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Does Social Capital Reduce Moral Hazard? A Network Model for Non-Life Insurance Demand*

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Abstract

We study the effect of social capital in an environment in which formal, marketed insurance contracts coexist with informal agreements. We show that in the absence of peer monitoring and social pressure, non-marketed contracts crowd out formal ones due to moral hazard. We prove, by means of an equilibrium concept typical of the network literature, that social capital can reduce moral hazard in informal agreements. We then show that under certain conditions, social capital increases the demand for marketed insurance contracts. The theoretical model we outline provides us clear guidance to measure social capital in a provincial-level data set. The empirical model, which is estimated controlling for panel and spatial structure, supports our claim that social capital increases the demand for non-life insurance.

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I. Introduction

The research question we want to investigate is whether social capital influences individual choices about insurance expenditure. In particular, we are interested in demand for non-life insurance contracts. While life insurance can be assimilated into pension funds and other financial assets in terms of economic rationale – it is an investment that gives a return in the future – non-life insurance is different. Households buy a non-life insurance contract to avoid the risk of suffering losses in some states of the world: they pay a fixed price (the premium) to transfer money from one future uncertain state of the world to another.

Arnott and Stiglitz (1991) set up a model in which, as well as market insurance, individuals could enter non-market mutual insurance agreements. In their model, the role played by non-market insurance was related to peer monitoring: if informational asymmetry between the insurer and the customer held in non-market contracts, they would be dysfunctional and non-market insurance would displace market contracts, reducing social welfare. Vice versa, if individuals could observe the efforts of others, non-market contracts would be welfare enhancing since they provided extra insurance coverage at the market price set by the insurance company. What the authors call peer monitoring is the severity of moral hazard in non-market agreements.

We will investigate the relationship between moral hazard involved in non-market insurance contracts and the demand for market insurance. We will also formally link moral hazard and social capital, concluding that the latter increases the aggregate demand for insurance. Social capital is not a precise economic concept but covers many different but related research fields. A careful and theory-consistent definition of it allows us to test our conclusions empirically on Italian data.

The choice of Italy as a data source is quite common in the social capital literature: the seminal book by Putnam, Leonardi and Nanetti (1993) about democracy and institutions' efficiency is a source of overwhelming evidence on the relevance of social capital in Italian social life. Focusing on economics, Guiso, Sapienza and Zingales (2004) found that social capital influences the asset-allocation choices of Italian households: they started from the idea that any financial contract involves trust, which is strongly correlated to social capital, and found empirical evidence supporting this relation. Moreover, Millo and Lenzi (2005) found that the Italian insurance market exhibits a large unexplained spatial heterogeneity and spatial correlation at the provincial level, even after controlling for a number of demographics. Durlauf and Fafchamps (2004) pointed out that a possible role for social capital in economic models is to limit market inefficiencies when institutions fail to resolve them: in Italy, family ties are frequently substitutes for inefficient institutions. Religious communities as well as some other professional and voluntary associations play a role in supplementing part of the social welfare not provided by the state; disabled and elderly people's assistance or scholarships are some examples. We therefore claim that social capital can explain a substantial part of the heterogeneity in insurance demand.

We estimate our model on a panel database of Italian provinces, explicitly taking spatial correlation into account. Spatial panel estimation techniques, first outlined in Anselin (1988), have not become a standard in the insurance literature because of computational difficulties. Based on the comprehensive treatment of Elhorst (2003), we develop new procedures in the R language for maximum likelihood estimation of spatial autoregressive and spatial error panel models.

The paper is structured as follows. The next section describes the economic model and provides a formal definition of social capital. Section III describes the data at hand, while Section IV is dedicated to the definition of an empirical measure for social capital. Section V describes the estimation procedure and results, and conclusions are drawn in Section VI.

II. The model

Arnott and Stiglitz (1991) were interested in the general equilibrium and welfare effects of non-market insurance and peer monitoring. Their model provides the background to study the effects of moral hazard and social capital on the demand for market insurance. In this section, we describe the main results and intuitions of the model, while a formal derivation of the required results can be found in Appendix A.

The starting point is the canonical moral hazard model without non-market insurance. There is a single and fixed-damage accident, and the probability of its occurrence, $p(e)$, is strictly convex and decreasing in the individual's effort at accident avoidance, e, which is not observable to the insurer. At the competitive, constrained equilibrium, the insurer offers less than full insurance to induce its clients to augment their effort at accident avoidance. This equilibrium is stable only if clients purchase no additional insurance. This exclusivity condition is similar to what happens in the real world: insurance companies cannot force their clients to buy just one contract, but they ask them what other contracts they have covering the same risk and, in the case of accident occurrence, payout is divided proportionally among insurers.

Non-market insurance is introduced as follows: a couple of symmetric individuals, i and j, agree that if only one of them has an accident, the other will transfer δ to the former. If moral hazard affects the non-market agreement – i.e. if each individual does not observe the other's effort and there are no incentives to cooperate – the exclusivity provision cannot be enforced. It is optimal for clients to reduce their effort, while the insurance company is still offering the same contract. This is a partial equilibrium result since it does not consider the reaction of insurance companies to agents' behaviour. In a general equilibrium context, the company knows that the required level of effort for the offered contract cannot be enforced: non-market insurance crowds out market insurance and individuals substitute insurance provided by a risk-neutral insurer with that provided by a risk-averse one. Expected utility is then lower than without non-market insurance. Moral hazard does not play a role if the insured perfectly observe each other's efforts or if there are incentives to cooperate. Arnott and Stiglitz (1991) show that, in this event, each client provides non-market insurance up to full coverage in order to augment the risk-sharing opportunity.

Compared with Arnott and Stiglitz (1991), we need a further step: while they were interested in the welfare effects of non-market agreements, we want to investigate how demand for insurance changes if non-market agreements are available. In order to achieve this, we restrict the shape of individual utility functions and of contracts offered by insurance companies in order to have clear empirical implications, at the price of a set of assumptions common to the applied literature on insurance.

The first assumption is that insurance companies can offer only linear contracts, i.e. $q(\alpha, \beta) = \beta/\alpha$, where q is the contract's price, β is the premium paid by the client and α is the net payout received if the accident occurs. Second, market insurance contracts are exclusive, meaning that agents can sign just one contract with one insurance firm to cover a given risk. Third, the insurance market is competitive and companies set the price in order to make zero profit. Therefore, at equilibrium, $q = \beta/\alpha = p(e)/\{1-p(e)\}$.

Drawing from the analytical treatment of moral hazard models in Arnott and Stiglitz (1988), under a set of assumptions about the utility function detailed in Appendix A, we can characterise the demand functions: first, demand for insurance decreases with the price of insurance and effort increases with price; second, if there exists an equilibrium without non-market agreements $E_0 : \{\tilde{e}, \tilde{q}, \tilde{\delta} = 0\}$ and one with non-market agreements and no moral hazard $E_1 : \{e^*, q^*, \delta^* > 0\}$, demand for market insurance is higher in E_1 than in E_0.[1]

One important feature of the model is that market insurance and non-market agreements can coexist only if the latter are not affected by moral hazard. Arnott and Stiglitz (1991) distinguish between the cases in which

[1]Note that we obtained a testable implication about insurance demand but not an existence result: while it is possible to prove that an equilibrium with linear pricing always exists (see Arnott and Stiglitz (1988) for details), it may entail corner solutions, i.e. zero insurance or positive profits. The additional assumptions we make rule out corner solutions; therefore E_1 may not exist.

effort is observable by peers (no moral hazard) and those in which it is not. We claim that peer monitoring is not the only way to avoid moral hazard. This is a natural assumption within a couple or a family, but not among people with looser ties, such as members of a religious community or people living in a small, isolated village. In a broader setting, the level of trust between individuals entering the informal agreement, the severity of punishment for deviating, the power of reputation and social pressure can induce cooperative behaviour even without perfect peer observability. In a nutshell, social capital can reduce moral hazard in non-market agreements.

Social capital is an elusive concept which has particular meanings depending on the context in which it is used, but in order to have a testable model we need to formalise this concept. Durlauf and Fafchamps (2004) pointed out that a common feature of definitions of social capital is the focus on interpersonal relationships and social networks. This is the reason why we use a network approach proposed by Vega-Redondo (2006).

Suppose that pairs of individuals entering a non-market insurance agreement can choose in each period whether to put in effort e_{MH}, the one with moral hazard in the Arnott–Stiglitz framework, or e^*, effort without moral hazard. Once this game is put in a dynamic setting, we have a finite population of agents where each pair of interacting agents (i, j) is involved in an infinite repetition of a prisoner's dilemma game. For any agent i, the strategy is of the following type:

1. Player i chooses whether to start her interaction with j putting in effort e^* (which is to cooperate) or to put in effort e_{MH}.
2. In following rounds, she reacts immediately to the news that j did not start with e^* with some other agent in j's network by switching irreversibly to e_{MH} in her game with j.

Under this setting, we prove that there exists a pairwise-stable network (PSN), i.e. a network where, for every separate link, both players have incentives to sustain the cooperative equilibrium. Given a characterisation of the expected utility of players, Vega-Redondo (2006) showed that a PSN is more likely to be achieved in networks characterised by a large stock of social capital, which is defined as the average number of links per agent.

The first part of the model, derived from Arnott and Stiglitz (1991), shows that if non-market insurance agreements do not involve moral hazard, their presence positively affects demand for market insurance. We then invoke Vega-Redondo (2006) to prove that moral hazard is inversely related to network stability. Since the likelihood of achieving a pairwise-stable network is increasing in the stock of social capital, we conclude that social capital positively affects the demand for market insurance.

III. Demographics and insurance data

We consider the total of all non-life insurance classes, excluding only mandatory motor third-party liability (TPL) because of its compulsory nature. In order to measure the effect of social capital on insurance purchases, we have to control for the determinants of insurance development. Theoretical models of non-life insurance demand, starting from the seminal paper of Mossin (1968), predict that, for a given level of risk exposure, insurance demand is increasing with risk aversion, probability of loss and wealth at stake. Empirical studies identify some observable counterparts. Wealth, when not observable, is generally proxied by means of income or bank deposits; so is risk exposure, which is in turn related to total wealth and the level of economic activity. Loss probability may too be related to income as a measure of economic activity; urbanisation has also been suggested for this purpose (Browne, Chung and Frees, 2000). The loss ratio – i.e. the ratio between claims paid by the insurer and premiums collected – has also been suggested as a proxy for the probability of loss (Browne, Chung and Frees, 2000). Aspects of risk aversion may be captured by education or the age structure of the population, even though the expected sign of the effect is unclear.[2]

1. Controlling for supply-side variables

We stated in Section II that an insurance company has limited discriminating power, i.e. if individuals are heterogeneous, it can offer different contracts (which means different prices) based on observable characteristics of individuals in a particular subpopulation but it cannot offer individual contracts based on effort, which is always unobserved by the insurer. This means that in an empirical investigation on demand for insurance, it is crucial to control for supply-side changes (i.e. for offered prices), in order to be sure that the marginal effects of interest (which we investigate based on the demand equation) are not completely absorbed by equilibrium prices. This is not a trivial problem: as Schlesinger (2000) notes,

> it is often difficult to determine what is meant by the price and the quantity of insurance. ... the fundamental two building blocks of economic theory have no direct counterparts for insurance.

In practice, we can observe only insurance consumption, the product between equilibrium price and quantity, jointly determined by the interplay of supply and demand. The choice of a price variable, when available, is therefore far from obvious. We do not observe the amounts insured;

[2]See Grace and Skipper (1991), Browne and Kim (1993) and the discussion in Browne, Chung and Frees (2000).

therefore mean premium rates – which would probably be best – are ruled out. We resort therefore to the loss ratio, as, for example, in Esho et al. (2004), observing that the role of this index as a proxy for market riskiness could lead to ambiguity. Due to unavailability of data on losses for the non-life market, we include the aggregate loss ratio for the property sector only (fire, motor non-third-party liability, other material loss).

Lastly, given the importance of tied agents in the distribution of insurance products (this channel accounted in 2000 for 88.3 per cent of non-life premium volume[3]), the log of agencies per capita has been included as a supply-side driver, inversely related to the opportunity cost of searching for insurance cover.

Our data set consists of an excerpt for the years 1998–2000 from the Geo-Starter database. We chose these three years of data in order to have homogeneous definitions of provinces (provinces' boundaries changed in 1996 and, to a lesser extent, in 2001) and a large set of controls, which are not all available in each yearly release of the database. Geo-Starter provides both first-hand data and an organised collection of variables from various institutional sources. Disposable income, value added by branch, exports, unemployment, family size, population density, land shape and surface and the age structure of the population are collected at the provincial level from Istituto Tagliacarne, the regional statistics branch of the Italian statistical service Istat. The data on bank deposits are collected by the Bank of Italy. Data on insurance premiums are collected on a provincial basis by ISVAP, the Italian insurance authority, aggregated into three categories: life, compulsory third-party liability (the vast majority of which involves motor vehicles) and other non-life. While motor third-party liability is a homogeneous class, both life and other non-life comprise very different kinds of policies. Different classes of non-life insurance cover different protection needs, but unfortunately complete data for subsectors of non-life are not available at this territorial disaggregation level. Nevertheless, the economic rationale behind the purchase of insurance coverage is similar and thus it is appropriate to consider non-life (or *property-liability*) insurance as a whole, as done also in most of the empirical literature.[4]

2. Measuring insurance consumption

As noted above, we can observe the equilibrium value of insurance consumption but neither the quantity nor the price of insurance. Furthermore, measuring insurance consumption across administrative regions of different economic and demographic size requires some sort of

[3]Including motor third-party liability. Source: Italian Insurers' Association (ANIA).

[4]See, for example, Beenstock, Dickinson and Khajuria (1988), Outreville (1990), Browne, Chung and Frees (2000), Enz (2000) and Esho et al. (2004).

rescaling. Two common normalised measures are used in the literature as well as among practitioners: insurance penetration, defined as how much insurance premiums contribute to GDP, which accounts for the relative importance of the insurance sector; and insurance density, defined as premiums per capita, which measures average per-capita expenditure. In accordance with most relevant papers in the empirical literature on insurance development,[5] we focus on insurance density.[6] In the same fashion, all variables subject to a size bias in the information set have been normalised with respect to the relevant benchmark.

3. Locational issues

Premium data are registered according to the location of the sales point provided by companies. Our observations are for the Italian administrative units called *provincie*, corresponding to level 3 in the NUTS (Nomenclature of Territorial Units for Statistics) classification by Eurostat. When we refer to macro-regions, we divide the 20 NUTS2 Italian *regioni* into five aggregates – North-West, North-East, Centre, South and Islands – according to Istat, the Italian statistics bureau. Besides the unavoidable aggregation bias due to the arbitrariness of administrative boundaries with respect to the geographic dimension of economic phenomena,[7] some important additional biases may arise if the location of the sales point differs from the actual location of the insured.

First, for most big contracts negotiated by brokers and also for some distribution agreements (for example, in bancassurance), big units usually located at important industrial or financial centres are accountable for all business nationwide. This is the case for marine insurance premiums collected by business units located in the main ports for customers doing business elsewhere, and for some nationwide salesperson networks whose business goes through a single agency typically located at the company headquarters.

Second, collective policies purchased by firms as mandatory cover or as a fringe benefit for their employees, most typically in the accident, health and life classes, are bound to one sales point location even if they are actually insuring risks spread over a wider territory.

[5]Specifically, Beenstock, Dickinson and Khajuria (1988), Outreville (1990), Browne, Chung and Frees (2000) and Esho et al. (2004).

[6]The density measure is selected for convenience in the specification, in order to avoid having GDP at the denominator of the regressand and then also as a right-hand-side variable.

[7]See Anselin (1988).

IV. How to measure social capital

In Section II, we tackled one of the major problems pointed out by Durlauf and Fafchamps (2004), which is to give a sound economic meaning to social capital. Now we have to address a second controversial issue: a reasonable empirical measure of this concept. Since we have province-level data, our definition suggests a somewhat natural way to measure social capital: we want to measure the density and cohesiveness of social networks characterising each province. We are not the first to propose such a measure: Goldin and Katz (1999) based their empirical measure of social capital intensity on Coleman's (1988) definition of closure, which is the same concept as network cohesiveness in Vega-Redondo (2006). They had a data set on schooling and some economic variables on Iowa in the US in 1915. The detail was at the level of counties, comparable to Italian provinces. Goldin and Katz's measure was the proportion of the county population living in small towns. Their claim was that

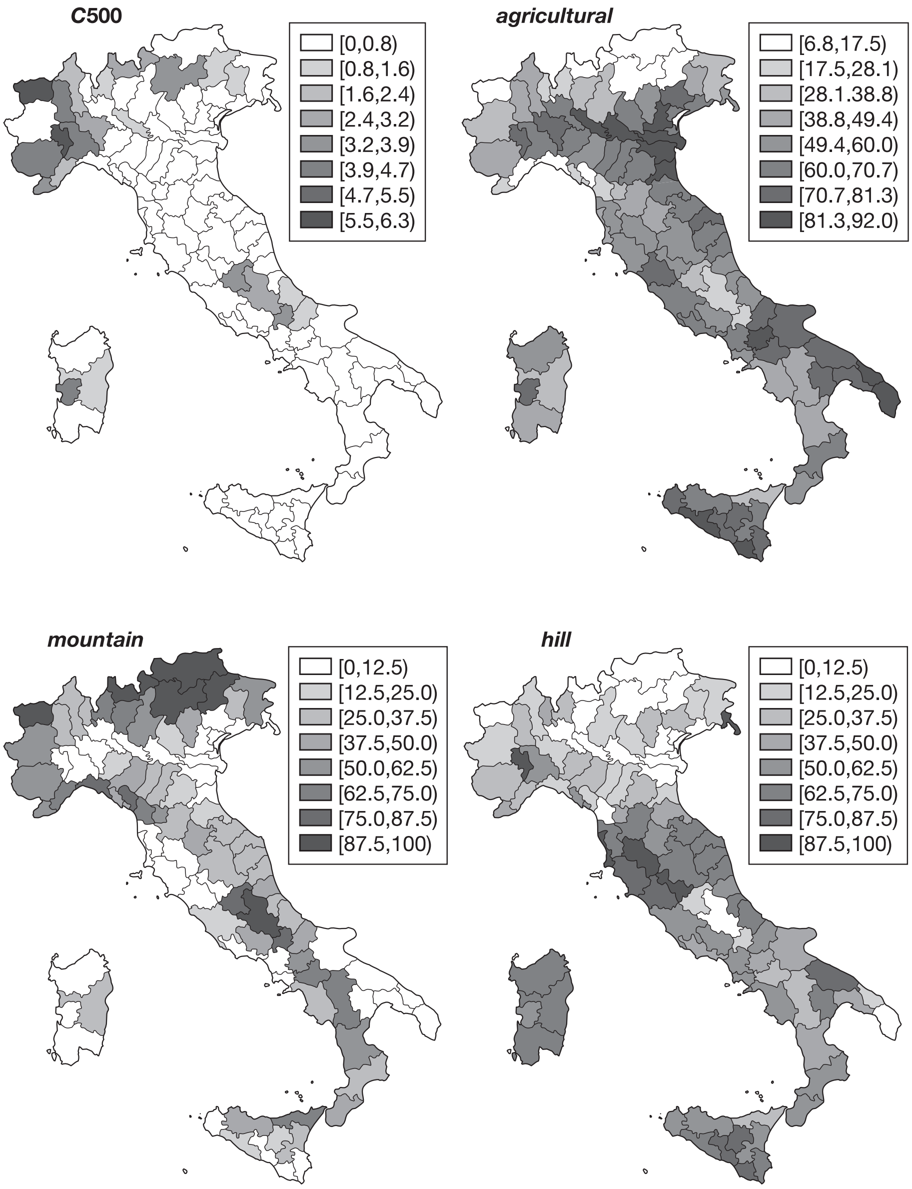
> Small town in America was a locus of associations (religious, fraternal/sororal, business, and political organizations) that could have played an important role in galvanizing support for the provision of local publicly provided goods …. These associations … provide another indicator of community cohesion.

Like them, we measure social capital by the fraction of the provincial population living in small and isolated communities. Allcott et al. (2007) provide a theoretic foundation to such an indicator: their argument is that in small communities, the number of potential relations is limited; thus the probability that the network neighbourhoods of two friends overlap is higher even when the total number of friends is fixed. This means social networks in small communities are more interconnected and therefore the density of social interactions is higher.

Goldin and Katz's measure can be replicated for our data, but it is not sufficient to identify isolated communities: in 1915 Iowa, the overall population density was very low; therefore, living in a small town meant living far from other towns. Present-day Italy, on the contrary, is characterised by a high population density. This means that living in a small town is not necessarily the same as living in an isolated place. An example is the Po valley in northern Italy: towns can be really small (below 500 inhabitants) but they are often next to others, with no free land in between. This means that the percentage of the population living in small towns does not necessarily identify isolated communities. Therefore, the closure of social networks characterising an Italian province is identified by the percentage of the population living in towns with fewer than 500 citizens (*C*500) only after controlling for three other variables. The first two are the fraction of a province's hilly territory (*hill*) and the fraction of mountainous

FIGURE 1

Geographical distribution of social capital proxies



Source: Geo-Starter database, 1998–2000.

territory (*mountain*), which should control for the 'Po valley' effect. The third variable is the fraction of territory devoted to agriculture (*agricultural*), and it is meant to control for a different source of cohesiveness, pointed out by Putnam, Leonardi and Nanetti (1993): a province where people are mainly involved in agriculture could be assumed to be a closed community (in the Coleman sense), either for cultural reasons or for common working interests.[8] These variables are informative, i.e. they do not simply follow a north–south gradient (see Figure 1 and Table B3 in Appendix B).

The network definition we use for social capital is a local interaction concept: the social network is based on direct links among individuals and therefore on geographic proximity. In such a way, we are implicitly ruling out the possibility that long-distance relationships may affect our results. Unfortunately, our data set does not include clear migration measures, such as province-to-province migration flows, to account for such an effect directly. Nevertheless, internal mobility in Italy over a time span as short as the one we are using is a limited phenomenon.[9]

Moral hazard may well depend also on global interaction effects. To be specific, it may depend on a feeling of trust towards others not necessarily induced by direct linking, but based on mutual experience, prejudice, culture and so on. Local and global interaction effects are likely to be correlated; thus if the latter have a role in explaining moral hazard, a measure of them must be included among the regressors in order to obtain an unbiased estimate of the social capital effect. We follow Guiso, Sapienza and Zingales (2004) and use an index derived from a question from the World Values Survey in Italy in 1999. The question was

> Using the responses on this card, could you tell me how much you trust other Italians in general? (5) Trust them completely. (4) Trust them a little. (3) Neither trust nor distrust them. (2) Do not trust them very much. (1) Do not trust them at all.

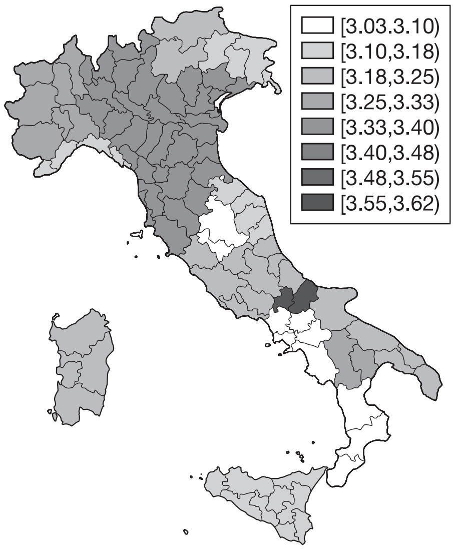
The results of the World Values Survey are available at regional level (NUTS2). This could generate a potential collinearity problem with the macro-area dummies. Nevertheless, trust index values do not follow exactly a north–south gradient (see Figure 2 and Table B3 in Appendix B).

[8]We also experimented with a more parsimonious version of the empirical specification in which *agricultural* does not appear, without significant differences in the parameter's estimate accounting for social capital.

[9]From the data provided by Guiso, Sapienza and Zingales (2004), we gather that 73 per cent of respondents were still resident in the province where they were born.

FIGURE 2

Geographical distribution of trust



Source: World Values Survey, 1999.

V. Model estimation and results

Our data set is a balanced panel; we have 103 observations from 1998 to 2000. A pooled ordinary least squares (OLS) is likely to be inefficient, since the IID (independent and identically distributed) hypothesis on the error terms is usually inappropriate in panel data settings. Once the longitudinal dimension of the data set is taken into account, such a hypothesis can be tested. If the poolability test rejects, the choice remains open between a fixed effects (FE) and a random effects (RE) specification. In our case, we are forced to choose RE: FE estimators are based on within-group heterogeneity, i.e. they require all the explanatory variables to vary within each group (in our case, within each province). Two of our key explanatory variables are based on the shape of provinces' territory, which is clearly invariant. Even excluding these regressors, many other variables have a low variability within each province, thus reducing the efficiency of an FE estimator.

1. The panel model

The econometric model to be estimated in its most general form is the following:

(1) $$y_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \nu_i + \varepsilon_{it} \quad i = 1,\dots,103;\ t = 0,\dots,2$$

where ν_i and ε_{it} are independent of each other and both uncorrelated with the explanatory variables, **X**. y_{it} is the log of non-life insurance premiums per capita in province i and year 1998+t.

Defining $\xi_{it} = \nu_i+\varepsilon_{it}$, the assumption that shocks are independent can be rewritten as

$$\begin{aligned}
&\mathrm{Var}(\xi_{it}) = \sigma_\nu^2 + \sigma_\varepsilon^2\,; \\
&\mathrm{Cov}(\xi_{it}, \xi_{is}) = \sigma_\nu^2 \quad \forall\, t \neq s\,; \\
&\mathrm{Cov}(\xi_{it}, \xi_{js}) = 0 \quad \forall\, t \neq s, i \neq j\,.
\end{aligned}$$

A test for the RE model against a pooled OLS is a test for

$$\begin{aligned}
&H_0 : \sigma_\nu^2 = 0 \\
&H_1 : \sigma_\nu^2 > 0
\end{aligned}.$$

Assuming normality of the errors, a parsimonious testing strategy can be based on the Lagrange multiplier (LM) principle: the OLS model is estimated and then maintained, while it is compared with the more general alternative in a maximum likelihood framework. Test statistics are based on the OLS residuals without need to estimate the panel model. Baltagi (1995) reports the original LM test derived by Breusch and Pagan (1980) together with some refinements. We run the King and Wu (1997) modification, which is distributed as a standard normal.[10] The result of the test is 0.8762, with p-value equal to 0.1905, thus not providing any evidence in favour of the RE model.

Relaxing the assumption of ‘well-behaved’ residuals (see equations (2) and (3) below), another test for unobserved individual effects feasible in short panels is given in Wooldridge (2002). The test statistic is 5.3016, with p-value smaller than 10^{-6}, this time favouring the RE specification. Given the test results and since RE estimators remain consistent under the OLS specification, we proceed estimating an RE model.

2. The random effects model

Under the RE specification with homoscedasticity in both ν_i and ε_{it} and no serial correlation in ε_{it}, the variance–covariance matrix of the errors becomes

[10]This is a locally mean most powerful refinement of the usual Breusch–Pagan χ^2 test. Breusch and Pagan test $H_0 : \sigma_\nu^2 = 0$ against $H_1 : \sigma_\nu^2 \neq 0$, thus rejecting for $\sigma_\nu^2 < 0$, which should be excluded by the model restrictions. The original Breusch–Pagan test strongly rejects the null.

$$V = \sigma_\nu^2 (I_N \otimes \mathbf{i}_T \mathbf{i}'_T) + \sigma_\varepsilon^2 (I_N \otimes I_T)$$

where I_N is the $N\times N$ identity matrix and $\mathbf{i}_N$ is an $N\times 1$ vector of 1s. Therefore, V is block-diagonal with

(2) $$V = I_N \otimes \Omega$$

where

(3) $$\Omega = \begin{bmatrix} \sigma_\varepsilon^2 + \sigma_\nu^2 & \sigma_\nu^2 & \dots & \sigma_\nu^2 \\ \sigma_\nu^2 & \sigma_\varepsilon^2 + \sigma_\nu^2 & \sigma_\nu^2 & \vdots \\ \dots & \sigma_\nu^2 & \ddots & \sigma_\nu^2 \\ \sigma_\nu^2 & \dots & \sigma_\nu^2 & \sigma_\varepsilon^2 + \sigma_\nu^2 \end{bmatrix}.$$

Observations regarding the same province share the same ν_i effect; thus the relative errors are autocorrelated, with $\text{Corr}(\nu_{is}\nu_{it}) = \frac{\sigma_\nu^2}{(\sigma_\varepsilon^2 + \sigma_\nu^2)}$. Ordinary least squares estimates for β in model (1) are therefore inefficient, though consistent. Generalised least squares (GLS) are the efficient solution if Ω is known. Various feasible GLS procedures exist drawing on consistent estimators of Ω. The standard approach to RE panels is to assume both (2) and (3). In 'large N' panels, a less restrictive approach is possible, termed the *general GLS* estimator (GGLS) by Wooldridge (2002), which allows for arbitrary *intra-group* heteroscedasticity and serial correlation of errors, i.e. inside the Ω covariance blocks, provided that these remain the same for every individual. GGLS estimates are reported in column 1 of Table B4 in Appendix B.

3. Spatial structure

As observed when describing the insurance data in Section III, there are good reasons to think that non-life insurance activity may not follow provincial administrative boundaries. For example, provinces may not overlap with operational areas of the sales force. As in many other studies about the spatial distribution of an economic phenomenon, this problem cannot be neglected. In particular, Millo and Lenzi (2005) found evidence of spatial correlation for several specifications of regressions of insurance on a set of demographics, based on the very same data set.[11]

[11]However, Millo and Lenzi carried out a cross-sectional spatial analysis of the determinants of insurance in Italy. As such, it suffered from unobservable heterogeneity issues which in later work, this paper included, were tackled through panel data techniques.

In econometric applications, geographic distance is characterised by means of a proximity matrix, W, containing a distance measure for every pair of data points.[12] Hence Wy, the spatial lag of y, stands for 'the value of y at *neighbouring* locations'.[13] Anselin (1988) warns about the relevant consequences on estimation and inference of the choice of W. Here we resorted to a proximity matrix where each entry w_{ij} is the inverse of the coordinates' distance between provinces i and j, with a cut-off point at 250 kilometres (i.e. any $w_{ij} < {}^{1}/_{250}$ is set equal to 0). W is row-standardised, so that Wy is simply the weighted average of values of y at neighbouring locations.

The two standard specifications for spatial effects in regression models are the *spatial lag* (SAR) model:

$$y = \rho Wy + \mathbf{X\beta} + \varepsilon$$

and the *spatial error* (SEM) model:

$$\begin{aligned} y &= \mathbf{X\beta} + e \\ e &= \lambda We + \varepsilon \end{aligned}.$$

Panel extensions have been considered by Anselin (1988) and Elhorst (2003), who provided efficient estimation procedures for both the SAR and SEM random effects models. Case (1991) considered an encompassing model, incorporating a SAR term, spatial autoregressive errors and random effects:[14]

$$\begin{aligned} y_{it} &= \rho Wy_{it} + \mathbf{X}_{it}\boldsymbol{\beta} + e_{it} \\ e_{it} &= \lambda We_{it} + \nu_i + \varepsilon_{it} \end{aligned}. \tag{4}$$

Elaborating on the procedures given in Elhorst (2003) for the SAR and SEM models, we estimate specification (4) by maximum likelihood. Results are reported in column 2 of Table B4.

Social capital effects are not completely absorbed by equilibrium prices: supply-side proxies (in particular, the log of insurance agencies per capita, *ag*/*pop*) do have a positive effect but two out of four social capital proxies have positive and significant coefficient estimates. The coefficient on *trust* is positive and significant, confirming the role of global interactions. Regarding spatial structure, as we expected, non-life insurance demand

[12]By convention, elements on the diagonal are set to 0.

[13]See Anselin (1988, chapter 3) for a classic treatment.

[14]As Case observed, one can subsequently test for SAR versus SEM alternatives by means of Wald tests on this nesting model.

TABLE 1

Spatial autoregressive and spatial error model (SAREM) specification, marginal effects

	Marginal effect
*C*500	2.790**
	(1.217)
mountain	–0.107
	(0.106)
hill	–0.072
	(0.076)
agricultural	–0.210
	(0.133)

Notes: Marginal effects are computed over the mean of the relevant variables. The relevant coefficient estimates are given in column 2 of Table B4 in Appendix B. Standard errors are given in parentheses. ** significant at 5 per cent.

exhibits spatial correlation: ρ is positive and significant. The significance of the interaction parameters suggests a non-linear dependence on our social capital proxies. We therefore compute marginal effects for the social capital variables, shown in Table 1.

The marginal effect of *C*500, which was the only variable interacted with all the other social capital variables, is positive and significant, while all others are not. All the social capital variables are measured in percentage points; the magnitude of such an effect is not negligible: a 10 per cent increase in social capital measured as the percentage of the population living in small towns (*C*500) leads to a 27.9 per cent increase in insurance demand. Given these results, we next investigate the relation between social capital and spatial correlation in the dependent variable.

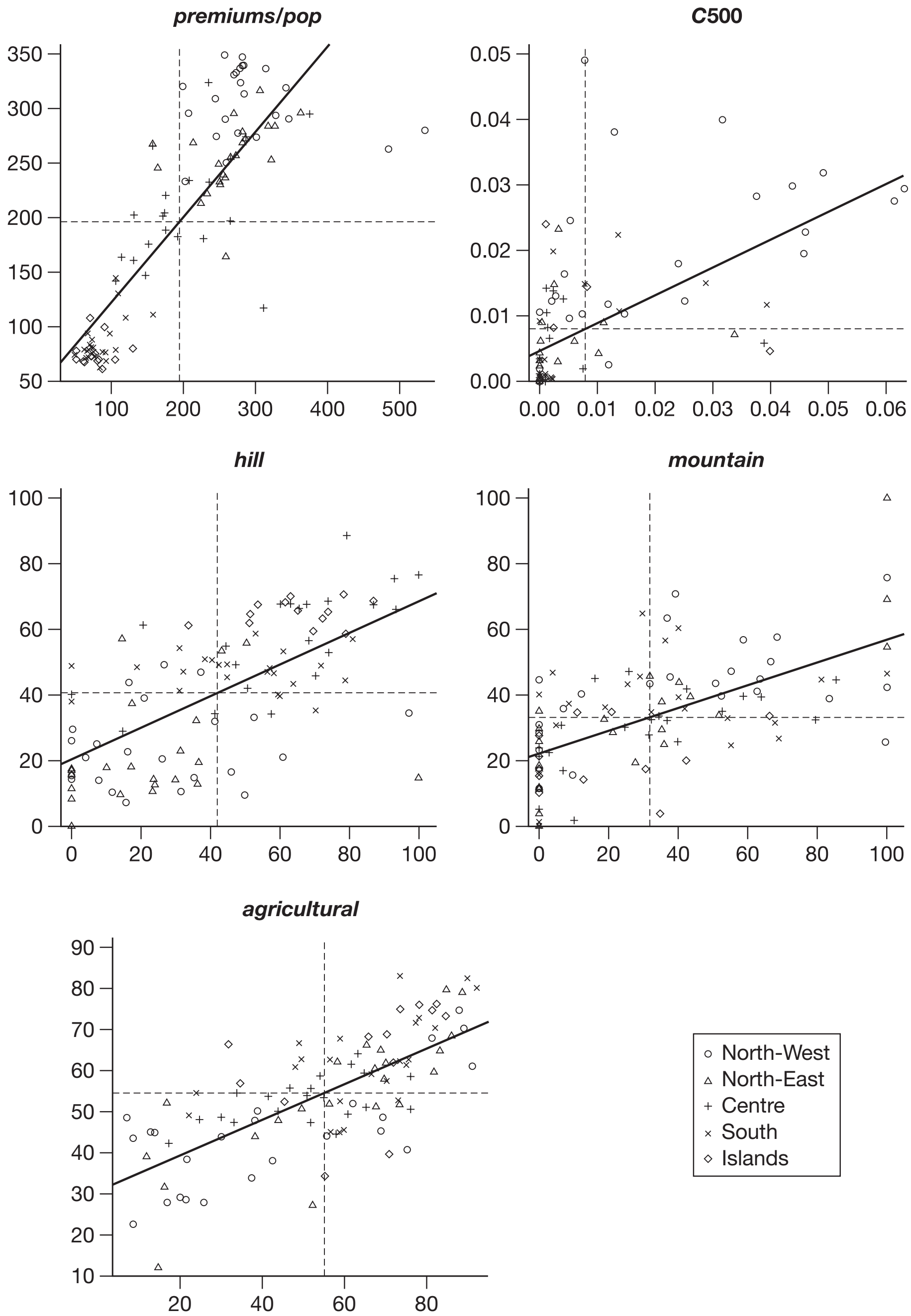
As for non-life insurance demand, social capital may not follow administrative boundaries and may exhibit a spatial structure. First evidence in this direction is obtained by plotting Moran's I statistics in Figure 3.

Moran's I statistic is a spatial correlation measure. If the proximity matrix is a row-standardised dichotomous matrix, Moran's I statistic boils down to the regression coefficient of the variable of interest over its spatial lag.[15] The Moran plot is the relative scatter plot where the variable of interest is plotted on the x-axis and its spatial lag is plotted on the y-axis. The solid straight lines on Figure 3 are the OLS estimated ones. The graphs show that both insurance demand (top-left panel) and the social capital variables exhibit spatial correlation. Moran's I statistics give the same indication if a distance-based *W* is used. Our expectation is that, since the empirical implication of our model is a causal relation between social capital and insurance demand, such a causality should be reflected in the spatial structure as well. In order

[15]See Anselin (1988).

FIGURE 3

Moran plots



Notes: The solid straight lines are the OLS estimated ones. The dashed lines mark the average value on each axis.

to test it, we repeated the panel SAREM estimation for a model that does not include social capital variables (column 3 of Table B4) and compared the magnitude of the spatial autoregressive coefficient, ρ, and the spatial error coefficient, λ. The results are in line with the causal relation implied by the model: a panel model without social interactions effects exhibits a significant spatial autocorrelation structure ($\rho \neq 0$) and augmenting the model with social capital variables significantly reduces the spatial autogressive coefficient. We interpret this finding as meaning that social capital has a positive marginal effect on non-life insurance demand, and its spatial structure accounts for a significant fraction of insurance demand's spatial structure.

Anselin (1988) points out the possible bias introduced by a wrong choice of the proximity matrix W. We performed a robustness check employing a binary contiguity matrix[16] and two different distance-based matrices, the first based on the inverse of road-travelling distance and the second on the inverse of the Euclidean distance between the geographic coordinates of capital cities in each province. Estimating the model with the contiguity matrix, the picture is virtually unchanged, except for the greater significance of the spatial error term, which may be reflecting aggregation bias, cross-border spillovers and effects related to direct neighbourhood in general. The results of the two alternative distance-based specifications are very similar as well, both given the same cut-off point and with different cut-off points.[17]

VI. Conclusions

Our starting point is Arnott and Stiglitz (1991)'s model on the coexistence of marketed and non-marketed insurance contracts. If there is peer observability or supervision so that the non-marketed contract can be enforced, their main conclusion is that informal agreements are not disruptive for the formal insurance market. We suggest that this is not the only way to reduce moral hazard in informal agreements: trust, social stigma, the power of reputation and social pressure – in a word, social capital – can induce cooperative behaviour even with asymmetric information. The two main issues the economic literature has to tackle when dealing with social capital are to provide a sound economic definition of this sociological concept and to find a credible empirical measure for it. We describe non-market agreements theoretically as strategic decisions of agents playing a cooperative game with neighbours. Each individual adopts a trigger strategy to punish neighbours deviating from the cooperative equilibrium in any

[16]A binary contiguity matrix is a 0/1 matrix where w_{ij} = 1 if i and j share a common boundary and w_{ij} = 0 otherwise.

[17]Results of these alternative specifications are not reported here but all are available from the authors upon request.

game they are involved in. Such behaviour leads to a pairwise-stable equilibrium, which is more likely the higher the level of social capital embedded in the social network. The network approach we choose provides us with a formal definition of social capital, which allows us to extend the Arnott–Stiglitz model and to obtain a clear testable implication. The empirical part of the paper uses a province-level Italian data set. We carefully choose a set of proxies for social capital and estimate a spatial autoregressive random effects panel model. Our results confirm that social capital has a positive marginal effect on the demand for market non-life insurance.

Appendix A. Formal derivation of the theoretic model

The starting point is the canonical moral hazard model without non-market insurance. There is a single and fixed-damage accident. The probability of its occurrence, $p(e)$, is strictly convex and decreasing in the individual's effort at accident avoidance, e, which is not observable to the insurer. Individual wealth is w and the damage caused by the accident is d. Individuals pay a premium β and receive a net payout α if the accident occurs. Expected utility has the following form:

$$\begin{aligned} EU^M &= \left(1 - p(e)\right)U(w - \beta) + p(e)U(w - d + \alpha) - e \\ &= \left(1 - p(e)\right)u_0 + p(e)u_1 - e. \end{aligned}$$

EU^M is well behaved (increasing and strictly concave) and separable, meaning that in both states of the world it is strongly separable in w and effort; disutility of effort is event independent, the effort is measured by the disutility it causes and utility of consumption $u(\cdot)$ is event independent. At the competitive, constrained equilibrium, the insurer offers less than full insurance to induce its clients to augment their effort at accident avoidance, i.e. $d - \alpha > \beta$. This equilibrium is stable only if clients purchase no additional insurance.

Non-market insurance is introduced as follows: a couple of symmetric individuals, i and j, agree that if only one of them has an accident, the other will transfer δ to the former. Each of them realises that the extra insurance will pay out if they have an accident and their partner does not; therefore their expected utility changes:

$$\begin{aligned}
EU_i &= \left(1-p(e_i)\right)\left(1-p(e_j)\right)U(w-\beta)+p(e_i)p(e_j)U(w-d+\alpha) \\
&\quad +\left(1-p(e_i)\right)p(e_j)U(w-\beta-\delta) \\
&\quad +p(e_i)\left(1-p(e_j)\right)U(w-d+\alpha+\delta)-e_i \\
&= \left(1-p(e_i)\right)\left(1-p(e_j)\right)u_0+p(e_i)p(e_j)u_1 \\
&\quad +\left(1-p(e_i)\right)p(e_j)u_2+p(e_i)\left(1-p(e_j)\right)u_3-e_i.
\end{aligned} \tag{A1}$$

Individuals maximise their utility considering α and β and therefore the contract's price $q = q(\alpha, \beta)$ as given: they perceive that by entering a mutual contract, they can buy extra insurance at the market price q. They choose δ, which is the premium but also the pay-off of the non-market agreement.

If moral hazard affects the non-market agreement – i.e. if each individual does not observe the other's effort and there are no incentives to cooperate – the exclusivity provision cannot be enforced: each client pays an extra premium δ if the partner has an accident and she does not, while she receives an extra pay-off δ in the opposite case. It is optimal for them to reduce their effort, while the insurance company is still offering the same contract. This is a partial equilibrium result since it does not consider the reaction of insurance companies to agents' behaviour. In a general equilibrium context, the company knows that the required level of effort for the offered contract cannot be enforced: non-market insurance crowds out market insurance and individuals substitute insurance provided by a risk-neutral insurer with that provided by a risk-averse one. Expected utility, $EU = EU^{MH}$, is then lower than without non-market insurance.

Moral hazard does not play a role if the insured perfectly observe each other's efforts or if there are incentives to cooperate. Individuals choose δ and e_i given $q(\alpha,\beta)$. Again, each of them assumes peers entering non-market agreements to be rational; therefore the optimal level of effort will be the same for everybody; thus $e_i = e_j \Rightarrow p(e_i) = p(e_j)$ and (A1) simplifies to

$$EU = EU^{NMH} = (1-p)^2u_0 + p^2u_1 + p(1-p)(u_2+u_3) - e.$$

The utility-maximising non-market agreement is $\delta^* = (d-\alpha-\beta)/2$, which brings coverage up to full insurance.

In the presence of moral hazard, this risk reduction induces individuals to reduce effort, thus displacing the insurance company, which is no longer able to enforce a positive level of effort. The effort-reducing effect of the extra coverage is present even without moral hazard, but in this case a positive provision of informal insurance δ implies a positive level of effort e by each agent entering the non-market agreement. Furthermore, it is relatively easy to prove that the effort is not only positive but also increasing in δ between 0 and the optimal level δ^* as long as $p(e) < ½$.[18] This is due to the fact that as δ increases, individuals become less selfish in their choice of effort. Thus, non-market agreements in this case have two opposite effects on e. Arnott and Stiglitz (1991) prove the following proposition:

Proposition 1. *If non-market agreements are available (i.e.* $0 \leq \delta \leq \delta^*$*) and they do not involve moral hazard and if* $p < ½$*, then holding the contract offered by the insurance company* $\tilde{q} = q(\tilde{\alpha}, \tilde{\beta})$ *constant, non-market agreements are welfare enhancing, i.e.* $EU^{NMH} > EU^{M}$.

Thus the direct utility-increasing effect of informal agreements dominates the effort-reducing effect of extra coverage. Again, Proposition 1 is a partial equilibrium result. Allowing the insurer to adjust the price q, it maximises its expected utility with respect to β and α under the zero-profit condition $\alpha = \frac{1-p}{p}\beta$ and assuming that individuals maximise their own utility (i.e. $e = e^*$ and $\delta = \delta^* = (d - \alpha - \beta)/2$).[19]

We can now characterise the demand function of marketed insurance contracts. We assume that insurance companies can offer only linear contracts, i.e. $q(\alpha,\beta) = \beta/\alpha$. Second, market insurance contracts are exclusive, meaning that agents can sign just one contract with one insurance firm to cover a given risk. Third, the insurance market is competitive and companies set the price in order to make zero profit, i.e. at equilibrium $q = \beta/\alpha = p(e)/\{1-p(e)\}$.

Insurers discriminate on the basis of all observable characteristics of agents and thus, conditional on a set of demographics $\mathbf{X}$, potential clients differ only by their effort. Thus we assume without loss of generality that all individuals are identical.[20]

Drawing from the analytical treatment of moral hazard models in Arnott and Stiglitz (1988), we can now restrict the utility functions of individuals in order to have a characterisation of demand functions:

Proposition 2. *Assume the expected utility function falls in the class* $EU = (1 - p(e))U(w) + p(e)U(w-d) - e$*, i.e. it is separable, disutility of effort is event independent, e is measured by the disutility it causes and utility of consumption* $U(\cdot)$ *is event independent. Assume also that*

[18]Such a condition is reasonable: individuals want to insure against events with high losses d but small probability p. See Arnott and Stiglitz (1991) for details on the proof.

[19]The model can easily be extended to a heterogeneous agents setting. Insurers offer different contracts based on a vector $\mathbf{X}_j$ of observable variables such as age, gender, marital status and loss ratios (the ratio between claims paid and premium received) in a particular region. What they are not able to do, due to information asymmetry, is to offer different contracts based on individual effort.

[20]This is just in order to simplify notation. Alternatively, given a population in which individuals differ along $\mathbf{X}$ and their effort, the results in the remainder of this appendix can be thought of as conditional on $\mathbf{X}$.

$\lim_{e \downarrow 0} \frac{(\partial p/\partial e)^3}{\partial^2 p/\partial e \partial e} > -\infty$. *Then demand for insurance decreases with the price of insurance and effort increases with price.*

Arnott and Stiglitz (1988), differentiating the first-order conditions of the individual's effort-choice problem, show that for a generic separable utility function, insurance purchases decrease and effort increases with price but for discontinuity points in the price–consumption line, which is the locus of utility-maximising linear contracts. Moreover, the authors show that a sufficient condition for this line to be everywhere continuous is convexity of indifference curves. The last assumption of the proposition fulfils this requirement: the limit condition implies that p is not too responsive to the effort e (i.e. p' is low) and that the curvature is high enough (i.e. p'' is high) at any point (α,β). An example of such a $p(e)$ function is $p(e) = \overline{p} - e^{\gamma}$, where $\gamma > ½$: if individuals put no effort into accident avoidance, i.e. $p(e) = \overline{p}$, then the probability of suffering a wealth loss d is decreasing with a power function of the effort.

Proposition 2 states that insurance demand and effort e depend on insurance price q. Effort e and price q are chosen simultaneously: if only market contracts are available, agents choose $e = \tilde{e}$ to maximise their expected utility, considering $\tilde{q}$ as given. On the other hand, firms internalise agents' best responses while pricing the contract; thus $q = \tilde{q}$ is the best response to $\tilde{e}$. If agents can enter non-market agreements that do not involve moral hazard, equilibrium effort and price change.

Proposition 3. *Assume insurance companies offer only linear contracts, i.e.* $q(\alpha,\beta) = \beta/\alpha$, *market insurance contracts are exclusive, the insurance market is competitive and companies set* q *in order to make zero profit. Assume also that the utility function falls in the class* $EU = (1 - p(e))U(w) + p(e)U(w-d) - e$ *and that* $p(e)$ *is such that* $p(e) < ½$ *and* $\lim_{e \downarrow 0} \frac{(\partial p/\partial e)^3}{\partial^2 p/\partial e \partial e} > -\infty$. *Then if there exists an equilibrium without non-market agreements* $E_0 : \{\tilde{e}, \tilde{q}, \tilde{\delta} = 0\}$ *and one with non-market agreements and no moral hazard* $E_1 : \{e^*, q^*, \delta^* > 0\}$, *demand for market insurance is higher in* E_1 *than in* E_0.

Proof

Without moral hazard, it is optimal for clients to enter a mutual agreement δ such that the total coverage $\alpha + \delta$ reaches full coverage, $\overline{f}$.

Arnott and Stiglitz (1991) prove that e is increasing in δ; thus $q = \tilde{q}$ and $\delta > 0 \Rightarrow e > \tilde{e}$.

The insurers acknowledge the presence of informal agreements and internalise it: given that for any level of q the effort is higher than with $\delta = 0$ and since the insurance market is competitive, there will always be a firm willing to undercut q until the new equilibrium price q^* satisfies the zero-profit condition $q^* = p(e^*)/\{1-p(e^*)\}$. Therefore, $q^* < \tilde{q}$.

At q^*, the client can reach $\overline{f}$ by buying extra coverage on the market $\alpha^* > \tilde{\alpha}$ and setting $\delta^* = \overline{f} - \alpha^*$.

Proposition 2 states that demand is decreasing in price. Thus, since $q^* < \tilde{q}$, demand is higher in E_1 than in E_0. ***QED***

Note that the way we modelled informal agreements implies a hidden assumption: once i and j enter the non-market insurance contract, they can choose their level of effort but they must respect the contract. In other words, we assume that i will transfer δ^* to j every time j has an accident and i does not. Given the informal nature of the agreement, this assumption may not be without loss of generality. In order to relax it, we could have considered the transfer δ as uncertain and rewritten the model in terms of its expectation E[δ].

Suppose now that pairs of individuals entering a non-market insurance agreement with a given $\delta_{i,j}$ can choose in each period whether to put in effort e_{MH}, the one with moral hazard in the Arnott–Stiglitz framework, or e^*, effort without moral hazard. If expected utility is decreasing in effort, this is a simple discrete coordination game. From (A1),

$$\begin{aligned}\frac{\partial EU^i}{\partial e_i} &= \left[-\left(1-p(e_j)\right)u_0 + p(e_j)u_1 - p(e_j)u_2 + \left(1-p(e_j)\right)u_3\right]p'(e_i) - 1 \\ &= \left[(u_3 - u_0)\left(1-p(e_j)\right) + (u_1 - u_2)p(e_j)\right]p'(e_i) - 1,\end{aligned}$$

which is decreasing in e_i if $\beta^* + \delta_{i,j} < d - \alpha^* - \delta_{i,j}$, i.e. the total cost of insurance $\beta^* + \delta_{i,j}$ must be lower than the loss suffered when the accident occurs, $d - \alpha^* - \delta_{i,j}$.[21] If this condition holds (together with $p(e) < ½$), the game rewritten in strategic form with expected utilities as pay-offs is of the prisoner's dilemma type (see Figure A1). Since marginal utility is decreasing in (own) effort, for individual i we can write

[21] In order to prove Proposition 3, we used the fact that at E_1, i.e. the equilibrium with non-market agreements, each client reaches full coverage, i.e. $\beta^* + \delta^* < d - \alpha^* - \delta^*$. This does not contradict the assumption that $\beta^* + \delta_{i,j} < d - \alpha^* - \delta_{i,j}$: as will be clear in the remainder of this appendix, each individual can play the same game with all her neighbours; therefore $\delta^* = \Sigma\delta_{i,j}$ and the two conditions can hold simultaneously.

FIGURE A1

The non-market insurance game in strategic form

		Player j	
		e^*	e_{MH}
Player i	e^*	EU_{ij}^*, EU_{ji}^*	EU_{ij}^L, EU_{ji}^H
	e_{MH}	EU_{ij}^H, EU_{ji}^L	$EU_{ij}^{MH}, EU_{ji}^{MH}$

$$EU_{ij}^H = EU(e_i = e_{MH}, e_j = e^*) > EU_{ij}^*$$
$$EU_{ij}^L = EU(e_i = e^*, e_j = e_{MH}) < EU_{ij}^{MH} .$$

Once this game is put in a dynamic setting, the social network can be described as in Vega-Redondo (2006): we have a finite population of agents $N = \{1,2,\ldots,n)$ where each pair of interacting agents (i,j) is involved in an infinite repetition of the described game. Players' decisions to connect are captured by a directed graph $\vec{g} \subset N \times N$, where each directed link $(i, j) \in \vec{g}$ is player i's decision to connect with player j. Suppose now that every linking decision leads to play. We have a definition for social network:

Definition 1 (social network). *The social network induced by the linking decision* $\vec{g}$ *is the undirected graph* $g \subset N \times N$ *defined as*

$$\forall\, i, j \in N, \quad (i, j) \in g \Leftrightarrow [(i, j) \in \vec{g} \vee (j,i) \in \vec{g}]$$

and for any player i the set of her neighbours is $N_i = \{j \in N : (i, j) \in g\}$.

In order to complete the repeated game model, we need a rule for information diffusion within the network: in our model, that is information spread around the network gradually. To be specific, at each round before playing, i and j share information about their behaviour with their neighbours, i.e. whether they deviated from the cooperative strategy. To sustain a cooperative equilibrium, it is also necessary for each agent to adopt a strategy to punish defiance: i forces herself to play a trigger strategy, i.e. she will switch to defect from j if she discovers j deviated with some of her neighbours. More formally, for any agent i, the strategy s^g is of the following type:

1. Player i chooses whether to start her interaction with j putting in effort e^* (which is to cooperate) or to put in effort e_{MH}.
2. In following rounds, she reacts immediately to the news that j did not start with e^* with some $k \in N_j$ by switching irreversibly to e_{MH} in her game with j.

In order to define equilibrium, some additional notation is needed: $\pi_i(s^g)$ is the overall pay-off from the link (i,j) given the strategy s^g; for every agent i, s_C^g and s_D^g are the strategies that start respectively with cooperation and defection with all the agents $k \in N_i$.

Definition 2 (pairwise-stable network, PSN). *A PSN is a network where for every separate link, both players have incentives to sustain the cooperative equilibrium, i.e. for all* $(i,j) \in g$, $\pi_i(s_C^g) \geq \pi_i(s_D^g)$.

The connection of this definition with the social capital literature is clear once the PSN is characterised in terms of cohesiveness.

Definition 3 (*i*-excluding distance). *The i-excluding distance between j and k,* $d^i(j,k)$*, is the shortest path joining j and k that does not involve player i. In other words, it is the number of steps needed for any information held by j to reach k (and vice versa) without the concourse of i.*

Given Definitions 2 and 3, it is possible to state the following proposition:

Proposition 4. *Let g be a social network where agents play the described game, and they all face a common discount factor* $\eta \in (0,1)$. *Define* $v_{ik} = EU_{ik}^* - EU_{ik}^L$. *Then g is a PSN if and only if for all* $(i,j) \in g$,

$$EU_{ij}^* + \sum_{k \in N_i / \{j\}} \eta^{d^i(j,k)} \left[\eta EU_{ik}^* + (1-\eta) v_{ik} \right] \geq (1-\eta) EU_{ij}^H .$$

Proof

Proof of Proposition 4 follows the one in Vega-Redondo (2006).

The normalised pay-off function if i cooperates with j is

$$\pi_i(s_C^g) = \sum_{k \in N_i} \left\{ (1-\eta) \sum_{\tau=0}^{\infty} \eta^\tau EU_{ij}^* \right\} = \sum_{k \in N_i} EU_{ij}^* ,$$

while if i deviates her anticipated pay-off is

$$\begin{aligned}
\pi_i(s_D^g) &= (1-\eta) EU_{ij}^H + \sum_{k \in N_i / \{j\}} \left\{ \left[\sum_{s=0}^{d^i(j,k)-1} (1-\eta)\eta^s EU_{ik}^* \right] + (1-\eta)\eta^{d^i(j,k)} EU_{ik}^L \right\} \\
&= (1-\eta) EU_{ij}^H + \sum_{k \in N_i / \{j\}} \left\{ \left[\sum_{s=0}^{d^i(j,k)-1} (1-\eta)\eta^s EU_{ik}^* \right] + (1-\eta)\eta^{d^i(j,k)} EU_{ik}^* - (1-\eta)\eta^{d^i(j,k)} v_{ik} \right\} \\
&= (1-\eta) EU_{ij}^H + \sum_{k \in N_i / \{j\}} \left\{ \left(1 - \eta^{d^i(j,k)+1} \right) EU_{ik}^* - (1-\eta)\eta^{d^i(j,k)} v_{ik} \right\}.
\end{aligned}$$

Therefore, the stability condition $\pi_i(s_C^g) \geq \pi_i(s_D^g)$ can be rewritten as

$$\sum_{k\in N_i} EU_{ij}^* \geq (1-\eta)EU_{ij}^H + \sum_{k\in N_i/\{j\}} \left\{ \left(1-\eta^{d^i(j,k)+1}\right) EU_{ik}^* - (1-\eta)\eta^{d^i(j,k)}\nu_{ik} \right\}$$

$$EU_{ij}^* + \sum_{k\in N_i/\{j\}} \left(1-1+\eta^{d^i(j,k)+1}\right) EU_{ik}^* \geq (1-\eta)\left[EU_{ij}^H - \sum_{k\in N_i/\{j\}} \eta^{d^i(j,k)}\nu_{ik} \right]$$

$$EU_{ij}^* + \sum_{k\in N_i/\{j\}} \left\{ \eta^{d^i(j,k)+1} EU_{ik}^* + (1-\eta)\eta_{i,j}^{d^i(j,k)}\nu_{ik} \right\} \geq (1-\eta)EU_{ij}^H$$

$$EU_{ij}^* + \sum_{k\in N_i/\{j\}} \eta^{d^i(j,k)} \left[\eta EU_{ik}^* + (1-\eta)\nu_{ik} \right] \geq (1-\eta)EU_{ij}^H,$$

which is in the form of Proposition 4. ***QED***

The implications of this proposition are:

- stability is more likely in *large-span* networks, i.e. in networks where each agent i has a large neighbourhood N_i;
- stability is more likely in *cohesive* networks, i.e. in networks with small excluding distances $d^i(j,k)$.

Given this formalisation,

Definition 4 (social capital). *The stock of social capital of network g is the density of g.*[22]

The network model presented in this appendix restricts the efforts' space of agents entering a non-market agreement to a high and a low effort level. We chose this approach in order to simplify the exposition, but this is not a crucial assumption: what really matters for community enforcement of cooperative behaviour is information transmission among community members. Buonanno, Pasini and Vanin (2008) obtained a similar result through a model of repeated interaction on a continuous social network, adapted from the work by Dixit (2003) on the extent of honest trade. The conclusion of the theoretic model is that in a pairwise-stable network, agents have no incentives to reduce their effort, i.e. moral hazard is inversely related to network stability. Therefore, the empirical implications of the model are that demand for market insurance is increasing in network cohesiveness and, from Definition 4, in the stock of social capital.

[22]The density of a network is the average number of links per agent (degree) in the network.

Appendix B. Supplementary tables

TABLE B1

Variable descriptions

Variable	*Description*
agricultural	Percentage of the land devoted to agriculture
ag/pop	Log of agencies per capita
*C*500	Percentage of population living in towns with fewer than 500 inhabitants
den/1000	Population density, inhabitants per square kilometre (scaled by a factor of 1,000)
dep/pop	Log of bank deposits per capita
export/va	Share of exports in total value added
hill	Percentage of hilly territory
inef	Indicator of juridical system inefficiency: average duration of civil trials
lrpro	Loss ratio of the property sector for previous year
mountain	Percentage of mountainous territory
nfam	Average number of family members
pop25.54/pop60	Ratio of people aged 25–54 to people aged over 60
trust	Trust indicator as defined by the World Values Survey (see Section IV)
u.rate	Unemployment rate
va.ind/va	Share of industry in total value added
va.serv/va	Share of services in total value added
va/1000	Total value added (scaled by a factor of 1,000)
Yd/pop	Log of disposable income per capita

TABLE B2

Summary statistics

	Min.	*1st qu.*	*Median*	*Mean*	*3rd qu.*	*Max.*
Yd/pop	9.00	9.27	9.54	9.47	9.63	9.84
pop25.54/pop60	0.74	0.90	1.02	1.04	1.16	1.58
inef	1.44	2.74	3.47	3.79	4.59	8.32
den/1000	0.04	0.10	0.17	0.24	0.26	2.66
va.ind/va	0.11	0.21	0.28	0.28	0.33	0.46
va.serv/va	0.52	0.63	0.68	0.68	0.74	0.85
u.rate	1.71	5.01	7.55	10.90	16.14	33.16
export/va	0.01	0.09	0.20	0.20	0.30	0.63
nfam	2.05	2.46	2.61	2.62	2.78	3.15
lrpro	0.25	0.43	0.49	0.52	0.59	1.82
trust	3.03	3.17	3.25	3.26	3.35	3.62
*C*500	0	0	0.11	0.79	0.76	6.31
mountain	0	0	30.68	31.92	52.43	100
hill	0	17.25	42.40	41.95	63.14	100
agricultural	6.84	38.01	58.61	54.85	73.28	91.97
dep/pop	1.35	1.78	2.20	2.11	2.38	3.09
va/1000	1.27	4.21	6.22	10.04	10.18	112.10
ag/pop	–8.98	–8.01	–7.73	–7.83	–7.62	–7.32

TABLE B3

Geographical distribution

	Area	*Min.*	*1st qu.*	*Median*	*Mean*	*3rd qu.*	*Max.*
*C*500	North-West	0	0.49	1.24	2.14	3.90	6.31
	North-East	0	0	0	0.32	0.31	3.38
	Centre	0	0	0.10	0.29	0.14	3.88
	South	0	0	0.10	0.51	0.23	3.93
	Islands	0	0	0	0.41	0.11	3.99
mountain	North-West	0	9.08	44.96	43.18	64.31	100
	North-East	0	0	24.54	29.17	40.20	100
	Centre	0	7.08	31.68	31.02	42.48	85.32
	South	0	3.99	29.73	32.12	54.20	100
	Islands	0	0	11.10	16.86	30.68	66.30
hill	North-West	0	6.50	18.70	25.24	38.25	97.29
	North-East	0	0	20.38	23.12	35.91	100
	Centre	0	47.31	65.50	60.58	74.14	100
	South	0	32.10	52.95	47.59	60.98	80.91
	Islands	33.70	53.52	65.20	64.61	73.88	86.97
agricultural	North-West	6.84	19.11	37.66	42.54	68.84	91.01
	North-East	11.73	45.16	66.26	57.35	72.44	88.43
	Centre	17.17	41.33	51.66	50.35	61.47	76.03
	South	22.02	56.42	66.38	63.72	75.19	91.97
	Islands	31.58	55.12	70.80	64.92	78.05	84.43
trust	North-West	3.17	3.31	3.31	3.32	3.37	3.37
	North-East	3.13	3.22	3.35	3.30	3.39	3.40
	Centre	3.07	3.11	3.19	3.24	3.35	3.35
	South	3.03	3.09	3.24	3.20	3.25	3.63
	Islands	3.17	3.17	3.17	3.19	3.24	3.24

TABLE B4

Estimation results

	(1)	(2)	(3)
Yd/pop	1.200*** (0.162)	1.238*** (0.173)	1.301*** (0.178)
dep/pop	0.200*** (0.051)	0.089* (0.048)	0.071 (0.049)
pop25.54/pop60	0.329** (0.118)	0.250** (0.124)	0.182 (0.123)
va/1000	0.002** (0.001)	0.003** (0.001)	0.003* (0.001)
va.ind/va	0.404 (0.439)	0.451 (0.449)	0.559 (0.448)
va.serv/va	0.376 (0.430)	0.364 (0.449)	0.366 (0.438)
export/va	0.0084 (0.091)	0.052 (0.083)	0.091 (0.084)
u.rate	–0.00034 (0.002)	–0.001 (0.002)	0.00003 (0.002)
nfam	0.0083 (0.108)	0.017 (0.109)	0.043 (0.108)
inef	–0.047*** (0.011)	–0.041*** (0.013)	–0.030** (0.017)
den/1000	0.082** (0.049)	0.107* (0.056)	0.087 (0.056)
ag/pop	0.174*** (0.054)	0.117** (0.051)	0.120** (0.051)
lrpro	0.018 (0.022)	0.016 (0.021)	0.015 (0.021)
trust	0.414*** (0.118)	0.394*** (0.134)	0.250* (0.137)
*C*500	41.565*** (10.884)	36.771*** (12.049)	
mountain	0.142*** (0.091)	0.181* (0.104)	
hill	–0.0037 (0.071)	0.033 (0.082)	
agricultural	0.0013 (0.112)	0.033 (0.125)	
*C*500×*mountain*	–40.717*** (9.822)	–36.313*** (10.877)	
*C*500×*hill*	–12.563*** (4.209)	–13.302*** (4.790)	
*C*500×*agricultural*	–36.972*** (12.226)	–30.652** (13.510)	
ρ		0.148*** (0.023)	0.208*** (0.025)
λ		–0.526 (0.345)	–0.494 (0.331)

Notes to Table B4
Column 1 reports the generalised GLS estimation for a random effects panel data model and no correction for spatial correlation. Column 2 reports estimates assuming random effects and accounting for spatial lag (SAR) and spatial autoregressive errors. The proximity matrix *W* is based on the coordinates' distance between provinces, with a cut-off at 250 kilometres. ρ is the spatial autoregressive coefficient and λ the spatial error coefficient. Column 3 estimates are obtained with the same procedure as column 2, not accounting for social capital. Standard errors are given in parentheses. * significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.

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