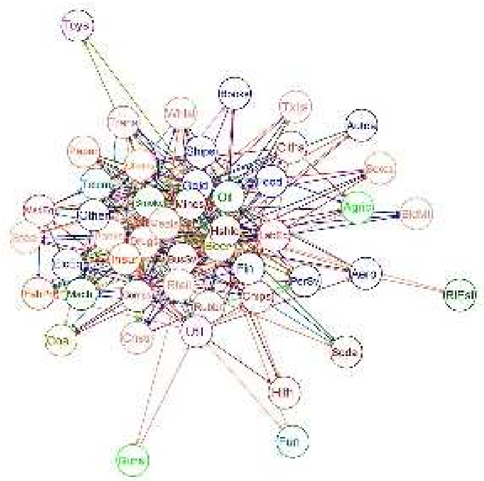


(c) Q_{90} Quantile on Quantile

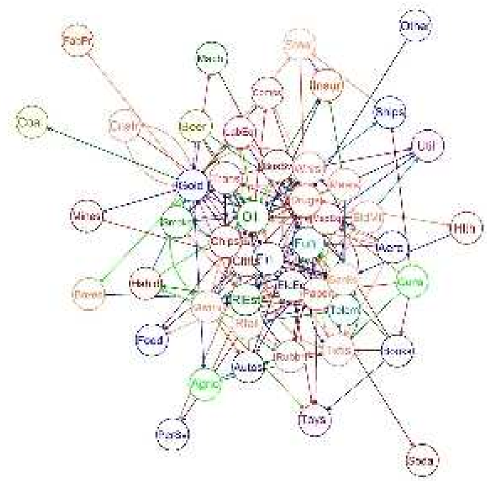


(d) Q_{90} Not Parametric

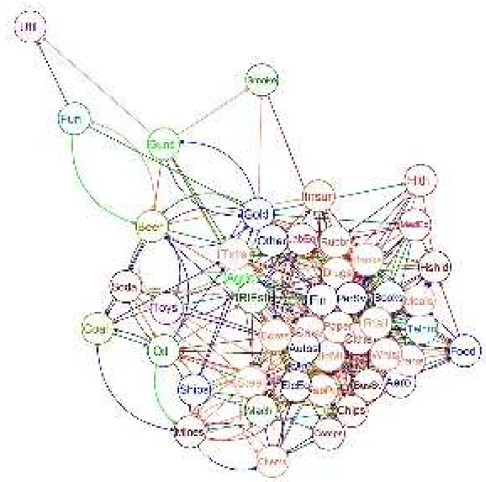
Figure 2.14: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 Insurers ordered for market capitalization. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 90% quantile q_{90}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 90% quantile q_{90}. Panel d) reports the network extracted by a not parametric methodology on the 90% quantile q_{90}. All the causality regression are computed without the market factor.



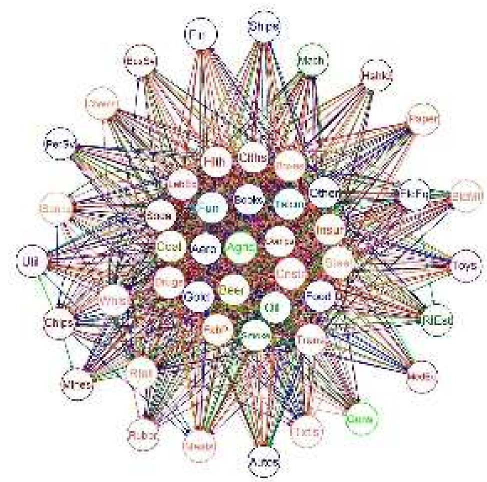
(a) Granger



(b) Q_{10} Base Quantile

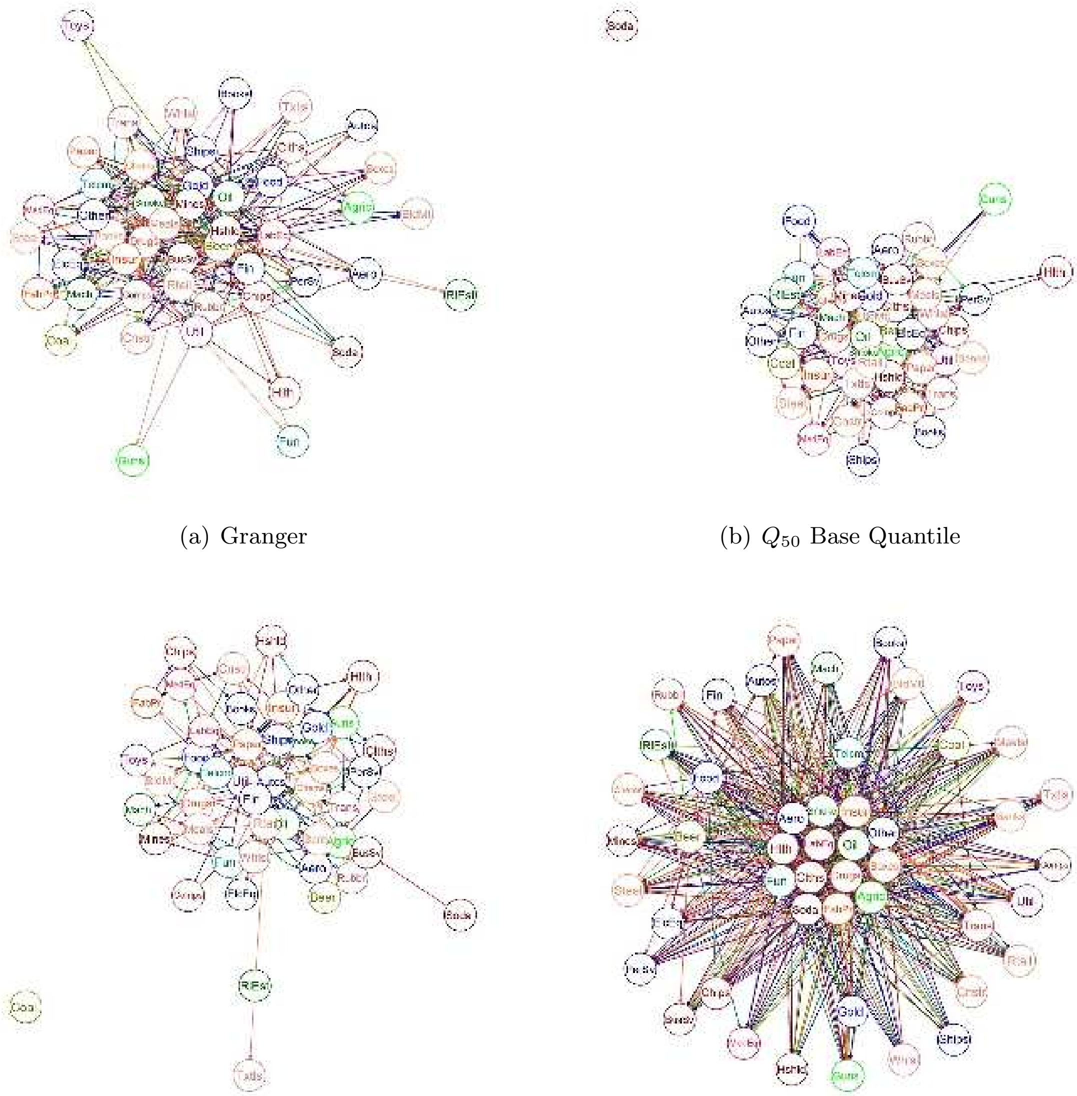


(c) Q_{10} Quantile on Quantile



(d) Q_{10} Not Parametric

Figure 2.15: This figure visualizes 4 different networks for the period 2006-2008 relative to the 48 Fama and French industry portofolios. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 10% quantile q_{10}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 10% quantile q_{10}. Panel d) reports the network extracted by a not parametric methodologie on the 10% quantile q_{10}. All the causality regression are computed without the market factor.



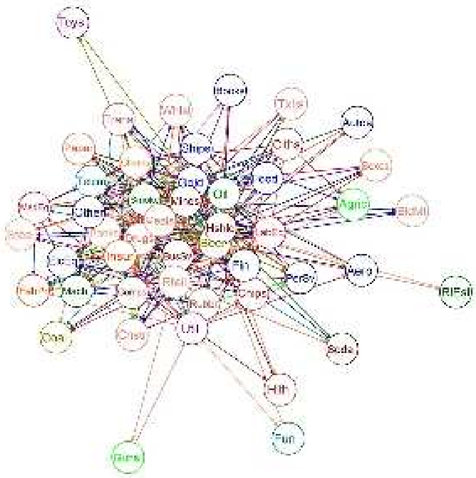
(a) Granger

(b) Q_{50} Base Quantile

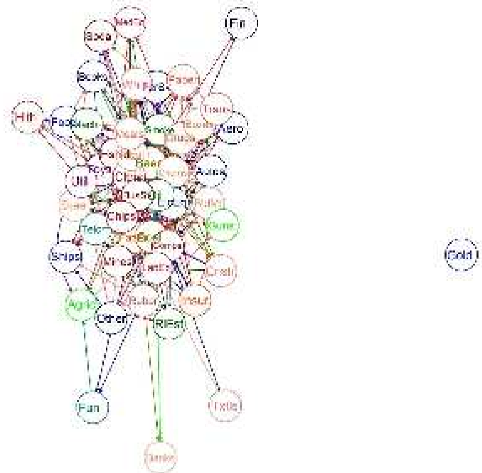
(c) Q_{50} Quantile on Quantile

(d) Q_{50} Not Parametric

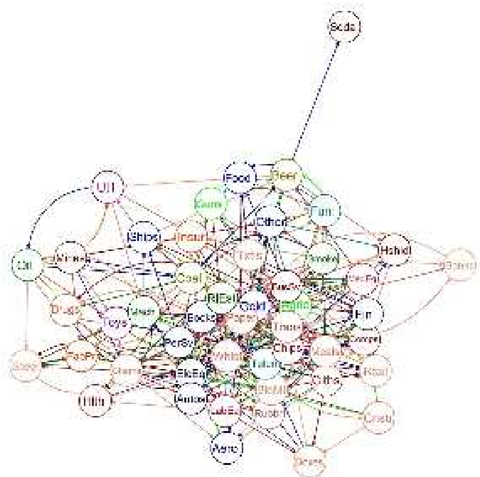
Figure 2.16: This figure visualizes 4 different networks for the period 2006-2008 relative to the 48 Fama and French industry portofolios. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 50% quantile q_{50}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 50% quantile q_{50}. Panel d) reports the network extracted by a not parametric methodology on the 50% quantile q_{50}. All the causality regression are computed without the market factor.



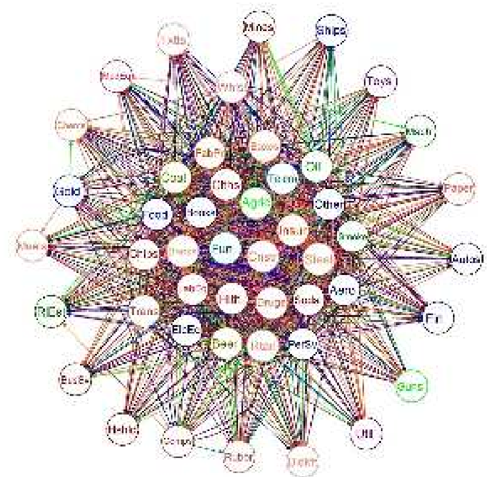
(a) Granger



(b) Q_{90} Base Quantile

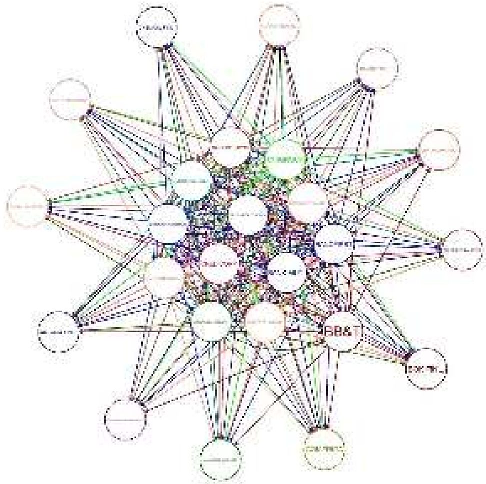


(c) Q_{90} Quantile on Quantile

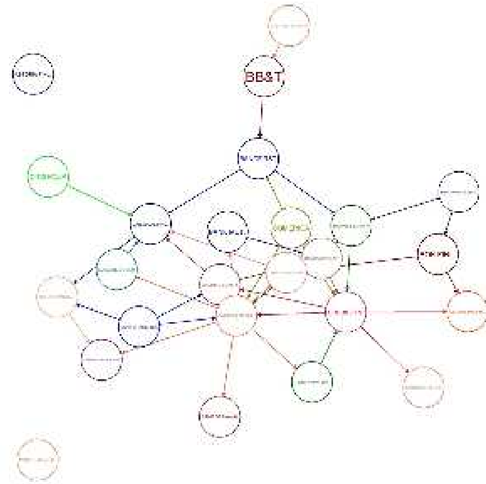


(d) Q_{90} Not Parametric

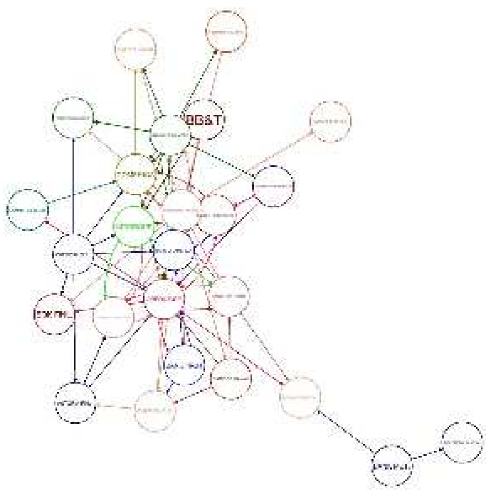
Figure 2.17: This figure visualizes 4 different networks for the period 2006-2008 relative to the 48 Fama and French industry portofolios. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by the standard granger causality. Panel b) indicates the network extracted by a quantile baseline regression methodology on the 90% quantile q_{90}. Panel c) indicates the network extracted by a quantile on quantile methodology on the 90% quantile q_{90}. Panel d) reports the network extracted by a not parametric methodology on the 90% quantile q_{90}. All the causality regression are computed without the market factor.



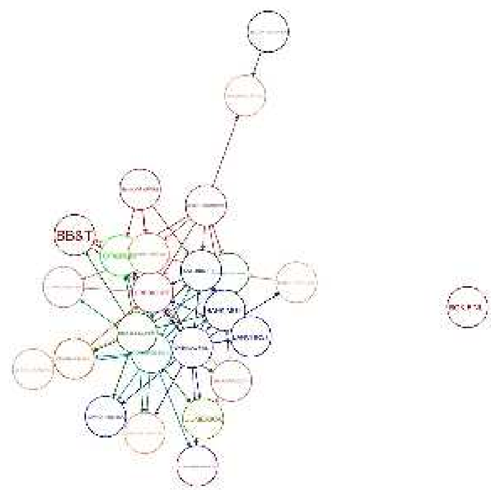
(a) Q_{10} Not Parametric



(b) Q_{50} Quantile on Quantile

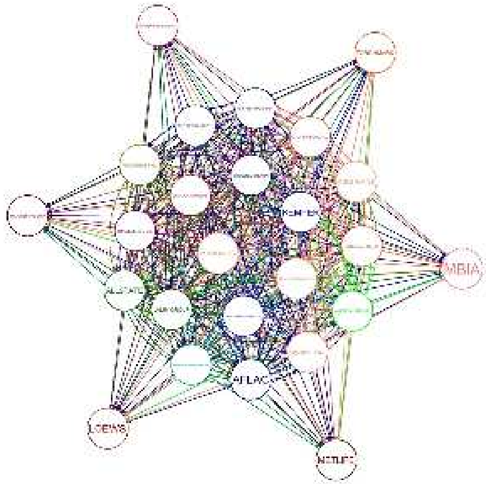


(c) Q_{90} Base Quantile

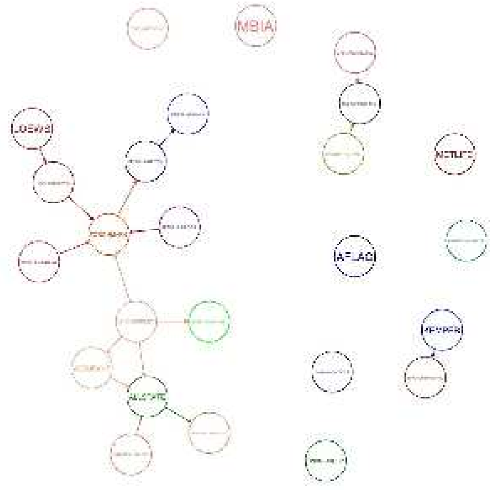


(d) Granger

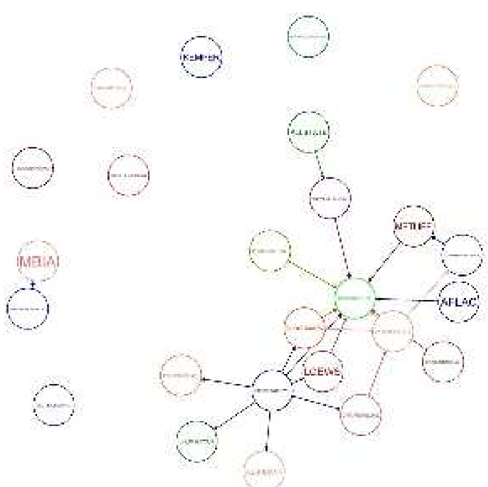
Figure 2.18: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 banks ordered for market capitalization. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by a Not parametric methodologie on the 10% quantile q_{10}. Panel b) indicates the network extracted by a quantile on quantile methodology on the median q_{50}. Panel c) displays the network extracted by a Not parametric methodologie on the 10% quantile q_{10}. Panel b) indicates the network extracted by a quantile on quantile methodology on the 90% quantile q_{90}. Panel d) reports the network extracted by the standard granger causality. All the causality regression are computed without the market factor.



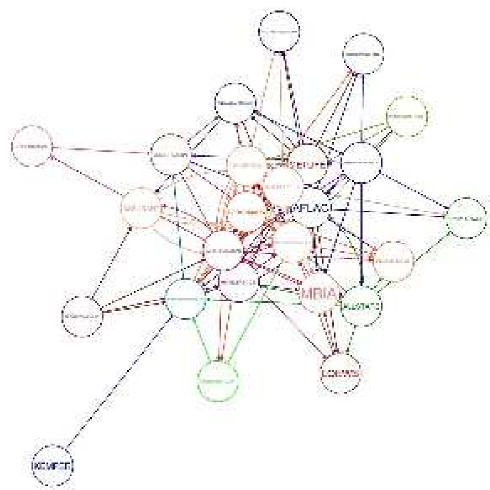
(a) Q_{10} Not Parametric



(b) Q_{50} Quantile on Quantile

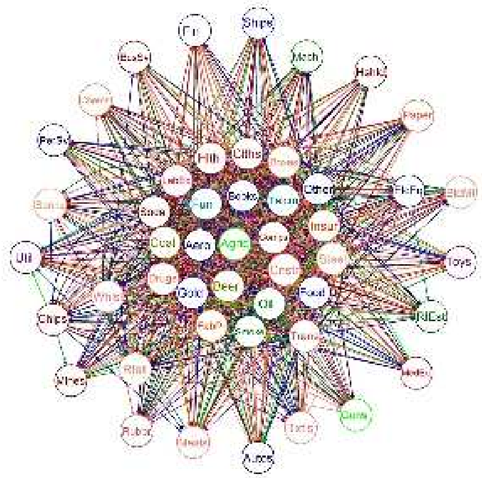


(c) Q_{90} Base Quantile

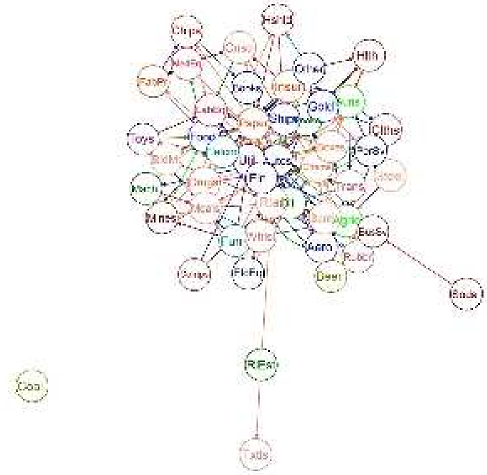


(d) Granger

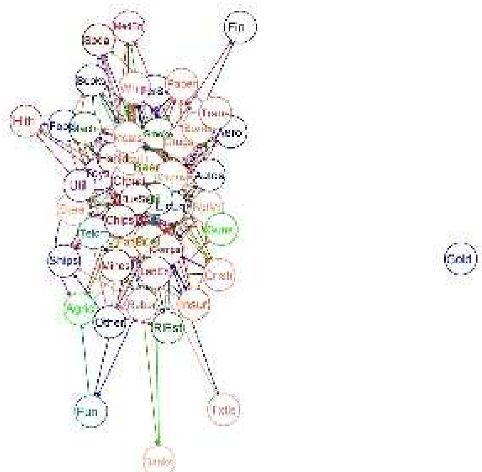
Figure 2.19: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 25 Insurers ordered for market capitalization. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by a Not parametric methodologie on the 10% quantile q_{10}. Panel b) indicates the network extracted by a quantile on quantile methodology on the median q_{50}. Panel c) displays the network extracted by a Not parametric methodologie on the 10% quantile q_{10}. Panel b) indicates the network extracted by a quantile on quantile methodology on the 90% quantile q_{90}. Panel d) reports the network extracted by the standard granger causality. All the causality regression are computed without the market factor.



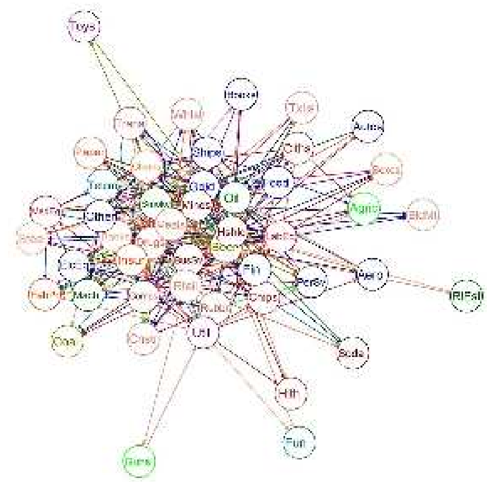
(a) Q_{10} Not Parametric



(b) Q_{50} Quantile on Quantile



(c) Q_{90} Base Quantile



(d) Granger

Figure 2.20: This figure visualizes 4 different networks for the period 2006-2008 relative to the first 48 Fama and French industry portfolios. In this case the networks visualized are some of the primitive networks used for the resulting network computations. Panel a) reports the network extracted by a Not parametric methodology on the 10% quantile q_{10}. Panel b) indicates the network extracted by a quantile on quantile methodology on the median q_{50}. Panel c) displays the network extracted by a Not parametric methodology on the 10% quantile q_{10}. Panel b) indicates the network extracted by a quantile on quantile methodology on the 90% quantile q_{90}. Panel d) reports the network extracted by the standard granger causality. All the causality regression are computed without the market factor.

2.6.4 Networks summary measures

The network *Density* monitors the number of edges of the network relative to the maximum number of edges that the network might present. The *Density* equals $D = \dfrac{E}{V(V-1)}$ where E is the total number of edges observed in a given network and V is the number of nodes of the network. For further details we refer to Wasserman and Faust (1994).

The second measure we consider is *Assortativity*, denote by r, also called homophily, which captures the nodes tendency to connect with nodes having similar properties. In this work, we use a special type of assortativity, called assortativity by degree, see Newman (2010) and Newman (2002). This measure monitors the node willingness to create links with nodes having similar degree. In this case, the degree $k_i, \quad i = 1, 2, \ldots V$, has a double role, the first (the standard one) represents the number of links ending at node i, the second one is the value assigned to that node i for computing the assortativity. In the latter case, the degree might be a measure of the number of edges connecting the node to other nodes of the network, but could also be any continuous variable, for instance associated with the relevance of the edges. In order to distinguish between these two roles, we denote the degree by k_i in the first case, and x_i in the second case. Note that, the two values might be identical. We define the mean value μ of x_i as:

$$\mu = \frac{\sum_i^K \sum_j^K W_{ij} x_i}{2E} = \frac{\sum_i k_i x_i}{2E} \tag{2.27}$$

where $2E$ are the ends for all edges across the network, and W_{ij} is the element of the un-normalized and un-weighted adjacency matrix W. The covariance between x_i and x_j is a way to measure the co-variation between node i and node j with respect to the variable x, which is, in the simplest case, the degree. Across the edges, this covariance can be formally defined as:

$$\begin{aligned}
cov(x_i, x_j) &= \frac{\sum_{ij} W_{ij}(x_i - \mu)(x_j - \mu)}{\sum_{ij} W_{ij}} = \frac{1}{2E} \sum_{ij} W_{ij}(x_i - \mu)(x_j - \mu) \qquad (2.28)\\
&= \frac{1}{2E} \sum_{ij} W_{ij}(x_i x_j - \mu x_i - \mu x_j + \mu^2)\\
&= \frac{1}{2E} \sum_{ij} W_{ij} x_i x_j - \frac{\sum_{ij} W_{ij} x_i \mu}{2E} - \frac{\sum_{ij} W_{ij} x_j \mu}{2E} - \frac{\sum_{ij} W_{ij} \mu^2}{2E}\\
&= \frac{1}{2E} \sum_{ij} W_{ij} x_i x_j - \mu^2\\
&= \frac{1}{2E} \sum_{ij} W_{ij} x_i x_j - \frac{\sum_{ij} k_i k_j x_i x_j}{(2E)^2} = \frac{1}{2E} \sum_{ij} \left(W_{ij} - \frac{k_i k_j}{2E} \right) x_i x_j
\end{aligned}$$

In order to bound the assortativity coefficient in $-1 \leq r \leq 1$, the covariance is normalized by the maximum covariance value that can be reached by the network. The latter corresponds to the case where all the nodes share edges with nodes having the same degree (or $x_i = x_j$).

$$cov(x_i, x_j)_{max} = cov(x_i, x_i) = \frac{1}{2E} \sum_{ij} \left(W_{ij} - \frac{k_i k_j}{2E} \right) x_i^2 \tag{2.29}$$

Finally, as out interest lies in the evaluation of the assortativity by degree, we substitute x_i and x_j with k_i and k_j, and obtain:

$$r = \frac{\sum_{ij} \left(W_{ij} - k_i k_j / 2E \right) k_i k_j}{\sum_{ij} \left(W_{ij} - k_i k_j / 2E \right) k_i^2} \tag{2.30}$$

If the W matrix is not symmetric, then the network associated with this matrix is *directed*, and equation (2.30) must be modified.[7] In that case, $2E$ becomes $\sum_{ij} W_{ij} = M$ and we distinguish the *degree* in *indegree* k_i^{in} and *outdegree* k_i^{out}, respectively, for the $i - th$ node.

Formula 2.31 must be slightly modified. We are not using directly k^{in} and k^{out} but the *excess degree*, labeled with the symbol e. For an un-directed network, the *excess degree* or *remaining degree* is the number of edges leaving a given vertex minus one. As an example, if the $l - th$ edge links the vertex i with the vertex j, and the two vertexes have degree k_i and k_j, respectively, then the *excess degree* for the i_{th} and j_{th} node is $e_i = k_i - 1$ and $e_j = k_j - 1$, respectively. If we have a directed network, each node has an *excess outdegree* e^{out} and an *excess indegree* e^{in}. Thus, if the $l - th$ edge starts from vertex i and goes to vertex j, then the *excess outdegree* for the $i - th$ node is $e_i^{out} = k_i^{out} - 1$ and *excess indegree* for the $j - th$ node is $e_j^{in} = k_j^{in} - 1$.

In the case of a directed network, to compute the assortativity by degree we use:

$$r = \frac{\sum_{ij} e_i^{in} e_j^{out} - \frac{1}{M} \sum_i e_i^{in} \sum_j e_j^{out}}{\sqrt{\left(\sum_i (e_i^{in})^2 - \frac{1}{M} (\sum_i e_i^{in})^2 \right) \left(\sum_j (e_j^{out})^2 - \frac{1}{M} (\sum_j e_j^{out})^2 \right)}}. \tag{2.31}$$

Since the assortativity measure is a ratio, indeterminate forms are also possible. The probability having indeterminate forms $\frac{0}{0}$ increases with a limited number of nodes and high number of edges. In this circumstances the actual number of links among the nodes is almost equal to that we would expect if the links were random, the effect is therefore the reduction of the numerator to zero. In addition, the almost completeness of the network makes null denominator because all the nodes have the same degree and consequently they behave as in a perfect assortativity mixing pattern (nodes with same degree are connected with node having exactly the same degree) where there is only one category given by the degree. Therefore, the indeterminateness arises for the impossibility to capture the network homophily tendency, because of the coexistence of two scenarios: a fully assortative pattern from one side and completely random from the other.

The last two measures we consider are closely related. The first, is the *Eigenvector Centrality*

[7] For details see Newman (2002) and Newman (2003).

introduced by Bonacich (1987) This measure captures the nodes relevance (or centrality) as a function of the relevance of neighbor nodes. In other words, we make the prestige of the node proportional to the prestige of its neighbors. Formally, if we define with x_i the prestige of the i_{th} node and W the adjacency matrix, we assume that

$$x_i = \sum_j W_{ij} x_j. \tag{2.32}$$

We can rewrite the previous expression 2.32 by using a matrix notation. We denote by $\mathbf{x}$ the V-dimensional vector collecting the centrality score. The vector must satisfy the following equality:

$$\mathbf{x} = W\mathbf{x} \tag{2.33}$$

The estimation of the eigenvector centrality requires the use of an iterative procedure. In particular, starting from an initial guess for the centrality scores, $\mathbf{x}_0$, which we set equal to a vector of ones, the centrality scores are updated following

$$\mathbf{x}_t = W\mathbf{x}_{t-1} = W^t \mathbf{x}_0 \tag{2.34}$$

where t denotes th $t-th$ iteration. The vector $\mathbf{x}_0$ can also be seen as a decomposition of linear independent vectors, where c_i is the scalar associated with the $i-th$ component.

$$\mathbf{x}_0 = \sum_i^N c_i \mathbf{v}_i \tag{2.35}$$

If we plug equation 2.35 into equation 2.34, by using the equivalence that $W\mathbf{x} = \lambda\mathbf{x}$ we obtain:

$$\begin{aligned} \mathbf{x}_t &= W^t \mathbf{x}_0 = W^t \sum_i^N c_i \mathbf{v}_i = \sum_i^N c_i W^t \mathbf{v}_i = \sum_i^N c_i W^{t-1} \lambda_i \mathbf{v}_i = \sum_i^N c_i \lambda_i^t \mathbf{v}_i \\ &= \left(\frac{\lambda_1}{\lambda_1}\right)^t \sum_i^N c_i \lambda_i^t \mathbf{v}_i = \lambda_1^t \sum_i^N c_i \left(\frac{\lambda_i}{\lambda_1}\right)^t \mathbf{v}_i \end{aligned} \tag{2.36}$$

where λ_i is the $i-th$ eigenvalue associated to the $i-th$ eigenvector, and λ_1 is the maximum eigenvalue.[8] What we learn from the expression in 2.37 is the following:
since λ_1 is the maximum eigenvalue, as soon $t \to \infty$ the $\sum_i^N c_i \left(\frac{\lambda_i}{\lambda_1}\right)^t \mathbf{v}_i$ tends to $c_1\mathbf{v}_1$ and thus the eigenvector centrality is proportional to the first eigenvalue as in the equation 2.37 we have[9]

[8] The existence of the maximum eigenvalue is guaranteed by the Perron- Frobenius theorem.

[9] The eigenvector centrality does not converge when the maximum eigenvalue λ_1 tends to zero. The maximum eigenvalue coefficient decreases with the sparsity of the adjacency matrix, Van Mieghem (2010)

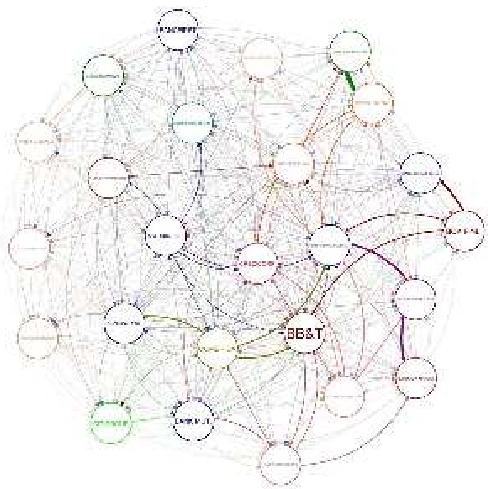
$$\mathbf{x}_t = \lambda_1^t c_1 \mathbf{v}_1 \tag{2.37}$$

In other words, combining equation 2.37 with 2.32, we can observe that the centrality score is a function of the first eigenvalue

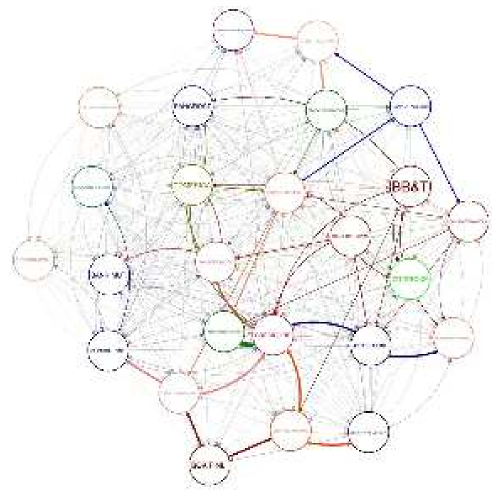
$$x_i = \frac{1}{\lambda_1} \sum_j W_{ij} x_j. \tag{2.38}$$

The eigenvector centrality can be computed not only for adjacency matrix W but also for the normalized adjacency matrix.

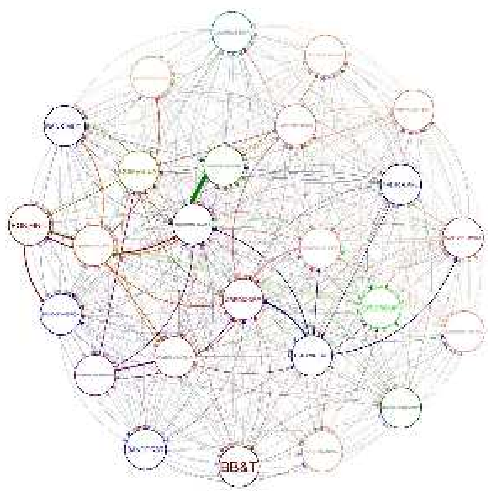
2.6.5 Figures of Combined Network



(a) Q_{10}

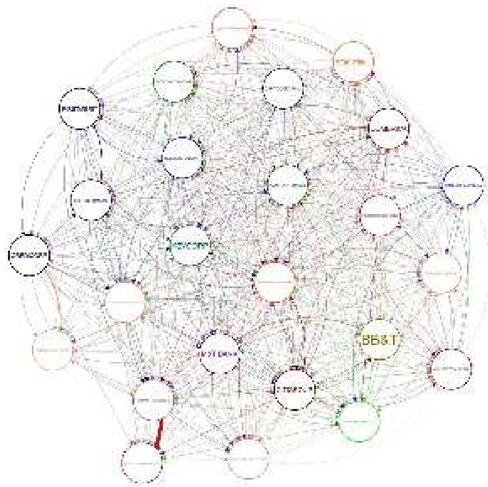


(b) Q_{50}

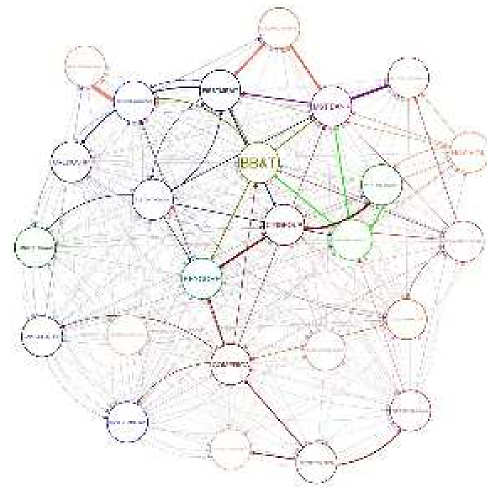


(c) Q_{90}

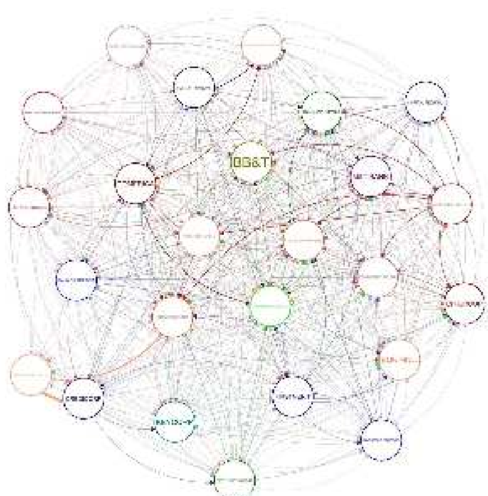
Figure 2.21: This figure visualizes the 3 different resulting networks for the period 2006-2008 relative to the first 25 banks ordered for market capitalization. Panel a) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method. Panel b) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 50% quantile, and the standard granger causality method. Panel c) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 90% quantile, and the standard granger causality method. All the causality regression are computed without the market factor.



(a) Q_{10}

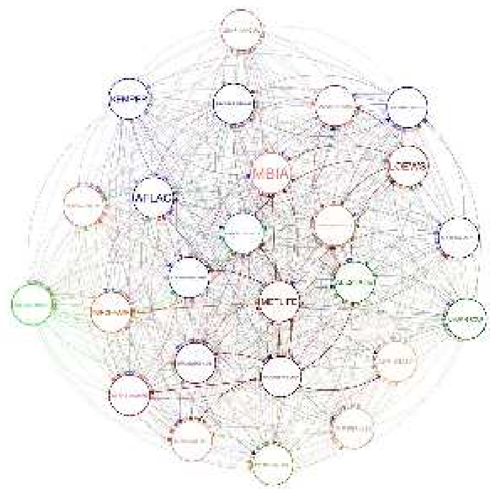


(b) Q_{50}

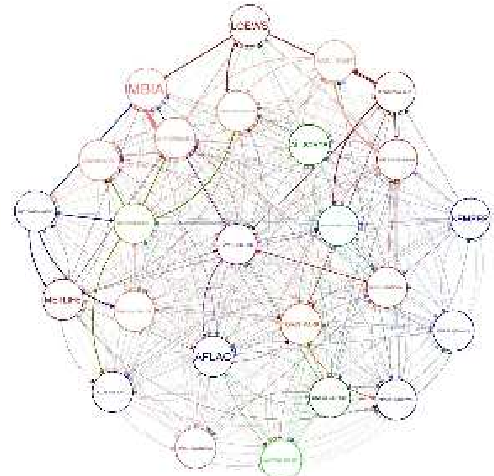


(c) Q_{90}

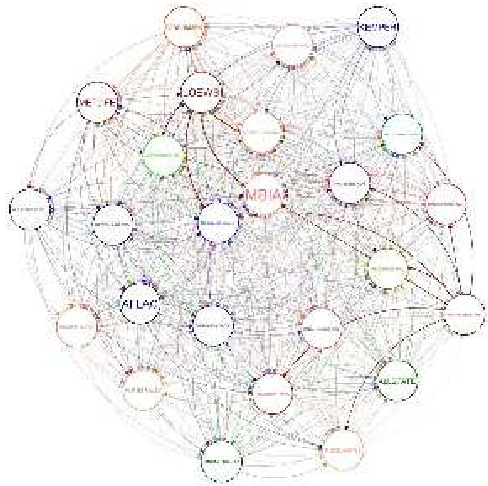
Figure 2.22: This figure visualizes the 3 different resulting networks for the period 2011-2015 relative to the first 25 banks ordered for market capitalization. Panel a) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method. Panel b) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 50% quantile, and the standard granger causality method. Panel c) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 90% quantile, and the standard granger causality method. All the causality regression are computed without the market factor.



(a) Q_{10}

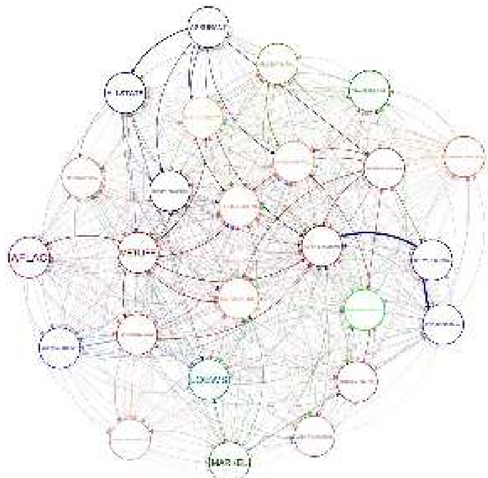


(b) Q_{50}

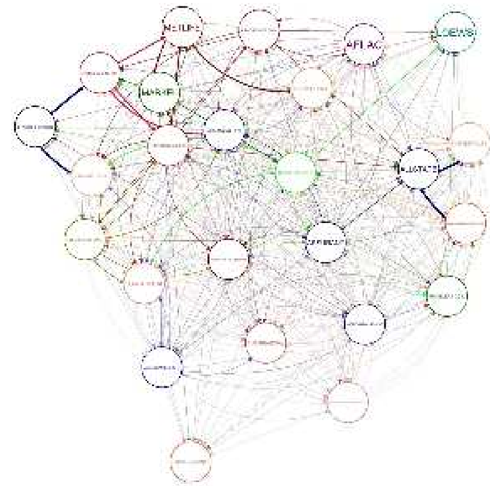


(c) Q_{90}

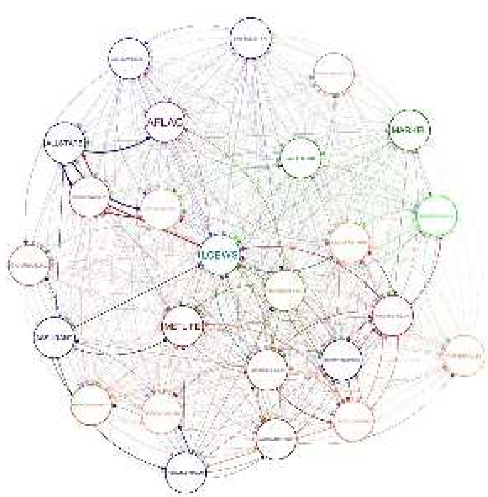
Figure 2.23: This figure visualizes the 3 different resulting networks for the period 2006-2008 relative to the first 25 Insurance companies ordered for market capitalization. Panel a) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method. Panel b) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 50% quantile, and the standard granger causality method. Panel c) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 90% quantile, and the standard granger causality method. All the causality regression are computed without the market factor.



(a) Q_{10}

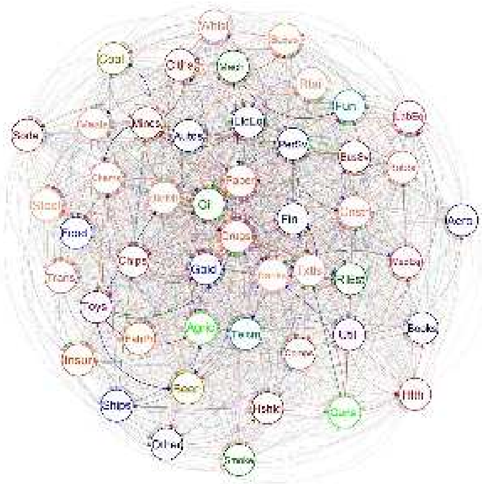


(b) Q_{50}

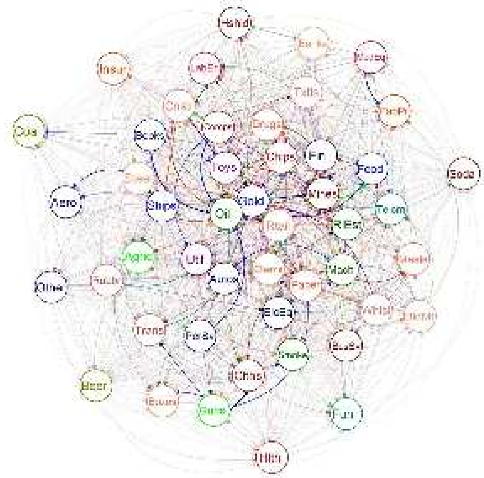


(c) Q_{90}

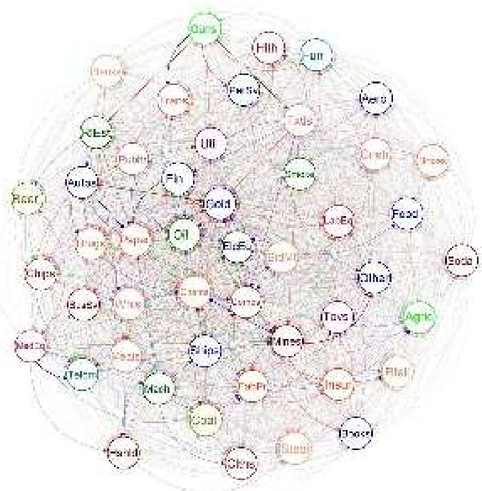
Figure 2.24: This figure visualizes the 3 different resulting networks for the period 2011-2015 relative to the first 25 Insurance companies ordered for market capitalization. Panel a) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method. Panel b) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 50% quantile, and the standard granger causality method. Panel c) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 90% quantile, and the standard granger causality method. All the causality regression are computed without the market factor.



(a) Q_{10}

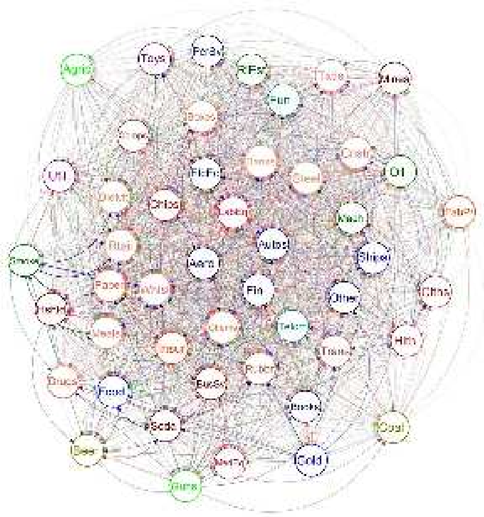


(b) Q_{50}

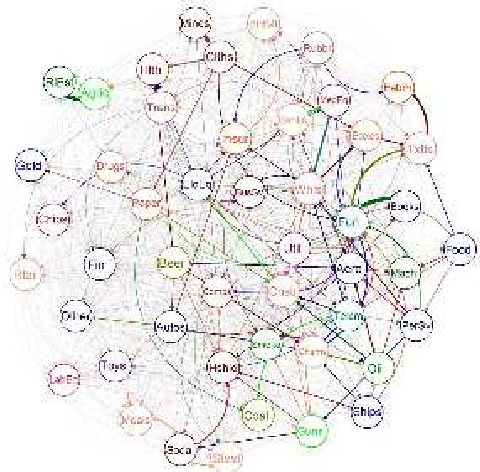


(c) Q_{90}

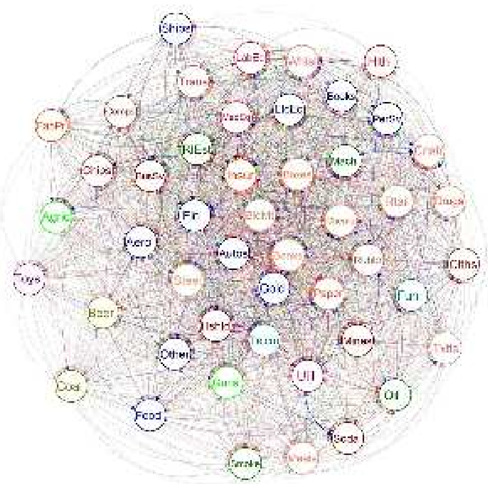
Figure 2.25: This figure visualizes the 3 different resulting networks for the period 2006-2008 relative to 48 Industry portfolios. Panel a) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method. Panel b) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 50% quantile, and the standard granger causality method. Panel c) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 90% quantile, and the standard granger causality method. All the causality regression are computed without the market factor.



(a) Q_{10}



(b) Q_{50}



(c) Q_{90}

Figure 2.26: This figure visualizes the 3 different resulting networks for the period 2011-2015 relative to 48 Industry portfolios. Panel a) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 10% quantile, and the standard granger causality method. Panel b) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 50% quantile, and the standard granger causality method. Panel c) reports the network extracted by combining causality network by using quantile regression (QB, Qo and QN) at the 90% quantile, and the standard granger causality method. All the causality regression are computed without the market factor.

2.6.6 Sensitivity analysis for weekly Returns

Table 2.15: The table reports the δ of model (2.5) that represent the weights for networks combination. The top panel focused on the banks dataset, the middle panel on the insurance companies dataset and the bottom panel on the industry portfolios dataset. The first column identifies the quantiles used to estimate the quantile-based network, and the second column indicates if a common factor was used (Y) or not used (N) in the estimation of the causality networks. Columns 3 to 5 refer to the crisis sample while columns 6 to 8 to the most recent sample. The second row identifies the three different networks which are optimally combined: baseline quantile causality - QB; quantile-on-quantile causality Qo; non-parametric quantile causality - QN. Parameters are, by construction, positive and sum up to one (within each row and within each period). A star identifies parameters significant at the 5% confidence level.

		2006-2008			**2010-2015**		
Quantile	Factor	**QB**	**Qo**	**QN**	**QB**	**Qo**	**QN**
			25 Banks				
10%	N	0.060	0.054*	0.885*	0.001	0.625	0.374
50%	N	0.142	0.108*	0.750*	0.094	0.067	0.838*
90%	N	0.028	0.026	0.946*	0.000	0.725*	0.275*
10%	Y	0.024	0.109	0.868*	0.000*	0.526*	0.474*
50%	Y	0.054	0.062*	0.885*	0.201	0.066*	0.733*
90%	Y	0.123	0.020	0.857*	0.000	0.877*	0.123*
			25 Insurance Companies				
10%	N	0.000	0.034	0.966*	0.058	0.831*	0.111*
50%	N	0.842*	0.125	0.034	0.059	0.045	0.896*
90%	N	0.000	0.028	0.972*	0.000	0.456*	0.544*
10%	Y	0.001	0.028	0.972*	0.000	0.488*	0.512*
50%	Y	0.678*	0.106	0.216*	0.053	0.041	0.907*
90%	Y	0.000	0.046	0.954	0.000	0.554	0.446
			48 Industry Portfolio				
10%	N	0.000	1.000*	0.000	0.032	0.968*	0.000
50%	N	0.202	0.000	0.798	0.214	0.023	0.763
90%	N	0.108	0.892*	0.000	0.016	0.984*	0.000
10%	Y	0.390	0.540	0.071	0.038	0.755*	0.207
50%	Y	0.237	0.613	0.150	0.089	0.024	0.888*
90%	Y	0.000	1.000*	0.000	0.111	0.857*	0.032

Table 2.16: The table reports residual correlation descriptive analyses for the Banks dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

				2006-2008				
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.279	0.584	-0.108	0.071	0.279	11.3%
Q(50%)	4	N	-0.344	0.597	-0.106	0.060	0.316	11.0%
Q(90%)	4	N	-0.297	0.597	-0.127	0.062	0.299	14.0%
Q(10%)	4	Y	-0.291	0.567	-0.135	0.046	0.253	16.0%
Q(50%)	4	Y	-0.346	0.479	-0.118	0.055	0.251	11.7%
Q(90%)	4	Y	-0.301	0.533	-0.137	0.038	0.235	16.3%
G	1	N	-0.381	0.670	-0.128	0.111	0.372	13.3%
G	1	Y	-0.394	0.641	-0.128	0.089	0.378	11.7%
4-F-CAPM	0	N.A	-0.358	0.678	-0.108	0.257	0.502	10.7%
				2011-2015				
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.265	0.424	-0.121	-0.015	0.137	14.7%
Q(50%)	4	N	-0.390	0.643	-0.107	0.053	0.282	13.3%
Q(90%)	4	N	-0.248	0.432	-0.125	0.010	0.136	15.3%
Q(10%)	4	Y	-0.281	0.505	-0.131	-0.011	0.145	18.7%
Q(50%)	4	Y	-0.316	0.609	-0.127	0.054	0.245	15.0%
Q(90%)	4	Y	-0.304	0.508	-0.139	0.001	0.132	17.7%
G	1	N	-0.211	0.598	-0.027	0.151	0.362	3.0%
G	1	Y	-0.211	0.598	-0.027	0.146	0.361	3.3%
4-F-CAPM	0	NA	-0.122	0.669	0.054	0.266	0.487	0.3%

Table 2.17: The table reports residual correlation descriptive analyses for the Insurance Companies dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

2006-2008								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.440	0.682	-0.222	0.002	0.248	27.0%
Q(50%)	4	N	-0.423	0.694	-0.161	0.044	0.260	16.7%
Q(90%)	4	N	-0.448	0.676	-0.207	0.009	0.255	25.7%
Q(10%)	4	Y	-0.455	0.686	-0.212	0.002	0.257	26.7%
Q(50%)	4	Y	-0.369	0.515	-0.181	0.018	0.225	20.7%
Q(90%)	4	Y	-0.464	0.671	-0.214	0.001	0.253	27.0%
G	1	N	-0.466	0.831	-0.166	0.044	0.316	17.7%
G	1	Y	-0.460	0.714	-0.166	0.048	0.323	15.0%
4-F-CAPM	0	N.A	-0.370	0.847	-0.149	0.089	0.422	14.0%
2011-2015								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.290	0.504	-0.121	0.009	0.157	14.7%
Q(50%)	4	N	-0.258	0.547	-0.149	0.019	0.202	16.7%
Q(90%)	4	N	-0.289	0.345	-0.140	-0.004	0.168	18.3%
Q(10%)	4	Y	-0.333	0.503	-0.153	-0.012	0.189	20.7%
Q(50%)	4	Y	-0.268	0.590	-0.157	0.019	0.191	18.3%
Q(90%)	4	Y	-0.299	0.398	-0.152	-0.001	0.199	21.3%
G	1	N	-0.136	0.658	-0.005	0.121	0.317	1.7%
G	1	Y	-0.136	0.658	-0.014	0.116	0.315	1.7%
4-F-CAPM	0	N.A	-0.103	0.658	0.017	0.138	0.332	0.3%

Table 2.18: The table reports residual correlation descriptive analyses for the Industry portfolios dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

2006-2008								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.465	0.611	-0.191	-0.001	0.201	25.6%
Q(50%)	4	N	-0.380	0.661	-0.176	0.011	0.247	22.9%
Q(90%)	4	N	-0.443	0.608	-0.195	-0.006	0.206	25.9%
Q(10%)	4	Y	-0.517	0.624	-0.217	-0.011	0.211	27.1%
Q(50%)	4	Y	-0.467	0.690	-0.199	0.006	0.237	25.2%
Q(90%)	4	Y	-0.533	0.599	-0.195	-0.014	0.216	25.2%
G	1	N	-0.384	0.687	-0.146	0.025	0.257	18.6%
G	1	Y	-0.401	0.687	-0.157	0.011	0.239	19.8%
4-F-CAPM	0	N.A	-0.486	0.733	-0.219	0.003	0.267	27.1%
2011-2015								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.463	0.567	-0.140	-0.008	0.135	19.7%
Q(50%)	4	N	-0.447	0.519	-0.138	0.007	0.176	16.6%
Q(90%)	4	N	-0.470	0.572	-0.144	-0.013	0.138	19.6%
Q(10%)	4	Y	-0.442	0.501	-0.148	-0.003	0.145	19.3%
Q(50%)	4	Y	-0.454	0.508	-0.136	0.003	0.160	16.7%
Q(90%)	4	Y	-0.443	0.567	-0.144	-0.005	0.153	18.4%
G	1	N	-0.470	0.577	-0.140	0.007	0.199	18.0%
G	1	Y	-0.503	0.577	-0.139	0.006	0.177	17.7%
4-F-CAPM	0	N.A	-0.456	0.592	-0.147	0.007	0.208	18.4%

Table 2.19: The table report the δ of model (2.5) that represent the weights for networks combination. The top panel focused on the banks dataset, the middle panel on the insurance companies dataset and the bottom panel on the industry portfolios dataset. The first column identifies the quantiles used to estimate the quantile-based network, and the second column indicates if a common factor was used (Y) or not used (N) in the estimation of the causality networks. Columns 3 to 5 refer to the crisis sample while columns 6 to 8 to the most recent sample. The second row identifies the three different networks which are optimally combined: quantile-on-quantile causality Qo; non-parametric quantile causality - QN and Granger Causality. Parameters are, by construction, positive and sum up to one (within each row and within each period). A star identifies parameters significant at the 5% confidence level.

		2006-2008			**2010-2015**		
Quantile	Factor	**Qo**	**QN**	**GR**	**Qo**	**QN**	**GR**
			25 Banks				
10%	N	0.071	0.915*	0.014	0.630	0.354	0.017
50%	N	0.128	0.848*	0.024	0.132	0.714*	0.154
90%	N	0.008	0.884*	0.108	0.706*	0.243*	0.051*
10%	Y	0.082	0.843*	0.076	0.538	0.428*	0.034*
50%	Y	0.094	0.726	0.180	0.092	0.745*	0.163
90%	Y	0.002	0.893*	0.105	0.876*	0.121*	0.003*
			25 Insurance Companies				
10%	N	0.034	0.966*	0.000	0.804	0.141	0.055*
50%	N	0.000	0.942*	0.058	0.054	0.615	0.331
90%	N	0.028	0.972	0.000	0.364	0.436	0.200
10%	Y	0.006	0.949*	0.045	0.489	0.511	0.000
50%	Y	0.516	0.474	0.009	0.051	0.846*	0.102
90%	Y	0.046	0.954*	0.000	0.554	0.446	0.000*
			48 Industry Portfolio				
10%	N	0.173	0.057	0.770	1.000*	0.000	0.000*
50%	N	0.079	0.248	0.673	0.030	0.868*	0.102
90%	N	1.000*	0.000	0.000	1.000*	0.000	0.000*
10%	Y	0.619	0.052	0.329	0.640	0.320	0.039
50%	Y	0.000	0.676	0.324	0.029	0.876*	0.095
90%	Y	0.810	0.000*	0.190	0.918	0.032	0.050

Table 2.20: The table reports residual correlation descriptive analyses for the Banks dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (Qo and QN) at the 10% quantile, combined with the Granger Causality Network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

2006-2008								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.304	0.584	-0.117	0.067	0.273	12.0%
Q(50%)	4	N	-0.319	0.587	-0.105	0.072	0.342	11.0%
Q(90%)	4	N	-0.269	0.600	-0.147	0.050	0.278	16.0%
Q(10%)	4	Y	-0.295	0.571	-0.136	0.035	0.236	15.3%
Q(50%)	4	Y	-0.346	0.490	-0.119	0.048	0.288	12.3%
Q(90%)	4	Y	-0.313	0.485	-0.142	0.031	0.244	18.0%
G	1	N	-0.381	0.670	-0.128	0.111	0.372	13.3%
G	1	Y	-0.394	0.641	-0.128	0.089	0.378	11.7%
4-F-CAPM	0	N.A	-0.358	0.678	-0.108	0.257	0.502	10.7%
2011-2015								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.263	0.422	-0.122	-0.013	0.135	15.3%
Q(50%)	4	N	-0.332	0.528	-0.116	0.052	0.243	12.7%
Q(90%)	4	N	-0.253	0.431	-0.127	0.010	0.138	15.7%
Q(10%)	4	Y	-0.283	0.503	-0.132	-0.008	0.140	19.0%
Q(50%)	4	Y	-0.311	0.522	-0.122	0.052	0.237	13.0%
Q(90%)	4	Y	-0.304	0.508	-0.140	0.001	0.132	17.7%
G	1	N	-0.211	0.598	-0.027	0.151	0.362	3.0%
G	1	Y	-0.211	0.598	-0.027	0.146	0.361	3.3%
4-F-CAPM	0	NA	-0.122	0.669	0.054	0.266	0.487	0.3%

Table 2.21: The table reports residual correlation descriptive analyses for the Insurance Companies dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (Qo and QN) at the 10% quantile, combined with the Granger Causality Network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

				2006-2008				
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.441	0.682	-0.222	0.002	0.248	27.0%
Q(50%)	4	N	-0.435	0.756	-0.169	0.027	0.335	20.7%
Q(90%)	4	N	-0.448	0.676	-0.207	0.009	0.255	25.7%
Q(10%)	4	Y	-0.436	0.684	-0.203	0.005	0.246	28.0%
Q(50%)	4	Y	-0.468	0.574	-0.185	0.016	0.238	22.7%
Q(90%)	4	Y	-0.464	0.671	-0.214	0.001	0.253	27.0%
G	1	N	-0.466	0.831	-0.166	0.044	0.316	17.7%
G	1	Y	-0.460	0.714	-0.166	0.048	0.323	15.0%
4-F-CAPM	0	N.A	-0.370	0.847	-0.149	0.089	0.422	14.0%
				2011-2015				
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.293	0.482	-0.123	0.009	0.158	14.7%
Q(50%)	4	N	-0.238	0.593	-0.132	0.025	0.217	15.0%
Q(90%)	4	N	-0.289	0.348	-0.137	-0.006	0.167	19.3%
Q(10%)	4	Y	-0.333	0.503	-0.153	-0.012	0.189	20.7%
Q(50%)	4	Y	-0.276	0.590	-0.140	0.020	0.210	17.0%
Q(90%)	4	Y	-0.299	0.398	-0.152	-0.001	0.199	21.3%
G	1	N	-0.136	0.658	-0.005	0.121	0.317	1.7%
G	1	Y	-0.136	0.658	-0.014	0.116	0.315	1.7%
4-F-CAPM	0	N.A	-0.103	0.658	0.017	0.138	0.332	0.3%

Table 2.22: The table reports residual correlation descriptive analyses for the Industry portfolios dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (Qo and QN) at the 10% quantile, combined with the Granger Causality Network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

2006-2008

Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.370	0.592	-0.153	0.013	0.237	20.0%
Q(50%)	4	N	-0.357	0.604	-0.151	0.020	0.251	19.3%
Q(90%)	4	N	-0.465	0.660	-0.196	-0.002	0.212	25.8%
Q(10%)	4	Y	-0.431	0.595	-0.182	0.007	0.221	22.5%
Q(50%)	4	Y	-0.415	0.687	-0.169	0.006	0.231	21.5%
Q(90%)	4	Y	-0.508	0.592	-0.187	-0.007	0.215	23.8%
G	1	N	-0.384	0.687	-0.146	0.025	0.257	18.6%
G	1	Y	-0.401	0.687	-0.157	0.011	0.239	19.8%
4-F-CAPM	0	N.A	-0.486	0.733	-0.219	0.003	0.267	27.1%

2011-2015

Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.463	0.567	-0.138	-0.008	0.133	19.3%
Q(50%)	4	N	-0.464	0.519	-0.137	0.003	0.172	16.8%
Q(90%)	4	N	-0.471	0.572	-0.144	-0.013	0.139	20.0%
Q(10%)	4	Y	-0.434	0.495	-0.148	-0.005	0.145	19.1%
Q(50%)	4	Y	-0.509	0.513	-0.141	0.004	0.163	16.5%
Q(90%)	4	Y	-0.424	0.563	-0.144	-0.004	0.150	19.3%
G	1	N	-0.470	0.577	-0.140	0.007	0.199	18.0%
G	1	Y	-0.503	0.577	-0.139	0.006	0.177	17.7%

2.6.7 Tables for Monthly returns

Table 2.23: The table reports the δ of model (2.5) that represent the weights for networks combination. The top panel focused on the banks dataset, the middle panel on the insurance companies dataset and the bottom panel on the industry portfolios dataset. The first column identifies the quantiles used to estimate the quantile-based network, and the second column indicates if a common factor was used (Y) or not used (N) in the estimation of the causality networks. Columns 3 to 6 refer to the crisis sample while columns 7 to 10 to the most recent sample. The second row identifies the four different networks which are optimally combined: baseline quantile causality - QB; quantile-on-quantile causality Qo; non-parametric quantile causality - QN; Granger causality. Parameters are, by construction, positive and sum up to one (within each row and within each period). A star identifies parameters significant at the 5% confidence level.

		2006-2008				**2010-2015**			
Quantile	Factor	**QB**	**Qo**	**QN**	**QR**	**QB**	**Qo**	**QN**	**QR**
25 Banks									
10%	N	0.031	0.091	0.878	0.000	0.000	0.692*	0.271	0.037
50%	N	0.495	0.000*	0.345	0.159	0.083	0.123*	0.689*	0.105
90%	N	0.002	0.007	0.872*	0.119	0.000	0.739*	0.142	0.119
10%	Y	0.061	0.182	0.681*	0.077	0.000	0.604	0.375	0.022
50%	Y	0.131	0.109*	0.451*	0.310*	0.075	0.046*	0.746*	0.132
90%	Y	0.131	0.022	0.639*	0.207	0.000	0.954*	0.000	0.046
25 Insurance Companies									
10%	N	0.248	0.000*	0.638*	0.115	0.000	0.651	0.137	0.213
50%	N	0.689	0.000	0.175*	0.136	0.052	0.063	0.637	0.248
90%	N	0.000	0.042*	0.829*	0.129	0.000	0.449	0.453	0.098
10%	Y	0.000	0.005*	0.916*	0.079	0.000	1.000*	0.000	0.000
50%	Y	0.000	0.071*	0.831*	0.098	0.082	0.054	0.862	0.003
90%	Y	0.000	0.000	0.907	0.093	0.000	0.186	0.814*	0.000
48 Industry Portfolio									
10%	N	0.149	0.253	0.599	0.000	0.020	0.980	0.000	0.000
50%	N	0.085	0.119	0.000	0.797	0.309	0.031	0.520	0.141
90%	N	0.140	0.000	0.860	0.000	0.014	0.203	0.633*	0.150
10%	Y	0.304	0.226	0.356*	0.114	0.012	0.576	0.294	0.118
50%	Y	0.426	0.137	0.000	0.437	0.093	0.027	0.767*	0.113
90%	Y	0.166	0.030	0.749	0.055	0.103	0.668	0.106	0.123

Table 2.24: The table reports residual correlation descriptive analyses for the Banks dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

2006-2008								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements** ≤ -0.1
Q(10%)	4	N	-0.485	0.748	-0.229	0.062	0.358	23.7%
Q(50%)	4	N	-0.401	0.736	-0.193	0.095	0.412	20.7%
Q(90%)	4	N	-0.496	0.696	-0.236	0.071	0.367	26.3%
Q(10%)	4	Y	-0.499	0.797	-0.248	0.034	0.325	30.3%
Q(50%)	4	Y	-0.495	0.755	-0.226	0.055	0.351	26.3%
Q(90%)	4	Y	-0.504	0.737	-0.257	0.050	0.323	28.3%
G	1	N	-0.605	0.756	-0.172	0.190	0.528	17.0%
G	1	Y	-0.599	0.826	-0.190	0.141	0.505	18.0%
4-F-CAPM	0	N.A	-0.404	0.826	0.040	0.417	0.699	7.0%
2011-2015								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements** ≤ -0.1
Q(10%)	4	N	-0.415	0.527	-0.209	-0.007	0.209	28.0%
Q(50%)	4	N	-0.536	0.602	-0.189	0.033	0.288	21.3%
Q(90%)	4	N	-0.455	0.512	-0.200	0.007	0.227	27.7%
Q(10%)	4	Y	-0.382	0.563	-0.226	-0.011	0.228	28.0%
Q(50%)	4	Y	-0.449	0.582	-0.201	0.038	0.280	22.7%
Q(90%)	4	Y	-0.423	0.564	-0.223	-0.003	0.224	27.7%
G	1	N	-0.314	0.677	-0.083	0.165	0.460	8.3%
G	1	Y	-0.388	0.677	-0.083	0.162	0.455	8.3%
4-F-CAPM	0	NA	-0.155	0.793	0.098	0.385	0.604	0.7%

Table 2.25: The table reports residual correlation descriptive analyses for the Insurance Companies dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

2006-2008								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.684	0.693	-0.264	0.040	0.372	26.3%
Q(50%)	4	N	-0.674	0.760	-0.261	0.039	0.366	26.0%
Q(90%)	4	N	-0.694	0.744	-0.276	0.044	0.367	27.3%
Q(10%)	4	Y	-0.674	0.734	-0.277	0.054	0.383	29.0%
Q(50%)	4	Y	-0.694	0.755	-0.271	0.041	0.370	28.7%
Q(90%)	4	Y	-0.679	0.734	-0.270	0.055	0.383	28.3%
G	1	N	-0.665	0.771	-0.267	0.055	0.399	27.7%
G	1	Y	-0.629	0.771	-0.240	0.065	0.398	24.7%
4-F-CAPM	0	N.A	-0.639	0.886	-0.190	0.157	0.519	16.7%
2011-2015								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.543	0.610	-0.206	0.010	0.236	26.0%
Q(50%)	4	N	-0.428	0.648	-0.224	0.037	0.283	24.3%
Q(90%)	4	N	-0.450	0.577	-0.229	0.001	0.247	27.7%
Q(10%)	4	Y	-0.533	0.629	-0.239	0.008	0.264	31.7%
Q(50%)	4	Y	-0.442	0.697	-0.236	0.036	0.287	26.7%
Q(90%)	4	Y	-0.446	0.626	-0.242	0.002	0.280	31.0%
G	1	N	-0.230	0.826	-0.015	0.221	0.473	2.3%
G	1	Y	-0.230	0.826	-0.023	0.218	0.473	2.7%
4-F-CAPM	0	N.A	-0.204	0.826	0.045	0.246	0.475	0.7%

Table 2.26: The table reports residual correlation descriptive analyses for the Industry portfolios dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

2006-2008

Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements \le -0.1**
Q(10%)	4	N	-0.702	0.653	-0.338	-0.029	0.267	39.0%
Q(50%)	4	N	-0.654	0.680	-0.353	-0.032	0.296	39.7%
Q(90%)	4	N	-0.619	0.658	-0.347	-0.027	0.289	38.7%
Q(10%)	4	Y	-0.749	0.638	-0.319	-0.022	0.265	37.3%
Q(50%)	4	Y	-0.675	0.675	-0.371	-0.031	0.318	40.8%
Q(90%)	4	Y	-0.690	0.689	-0.348	-0.030	0.277	39.5%
G	1	N	-0.654	0.685	-0.368	-0.023	0.293	39.2%
G	1	Y	-0.695	0.705	-0.373	-0.020	0.301	40.3%
4-F-CAPM	0	N.A	-0.667	0.713	-0.378	-0.025	0.309	39.5%

2011-2015

Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements** ≤ -0.1
Q(10%)	4	N	-0.583	0.623	-0.234	-0.008	0.210	30.4%
Q(50%)	4	N	-0.499	0.617	-0.206	0.014	0.248	26.1%
Q(90%)	4	N	-0.551	0.589	-0.224	-0.006	0.244	29.1%
Q(10%)	4	Y	-0.534	0.543	-0.228	-0.002	0.244	29.5%
Q(50%)	4	Y	-0.443	0.529	-0.216	0.008	0.241	25.3%
Q(90%)	4	Y	-0.446	0.585	-0.230	-0.002	0.242	29.5%
G	1	N	-0.502	0.579	-0.228	0.009	0.259	28.0%
G	1	Y	-0.478	0.594	-0.220	0.010	0.251	27.7%
4-F-CAPM	0	N.A	-0.502	0.626	-0.231	0.021	0.283	28.4%

2.6.8 Homogeneity

Table 2.27: The table reports the δ of model (2.5), that represent the weights for networks combination. The model replaces the matrix $\mathcal{R}$ with a scalar coefficient, and thus we have, across assets, a homogeneous impact of the network. The top panel focused on the banks dataset, the middle panel on the insurance companies dataset and the bottom panel on the industry portfolios dataset. The first column identifies the quantiles used to estimate the quantile-based network, and the second column indicates if a common factor was used (Y) or not used (N) in the estimation of the causality networks. Columns 3 to 6 refer to the crisis sample while columns 7 to 10 to the most recent sample. The second row identifies the four different networks which are optimally combined: baseline quantile causality - QB; quantile-on-quantile causality Qo; non-parametric quantile causality - QN; Granger causality. Parameters are, by construction, positive and sum up to one (within each row and within each period). A star identifies parameters significant at the 5% confidence level.

		2006-2008				**2010-2015**			
Quantile	Factor	**QB**	**Qo**	**QN**	**QG**	**QB**	**Qo**	**QN**	**QG**
				25 Banks					
10%	N	0.000	0.159	0.841*	0.000	0.028	0.656*	0.264*	0.052
50%	N	0.199	0.146*	0.589*	0.066*	0.140*	0.273*	0.349*	0.238*
90%	N	0.001	0.000	0.984*	0.000	0.048	0.565*	0.281*	0.106
10%	Y	0.000*	0.398*	0.403*	0.199*	0.036	0.771*	0.160	0.033*
50%	Y	0.140*	0.204*	0.444*	0.212*	0.198*	0.187*	0.409*	0.206*
90%	Y	0.247*	0.000*	0.471*	0.282*	0.000	0.939*	0.061*	0.000*
				25 Insurance Companies					
10%	N	0.061	0.151*	0.789*	0.000*	0.078	0.922*	0.000	0.000
50%	N	0.193	0.099*	0.495*	0.212*	0.158	0.111*	0.659*	0.072*
90%	N	0.000*	0.000*	1.000*	0.000*	0.000*	0.492*	0.508*	0.000*
10%	Y	0.040	0.082	0.856*	0.022	0.007	0.645*	0.347*	0.000
50%	Y	0.090	0.218*	0.631*	0.060	0.038	0.072	0.831*	0.058
90%	Y	0.000	0.000	0.973*	0.027	0.000*	0.566*	0.434*	0.000*
				48 Industry Portfolio					
10%	N	0.000*	0.000*	0.000*	1.000*	0.074	0.926*	0.000*	0.000*
50%	N	0.000	0.213	0.177	0.610	0.000*	1.000*	0.000*	0.000*
90%	N	0.000*	0.000*	0.000*	1.000*	0.000*	1.000*	0.000*	0.000*
10%	Y	1.000*	0.000*	0.000*	0.000*	0.000*	1.000*	0.000*	0.000*
50%	Y	1.000*	0.000*	0.000*	0.000*	0.705	0.001*	0.294*	0.000*
90%	Y	0.782*	0.218*	0.000*	0.000*	0.000*	1.000*	0.000*	0.000*

Table 2.28: The table reports scalar coefficient ρ replacing matrix $\mathcal{R}$ in model (2.5), to impose homogeneous reaction of the assets to network exposure. The top panel focused on the banks dataset, the middle panel on the insurance companies dataset and the bottom panel on the industry portfolios dataset. The first column identifies the quantiles used to estimate the quantile-based network, and the second column indicates if a common factor was used (Y) or not used (N) in the estimation of the causality networks. The results identify the four different networks which are optimally combined: baseline quantile causality; quantile-on-quantile causality; non-parametric quantile causality; Granger causality. A star identifies parameters significant at the 5% confidence level.

Quantile	**Factor**	**2006-2008**	**2011-2015**
25 Banks			
10%	N	0.687*	0.727*
50%	N	0.756*	0.851*
90%	N	0.604*	0.774*
10%	Y	0.656*	0.713*
50%	Y	0.894*	0.886*
90%	Y	0.639*	0.673*
25 Insurance Companies			
10%	N	0.497*	0.554*
50%	N	0.301*	0.613*
90%	N	0.469*	0.618*
10%	Y	0.491*	0.581*
50%	Y	0.472*	0.638*
90%	Y	0.477*	0.564*
48 Industry companies			
10%	N	-0.077*	0.460*
50%	N	-0.117*	0.025*
90%	N	-0.077*	0.324*
10%	Y	0.175*	0.282*
50%	Y	0.129*	0.123*
90%	Y	0.100*	0.252*

Table 2.29: The table reports residual correlation descriptive analyses for the Banks dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

2006-2008								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
10%	4	N	-0.443	0.578	-0.207	0.082	0.364	23.0%
50%	4	N	-0.469	0.640	-0.205	0.114	0.425	19.3%
90%	4	N	-0.461	0.602	-0.193	0.031	0.371	23.3%
10%	4	Y	-0.377	0.573	-0.198	0.061	0.322	21.3%
50%	4	Y	-0.526	0.558	-0.184	0.057	0.329	18.0%
90%	4	Y	-0.588	0.546	-0.206	0.061	0.347	19.3%
Granger	1	N	-0.366	0.662	-0.120	0.221	0.475	12.3%
Granger	1	Y	-0.591	0.626	-0.143	0.155	0.428	12.3%
Multifactor	-	-	-0.358	0.678	-0.108	0.257	0.502	10.7%
2011-2015								
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
10%	4	N	-0.450	0.394	-0.146	-0.019	0.186	20.0%
50%	4	N	-0.416	0.594	-0.145	0.091	0.308	15.7%
90%	4	N	-0.639	0.444	-0.136	0.005	0.169	17.7%
10%	4	Y	-0.320	0.462	-0.154	-0.013	0.181	22.0%
50%	4	Y	-0.423	0.560	-0.168	0.071	0.290	17.7%
90%	4	Y	-0.369	0.482	-0.156	-0.005	0.166	23.0%
Granger	1	N	-0.468	0.598	-0.052	0.169	0.369	6.7%
Granger	1	Y	-0.472	0.598	-0.053	0.167	0.369	6.7%
Multifactor	-	-	-0.122	0.669	0.054	0.266	0.487	0.3%

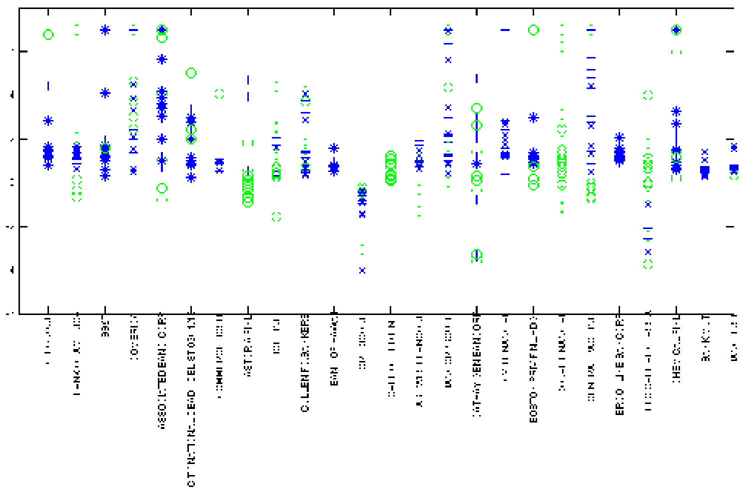
Table 2.30: The table reports residual correlation descriptive analyses for the Insurance Companies dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
				2006-2008				
Q(10%)	4	N	-0.499	0.809	-0.261	-0.004	0.294	31.7%
Q(50%)	4	N	-0.468	0.812	-0.213	0.018	0.379	23.3%
Q(90%)	4	N	-0.477	0.804	-0.257	-0.008	0.315	30.7%
Q(10%)	4	Y	-0.475	0.806	-0.259	-0.008	0.325	30.7%
Q(50%)	4	Y	-0.461	0.810	-0.243	0.009	0.346	26.3%
Q(90%)	4	Y	-0.485	0.802	-0.266	-0.011	0.314	30.7%
G	1	N	-0.425	0.831	-0.190	0.047	0.398	20.0%
G	1	Y	-0.420	0.836	-0.188	0.046	0.384	20.0%
4-F-CAPM	-	-	-0.370	0.847	-0.149	0.089	0.422	14.0%
				2011-2015				
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.302	0.554	-0.115	0.002	0.182	14.7%
Q(50%)	4	N	-0.293	0.636	-0.135	0.032	0.235	15.3%
Q(90%)	4	N	-0.313	0.510	-0.136	0.001	0.181	18.0%
Q(10%)	4	Y	-0.314	0.593	-0.152	-0.002	0.193	21.0%
Q(50%)	4	Y	-0.249	0.650	-0.142	0.031	0.220	19.0%
Q(90%)	4	Y	-0.292	0.545	-0.149	0.006	0.194	22.0%
G	1	N	-0.109	0.658	0.001	0.116	0.322	1.0%
G	1	Y	-0.103	0.658	-0.011	0.120	0.318	1.0%
4-F-CAPM	-	-	-0.103	0.658	0.017	0.138	0.332	0.3%

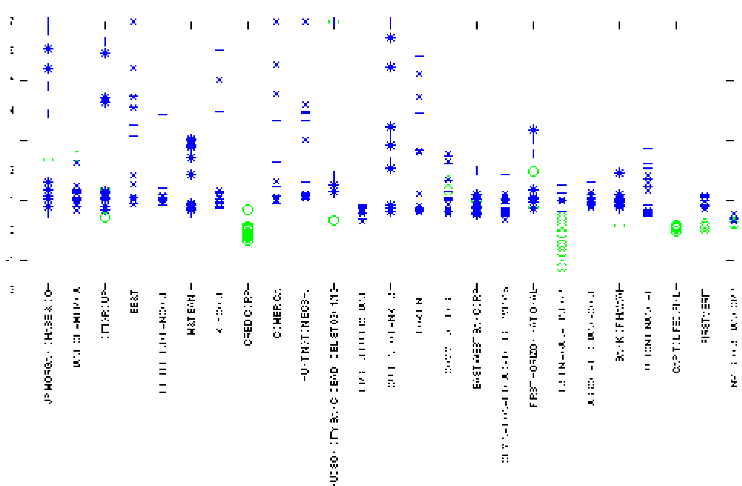
Table 2.31: The table reports residual correlation descriptive analyses for the Industry portfolios dataset. The first column identify the various models, while the second column indicates the number of networks used in the model. In the first column $Q\,(10\%)$ identifies the use of a combination of causality networks from quantile regression (QB, Qo and QN) at the 10% quantile, combined with the Granger causality network. Similarly, when the reference quantile is 50% or 90%. With G we denote the model using just the Granger casuality network, while the last line refers to the 4-factor CAPM. The table reports statistics for the residuals correlations: the minimum, maximum, the 10% quantile q_{10}, the median q_{50}, the 90% quantile and the number of elements of the correlation matrix lower than -0.1.

				2006-2008				
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.444	0.756	-0.204	0.007	0.274	25.6%
Q(50%)	4	N	-0.449	0.757	-0.198	0.014	0.276	24.9%
Q(90%)	4	N	-0.444	0.756	-0.204	0.007	0.274	25.6%
Q(10%)	4	Y	-0.476	0.731	-0.226	-0.013	0.253	28.2%
Q(50%)	4	Y	-0.494	0.733	-0.228	-0.007	0.265	28.2%
Q(90%)	4	Y	-0.463	0.728	-0.227	-0.005	0.261	28.5%
G	1	N	-0.444	0.756	-0.204	0.007	0.274	25.6%
G	1	Y	-0.415	0.752	-0.203	0.009	0.273	25.4%
4-F-CAPM	-	-	-0.486	0.733	-0.219	0.003	0.267	27.1%
				2011-2015				
Model	**N Networks**	**Factor**	**Min**	**Max**	**q10**	**q50**	**q90**	**% elements ≤ -0.1**
Q(10%)	4	N	-0.434	0.560	-0.161	-0.015	0.154	24.3%
Q(50%)	4	N	-0.450	0.588	-0.148	0.007	0.204	18.8%
Q(90%)	4	N	-0.424	0.551	-0.159	-0.010	0.170	23.5%
Q(10%)	4	Y	-0.431	0.564	-0.166	-0.010	0.179	23.0%
Q(50%)	4	Y	-0.461	0.589	-0.152	0.007	0.191	19.1%
Q(90%)	4	Y	-0.432	0.567	-0.166	-0.005	0.183	22.6%
G	1	N	-0.467	0.589	-0.144	0.009	0.208	18.4%
G	1	Y	-0.445	0.592	-0.148	0.008	0.208	18.4%
4-F-CAPM	-	-	-0.456	0.592	-0.147	0.007	0.208	18.4%

2.6.9 Estimated Parameters

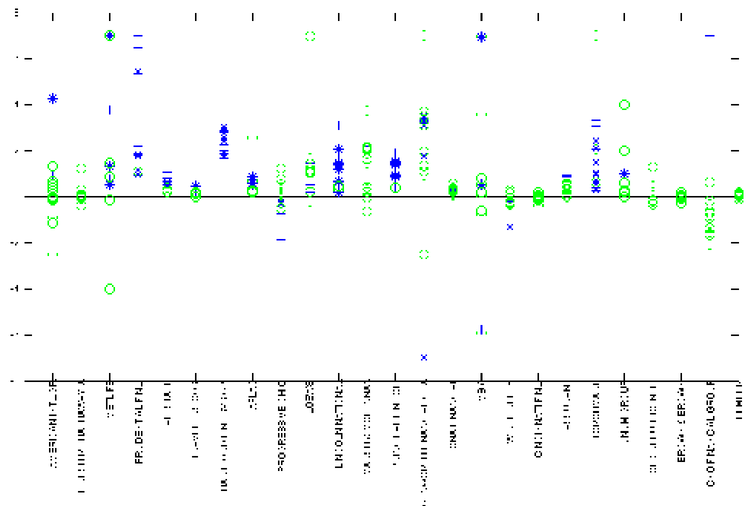


(a) 2006 − 2008

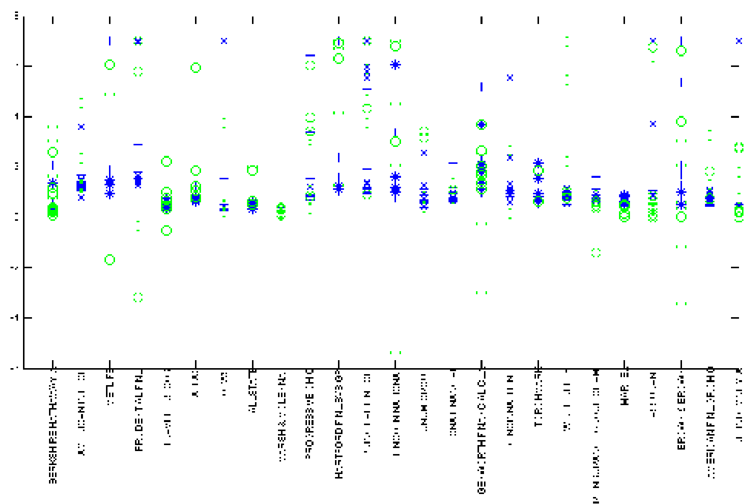


(b) 2011 − 2015

Figure 2.27: This figure exhibits the $\rho' s$ coefficients signficant (blue asterisks '*') and not significant (green circle 'o') by using different resulting networks obtained combining different causality methodologies. The $\rho' s$ parameters are relative to first 25 banks monthly returns ordered for market capitalization. Panel a) reports the coefficients relative to the period 2006 − 2008. Panel b) reports the coefficients relative to the period 2011 − 2015.

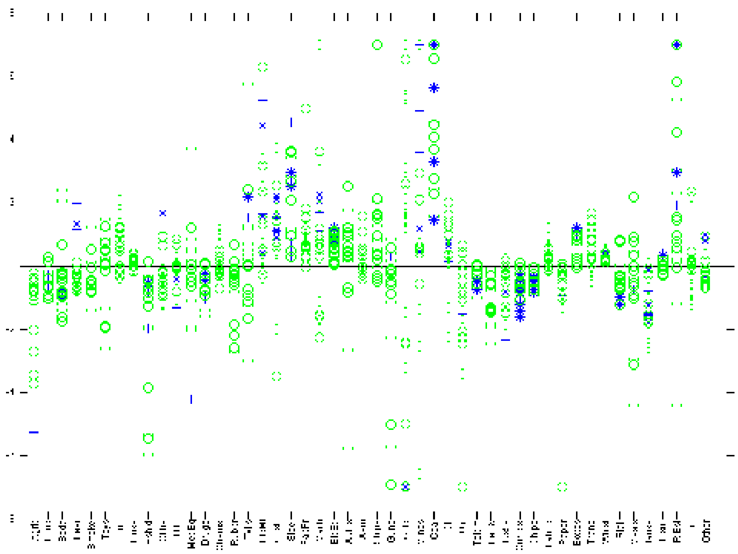


(a) $2006-2008$

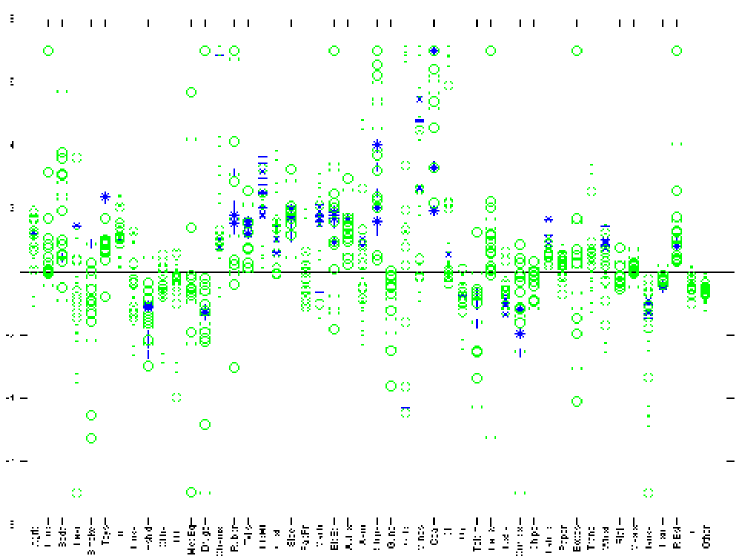


(b) $2011-2015$

Figure 2.28: This figure exhibits the $\rho's$ coefficients signficant (blue asterisks '*') and not significant (green circle 'o') by using different resulting networks obtained combining different causality methodologies. The $\rho's$ parameters are relative to first 25 Insurers monthly returns ordered for market capitalization. Panel a) reports the coefficients relative to the period $2006-2008$. Panel b) reports the coefficients relative to the period $2011-2015$.



(a) 2006 − 2008



(b) 2011 − 2015

Figure 2.29: This figure exhibits the $\rho's$ coefficients signficant (blue asterisks '*') and not significant (green circle 'o') by using different resulting networks obtained combining different causality methodologies. The $\rho's$ parameters are relative to 48 Fama and French industry portfolios monthly returns ordered for market capitalization. Panel a) reports the coefficients relative to the period 2006 − 2008. Panel b) reports the coefficients relative to the period 2011 − 2015.

Chapter 3

Idiosyncratic volatility puzzle: the role of assets' interconnections

3.1 Introduction

Increasing literature investigates the role of the aggregate volatility risk and its relations with expected stocks returns.[1] Ang et al. (2006) find that stocks with higher sensitivity to innovations in aggregate volatility have very low average returns, and at the same time stocks with high idiosyncratic risk have abysmally low average returns. The authors show that the change in aggregate volatility is a risk factor with a negative risk premium.[2] They supposed that idiosyncratic volatility puzzle exists because of the omitted factor aggregate volatility risk. The finding contradicts the conjecture, stocks having high idiosyncratic risk have lower returns for reasons not related to the exposition the aggregate volatility risk.

Besides, the empirical evidence contradicts the existing literature because the market should not expect any reward for holding stocks with higher idiosyncratic volatility since idiosyncratic risk is not priced, see Ross (1976). This is the reason why this problem is called idiosyncratic volatility (IVOL) puzzle. The IVOL puzzle is still an open research question because is not clear why the market needs compensation for taking a risk reducible through the diversification and moreover it is not yet evident why the market rewards this stocks with lower expected returns. Hou and Loh (2016) find that many real explanations explain less than 10% of the puzzle. Although the aggregation of the idiosyncratic shocks has no impact at aggregate level because they would average out (Lucas (1977)), recent papers questioned this claim, for example, Gabaix (2011) shows that the individual firm shocks don't average out if the distribution of firm size is fat tail; Acemoglu et al. (2012), using network analysis, find that idiosyncratic shocks may lead to aggregate fluctuations.

[1] Jackwerth and Rubinstein (1996), Bakshi et al. (2000), Chernov and Ghysels (2000), Buraschi and Jackwerth (2001), Coval and Shumway (2001),Pan (2002), Bakshi and Kapadia (2003), Eraker et al. (2003), and Carr and Wu (2008)

[2] The reason why the aggregate volatility has negative market price is imputable to hedging against the downside risk, see Campbell and Hentschel (1992), French et al. (1987) and Bakshi et al. (2003).

This paper investigates if the idiosyncratic volatility puzzle can be explained by considering the linkages among assets that are formally defined by a network. The network or some measure function of it can be useful to understand if the process of idiosyncratic shocks aggregation can be seen as a risk factor, endogenously determined and helpful to explain the puzzle or at least to locate stocks subjected to it.

The network used in this paper is estimated by using by using the methododolgy of Billio et al. (2012), following the Granger causality test Granger (1969), measuring how much the series i predicts the series j. In a bivariate framework, the Granger causality methodology can be seen as a vector autoregressive process (VAR), useful to understand as the risk can spread among the institutions. The network based on the Granger causality is not symmetric. Thus the number of links outgoing from a node (outdegree) differs from the number of connections ingoing to that node (indegree). Since the Granger causality defines a causality relation between two series, the measure indegree can collect these causality relationships for each stock. Nodes having higher indegree are shocks aggregator, in other words in network theory they are called "Authority" because they are nodes having a lot of ingoing links, see Newman (2010). The causality relation in the sense of Granger is purely an econometric test that differs from economic causality. Therefore an economic interpretation is challenging. There are two different ways to interpret the Granger causality test; the first one is related to the shocks: the causality relation in the sense of Granger represents a proxy channel for which an idiosyncratic risk can spread to an institution to the other. For example, an exogenous shock in oil returns could affect the returns of automotive companies; a Granger causality test can detect this relation. In this framework, the indegree is the most appropriate way to catch firms more exposed to shocks of others firms. Thus, through this mechanism, an idiosyncratic shock combined with others can aggregate endogenously using the channel of the causality link, and go beyond what can be explained by an exogenous factor, to solve the idiosyncratic volatility puzzle.

The paper investigates if centrality measures associated with the Granger causality (indegree) could be seen as an exogenous factor. Since the indegree affects the aggregation of idiosyncratic shocks, the second purpose aims to examine if the factor indegree can explain the IVOL puzzle. The analysis focuses on the period chosen by Ang et al. (2006).

Another alternative point of view, beyond the causality, is related to the predictability. To say the series j causes in the sense of Granger the series i, it is equivalent to say that series j predicts the return of series i at time t+1. In this work the causality inferred by Granger test is computed pairwise, filtering the common market factor. Thus stocks with higher indegree are stocks that are more predictable. The first interpretation helps to find a relationship between the indegree and the idiosyncratic volatility puzzle; the second one helps to understand why portfolios with stocks having increasing indegree have lower expected returns. This paper analyzes the relationship between expected returns and indegree based on Granger causality network for the first time. The reason for which indegree can be a factor and consequently have an impact on the expected returns is related to the nature of Granger causality: stocks having higher indegree are more predictable.

To consider higher indegree stocks as more predictable because they are caused or forecasted by different series at time t-1, would imply that these stocks would be attractive, and the relation with the expected returns will be negative. Albeit stocks predictability represents a puzzle from market efficiency perspective, to believe according to empirical findings, that returns stocks are predictable, it means that stocks having higher indegree based on Granger causality can be expressed through other stocks which could act as benchmark behaving as another source of information for the investors and therefore reducing the disagreement as in Cujean and Hasler (2017) or Garcia (2013). Another possible explanation is that stocks with higher indegree have lower returns because they have a higher idiosyncratic risk concerning Fama and French (1993). In this way, indegree would capture the hidden factor of IVOL indirectly. Robustness checks control for this hypothesis finding that portfolios having stocks with higher indegree have lower IVOL. Given this results, if indegree depended on IVOL then portfolios sorted by indegree at previous month would have increasing returns, not reducing as observed.

The relation detected by using Granger causality may reveal the latent interactions among traders, found by Cohen-Cole et al. (2014), i.e., stocks having higher indegree can be part of the trader's strategy which has more influence among others traders. Active fund managers who build forecasting models typically use autoregressive specification.[3]

In this paper, I show that portfolios having stocks with higher indegree (3^{th} tercile) have lower expected return than portfolios having lower indegree (1^{st} tercile). The first contribution of the paper is to show that IND, defined as difference between the (3^{th} tercile) - (1^{st} tercile) portfolio monthly returns based on the indegree, is a risk factor priced, having a negative premium, when the period 1986-2000 is considered.[4] The reasons are not related to the mimicking factor portfolio of the aggregate volatility changes $FVIX$ replicated in appendix 3.8.1.

If indegree is a risk factor priced like $FVIX$, then Fama and French (1993) augmented with these two factors could explain the decreasing expected returns found by Ang et al. (2006). The analysis show that the puzzle is still present.

The second contribution is to show that portfolios having higher idiosyncratic volatility stocks increase the exposition negatively to IND factor. There is a significant negative relationship between IVOL and IND.

The paper is organized as follows: Section 3.2 describes the current literature; section 3.3 defines the network estimation methodology; section 4.3 defines the collecting data procedure and provides some descriptive analysis; section 3.5 defines the indegree as a risk factor (IND) and investigates on the relation between IND and the idiosyncratic volatility risk, section 3.6 provides robustness checks, finally 3.7 concludes. Appendix 3.8.1 reproduces the idiosyncratic volatility puzzle and replicates the Ang et al. (2006) paper.

[3]see Gridold and Kahn (1999) chapter 5 and Stewart et al. (2011) chapter 10

[4]Time interval used in Ang et al. (2006)

3.2 Literature

The literature on the role of the idiosyncratic volatility risk and expected returns is discordant. In particular Merton (1987), Ewens et al. (2013) and Malkiel and Xu (2002) suggest that the relation between the expected returns and the idiosyncratic risk should be positive because investors necessitate compensation for holding stocks not easy to diversify. The relationship between expected stock returns and idiosyncratic volatility risk is puzzling because it is not clear why investors ask less compensation for stocks having higher IVOL. Ang et al. (2006), in their seminal work observe lower expected returns for stocks with high idiosyncratic volatility concerning the Fama and French (1993) model for reasons not related to the aggregated volatility changes to which the market assigns a negative premium. The IVOL puzzle is evidence not only associated with the US market but also in G7 countries, and 23 developed markets (see Ang et al. (2009)). Stambaugh et al. (2015) impute the negative relation between the expected return and the idiosyncratic volatility risk to the arbitrage asymmetry and the arbitrage risk. Stocks with higher idiosyncratic risk deter the arbitrageurs to find stock mispriced, and consequently, stocks having more idiosyncratic risk have higher arbitrage risk. Besides, since holding an extended position is more accessible than holding a short position in the actual financial market, the negative relationship observed between expected returns and idiosyncratic volatility is imputable to these two factors. Chen and Petkova (2012) decompose the aggregate market variance in two components: average correlation and the average variance component; they find that only the latter one is priced from the market and influences stocks expected returns. High idiosyncratic volatility risk assets have lower expected returns because they offer hedging opportunity to increases in the average stocks variance.

Empirical findings extensively experience negative relation between IVOL and expected returns,[5] Campbell et al. (2001) show that the increase of firm-level volatility in the period 1962-1997 is responsible for the market models declination and the failure of the diversification power in that period. Brandt et al. (2009) observed that the idiosyncratic volatility are higher among low-priced stocks that are held by retail investors. Baker and Wurgler (2006) define sentiment a state variable related to securities whose valuation are highly subjective, they find negative co-variation between sentiment and expected returns, in particular, high volatility stocks, have lower return only when the sentiment for that securities is high.

Herskovic et al. (2016) observe that idiosyncratic US firms volatility are synchronized and develop a theoretic model with an incomplete market of heterogeneous agents for explaining the negative relation between IVOL and expected returns. Mainly they suppose that the common idiosyncratic volatility (CIV) of the firms affects the pricing kernel of the firms through the labor market. In this paper, interconnections among assets returns are allowed to explain the IVOL puzzle; thus the aggregation mechanism is constrained to the network structure. In this direction,

[5] This is true if we believe that IVOL is a good proxy of IVOL of the month. However, since IVOL is time-varying, Fu (2009) using an EGARCH as proxy of the one-month lagged idiosyncratic volatility finds a positive relationship with the expected returns.

the way to concept the idiosyncratic shocks aggregation has changed after the global crisis in 2008 where different papers questioned Lucas (1977)' idea regarding that microeconomics shocks have no global impact. The interconnections among institutions, therefore, can vehicle idiosyncratic shocks among the financial system. For example, Acemoglu et al. (2012) used a network structure based on input-output relationships to show that aggregate fluctuations may originate from microeconomic shocks to firms. Kelly et al. (2013) developed a volatility model based on customer-supplier connectedness, in particular, they find costumers' concentration influences the volatility of their suppliers because the latter becomes less diversified. Gabaix (2011) shows that idiosyncratic firm-level shocks explain one-third of the variation in output growth. The idea is that the interconnections among assets can be used as an additional information for investigating the relationship between the idiosyncratic volatility risks and expected returns. Herskovic (2015) demonstrates that the "concentration" and the "sparsity," characteristics associated to networks, have asset pricing implications, (Ahern, 2013) finds industries that are more central in the network of intersectoral trade earn higher stock returns than industries that are less central. Buraschi and Tebaldi (2017) in their model defines two classes of equilibria. In the first class, the diversification benefits hold according to Lucas (1977), at contrary to the second case, shocks propagate endemically and persistently, and the power of diversification falls. The network topology lowers the distance between the two points of equilibrium. Since they highlight the shock causality, the network associated to these shocks is direct and thus distinguishes the "systemicness" (the contribution of each company to the aggregate network distress shock), and "vulnerability" (the exposure to aggregate network distress risk). This paper uses the same framework as Ang et al. (2006) to explain the puzzle and define the drivers influencing IVOL stocks by allowing the networks linkages among stocks. Differently from Chen and Petkova (2012), in this work, the direction is introduced on the links that can affect the aggregation of the shocks. In this case, the network used to infer the channel is based on the Granger (1969) test of the daily stocks returns applying the methodology of Billio et al. (2012). The network based on Granger Causality gives one of the most detailed stocks relationships, among all possible representations of interconnectedness,[6] considered the high number of assets in US market; in addition, to build a network by using a Granger causality permits to reach high frequency of links variations as in this case, at monthly level. The double interpretation of Granger test, from one hand causality and the other one predictability, can be useful to link the IVOL puzzle with the lower expected return for increasing values of indegree. Indegree, in this case, captures the "vulnerability" in the sense of Buraschi and Tebaldi (2017) i.e., stocks more exposed to shocks of other stocks (exposure to the network distress), from the other side measures most predictable stocks in the market. Cujean and Hasler (2017) in their model show that predictability rises when investors assess the uncertainty differently, especially in bad times, spreading disagreement among the investors. Stocks having indegree can be defined as most predictable stocks because they are

[6]Network based on the Sales relationship is not able to cover all stocks relationships in CRSP, especially with a dynamic of one month.

the function of lagged stocks returns.

The first contribution of the paper is to show that indegree is a relevant state variable for explaining the cross section of stocks returns, with a negative risk premium not related to the aggregate volatility risk changes. In addition, the empirical finding show that stocks having higher indegree have on average low idiosyncratic volatility; if we consider higher indegree stocks also as a proxy of "objectivity"[7] these findings are coherent with Baker and Wurgler (2006) showing consequently that the valuation of stocks with higher indegree are more objective because the information on that stocks are superior. It worth noting that Granger causality can display latent interactions among traders' strategies. Mainly, Cohen-Cole et al. (2014) find that returns from trading are correlated with the position agents occupying a trading network; investigate how traders positions in the network influence their profitability and how shocks are transmitted across the market. Stocks having high indegree could reflect the strategy of an influencer trader. Even though the paper does not solve the puzzle, the second contribution of the paper is to show that stocks with higher IVOL have the higher negative exposition on IND. The first part of the paper focuses on the Granger causality indegree as Factor. The second part of the paper is related to show the relationship between IVOL portfolios and IND factor.

3.3 Network estimation and Measures

The procedure for the network estimation is an extension of the Granger causality method Granger (1969) proposed for the network estimation in Billio et al. (2012). An alternative approach is Diebold and Yilmaz (2014) who use the variance decompositions of VAR to build weighted directed networks, this methodology is not adopted and suited in this work because of the number extremely high of stocks, such that to estimate a VAR analysis. The series are daily stock returns with one year time horizon and one-month rolling window. Stocks returns having less of three months daily returns observations are not considered. The Granger Causality tests on a bivariate basis the following equation:

$$R_{it} = a_{ii}R_{it-1} + a_{ji}R_{jt-1} + a_{MKT}MKT_{t-1} + e_{it} \tag{3.1}$$

$$R_{jt} = a_{ji}R_{jt-1} + a_{ij}R_{it-1} + a_{MKT}MKT_{t-1} + e_{jt} \tag{3.2}$$

where e_{it} and e_{jt} are the residuals of asset returns i and j. The asset return j causes in sense of Granger the asset i when the coefficient a_{ji} is significant, similarly the series i causes in sense of Granger the asset j when the coefficient a_{ij} is significant. The first assumption of the equations (3.1) and (3.2) is that the residuals e_{it} and e_{jt} are not correlated. In addition, the Granger causality test is augmented by the market index in order to filter the causality relations from some indirect

[7] The term is opposed to "subjective" Baker and Wurgler (2006), stocks having higher indegree, being more predictable, give more information to the investors who hold that stocks. In this case, the predictability is related to the Granger causality test.

relationship of other series through the market. The significance of the coefficient is corrected by autocorrelation and heteroskedasticity using HAC estimator from Newey and West (1987). In the bivariate model, the Granger causality test is thus a VARX if we add the Market Index. The causality presence, as detected with the above-outlined procedure, is used to determine the adjacency matrix and the associated network structure. In fact, the adjacency matrix computation is by setting $w_{i,j} = 1$ when the p-value of the test on the significance of parameters a_{ij} of the reference regression for asset j suggests that asset i Granger-cause asset j at the 5% confidence level. The adjacency matrix associated with the Granger causality is not symmetric, and consequently, the graph (network) associated to the adjacency matrix is directed. A network or graph $G = (V, E)$ is a collection of vertexes V and edges E, where the edges represent the links between the vertexes,[8] with $E \subseteq (V \times V)$. Networks are represented by using the adjacency matrix W, a binary matrix where each element $w_{i,j}$ can take only two values, 1 and 0. When $w_{i,j}$ is 1, the node j is linked to node i, with an information flow from i to j. A value of zero identifies the absence of a link. Since the network is direct, if the series i $\rightarrow$ causes in the sense of Granger the series j, the element w_{ij} of the matrix W is equal to one, and graphically we will observe a link starting from the node i to the node j, the direction of the arrow defines the causality relationship between the two series, and consequently the matrix associated with the network is asymmetric. When the graph is directed, the number of the ingoing links differs from the number of outgoing links for each node. Assuming N nodes in the network, the measures associated to the ingoing links is called indegree that counts the number of links inward pointing at a node coming from its neighbors. At contrary outdegree counts the number of outgoing links starting from the nodes to its neighbors. Formally, indeegree and outdegree are defined according to the following equations:

$$Indegree_i = \sum_{i=1}^{N} W_{ij} \tag{3.3}$$

$$Outdegree_i = \sum_{j=1}^{N} W_{ij} \tag{3.4}$$

The two measures aim to detect different kinds of effects. The first measure represents how much a node is affected by its neighbors; the second instead measures how much the node affects the neighbors. Combining indegree and outdegree through the sum and the difference is used to analyze other centrality perspectives. For example, computing the sum between indegree and outdegree as in equation (3.5) can be useful to group nodes more active in the networks concerning links. At the contrary, the difference between outdegree and indegree as in equation (3.6) captures the most unbalanced nodes: unbalanced outwardly when the measure is positive and unbalanced inwardly when it is negative. It's important to outline that the quantity of links is not relevant anymore for

[8]The terms *vertex* and *nodes* are equivalent, and both are used interchangeably in this work. In the same way, *edges* and *links* take on the same meaning.

this centrality measure.

$$Outdegree_i + Indegree_i = \sum_{j=1}^{N} W_{ij} + \sum_{i=1}^{N} W_{ij} \tag{3.5}$$

$$Outdegree_i - Indegree_i = \sum_{j=1}^{N} W_{ij} - \sum_{i=1}^{N} W_{ij} \tag{3.6}$$

Another centrality measure is the eigenvector centrality. Introduced by Bonacich (1987), which captures the node prestige as a function of the neighbors' prestige. Formally it is the eigenvector associated to the highest eigenvalue of the adjacency matrix. Defined with x_i the score of node i, λ_1 the maximum eigenvalue associated to the adjacency matrix W, the eigenvector centrality is defined as equation (3.7)

$$x_i = \frac{1}{\lambda_1} \sum_{j=1}^{N} W_{ij} x_j \tag{3.7}$$

Since with the Granger causality, the adjacency matrix is not symmetric, the left eigenvector differs from the right eigenvector. This work focuses on the effect coming from the system on the node, for this reason the eigenvector considered is exclusively the left one.

To detect the network sparsity is useful to define another centrality measure, the ratio between the actual number of links among the nodes over the all possible ones: the density, defined by this equation:

$$D = \sum_{i=1}^{N} \sum_{j=1}^{N} W_{ij} / (N(N-1)) \tag{3.8}$$

The density is always greater than zero and lower than 1. Higher density indicates networks full of interconnections, density close to zero indicates that the links among nodes are rare and the network is sparse.

3.4 Data

The time interval considered in this analysis is from January 1986 to December 2000.[9] This section reports the cleaning procedure adopted for the stocks returns available in CRSP. [10]

Figure (3.1) shows the monthly variation of the number of firms by looking at the steps during the clearing procedure.

The cleaning procedure can be summarized with the following method. The initial database is reduced by considering all the firms listed on AMEX, NYSE, NASDAQ. Once merged CRSP by

[9] As in Ang et al. (2006)

[10] `https://wrds-web.wharton.upenn.edu/wrds/query_forms/navigation.cfm?navId=128`

Compustat, all the stocks having missing book value are deleted from that month.[11] The number of firms even reduces considerably when the firms having missing book value are excluded. The pattern of sawtooth shape suggests a seasonality at the end of the year. The average number of firms across the whole sample is 4902. The total number keep reducing when we hold only the ordinary stocks and the stocks having daily observations for that month greater than 17.

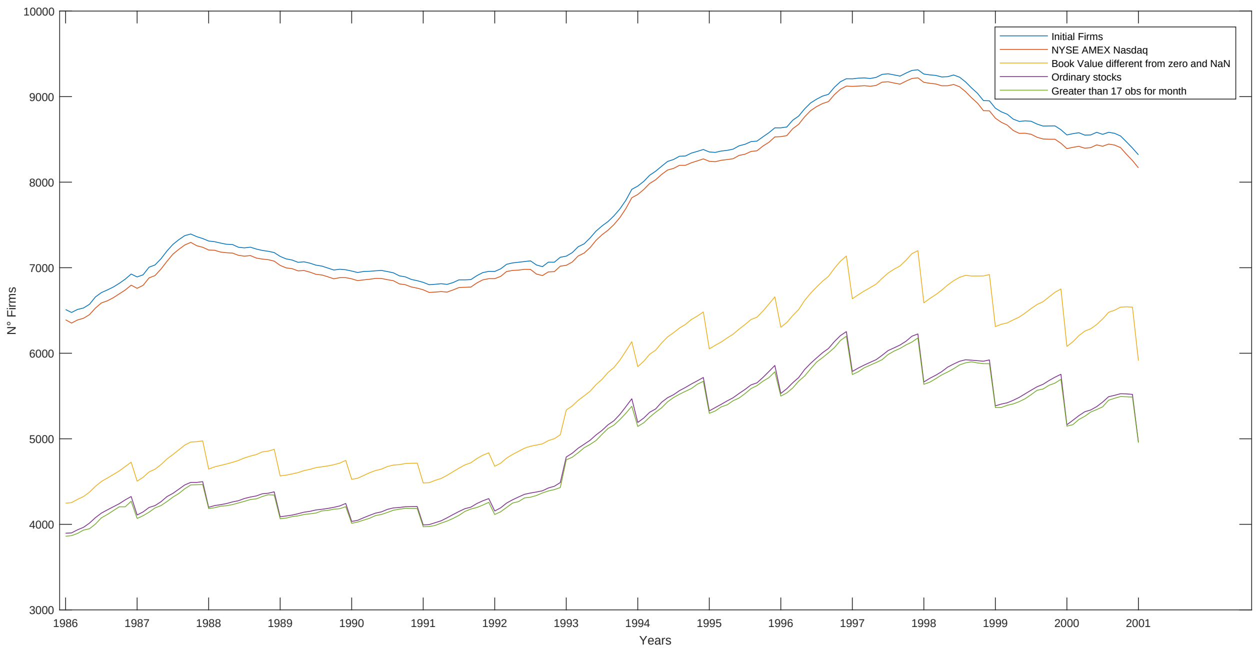


Figure 3.1: **Number of firms across time.** The figure exhibits the number firms monthly variations from January 1986 to December 2000. Each line represents a step in the cleaning procedure.

CRSP provides the average between the bid and ask price when the stock price information is missing.[12] The stock market capitalization is computed as the product between the price and the outstanding share.

Figure (3.2) indicates the centrality measures computed monthly by using the network estimated with the Granger Causality. The density is reported on the left axes. The density defines the network connectivity that has a positive trend starting from a value of 3% at the beginning of the period to 7% at the end of 2000. The right axis of the figure exhibits the average and the standard deviation of indegree. The average indegree according to the density, reveals an increasing pattern with a hump in the year 1999, where it reaches the global maximum of the sample, 440 links of average. The standard deviation has an increasing pattern positive and moderate which can manifest a disequilibrium and asymmetries in term of ingoing connections, and consequently to influence the way of shocks aggregations.

[11]Stocks having positive and negative book values are considered. The number of stocks having negative book value is hugely lower than stocks having positive book value.

[12]These observations in CRSP have denoted by a negative sign, and they are considered in the current analysis.

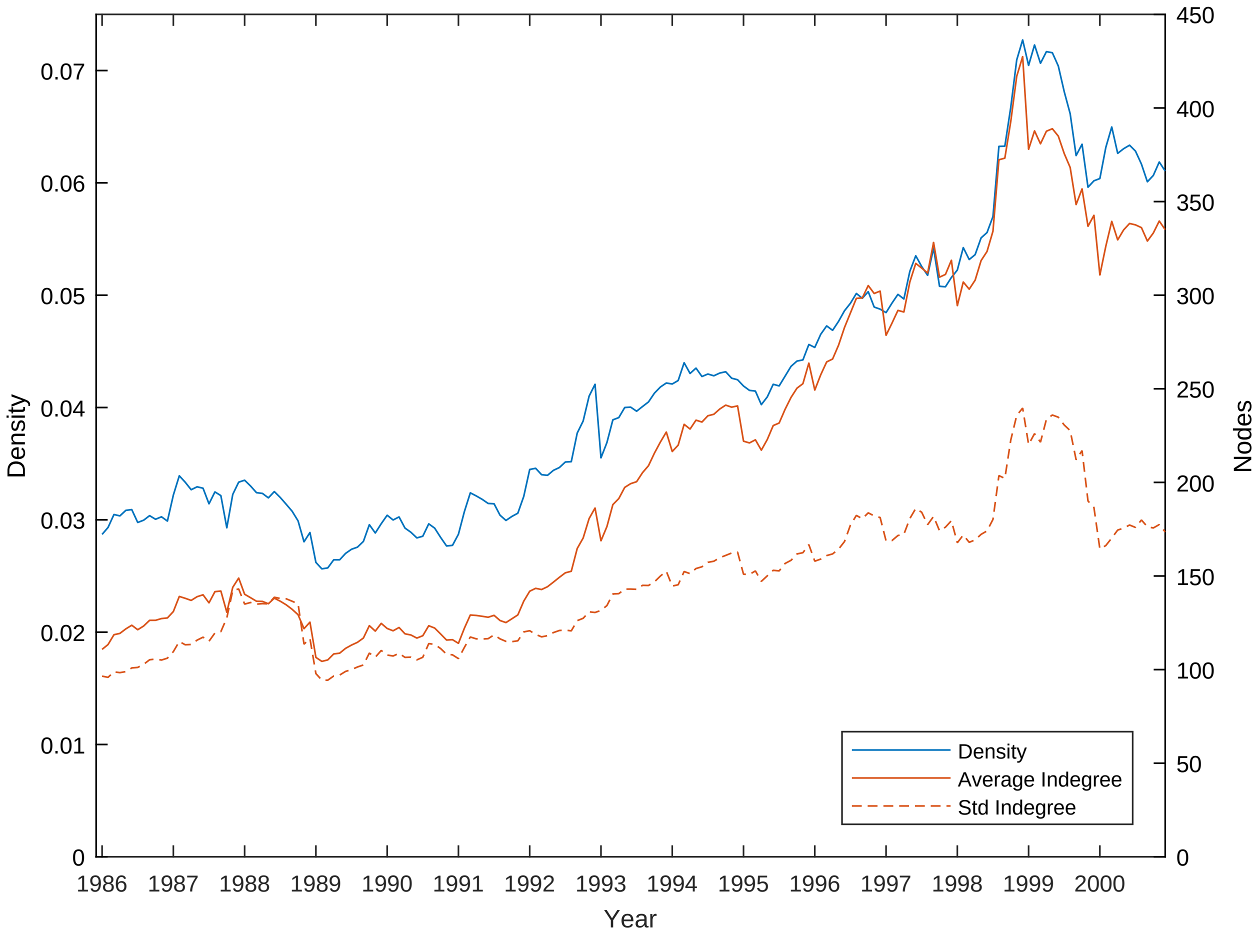


Figure 3.2: **Centrality measures of networks based on Granger causality.** The density (on the left axis), the average and the standard deviations of indegree (on the right axis) relative network estimated with the Granger causality by month, from January 1986 to December 2000.

Table (3.1) summarizes 25 portfolios statistics sorted by size and book-to-market value weighted. The ME indicates market capitalization and BM is the book-to-market ratio. As highlighted by Fama and French (1993) the expected returns are positively correlated with the market capitalization and the book-to-market ratio. The standard deviation of the monthly portfolios returns decreases by increasing the book-to-market exposure. The skewness of the returns distributions is close to zero or slightly negative, instead, the kurtosis is high. The 25 portfolios return distributions are leptokurtic. Table (3.2) reports the statistics for 48 industry portfolios. The returns are monthly and value-weighted; the stocks aggregation is according to SIC (Standard Industrial Classification). Financial, Pharmaceutical Products and Electronic Equipment have higher monthly returns in average respectively 1.75%, 1.79%, and 1.86%; Precious Metals have the higher standard deviations. Returns have negative skewness, and positive kurtosis[13] as for the 25 portfolios sorted by size and book-to-market. I used these two different kinds of portfolios returns to understand if

[13]It is necessary to subtract the number 3 to compare the portfolios returns kurtosis with the normal distribution case

indegree can explain the returns variations in cross section.

Table 3.1: **Descriptive analysis 25 Portfolios sorted by Size and Book-to-Market** The tables reports the statistics of portfolios monthly returns value weighted from January 1986 to December 2000.

Descriptive analysis 25 Portfolios sorted by Size and Book-to-Market						
Portfolio	**Mean**	**Standard Deviation**	**Min**	**Max**	**Kurtosis**	**Skewness**
ME1 BM1	0.49	8.48	-34.23	38.94	7.70	0.20
ME1 BM2	1.26	7.43	-30.94	40.94	9.83	0.40
ME1 BM3	1.22	5.68	-28.70	22.06	8.34	-0.70
ME1 BM4	1.47	5.46	-28.88	25.45	10.33	-0.64
ME1 BM5	1.39	5.27	-28.88	16.46	9.26	-1.19
ME2 BM1	0.90	7.47	-32.71	28.18	5.90	-0.53
ME2 BM2	1.18	5.84	-31.67	17.62	8.36	-1.18
ME2 BM3	1.21	4.81	-28.13	12.62	10.79	-1.72
ME2 BM4	1.33	4.56	-25.44	10.37	9.76	-1.64
ME2 BM5	1.36	5.29	-28.84	14.55	8.57	-1.32
ME3 BM1	1.09	7.08	-29.79	24.61	5.40	-0.61
ME3 BM2	1.28	5.45	-29.05	13.49	8.83	-1.26
ME3 BM3	1.13	4.53	-24.29	11.16	8.61	-1.36
ME3 BM4	1.33	4.41	-23.03	13.43	8.49	-1.31
ME3 BM5	1.50	4.77	-26.17	11.92	9.16	-1.42
ME4 BM1	1.40	6.33	-25.94	26.22	6.23	-0.29
ME4 BM2	1.29	4.95	-28.83	12.97	10.80	-1.49
ME4 BM3	1.24	4.76	-25.00	14.07	8.31	-1.20
ME4 BM4	1.40	4.12	-18.26	11.94	5.70	-0.71
ME4 BM5	1.42	4.84	-23.84	15.96	6.84	-0.90
ME5 BM1	1.49	4.96	-21.64	15.36	5.26	-0.67
ME5 BM2	1.36	4.77	-22.42	16.53	6.66	-0.81
ME5 BM3	1.28	4.61	-21.71	11.34	6.50	-1.08
ME5 BM4	1.24	4.51	-15.17	16.09	4.37	-0.53
ME5 BM5	1.52	5.02	-18.73	15.65	4.63	-0.51

Table 3.2: **Descriptive analysis 48 Industry Portfolios** The tables reports the statistics of portfolios monthly returns value weighted from January 1986 to December 2000.

Descriptive analysis 48 Industry Portfolios						
Portfolio	**Mean**	**Standard Deviation**	**Min**	**Max**	**Kurtosis**	**Skewness**
Agric	0.95	6.26	-28.79	28.88	6.99	-0.16
Food	1.39	5.35	-17.88	19.59	4.36	0.06
Soda	1.27	7.66	-25.94	38.27	6.31	0.41
Beer	1.79	6.13	-19.76	22.02	4.48	-0.15
Smoke	1.59	7.45	-24.93	22.80	4.07	-0.20
Toys	0.91	7.05	-34.41	20.09	5.98	-0.70
Fun	1.39	6.68	-31.86	19.26	6.59	-0.95
Books	1.26	5.34	-22.57	14.67	4.67	-0.31
Hshld	1.22	5.15	-21.64	18.54	5.45	-0.62
Clths	1.06	7.06	-30.90	25.06	5.66	-0.52
Hlth	1.00	7.43	-31.43	21.13	5.01	-0.64
MedEq	1.47	5.59	-20.56	16.33	4.07	-0.42
Drugs	1.79	5.57	-19.11	16.27	3.82	-0.29
Chems	1.16	5.55	-28.00	22.05	7.27	-0.48
Rubbr	1.25	6.00	-30.57	19.27	7.35	-0.85
Txtls	0.87	6.41	-32.51	23.11	6.93	-0.80
BldMt	1.16	5.88	-27.74	18.25	6.41	-0.71
Cnstr	1.08	6.64	-31.10	20.03	5.98	-0.52
Steel	1.14	7.05	-30.48	30.67	6.84	0.01
FabPr	0.82	6.53	-26.67	25.96	5.62	-0.29
Mach	1.18	6.07	-31.19	16.08	7.20	-1.03
ElcEq	1.71	6.37	-32.20	18.28	6.80	-0.67
Autos	1.16	6.56	-28.33	19.33	5.08	-0.63
Aero	1.27	5.98	-30.23	14.99	7.24	-1.05
Ships	0.41	6.97	-32.27	17.17	5.26	-0.47
Guns	0.96	6.58	-30.08	18.86	6.85	-1.01
Gold	0.33	11.52	-30.93	78.68	13.83	1.66
Mines	1.04	6.47	-33.32	20.50	7.11	-0.51
Coal	1.35	9.57	-30.11	44.04	6.70	0.78
Oil	1.20	4.94	-18.21	16.75	4.64	0.23
Util	1.04	3.93	-10.77	11.72	3.00	-0.13
Telcm	1.38	5.03	-15.58	14.35	3.90	-0.54
PerSv	0.72	6.37	-28.25	24.47	5.83	-0.43
BusSv	1.73	7.02	-27.54	24.08	4.85	-0.38
Comps	1.44	7.77	-24.37	23.10	3.70	-0.03
Chips	1.86	7.95	-27.82	27.27	4.85	-0.51
LabEq	1.40	6.90	-30.15	22.04	5.59	-0.21
Paper	1.14	5.67	-26.35	24.27	7.44	-0.03
Boxes	0.98	6.52	-28.24	20.05	5.58	-0.62
Trans	1.08	5.53	-27.90	14.20	6.70	-0.95
Whlsl	1.05	5.03	-28.64	12.64	9.49	-1.33
Rtail	1.46	6.01	-29.17	14.36	5.87	-0.77
Meals	1.05	5.56	-24.04	15.98	5.04	-0.58
Banks	1.55	6.22	-24.19	16.14	4.73	-0.68
Insur	1.35	5.47	-16.85	22.87	4.74	-0.25
RlEst	0.03	5.58	-22.68	14.20	4.51	-0.70
Fin	1.75	6.49	-25.91	18.45	5.48	-0.67
Other	0.84	7.15	-26.37	20.15	4.41	-0.43

3.5 Network as Exogenous Factor

This section investigates whether the indegree of the network based on the Granger causality test is a risk factor priced. Granger causality methodology is used in this work because is a compromise between estimation accuracy and computational time. In this work, the first assumption related the Granger causality is to neglect all the effects coming from the other series that are instead present in VARX, because of the number of stocks extremely high. For this reason, I discard the variance decomposition proposed by Diebold and Yilmaz (2014). By using the pairwise Granger causality test, there is an overestimation link that increases the density of the networks. On the other hand, to use VARX constrained to LASSO would underestimate the connections across the stocks returns.

There are different centrality measures defined for various applications. It is worth to notice that indegree is the only centrality measure able to capture the mechanism of idiosyncratic shocks aggregation. At the contrary, outdegree, since it measures the number of outgoing links, reveals the spreading mechanism of idiosyncratic shocks from a node to the system. The sum and the difference between outdegree and indegree as in equation (3.5) and (3.6) used in Billio et al. (2012) would make difficult to distinguish if the market cared more to indegree or outdegree. Finally, the eigenvector centrality would capture higher order aggregation mechanism of the idiosyncratic shocks, but as outlined by Buraschi and Tebaldi (2017) it is not useful for the directed network. Although this analysis focuses on indegree, I tested all the other measures as robustness check in table (3.13) in section 3.6.

The preliminary analysis is to sort the stocks in three quantiles concerning the indegree and to compute the portfolios returns at time t+1. The table (3.3) shows that the value-weighted average of the portfolios returns decreases as soon as the tercile portfolios have stocks with higher indegree. The market share, the size and the book to market ratio is roughly constant across the portfolios quintiles. Finally, the CAPM and Fama and French (1993) (3FF) model alphas are inversely proportional to the indegree loading, and they are statistically significant only in the last tercile **(3)**. There is a difference in -0.33% per month between the average of the highest tercile having higher indegree and the lowest one, this difference is not statistically significant when whole period is considered. Figure (3.3) shows the cumulative quantile portfolio returns having stocks with increasing indegree computed at the previous month $t-1$, particular portfolios with higher indegree have lower returns, especially in the second part of the period starting from 1991, the small and medium indegree portfolios outperform the more top indegree portfolios. The medium and lower indegree performances are so similar because the network is sparse especially in the first part of the sample with a density of 3% thus the smallest and the medium quantile are close to zero. In the second part of the sample, the density doubles to 7% as reported in figure (3.2) left axes. On the right axis, the table indicates the mean and the standard deviation of the indegree. As observed for the density, the average and the standard deviation inflate in the second half of the time horizon, the higher variance of indegree allows to distinguish the middle from the lowest quantile. In this works, although the difference is not so vast, the proposed risk factor based on the indegree of Granger causality test is the difference between the 3^{th}-1^{st} hereafter IND.

Table 3.3: **Portfolios sorted by indegree based on Granger Causality network.** The statistics are relative to the quantile portfolios ordered for the indegree computed by using equation (3.3). The value-weighted average and the standard deviation are relative to the returns monthly based. Market share defines the market capitalization of the portfolio; the logarithm of stock market capitalization represents the Size, and B/M is the Book-to-Market ratio average. Alpha columns represent the intercept by regressing the portfolio returns with the CAPM and the Fama and French (1993) model. The time interval is from January 1986 to December 2000 as Ang et al. (2006). Robust Newey and West (1987) t-statistics are reported in square brackets.

Portofolios Sorted by Indegree

Rank	**Mean**	**Std Dev.**	**Market Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**
1	1.51	5.29	32.19%	6.99	0.44	0.06	0.14
						[0.61]	[1.59]
2	1.45	4.60	38.18%	7.22	0.45	0.05	0.02
						[0.7]	[0.34]
3	1.18	4.32	29.64%	6.91	0.49	-0.15	-0.22
						[-1.34]	[-2.16]
3-1	-0.33					-0.21	-0.36
	[1.62]					[-1.05]	[-2.07]

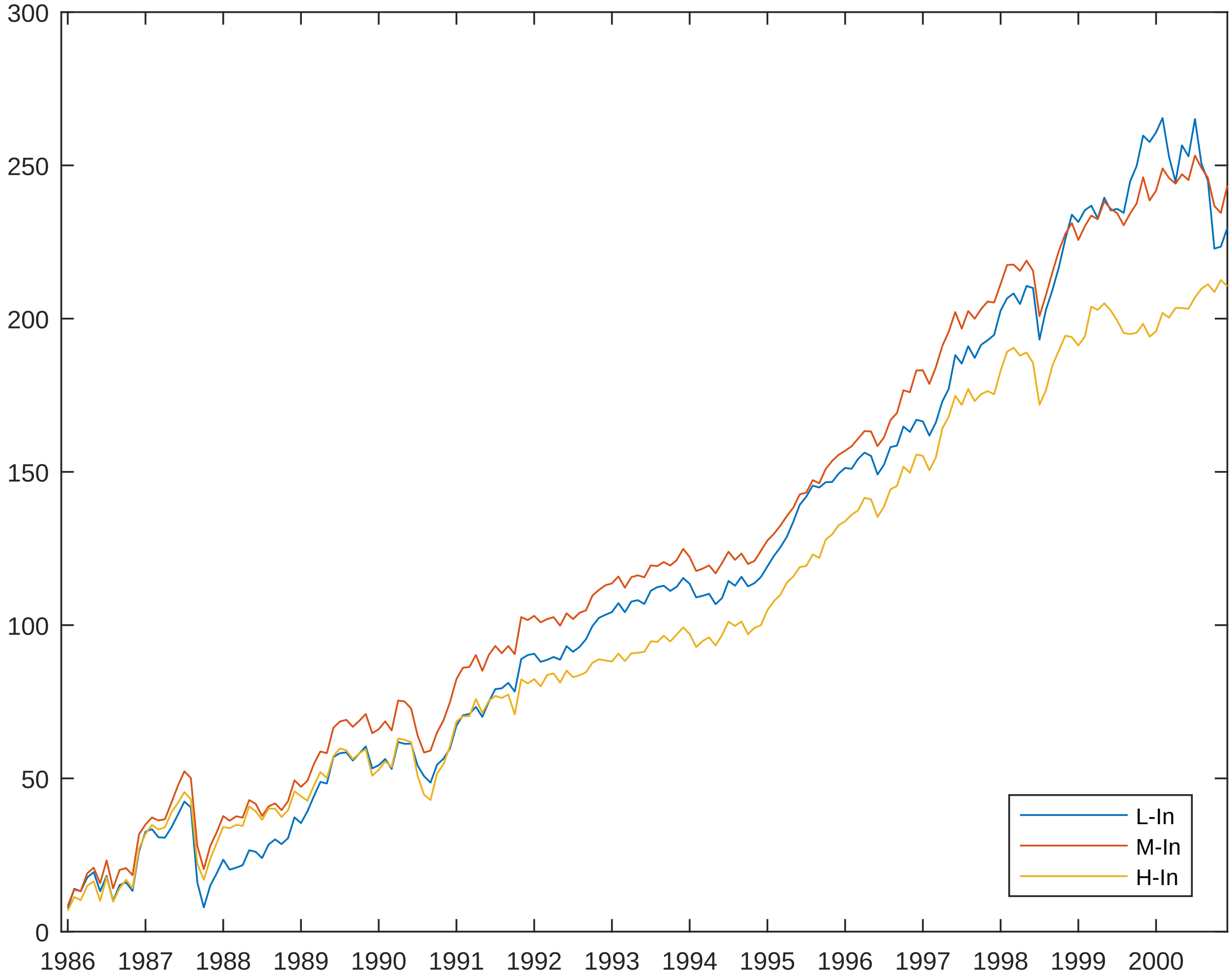


Figure 3.3: **Cumulative Returns Indegree based on the Granger causality.** Cumulative Returns of the portfolio quantile by picking the stocks having high Indegree for the network estimated with the Granger causality

3.5.1 Factors descriptive analysis

The table (3.4) displays the statistical analysis of the factors monthly based, from January 1986 to December 2000. The factors considered are respectively the risk free (RF), the extra market return (MKT), Small Minus Big size firms (SMB), High Minus Low growth (HML), Momentum (UMD), [14] Liquidity level (LIQ), liquidity Innovations (LIQ_INN) and liquidity value weighted (LIQVW) are respecitively aggregate liquidity level factor, innovations and traded liquidity factor value weighted see Pástor and Stambaugh (2003).[15] Aggregate volatility delta change (ΔVIX) and mimicking tracking portfolio on the aggregate volatility risk (FVIX) risk factors. The statistics show that except for the risk-free asset return all the other distributions behave as not normal

[14] RF MKT, HML, SMB and UMD are available in http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[15] LIQ, LIQ_INN and $LIQVW$ are available in https://wrds-web.wharton.upenn.edu/wrds/ds/famafrench/liq_ps.cfm?navId=204

distributions and have leptokurtic shapes. The MKT and LIQ have a negative skew, HML, UMD and $FVIX$ have roughly a distribution symmetric, while the other risk factors have a positive skewness. The risk-free asset has on average a monthly return of 0.4% with a standard deviation of 0.1%. The MKT has a positive monthly extra return with an average of 0.8% with the standard deviation of 4.5% instead the momentum has an average monthly return of 1

Table 3.4: **Risk factor descriptive analysis**. The table shows the statistics of the most common factors in the literature as well as indegree IND based on the Granger causality network. MKT, HML, SMB and UMD are Fama and French (1993) and Carhart (1997) momentum factors; LIQ, LIQ_INN, $LIQVW$ are respectively aggregate liquidity level, innovations and traded liquidity value weighted factors, see Pástor and Stambaugh (2003). Finally, ΔVIX and $FVIX$ represent the aggregate volatility innovations and its mimicking tracking portfolio. Monthly observations from January 1986 December 2000.

Descriptive Analysis						
Risk Factor	**Mean**	**Standard Deviation**	**Min**	**Max**	**Kurtosis**	**Skewness**
RF	0.441	0.122	0.210	0.790	2.916	0.338
IND	-0.332	2.713	-11.894	19.632	14.088	1.697
MKT	0.844	4.523	-23.240	12.470	7.389	-1.204
SMB	-0.216	3.692	-17.170	22.080	12.382	1.025
HML	0.259	3.083	-10.490	11.290	4.900	0.089
UMD	1.003	3.752	-9.080	18.380	7.076	0.628
LIQ	-0.019	0.066	-0.461	0.201	14.792	-2.217
LIQ_INN	0.002	0.065	-0.384	0.287	12.830	-1.564
LIQVW	0.000	0.035	-0.091	0.110	3.556	0.328
FVIX	-0.818	2.787	-7.961	14.785	7.972	1.224
Δ VIX	0.059	4.855	-15.380	39.030	27.294	3.113

Table (3.5) shows the factors correlation. Particularly it shows IND respectively correlated negatively with MKT at -0.21, with SMB -0.21 and with the Momentum UMD at -0.6 and positively correlated with ΔVIX aggregate volatility risk changes and its mimicking portfolio $FVIX$. The correlations with IND have magnitudes lower than 0.5, except the correlation with UMD. If we take in account the other factors, MKT is moderately correlated with SMB, UMD respectively at 0.13 and 0,21; strongly negatively correlated with $FVIX$ -0.99; and sufficiently with ΔVIX -0.56. The correlation between $FVIX$ and ΔVIX is 0.56.

Table 3.5: **Risk factor correlations**. Correlations table among risk factors. IND is the difference between the 3^{th}- 1^{st} tercile as in table (3.3). MKT, HML, SMB and UMD are Fama and French (1993) and Carhart (1997) risk factors; LIQ, LIQ_INN, $LIQVW$ are respectively aggregate liquidity level, innovations and traded liquidity value weighted factors, see Pástor and Stambaugh (2003). Finally, ΔVIX and $FVIX$ represent the aggregate volatility innovations and its mimicking tracking portfolio. Monthly observations from January 1986 December 2000.

	Correlation									
	IND	**MKT**	**SMB**	**HML**	**UMD**	**LIQ**	**LIQ_INN**	**LIQVW**	**FVIX**	**Δ VIX**
IND	1.000	-0.209	-0.212	0.457	-0.613	0.017	0.060	-0.102	0.213	0.105
MKT	-0.209	1.000	0.137	-0.434	0.212	0.254	0.300	-0.107	-0.992	-0.559
SMB	-0.212	0.137	1.000	-0.508	0.307	0.044	-0.009	-0.210	-0.152	-0.163
HML	0.457	-0.434	-0.508	1.000	-0.485	-0.016	0.015	0.101	0.454	0.169
UMD	-0.613	0.212	0.307	-0.485	1.000	0.005	-0.059	-0.025	-0.206	-0.088
LIQ	0.017	0.254	0.044	-0.016	0.005	1.000	0.874	0.051	-0.261	-0.353
LIQ_INN	0.060	0.300	-0.009	0.015	-0.059	0.874	1.000	0.050	-0.305	-0.348
LIQVW	-0.102	-0.107	-0.210	0.101	-0.025	0.051	0.050	1.000	0.111	0.062
FVIX	0.213	-0.992	-0.152	0.454	-0.206	-0.261	-0.305	0.111	1.000	0.561
Δ VIX	0.105	-0.559	-0.163	0.169	-0.088	-0.353	-0.348	0.062	0.561	1.000

3.5.2 Missing Factor on 25 Size-BM portfolios

This section tests the marginal contribution of IND on top of the standard Fama and French (1993) multifactor model. The dependent variables of equation (3.9) are the monthly extra returns of the 25 size and book-to-market portfolios.[16] The abnormal returns are defined as the difference Z_t between Y_t-$\hat{Y}_t$, where $\hat{Y}_t$ is the forecast of Y_t as in equation (3.10).

$$Y_t = \alpha + \beta_{MKT} MKT_t + \beta_{HML} HML_t + \beta_{SML} SML_t + \epsilon_t \tag{3.9}$$

$$\hat{Y}_t = \hat{\beta}_{MKT} MKT_t + \hat{\beta}_{HML} HML_t + \hat{\beta}_{SMB} SMB_t \tag{3.10}$$

Regressing the abnormal returns at monthly level with IND establishes whether the proposed factor contributes to explain the abnormal returns by looking at the significance of the factor loading. To make the analysis more robust, IND is tested separately but also compared and jointly tested with other two factors: the momentum UMD and the mimicking portfolios on the aggregate volatility changes $FVIX$. The choice of these factors is related to two different reasons: In the first case, UMD and IND have a correlation equal to -0.6. Therefore it is necessary to prevent that IND explains the abnormal returns because of the interaction with UMD. In the second case, although

[16] Datadownloadedfromhttp://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

the correlation with $FVIX$ is equal to 0.21, $FVIX$ can be useful to investigate if IND has a different component concerning the aggregate volatility. Thus, Z_t is regressed respectively with the IND risk factor, with the mimicking factor portfolio on ΔVIX , $FVIX$, and together as from equation (3.11) to equation (3.13).

$$Z_t = a + b_{IND} IND_t + \eta_t \tag{3.11}$$

$$Z_t = a + b_{FVIX} FVIX_t + \eta_t \tag{3.12}$$

$$Z_t = a + b_{IND} IND_t + b_{FVIX} FVIX_t + \eta_t \tag{3.13}$$

Table (3.6) panel A shows the indegree factor loading as in equation (3.11); on the right the t-statistic with Newey and West (1987) corrected standard errors in the square brackets. The betas are mostly significant, they don't increase their loading with respect to the size or book-to-market dimension. The Panel A shows that the indegree IND can be considered as relevant variable with 17 over 25 beta significant. Panel B reports instead the beta and the t-statistic as in equation (3.12), highlighting that only few β_{FVIX} are significant reflecting only a marginal role of this risk factor with respect the 25 size book-to-market portfolios. Finally, Panel C reports the results when both factors are in the same regression as in equation (3.13), the results show clearly that IND still remains significant while the t-statistics on β_{FVIX} are higher than Panel B.

$$Z_t = a + b_{UMD} UMD_t + \eta_t \tag{3.14}$$

$$Z_t = a + b_{IND} IND_t + b_{UMD} UMD_t + \eta_t \tag{3.15}$$

Table (3.7) panel A shows same results of (3.6) panel A, since they refer to the same equation (3.11). Panel B reports instead the beta and the t-statistic as in equation (3.14), highlighting that the number of factor loading significant β_{UMD} is only six over 25 portfolios. Finally, panel C reports the results when both factor are in the same regression as in equation (3.15), the number of factor loading significant reduces, from 17 to 11 for β_{IND} and from 6 to 4 for β_{UMD}. However it is possible to claim that the impact of IND is relavant and evident even though the interaction with the momentum reduces the global significance slightly below the half of the number of the portfolios.

Table 3.6: **25 size BM portfolios abnormal returns factors exposures on IND and $FVIX$.** Panel A shows indegree factor loading related to the equation (3.11). Panel B shows the factor loading related to the mimicking factor portfolio of aggregate volatility risk $FVIX$ related to the equation (3.12). Panel C shows the factor loading on IND and $FVIX$ related to the equation (3.13). On the right the t-statistic with Newey and West (1987) corrected standard errors in the square brackets, by looking the monthly data.

Panel A $Z_t = a + b_{IND} IND_t + \eta_t$

	beta						t-statistic				
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
1	-0.22	-0.14	0.05	-0.06	-0.06	**1**	[-4.08]	[-2.39]	[1.07]	[-1.72]	[-1.57]
2	0.15	0.22	0.16	0.09	0.13	**2**	[2.11]	[5.29]	[3.62]	[2.96]	[1.88]
3	0.18	0.26	0.19	0.22	0.14	**3**	[2.46]	[3.47]	[3.77]	[3.91]	[2.10]
4	0.07	0.19	0.25	0.18	0.17	**4**	[0.89]	[3.47]	[4.09]	[3.34]	[2.68]
5	-0.01	0.14	0.14	0.20	-0.02	**5**	[-0.17]	[2.95]	[1.85]	[3.76]	[-0.22]

Panel B $Z_t = a + b_{FVIX} FVIX_t + \eta_t$

	beta						t-statistic				
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
1	0.01	0.01	0.00	0.00	-0.01	**1**	[0.10]	[0.20]	[0.00]	[0.07]	[-0.14]
2	-0.02	-0.01	-0.01	-0.01	0.00	**2**	[-0.36]	[-0.27]	[-0.29]	[-0.29]	[-0.02]
3	-0.01	-0.02	-0.02	-0.02	-0.02	**3**	[-0.12]	[-0.42]	[-0.46]	[-0.32]	[-0.41]
4	-0.01	-0.01	-0.02	-0.01	-0.01	**4**	[-0.10]	[-0.26]	[-0.28]	[-0.11]	[-0.30]
5	0.00	0.00	0.00	-0.01	-0.01	**5**	[-0.12]	[-0.06]	[-0.04]	[-0.19]	[-0.22]

Panel C $Z_t = a + b_{IND} IND_t + b_{FVIX} FVIX_t + \eta_t$

	beta						t-statistic				
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
1	-0.23	-0.15	0.05	-0.07	-0.06	**1**	[-4.21]	[-2.71]	[1.14]	[-1.87]	[-1.53]
2	0.16	0.23	0.17	0.10	0.14	**2**	[2.29]	[5.07]	[3.68]	[3.29]	[1.93]
3	0.19	0.28	0.21	0.23	0.15	**3**	[2.71]	[3.53]	[4.01]	[4.09]	[2.15]
4	0.08	0.21	0.26	0.19	0.18	**4**	[0.95]	[3.47]	[4.11]	[3.48]	[2.86]
5	-0.01	0.14	0.15	0.21	-0.01	**5**	[-0.16]	[3.06]	[1.95]	[3.90]	[-0.19]

	beta						t-statistic				
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
1	0.06	0.04	-0.01	0.02	0.01	**1**	[1.04]	[0.84]	[-0.24]	[0.41]	[0.21]
2	-0.05	-0.06	-0.05	-0.03	-0.03	**2**	[-1.25]	[-1.67]	[-1.07]	[-1.05]	[-0.88]
3	-0.05	-0.08	-0.06	-0.06	-0.05	**3**	[-1.12]	[-1.86]	[-1.69]	[-2.06]	[-1.31]
4	-0.02	-0.06	-0.07	-0.04	-0.05	**4**	[-0.41]	[-1.01]	[-1.38]	[-0.99]	[-1.25]
5	0.00	-0.03	-0.03	-0.06	-0.01	**5**	[-0.07]	[-0.79]	[-0.50]	[-1.04]	[-0.17]

Table 3.7: **25 size BM portfolios abnormal returns factors exposures on IND and UMD.** Panel A shows factors exposures on IND related to the equation (3.11). Panel B shows the factor loading to the momentum UMD related to the equation (3.14). Panel C shows the factors exposures on IND and $FVIX$ related to the equation (3.15). On the right the t-statistic with Newey and West (1987) corrected standard errors in the square brackets.

Panel A $Z_t = a + b_{IND}IND_t + \eta_t$

	beta						t-statistic				
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
1	-0.22	-0.14	0.05	-0.06	-0.06	**1**	[-4.08]	[-2.39]	[1.07]	[-1.72]	[-1.57]
2	0.15	0.22	0.16	0.09	0.13	**2**	[2.11]	[5.29]	[3.62]	[2.96]	[1.88]
3	0.18	0.26	0.19	0.22	0.14	**3**	[2.46]	[3.47]	[3.77]	[3.91]	[2.10]
4	0.07	0.19	0.25	0.18	0.17	**4**	[0.89]	[3.47]	[4.09]	[3.34]	[2.68]
5	-0.01	0.14	0.14	0.20	-0.02	**5**	[-0.17]	[2.95]	[1.85]	[3.76]	[-0.22]

Panel A $Z_t = a + b_{UMD}UMD_t + \eta_t$

	beta						t-statistic				
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
1	-2.45	0.36	4.25	2.29	3.29	**1**	[-1.31]	[0.16]	[2.35]	[1.50]	[2.08]
2	-1.72	1.37	1.68	-0.26	-1.87	**2**	[-0.72]	[0.92]	[1.00]	[-0.18]	[-1.12]
3	-4.16	0.89	0.12	-0.76	1.67	**3**	[-2.50]	[0.40]	[0.04]	[-0.47]	[1.30]
4	-2.54	1.01	1.06	-0.08	2.99	**4**	[-1.22]	[0.47]	[0.57]	[-0.03]	[1.70]
5	-1.10	5.96	4.88	-0.77	-6.10	**5**	[-0.63]	[3.45]	[3.43]	[-0.30]	[-3.53]

Panel C $Z_t = a + b_{IND}IND_t + b_{UMD}UMD_t + \eta_t$

	beta						t-statistic				
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
1	-0.25	-0.15	0.04	-0.06	-0.07	**1**	[-3.41]	[-0.80]	[-0.02]	[-0.81]	[-2.79]
2	0.07	0.23	0.17	0.11	0.13	**2**	[1.03]	[4.48]	[1.75]	[1.81]	[2.09]
3	0.20	0.27	0.21	0.23	0.15	**3**	[2.37]	[3.30]	[1.57]	[3.39]	[1.27]
4	0.16	0.20	0.27	0.18	0.19	**4**	[1.56]	[1.84]	[2.30]	[3.28]	[2.23]
5	0.00	0.15	0.15	0.21	-0.01	**5**	[0.04]	[1.36]	[1.72]	[2.40]	[-0.96]

	beta						t-statistic				
	1	**2**	**3**	**4**	**5**		**1**	**2**	**3**	**4**	**5**
1	-0.03	0.08	-0.06	0.03	-0.10	**1**	[-0.45]	[0.83]	[-1.61]	[0.69]	[-2.21]
2	-0.09	0.00	-0.08	-0.01	0.02	**2**	[-2.03]	[-0.07]	[-1.26]	[-0.16]	[0.86]
3	0.03	-0.04	-0.12	-0.06	-0.06	**3**	[0.77]	[-0.80]	[-2.15]	[-1.37]	[-0.97]
4	0.11	-0.09	-0.13	0.03	-0.02	**4**	[1.25]	[-1.45]	[-1.96]	[0.56]	[-0.33]
5	0.01	-0.08	-0.01	-0.05	-0.08	**5**	[0.40]	[-1.98]	[-0.29]	[-1.59]	[-1.65]

3.5.3 Risk Premium

This section proposes to compute the price of the IND risk factor, by applying the Fama and MacBeth (1973) procedure. The expected returns are related to the market price of risk according to the equation (3.16). The equation puts in relation the expected returns of the assets or portfolios i, with the risk-free, the market price of the risk factors λ and the factor loading on that asset. The equation is in cross-section.

$$E[R_i] = rf + \beta\Lambda + \eta \tag{3.16}$$

Fama and MacBeth (1973) propose a procedure in two stages able to estimate the market price of risk, where the factor loading is the OLS time series estimates from January 1986 to December 2000. The second stage regression instead is an OLS regression where the covariates are the betas estimates in the first stage. The market price of risk for IND risk factor is computed by using both 25 size book-to-market portfolios and 48 industry portfolios. The procedure is applied to Fama and French (1993) factors model and successively stepwise augmented by Indegree IND, mimicking factor portfolio of aggregate volatility Index change $FVIX$, the Momentum factor of Carhart (1997) UMD and Liquidity Innovations factors LIQ_INN Pástor and Stambaugh (2003). Shanken (1992) procedure corrects the results.

Table (3.8) reports the premiums estimates by looking at the 25 size book-to-market portfolios. The left part of the table exhibits the results when the second stage regression considers the intercept for computing the premium coefficients, while on the right part, the intercept is removed and the results are corrected for Shanken (1992). The outcomes differ depending on whether the intercept is omitted or not: the model with intercept indicates that only the SMB and UMD are significant; the model without intercept determines the significance of MKT, $FVIX$, and UMD. The first model shows an adjusted R^2 higher than the model without the intercept, besides in the VI, VII, and VIII the adjusted R^2 is negative, suggesting that the intercept offers better performance results in term of adjusted R^2.

Table (3.9) reports the premium coefficients for the 48 Industry portfolios. In this case, the model with intercept without Shanken (1992) correction on the left part produces similar results if compared to the model without intercept. The MKT, HML, IND, $FVIX$ are significant in both cases. SMB and UMD lose the significance after the Shanken (1992) corrections. Finally, the adjusted R^2 increases roughly by 4% when we add the IND risk factor.Fama and MacBeth (1973) procedure produces higher adjusted R^2 for 48 Industry portfolios rather than for 25 portfolios sorted by size and book-to-Market. Although risk factor IND is significant only in case of 48 industry portfolios, in both circumstances is always negative. If the market decides to price IND negatively, means that IND stands for insurance for investors, i.e., offers good outcomes in the bad states and bad outcomes in good ones. The IND risk premium is equal to -0.5%. The coefficient significant does not nullify the significance of $FVIX$ showing that the IND is priced for reasons not related to the mimicking factor portfolio of the aggregate volatility change innovations. A possible explanation, assuming IND as the risk factor with a negative price of risk could be that stocks having higher indegree are the more predictable. Further developments in this paper will consider wider time intervals with a focus on the financial crisis.

Table 3.8: **Fama–MacBeth (1973) factor premiums 25 B/M portfolios.** The table shows the premium computed on the 25 portfolios sorted by size and book-to-market portfolios using Fama and MacBeth (1973) procedure. The Fama and French (1993) model is the benchmark in the first column and stepwise augmented by IND, $FVIX$, UMD and LIQ_INN. The left part and the right part of the table report the premium estimates with and without intercept. The results are corrected by Shanken (1992). The square brackets present t-statistic with Newey and West (1987) corrected standard errors.

Fama–MacBeth (1973) Factor Premiums 25 B/M portfolios

	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**
Constant	1.74	1.61	1.55	1.41	1.26	-	-	-	-	-
	[2.97]	[2.56]	[2.2]	[2.32]	[1.95]	-	-	-	-	-
MKT	-0.79	-0.63	-0.57	-0.44	-0.30	0.86	0.94	0.97	0.96	0.95
	[-1.41]	[-1.02]	[-0.81]	[-0.73]	[-0.46]	[2.54]	[2.75]	[2.83]	[2.78]	[2.75]
SMB	-0.19	-0.21	-0.21	-0.22	-0.22	-0.11	-0.17	-0.18	-0.19	-0.20
	[-2.44]	[-2.46]	[-2.4]	[-2.89]	[-2.84]	[-0.4]	[-0.61]	[-0.64]	[-0.67]	[-0.67]
HML	0.04	0.05	0.05	0.14	0.13	0.04	0.06	0.08	0.17	0.14
	[0.46]	[0.56]	[0.57]	[1.57]	[1.42]	[0.16]	[0.27]	[0.36]	[0.72]	[0.61]
IND		-0.17	-0.13	-0.16	-0.25		-0.43	-0.13	-0.17	-0.34
		[-0.55]	[-0.33]	[-0.48]	[-0.7]		[-1.49]	[-0.38]	[-0.43]	[-0.81]
FVIX			0.38	0.14	0.01			-0.45	-0.62	-0.72
			[0.96]	[0.42]	[0.02]			[-2.02]	[-2.64]	[-2.89]
UMD				1.85	2.14				2.11	2.60
				[2.83]	[2.76]				[3.21]	[3.08]
LIQ_INN					0.01					0.03
					[0.78]					[1.57]
R^2	25.89%	27.29%	27.42%	49.72%	51.21%	-5.21%	3.49%	8.96%	34.71%	40.28%
Adj R^2	15.31%	12.74%	8.32%	32.97%	31.12%	-14.77%	-10.29%	-9.25%	17.53%	20.38%
Shanken Correction	N	N	N	N	N	Y	Y	Y	Y	Y

Table 3.9: **Fama–MacBeth (1973) factor premiums 48 Industry portfolios.** The table shows the premium computed on the 48 Industry portfolios using Fama and MacBeth (1973) procedure. The Fama and French (1993) model is the benchmark in the first column and stepwise augmented by IND, $FVIX$, UMD and LIQ_INN. The left part and the right part of the table report the premium estimates with and without intercept. The results are corrected by Shanken (1992). The square brackets present t-statistic with Newey and West (1987) corrected standard errors.

Fama–MacBeth (1973) Factor Premiums 48 Industry Portfolios

	I	II	III	IV	V	VI	VII	VIII	IX	X
Constant	0.20	0.29	0.06	0.08	0.10	-	-	-	-	-
	[0.75]	[1.13]	[0.2]	[0.29]	[0.35]	-	-	-	-	-
MKT	0.74	0.72	0.97	0.98	0.96	0.93	0.99	1.03	1.06	1.06
	[2.94]	[3]	[3.34]	[3.43]	[3.32]	[2.71]	[2.86]	[2.97]	[3.05]	[3.05]
SMB	-0.38	-0.45	-0.42	-0.36	-0.35	-0.39	-0.46	-0.42	-0.36	-0.35
	[-2.36]	[-2.91]	[-2.74]	[-2.32]	[-2.25]	[-1.11]	[-1.34]	[-1.18]	[-1.05]	[-1.03]
HML	-0.67	-0.54	-0.58	-0.53	-0.54	-0.68	-0.57	-0.58	-0.54	-0.55
	[-5.83]	[-4.41]	[-4.68]	[-4.3]	[-4.31]	[-2.71]	[-2.25]	[-2.3]	[-2.1]	[-2.13]
IND		-0.59	-0.58	-0.55	-0.57		-0.58	-0.57	-0.55	-0.57
		[-4.35]	[-4.28]	[-4.18]	[-4.19]		[-2.09]	[-2.06]	[-1.97]	[-1.99]
FVIX			-0.55	-0.57	-0.55			-0.59	-0.61	-0.61
			[-3.44]	[-3.59]	[-3.47]			[-2.71]	[-2.77]	[-2.77]
UMD				1.05	1.07				1.05	1.07
				[3.53]	[3.56]				[1.96]	[1.95]
LIQ_INN					0.01					0.01
					[0.86]					[0.53]
R^2	53.14%	58.13%	60.23%	62.84%	63.26%	52.53%	56.88%	60.19%	62.77%	63.15%
Adj R^2	49.94%	54.23%	55.50%	57.41%	56.83%	50.42%	53.94%	56.49%	58.34%	57.75%
Shanken Correction	N	N	N	N	N	Y	Y	Y	Y	Y

3.5.4 Relationship with the Idiosyncratic volatility puzzle

Empirical evidence suggests that the IND can be considered as a risk factor priced by the market.This part of the analysis investigates if IND can explain the idiosyncratic volatility puzzle, and secondly which is the relation in term of factor exposure β_{IND} between portfolios sorted by IVOL and the risk factor IND. Table (3.10) displays the value weighted average of portfolios returns ordered by IVOL with respect to a Fama and French (1993) model as in equation (3.21) from January 1986 to December 2000. The last three colums report the alpha and factors exposures of IND and $FVIX$ of the equations (3.17).

$$r_{it} = \alpha_i + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{IND}IND_t + \beta_{FVIX}FVIX_t + \epsilon_t \quad (3.17)$$

Particularly, table (3.10) shows that the proposed factor IND is not able to explain the puzzle because the alpha coefficients are still statistically significant. The results are invariant with the removal of $FVIX$ from the equation (3.17). The results are more interesting if we observe how much change the exposition on IND as soon as the portfolios have an increasing IVOL, factor loading on IND β_{IND} decreases significantly for all portfolios. To deepen this behavior table (3.11) shows the factor exposure on indegree based on equation (3.17) of the 25 portfolios sorted by Indegree based on the Granger causality and IVOL. By construction, portfolios having stocks with higher indegree have a factor loading β_{IND} on IND increasing. When the quintile portfolios are controlled for indegree, then the factor loading on the Indegree decreases, and it is almost cases significant.

Table 3.10: **Portfolios sorted by idiosyncratic volatility.** Quantile portfolios ordered with respect to the IVOL of equation (3.21). The statistics Mean and Standard Deviation are relative to the total portofolio returns monthly percentage. The Alpha columns report the Jensens' alpha with respect to the CAPM and the Fama and French (1993). The columns β_{IND} and β_{FVIX} represent the exposure IND and $FVIX$ by using the full sample regression of equation (3.17). Robust Newey and West (1987) t-statistics are reported in square brackets. The sample period is from January 1986 to December 2000.

Portofolios Sorted by Idiosyncratic Volatility						
Rank	**Mean**	**Std Dev.**	**Market Share**	**Alpha**	β_{IND}	β_{FVIX}
1	1.40	4.16	61.42%	0.07	0.16	-0.10
				[0.7]	[3.29]	[-0.43]
2	1.33	4.83	24.45%	-0.46	0.09	-1.55
				[-3.59]	[2.13]	[-5.98]
3	1.31	6.21	8.96%	-0.65	-0.13	-2.07
				[-3.37]	[-2.26]	[-4.46]
4	0.72	7.74	3.81%	-0.88	-0.26	-1.16
				[-3.52]	[-4.3]	[-2.46]
5	-0.24	9.17	1.36%	-1.59	-0.52	-0.49
				[-4.31]	[-4.72]	[-0.6]
5-1	-1.47			-1.65	-0.67	-0.39
	[-2.37]			[-3.96]	[-5.63]	[-0.42]

Table 3.11: **Factor loading of 25 portfolios sorted by indegree and IVOL on IND risk factor.** The table displays the beta's on IND by considering the 25 portfolios returns sorted by Indegree and IVOL.

25 portfolios sorted by Indegree and IVOL: β_{IND}					
Rank	**1**	**2**	**3**	**4**	**5**
1	-0.34	-0.48	-0.46	-0.58	-0.73
	[-3.04]	[-5.31]	[-3.46]	[-5.16]	[-4.02]
2	-0.22	-0.16	-0.35	-0.40	-0.30
	[-3.37]	[-1.29]	[-2.92]	[-2.18]	[-2.59]
3	0.23	0.16	0.28	-0.02	-0.07
	[4.55]	[2.31]	[3.07]	[-0.13]	[-0.71]
4	0.41	0.36	0.21	0.27	-0.16
	[9.45]	[4.76]	[2.1]	[2.36]	[-1.22]
5	0.55	0.63	0.62	0.46	0.20
	[11.27]	[7.91]	[7.26]	[3.1]	[1.43]

3.6 Robustness check

3.6.1 Contemporaneous IVOL of Portfolios sorted by Indegree

This section investigates if the decreasing expected returns of portfolios having increasing indegree are linked to the fact that these portfolios have higher IVOL. If this Hypothesis were accepted, it would mean that IVOL would be hidden factor behind the negative relationship between indegree and expected returns. this section, therefore, analyzes if the observed effect of decreasing expected returns with respect to increasing indegree is defined "by construction" or could be related to economic reasons. The procedure is the following: for each month the contemporaneous IVOL in equation (3.9) is computed for all stocks contained in tercile portfolios. Statistics are computed monthly and then averaged across the whole sample.

Table (3.12) highlights that stocks contained in portfolios having lower indegree have in average higher IVOL mean, IVOL median and value-weighted average. It means that if indegree were priced for reasons related to IVOL, then the expected returns would have increasing values for higher indegree. Also, empirical findings show as market share drives idiosyncratic volatility concerning Fama and French (1993), as observed in table (3.10) because portfolios having higher IVOL are driven by small size firms stocks. At the contrary, this is not the case for portfolios sorted by indegree because their market share composition is constant roughly at 30 % across the terciles.

Therefore the negative relationship between IVOL and the factor loading on IND β_{IND} is not imputable to the size of firms.

Table 3.12: **Descriptive Analysis of contemporaneous IVOL for stocks belonging to tercile portfolios sorted by indegree**. For each IVOL statistics computed for each stocks daily return with respect to the Fama and French (1993) model, the results are averaged across whole sample.

Statistics of Idiosyncractic Volatility for portfolio sorted by Indegree						
Rank	**Mean**	**Median**	**Standard Deviation**	**Value Weighted Average**	**Min**	**Max**
1	18.61	2.86	72.33	6.13	-0.90	1821.39
2	12.24	2.06	34.99	4.58	-0.86	769.04
3	11.65	2.01	29.93	4.71	-0.82	615.30

3.6.2 Expected returns and centrality measures

The last part of robustness checks tests the relationship between other centrality measures and stocks expected returns. In other words, portoflios returns are computed by sorting stocks according the centrality measures described in section 3.3. Table (3.13) displays the results. Particularly, panel A exhibits the value weighted returns at time t+1 for portfolios terciles sorted by outdegree at time t according the equation (3.4), averaged across the sample. Surprisingly, the difference between the 3^{th} - 1^{st} is not significant and close to zero. On the contrary of indegree case in table (3.3), market share is higher for portfolio having lower outdegree. The last columns of the table shows alphas coefficient with respect to the CAPM and the Fama and French (1993), they are not significant.

Panel B reports the results by sorting the terciles portfolios by the sum of outdegree plus indegree as in equation (3.5). The variable takes into account of stock more active is a sense of links (ingoing and outgoing), the direction loses its role. As table (3.3), portfolios having stocks with higher indegree+outdegree have lower expected returns, the magnitude is low and not significant. In addition, portfolios having lower outdegree plus indegree have higher market capitalization, however, the alpha relative of the third tercile for Fama and French (1993) is the only one significant.

Panel C reports terciles value-weighted portfolios returns averaged across all sample, computed by sorting the difference between the outdegree and indegree as in equation (3.6). The measure considers the net effect of spreading and absorbing the shocks. In this case, portfolios having an increasing difference between outdegree and indegree have higher returns. The difference between the 3^{th} - 1^{st} is not significant and equal to 0.15%. The alphas with respect the CAPM and Fama and French (1993) are not significant and very low.

Panel D reports terciles value-weighted portfolios returns, averaged across the sample, computed by sorting the eigenvector centrality as in equation (3.7). The measure considers the indirect effect is coming from the neighbors. As table (3.3) portfolios having eigenvector centrality have lower expected returns, as indegree, because the left eigenvector captures the impact coming from the system. The difference between the 3^{th} - 1^{st} is not significant and equal to -0.12%. The alphas with respect the CAPM and Fama and French (1993) are not significant and very low. The results shown in table (3.13) indicate clearly that the centrality measures previously described have a weaker effect on expected returns than indegree. In addition, alphas t-statistic with respect to CAPM and Fama and French (1993) model suggest that these measures are not good candidates as missing factors of stocks returns.

Table 3.13: **Portfolios sorted by centrality measures based on Granger causality network, robusteness checks.** The statistics are relative to the quantile portfolios ordered with respect to outdegree in Panel A equation (3.4), with respect to outdegree plus indegree in Panel B, with respect to Outdegree minus indegree in Panel C, with respect to eigenvector centrality in Panel D. The value weighted average and the standard deviation are relative to the returns monthly based. Market share defines the market capitalization of the portfolio, Size is computed as logarithm of stock market capitalization and B/M is the Book-to-Market ratio average. Alpha columns represent the intercept by regressing the porfolio returns with the CAPM and the Fama and French (1993) model. The time interval is from January 1986 to December 2000 as Ang et al. (2006). Robust Newey and West (1987) t-statistics are reported in square brackets.

Rank	Mean	Std Dev.	Market Share	Size	B/M	CAPM Alpha	FF-3 Alpha
Panel A: Portofolios Sorted by Outdegree							
1	1.40	4.40	46.67%	7.40	0.44	0.04	0.05
						[0.44]	[0.8]
2	1.47	4.80	26.76%	6.87	0.48	0.01	0.03
						[0.18]	[0.37]
3	1.39	4.92	26.58%	6.83	0.47	-0.06	-0.08
						[-0.58]	[-0.87]
3-1	-0.01					-0.10	-0.13
	[-0.04]					[-0.55]	[-0.92]
Panel B: Portofolios Sorted by Outdegree+Indegree							
Rank	**Mean**	**Std Dev.**	**Market Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**
1	1.41	4.59	45.25%	7.38	0.43	0.02	0.06
						[0.17]	[0.71]
2	1.56	4.56	28.30%	6.92	0.46	0.16	0.15
						[1.77]	[1.77]
3	1.22	4.91	26.45%	6.83	0.48	-0.22	-0.27
						[-1.71]	[-2.28]
3-1	-0.19					-0.24	-0.33
	[-0.9]					[-1.08]	[-1.82]
Panel C: Portofolios Sorted by Outdegree-Indegree							
Rank	**Mean**	**Std Dev.**	**Market Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**
1	1.40	4.27	42.73%	7.29	0.45	0.06	0.04
						[0.93]	[0.79]
2	1.35	4.70	31.07%	7.01	0.46	-0.08	-0.05
						[-1.02]	[-0.69]
3	1.55	5.03	26.21%	6.80	0.46	0.06	0.07
						[0.63]	[0.8]
3-1	0.15					0.00	0.03
	[0.87]					[0.02]	[0.22]
Panel D: Portofolios Sorted by Eigenvector Centrality							
Rank	**Mean**	**Std Dev.**	**Market Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**
1	1.44	4.63	36.85%	7.11	0.46	0.05	0.07
						[0.46]	[0.71]
2	1.48	4.80	25.85%	6.83	0.48	0.02	0.04
						[0.28]	[0.45]
3	1.32	4.78	37.30%	7.12	0.45	-0.11	-0.15
						[-1.1]	[-1.42]
3-1	-0.12					-0.16	-0.22
	[-0.6]					[-0.82]	[-1.13]

3.7 Conclusion

The idiosyncratic volatility puzzle is still an open research question. It is not clear why portfolios sorted by increasing IVOL have lower expected returns. Hou and Loh (2016) find that many real explanations explain less than 10% of the puzzle. As far as I know, this paper is the first one to investigate the IVOL puzzle driver by using the indegree based on the Granger causality network. The contribution can be split in two parts: The first part outlines that network indegree based on the Granger causality affects stocks returns; stocks having higher indegree have lower expected returns. Once created the factor IND given as the difference of the 3^{th}-1^{st} tercile, it affects the cross-section of stocks returns having a negative price of risk: insurance for investors. This factor is relevant for explaining the covariation of the abnormal returns of the 25 portfolios sorted by size and Book-to-market. The Fama and MacBeth (1973) procedure shows evidence in the pricing in 48 industry portfolios but not for 25 portfolios sorted by size and Book-to-market. In the latter case, IND is a factor priced for reasons not related to the $FVIX$ Ang et al. (2006) i.e., the mimicking factor portfolio replicated in the appendix 3.8.1. Stocks having higher indegree hold lower contemporaneous IVOL indicating that indegree could help investors to increase the information for that stocks. The reasons why the portfolios having higher indegree have lower expected returns should be deepened, from one side can be related to the nature of the Granger causality stocks having higher indegree are at the same time the most predictable stocks Baker and Wurgler (2006), on the other hand, can reveal some potential trading strategies see Cohen-Cole et al. (2014). The other centrality measures, except indegree, described in section 3.3, have weaker and inconsistent relations with expected returns.

Although many other robustness checks should be done to support the thesis that IND is a risk factor priced by the market as also to extend the sample time interval until 2016, the second part of the paper shows that IVOL is priced for reasons not related to IND. However, the relation between IVOL and IND is negative that is the second contribution of the paper. Portfolios having higher and increasing IVOL have higher negative factor exposure to IND.

3.8 Appendix

3.8.1 Aggregate and Idiosyncratic volatility Puzzle

This section reports the results of Ang et al. (2006) replication, the pool of stocks and the time interval is the same I used to investigate the puzzle causes. According to the authors, stocks are ordered and grouped in quintile by looking at the sensitivity of the innovations on the aggregate volatility ΔVIX following this equation:

$$r_{it} = \alpha_i + \beta_{MKT} MKT_t + \beta_{\Delta VIX} \Delta VIX_t + \epsilon_t \tag{3.18}$$

where r_i indicates the excess return of the i_{th} stock, β_{MKT} measures the sensitivity on the market CRSP index, $\beta_{\Delta VIX}$ represents the exposure on the change of the aggregate volatility risk. The figure (3.4) shows the quintile portfolios cumulative returns sorted with respect to the exposition on the aggregate volatility of the previous month. The higher is the exposition on the aggregate volatility risk the lower are the portfolios' returns. Portfolios gathering stocks having lower exposure on the ΔVIX outperform portfolio having higher exposure to the change of the delta volatility index.

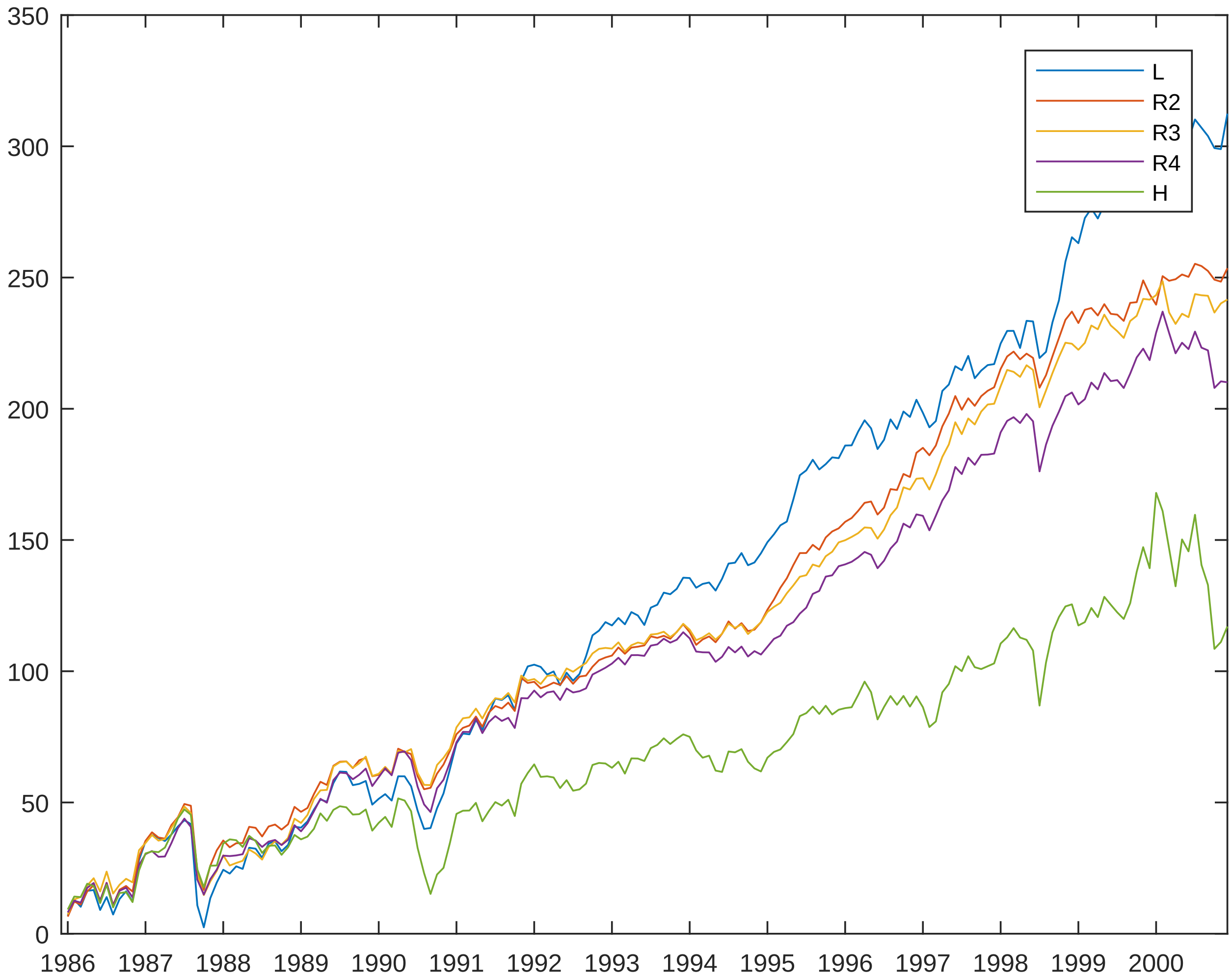


Figure 3.4: **Quintile portfolios cumulative returns sorted by ΔVIX.** The figure reports the cumulative returns of the five quintile portfolios, sorted to β_{VIX} the previous month. Each portfolio is value-weighted. L represents the portfolio made up with stocks having the lowest exposition on the aggregate volatility risk, R2 is the second quintile, R3 is the third quintile, R4 is the fourth quintile, H is the portfolio built with stocks having the highest exposure on the aggregate volatility risk.

What is shown in figure (3.4) is coherent with the second column of the table (3.14). The reason of the replication of the table (3.14) is to understand how much the results are close to Ang et al. (2006), in order to start the second analysis investigating if IVOL can be explained by using indegree based on the network estimated with the Granger causality test. Also, it is worth to understand if the pricing of indegree (assuming to be a risk factor) takes place in the same dimension of $FVIX$.

The first column of table (3.14) includes the portfolio quantile sorted by the exposure to ΔVIX, grouped in quintile. The second and the third column represent respectively totally returns value weighted average and the standard deviation. The monthly average is roughly 1.74 % for the lowest quintile and decreases until 0.65% for the highest quintile. They are computed by selecting the stocks according to with equation (3.18) by looking at the exposition to ΔVIX of daily returns of the previous month. Market capitalization at the end of the last month is used as the weight for computing the value-weighted portfolio. Portfolios co-varying more with the change volatility risk have lower expected returns.

The average market share of the quintile portfolios is calculated for each month as the ratio between the market capitalization of each quintile portfolio and the market capitalization of all portfolios. Size is the logarithm of the total market portfolio capitalization averaged by month. B/M (Book-to-Market) reports for each quintile portfolio the ratio between the market value and the book value at the end of the month. Firms having low market capitalization are in the extreme quintiles suggesting that the small size firms do not drive high exposition to the change of the aggregate volatility. Companies having higher market capitalization are located in the middle quantiles. Alpha columns with respect to the CAPM and three-factor model Fama and French (1993) present a decreasing pattern as soon as the exposition on ΔVIX increases, they are significant for the **5** and **5-1** portfolios quintile. The alpha coefficients significance indicates that a possible omitted risk factor can be present; CAPM and Fama and French (1993) are not enough to explain the cross-section of the stock returns.

To reduce the noise in the estimates, the authors compute according to Breeden et al. (1989) and Lamont et al. (2001), the mimicking portfolio $FVIX$ of the aggregate volatility risk ΔVIX , as in the equation (3.19).

$$\Delta VIX_t = a + b' X_t + e_t \tag{3.19}$$

a is the intercept and X_t are the excess returns of the quintiles portfolios according to (3.18). For each month, the estimation of $\hat{b}$ according to the equation (3.19) is $FVIX_t = \hat{b}' X_t$. Once defined the $FVIX$, they selected the stocks with respect to the factor mimicking aggregate volatility risk $FVIX$ and modifying the equation (3.18) that assumes this form.

$$r_{it} = \alpha_i + \beta_{MKT} MKT_t + \beta_{FVIX} FVIX_t + \epsilon_t \tag{3.20}$$

r_i indicates the excess return of the i_{th} stock, β_{MKT} measures the sensitivity on the Market CRSP index, β_{FVIX} is the sensitivity on $FVIX$ the mimicking factor portfolio of ΔVIX.

In table (3.14) columns $\beta_{\Delta VIX}$ and β_{FVIX} report the value-weighted average of the exposition to ΔVIX and $FVIX$ factor for each quintile portfolio, according to (3.18) and (3.20). As can be observed, both columns have the patterns, and in particular the portfolio sorted by ΔVIX exposures, are more two times higher than the portfolios sorted by $FVIX$.

Next month formation $\beta_{\Delta VIX}$ displays the value-weighted ex-post beta formation on the aggregate volatility risk. The computation procedure is the following according to the authors: Once selected the stocks about the exposure on aggregate volatility risk innovations at the month t, they compute the forecast of the daily returns quintile portfolio at the month $t + 1$. The post-formation beta is computed by using the equation (3.18) at the time $t+1$ and using quintile portfolio return at time $t+1$ as dependent variable. The results are averaged. The replication finds as the authors Ang et al. (2006) that ex-post exposure on aggregate volatility risk innovations is drastically lower than ex-ante exposure, but the pattern is still increasing. The last column Full sample post-formation reports the exposure on the regression monthly based between the Fama and French (1993) model augmented by the $FVIX$ monthly observation and the ex-post quantile portfolio returns ordered concerning the past loading on ΔVIX according to (3.18).

Table 3.14: **Portofolios Sorted by exposition on the aggregate volatility.** Value weighted portfolio quantile total returns sorted by the exposition on the $\beta_{\Delta VIX}$ as in equation (3.18). The statistics Mean, and Standard Deviation are relative to the total portfolio returns monthly percentage. Size defines the average log stock market capitalization within the quintile portfolios and B/M average of the Book-to-Market ratio. The Alpha columns report the Jensens' alpha with respect to the CAPM and the Fama and French (1993). The columns $\beta_{\Delta VIX}$ and β_{FVIX} represent the exposure to Δ VIX, and FVIX averaged for the whole sample. Finally, $\beta_{\Delta VIX}$ reports the next month exposure on Δ VIX averaged across the month, and β_{FVIX} defines the post-formation of all sample by using daily portfolios returns. Robust Newey and West (1987) t-statistics are reported in square brackets. The sample period is from January 1986 to December 2000.

Rank	**Mean**	**Std Dev.**	**Market Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**	**Pre Formation** $\beta_{\Delta VIX}$	**Pre Formation** β_{FVIX}	**Next Month Formation** $\beta_{\Delta VIX}$	**Full Sample Post Formation** β_{FVIX}
1	1.74	5.66	9.71%	5.89	0.45	0.27	0.32	-3.97	-1.35	-0.044	-5.04
						[1.41]	[1.65]				[-15.76]
2	1.41	4.45	28.80%	7.10	0.45	0.16	0.08	-1.41	-0.43	0.005	-0.94
						[1.51]	[0.91]				[-2.43]
3	1.34	4.42	30.85%	7.18	0.46	0.10	0.05	0.38	0.03	0.006	-0.26
						[0.95]	[0.6]				[-0.85]
4	1.17	4.81	23.25%	6.87	0.46	-0.13	-0.12	1.91	0.49	-0.004	0.28
						[-1.38]	[-1.19]				[0.77]
5	0.65	6.67	7.39%	5.67	0.46	-0.87	-0.52	4.73	1.42	0.061	2.33
						[-3.19]	[-2.32]				[3.52]
5-1	-1.09					-1.55	-1.04				
	[-3.07]					[-4.29]	[-3.61]				

The contribution of Ang et al. (2006) is to show that the change in aggregate volatility risk is a price factor. In particular, $FVIX$, the mimicking portfolio of the ΔVIX has a negative price of risk and significant.[17] Table (3.15) displays the results by combining the FVIX with Fama and French (1993), Carhart (1997), and Pástor and Stambaugh (2003) factors.

Table 3.15: **Fama–MacBeth (1973) Factor Premiums** The table shows the premium computed on the 25 portfolios sorted on the Market exposure β_{MKT} and $\beta_{\Delta VIX}$ by using Fama and MacBeth (1973) procedure. The first column reports the Fama and French (1993) factors premium and the mimicking factor portfolio premium. The second column adds the Carhart (1997) factors premium.The third column adds the Pástor and Stambaugh (2003) factors premium. In all cases the FVIX premium is always significant.

Fama–MacBeth (1973) Factor Premiums

	I	**II**	**III**	**IV**	**V**	**VI**
Constant	2.19	2.30	2.00	-	-	-
	[3.53]	[2.87]	[2.17]	-	-	-
MKT	-0.83	-0.93	-0.64	1.32	1.29	1.28
	[-1.35]	[-1.19]	[-0.72]	[3.81]	[3.73]	[3.67]
FVIX	-2.53	-2.57	-2.89	-3.56	-2.97	-3.62
	[-2.77]	[-2.70]	[-2.71]	[-2.79]	[-2.56]	[-2.57]
SMB	2.52	2.53	2.55	2.21	2.27	2.41
	[9.76]	[9.48]	[9.37]	[4.74]	[4.86]	[4.50]
HML	-0.92	-0.91	-0.90	-0.16	-0.51	-0.62
	[-3.33]	[-3.13]	[-3.06]	[-0.37]	[-1.16]	[-1.27]
UMD		0.88	0.55		-0.66	-0.98
		[1.15]	[0.60]		[-0.83]	[-1.05]
LIQ			0.00			0.01
			[0.52]			[1.07]
Adj R^2	89.1%	88.61%	88.33%	82.3%	83.65%	85.27%
Shanken Correction	N	N	N	Y	Y	Y

From the other side if the Fama and French (1993) is the correct model and the FVIX is a priced factor then the omitted factor should be shown by looking at the residuals of the equation (3.21).

$$r_{it} = \alpha_i + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \epsilon_t \tag{3.21}$$

Although the mimicking tracking portfolio of aggregate volatility risk $FVIX$ is a risk factor with negative premium, Ang et al. (2006) showed that the cause IVOL puzzle is not related to the omitted factor $FVIX$. Portfolios monthly returns are computed by ordering stocks according to the total volatility and IVOL with respect to the equation (3.21) at the previous month, daily observations. Table (3.16) indicates the average and standard deviation of the value-weighted quintile portfolio returns. The behavior observed by the authors as in table (3.16) states that high

[17]The results are with and without the significance correction proposed by Shanken (1992)In this part of the paper, the first goal is to obtain results as close as possible to the Ang et al. (2006).

idiosyncratic risk portfolios have a lower expected return. At the contrary in table (3.14) small size firms have higher IVOL and total volatility, as reported by the Market share column. The last two columns display the CAPM and Fama and French (1993) alphas, relative to the quintile portfolios monthly returns. The pattern is decreasing, and according to the α's relative to CAPM and Fama and French (1993) in panel B table (3.16), there is an omitted factor but not related to $FVIX$ according to the authors. The causes of this decreasing pattern puzzle the researchers, the IVOL risk is not priced because this kind of risk can be diversified.[18] Since the IVOL risk is not priced then the expected returns of stocks should not evidence any pattern with respect to the portfolios ordered by idiosyncratic volatility, and moreover the alphas of model CAPM and Fama and French (1993) reported in the last two columns (3.16) would be not statistically significant.

[18]Ross (1976) showed that the IVOL risk is diversifiable by increasing the number of stocks held in the portfolio. Assuming that the assets are not cross-correlated, and they have the same variance, then the idiosyncratic risk tend to zero when the number of assets tends to infinity.

Table 3.16: **Portfolio sorted by total (idiosyncratic) volatility Panel A (Panel B).** The statistics are relative to the quantile portfolios ordered with respect to the total volatily (IVOL) of equation (3.21). The value weighted average and the standard deviation are relative to the returns monthly based. Market share defines the market capitalization of the portfolio, Size is computed as logarithm of stock market capitalization and B/M is the Book-to-Market ratio average. Alpha columns represent the intercept by regressing the porfolio returns with the the CAPM and the Fama and French (1993) model. The time interval of the analysis is from January 1986 to December 2000 as Ang et al. (2006). Robust Newey and West (1987) t-statistics are reported in square brackets.

Portofolios Sorted by Total Volatility

Rank	**Mean**	**Std Dev.**	**Market Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**
1	1.33	3.92	49.79%	7.63	0.47	0.17	-0.00
						[1.37]	[-0.07]
2	1.42	4.68	31.94%	7.20	0.44	0.15	0.05
						[1.39]	[0.61]
3	1.40	5.96	11.80%	6.16	0.44	-0.01	0.14
						[-0.09]	[1.00]
4	1.03	7.79	4.79%	5.22	0.44	-0.57	-0.13
						[-1.78]	[-0.59]
5	-0.11	9.34	1.68%	4.10	0.44	-1.78	-1.25
						[-4.21]	[-4.11]
5-1	-1.44					-1.96	-1.24
	[-2.08]					[-3.72]	[-3.44]

Portofolios Sorted by Idiosyncratic Volatility

Rank	**Mean**	**Std Dev.**	**Market Share**	**Size**	**B/M**	**CAPM Alpha**	**FF-3 Alpha**
1	1.40	4.16	61.42%	7.87	0.44	0.19	0.03
						[1.63]	[0.36]
2	1.33	4.83	24.45%	6.94	0.45	0.04	0.02
						[0.47]	[0.22]
3	1.31	6.21	8.96%	5.92	0.45	-0.16	0.02
						[-0.85]	[0.20]
4	0.72	7.74	3.81%	5.03	0.46	-0.85	-0.44
						[-3.10]	[-2.68]
5	-0.24	9.17	1.36%	3.97	0.46	-1.80	-1.29
						[-4.04]	[-4.54]
5-1	-1.47					-2.00	-1.32
	[-2.37]					[-3.70]	[-3.91]

Chapter 4

Systemic risk and financial interconnectedness: network measures and the impact of the indirect effect

4.1 Introduction

The global financial crisis of 2007/2008 and the European sovereign debt crisis have led academics and policy makers to focus on the stability of the financial system which plays a pivotal role in the transmission of shocks to the real economy (see Creel et al., 2015).
Since the financial system is increasingly complex and strongly interrelated, the interconnectedness among financial institutions in period of financial distress can lead to a rapid propagation of illiquidity, insolvency, and losses. In this regard, financial interconnectedness represents a key aspect of the financial stability. In fact, a highly interconnected financial network can absorb shocks through its linkages and be robust, but beyond a given magnitude, the same linkages may act as a propagator mechanism for those shocks leading to financial contagion and thus systemic risk. Haldane (2009) has characterized such a (financial) system aptly as *robust-yet-fragile*, that is robust, i.e. risk absorber in most of the cases, but suddenly risk-spreader where fragility prevails (for an analysis of the properties of a robust-yet-fragile system see Acemoglu et al., 2015; Bisias et al., 2012; Chinazzi and Fagiolo, 2015, for an update survey on systemic risk.)
As suggested by Schweitzer et al. (2009), the complexity of the economic system can be revised and extended with new paradigms using economic networks; and recently, the literature on systemic risk has started to use network theory to investigate the topology of financial networks in order to measure systemic risk (see Billio et al., 2012; Diebold and Yilmaz, 2014; Hautsch et al., 2014; Diebold and Yilmaz, 2015).
This paper is related to this stream of the literature. We apply several network measures on the networks extracted using pairwise quantile regressions. The purpose is to assert the different infor-

mative content between quantile based network measures and systemic risk indicators also based on quantile regression such as the quantile based loss measure ΔCoVaR proposed by Adrian and Brunnermeier (2016). The key idea is that network measures based on the connectedness of the single institution to the others is a good proxy of his ability to spread or absorb risk in the system and therefore a good proxy for identify systemically important financial institution. These measures do not consider only the direct linkages but also the "indirect linkages", i.e. two institutions could be connected not directly but simply because they are both connected to a third institution. The aim of this paper is to propose several measures that do not capture only direct shocks but also indirect shocks that dynamically propagate into the system. These measures are therefore different than the systemic risk measures that just look to the "contemporaneous" shock propagation during distress like ΔCoVaR.
We consider Banks and Insurers selected by the Financial Stability Board (FSB) as Global Systemically Important Financial Institutions (G-SIFIs) as well as Hedge Funds indices given that in many circumstances Hedge Funds has been indicated as the drivers of shocks spillover.
We compare the ranking of the financial institutions based on network measures and losses measures. The analysis shows that there is not so much similarities among the two ranking indicating that the two measures captures different features of systemic risk.
Moreover, our analysis shows that Hedge Funds are not the main central financial institutions and are largely absorbing risk rather than spreading risk in the system. We also investigate the predicting power of the network measure with respect to the loss measures and show that network measures have a larger predicting power than loss measures.
The paper is organized as follows. Section 4.2 presents the methodology we use to estimate loss measures and network measures. Section 4.3 presents the data and the descriptive statistics. Section 4.4 presents the results. Finally, Section 4.5 concludes.

4.2 Methodology

In this Section we present the quantile based measures we use to identify the importance of systemically important financial institutions. We consider two quantile based systemic risk measures: the quantile based loss measure ΔCoVaR proposed by Adrian and Brunnermeier (2016) and the quantile based network measures.

4.2.1 Quantile based loss measures: ΔCoVaR

ΔCoVaR represents the Value at Risk (VaR) of an institution (or a set of financial institutions, i.e. the financial system) conditional to an other institutions being under distress. The well-known VaR_q^i is defined by the quantile $q \in (0, 1)$,

$$\mathbb{P}(X^i \leq VaR_q^i) = q, \tag{4.1}$$

where X^i is the loss return of institution i. Consequently, the higher VaR_q^i, the higher the risk. Adrian and Brunnermeier (2016) define $CoVaR_q^{j|i}$ as the VaR of institution j conditional on some event $\mathcal{C}(X^i)$ of institution i,

$$\mathbb{P}\left(X^j|\mathcal{C}(X^i)\right) = q. \tag{4.2}$$

The authors define a contribution of a given institution i to j as ΔCoVaR that is the difference between the VaR of institution j conditional on the institution i being under distress, i.e. the $CoVaR_q^{j|X^i=VaR_q^i}$ and the VaR of institution j when returns of institution i are at 50^{th} percentile. More formally, that is,

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{0.5}^i}, \tag{4.3}$$

In case both j and i in ΔCoVaR refer to individual institutions, the analysis involves the tail-dependency across the network of financial institutions: the Network-ΔCoVaR. Differently, if j represents the financial system (i.e., a set of financial institution or a market index), we refer to the System-ΔCoVaR,

$$\Delta CoVaR_q^{\text{system}|i} = CoVaR_q^{\text{system}|X^i=VaR_q^i} - CoVaR_q^{\text{system}|X^i=VaR_{0.5}^i}. \tag{4.4}$$

and is suggested by the authors as a measure of systemic risk, i.e. the contribution of institution i to the risk of the system. Adrian and Brunnermeier (2016) suggest to estimate ΔCoVaR using quantile regression, that is,

$$\begin{aligned} X_t^i &= \alpha_q^i + \gamma_q^i \mathbf{M}_{t-l} + \varepsilon_{q,t}^i, \\ X_t^{j|i} &= \alpha_q^{j|i} + \beta_q^{j|i} X_t^i + \gamma_q^{j|i} \mathbf{M}_{t-l} + \varepsilon_{q,t}^{j|i}, \end{aligned} \tag{4.5}$$

where $i \neq j$, $\forall i, j = 1, \ldots, n_t$ and $\varepsilon_{q,t}^{j|i}$ is a white noise process with $q \in (0,1)$ and $\mathbf{M}_{t-l}$ is a vector of lagged state variables. Then, the predicted values from equation 4.5 can be used to obtain $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$,

$$\begin{aligned} VaR_{q,t}^i &= \hat{\alpha}_q^i + \gamma_q^i \mathbf{M}_{t-l}, \\ CoVaR_{q,t}^i &= \hat{\alpha}_q^{j|i} + \hat{\gamma}_q^{j|i} \mathbf{M}_{t-l} + \hat{\beta}_q^{j|i} VaR_{q,t}^i. \end{aligned} \tag{4.6}$$

Finally, the $\Delta CoVaR_{q,t}^i$ for the given institution i is equal to

$$\Delta CoVaR_{q,t}^i = \beta_q^{j|i} \left(VaR_{q,t}^i - VaR_{0.5,t}^i\right). \tag{4.7}$$

4.2.2 Network systemic risk measures

A network at time t is defined as a set of nodes $V_t = \{1, 2, \ldots, N_t\}$ and E_t edges among nodes. It can be represented through an N_t-dimensional adjacency matrix A_t, with the element $a_{ijt} = 1$, if there is an edge from i to j with $i, j \in V_t$ and 0, otherwise. The adjacency matrix A represents formally a network defining with a_{ij} the element in the row i and column j. In our framework self-loops are not allowed, in other words the elements of the diagonal are equal to zero. As an example, we define below an adjacency matrix with $n = 6$ and the associated graph in Figure 4.1.

$$A = \begin{bmatrix} 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 \end{bmatrix} \tag{4.8}$$

Each graph is defined by N nodes and E edges, the E edges link the nodes of the graph. In our

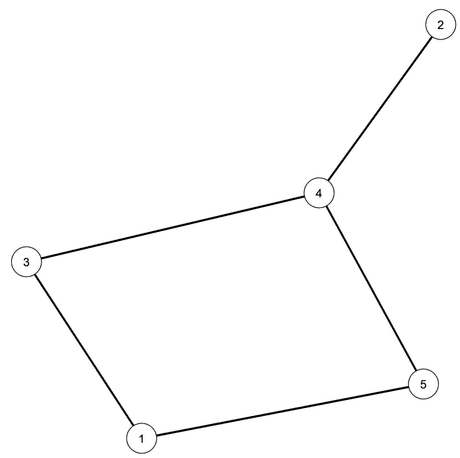


Figure 4.1: This Figure shows the resulting graph by using the adjacency matrix presented in the equation 4.8. Since the adjacency matrix is symmetric the graph is undirected. In this example, we show that each graph can be formally described by the adjacency matrix.

example the matrix A is symmetric, i.e. $a_{ij} = a_{ji}$ and consequently the associated graph is an undirected one, that is the effect of the node i on the node j is equal to the one of the node j on the node i. This type of graph is useful to model social interaction, web, molecular system and many more.

Differently, when the direction of the link matters, namely the link $i - j$ is different from $j - i$ then the graph is direct or called digraph. The matrix associated to this graph is not symmetric, and the edges have a direction represented by an arrow. In our analysis the networks are directed, in particular the convention we use for construct the adjacency matrix is the following: the element in the row i and column j is equal to 1 if the node j point out to the node i, i.e. $j \to i$ (for further information see Newman, 2010).

In this work, we represent the financial system with a network or a graph where nodes are the financial institutions and the links among nodes are estimated by the the statistically significant relationship of tail dependence among institutions. Then we use network measures provided by the network theory to investigate the role of the different financial institution in the network in terms of risk spillovers and risk absorbers and therefore to identify whether one institution is more systemically important than another given its role in the network, i.e. in the financial system. In the next two Sections, we present in details first the methodology we use to construct the network using quantile regression. Second, we present the network measures that we then calculate from the network based on quantile regressions to investigate the role of each financial institution in propagating risk to the system that is the quantile based network measures we investigate later on in the empirical analysis reported in Section 4.4.

Network based on quantile regressions

The matrix A_t is estimated by using a pairwise quantile regression approach to detect the contemporaneous relationship in the (left) tail among the different financial institutions.
In order to test the quantile relationship the following model is estimated,

$$\begin{aligned} X_t^i &= \alpha_q^i + \sum_{l=1}^{p} \gamma_q^i X_{t-l}^j + \varepsilon_{q,t}^i, \\ X_t^{j|i} &= \alpha_q^{j|i} + \beta_q^{j|i} X_t^i + \sum_{l=1}^{p} \gamma_q^{j|i} X_{t-l}^j + \varepsilon_{q,t}^{j|i}, \end{aligned} \tag{4.9}$$

and

$$\begin{aligned} X_t^j &= \alpha_q^j + \sum_{l=1}^{p} \gamma_q^j X_{t-l}^i + \varepsilon_{q,t}^j, \\ X_t^{i|j} &= \alpha_q^{i|j} + \beta_q^{i|j} X_t^j + \sum_{l=1}^{p} \gamma_q^{i|j} X_{t-l}^i + \varepsilon_{q,t}^{i|j}, \end{aligned} \tag{4.10}$$

where $i \neq j$, $\forall i, j = 1, \ldots, n_t$ and $\varepsilon_{q,t}^{j|i}$ and $\varepsilon_{q,t}^{i|j}$ are uncorrelated white noise processes with $q \in (0, 1)$. X_{t-l}^i and X_{t-l}^j are the autoregressive components. The relationship implies, $t = 1, \ldots, T$,

- if $\beta_q^{j|i} X_t^i \neq 0$ and $\beta_q^{i|j} X_t^j = 0$, X_t^j is tail dependent from X_t^i and $a_t^{ij} = 1$ but not vice versa, $a_t^{ji} = 0$;
- if $\beta_q^{j|i} X_t^i = 0$ and $\beta_q^{i|j} X_t^j \neq 0$, X_t^i is tail dependent from X_t^j and $a_t^{ji} = 1$ but not vice versa, $a_t^{ij} = 0$;
- if $\beta_q^{j|i} X_t^i \neq 0$ and $\beta_q^{i|j} X_t^j \neq 0$, there is a tail mutual dependence among X_t^i and X_t^j, and $a_t^{ij} = a_t^{ji} = 1$.

The relationship between the financial institutions using the quantile regression is asymmetric which in turn implies an asymmetric adjacency matrix. Our approach is in spirit similar to the

Network-ΔCoVaR proposed by Adrian and Brunnermeier (2016). In fact, equation 4.5 is very similar to equations 4.9 and 4.10, the only difference are the covariates. However, in their case they look to the magnitude of the coefficient $\beta_q^{i|j}$ to estimate the loss as shown in equation 4.7 instead in our case we are looking at the significance of the coefficient $\beta_q^{i|j}$ to generate the network of financial institution so that to apply the network measures that we describe in the next Section. Finally, we are similar in spirit to Billio et al. (2012) who also use network measure to investigate the systemically importance of financial institutions. The main difference between our approach and theirs is that the network in our case is based on quantile conditional dependence instead in Billio et al. (2012) it is based on Granger causality.

Quantile based Network measures

In this Section, we use the adjacency matrix A estimated using the quantile regressions in the previous Section to describe the network measures adopted for our analysis.
We distinguish the measures we consider between global measures if they aim to describe some particular feature of the network, and therefore measure the stability or fragility of the whole system, and local measures if they concentrate on the node or vertex level and measure the systemically importance of financial institutions.

Global Measures The measures we describe in this paragraph are labelled as "global" because, in contrast to the local measures, they give information on the whole network. These measures highlightsthe sparsity of the network or whether the links among the nodes are randomly distributed.

- **Density** is defined as the proportion between the number of edges actually present E and the number of edges theoretically possible N_t (the number of order 2 combination C_2^N among N nodes if the network is undirected; the number of order 2 permutation P_2^N among N nodes in the directed case),

$$D = \frac{E}{N_t} = \frac{E}{P_2^N} = \frac{E}{N(N-1)}. \tag{4.11}$$

  The Density is equal to 0 if there are no edges E while it is equal to 1 if all linkages among nodes are present (full dense). According to Wasserman and Faust (1994), the density is a good indicator for capturing the whole network interconnectedness level.

- **Assortativity**

  Assortativity by scalar properties

  It is the difference between the number of edges among vertexes having the same characteristic and the expected number of edges among these vertexes if the attachment were purely random (Newman, 2002, 2003). We define m_i the class of the vertex i, with n_m as the total number of classes in the network.

In the case of directed network, the number of edges among the vertexes of the same type results,

$$\sum_{ij} a_{ij}\delta(m_i, m_j), \tag{4.12}$$

where $\delta(m_i, m_j)$ is the delta Kronecker.

Assuming a random attachment, the expected number of edges among vertex of the same type is equal to

$$\sum_{ij} \frac{k_i^{out} k_j^{in}}{E}\delta(m_i, m_j), \tag{4.13}$$

where k_i^{out} is the OutDegree of the node i and k_j^{in} is the InDegree of node j.

The assortativity Q divided by the number of edges E for the directed graphs results,

$$Q = \frac{1}{E}\left(\sum_{ij} a_{ij} - \frac{k_i^{out} k_j^{in}}{E}\delta(m_i, m_j)\right). \tag{4.14}$$

Since we want $-1 \leq Q \leq 1$ then we normalize Q with the maximum Q that can be obtained starting from N nodes and E edges; it happens when all E edges connecting all the vertexes which belong to the same category, so we can write the Q_{max} is equal to

$$Q_{max} = \frac{1}{E}\left(E - \sum_{ij} \frac{k_i^{out} k_j^{in}}{E}\delta(m_i, m_j)\right). \tag{4.15}$$

Therefore, the assortativity measures normalized is equal to,

$$r = Q/Q_{max}. \tag{4.16}$$

Since r can assume the values which belong in the range $-1 \leq r \leq 1$, they are interpreted in the following way

- if $0 < r \leq 1$, indicates the nodes have an homophily behaviour;
- r close to zero shows the network is a random graph, in other word the nodes don't have any preferential attachment;
- $-1 \leq r < 0$ indicates, the nodes offer disassortative pattern, in sense that nodes prefer to be linked to nodes belonging to different classes.

The assortativity is a measure related to the homophily of the network. The homophily is the behavior for which nodes with the same characteristics tend to connect each other. Sociologist evidenced assortative mix in the friendship, especially for these variables race and language (Moody, 2001). The assortativity measure is very important for measuring systemic risk because it is useful to detect clusters in the network that can be useful to block the shocks propagation in some circumstances as a firewall.

Assortativity by degree

The assortativity can be also applied to the vertex degree. In other words, this measure is useful to capture the tendency of each node to connect with vertex having similar or different degree. This measure is interesting because it is able to detect a core-periphery structure of the graph when the assortativity coefficient is high. In Newman (2003), the assortativity by degree for undirected graph is defined as,

$$r = \frac{\sum_{jk} jk(e_{jk} - q_j q_k)}{\sigma_q^2} \tag{4.17}$$

where,

- e_{jk} is the edges fraction connecting vertexes of j-th degree to vertexes of k-th degree;
- q_j is the probability to have an excess degree equal to j;
- q_k is the probability to have an excess degree equal to k;
- σ_q^2 standard deviation of the distribution of q_k.

For directed graph the assortativity measure is defined in the following way.

$$r = \frac{\sum_{jk} jk(e_{jk} - q_j^{in} q_k^{out})}{\sigma_{in}\sigma_{out}} \tag{4.18}$$

where q_j^{in} and q_k^{out} are respectively the probability to have a excess InDegree equal to j and OutDegree equal to k.

Local Measures

In this Section, we explore some of the numerous local measures used to characterize the node centrality, i.e. the network measures used to identify which are the more central vertex, i.e. financial institutions that are more important, differentiating the directed case from the indirect one.

- **Degree**

  In the undirected network, the degree indicates the number of links for which each vertex is linked to. If A is the adjacency matrix, then the degree is equal to

$$k_i = \sum_j A_{ij} \tag{4.19}$$

  In the directed graphs, it is not possible to define the concept of a degree, because the edges are oriented, therefore is useful to distinguish the measures InDegree and OutDegree. Given the convention the same in Newman (2010), we use for representing the directed graph, the k_i^{in} InDegree and k_i^{out} OutDegree as defined according to these equations,

$$k_i^{out} = \sum_i A_{ij}, \tag{4.20}$$

$$k_i^{in} = \sum_j A_{ij}. \tag{4.21}$$

In particular, k_i^{in} (the InDegree of the node i) counts the number of edges pointing at the node i and k_i^{out} (the out degree of the node i) collects the number of outgoing edges from the node i. These measures are also known as InDegree centrality and OutDegree centrality which assess the centrality of a node and having explanatory power for the max percentage of financial losses (see Billio et al., 2012). In particular, they indicate which are the nodes in the network spreading risk and which absorb it.

- **Eigenvector Centrality**
  This measure proposed by Bonacich (1987), states that the centrality of one node is determined by the centrality of its neighbourhood. This could be formally defined as,

$$x_i = \sum_j A_{ij} x_j, \tag{4.22}$$

where the score x_i is related by the score of its neighbourhood and A is the usual adjacency matrix for undirected graph. Since this equation is self-referential,[1] in order to solve this equation it is necessary to apply an iterative process of t steps (Newman, 2010) that converges to this equation,

$$A\mathbf{x} = \lambda_1 \mathbf{x} \tag{4.23}$$

where $\mathbf{x}$ is the score vector collecting each vertex centrality x_i, and λ_1 is the maximum eigenvalue of the matrix A.[2] Therefore, for each vertex the centrality x_i is equal to the scored of its neighbours scaled by the maximum eigenvalue of the adjacency matrix A, that is,

$$x_i = \frac{1}{\lambda_1} \sum_j A_{ij} x_j \tag{4.24}$$

The concept of the eigenvector centrality could be applied to the directed network, but since the adjacency matrix is not symmetric the right and the left eigenvector are different. The question on which eigenvector to use is relevant. In general, this depends on the concept of centrality we give. If we consider a social network where each person can be represented by a node, then it is reasonable to think that, the node is more central as much as its neigh-

[1] See Jackson et al. (2008).
[2] Perron-Frobenius theorem guarantees there exists only max real eigenvalue λ_1 if A is non-negative.

bours have outgoing edges on it.[3] In this case, the right eigenvector should be used. At the contrary, if we use the left eigenvector, then the node more central is the node having more outgoing edges pointing at nodes with high score.[4] We chose this centrality measure because it explains the propagation of economic shocks better than other measure as closeness and between centrality (see Ahern, 2013). The explanatory power of eigenvector centrality for the max financial loss percentage is also reported in Billio et al. (2012). In addition, this measure from another perspective is the first principal component able to explain the greatest variation among the edges. Therefore, nodes having higher values are more central and they contribute more respectively to spread the risk (if we want to capture the OutDegree effect), or absorbing it (if we want to detect the InDegree effect).
Finally, this measures fit well to the systemic risk phenomenon because the shocks are characterized by the feedback effect (see Ahern, 2013) or called also indirect effect (see LeSage and Pace, 2009; Abreu et al., 2005). With this formula, we are able to capture not just the contemporaneous shocks from one institutions to the others but also the following effects that this shock has on the institutions that are not directly connected to the one originating the shock, i.e. it captures the dynamic propagations of the shocks.

- **Katz Centrality**
  The Katz centrality is slightly different with respect to the standard eigenvector centrality proposed by Bonacich (1987). The measure proposed by Katz (1953), considers a node centrality as a function of the directed and undirected walks of its neighbours, weighted by an attenuation parameter alpha $0 < \alpha < 1$.[5]
  The Katz centrality relative to the node i is defined as,

$$x_i = \alpha \sum_j A_{ij} x_j + \beta \tag{4.25}$$

where α is the attenuation parameter and β is an arbitrary term that avoids to consider in the centrality score all vertex having degree equal to zero. This term assumes the value of 1. For $\alpha = 1/\lambda_1$ and $\beta = 0$, the Katz centrality reduces to the centrality measure introduced by Bonacich (1987).[6] If we write equation 4.25 in matrix form, we obtain,

$$\mathbf{x} = \alpha A \mathbf{x} + \beta \mathbf{1}. \tag{4.26}$$

[3] The more central nodes have high InDegree, and they are pointed by nodes with high InDegree.
[4] The more central nodes have high OutDegree, and they are pointed by nodes with high OutDegree.
[5] A walk is a sequence of vertex and edges through which two vertex are linked. Some authors distinguish the concept of *path* from the concept of *walk*. For them a path is a walk where the intermediate vertex and edges are all different. The number of walk of length k from node i to node j is equal to A^k_{ij}.
[6] The Bonacich centrality is a particular case of the Katz Centrality. We use both in our empirical analysis because they are able to capture the indirect effect coming from the neighbours. The first one is very common in the standard literature $\alpha = 1/\lambda_1$ and $\beta = 0$, the second one allows more freedom, because we can choose the α and β parameters.

If we write the expression function of x, we obtain,

$$\mathbf{x} = (I - \alpha A)^{-1}\beta\mathbf{1}. \tag{4.27}$$

Since the $0 < \alpha < 1$,$(I - \alpha A)^{-1}$ is a convergence of a geometric series with

$$\mathbf{x} = (I + \alpha A + \alpha^2 A^2 + ... + \alpha^k A^k)\beta\mathbf{1}. \tag{4.28}$$

Equation 4.28 is useful to understand the indirect impacts of connections, i.e. in which way the neighbours, and the neighbours of neighbours, affect the nodes centrality. The word "indirect effect" is used in spatial econometric in order to capture the spatial or the spillover impacts that arise in these models in response to neighbours changes in the explanatory variables (see LeSage and Pace, 2009; Abreu et al., 2005). In this case, we use the term "indirect effect", because we aim to detect the effect coming from the neighbours using the Katz centrality equation that distinguishes the propagation of the shocks as a function of the number of walks. Short length walks are weighted more than higher order walks because of the attenuation parameter α. All the effects due to the neighbourhood are collected in this centrality measure.

In the empirical analysis, we compute the Katz centrality, both by making the matrix symmetric and by studying the behaviour of each single financial institution disentangling the ingoing effect and the outgoing effect separately. In this way, we can distinguish the nodes spreading the risk from those that absorb it with the Bonacich measure. The gain we obtain using the Katz centrality is the freedom to weight the feedback effects by choosing an appropriate attenuation parameter α. We are not the first to use this measure in finance: Branger et al. (2014) uses the Katz centrality to analyse shocks propagation in an equilibrium asset pricing framework.

4.3 The data

We use monthly returns data for Banks, Insurers and Hedge Funds downloaded from Datastream and Hedge Fund Research (HFR). We consider for the Banks and the Insurers the list of the global systemically important Banks (G-SIBs) and the list of the global systemically important Insurers (G-SIIs) as indicated by FSB.[7]

In particular, we include for the Banks the components of the fourth, third and second buckets[8] while, for the Insurers, we include all the components. Therefore, the considered G-SIBs comprises HSBC, JP Morgan Chase (JP), Barclays, BNP Paribas (BARC), Citigroup (CITI), Deutsche Bank

[7] Lists updated in November 2015 available at http://www.fsb.org/wp-content/uploads/2015-update-of-list-of-global-systemically-important-banks-G-SIBs.pdf and http://www.fsb.org/wp-content/uploads/FSB-communication-G-SIIs-Final-version.pdf, for Banks and Insurers, respectively.

[8] Buckets identify the higher loss absorbency requirements that Banks will be required to hold.

(DB), Bank of America (BoA), Credit Suisse Group (CSR), Goldman Sachs (GS), Mitsubishi UFJ FG (MUFG) and Morgan Stanley (MS). The considered G-SIIs are: Aegon N.V. (AGN), Allianz SE (ALC), American International Group Inc. (AIG), Aviva plc (AVA), Axa S.A. (AXA), MetLife, Inc. (MET), Ping An Insurance Group Company of China, Ltd. (PAI), Prudential Financial (PRU FIN), Inc. and Prudential plc (PRU).

The hedge-fund data consists of aggregated indices from the HFR provider where we consider two macro-categories: geographic (HFRX) and strategy (HFRI).[9] For the geographic category, the following indices are included: Asia excluding Japan (ASIAexJP), Japan (JP), North America (NA), Brasil (BR), China (CN), India (IND), Latin America (LA), Northern Europe (NE), Russia (RUS) and Western/Pan Europe Index (WPE). For the strategy category, the following indices are included: Equity hedge (EH), Emerging markets (EM), Event driven (ED), Fond of Funds (FOF), Macro and Relative value (RV).

As proxy for the market, we consider the MSCI World index which represents a broad global equity benchmark. Table 4.1 reports the full sample and biannual aggregated statistics including the annualized mean, annualized standard deviation, minimum, maximum, annualized median, skewness, kurtosis and the first-order autocorrelation coefficient ρ_1 for Banks, Insurers and Hedge Funds from January 2005 to January 2016. We consider equally weighted aggregated indices for Hedge Funds (Geographic and investment strategy), Insurers, and Banks. Insurers have the highest annual mean of 13% and the highest standard deviation of 31%. Banks have the lowest mean, 3%, and second highest standard deviation, 28%. Hedge Funds Geographic strategy indices have the highest first-order autocorrelation of 0.34, Hedge Funds Investment Strategy 0.21, Banks 0.25, and Insurers 0.25. This finding is consistent with the hedge-fund industry's higher exposure to illiquid assets and return-smoothing (see Getmansky et al., 2004) but it is striking for the Banks sector. We calculate the same statistics for different time periods: January 2005 - December 2007, 2008-2010, 2011-2013 and 2014-2016. These subsamples reflects tranquil, boom, and crisis periods. It is worth noting that the period 2014-2016 shows negative mean returns for both Hedge Funds categories and Banks. The period 2008-2010 is characterized by very large standard deviations, skewness, and kurtosis. In particular, the Insurers have the highest kurtosis in the full sample 8.23 and in almost all the subperiods.

4.4 Empirical Analysis

In this Section, we estimate the systemic risk measures defined in Section 4.2 using data described in Section 4.3. To estimate systemic risk measures, we use a rolling window approach (e.g., see Zivot and Wang, 2003; Billio et al., 2012) with a window size of 36 monthly observations. Section 4.4.1 contains the results of the quantile based loss measure ΔCoVaR, and Sections 4.4.2 reports

[9]The minimum Asset Size for fund inclusion in the HFRX dataset is \$50 Mil. with at least 24-Month track-record while for the HFRI dataset is \$50 Mil. or at least 12-Month track record. For further details please see https://www.hedgefundresearch.com/compare-hfr-index-types.

Table 4.1: Summary statistics for monthly returns of Geographic and Investment strategy Hedge Funds, Banks, and Insurers for the full sample: January 2005 to January 2016, and five time periods: 2005-2007, 2008-2010, 2011-2013, and 2014-(January)2016. The annualized mean, annualized standard deviation, minimum, maximum, annualized median, skewness, kurtosis, and first-order autocorrelation are reported. We consider equally weighted aggregated indices for Hedge Funds (Geographic and investment strategy), Insurers, and Banks.

	Full Sample							
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.
HF Geographic	4	6	-7	5	7	-1.00	5.66	0.34
HF Strategy	6	9	-8	7	8	-0.57	3.51	0.21
Insurers	13	31	-39	35	15	-0.20	8.23	0.16
Banks	3	28	-26	31	6	0.26	5.26	0.25
	January 2005 - December 2007							
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.
HF Geographic	11	5	-2	3	12	-0.51	2.46	0.01
HF Strategy	18	8	-4	5	21	-0.69	2.98	-0.03
Insurers	20	14	-10	9	24	-0.56	3.58	0.02
Banks	9	12	-9	7	13	-0.73	2.98	0.24
	January 2008 - December 2010							
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.
HF Geographic	2	9	-7	5	6	-0.94	4.24	0.50
HF Strategy	3	12	-8	7	7	-0.56	3.05	0.31
Insurers	6	51	-39	35	14	-0.03	3.91	0.20
Banks	-4	42	-26	31	-35	0.57	3.48	0.32
	January 2011 - December 2013							
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.
HF Geographic	3	5	-4	3	6	-0.84	3.53	0.13
HF Strategy	2	8	-5	4	4	-0.62	2.87	0.11
Insurers	17	24	-16	18	21	-0.26	3.42	0.03
Banks	11	28	-17	15	25	-0.39	2.47	0.12
	January 2014 - January 2016							
	Mean (%)	SD (%)	Min (%)	Max (%)	Median (%)	Skew.	Kurt.	Autocorr.
HF Geographic	-1	4	-3	2	-1	-0.32	2.53	0.17
HF Strategy	-1	7	-4	4	-3	0.21	2.48	0.15
Insurers	4	15	-10	10	11	-0.42	3.88	0.05
Banks	-7	19	-16	11	3	-0.83	4.30	-0.02

the quantile based network measures including a simple visualizations via network diagrams.

4.4.1 Quantile based loss measures:ΔCoVaR

We perform the rolling window quantile regression and estimate the ΔCoVaR for the 11 Banks, the 10 Insurers, 10 Hedge Funds geographical indices and 5 Hedge Funds strategy indices. Figure 4.2 shows the estimation results in terms of inter-quantile range at the 95% (gray area) and the mean (solid line) of the cross-sectional distribution of ΔCoVaR for Hedge Funds investment strategy, Hedge Funds geographic, Banks and Insurers over time. Figure 4.2 shows that Hedge Funds investment strategy and Banks have a ΔCoVaR dispersion higher (gray area) than the Insurers and Hedge Funds geographic, this also points out the systemic contribution heterogeneity of the institutions.

The Figure shows also a level shift for the mean and the median from 2008 to 2011 for all the considered financial institutions. The dispersion is also larger during the global financial crisis of 2007/2008 indicating the different roles of the financial institutions in contributing to systemic risk during the crisis.

For all the four categories we observe a reduction in the contribution to systemic risk in the last part of the sample indicating that either the economic and financial environment has been stabilized or the huge intervention of regulators on one side, that imposes a strong recapitalization of both Banks and Insurers, and the large injections of liquidity by central Banks has reduced indeed systemic risk.

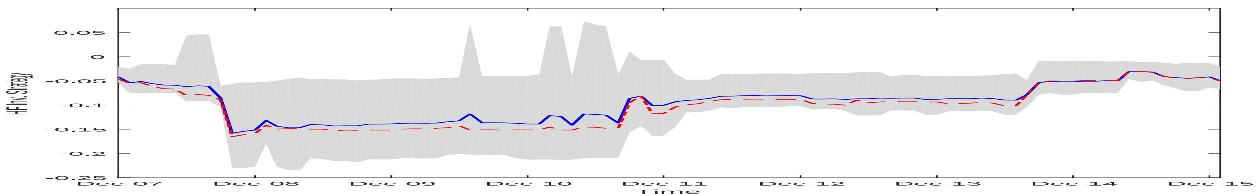
Several other papers have investigated the performance of ΔCoVaR in identifying systemic risk (see in particular Giglio et al., 2016), we prefer to concentrate more on quantile based network measures and the comparison between quantile based loss measures ΔCoVaR and quantile based network measures.

Although the ΔCoVaR method can be easily implemented, one of its drawbacks is the systemic risk underestimation, because of its inadequacy in capturing the non-linear tail effect (Jiang, 2013). This is the main purpose of the comparison that we perform in the following Sections.

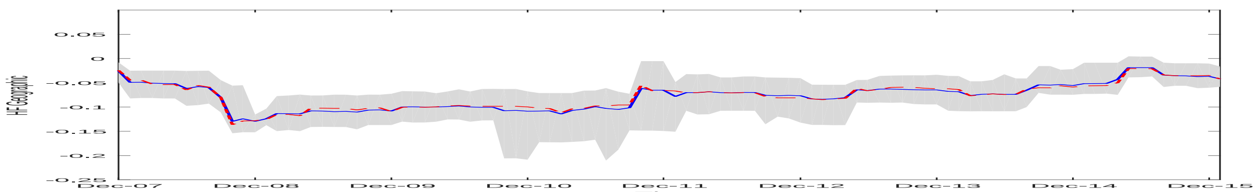
4.4.2 Quantile based network measures

This Section reports the results of the centrality measures for the network estimated with the pairwise quantile regression. Figure 4.3 shows the network diagrams for June 2014 and July 2015. The total number of connections between financial institutions was 864 and 507, respectively, over a total of potential connections of 1260.

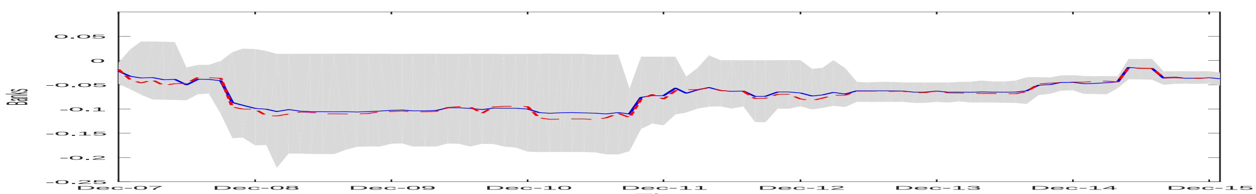
Figure 4.4 reports the global network measure we describe in Section 4.2.2. Figure 4.4 Panel a) shows the first of these global measure: the density of the network (equation 4.11), i.e. the percentage of significant connection through time. The figure shows a positive trend of the network density, from December 2007 until June 2014 and successively a sharply drop in July 2015 from 0.7 to 0.25. This pattern is in line with the reduction of systemic risk contribution of the different



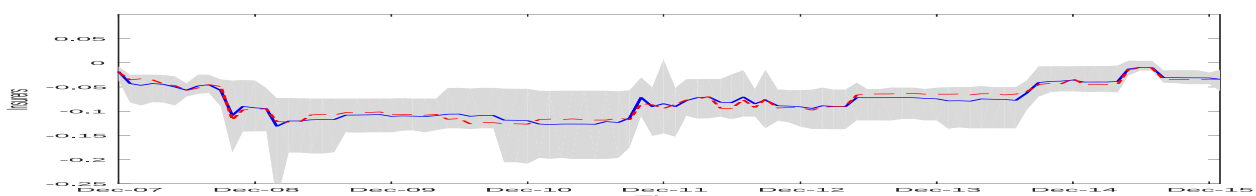
(a) - Hedge Funds Investment strategy



(b) - Hedge Funds Geographic



(c) - Banks



(d) - Insurers

Figure 4.2: 95% high density region (gray area) and the cross-section mean (solid blue line) and median (dashed red line) of ΔCoVaR for Hedge Funds investment strategy (first Panel), Hedge Funds geographic (second Panel), Banks (third Panel) and Insurers (forth Panel) over time.

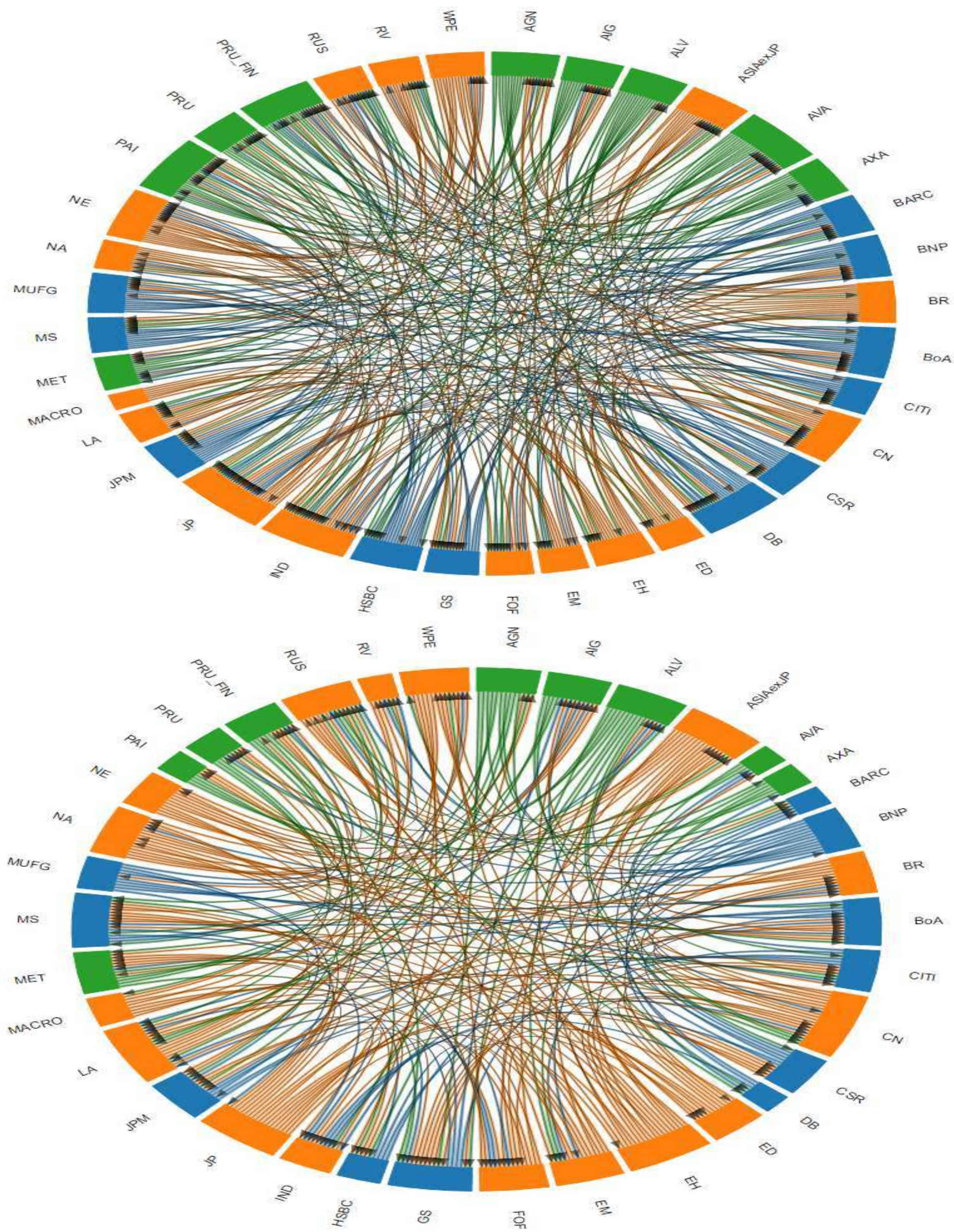


Figure 4.3: Network diagrams of pairwise quantile relationships that are statistically significant at the 1% level among the monthly returns in June 2014 (top) and July 2015 (bottom). Each node represents Hedge Funds indices (orange), Banks (blue), Insurers (green) and the edge describes the financial linkages. Labels are described in Section 4.3.

financial institutions reported for the ΔCoVaR measure and indicates that the level of connections in the system are very low compared to the past.

Figure 4.4 Panel b)shows the behaviour of the Assortativity by degree (equation 4.18). This measure oscillates from a value close to zero in May 2008 to a negative values, or properly from a random graph to a graph with a slight disassortative tendency.

A disassortative network has the property that high degree node tends to connect low degree nodes. A possible explanation of this behaviour can be imputed to the high density we observe in the period, the average is 0.5. The assortativity by degree reaches its minimum value in October 2008 with a value of -0.21. Acemoglu et al. (2012) highlight that the relationship between this measure and the systemic risk is relevant since in highly assortative or disassortative networks (as in this case), the moderate rate for which the aggregate idiosyncratic shock cancels out the diversification benefit. Thus, in a network with assortative or dissociative patterns, the shock propagation could be difficult to absorb. This is exactly what happens just after Lehman default in September 2008 as this measure indicates.

Figure 4.4 Panel c) reports the behaviour of the Assortativity by scalar properties (equation 4.16). The Figure shows that the network has an higher assortativity values respectively in the period from 2008-2011 and after June 2015. A deeper analysis of the measure (available upon request) indicates that during these periods Banks, Insurers and Hedge Funds tend to form groups separately. From June 2012 to December 2014, instead, the network could be associated to a random graph because the assortativity is close to zero. We then move to the local measures reported in Figure 4.5.

Figure 4.5 Panel a) and Figure 4.5 Panel b) exhibit respectively for each node the monthly rolling window InDegree and OutDegree (equation 4.21) and (equation 4.20), with the median (blue dotted line) and the mean (red line with circle 'o' marker). In addition, we computed the median for the three financial institutions groups: Hedge Funds (green line), Insurers (magenta line with asterisk '*' marker) and Banks (black dashed line).[10] The Figure shows that the dispersion of the degree (the grey shadow area) is higher for InDegree than the OutDegree. Focusing on institutions categories by looking to the medians of the Figure 4.5 Panel a), we observe that before July 2011 there is a clear difference between Insurers (with the highest degree) and Hedge Funds and Banks (with the lowest InDegree). This indicates that Insurers during the global financial crisis where largely risk absorbers.

In the last part of the sample, there is a convergence among the median of the three groups. Figure 4.5 Panel b) shows that Hedge Funds (green line) have the highest OutDegree before October 2011, successively, the difference with the other institutions classes is unclear. Thus, after the 2011, the system becomes more interconnected and the categories start to be more connected in line with the drop of the assortativity for that period as reported in Figure 4.4 Panel c).

Finally, we report centrality measures. Figure 4.7 reports the Katz centrality measure (see equation 4.27). We distinguish two kinds of centrality, the first type considers the node prestige (centrality)

[10]We also computed the average for each institutions class that can be compared with the median values.

directly related to the number of neighbours pointing at this node; the second type, instead, defines the centrality as function of outgoing links starting from that node and pointing at its neighbours. This differentiation allows us to understand how the orientation can influence the aggregation of the contribution to systemic risk of each financial institution. Panel a) of Figure 4.7 shows a large dispersion in the last part of the period, instead, Figure 4.7 Panel b) has the highest peak in December 2011. For both Figures, we computed the median (blue dotted line) and the mean (red line with circle 'o' marker) for all the nodes, and also the median by institutions. Panel a) of Figure 4.7 shows that the Insurers Katz centrality dominates the other instituitions classes until October 2011. In Figure 4.7 Panel b), the Hedge Funds Katz centrality dominates the other institutions until December 2011. In the last part of the sample, we observe again the convergence of the medians.

Figure 4.7 provides to us an overview of the heterogeneous centrality of the different institutions through time. However, it is important to investigate which institutions contribute more to the risk of the system or absorbed more risk. The median per group of institution already provides an idea. However, in order to analyse the centrality evolution among the institution classes, once computed all the Katz Centrality measures with $\alpha = 0.5$ and $\beta = 1$, we rank all the institutions, and choose the first 10% best centrality score, and successively we group them by class for each period, as in Figure 4.6. Panel A shows that after the July 2011, the Hedge Funds (blue area) are the more central institutions if we take into account the InDegree effect. Before July 2011, they were more central by looking at the OutDegree effect. This is also confirmed by Figure 4.5. Looking at the dynamic of the centrality, we observe a structural break in the last part of 2011 where there is a change in the topology property of the network.

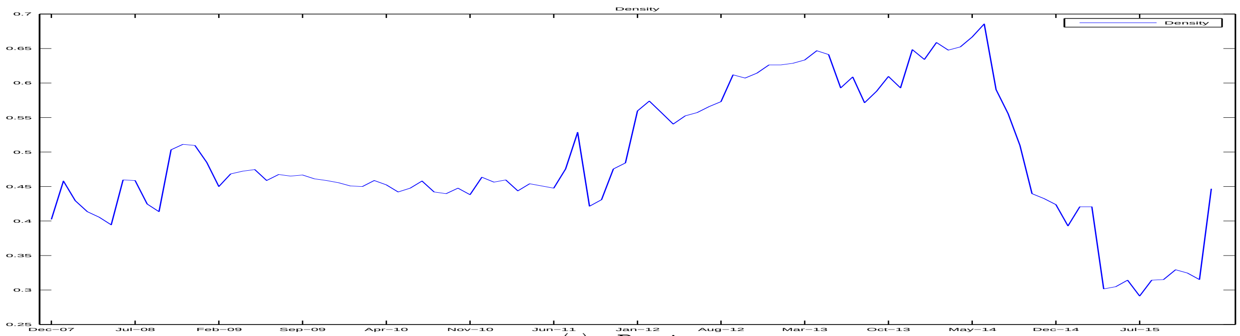
In particular, the Hedge Funds role appears mutated although always central. If we consider the graph orientation, they behave as an "Hub" spreading the risk from December 2007 till December 2011, and as an "authority" absorbing the risk in the last part on the sample.[11]

4.4.3 Rank correlation among the Δ CoVaR and network measures

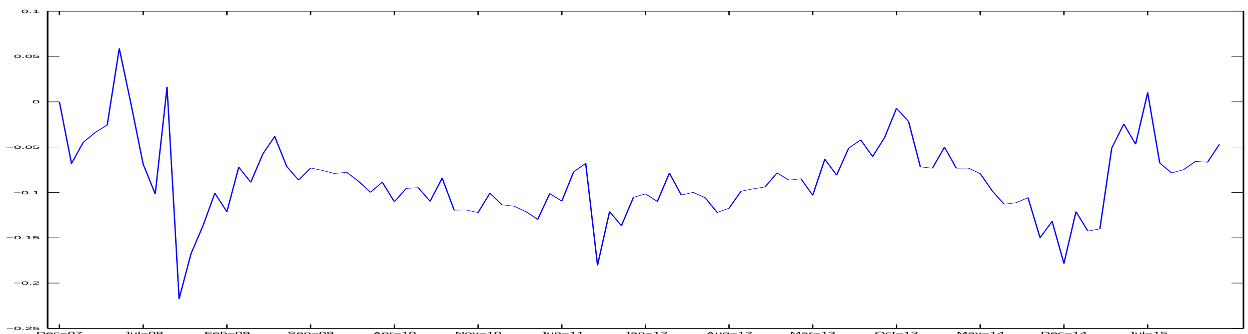
To highlight the different information content of the quantile based loss measure and the quantile based network measure, we perform a rank correlation over time.

We rank the financial institutions from 1 to 36 using both the quantile based loss measure ΔCoVaR and the quantile based network measures such as the Katz centrality InDegree and OutDegree with $\alpha = 0.75$. We then perform a rank correlation of the rankings. Results are reported in Figure 4.8. Figure 4.8 shows that the correlation assumes negative and positive values with the rank correlation ranging from -0.40 to 0.40 both for the In and Out Katz centrality measures. Moreover, Katz centrality measure based on InDegree and OutDegree have a different rank correlation through time with ΔCoVaR indicating that they provide a different information content. Thus, a deeper

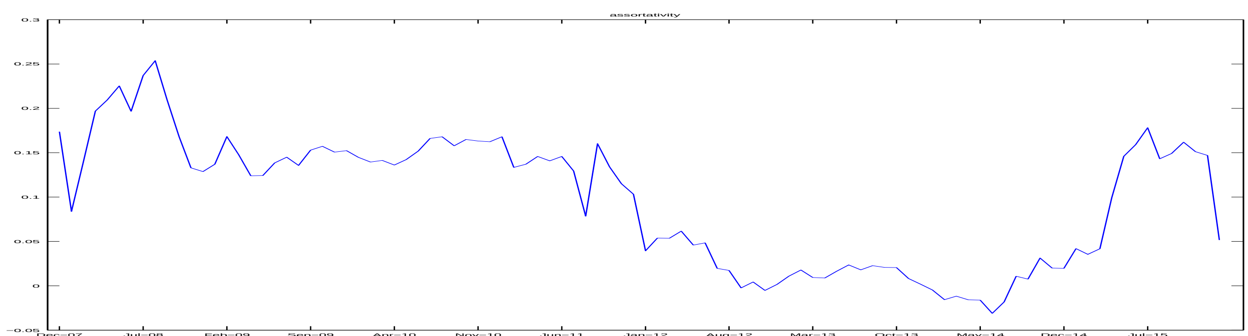
[11] In this context, the concept of hub and authority is purely network related (Newman, 2010). A hub is a central node pointing other central nodes while authorities are central nodes that are pointed by hubs or other nodes.



(a) - Density

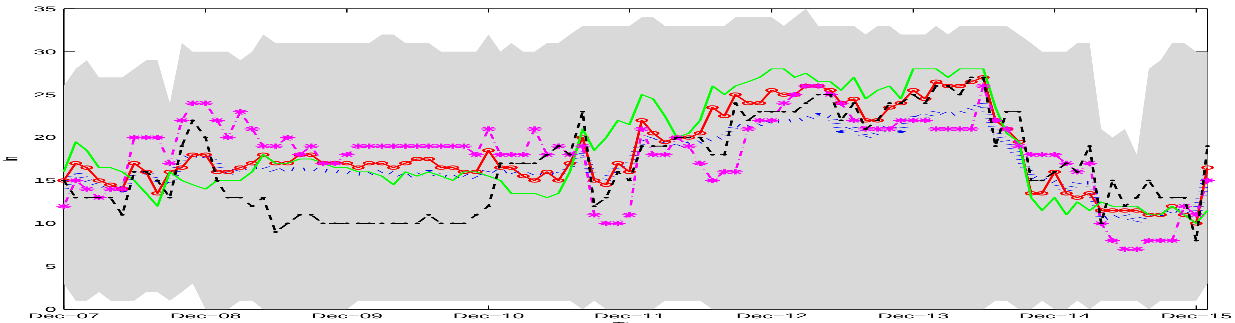


(b) - Assortativity by degree

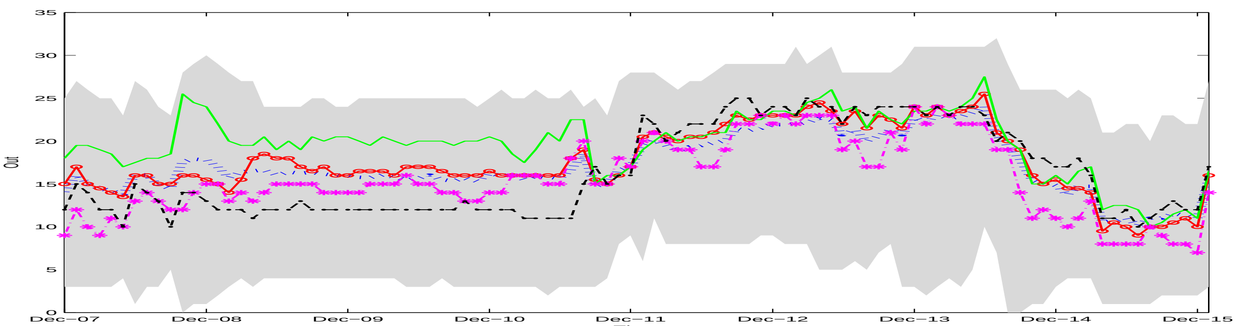


(c) - Assortativity by scalar characteristics

Figure 4.4: This Figure shows the global network measures from December 2007 till January 2016. Panel a) reports the density measures. Panel b) reports the assortativity measures by degree. Panel c) reports the assortativity by scalar characteristics.

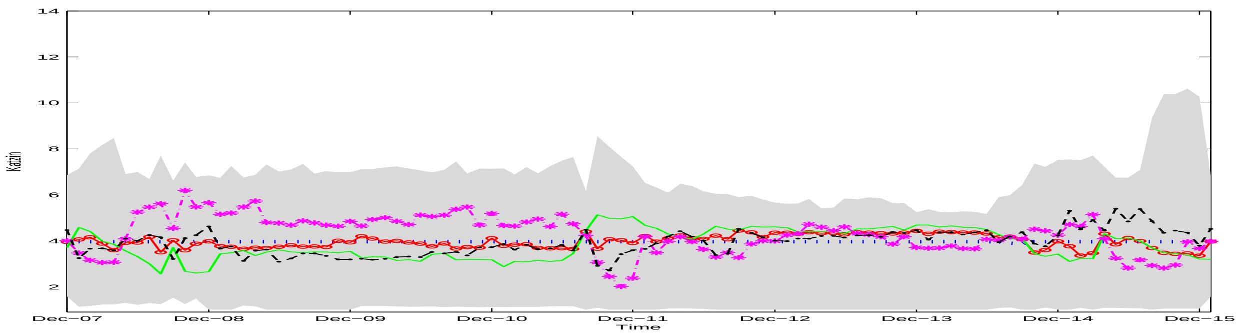


(a) - InDegree

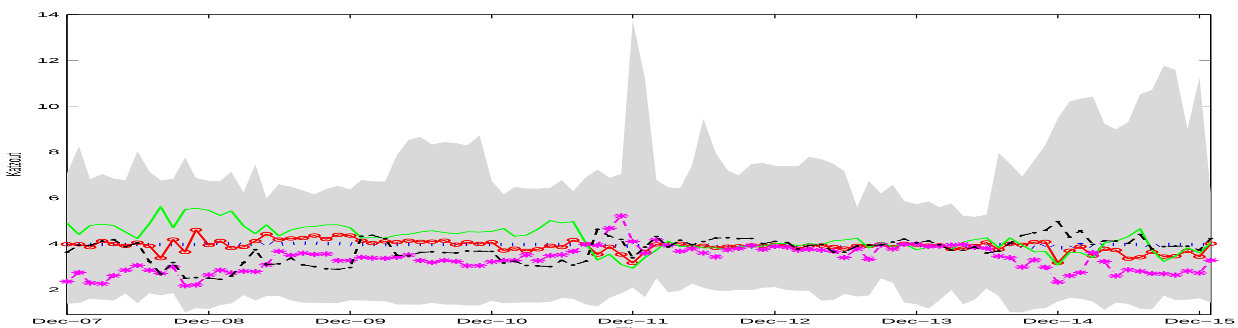


(b) - OutDegree

Figure 4.5: The Figure reports the local measure based on degrees for the period December 2007 to January 2016. Panel a) shows the dispersion of the InDegree, the red line (with 'o' marker) represents the InDegree average, the blue dotted line indicates the median. The green line, magenta line (with '*' marker) and black dashed line represent the median respectively for Hedge Funds, Insurers and Banks InDegrees. Panel b) shows the dispersion of the OutDegree. The red line (with 'o' marker) represents the InDegree average, the blue dotted line indicates the median. The green line, magenta line (with '*' marker) and black dashed line represent the median respectively for Hedge Funds, Insurers and Banks OutDegrees.

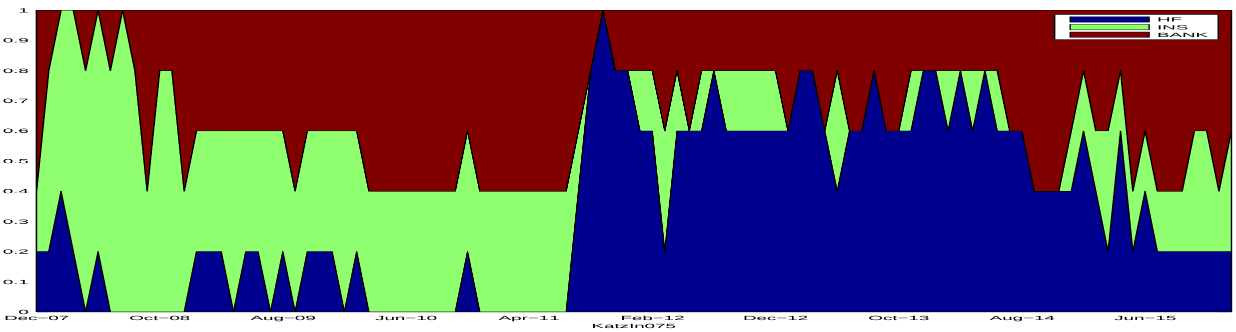


(a) - Katz Centrality Indegree Effect

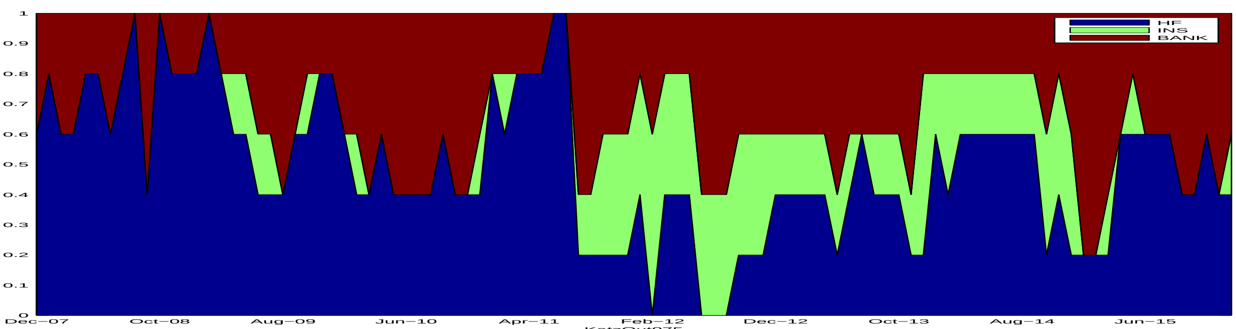


(b) - Katz Centrality OutDegree Effect

Figure 4.6: The Figure reports the Katz centrality measure for the sample period December 2007 to January 2016. Panel a) shows Katz centrality dispersion with $\alpha = 0.75$ and $\beta = 1$ based on InDegree. The red line (with 'o' marker) represents the average and the blue dotted line indicates the median. The green line, magenta line (with '*' marker) and black dashed line represent the median respectively for Hedge Funds, Insurers and Banks. Panel b) shows Katz centrality with $\alpha = 0.75$ and $\beta = 1$ based on OutDegree. The red line (with 'o' marker) represents the average and the blue line indicates the median. The green line, magenta (with '*' marker) line and black dashed line represent the median respectively for Hedge Funds, Insurers and Banks.



(a) - Top Katz Central Institutions InDegree Effect



(b) - Top Katz Central Institutions OutDegree Effect

Figure 4.7: The Figure reports the top 10% central institutions by using the Katz centrality with $\alpha = 0.75$ and $\beta = 1$ from December 2007 to January 2016. Panel a) reports the Top Central institutions based on on the Katz centrality InDegree. Panel b) reports the Top Central institutions based on the Katz centrality OutDegree. The blue area indicates the fraction of top central Hedge Funds, the green area the fraction of the top central Insurers, the red area the fraction of the top central Banks.

investigation on the "directed" centrality measures is useful to understand in which way the directionality matters. Overall, our findings confirm that loss and connectedness measures exploit different dimensions of systemic risk.

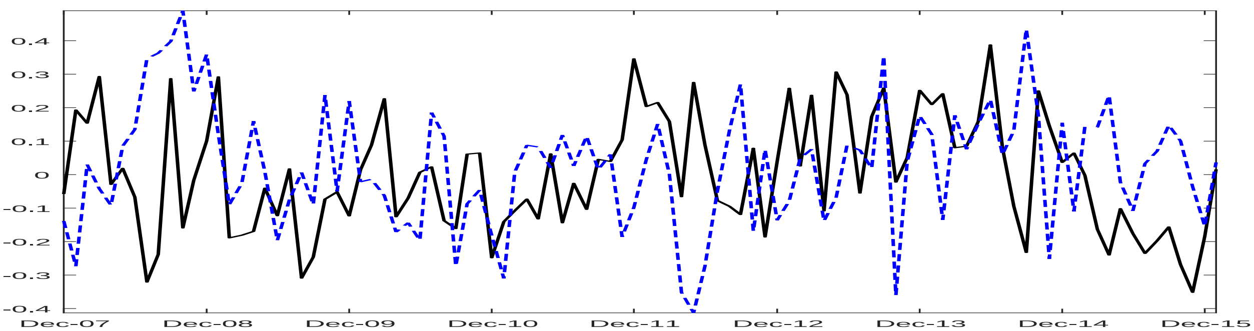


Figure 4.8: Figure reports the rank correlation patterns computed respectively between ΔCoVaR and Katz-In (black line) and ΔCoVaR and Katz-Out (dashed blue line) with $\alpha = 0.75$.

4.4.4 Predictive power of the measures

To evaluate the predictive power of the quantile based loss measure $\Delta CoVaR$ and quantile based network measures, we follow an out-of-sample analysis as in Billio et al. (2012). We first compute the maximum percentage financial loss (Max%Loss) suffered by each of the financial institutions during the crisis period from January 2008 to June 2009. We then perform a cross-sectional analysis among institutions by considering the Max%Loss as dependent and systemic risk measures. The results are reported in Table 4.2 for the sample January 2005 to December 2007. The Table shows that quantile based network measures such as Katz centrality and degrees measures are significant determinants of the Max%Loss variable. In particular, orientation matters for explaining the maximum percentage financial loss. The Katz centrality measure based on the outgoing links is significant and has an R^2 of 0.29. Instead, the Katz centrality measure based on the ingoing links is not significant. Similarly, the InDegree is significant but the R^2 is 0.13 and the OutDegree is also significant but have an R^2 of 0.25. Based on the R^2 criterion, the Katz centrality measure based on outgoing links provides a superior information content and a better prediction ability than the other network measures. Surprisingly, the $\Delta CoVaR$ it is also significant but is shows a negative dependence with the maximum percentage financial loss, revealing, in this case, a meaningless measure, i.e. financial institutions of which the ΔCoVaR predicts the largest losses are the one that loose less during the crisis. Also the network measures have negative signs. This result is coherent with Allen and Gale (2000) and Freixas et al. (2000b) who suggested that a more interconnected architecture enhances the resilience of the system and consequently, the chances to tackle the insolvency of any individual Bank. In summary, the results confirm the goodness of the quantile based network measures as valid tools for policy makers to investigate systemic risk and G-SIFIs.

Table 4.2: Out-of-sample analysis. Parameter estimates of a multivariate rank regression of Max% Loss for each financial institution during January 2008 to June 2009 on loss measures and network measures. The maximum percentage loss (Max% Loss) for a financial institution is the maximum decline in returns for each financial institution during January 2008 - June 2009. Loss measures and network measures are calculated over January 2005 - December 2007. The table reports the coefficients and the standard errors in round brackets. Parameter estimates that are significant at the 5% level are shown in bold. All the Katz centrality measures are computed with $\alpha = 0.75$.

Variable	Max%Loss				
	January 2005 - December 2007				
(intercept)	**0.58**	**0.60**	**0.88**	**0.66**	**0.79**
	(0.11)	(0.18)	(0.15)	(0.13)	(0.11)
ΔCoVaR	**-9.13**				
	(3.89)				
Katz-In		-0.06			
		(0.04)			
Katz-Out			**-0.13**		
			(0.04)		
InDegree				**-0.02**	
				(0.21)	
OutDegree					**-0.03**
					(0.18)
R^2 0.17	0.14	0.06	0.29	0.13	0.25

4.5 Conclusion

In designating G-SIFIs a variety of factors have been considered by regulators with interconnectedness being one of the criteria. The key reason is that the complexity of the financial system highlights the importance of the interconnectedness among financial institutions in generating systemic risk. In this paper, we apply several econometric measures of connectedness on the network extracted using pairwise quantile regressions. We highlight the different informative content between quantile based network measures and quantile based loss measures such as $\Delta CoVaR$. We consider G-SIFI Banks and Insurers and Hedge Funds. We use the degree and the Katz Centrality measures for capturing the indirect network effect on risk spillover.

The results show the following: Firstly, the network measures and the loss measures are not highly correlated, this means that they are capturing different features of systemic risk. Secondly, Hedge Funds that during the Global financial crisis were among the institutions that largely spread risk, in the recent period largely absorb risk. Instead, Insurers largely absorb risk during the global financial crisis and more recently are playing a lower role both as risk spreader and risk absorber. Banks are always having an important role both as risk absorber and risk spreader. Thirdly, the centrality measures substantially explain the Max financial loss percentage more than the loss measures based on $Delta$CoVaR. Finally, centrality measures based on an oriented graph have a higher explanatory power than degree measures. These results confirm the importance of investigating the role plaid in the financial system of the different financial institutions using network measures since they better capture the “indirect” effects of risk spillovers.

Chapter 5

The Demand for Central Clearing: To Clear or Not to Clear, That is the Question

5.1 Introduction

The Global Financial Crisis exposed a number of systemic weaknesses in the market for over-the-counter (OTC) derivative securities. In response, the G20 Leaders in 2009 initiated a fundamental overhaul of OTC derivatives markets with the objectives to mitigate systemic risk, improve transparency, and protect against market abuse. The G20 Leaders made five commitments to reform OTC derivatives markets: 1) standardized OTC derivatives should be centrally cleared; 2) non-centrally cleared derivatives should be subject to higher capital requirements; 3) non-centrally cleared derivatives should be subject to minimum standards for margin requirements; 4) OTC derivatives should be reported to trade repositories; and 5) standardized OTC derivatives should be traded on exchanges or electronic trading platforms, where appropriate.[1]

As a regulatory response, the U.S. Congress signed the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA) into law in July 2010, and the European Parliament and the Council of Ministers agreed on the European Market Infrastructure Regulation (EMIR) in August 2012.

While in Europe and in the US credit default swap (CDS) indices must be cleared under the MiFID regulation,[2] a rule for single name CDS reference entities has not yet been finalized, therefore the decision to clear single name CDS is still voluntary to date. From the BIS reports[3] one can deduce that the share of cleared derivatives contracts continues to be a relatively small fraction of

[1] See the FSB report to G20 Leaders on progress in financial regulatory reforms, available at `http://www.fsb.org/2017/07/fsb-reports-to-g20-leaders-on-progress-in-financial-regulatory-reforms/`.

[2] The Markets in Financial Instruments Directive 2004/39/EC and Exchange Act Section 3C(b)(4)(B).

[3] See the BIS over-the-counter (OTC) derivatives statistics database, available at `http://stats.bis.org/statx/srs/table/d10.4?p=20162&c=`.

the total notional amount outstanding (around 37% as reported by Financial Stability Board, 2017), though this fraction is increasing over time. While there is not yet a regulatory obligation to clear single-name contracts in the EU and in the US, there may be relevant economic incentives to do so. The research question of this paper is why only some sovereign CDS transactions currently eligible for central clearing are cleared while others are not. We investigate this from a clearing member perspective, and focus on what are the drivers of this decision by considering factors impacting (i) collateral cost, (ii) capital cost and (iii) transparency.

We investigate empirically the relevance of these different drivers in the decision to clear by using a unique regulatory dataset: the confidential European trade repository data on single-name sovereign CDS transactions ruled by the EMIR. The database used for our analysis includes all derivatives transactions by EU financial institutions in 2016. However, our analysis focuses on the most traded European sovereign CDS contracts: Italy (IT), France (FR) and Germany (GE). The choice of the CDS contracts is not done only due to the trading activity but also to reflect differences in risk characteristics of the underlying reference entities. Finally, we concentrate on sovereign CDS contracts, because they are the contracts mostly traded by European institutions, and therefore well represented in our database (see Abad et al. (2016)).

To our knowledge, our paper is the first that investigates empirically the fraction of eligible contracts for clearing and the drivers of the decision to clear a contract. We find that in our sample about 48% of the notional amount traded in 2016 has been cleared, 42% were not cleared despite being eligible for central clearing, while 9% of the contracts were not clearable because they did not satisfy certain Central Counterparty Clearing house (CCP) clearing criteria.

However, we notice a strong differentiation in the decision to clear between clearing members and non-clearing members. Clearing members account for 96.5% for the gross notional amount traded in our sample, and they are net buyers for an aggregate 9.7 billion US dollars, a size comparable to net selling position of non-clearing members that are not subject to capital requirements (-8.1 B$). For clearing members, we find that the fraction of cleared contracts is larger, 53%, while the fraction of non-eligible contracts is 8%. All clearing members are subject to capital requirements, and have capital charge benefit if they clear the contracts. Nevertheless, among non-clearing members, both those subject to capital requirements (banks and insurances) and the others not subject to capital requirements, do not clear their CDS contracts to a large extent. This might be due to two main reasons. First, capital requirements charged for the default funds for central clearing as well as the costs for becoming a clearing member are too high for them. Second, the indirect clearance is also more costly for them than the benefit they get from the reduction of the capital requirement charge.

Regarding the drivers of the decision to clear for clearing members, we look at different characteristics of the contracts that could capture the differences in terms of margin and capital costs between cleared and not cleared contracts. Concerning collateral requirements, one key aspect is the existing disparity between initial and variation margins between cleared and non cleared contracts. In fact, for the most part, margins are not exchanged or are lower in the OTC transactions, while they are always required for cleared trades (at least until the new regulation on OTC derivatives is in place). On the other side, Counterparty Credit Risk (CCR) capital charge introduced by the Basel III for bilateral trades is larger for non cleared transactions than for centrally cleared trades. This should provide a relevant incentive to clear, at least for institutions subject to capital requirements.[4]

We model the incentives to clear (or not) a contract based on the characteristics of the contract that affect both the margin setting by CCPs and CCR capital requirements such as (i) price; (ii) change in the price; (iii) volatility of the price; (iv) liquidity of the contract; and (v) size of the transaction. In principle, more risk could encourage clearing in order to reduce CCR capital requirements, but on the other side, more risk means larger margins and therefore costs. Only by investigating this issue empirically we can disentangle which element prevails.

Moreover, one key aspect that should be considered is that the counterparties must agree on the decision to clear, therefore not only the characteristics of the contract are relevant for the decision to clear in terms of margin costs but the individual incentives of each trader related to their portfolio exposures with the CCP also matters. For this reason, we look at the net position at CCP because it might be a relevant variable for the decision to clear. If a transaction reduces the counterparty's outstanding exposures against the CCP, the willingness to clear is expected to be larger since it will reduce margin requirements. Another main incentive to clear refers to CCR itself, independently on the size of the exposure or the riskiness of the reference entity. The CCR plays an important role since the "safer" counterparty should prefer to clear, at least above a certain level of CCR, other things the same. We capture the CCR itself by looking at the CDS spread of the traders.

The last main driver that we consider for the decision to clear is the difference in post-trade transparency between cleared and non cleared contracts. Cleared contracts are subject to post-trade transparency through the CCP. Non cleared contracts are not subject to post-trade transparency at least till the beginning of 2018 when MiFID II would be effective and the post-trade reporting requirements also for OTC derivatives are in place. Transparency might offer speculation opportunities to other traders, in particular if the size of the transaction is large. Therefore, if this is an important driver in the decision to not clear the contract, we should find that the larger contract size lowers the incentive to clear the contract.

Focusing on clearing members, our analysis reveals that there are significant differences in the main drivers of the decision to clear among the three sovereign CDS contracts we considered. The riskiness of the reference entity, measured by the level of the CDS spread, increases the probability to go through central clearing. However, daily increases in the CDS spread or CDS spread volatility

[4]In the paper we refer to the difference in terms of CCR capital requirements between cleared and not cleared transactions, but in general, a large counterparty credit risk exposure should already be an incentive to clear the contract, independently from the different treatment in terms of capital requirements. However, since this was not a sufficient incentive in the past to clear contracts, we prefer to refer to capital cost reduction of cleared contracts as one of the drivers to clear the contract and not just the CCR exposure.

reduce the probability of clearing for German and French sovereign CDS but increase it for the Italian sovereign CDS. It seems therefore that the main drivers of the decision to clear for the Italian CDS are margin costs instead for France and Germany CCR capital requirements. Furthermore, higher notional amounts are more likely to be cleared across all three sovereign CDS contracts, indicating that CCR capital requirement benefits prevail with respect to transparency issues.

We investigate how counterparty credit risk stand-alone effects the decision to clear by examining the riskiness of the two counterparties that agree to trade. We find that both the seller and the buyer manage counterparty exposures strategically choosing to clear when the counterparty is riskier. This means that the benefit in the reduction of CCR capital requirements provide strong incentives for clearance to clearing members.

Consistent with the notion that clearing members need to post greater initial and maintenance margins with the CCP when their net exposure with the CCP is larger, we find evidence that when the trade reduces the counterparty's outstanding net positions with CCP, the probability to clear the trade is higher. Thus, overall we find that the decision to clear is a complex decision not just related to a single contract but to the portfolio holdings and total exposures with the CCPs, as well as to the ability of CCP to post rules for automate netting/cancellation of offsetting contracts.

The paper is organized as follows. In Section 5.2 we describe the regulatory framework and review related literature. In Section 5.3 we formulate the hypotheses tested in the paper. In Section 5.4 we briefly describe the dataset. In Section 5.5 we provide an overview of trading and clearing in sovereign CDS. In Section 5.6 we report the empirical evidence regarding the decision to clear or not an eligible contract and finally Section 5.7 concludes.

5.2 Regulatory framework and related literature

The regulatory framework underlying the paper follows the agreement the G20 Leaders reached in 2009, which requested that OTC derivatives contracts should be cleared through CCP. This decision came after the Global Financial Crisis of 2007-2009, which highlighted the systemic weaknesses in the financial market infrastructure, especially for the OTC derivative securities. In particular, the market for CDS was characterized by highly concentrated and interconnected positions that serve as a conduit for the transmission of systemic risk in the event of a counterparty failure. Since that, the regulators have advanced a number of reforms that are likely to affect the incentives for central clearing of these contracts. To improve coordination, the OTC Derivatives Coordination Group was formed.[5]

The primary regulatory response has been in the US in 2010, where the U.S. Congress signed the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA), and in Europe, where

[5] The institutions belonging to the OTC Derivatives Coordination Group are: the Financial Stability Board (FSB), the Basel Committee on Banking Supervision (BCBS), the Committee on the Global Financial System (CGFS), the International Organization of Securities Commissions (IOSCO) and the Committee on Payments and Market Infrastructures (CPMI), previously known as the Committee on Payment and Settlement Systems (CPSS).

the European Parliament as well as the Council of Ministers agreed on the European Market Infrastructure Regulation (EMIR) in August 2012. Both of these reforms are designed to promote financial stability by improving accountability and transparency in the financial system. In the US, the Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) have been delegated to implement the DFA, while in Europe, the European Securities and Markets Authority (ESMA), has been delegated for the implementation of the EMIR.

In the Basel III framework (Bank for International Settlements, 2012), banks' collateral and mark-to-market exposures to the central counterparties are subject to a lower risk weight, while the default fund exposure to the CCP is subject to capital requirements. On the contrary, the regulatory reforms of the derivatives markets include requirements to exchange initial and variation margins for non-centrally cleared derivatives exposures. The two main regulatory acts are the "Margin requirements for non-centrally cleared derivatives" (BCBS-IOSCO) and the "Principles for Financial Market Infrastructures" (CPMI-IOSCO). In view of these regulatory changes, the OTC Derivatives Assessment Team at BIS performed a study in 2014 to assess incentives to centrally clear OTC derivatives (Bank for International Settlements, 2014). This survey identified that the main drivers for the decision to clear are margin costs and capital costs. Moreover, it performed a quantitative analysis and found that CCP's clearing member banks have incentives to clear centrally, while incentives for market participants that clear indirectly are less obvious. Our paper aims to shed some light on these issues.

In 2017, the OTC Derivatives Coordination Group agreed to make an evaluation of the impact of G20 reforms on incentives to centrally clear the OTC derivatives. The Derivative Assessment Trades (DAT) at FSB conducted a study in order to understand whether the G20 financial regulatory reforms have achieved their intended outcomes. The report stressed the difficulties in identifying the fraction of standardized OTC contracts eligible to clear, and therefore to measure the total proportion of standardized OTC derivatives that are centrally cleared. The report also indicates that more favorable regulation for cleared transactions combined with higher OTC transactions capital requirement would incentivize banks to clear new transactions. The DAT report provides evidence that the number of contracts cleared related to interest rate derivatives and credit derivatives has increased markedly after 2009. The report shows that, at the end of 2016, the central clearing rate of the stock of outstanding CDS is estimated to have reached 28% globally, and 37% in EU (Financial Stability Board (2017)).[6]

Both the theoretical and empirical literature on central clearing is growing, in particular on the CDS market, especially after ICE launched the first dedicated clearing house in March 2009. However, already before the Global Financial Crisis, there were authors suggesting that an im-

[6] Our paper complements the FSB work and extends it along the following dimensions. First, our study is able to distinguish whether the OTC derivatives contracts are eligible for clearing or not, therefore increasing the accuracy of the evidence on the extent of central clearing occurring. Second, by focusing on certain asset derivative class, sovereign CDS in our case, we are able to dig deeper into the main drivers of the decision to clear the derivatives contract.

portant public policy issue is whether and how to (i) encourage the use of the CCPs; and (ii) standardize part of the OTC derivative market. Bliss and Steigerwald (2006) recognize that CCPs bring a bundle of interrelated services to the market, including credit risk management, delegated monitoring, and liquidity enhancement. In particular, they stressed that one of the key advantages of CCP is that credit risk becomes homogenized, at least as far as clearing members are affected. Moreover, in a centrally cleared derivatives market, the clearing house typically sets the rules for the automatic netting and cancellation of offsetting contracts. Further, clearing derivatives through a CCP facilitate market liquidity. It allows, for instance, three different counterparties to exit the contracts without the need for an agreement by them and eliminating the credit risk of the offset contracts.

Duffie and Zhu (2011) provide a framework where the introduction of clearing for a single asset class, like CDS, could limit netting efficiencies increasing collateral demand and counterparty exposures at the same time. With a different parameterization of the model and different assumptions, Cont and Kokholm (2014) find that multi-asset class central clearing reduce interdealer exposures, but a single non-specialized clearing house can pose systemic risk issues. Acharya and Bisin (2014) show in their theoretical model that central clearing limits the excess risk-taking by the counterparties because of greater transparency and margin requirements. In the model of Biais et al. (2016) central clearing and an optimal margin design mitigate the moral hazard of excessive risk-taking and reduce counterparty risk. This prediction is consistent with Koeppl et al. (2012). Zawadowski (2013) shows that welfare improves when the OTC contracts are taxed to finance a bailout fund. Duffie et al. (2015) in their theoretical model calibrated with DTCC data find that collateral demand does not increase with mandatory central clearing. The model of Ghamami and Glasserman (2017) identify three main drivers to centrally clear a transaction when there is no clearing obligation, from the dealer's perspective. The first is the netting efficiency across asset classes; the second is the margin period of risk, i.e., the time between the counterparty's default and the closing of position; and the third is the size of the clearing members' contribution to the default fund.

The empirical literature on central clearing and CDS mainly uses DTCC data. Shachar (2012), for example, uses a sample of trades from 2007 to mid-2009 and finds that, as long as the cross exposure between dealers accumulates, the liquidity worsens. Loon and Zhong (2014), using a sample of 132 reference entities cleared by ICE and Markit quoted CDS spread, find that CDS spread increases after the introduction of central clearing, indicating that counterparty risk is priced. However, Du et al. (2016) using DTCC transaction data find the opposite results, i.e. cleared trades have lower spreads compared to uncleared trades. The latter result is consistent with Arora et al. (2012) who, with a proprietary dataset, show that the counterparty risk is priced, but is economically very small in magnitude. Siriwardane (2015) shows that the high concentration of the market around the dealers results in more volatile CDS premiums, while Mayordomo and Posch (2016) find that central clearing could lead to an increase in market activity especially for riskier dealers.[7]

Our paper is complementary to the above literature as it provides empirical evidence on the extent of central clearing and the underlying causes for the clearing decision. To our knowledge, this is the first academic paper that empirically investigates these issues.

5.3 The Drivers of the Decision to Clear: Testable Hypotheses

Central clearing removes direct counterparty credit risk and replaces it with an exposure to a CCP. Under central clearing, a bilateral trade between two counterparties is replaced by two separate trades with the CCP. Since the CCP creates a legal separation between the original counterparties, she absorbs the risk associated with a counterparty default and protects the non-defaulting counterparty. The effectiveness of a CCP is predicated on the requirement that clearing members post adequate capital and maintain sufficient collateral (margin) so that impacts of a defaulting clearing member can be mitigated. Moreover, these amounts should be sufficient so that the clearing house and its non-defaulting clearing members can absorb a clearing member default.

The SEC and the ESMA are both granted the power to determine which types of derivatives contracts are to be obligatory or voluntary centrally cleared. The eligibility depends on a number of specific factors, which include: 1) sufficient activity, trading liquidity, and adequate pricing data; 2) a well-functioning infrastructure to support clearing; 3) the opportunity for systemic risk mitigation; 4) the impact on competition; and 5) the opportunity to resolve failures of the clearing house or clearing members with reasonable legal certainty.[8] On top of these factors identified for eligibility, the CCPs define other specific criteria for clearing eligibility of the different types of contracts. In Europe, beyond certain interest rate derivative classes, the clearing obligation concerns only untranched index CDS classes. Thus, the decision to clear single name CDS contracts is voluntary.[9] This creates the conditions to study the factors that influence the decision to voluntarily clear a

[7]The literature on CCP and systemic risk is also large. The financial regulators identify the OTC derivatives market as a key source of instability, due to their interconnected nature of CDS counterparties that can potentially collapse in sequential failures of other counterparties (domino effect) starting from the failure of a single counterparty, as stressed by Pirrong (2011). For these reasons, an overarching aim of EMIR regulation is to mitigate the buildup and transmission of systemic risk in the derivative market. Given the large size of the net economic exposures between derivative dealers, the possibility of correlated counterparty failures is systemically important (see Getmansky et al. (2016)). Domanski et al. (2015) discuss how clearing houses could propagate systemic risk in financial markets through domino effects and deleveraging mechanisms. They suggest to increase the financial strength of both clearing members and CCPs, and develop robust risk management practices for the clearing houses. Lewandowska (2015) shows by using a simulation approach, that the mandatory clearing of all standardized OTC derivatives by a Central Clearing Counterparty would significantly decrease systemic risk only if the regulators ensure a sufficient number of clearing member and asset cleared. Amini et al. (2015) show how central clearing counterparties not only reduce the systemic risk but also increase the utility of banks through the netting benefits and the redistribution of default management resources within the financial market. Menkveld et al. (2015) analyze the effect of the central clearing counterparties on price stability by looking at the Nordic equity market, and find a volatility and volume reduction without any deterioration in market quality.

[8]See Exchange Act Section 3C(b)(4)(B) and discussion in Porter (2015).

[9]See ESMA for further information regarding clearing obligation of derivative contracts available at `https://www.esma.europa.eu/regulation/post-trading/otc-derivatives-and-clearing-obligation`

CDS single name contract. In this paper we investigate the following question: why only some sovereign CDS transactions currently eligible for multilateral clearing are being cleared while others are not? We analyze, from the clearing member perspective, what are the drivers of this decision by considering the following factors:

1. Margin costs: margin costs are related to both (i) the characteristics of the CDS contract and (ii) counterparty credit risk. Characteristics of the CDS contract, such as the liquidity and the risk of the underlying reference entity have a direct impact on the margin. Moreover, CCPs differentiate margins among counterparties having different ratings, i.e. having different CCR. We model CCR as a function of the stand-alone risk of the counterparties. Therefore, the higher is the risk of the reference entity or the stand-alone CCR, the larger are the margin costs and the lower would be the incentive to clear.

2. Counterparty credit risk (CCR) capital requirements: Capital costs due to capital requirements are larger the higher is the CCR exposure. Since CCR capital requirements are lower for cleared contracts, higher is the CCR exposure larger would be the benefit in terms of capital requirements reduction if the contract has been cleared and therefore higher would be the incentive to clear. The ingredients are therefore the same as those of margin costs, but have the opposite effects on the incentives to clear. The reduction of CCR capital requirements through clearance is larger when (i) the CCR stand-alone is high and (ii) the exposure or the risk of the position is high.

3. Risk management: reduction of the clearing member CCP total margins exposure, which we model as a function of the size of the counterparties' outstanding exposures towards the CCP;

4. Transparency: differences in post-trade transparency between cleared and not cleared contracts might also provide lower incentives to clear because transparency might offer speculation opportunities to other traders. This is one of the main reasons why large size trades are usually performed OTC. We proxy the transparency incentives to not clear through the size of the contract.

These four factors are not independent. Clearly Factors 1 and 2 are largely related, and in most of the cases, they are the two faces of the same coin. In fact, on one side, clearance allows to reduce CCR capital requirements, but at the same time, the larger are the CCR exposures, the larger are the margin costs. Factor 3 includes a different perspective regarding margin costs, i.e. the fact that the cost of margins is based on the total net exposure the clearing member is having with the CCP and does not refer to just the single contract as in Factors 1 and 2.

Another factor that would be interesting to add to our analysis is the trade-off between multilateral netting through the CCP and bilateral netting between counterparties. Unfortunately, for the German and the French sovereign CDS contracts we cannot identify the counterparty of the

CCP, and for the Italian CDS we were able to identify it only for a fraction of transactions. For this reason, we leave the investigation of this issue to further research.

We analyze the role of the above factors in the decision to clear, using a probit model. Specifically, we examine how clearing members react to the incentives and costs provided by central clearance. We test the following Hypothesis:

Hypothesis 1: Willingness to clear is larger if the contract is less liquid, has a large size and the reference entity is more risky.

The features of the contract can affect the clearing decision because margins and capital costs are largely related to the riskiness of the reference entity and the size of the contract. In particular, when the reference entity is risky or is becoming riskier, or when the size of the contract is large, margins would be high, both at the initial and maintenance level. For these reasons, the dealer has a lower incentive to clear. This refers to Factor 1 described above. Moreover, if the size of the contract is large, the dealer might prefer to avoid to clear it for transparency reasons. This also provides an incentive of not clearing the contract and refers to the Factor 4 reported above. However, reference entity risk and size of the contract affect CCR capital requirement costs as described in Factor 2 above. Therefore, the larger is the risk or the volume of the contract, the higher is the incentive to clear. To disentangle which of the factors prevails, an empirical analysis is required.

We formulate Hypothesis 1 as if CCR capital requirement reduction costs prevail as a reason to clear with respect to larger margin costs and transparency, i.e. Factor 2 versus Factors 1 and 4. If this Hypothesis were to be rejected empirically, margin costs and the need for opacity would be the main drivers in the decision to clear instead of the reduction of CCR capital requirements. The opposite is true if the Hypothesis 1 is not rejected. The empirical analysis sheds light on the relevance of margin and opacity versus CCR capital requirements costs.

The riskiness of the contract is proxied in our analysis by both (i) the Markit CDS quoted spread and (ii) the percentage change in the CDS quotes from the previous day. Additionally, we calculate a forecast of the volatility of the CDS using Exponential Weighted Moving Average Volatility according to RiskMetrics (1996) parameters.[10]

The liquidity of the reference entity might also play a relevant role in the decision to clear a contract. On the one side, more liquid contracts face lower margin requirements by the CCP (this refers to Factor 1). Moreover, the incentive to clear becomes larger when a certain reference entity in a given day is observing a significant amount of transactions because it would be easier to rebalance the CCP exposure (i.e. Factor 3). However, on the other side, if the increase of transactions is due to a large sovereign credit risk shock, like e.g. Brexit, market imbalance might generate difficulties to rebalance the CCP exposure (again Factor 3). In our empirical analysis we investigate these contrasting effects. We empirically proxy the liquidity of the contracts by looking

[10] In particular, we use the logarithm of changes of the CDS Markit quotes and 150 daily observations to set the initial volatility and then we apply the recursive formula using a rolling window of 75 days, with a decay factor of 0.94.

at the number of daily trades for each reference entity.

Another important variable is the size of the transaction that also affects the decision to clear in two different ways. On the one hand, the larger is the transaction, the larger is the margin cost and therefore the incentive to clear would be lower (Factor 1). Moreover, a real-time reporting regime exists in the CDS market. However, this regime permits to report on a delayed basis the block trades, but at the same time, indirectly offers some speculation opportunities to other traders. Traders observing this real-time information flow may have the chance to front run the dealer that needs to unwind its exposure. This is the second reason of why large size contracts should reduce the probability to clear (Factor 4). However, on the other hand, large transactions generate a larger counterparty credit risk exposure (i.e. Factor 2), and a larger benefit in terms of CCR capital requirements reduction if the contract were to be cleared. In our analysis, we investigate which of these opposing effects prevails. Therefore, the second Hypothesis we investigate is:

Hypothesis 2: Willingness to clear is larger if the transaction helps to manage margins, i.e. it decreases the amount of collateral to be posted because it reduces the exposure to the CCP.

To put the clearing decision into context, we consider the trade-offs associated with managing collateral on OTC transactions relative to those that are centrally cleared (factor 3). On the one hand, clearing members collect and post collateral with their bilateral counterparties on OTC transactions and most of the OTC non-cleared transactions are covered by bilateral master agreements that require the posting of variation margin and permit closeout netting in the event of a counterparty default for the sample period we considered. By contrast, when a dealer decides to centrally clear a trade, she is obligated to post initial and variation margins.[11]

The clearing decision depends on two components: (i) the net positions with the transacting counterparty and (ii) the net position with the CCP. By considering these aspects, a dealer would choose to clear a contract when the overall collateral commitment is smaller, that usually happens when the net exposure is reduced overall. Specifically, the dealers would face the problem to evaluate the margin costs between bilateral and multilateral netting as highlighted by Duffie and Zhu (2011) and Cont and Kokholm (2014). Generally, bilateral netting reduces the exposure to collateralize to a lesser extent than multilateral netting. However, in case of counterparty concentration, bilateral netting can also achieve significant reduction of exposures and bilateral arrangements may not require full collateralization.[12]

Another important aspect to consider is the ability to re-hypothecate collateral that can also have an impact on the decision to clear. Whereas dealers typically re-hypothecate collateral received

[11] In the meantime, the regulation has been changed from January 2017 onwards and now initial and variation margins are mandatory to collect also for the OTC derivative transactions (see the Commission Delegated Regulation (EU) 2016/2251 of October 4, 2016). However, our analysis covers transactions made in 2016, and therefore there is still a significant difference in margin requirements between cleared and non-cleared contracts for the sample considered.

[12] Unfortunately, bilateral netting situations cannot be analyzed in this paper due to the lack of reliable data. Therefore, we are aware that our analysis can provide only a partial and potentially biased view of the incentive to clear that derives from margin risk management purposes. However, it is the first attempt to perform this analysis not by simulation but through empirical evidence.

on OTC derivatives trades, amounts received on margin accounts at the CCP are not typically re-hypothecated. Although CCPs will rebate back income earned on these assets, the relative marginal returns on the posted collateral can have an impact on the clearing decision. The trade-off between clearing a trade or remaining OTC is, in principle, related to the net position of the dealer with the CCP and the characteristics of the reference entity. Most clearing houses[13] usually provide netting services, collateral management and calculation of margins at the portfolio level.

Since our database covers only part of the transactions of the clearing members (as we have focused on three sovereign CDS), and due to the fact that most of the clearing members are non-EU, we cannot rebuild their complete open position with the central counterparty across all asset classes and calculate exactly what is the amount of margin that a dealer is required to post (or save, if she trades in the opposite direction), as well as it is difficult to estimate the bilateral netting position for non-cleared transactions for all the traders.

Given the data available, the best that we can do is to calculate the daily open position of the dealer with the CCP as a proxy of the inventories and the additional costs of a new trade. CCP usually applies a short charge when a dealer is a net seller of protection. Given that both counterparties have to post margins, they can achieve sufficient economies of scale trying to have the smallest exposure with the CCP. Our Hypothesis is then related to the net position with the CCP: if a dealer is a net buyer, she prefers to clear the next trade only if it is going to take the opposite position (selling CDS) in order to reduce her position.

The same argument applies in the other case i.e. when a dealer is a net seller, she is willing to clear when the next transaction is a buy. However, it is fundamental to recall that both parties must agree on the decision to clear. Unfortunately, given the data we have, we cannot jointly test if the probability to clear is larger when both the traders have an incentive to clear because of margin risk management reasons. We can only investigate individually whether, if the buyer is a net seller or the seller is a net buyer, the probability to clear is higher. In the case Hypothesis 2 is rejected we could not disentangle if this is because the incentive is not strong enough or the other trader disagrees to clear.

The third Hypothesis we study is:

Hypothesis 3: Willingness to clear is larger when the counterparty risk is larger.

The creditworthiness of a counterparty may also affect the demand for central clearing. Du et al. (2016) show that market participants manage counterparty risk by choosing counterparties that are less exposed to the wrong way risk and have better creditworthiness. In our analysis, we aim to verify whether the decision to clear is influenced by the riskiness of the counterparties stand-alone that provides two opposite incentives to clear: an increase of margin costs (factor 1) and a reduction of CCR capital requirements in case of clearance (factor 2).

We measure the CCR as a function of the stand-alone risk of the counterparties, proxied by the CDS spread of both seller and buyer. This variable could be considered both as (i) a proxy of the

[13]See ICE (2015) for further details on margin calculation.

larger margins required by the CCP for riskier counterparties and (ii) the potential reduction of capital requirements, given that in Basel III regulation cleared contracts obtains lower risk weights for the counterparty credit risk capital requirements than non-cleared OTC contracts (Bank for International Settlements, 2012). The benefit of the reduction in capital requirements is larger for risky contracts, therefore, the probability to clear a contract should be larger if counterparties are more risky.

Other regulatory reforms may indirectly affect the clearing decision. For example, since the largest security swap dealers are affiliated with bank holding companies, swap dealers have been gradually flattening their trading books to comply with the Volcker Rule, according to Getmansky et al. (2016). This may be an endogenous response to prohibition on proprietary trading because non-zero net positions expose dealers to credit risk. If a position becomes large, regulators could view it as a proprietary trade rather than the outcome of legitimate market making. At the margin, the decision to comply with this regulation could have implications on the decision whether to transact with a specific counterparty or the CCP.

The Hypothesis described above are formulated from the perspective of a clearing member. They also apply to non-clearing members, but in this case, another relevant factor should be included: the cost faced by the non-clearing members to clear a contract through a broker (i.e. a clearing member). Unfortunately, we do not have information about these costs in our database, and therefore we do not include non-clearing members in our probit analysis. However, with our descriptive analysis, we provide some evidence on the actual clearance of contracts through non-clearing members, with the distinction of those subject to counterparty risk capital requirements and the others.

5.4 Data description

According to the Article 9 of the EMIR, the counterparties of a derivative contract have to report the details of the transaction, including modifications and cancellations to a trade repository, "no later than the working day following the conclusion, modification or termination of the contract."The set of details shall be reported to a trade repository (TR) registered according to Article 55 title VI or recognized in accordance with Article 77 of the EMIR. Consequently, information of EU counterparties' trades is made available to ESMA and European Systemic Risk Board (ESRB), while country-specific information is made available to relevant domestic supervisory authorities. It is worth noting that the transaction is present in the dataset when at least one of the two counterparties is located in EU. If for instance, two US counterparties are trading a European sovereign CDS, this transaction is not reported in our database. If both or one of the two is EU domiciliated EU, then the details are reported in one of the EU registered trade repositories. According to the EMIR, the reporting obligation applies to the contracts that were entered before the August 16, 2012 and are still outstanding, and the new contracts entered after August 16, 2012.

We use the EU wide dataset available at the ESRB. Abad et al. (2016) provide a comprehensive description of the data structure, as well as issues related to data quality. Hence, we borrow some of the insights provided in the paper to describe our sub-sample of the data. We focus our analysis on a subset of Sovereign CDS, where the reference entities are the Republic of Italy (Italy), the Federal Republic of Germany (Germany) and the French Republic (France). The entire database comprises all derivative classes (such as credit, commodity, equity, interest rate and foreign exchange). Six different TRs provide data to ESMA and ESRB.[14] In general, the TRs provide two types of data: a mandatory report called "trade activity" that contains all the new trades, modifications and cancellations; and a second set of data, called "trade state" with the outstanding positions up to a certain date. We use the trade activity dataset for the daily analysis.

Regarding the sample that we extract from the trading activity raw data, we face a number of challenges that have been extensively described by Abad et al. (2016) and Fache Rousová et al. (2015). We briefly summarize the data cleaning procedure, referring to the aforementioned papers for more details.

In order to extract the correct reference entities for the German, French and Italian CDS contracts, we first retrieve all the unique underlying codes from the EMIR data. A formal distinction between sectors for the underlying is not present in the reporting mandatory fields, so we use different data providers to identify the reference entities. We use the ISIN codes of the sovereign bonds auctioned in the last ten years as a first source. We complement the auction data with the ECB-CSDB data, Datastream, the list of eligible ISINs from ICE Clear Credit, and the list of the RED6 code from Markit. Our broad list of underlying securities contains 8,858 unique identifiers, where roughly 2000 are related to sovereign debt and the remaining to public entities owned by the government that are also categorized as Sovereign by the data providers. These we ignore in the analysis. We then extract only the trades related to these codes from the raw daily files, both for the OTC and the Exchange Traded Derivative (ETD) repositories. The initial database consists of 285,169 observations, with initial dates that span from 2004 to 2016. Roughly 70% of the observations is from 2016, where the quality and quantity of data has significantly improved. The EMIR regulation requires that both counterparties of the transaction have to report the trade to one of the authorized trade repository, i.e. this is the so-called "double-reporting" obligation. Thus, if a trade involves two EU counterparties, we find both records in the database, compared to the case where one counterparty is non-EU, where we find only one record. We unambiguously identify these two sets of transactions: the unique observations that cannot be matched, and the two observations reported by the EU counterparties and keep track of them. A specific flag, called "action type" allows us to partially track changes in the contract, features such as the notional amount, the upfront, the spread and so on. There are three timestamps reported for each transaction: the *reporting timestamp*, that refers to the moment when the counterparty communicates the trade to the TR; the *execution timestamp*, that indicates the moment when the transaction takes place;

[14] The six TR are CME, DTCC, ICE, KDPW, Regis-TR and UnaVista.

for some trades there is also the *confirmation timestamp.* We first drop the exact duplicates and the observations where the information regarding the spread (price), the notional and the upfront together are missing. Then, in order to be as conservative as possible, in the case of duplicate observations, we try to assess the quality of one of the two and possibly integrate the missing values of one with the other. For some trades, the CDS spread is directly reported, while for some others only the indication of the coupon is provided.[15] However, we keep all the observations even if sometimes the price is not reported or not reliable. We prefer to avoid the use of the reported transaction price in our analysis because of lack of reliability or misreporting issues.

5.5 Sovereign CDS Transactions

As described in the previous section, the database used for our analysis includes all the sovereign single-name CDS transactions by EU financial institutions. Our analysis focuses on sovereign CDS, and in particular, the most traded European sovereign CDS: Italy (IT), France (FR) and Germany (GE). According to the globally aggregated transaction data provided by the DTCC on the TIW (Trade Information Warehouse) database, in the last quarter of 2016, the Italian CDS was the 5th most traded single name CDS by average daily notional amount, the French CDS was in the 20th position, and the German CDS in the 54th position.[16]

Table 5.1 describes the transactions reported in the EMIR database of the three sovereign CDS, and in particular, the gross and the net notional amounts and the number of counterparties, classified by the type of market participants. The counterparty categories reported in the database are "Banks", "Dealers", "Funds", "Other Institutions" and "Others". The category "Dealers" includes the group of the largest 16 dealers identified by the occasional paper Abad et al. (2016).[17] The category "Other Institutions" includes Insurances, Pension funds, and Non-financial organizations. The category "Others" includes all the non-classifiable institutions. As Table 5.1 shows, the gross notional amount traded in 2016 and reported in the EMIR database is 797 billion of US dollars (B$). The "Dealers" are the most active with 576 B$ of gross notional amount (74.8% of the total gross notional amount) followed by the category "Banks" (96 B$) and the category "Funds" (95B$) with 12.01% and 11.92%, respectively. The other two categories, "Other Institutions" and "Others", account for 7.72 B$ and 2.19 B$, respectively, that is 0.97% and 0.27% of the total gross notional. These numbers are in line with the evidence provided by Peltonen et al. (2014), and Abad et al. (2016), confirming that the CDS market is highly concentrated around a small number of counterparties.[18] Our analysis confirms that the concentration of the market is a persistent feature.

[15] When the contract is standardized the difference of cash called upfront is added. For the sovereign CDS, the fixed coupon is 25 or 100 bps.

[16] Other European sovereigns that are in the 100 most actively traded single name CDS are Spain, Belgium and Portugal.

[17] The 16 largest dealers are Bank of America, Barclays, BNP Paribas, Citigroup, Crédit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Nomura, Royal Bank of Scotland, Société Générale, UBS, and Wells Fargo.

[18] This evidence is also confirmed for the US corporate CDS market by Brunnermeier et al. (2013) and Getmansky

In fact, Abad et al. (2016) focuses on the CDS exposures at November 2nd, 2015; we instead look at all the transactions in 2016 and highlight the same feature.

Regarding the net notional amount, i.e. the difference between the amount bought and sold during 2016, panel A of Table 5.1 shows that the category "Dealers" presents a net exposure lower than the categories "Funds" and "Banks", 3.70 B$ versus -7.22 B$ and 5.54 B$, respectively. Moreover, "Dealers" in 2016 present a positive net amount: they are net buyers of CDS protections for the transactions done during the 2016. Instead, the net seller of protections are largely "Funds" and "Other Institutions" that includes Insurances and Pension funds. Among the 16 Dealers, the analysis shows that only 15 are active in the sovereign CDS market of Italy, France, and Germany. There are 33 'Banks" and 233 "Funds" in the sample. In addition, there are 40 other institutions like insurances and pension funds. Moreover, there are 123 institutions which type cannot be identified.

In the previous section, we highlight the peculiarities of clearing members versus non-clearing members, as well as the differences in the incentive to clear for the institutions that are subject to CCR capital requirements versus those that are not. For this reason, we report in Panel B of Table 5.1 the information of Panel A with the distinction between clearing member and all other institutions that are not clearing members, distinguishing among those that are subject to capital requirements and those that are not. The motivation behind this classification is that institutions subject to capital requirements could have advantages to clear derivatives transactions because of the reduction in the amount of capital requirements.

All dealers are clearing members in our dataset and the other 11 clearing members are all banks.[19] Therefore, they are all subject to capital requirements and we avoid the distinction on being subject to capital requirements or not for this category. Thus, we consider the following categories: clearing members; non-clearing members subject to capital requirements (CR); non-clearing members not subject to capital requirements (NCR); and not classifiable institutions (Others).

INSERT TABLE 5.1 HERE

Table 5.1 Panel B shows that clearing members are responsible for the largest fraction of contracts, roughly 96% in terms of gross notional amount, considering both cleared or not cleared contracts. The clearing members have a positive net notional amount of 9.3 B$ versus the negative total net notional amount of -10.3 B$ for the non-clearing members (-2.2 B$ and -8.1 B$, respectively for those subject to capital requirements and those not). Among the non-clearing members, the large fraction of the transactions is performed by traders not subject to capital requirements,

et al. (2016).

[19]We define the set of clearing members according to the LEI (Legal Entity Identifier) membership list provided by ICE (www.theice.com). However, the same Global Ultimate Owner (GUO) could employ different LEI, which falls into the category of Dealer, Bank, or Fund. Table 5.1, Panel A, classify each market participant according to the LEI, while Table 5.1, Panel B takes into account the clearing membership dictated by ICE. For that reason, a LEI whose global ultimate owner is a Dealer or a Bank, falls into the category of Funds in Panel A, but is a Clearing Member on Panel B.

2.15% of the total gross notional amount that corresponds to 17.1 B$. This group of traders is instead the one having the largest net notional amount, -8.1 B$, and are net sellers. This category is also the one with the largest number of counterparties, 266, versus non-clearing members subject to capital requirements that are 29.

According to ICE,[20] a single-name sovereign CDS reference entity can be cleared according to the following criteria:

- The contracts must be in USD and may be cleared to either ICE Clear Credit or ICE Clear Europe;
- For ICE Clear Credit, the Restructuring Clauses applicable are CR, CR14, MR, and MR14. For ICE Clear Europe, CR and CR14[21];
- The fixed interest rate on the contract is either 25 or 100 basis points for the three reference entities selected;
- The tenor of the contract is less than 10 years;
- The reference Obligations are SNRFOR Tier (Senior Debt).

The BIS statistic[22] reports that 1.7 trillions of dollars (T$) of gross notional single name CDS on sovereign bond are outstanding at the end of the year 2016, and 551 B$ of this amount is cleared. Figure 5.1 shows the ratio between the gross notional amount of outstanding CDS contracts on sovereign bonds cleared over the total gross notional amount of outstanding CDS contracts on sovereign bonds. The ratio increases up to 32% for the single name sovereign CDS and up to 19% for the multi-name index sovereign CDS at the end of 2016.

INSERT FIGURE 5.1 HERE

Moreover, the Financial Stability Board (2017) report indicates that clearing rates for the flow of new transactions in the OTC credit derivatives (both corporate and sovereign) as a whole are estimated at 37% in the EU and in index CDS at 80% in the US. In our analysis, we investigate the share of clearing vs. not clearing of the selected three sovereign CDS contracts. Differently from the statistics reported by the BIS and FSB, we also report the percentages of contracts that are eligible to clear but are not cleared, as well as those that are not eligible for clearance because they are not standard contracts accepted by the clearing houses. This information is crucial because it already provides an idea whether the contracts that are not cleared could not be cleared because they are not standard or because the traders decided not to clear.

[20]see `https://www.theice.com/clearing`. The criteria of ICE are applied in the study to define eligibility for clearing.

[21]In addition, both ISDA 2003 and ISDA2014 Credit Derivatives Definitions can be cleared on both CCPs. The CDS for Italy can be cleared on both CCPs, while for German and Frech CDS only ICE Clear Europe accepts these contracts for clearing.

[22]Data from BIS `http://stats.bis.org/statx/srs/table/d10.4?p=20162&c=`

Figure 5.2 reports the percentage of the gross amount cleared, the one eligible for clearing, and the percentage not eligible for clearing. The first bar of Figure 5.2 shows the percentages for all samples and indicates that the gross notional amount cleared is 48%, the share of contracts not cleared but eligible for clearing is 43%, while the share of not clearable contracts is 9%, respectively.

The most common reasons why a contract is not eligible for clearing are the following: the currency of the contract is Euro (89.21%), the tenor is greater than 10 years (10.41%), and the remaining (0.38%) are securities (ISINs) not accepted by the clearing house for a specific reference entity. There is indeed a trend towards clearance as the clearing rate of 48% of the flow of new contracts in the sample is larger than the clearing rate of the stock of contracts reported by the BIS statistical reports (see Figure 5.1 at the end 2016). The percentage is also larger than the fraction of the flows of cleared contracts reported by Financial Stability Board (2017), indicating that sovereign CDS clearing is larger than corporate clearing.[23]

The second bar in Figure 5.2 shows the percentage of gross notional amount cleared, not cleared but eligible for clearing, and not clearable, for contracts where both counterparties are clearing members. The Figure shows that the fraction of cleared contracts among clearing members is larger than one half (53%), that is a larger fraction of contracts has been cleared. The non-eligible to clear contracts are 8%, therefore among the clearable contracts 58% of the gross notional amount has been cleared. This implies that there are indeed significant incentives for clearing members to clear even if clearance of single-names CDS contracts is not mandatory.

The last bar instead shows the percentages of cleared and non cleared contracts where at least one of the two counterparties is not a clearing member. In this case, the percentage of the notional amount cleared is close to zero (0.05%), not comparable to the clearance fraction of clearing members (53%). We argue that this is due to the fact that non-clearing members must go through a clearing member to clear the transaction (indirect clearing). We do not have information about these fees, but clearly if the fees requested by a broker to clear the contracts are relatively too high, the non-clearing members have no incentives to clear. Instead, the fraction of transactions that are not eligible to clear because they are not standard, are about 20% of the gross notional amount. The difference is significant compared to the clearing members' transactions that have a percentage of 8% of non-eligible contracts.

Since one of the incentives to clear is the reduction of capital costs through lower capital requirements, Figure 5.3 reports the percentage of cleared versus clearable contracts distinguishing between non-clearing members that are either subject to capital requirements (CR) or not (NCR).

INSERT FIGURE 5.2 HERE

Figure 5.3 shows that independently from capital requirement restrictions, the percentage of cleared notional amount is practically zero for non-clearing members subject to capital requirements

[23] The analysis might potentially overestimate the actual volume of the cleared transactions because sometimes it is impossible to match the two legs of the contract. For instance, we observe only one leg of the contract, when the contract is cleared, one of the counterparties is not EU regulated and the transaction is cleared through a US CCP.

and very low (0.09%) for those not subject to capital requirements. This indicates that there are no incentives at all for non-clearing members to clear a contract, with no distinctions between institutions subject to capital requirements or not. Moreover, there is also a distinction between the two categories for a fraction of contracts that are eligible to clear. For non-clearing members subject to capital requirements, this fraction is 75%, and for those non-clearing members not subject to capital requirements it is 85%. This means that a larger fraction of contracts for non-clearing members subject to capital requirements are tailor-made contracts (25%), potentially for their specific needs (in this category there are banks and insurances) or for the specific needs of banks' clients. Overall, this shows the dichotomy in the behavior of clearing members versus non-clearing members in their decision to clear (and incentives) as well as on the characteristics of the contracts that these different categories of counterparties are entering.

INSERT FIGURE 5.3 HERE

The histogram in Figure 5.4 shows the distribution of sovereign CDS contracts' tenor in our sample. The Figure shows that most of the activity is concentrated in the 5-year bucket, that covers around 30% of the total notional amount traded. More generally, 82% of the activity on CDS market in our sample is concentrated in contracts with maturity less then or equal to 5 years. For short-term contracts (tenor less of one year), the percentage is very small, around 2%.

INSERT FIGURE 5.4 HERE

Finally, Figure 5.5 displays the share of the gross amount traded among the three reference entities considered: Germany, France and Italy. It shows that the mostly traded contract is the Italian one, 68% of the total amount traded in 2016, the second is France, 19% and the third is Germany, around 15%. The ranking of the activity is in line with the market price of riskiness of these three sovereign CDS contracts. The heterogeneity among the different reference entities allows us to disentangle the role of the riskiness of the reference entity on the decision to clear.

INSERT FIGURE 5.5 HERE

5.6 The Drivers of the Decision to Clear: Empirical Evidence

What are the drivers of the decision to clear? We introduce several variables to test the hypotheses introduced in section 5.3, that are summarized in Table 5.2.

INSERT TABLE 5.2 HERE

We define several variables that are related to the characteristics of the contract and liquidity risk of the trade (Table 5.2 Panel A), the inventory position of the dealer with the CCP (Table 5.2 Panel B) and the riskiness of the two counterparties involved in a trade (Table 5.2 Panel A). In the same fashion, Table 5.3 provides the descriptive statistics for our sample.

INSERT TABLE 5.3 HERE

The characteristic of the single contracts are summarized in Table 5.3 Panel A. The liquidity of the contract is captured by the variable "N. of Trades", that represents the number of daily trades in the sample for each of the three sovereign CDS conditional to observing at least one trade on that day (i.e. zero trades days are not considered in the statistics). The CDS contracts for the three sovereigns display a relatively similar average number of trades per day, ranging from 128 for Italy to 191 for Germany. However, we have far more observation for Italy than for Germany and France because we have less days with zero trades. The "Log Notional Amount" represents the log of the contracts' notional amount, also quite similar across reference entities. Using daily quotes from Markit, we introduce three variables that capture various aspects of the riskiness for each reference entity. The "CDS Volatility" is calculated as the Exponential Weighted Moving Average Volatility of the daily quotes.[24] The three countries display a similar level of volatility in the sample. The "CDS Quote Spread" and "Δ CDS Spread" represents the level of the current CDS spread for each country, and the change in the spread from the previous day, respectively. The different level of riskiness of each country is clear from Table 5.3 Panel A. The lowest level of CDS spread belongs to Germany (average of 12 bps), while Italy displays a spread roughly ten times larger (average of 128 bps).

We also extract from the trade repository also the open positions of each trader with respect to the Clearing House, in order to calculate the daily net exposure. Thus, the net position with the CCP is defined as:

$$Position\_wt\_CCP_{ijt} = \frac{Net\_Not.\_wt\_CCP_{ijt}}{G.\_Bought\_Not.\_Cl._{ijt} + G.\_Sold\_Not.\_Cl._{ijt}}. \tag{5.1}$$

where $Net\_Not.\_wt\_CCP_{ijt}$ represents the net notional position with the CCP for the counterparty i, on reference entity j and day t. The gross notional bought and sold are similarly defined. By construction, this ratio varies from -1 to +1, where a negative number implies that the counterparty is a net seller of CDS protection. The statistics of Table 5.3 Panel B shows that for Germany and France most of the counterparties, either buyers or sellers, have an average positive position (net buyers of CDS protection). The opposite is true for Italy. Finally, as a proxy for the riskiness of each counterparty in a trade, we use the quoted 5 year CDS spread for both the buyer of CDS protection (*Spread B_Dealer*) and the seller of CDS protection (*Spread S_Dealer*). From Table 5.3 Panel C we can see that the traders on average have a CDS spread around 100 bps for all the three contracts.

In order to formally test our three hypotheses, we estimate the following probit regressions separately for each sovereign CDS reference entity k (Italy, Germany, and France):

[24] The Exponential Weighted Moving Average Volatility is calculated using a constant smoothing lambda parameter of 0.94. The initial volatility is computed by considering a time interval of 150 observations with a rolling window of 75 observations according to Risk metrics.

$$Pr(Y_{t,k} = 1) = \alpha_0 + \beta \times X_{t,k} + \epsilon_{t,k} \tag{5.2}$$

where $Y_{t,k}$ is equal to one if the transaction on the reference entity k has been centrally cleared, and zero otherwise, also taking into account the eligibility rules of central clearing. The matrix X contains a set of control variables, different for each Hypothesis tested, as well as a month fixed effect.

As presented in Section 5.5, our database shows that only transactions between two clearing members present a significant fraction of cleared contracts. Therefore, our analysis on the drivers for central clearing concentrates only on the transactions among clearing members and includes only the contracts that are eligible for central clearing. The inclusion of the contracts not eligible for clearing could potentially bias the results. Collateral to be posted or capital requirements do not influence the decision to clear since the characteristics of the contract preclude from the beginning this option.

5.6.1 Hypothesis I: Contract and Liquidity Risk

Hypothesis 1: Willingness to clear is larger if the contract is less liquid and when the reference entity is more risky.

As described in Table 5.2, Hypothesis 1 investigates the drivers of clearing looking at the contract characteristics, namely the CDS Spread, the change of the CDS spread, the CDS sovereign volatility of the reference entity, the trade size and the total number of daily trades for a specific reference entity.

Theoretically, some of these variables capture different dimensions that might have contrasting effects on the decision to clear. The empirical analysis allows us to disentangle which effect is prevailing. In particular, the size of the trade might have a positive impact on the willingness to clear, given the larger risk of the transaction. However, e.g. in order to avoid transparency, the trader might decide not to clear the contract. The number of daily trades for a specific reference entity might also increase the willingness to clear the contract because it indicates larger market liquidity, which usually lowers the margins. However, larger liquidity might reduce the willingness to clear the contract because of the counterparty credit risk, in this case, is lower since the contract would be easily matched. Again we have the trade-off between margin costs and CCR exposures. We have already explained that CCR exposures and capital requirements, as well as capital costs, are different dimensions of the same phenomena. In the discussion of results, when we refer to higher CCR exposures, we implicitly mean also higher capital requirements and higher capital costs. Volatility of the CDS market and the riskiness of the reference entity might be negatively correlated with the willingness to clear the contract because the margin requested by CCPs would be higher. However, the reference entity volatility might incentivize the decision to clear because the larger is the risk of the transaction, the larger is the CCR exposure, based on the fact that the higher is the volatility of the reference entity, the larger is the amount lost in case of default of one of the counterparties. Again, we allow the data to disentangle among these two potential effects that reject or confirm Hypothesis 1.

Table 5.4 reports the results of the multivariate regressions for Germany, France, and Italy, with and without month fixed effect.

INSERT TABLE 5.4 HERE

In line with Hypothesis 1, when the reference entity is risky, the probability to clear the contract is larger. The coefficient for the variable "CDS Quote Spread" is positive across countries, albeit statistically significant at the 1% level only for France and Italy. Higher potential margin costs do not prevent the counterparties to agree on clearance because CCR exposures are prevailing in the decision to clear. For Germany, the coefficients are not significant with and without fixed effect. This could be due to the fact that this variable is quite stable through time or the riskiness of Germany is so low that it is not having an impact both on margins costs and on CCR exposures. If we perform the same analysis including time fixed effects, the overall results are confirmed.

The second variable that we consider in our analysis is the change in the CDS spread level, "Δ CDS Spread." As the estimated coefficient shows, this variable has a negative and statistically significant coefficient for Germany and France, in line with the idea that an increase of the CDS spread of the reference entity increases margins, and therefore reduces the incentives to clear. For Italy, the sign of the estimated coefficient is positive, with stronger significance when including also the month fixed effect. This indicates that there are periods in the sample characterized by specific shocks that increase or reduce the probability to clear (like the outcome of the Brexit vote), potentially inducing a bias in the estimation if this aspect is not captured by time fixed effects. Overall, the results on the change in the CDS spread indicates that the potential increase of the risk of the reference entity induces to clear more in line with Hypothesis 1 and CCR exposure motivations, but only for the riskier country in the sample. For Germany and France, margin costs prevail on the CCR exposures on the decision to clear.

Considering the trade size ("Log Notional Amount"), the analysis shows that the larger is the volume of the transaction, the higher is the probability to clear. If the trader has to choose between disclosing the intention to take a large position on a contract or to incur in a large counterparty credit risk exposure, there is a preference for reducing the second one. This result is significant at the 1% level also including the time fixed effects analysis for France and Italy. However, for Germany, the estimated coefficient is not statistically significant, indicating that the CCR exposures are less relevant for the clearing decision.

The volatility of the quoted CDS spread, "CDS Volatility," has a negative sign for the three countries, indicating that the probability to clear is lower if the contract is more volatile, and therefore characterized by larger margins. However, the inclusion of the time fixed effect controls change the magnitude of the coefficient, and for Italy also the statistical significance of the coefficient. The econometric reasons for this result are the same as before: the inclusion of the time fixed effects controls for the variability of the clearance which is due to time series shocks. It seems, therefore, that for the Italian contract margin costs are not as relevant as the CCR exposures. Overall, according to the CDS volatility, we confirm that margin costs matter for the decision to clear a contract.

Finally, the number of transactions "N. of trades" shows a negative coefficient for all the reference entities. This indicates that the incentive to clear is lower when the contract is traded more. However, the coefficients for Germany and France are not statistically significant when including the time fixed effects to the regression. This indicates that there are clusters of periods when these contracts are either largely traded and others when their trading activity is low. This variability is captured by the time fixed effects and not by the cross-sectional variability generated by the different characteristics of the contracts between cleared and non-cleared transactions. Besides, the number of contracts written on sovereign CDS for Germany and France as reference entities are far lower than the contracts written on the Italian sovereign CDS (832 observation for German CDS, 1,713 observations for French CDS and 5,132 observations for Italian CDS).

In the appendix, Table 5.9, Table 5.10, and Table 5.11 report the probit results by regressing the dependent variable (clearing choice) with stand-alone explanatory variables, not controlling for month fixed effect. The analyses of the single variables are characterized by the omitted variable bias. Although these results do not contradict the analysis based on Table 5.4, they are less robust especially for contracts having Germany as reference entity, where only the variable "N of Trades" remains significant. In particular, "CDS Quote Spread" is still positive but only for France statistically significant; on the contrary, the coefficients are no longer significant for Germany and Italy. "Δ CDS Spread" is negative for France and positive for Italy and in both cases significant. These results are in line with the Table 5.4, and we can confirm that margin costs are found to be incentives impacting the decision to clear for France, and on the contrary, reference entity risk prevails for Italy. "Log Notional Amount" is positive and statistically significant for Italy and France indicating that the desire to hedge against a counterparty risk exposure overcomes the consequential cost of disclosing trading information. Although the sign of "CDS volatility" coefficient is coherent with the results of the Table 5.11 for all the reference entities, only for France it is significant, indicating that the margin is a relevant incentive for contracts having France as reference entity. Finally, the "N. of Trades" is negative and significant for all the three reference entities, confirming that the incentive to clear is less relevant when the contract is more liquid.

In general, our analysis confirms Hypothesis 1 for Italian CDS contracts: clearance is larger when the reference entity is riskier and therefore CCR exposures motivation for clearing prevails on the margin cost motivation for the decision to clear. For the German CDS, it seems that the incentives that prevail for clearing are those provided by margin costs. For France the results are mixed. It appears that both incentives, provided by margin costs and CCR exposures are relevant for the decision to clear French CDS. The mixed results justify the need to perform a separate analysis of the three contracts.

5.6.2 Hypothesis 2: Position with the CCP

Hypothesis 2: Willingness to clear is larger if the transaction helps to manage margins, i.e., it decreases the amount of collateral to be posted because it reduces the exposure to the CCP.

In this section, we consider the position of the single dealer vis-à-vis with the Central Counterparty. We model the decision to clear based on the intuition that, if a transaction helps to reduce the position with the CCP, dealers have the incentive to centrally clear, reducing the amount of collateral that has to be posted for this transaction.

In order to capture this behavior, we use the Position with the CCP (see equation 5.1) of the previous day for each counterparty, with respect to each reference entity (DE, FR, IT). We define the position as "flat" when the ratio is between plus and minus 5% of the total activity. A counterparty is a net buyer if this ratio is above 5% and net seller if the ratio is below minus 5%. A number close to zero means that the counterparty is almost flat, while a number close to plus one or minus one displays a directional exposure with the CCP. We combine this information with the side of each trader (buyer or seller), and we isolate the two relevant cases: (i) when a buyer is a net seller, and (ii) when a seller is a net buyer. In principle, once a buyer is a net buyer, she does not have an incentive to go through the CCP, while when it is a net seller, clearing a transaction reduces her net exposure to the CCP and consequently the margins. The same argument also applies to the seller. Table 5.5 shows the results of the probit regressions on the position with the CCP, for the buyer in Panel A and for the seller in Panel B.

INSERT TABLE 5.5 HERE

For all the three countries, when the buyer is a net seller, and thus has the incentive to clear the contract, the probability that she would clear the contract is higher. The estimated coefficient is positive and significant at the 1% level. Adding time fixed effect leaves the sign of the coefficients invariant, but reduces the statistical significance for Germany. Table 5.5 panel B reports how the probability to clear is affected by the position of the seller with the CCP. In the univariate case, the coefficient is negative and significant, confirming that the probability to clear a transaction is lower when the seller has no incentive to do so. However, looking at the descriptive statistics in Table 5.3 Panel B, it appears that for the French and especially for the Italian contracts, the position of the single traders is on average flat. The incentives are higher when there is a strong directional position against the CCP. A close-to-flat position could not give enough benefit to offset the costs of clearing a transaction. In other words, we argue that the effect of the position with the CCP (the dummy for net buyer or net seller) is different based on the level of the position itself ("Exposure to the CCP"). For this reason, we introduce the interaction effect of the dummies with the level of the inventory.

We discuss only the coefficient of the interaction terms, since the interpretation of the "main-effects" coefficients in the regression with interaction terms is not straightforward. The work of Jaccard and Turrisi (2003) provides a detailed discussion of this issue. Table 5.6 shows the results of the probit regression with interaction terms for both buyer and seller.

INSERT TABLE 5.6 HERE

The probit regressions of Table 5.6 Panel A show that the interaction term is positive and highly significant for French and Italian CDS contracts: the larger is the position with the CCP, the higher is the incentive to clear because this transaction might reduce the margins. This is not true for the contract written on Germany, where the coefficient is negative and significant only when including the time fixed effect. Therefore, for the buyer net seller for France and Italy, the results confirm the Hypothesis 2.

On the seller side, the results are confirmed only for the Italian contracts: when the seller is a net buyer, the incentive to clear this transaction is lower. For the German and the French CDS, the sign and significance are mixed. There are potential explanations for these heterogeneous results. The first is related to our proxy for the inventory position with the CCPs. Unfortunately, we cannot accurately reconstruct the seller position with the CCP. In fact, as in Du et al. (2016), the market participants avoid wrong-way risk, i.e., buying protection from a counterparty, whose credit risk is correlated with the underlying risk of the reference entity. Therefore, some of the sellers of sovereign CDS might not be European traders, and thus not obliged by the EMIR to report the transactions when the buyer is not European counterparty. Another potential explanation is that the buyer of the CDS is the one having the market power to impose clearance. If in the majority of the cases, the seller that is net buyer ends up to have as a counterparty a buyer that is not a net seller, the contract would not be cleared. On the opposite, if the seller is not a net buyer, but the buyer is a net seller the contract would be cleared. For these reasons, the results for the seller side must be interpreted with caution.

Unfortunately, our database does not allow us to identify, for a large fraction of the cleared transactions, who are the two parties. Therefore, we could not disentangle the cases when both counterparties have incentives to clear versus the case when only one of two has this incentive.

With the limitations due to the data availability, we could, in any case, conclude that the results in Table 5.5 and 5.6, on the one side, confirm Hypothesis 2, but on the other side highlight the strategic behavior of the dealers in particular regarding their book conditions. If the buyer, as opposed to the seller, has strong incentive to maintain a directional position, they will try to avoid additional cost in terms of margin requirements and margin calls. If the buyer has a different incentive with respect to the seller to clear, in most of the cases, their incentives prevail in the decision to clear the contracts.

5.6.3 Hypothesis 3: Counterparty Credit Risk

Hypothesis 3: Willingness to clear is larger when the counterparty credit risk is larger.

In the last Hypothesis we test whether the riskiness of the counterparty, i.e., the CCR *per se* can influence the willingness to clear a contract, independently on the size of the contract and the riskiness of the reference entity. The proxy used for detecting the counterparty credit risk is the

Dealer CDS spread with a tenor of 5 years.

INSERT TABLE 5.7 HERE

Table 5.7 shows the results of the probit estimation, including the CDS Spread of the buyer (Panel A) or the seller (Panel B). In all cases, also including time fixed effect, the coefficients of the CDS buyer or CDS seller are positive and largely statistically significant. Thus, the probability to clear the contract is larger when either the buyer or the seller presents a large credit default risk measured with the CDS spread.

The main differences across the countries are the magnitude of the coefficients. For the German CDS contracts, the coefficient of the buyer or the seller has a comparable size. For the French CDS contracts, the coefficient of the seller is almost twice as big as the one of the buyer, indicating larger probability to clear if the seller is risky, versus the case when the buyer is risky. The same conclusions hold for the Italian CDS contract. In particular, the univariate analysis shows that the coefficient of the CDS of the seller is positive and significant at the 1% level and is three times larger than the CDS of the buyer. This indicates that in both cases, the larger is the counterparty risk, the larger is the probability that the contract would be cleared. However, for the same level of counterparty risk, the incentive to clear is three times larger when the seller is risky than when the buyer is risky.

In summary, in all cases, the spread of the CDS dealers has a positive and significant relation with the probability to clear a contract, both the CCR of the buyer or the seller. Therefore, these empirical findings confirm the statement on Hypothesis 3.

For a fraction of the Italian CDS contracts cleared, we can identify the two counterparties that clear the contract with the CCP. Table 5.8 reports the results of the probit estimation including both buyer and seller CDS spread. We find that for both buyer and seller, counterparty credit risk matters. The result is robust to the inclusion of time FE. Therefore, Hypothesis 3 is largely confirmed.

INSERT TABLE 5.8 HERE

5.7 Conclusion

This paper studies whether the post-crisis regulatory reforms developed by global standard-setting bodies have created appropriate incentives for different types of market participants to centrally clear OTC derivatives contracts. In particular, we analyze three main drivers for the decision to clear: 1) the liquidity and riskiness of the reference entity; 2) the credit risk of the counterparty; and 3) the clearing member's portfolio net exposure with the CCP.

We investigate empirically the relevance of these different drivers in the decision to clear by using a unique regulatory dataset: the confidential European trade repository data on single-name sovereign CDS transactions ruled by the EMIR. The database used for our analysis includes all derivatives transactions by EU financial institutions. However, our analysis focuses on transactions on sovereign CDS in 2016, and in particular, the most traded European sovereign CDS: Italy, France and Germany.

Our results demonstrate that the large majority of the transaction cleared are between CCP clearing members, while in our dataset there is almost no evidence of clearance of transactions by non-clearing members, independently whether they are subject to capital requirements or not. We also find that a large majority of the contracts could be cleared if the contract parties would agree on clearing these contracts. The fraction of non-eligible contracts for clearance is about 8% for the clearing members and between 15% and 25% for non-clearing members, depending on whether they are subject to capital requirements or not.

Focusing on contracts that are eligible for clearing, we investigate factors that drive clearing members' decision to clear. First, we find that both capital costs and margin costs are relevant for the decision to clear with some differences among the three sovereign CDS contracts. For the Italian sovereign CDS, the counterparty credit risk exposure is more relevant than the margin costs in the decision to clear, while for the German sovereign CDS contracts margin costs are the most important. Instead, the French sovereign CDS contract it is difficult to disentangle which of the two main drivers prevails. Second, we find that when a net seller of a specific sovereign CDS buys an additional contract, its propensity to clear increases. We find this for all the three reference entities, indicating that portfolio positions with the CCP also matter on the decision to clear the single contracts. Finally, we find that the counterparty credit risk alone is an important incentive to clear a contract, as this factor is significant for all analyzed reference entities.

Our study has several potential policy implications. First, it shows that the indirect clearing of non-clearing members, independently whether they are subject to capital requirements, is very low. Thus, regulators should further investigate reasons for this, and better understand the cost factors and other potential obstacles for client clearing. Second, our results show that factors impacting the incentives for central clearing are not the same for all analyzed CDS reference entities.

Therefore, further detailed analysis of the role of the different reference entity characteristics should be considered. Finally, our analysis shows that the decision to clear is also related to net exposure with the CCP, in addition to the characteristics of the contract and the counterparty credit risk. This should give incentives for cross-asset clearance, which implications should be further analyzed.

Figures

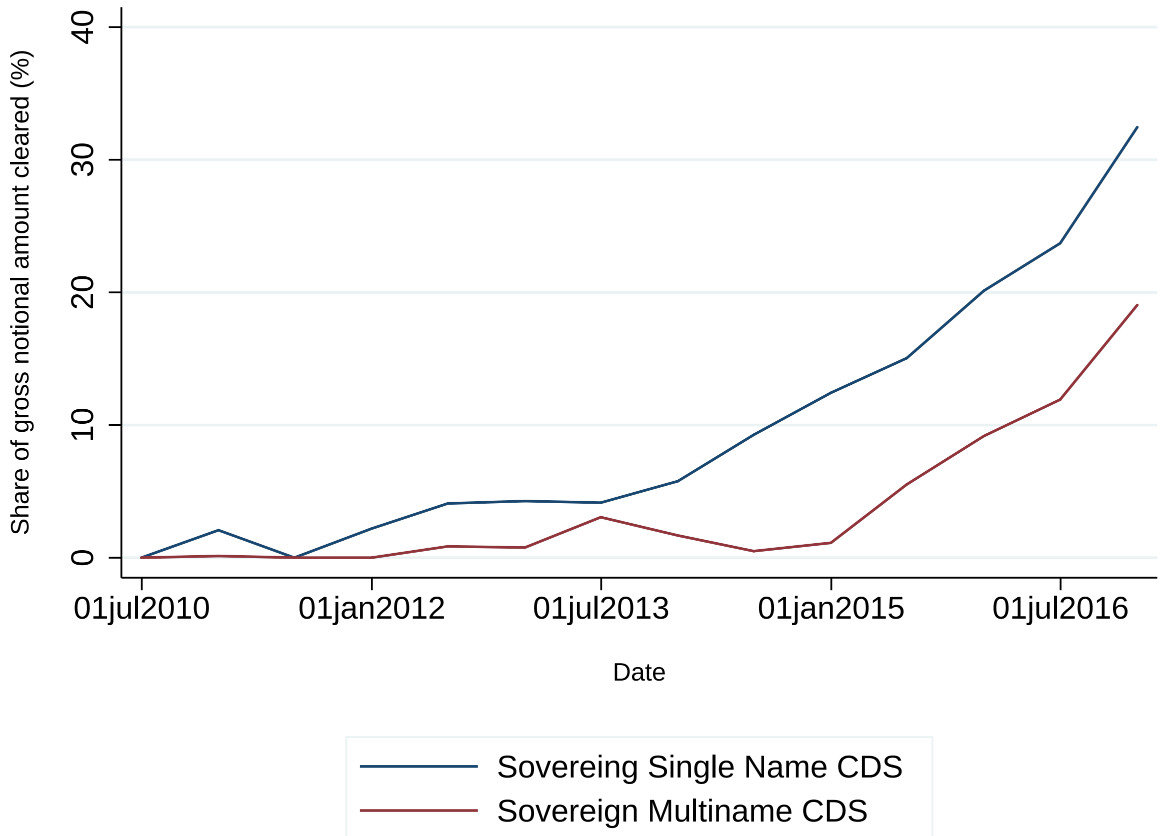


Figure 5.1: **Share of cleared sovereign CDS contracts of gross notional amount** This figure shows the ratio between the gross notional cleared and the total gross notional amount for single name sovereign CDS and multi-name sovereign CDS contracts. The ratio is calculated starting from the semi-annual open positions with a sample from June 2010 to December 2016. The source of data is the BIS over-the-counter (OTC) derivatives statistics database, available at `http://stats.bis.org/statx/srs/table/d10.4?p=20162&c=`

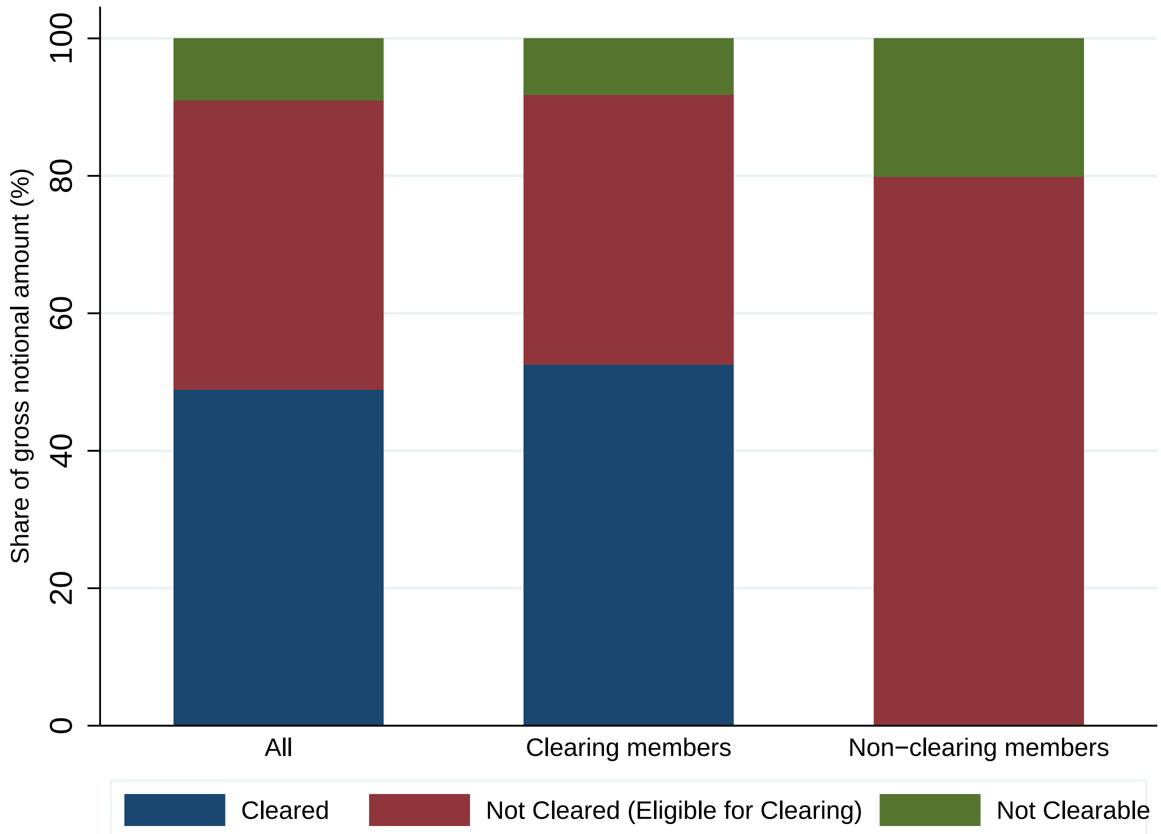


Figure 5.2: **Clearing of sovereign CDS contracts by counterparty type**
This figure shows the share of gross notional amount traded in our sample, classifying each trade under the following categories: cleared, not cleared, and not eligible for clearing, as described in Section 5.5. The first bar includes all contracts traded in our sample, the second bar includes only the contracts where both of the counterparties are clearing members, while the third bar includes the contracts where one of the two counterparties is a clearing member. The sample is composed of single-name sovereign CDS contracts written on Italy, Germany and France as a reference entity in 2016. Data comes from trade repositories under the the EMIR reporting requirement.

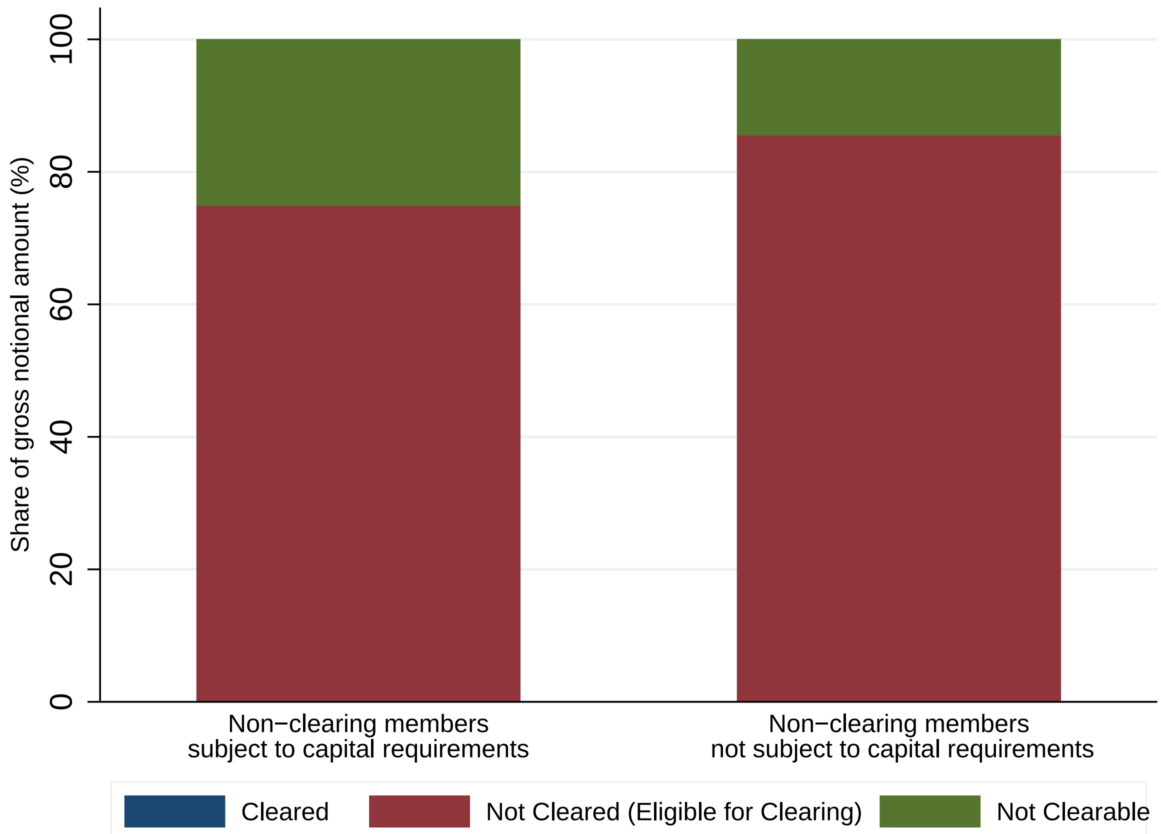


Figure 5.3: **Central Clearing Eligibility, Client Clearing and Capital Requirements** This figure shows the share of gross notional amount traded in our sample, including only the trades where only one of the two counterparties is a clearing member. We classify each trade under the the following categories: cleared, not cleared, and not eligible for clearing, as described in Section 5.5. The first bar includes all the contracts where the non-clearing member is subject to capital requirements. The second bar includes all the contracts where the non-clearing member is not subject to capital requirements. The sample is composed of single-name sovereign CDS contracts written on Italy, Germany and France as a reference entity in 2016. Data comes from trade repositories under the the EMIR reporting requirement.

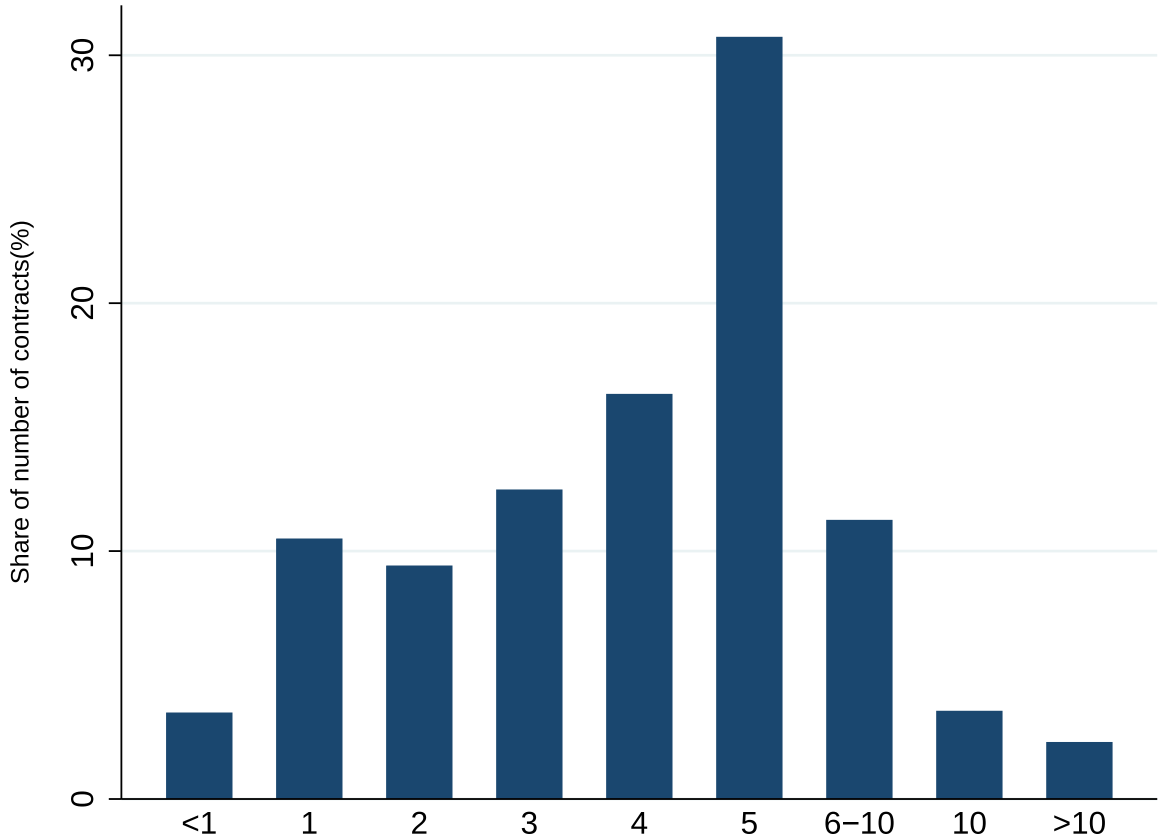


Figure 5.4: **Distribution of sovereign CDS contracts' tenor**
This figure shows the relative frequency of CDS transactions, grouped by buckets of tenors. The sample is composed of single-name sovereign CDS contracts written on Italy, Germany and France as a reference entity in 2016. Data comes from trade repositories under the the EMIR reporting requirement.

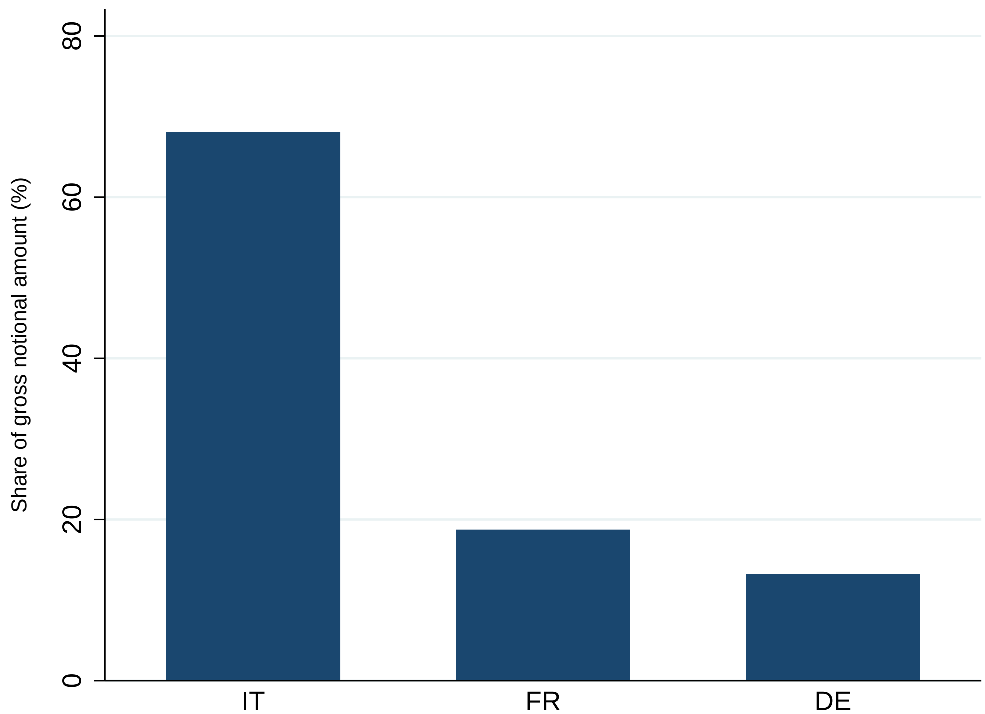


Figure 5.5: **Share of the gross notional amount traded**
This figure shows the share of the total gross notional amount traded for each of the three sovereign CDS reference entity included in our sample. The sample is composed of single-name sovereign CDS contracts written on Italy, Germany and France as a reference entity in 2016. Data comes from trade repositories under the the EMIR reporting requirement.

Tables

Table 5.1: **Notional amounts and number of counterparties by type of market participant**

For both panels, we report the gross notional amount both in US dollar billion and in percentage, the net notional amount, and the number of counterparties for each market participant category. Panel A shows the data by the market participant type. The category "Other Institutions" includes Insurances, Pension, and Not financial organizations. The category "Others" contains all the others not classifiable institutions. Panel B shows the data by institutions grouped in categories: "Non-Clearing Members (CR)" are the non-clearing members institutions subject to capital requirements“, "Non-Clearing Members (NCR)" are the non-clearing members institutions not subject to capital requirements, while "Others" holds all the other non-classifiable institutions.

Panel A

Market Participants	**Gross Notional Amount (B$)**	**Gross Notional Amount (%)**	**Net Notional Amount (B$)**	**Number of Counterparties**
Banks	95.8	12.0%	5.5	33
Dealers	596.6	74.8%	3.7	15
Funds	95.1	11.9%	-7.2	233
Other Inst.	7.7	1.0%	-2.1	40
Others	2.6	0.3%	0.0	123

Panel B

Market Participants	**Gross Notional Amount (B$)**	**Gross Notional Amount (%)**	**Net Notional Amount (B$)**	**Number of Counterparties**
Clearing Members	769.1	96.5%	9.7	26
Non-Clearing Members (CR)	8.5	1.1%	-2.2	29
Non-Clearing Members (NCR)	17.1	2.1%	-8.1	266
Others	2.6	0.3%	-0.3	123

Table 5.2: **Description of variables**
The table shows the explanatory variables used for testing the following three Hypothesis: 1) Contract and Liquidity Risk (Panel A), 2) Position with the CCP (Panel B) and 3) Counterparty Credit Risk (Panel C). The table reports the variables considered, their description and data source.

Panel A Hypothesis 1: Contract and Liquidity Risk

Variable	**Description**	**Data source**
N. of Trades	Daily trades: Number of daily trades of a particular reference entity	EMIR
Log Notional Amount	Trade Volume : The logarithm of the contracts' notional amount	EMIR
CDS Volatility	Exponential Weighted Moving Average Volatility of the CDS spread Market	Markit
CDS Quote Spread	CDS Quote Spread of a particular reference entity	Markit
Δ CDS Spread	CDS Spread of a particular reference entity change	Markit

Panel B Hypothesis 2 : Position with the CCP

Variable	**Description**	**Data source**
Seller is net buyer with CCP (Dummy)	Net buyer sells protection: Trades where the Seller is a net buyer	EMIR
Buyer is net seller with CCP (Dummy)	Net seller buys protection: Trades where the Buyer is a net seller	EMIR
Buyer's exposure to the CCP	Inventories of the Buyer : Net open position with the CCP at a reference entity level	EMIR
Seller's exposure to the CCP	Inventories of the Seller: Net open position with the CCP at a reference entity level	EMIR

Panel C HP 3 : Counterparty Credit Risk

Variable	**Description**	**Data source**
Spread Buyer - 5Y	Buyer CDS spread with Tenor 5 years	Markit
Spread Seller - 5Y	Seller CDS spread with Tenor 5 years	Markit

Table 5.3: **Descriptive statistics**

The table shows descriptive statistics for the explanatory variables used for testing the following three hypotheses: 1) Contract and Liquidity Risk (Panel A), 2) Position with the CCP (Panel B) and 3) Counterparty Credit Risk (Panel C).

Panel A

	DE			FR			IT		
Variables	**N. Obs.**	**Mean**	**S.dev.**	**N. Obs.**	**Mean**	**S.dev.**	**N. Obs.**	**Mean**	**S.dev.**
N. of trades	1363	191.511	192.203	2748	173.081	156.305	8289	128.257	138.735
Log Notional Amount	1332	15.838	2.445	2666	15.432	2.297	8053	16.112	1.882
CDS Volatility	1147	0.031	0.017	2360	0.027	0.016	7391	0.028	0.012
CDS Quote Spread	1336	12.565	10.093	2705	30.107	16.128	8219	128.765	41.065
Δ CDS Spread	1336	0.036	0.659	2705	0.231	1.172	8219	0.172	4.650

Panel B

	DE			FR			IT		
Variables	**N. Obs.**	**Mean**	**S.dev.**	**N. Obs.**	**Mean**	**S.dev.**	**N. Obs.**	**Mean**	**S.dev.**
Buyer's exposure to the CCP	231	0.273	0.439	674	0.107	0.300	2947	-0.064	0.310
Seller's exposure to the CCP	207	0.257	0.424	521	0.053	0.393	2653	-0.089	0.323

Panel C

	DE			FR			IT		
Variables	**N. Obs.**	**Mean**	**S.dev.**	**N. Obs.**	**Mean**	**S.dev.**	**N. Obs.**	**Mean**	**S.dev.**
Spread Buyer - 5Y	877	99.707	18.813	2120	99.887	16.098	5838	97.589	24.684
Spread Seller - 5Y	895	99.278	18.501	1940	101.141	21.223	4997	99.385	26.437

Table 5.4: **Hypothesis 1: Contract and Liquidity Risk estimations for sovereign CDS** This table shows the estimated probit model results for contracts having Germany France and Italy as reference entity, and where both of the counterparties are clearing members (CM). The dependent variable is a dummy variable equal to one when the contract is cleared. The explanatory variables used are: the CDS spread of the reference entity (CDS Quote Spread), the first difference of the CDS spread (ΔCDS Spread), the logarithm of the Notional amount of the contract (Log Notional Amount), the exponential weighted moving average of the CDS returns of the reference entity (CDS Volatility), the number of the daily transactions (N. of trades). In the model presented in the last column of the table, controls for month fixed effects are included.

	DE		**FR**		**IT**	
Models	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CDS Quote Spread	0.0008	0.0006	0.0067***	0.0098***	0.0016***	0.0028***
	(0.0048)	(0.0054)	(0.0022)	(0.0023)	(0.0004)	(0.0005)
Δ CDS Spread	-0.163*	-0.270**	-0.125***	-0.122**	0.0074*	0.0188***
	(0.0964)	(0.127)	(0.0469)	(0.0579)	(0.0040)	(0.0045)
CDS Volatility	-12.72***	-34.86***	-14.09***	-6.873**	-0.473	5.358**
	(3.496)	(8.142)	(2.753)	(3.398)	(1.606)	(2.292)
Log Notional Amount	0.0272	0.0249	0.224***	0.237***	0.262***	0.265***
	(0.0321)	(0.0327)	(0.0278)	(0.0336)	(0.0134)	(0.0142)
N. of Trades	-0.0019***	-0.0007	-0.0011***	-0.0006	-0.0016***	-0.0011***
	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0001)	(0.0001)
Constant	-0.208	0.424	-3.917***	-3.870***	-4.541***	-4.558***
	(0.568)	(0.644)	(0.471)	(0.593)	(0.242)	(0.271)
Observations	832	832	1,713	1,713	5,132	5,132
Adj R2	0.0614	0.147	0.140	0.157	0.0987	0.136
Month FE	N	Y	N	Y	N	Y

Robust standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5.5: **Hypothesis 2: Position with the CCP**

This table shows the estimated probit model results for contracts having Germany France and Italy as reference entity, and where both of the counterparties are clearing members (CM). The dependent variable is a dummy variable equal to one when the contract is cleared. Panel A shows the estimation results when considering the buyer side. The first explanatory variable is a dummy equal to one when the buyer is a net seller with the CCP . Panel B indicates the estimation results when considering the seller side. The first explanatory variable is a dummy equal to one when the seller is a net buyer with the CCP. In the models presented in the last two columns of the table, controls for month fixed effects are included.

Panel A

	DE		**FR**		**IT**	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Buyer is net seller with CCP (Dummy)	0.598**	0.303	0.886***	0.775***	0.130***	0.140***
	(0.299)	(0.319)	(0.122)	(0.128)	(0.047)	(0.049)
Constant	-0.598***	-0.319**	-0.820***	-0.249	-0.297***	0.008
	(0.043)	(0.160)	(0.032)	(0.153)	(0.018)	(0.090)
Observations	224	205	416	416	2,159	2,159
Adj R2	0.003	0.110	0.024	0.059	0.001	0.0431

Panel B

	DE		**FR**		**IT**	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Seller is net buyer with CCP (Dummy)	-1.008***	-0.946***	-0.907***	-0.976***	-0.304***	-0.279***
	(0.135)	(0.152)	(0.0877)	(0.098)	(0.0349)	(0.036)
Constant	0.305**	0.628***	0.0156	0.806***	-0.076***	0.266***
	(0.128)	(0.220)	(0.081)	(0.168)	(0.028)	(0.097)
Observations	199	199	456	456	2,251	2,251
Adj R2	0.048	0.146	0.0493	0.089	0.009	0.049
Month FE	N	Y	N	Y	N	Y

Robust standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5.6: **Hypothesis 2: Position with the CCP**

This table shows the estimated probit model results for contracts having Germany France and Italy as reference entity, and where both of the counterparties are clearing members (CM). The dependent variable is a dummy variable equal to one when the contract is cleared. Panel A shows the estimation results when considering the buyer side. The interaction term is the variable to analyze, capturing the jointed effect between two terms: The first one (A) is a dummy equal to one when the buyer is a net seller with the CCP for the respective sovereign CDS; the second one (B) indicates the buyer's exposure to the CCP. Panel B indicates the estimation results when considering the seller side. In this case the interaction term captures the combinations of two effects: the first variable (A) is a dummy equal to one when the seller is a net buyer with the CCP for the respective sovereign CDS. The second variable (B) indicates the seller's exposure to the CCP. In the models presented in the third and the sixth columns of the table, controls for month fixed effects are included.

Panel A

	DE		FR		IT	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Buyer - Interaction term (A)*(B)	-0.645	-146.1***	4.131***	6.025***	4.316***	5.376***
	(7.031)	(4.897)	(1.354)	(2.011)	(0.388)	(0.418)
Buyer is net seller with CCP dummy (A)	-0.0881	-22.11***	1.084***	0.515	0.560***	0.608***
	(0.660)	(0.492)	(0.307)	(0.364)	(0.0786)	(0.0866)
Buyer's exposure to the CCP (B)	-0.814***	-0.584**	-0.837***	-4.132**	-0.503***	-1.037***
	(0.212)	(0.279)	(0.299)	(1.694)	(0.142)	(0.158)
Constant	-0.0285	1.455***	-0.286***	0.389	-0.0127	0.824***
	(0.107)	(0.529)	(0.0824)	(0.367)	(0.0361)	(0.213)
Observations	224	205	416	416	2,159	2,159
Adj R2	0.0523	0.187	0.0432	0.201	0.0902	0.164

Panel B

	DE		FR		IT	
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Seller - Interaction term (A)*(B)	-7.179**	13.07	-0.865*	-0.00776	-1.117***	-2.024***
	(3.658)	(9.086)	(0.511)	(0.631)	(0.252)	(0.259)
Seller is net buyer with CCP Dummy (A)	0.338	3.751***	0.0584	-1.316***	0.247**	0.576***
	(0.256)	(1.382)	(0.161)	(0.323)	(0.101)	(0.109)
Seller's exposure to the CCP (B)	5.834	-18.72*	-0.713*	-0.256	0.191*	0.284**
	(3.646)	(10.53)	(0.372)	(0.404)	(0.105)	(0.112)
Constant	0.423***	-2.081*	-0.115	0.827***	-0.0478	0.347*
	(0.139)	(1.213)	(0.104)	(0.262)	(0.0323)	(0.184)
Observations	199	199	456	456	2,251	2,251
Adj R2	0.102	0.265	0.0744	0.182	0.00714	0.0668
Month FE	N	Y	N	Y	N	Y

Robust standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5.7: **Hypothesis 3: Counterparty Credit Risk**
This table shows the estimated probit model results for contracts having Germany France and Italy as reference entity, and where both of the counterparties are clearing members (CM). The dependent variable is a dummy variable equal to one when the contract is cleared. Panel A reports the impact of the buyer CDS spread on the probability to find a contract cleared. Panel B reports the impact of the seller CDS spread on the probability to find a contract cleared. Month fixed effects controls are included.

Panel A

	DE		**FR**		**IT**	
Models	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Spread Buyer - 5Y	0.010***	0.025***	0.010***	0.020***	0.004***	0.0066***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.0009)
Constant	-2.035***	-3.272***	-2.193***	-2.341***	-1.083***	-1.271***
	(0.298)	(0.463)	(0.249)	(0.377)	(0.079)	(0.144)
Observations	751	751	1,601	1,601	4,162	4,162
Adj R2	0.017	0.121	0.014	0.073	0.004	0.0431

Panel B

	DE		**FR**		**IT**	
Models	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Spread Seller - 5Y	0.013***	0.025***	0.019***	0.023***	0.012***	0.0154***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.0010)
Constant	-2.226***	-3.197***	-3.055***	-2.803***	-1.938***	-1.677***
	(0.282)	(0.435)	(0.197)	(0.344)	(0.088)	(0.147)
Observations	768	768	1,638	1,638	4,176	4,176
Adj R2	0.027	0.145	0.092	0.144	0.052	0.110
Month FE	N	Y	N	Y	N	Y

Robust standard errors in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5.8: **Hypothesis 3: Counterparty Credit Risk estimations for Italian sovereign CDS**

This table shows the estimated probit model results for the contracts having Italy as reference entities, and where counterparties are clearing members (CM). The dependent variable is a dummy variable equal to one when the contract is cleared. The explanatory variables used are the buyer CDS spread (Spread Buyer 5Y) and the seller CDS spread (Spread Seller 5Y), both with 5 year tenors. In the models presented in the second column of the table, controls for month fixed effects are included.

Models	**(1)**	**(2)**
Spread Buyer - 5Y	0.005***	0.008***
	(0.001)	(0.001)
Spread Seller- 5Y	0.0097***	0.0119***
	(0.001)	(0.002)
Constant	-3.158***	-4.669***
	(0.129)	(0.413)
Observations	2,814	2,226
Adj R2	0.042	0.193
Month FE	N	Y

Robust standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

5.8 Appendix

Table 5.9: **Hypothesis 1: Contract and Liquidity Risk estimations for German sovereign CDS**

This table shows the estimated probit model results for contracts having Germany as reference entity, and where both of the counterparties are clearing members (CM). The dependent variable is a dummy variable equal to one when the contract is cleared. The explanatory variables used are: the CDS spread of the reference entity (CDS Quote Spread), the first difference of the CDS spread (ΔCDS Spread), the logarithm of the Notional amount of the contract (Log Notional Amount), the exponential weighted moving average of the CDS returns of the reference entity (CDS Volatility), the number of the daily transactions (N. of trades).

			DE		
Models	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
CDS Quote Spread	0.0033				
	(0.0043)				
Δ CDS Spread		-0.149			
		(0.0965)			
Log Notional Amount			0.0081		
			(0.0260)		
CDS Volatility				-2.075	
				(2.854)	
N. of Trades					-0.0018***
					(0.0002)
Constant	-0.663***	-0.628***	-0.720*	-0.442***	-0.216***
	(0.0714)	(0.0432)	(0.432)	(0.0941)	(0.0633)
Observations	989	989	1,004	832	1,004
Adj R2	0.0005	0.002	0.0001	0.0005	0.0551
Month FE	N	N	N	N	N

Robust standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5.10: **Hypothesis 1: Contract and Liquidity Risk estimations for French sovereign CDS**

This table shows the estimated probit model results for contracts having France as reference entity, and where both of the counterparties are clearing members (CM). The dependent variable is a dummy variable equal to one when the contract is cleared. The explanatory variables used are: the CDS spread of the reference entity (CDS Quote Spread), the first difference of the CDS spread (ΔCDS Spread), the logarithm of the Notional amount of the contract (Log Notional Amount), the exponential weighted moving average of the CDS returns of the reference entity (CDS Volatility), the number of the daily transactions (N. of trades).

	FR				
Models	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
CDS Quote Spread	0.0064***				
	(0.0021)				
Δ CDS Spread		-0.105**			
		(0.0462)			
Log Notional Amount			0.211***		
			(0.0241)		
CDS Volatility				-7.759***	
				(2.602)	
N. of Trades					-0.0012***
					(0.0002)
Constant	-0.966***	-0.766***	-4.121***	-0.511***	-0.554***
	(0.0715)	(0.0314)	(0.395)	(0.0727)	(0.0467)
Observations	1,997	1,997	2,034	1,716	2,034
Adj R2	0.0052	0.0051	0.0935	0.0059	0.0170
Month FE	N	N	N	N	N

Robust standard errors in parentheses: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table 5.11: **Hypothesis 1: Contract and Liquidity Risk estimations for Italian sovereign CDS**

This table shows the estimated probit model results for contracts having Italy as reference entity, and where both of the counterparties are clearing members (CM). The dependent variable is a dummy variable equal to one when the contract is cleared. The explanatory variables used are: the CDS spread of the reference entity (CDS Quote Spread), the first difference of the CDS spread (ΔCDS Spread), the logarithm of the Notional amount of the contract (Log Notional Amount), the exponential weighted moving average of the CDS returns of the reference entity (CDS Volatility), the number of the daily transactions (N. of trades).

	IT				
Models	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
CDS Quote Spread	0.0004				
	(0.0004)				
Δ CDS Spread		0.0085**			
		(0.0035)			
Log Notional Amount			0.263***		
			(0.0123)		
CDS Volatility				0.742	
				(1.460)	
N. of Trades					-0.0016***
					(0.0001)
Constant	-0.336***	-0.282***	-4.598***	-0.289***	-0.0822***
	(0.0544)	(0.0166)	(0.206)	(0.0435)	(0.0220)
Observations	5,925	5,925	5,816	5,282	5,985
Adj R2	0.0001	0.0007	0.0846	3.51e-05	0.0186
Month FE	N	N	N	N	N

Robust standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

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