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# Empirical Studies on Social Interactions

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The undersigned Giacomo Pasini, in his quality of doctoral candidate for a Ph.D. degree in Economics and Organization granted by the Università Ca' Foscari di Venezia, Università IUAV di Venezia and Fondazione Scuola Studi Avanzati in Venezia attests that the research exposed in this dissertation is original and that it has not been and it will not be used to pursue or attain any other academic degree of any level at any other academic institution, be it foreign or Italian.

# Contents

# Introduction

The topic of this dissertation is the estimation of economic models of individual behavior taking explicitly into account social interactions, i.e. models in which choices of a reference group have an impact on individual behavior. According to the context in which they are applied, social interactions effects have been called peer effects, network effects, social multiplier. Again, depending on the application the reference group can be the family, the community in which a person live, the network of friends, the colleagues and so on. The recent literature has shown a growing awareness in the economic community that individual interdependencies can have an economic impact over and above the standard market mechanism, an awareness which is also supported by the development of game theoretical models. This led to an increasing interest in interaction–based models and to the theoretical and empirical issues they involve.

In a nutshell, social interactions modelling and estimation require an analytical description of the simultaneous choices of reference group's members and of their interdependencies. The theoretical framework is based on game theory models and on the growing literature on networks: an early review on the topic is Brock and Durlauf (2000), extended by Ioannides (2006)and Scheinkman (2004). Interaction–based models relate also with the social capital literature: when interactions are based on reciprocal trust and build up community ties differences between the concepts of social interactions and social capital fade away.

From an empirical point of view the main tasks depend on the 'reflection problem', as it was defined by Manski (1993) in a seminal paper: in a regression model social interactions appear among the independent variables as the expected value on the reference group of the dependent variable $Y$ (endogenous effect) or of a regressor $X$ (contextual effect). The fact that the same variable $Y$ appears on both sides of the equation rise an endogeneity issue. Further on, if the model is linear in the expected values endogenous and contextual effects are not separately identifiable. Last but not least, even if those two issues are solved maximum likelihood estimation involves the inversion of an $n \times n$ matrix, where $n$ is the number of observations. Since this matrix needs not to be symmetric, this inversion rises computational problems for large datasets.

Endogeneity is usually solved by Instrumental Variables estimation, even if the search for a valid instrument is not easy. Identification is achieved either assuming out contextual effects (or, more rarely, endogenous effects), or imposing exclusion restrictions on characteristics of the reference group influencing the two effects: see Bramoullé et al. (2007) for an exhaustive discussion on this topic.

The computational problem often is not an issue since dataset providing information on interactions are usually small. This is not the case in the present work: the first chapter's model is estimated on CEX, which is a US population wide survey, and the third chapter's on a European dataset of similar dimension. This choice allows to draw inference and conclusions which are easy to generalize, at the price of developing an estimation strategy that cope with all the issues arising from the reflection problem, including the computational difficulties. Such an approach is based on a GMM estimator that do not require the $n \times n$ matrix inversion taken from the spatial econometrics literature: details on this procedure are given in the first chapter.

Using survey data which was not originally collected to study social interactions rises an additional problem, which is the identification of the reference group of each individual. A building block of the proposed estimation procedure is the claim that people belonging to the same reference group are in some way similar, where the dimensions on which similarity is measured depend on the problem at hand. In other words, it is possible to measure an 'economic distance' between individuals. This concept is not new in the social interactions literature: Akerlof (1997) set up a model where individual preferences depend on a 'social distance' similar to the similarity measure I will adopt.

The dissertation is composed of three chapters in the form of self–contained papers which examine the economic modelling of social interactions on different settings, and share a common estimation procedure as described above.

The first chapter, 'A demand system with Social Interactions: evidence from CEX' tackle directly the problem of identifying reference groups in a population–wide survey as the American Consumers' Expenditures Survey, which does not have any direct information on relations among respondents and peer membership. Similarity between individuals is captured by an 'economic distance' measure, which allows to order correctly the probabilities of peer membership and thus solves the identification problem. Given this ordering social interactions effects are consistently estimated writing the demand system at hand as a Spatial Autoregressive model and estimating it with the appropriate GMM estimator.

In 'Does Social Capital reduce moral hazard? A network model for non–life insurance demand', a joint work with Giovanni Millo, the objective is to study the demand for insurance of agents that can enter informal risk–sharing agreements with members of their community. The number of potential partners in those agreements constitutes the 'Social Capital' of each individual, which is defined in terms of density of the network describing communities. A network–based definition of Social Capital allows us to use the econometric tools developed in the first chapter to estimate the model on a province–level Italian dataset.

The last chapter, 'Social interaction effects in an inter–generational model of informal care giving', joint with Lisa Callegaro, deals with the interactions among children facing the decision of providing care to their elderly parents. The aim was to investigate whether adult children choose strategically, meaning taking into account brothers and sisters choices, and what is the effect of such a behavior on their parents satisfaction. We set up the model as a non–cooperative game among parents and each of their siblings and again we use the spatial econometric tools to identify the set of instruments that allows us to solve the endogeneity problem embedded in social interactions models. We use SHARE data, an European dataset on the 50+ population, to estimate the model. We chose this in order to have an heterogeneous sample with respect to institutional settings and cultural differences, thus providing data to check whether social interactions matter once those differences are accounted for.

# Chapter 1

# A demand system with social interactions: evidence from CEX


### abstract

A Quadratic Almost Ideal Demand System that allows for social interactions is described and then estimated on CEX data. Social interactions are introduced as mean budget shares and depend on peer membership and visibility. Peer identification is obtained by means of a similarity index which measures the probability of group membership. Reflection problem is tackled directly and therefore estimation is carried on with a Generalized Spatial 2SLS that deal with two types of endogeneity: the first is due to contemporaneous choices of households, the second is due to contemporaneous choice of goods. Results support the hypothesis that expenditure allocation to budget shares depends both on social interaction and visibility.


## 1.1 Introduction

Men are social animals. People do not live in isolation, almost any economically relevant action and choice is taken in a particular social environment, and behavior of others are likely to influence individual activities. Even if this can be considered a common sense statement, traditional economic models of individual behavior assume that agents choose in perfect isolation and preferences are not directly influenced by the behavior of others. Nevertheless the idea that peer effects do matter attracted a number of economists in different fields, that tried to include social interactions in models of educational attainment, job search, crime and deviating behavior, early pregnancy and many others[1]. Unfortunately, most of the empirical evidence is drawn from specific datasets or natural experiments, therefore limiting the validity of the results to particular sub–populations.

Interdependent preferences were considered also in consumption literature: if Mr Smith buys a brand new car to keep up with Mr Jones, this means that Mr Smith preferences are influenced by Mr. Jones' one. The question is whether social interactions matter in consumption choices: is it reasonable to think that at least for some goods consumption choices of friends, colleagues or in general peers play a role in individual choices? This paper aims to shed some light on this issue.

This study is mainly empirical: although a complete characterization of preferences is not provided, social interactions will be explicitly allowed for and introduced as a conditioning factor in a demand system. The objective is to assess their relevance using a US–wide survey as the Consumers' Expenditures Survey (CEX). Results suggest that social interactions do matter.

The introduction of peer effects in an empirical consumption model rises two econometric issues: the definition of the relevant reference group for each individual, and a particular kind of endogeneity, called reflection problem by Manski (1993). The estimation strategy proposed in this paper tackles both of them directly. The idea is to use a measure of similarity to identify peer membership and on this basis re–define the demand system as a Spatial Autoregressive Model (SAR).

Next section describes the Economic Model - the Quadratic Almost Ideal Demand System (QUAIDS) proposed by Banks et al. (1997) - the separability assumptions needed to restrict the attention to demand systems, the inclusion of conditioning factors and how social interactions are modelled. In section 3 the dataset is described, the following one is devoted to the estimation strategy and results. Conclusions are in Section 5.

## 1.2 The Economic Model

The framework on which consumption behavior is modelled is the Life Cycle Hypothesis of Modigliani. The model describes consumers' choices as the maximization of an expected intertemporal utility function under an appropriate budget constraint. The utility function depends on consumption of durables and non–durables in each period and hours of work on each period. In order to reduce this general problem to a treatable one, an intertemporal separability assumption is needed.

[1]A useful review is Brock and Durlauf (2000). Durlauf and Young (2001) tried to put the recent literature within a common framework.

To be specific, it is assumed that the objective function is intertepo-rally additive in consumption of non–durable goods. It is well known that this assumption implies two–stage budgeting: in the first stage households equates the discounted marginal utility of each period and determines total non–durables expenditures, hours of work and durables' consumption of each period. In the second stage consumers allocate total expenditures to each non–durable good. This allocation process can be described by means of a demand system.

The second key assumption is that social interaction matters only at the second stage. As to say, saving decisions are not affected by others' behavior, therefore peer group effect on consumption is conditional on total expenditure and enter in the demand system, yet not in the Euler equation describing the first–stage.

While intertemporal separability is a standard assumption even if it's not innocuous, the second one is not and it's crucial in this paper. Binder and Pesaran (2001) propose a theoretic life–cycle model where social interactions' impact on optimal consumption depend on intertemporal considerations. However, they do not rule out the possibility that social interactions matter also in total expenditure allocation, and even if they infer that intertemporal considerations should be more relevant then static ones, their paper is purely theoretic, so still there is no empirical evidence on the relative importance of peer effects on savings and consumption allocation. Further on, the second assumption can be substituted by the following: social interactions effects on savings and on consumption are separable. In this way social interactions in first stage are not ruled out. The key point is that whatever the assumption it is meaningful to concentrate the attention on the demand system.

### 1.2.1 Social interactions

Social Interactions' effect can be defined as follows: "the propensity of an individual to behave in some way varies with the prevalence of that behavior in some reference group containing the individual" (Manski (1993)). This definition is as broad as possible and in a demand analysis framework it has been previously called preference interdependence (Alessie and Kapteyn (1991)), meaning that consumer's preferences are influenced by the behavior of others.

Manski makes three hypotheses to explain this empirical observation:

1. Endogenous effects: the propensity of an individual to behave in some way is affected by the behavior of the group. That is, demand of good

$i$ of consumer $h$ changes with the average demand of good $i$ by other people in his reference group;

2. Contextual effect: the propensity of an individual to behave in some way is affected by the exogenous characteristics of the group. That is, demand for good $i$ by household $h$ depends on the average total expenditure or on the average characteristics in $\boldsymbol{z}$ of individuals in the reference group.

3. Correlated effects: individuals in the same group tend to behave similarly because they have similar (unobserved) individual characteristics.

Endogenous and contextual effect are then 'economically meaningful' social interactions' effects, while correlated effect reflects an omitted variable problem, and therefore it is not a social effect of the variety we want to identify.

Manski sets up a general linear–in–means model where the output $y$ depend linearly on the averages on the reference group of the output itself, of the independent variables and of the unobserved attributes. The presence of the average output variable on the right–hand–side of the regression equation rises what the author calls the "reflection problem", which does not allow to separately identify endogenous and contextual effects. Nevertheless, in the reduced form of the model it is possible to identify a composite parameter capturing truly social interactions' effects separately from correlated effects.

The aim of this paper is to detect whether or not there is any significant effect of social interactions on demand. To keep things as easy and tractable as possible, the assumption is that there are no contextual effects. In other words the effect of the peers is fully captured by the average demand in the reference group. This hypothesis is somewhat unavoidable: the demand system is linear–in–means, therefore without assuming out contextual effect it's possible to estimate just the reduced form in which social effects are captured by one social effects' composite parameter.

### 1.2.2 Conditional demand

Conditional demand functions were firstly introduced by Pollak (1969). They turn out to be useful since they allow to model demand for $I$ goods $w_i$ without explicitly modelling the utility dependence on a second set $I'$ of goods. Pollak's idea was to deal with non–market goods, or more generally goods which are allocated independently on the market mechanism. This is the case of social interactions: given the assumption on absence of contextual effect, the social interaction effect on $w_i$ is the average demand for good $i$,

$E[w_i|X_h]$, where $X_h$ stands for $h$'s social network. the objective is to study the effect of being part of a given social network on the demand for a set of goods.

Then, each individual maximizes $U_h(w_1, \ldots, w_I)$ subject to the usual budget constraint

$$\sum_{i=1}^{I} p_i w_i = m$$

and to the additional constraints $E[w_i|X_h] = \tilde{w}_i \ \forall i = 1, \ldots I$. Note that this does not mean $\tilde{w}_i$ is exogenous, but simply it is not a choice variable of the individual. Demand functions for each good $i$ depend on prices and quantities of the other $I-1$ goods, total expenditure on them $m$, and on the mean demand on each good $\tilde{w}$:

$$w_i = f(\{w_j\}_{j \neq i}, \{p_j\}, \{\tilde{w}_j\})$$

Pollak (1971) proves that, differently from unconditional demand, it does not depend on prices of $\tilde{w}$ goods, nor on $\tilde{m}$, total expenditure on conditional goods. Hence a test for separability consists on testing whether demands $w_i$ depend on quantities $\tilde{w}$. In the present context testing separability means testing relevance of social interactions on consumer choices. Non–separability force to consider any implication of the demand system's study as conditional on the social network an individual is part of. It's difficult to go further without tackling directly utility dependence on social interactions: as Browning and Meghir (1991) point out, it's not possible to infer anything on preferences over social interactions observing conditional demands alone. Thus, the main focus of the present paper will be to test whether non–durable commodity demands are separable from social interactions.

### 1.2.3 The Demand System: QUAIDS

The starting point is the Quadratic Almost Ideal Demand System (QUAIDS) of Banks et al. (1997). This is a quadratic extension of the well–known Almost Ideal Demand System (AIDS) of Deaton and Muellbauer (1980), shares all its features plus it allows for heterogeneous Engel curves. QUAIDS can be seen as a quadratic local approximation of almost any demand system that is exactly aggregable, meaning that it's linear in (functions of) total expenditure. Define

$I$ number of consumption goods;

$H$ number of consumers;

$m$ total expenditure;

$w_i$ expenditure share on good $i$[2];

$p_i$ price of good $i$ and $\boldsymbol{p}$ prices' vector;

The budget share for good $i$ by household $h$ is

$$w_i^h = \alpha_i + \sum_{j=1}^{I} \gamma_{ij} \ln p_j + \beta_i \ln \left[ \frac{m^h}{a(\boldsymbol{p})} \right] + \frac{\lambda_i}{b(\boldsymbol{p})} \left( \ln \left[ \frac{m^h}{a(\boldsymbol{p})} \right] \right)^2 \tag{1.1}$$

where

$$\begin{aligned} \ln a(\boldsymbol{p}) &= \alpha_0 + \textstyle\sum_{i=1}^{I} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{I} \sum_{j=1}^{I} \gamma_{ij} \ln p_i \ln p_j \\ b(\boldsymbol{p}) &= \textstyle\prod_{i=1}^{I} p_i^{\beta_i} \end{aligned}$$

$a(\boldsymbol{p})$ and $b(\boldsymbol{p})$ are price aggregators: the former takes a translog form, the latter a Cobb–Douglas. It's relevant for estimation purposes to discuss properties and possible restrictions on these price aggregators: conditional on $a(\boldsymbol{p})$ and $b(\boldsymbol{p})$ demands are linear in prices and quadratic in total expenditure. Restrictions on $b(\boldsymbol{p})$ have to do with the rank of the demand system, which Lewbell (1991) defines as the dimension of the space spanned by its Engel curves. Therefore, (1.1) has a rank lower or equal to 3. Banks et al. (1997) prove that in any rank 3 exactly aggregable demand system the squared term's coefficient must be price dependent, i.e. $b(\boldsymbol{p})$ cannot be constant. The authors refer to Gorman (1981) where it is proved that the maximum possible rank for any exactly aggregable demand system is 3. Therefore, there's no gain adding cubic and higher terms to the demand equations. They also show that empirical Engel curves estimated on British data indicates that the demand system has rank 3. Note that (1.1) nests QUAIDS with constant $b(\boldsymbol{p})$, which is simpler to estimate at the price of restricting Engel curves' shape. This latter model itself nests AIDS. Blundell et al. (1993) obtain a good fit with a QUAIDS where $b(\boldsymbol{p})$ is set to 1 and therefore rank is 2. In this paper the choice is to write a general rank 3 QUAIDS with social interactions, but then carry out the estimation setting $b(\boldsymbol{p}) = 1$[3].

[2]For the sake of simplicity and in order not to complicate notation, we use the same symbol for amounts and shares

[3]Estimation has been carried on also restricting to AIDS. Results (which are not reported) suggest that as long as the interest is in social interactions' effect, conclusions are qualitatively similar

### 1.2.4 Properties of Demand Systems

In order to be a demand system, (1.1) must respect adding up, zero–homogeneity in $\boldsymbol{p}$ and $m$ simultaneously, symmetry and negative semi–definiteness of the Slutsky matrix of compensated price elasticities. All of them but for Slutsky matrix negative semi–definitness (which therefore has to be checked ex–post) can be modelled in terms of linear restrictions on the parameters:

$$\sum_{i=1}^{I} \alpha_i = 1; \quad \sum_{i=1}^{I} \gamma_{ij} = 0; \quad \sum_{i=1}^{I} \beta_i = 0; \quad \sum_{i=1}^{I} \lambda_i = 0 \tag{1.2}$$

$$\sum_{j=1}^{I} \gamma_{ij} = 0; \tag{1.3}$$

$$\gamma_{ij} = \gamma_{ji} \ \forall i, j \tag{1.4}$$

(1.2) implies adding up; (1.2) and (1.3) together imply zero–homogeneity. Conditions (1.2) and (1.4) together imply Slutsky symmetry. Among them, if price aggregators were known only (1.4) would set cross–equations restrictions. This observation will be useful for estimation: conditioning on preliminary estimates of $a(\boldsymbol{p})$ and setting $b(\boldsymbol{p}) = 1$ it's possible to impose adding up and homogeneity (i.e. restriction (1.2) and (1.3)) and estimate the system equation by equation.

Income elasticities are linear transformations of the parameters:

$$e_i^h = \frac{\beta_i + 2\gamma_i \ln m^h}{w_i^h} + 1 \tag{1.5}$$

Uncompensated and compensated price elasticities are computed similarly:

$$e_{ij}^h = \frac{\gamma_{ij}}{w_i^h} - (\beta_i + 2\gamma_i \ln m^h)\frac{w_j^h}{w_i^h} - K\delta \tag{1.6}$$

$$\tilde{e}_{ij}^h = e_{ij}^h + e_i^h w_j^h \delta \tag{1.7}$$

Where $K\delta$ is the Kronecker delta.

### 1.2.5 Demographics

With household data consumer preferences must be allowed to depend on individual characteristics, i.e. demographics $\boldsymbol{z}$[4] must enter (1.1). There are

[4] $\boldsymbol{z}$ is a $K$ dimensional vector, where K is the number of observable individual characteristics

different ways to do it, a simple one is to consider $\alpha_i$, $\beta_i$, $\lambda_i$ as household–$h$ specific: they are re–written as polynomials in $\boldsymbol{z}$ to make demographics' effect explicit. Note also that $\boldsymbol{z}$ include deterministic time–dependent variables (seasonal/year dummies). Then, $\forall i \neq 0$:

$$\alpha_i^h = \alpha_{i0} + \sum_{k=1}^{K} \alpha_{ik} z_k^h \tag{1.8}$$

$$\beta_i^h = \beta_{i0} + \sum_{k=1}^{K} \beta_{ik} z_k^h \tag{1.9}$$

$$\lambda_i^h = \lambda_{i0} + \sum_{k=1}^{K} \lambda_{ik} z_k^h \tag{1.10}$$

This is the most general formulation including demographics. The three polynomials need not to depend on all the $K$ elements of $\boldsymbol{z}$: it is enough to set a–priori (or test ex–post) the relevant parameters equal to zero. Nevertheless, it is not innocuous to limit demographics to change $\alpha_i^h$ but not $\beta_i^h$ or $\lambda_i^h$: looking back to (1.5), (1.6) and (1.7), this means such a demographics affect only the intercept and thus the level of a particular consumption share $w_i$, but not its elasticities. Back to the main case, substituting the new $\alpha_i^h$, $\beta_i^h$ and $\lambda_i^h$ into (1.1):

$$\begin{aligned} w_i^h = {} & \alpha_{i0} + \sum_{k=1}^{K} \alpha_{ik} z_k^h \\ & + \sum_{j=1}^{I} \gamma_{ij} \ln p_j \\ & + \beta_{i0} \ln \left[ \frac{m^h}{a(\boldsymbol{p}, \boldsymbol{z})} \right] + \sum_{k=1}^{K} \beta_{ik} \left( z_k^h \ln \left[ \frac{m^h}{a(\boldsymbol{p}, \boldsymbol{z})} \right] \right) \\ & + \frac{\lambda_{i0}}{b(\boldsymbol{p}, \boldsymbol{z})} \left( \ln \left[ \frac{m^h}{a(\boldsymbol{p}, \boldsymbol{z})} \right] \right)^2 + \sum_{k=1}^{K} \frac{\lambda_{ik}}{b(\boldsymbol{p}, \boldsymbol{z})} \left( z_k^h \left( \ln \left[ \frac{m^h}{a(\boldsymbol{p}, \boldsymbol{z})} \right] \right)^2 \right) \end{aligned} \tag{1.11}$$

where also the price aggregators are household–dependent. Restrictions (1.2) must be rewritten in terms of the new parameters:

$$
\begin{array}{l}
\sum_{i=1}^{I} \alpha_{i0} = 1; \\
\sum_{i=1}^{I} \alpha_{ik} = 0 \quad \forall k = 1, \dots K; \\
\sum_{i=1}^{I} \gamma_{ij} = 0; \\
\sum_{i=1}^{I} \beta_{ik} = 0 \quad \forall k = 0, \dots K; \\
\sum_{i=1}^{I} \lambda_{ik} = 0 \quad \forall k = 0, \dots K
\end{array}
\tag{1.12}
$$

### 1.2.6 Conditioning Goods

Conditioning goods are treated as demographics: they enter the $\boldsymbol{z}$ vector. Thus testing for separability boils down to test for significance of the relevant $\alpha_{ik}$ and $\beta_{ik}$. Durables and labor market decisions are included amongst the regressors, nevertheless the focus is on the conditioning factor accounting for network effects. Recall that social interactions' goods $\tilde{w}_{ih}$ are defined as the average demand for good $i$ in $h$'s reference good. Since the demand system (1.11) is expressed in terms of budget shares, define 'mean budget share' of good $i$ for household $h$ as

$$
\tilde{w}_i^h := \sum_{n=1}^{N} \delta_{in}^h w_i^n \tag{1.13}
$$

$\tilde{w}_i^h$ is a weighted average of individual demands for good $i$, $w_i^n$. The reference weights $\delta_{in}^h$ capture the importance household $h$ attaches to consumption of good $i$ by family $n$. Assume without loss of generality that $\delta_{ih}^h = 0$.[5]

Alessie and Kapteyn (1991) define (1.13) as 'mean perceived budget share'. In their model the reference weights are individual parameters, as to say that heterogeneity in preference interdependence among agents depend on differences in the perception of other households' demand. In this terms, it can be interpreted as a framing problem: unobserved individual characteristics determining reference weights lead households to 'measure' differently.

In this paper the assumption is that consumers observe correctly other households' expenditures, and the reference weights are determined by the 'similarity' between agents and the 'visibility' of good $i$:

$$
\delta_{in}^h = \theta_i \pi_n^h \tag{1.14}
$$

Where $\theta_i$ measures 'visibility' of commodity $i$ and $\Pi = \left[\pi_n^h\right]$ is the $H \times H$ matrix whose elements represent pair–wise similarities between households.

[5] It's just a rescaling: if $\delta_{ih}^h \neq 0$ the system can be written in terms of $\ddot{w}_i^h = (1-\delta_{ih}^h) w_i^h$.

In this context similarity has no direction, i.e. $\pi_n^h \equiv \pi_h^n$, therefore $\Pi$ is symmetric and with zeros on the diagonal.

The motivation behind similarities is peer identification: the behavior of consumer $n$ can have an impact on consumer $h$'s choices only if they belong to the same peer. A microeconomic data–set with both direct information about reference groups and the required detail about expenditure patterns would provide a measure of peer membership, but unfortunately such data are not available. Without direct observation, the best the researcher can do is to infer the probability that two individuals belong to the same reference group from available information as physical residence, family characteristics, race, education and so on. The underling hypothesis is that similarity is a valid measure of reference group membership, and therefore $\delta_{in}^h$ will be high if households $h$ and $n$ are likely to be in the same peer, vice versa it will be low. Case (1991) sets up a model where mean demand depends on physical proximity: individuals belong to the same peer if they live in the same neighborhood. Conley (1999) provides tools to estimate models with generic economic distances, possibly measured with error.

The second factor determining reference weights is visibility: it's reasonable to think that consumers care more about peer members' expenditure in clothing rather than in toothpaste, i.e. social interactions effect matter more for visible goods' demand rather than for non–visible ones. There are two possible motivations: first, individuals may not be able to observe peer members' consumption of non–visible goods as groceries or underwear. Second, visibility may be a valuable characteristic of goods itself. Heffetz (2004) characterizes a class of utility functions that depend on conspicuousness of goods: the idea is that consumption has a direct effect on individual utility, but also an indirect *social* effect resulting from peers observing his choice.

Now plugging (1.14) into (1.13)

$$\tilde{w}_i^h = \theta_i \bar{w}_i^h \quad \text{where } \bar{w}_i^h = \sum_{n}^{N} \pi_n^h w_i^n$$

Social interactions enter (1.11) as a conditioning factor, hence $\alpha_{i0}$ is a polynomial in $\tilde{w}_i^h$:

$$\alpha_{i0} = \tilde{\alpha}_{i0} + \sum_{j=1}^{I} (\tilde{\alpha}_{ij}\theta_i) \bar{w}_j^h \tag{1.15}$$

Note it is implicitly assumed that social interactions change intercepts but not slopes: this is the assumption that will be made for all the demographics and conditioning factors. As it has been explained in the previous section this is not innocuous, but it has the advantage to maintain the estimation procedure and the interpretation of the result reasonably simple, given that the focus is on the social interaction condition factor. Restrictions (1.12) has to be modified as well:

$$\begin{array}{l} \sum_{i=1}^{I}\tilde{\alpha}_{i0}=1; \\ \sum_{i=1}^{I}\tilde{\alpha}_{ij}=0 \quad \forall j=1,\dots I; \\ \sum_{i=1}^{I}\alpha_{ik}=0 \quad \forall k=1,\dots K; \\ \sum_{i=1}^{I}\gamma_{ij}=0; \\ \sum_{i=1}^{I}\beta_{ik}=0 \quad \forall k=0,\dots K; \\ \sum_{i=1}^{I}\lambda_{ik}=0 \quad \forall k=0,\dots K \end{array} \tag{1.16}$$

At this point in order to obtain the complete demand system unobservables $u_i^h$ are needed. Estimation will be done in a GMM framework, so no particular distributional assumption across goods will be done. Nevertheless unobservable factors may have the same structural dependence as demands (correlated effect), therefore the $h$ dimension of the error term will be modelled as follows:

$$u_i^h=\rho\sum_{n=1}^{N}\pi_n^h u_i^n+\epsilon^h \tag{1.17}$$

All the $I$ equations constituting the demand system to be estimated are then obtained adding (1.17) and substituting (1.15) into (1.13):

$$\begin{aligned} w_i^h &= \tilde{\alpha}_{i0}+\phi_{i1}\bar{w}_1^h+\cdots+\phi_{iI}\bar{w}_I^h \\ &+\sum_{k=1}^{K}\alpha_{ik}z_k^h \quad + \quad \sum_{j=1}^{I}\gamma_{ij}\ln p_j \\ &+\beta_{i0}\ln\left[\frac{m^h}{a^h(\boldsymbol{p},\boldsymbol{z},\bar{\boldsymbol{w}})}\right]+\sum_{k=1}^{K}\beta_{ik}z_k^h\ln\left[\frac{m^h}{a^h(\boldsymbol{p},\boldsymbol{z},\bar{\boldsymbol{w}})}\right] \\ &+\frac{\lambda_{i0}}{b^h(\boldsymbol{p},\boldsymbol{z})}\left(\ln\left[\frac{m^h}{a^h(\boldsymbol{p},\boldsymbol{z},\bar{\boldsymbol{w}})}\right]\right)^2 \\ &+\sum_{k=1}^{K}\frac{\lambda_{ik}}{b^h(\boldsymbol{p},\boldsymbol{z})}z_k^h\left(\ln\left[\frac{m^h}{a^h(\boldsymbol{p},\boldsymbol{z},\bar{\boldsymbol{w}})}\right]\right)^2 \\ &+u_i^h \end{aligned} \tag{1.18}$$

where $\phi_{ij}=\tilde{\alpha}_{ij}\theta_i$. $\theta_i$ are not separately identifiable from $\tilde{\alpha}_{i1}$ for all $i$. This lack of identifiability will complicate interpretation: pure social interaction effect, captured by $\tilde{\alpha}_{ij}$ may well have a different sign and different magnitude from visibility effect, $\theta_i$.

The price aggregators depend now on all the conditioning factors:

$$\begin{aligned}\ln a^h(\boldsymbol{p}, \boldsymbol{z}, \bar{\boldsymbol{w}}) = \alpha_0 + \sum_{i=1}^{I} \ln p_i \left( \tilde{\alpha}_{i0} + \sum_{k}^{K} \alpha_{ik} z_k^h + \sum_{j}^{I} \phi_{ij} \bar{w}_j^h \right) \\ + \sum_{i=1}^{I} \sum_{j=1}^{I} \gamma_{ij} \ln p_i \ln p_j\end{aligned} \tag{1.19}$$

$$b^h(\boldsymbol{p}) = \prod_{i=1}^{I} p_i^{\beta_{i0} + \sum_{k=1}^{K} \beta_{ik} z_k^h} \tag{1.20}$$

## 1.3 The data: Consumer Expenditure Survey (CEX) and Consumer's Price Index (CPI)

CEX is a detailed survey on individual expenditures. There are quarterly data from 1980 until 2002 on approximately 600 consumption categories. This survey is issued by the Bureau of Labor Statistics, that is the Office which publishes the CPI price indexes. The long and detailed repeated cross–sections dataset under analysis is obtained merging together CPI prices and CEX expenditures. CEX provides also a large number of demographic details about individuals, but as pointed out in the previous section there are no direct questions about reference groups. The claim is that the information is adequate to compute similarities among individuals.

In particular, 10 years of data are considered - from 1993 until 2002 - since in this period the state of residence identifier is available. For non–disclosure problems the variable STATE is suppressed for some observations in a subset of states and it is suppressed for all the observations on some other states. All the observations from those states are dropped, so we are left with observations from Arizona, Arkansas, California, Colorado, Connecticut, District of Columbia, Florida, Hawaii, Illinois, Missouri, New Hampshire, New Jersey, Pennsylvania, South Carolina, Utah, Virginia and Washington. The heterogeneous distribution of those states across US still allows to draw population–wide inference (see figure 1.1).

Data are summed up at yearly level, and only households with four consecutive quarterly observations are considered. After some extra data cleaning, the final sample consists of 11,769 observations. In the appendix means

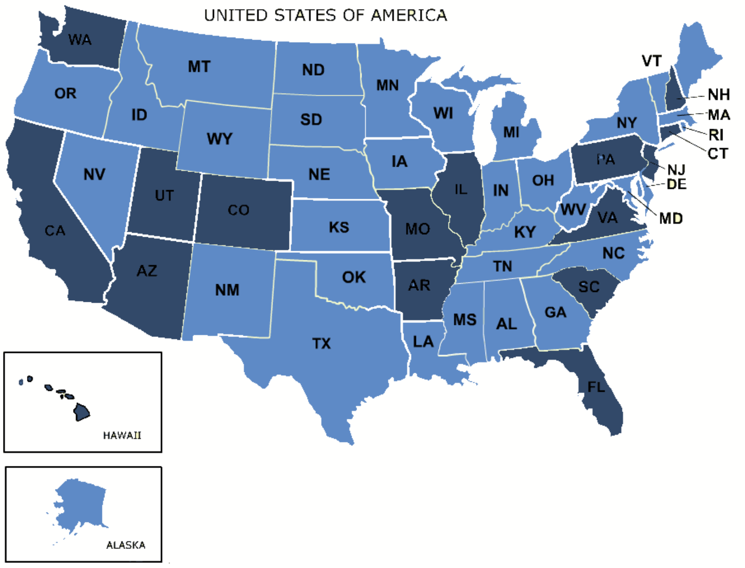


Figure 1.1: selected States are dark–blue

and standard deviations are reported for a set of relevant demographics on the selected subsample and on the US–wide sample. Differences suggest the sample is still representative for the US population.

## 1.4 Estimation Strategy

The estimation strategy is based on the one that Banks et al. (1997) and Blundell et al. (1993) used. However, an extension is needed in order to deal with the reflection problem. The estimation is divided into three steps:

1. $\Pi$ Matrix estimation: similarities are measured on the basis of a set of geographical and demographic individual characteristics.

2. Equation–by–equation estimates: parameters on each equation are estimated after imposing adding–up and homogeneity restrictions (1.16) and (1.3). Using the Generalized Spatial 2SLS (GS2SLS) procedure of Kelejian and Prucha (1998) the reflection problem is taken into proper account. GS2SLS estimator is a GMM spatial estimator within the class defined by Conley (1999). The author proves that as long as estimates in step–1 are imprecise measurements of true group membership probabilities, but they are not mis–measurement, step–2 estimates are

consistent[6].

3. Restricted system estimation: a Minimum Distance estimator is applied to step–2 estimates of parameters to impose cross–equation restrictions (1.4).

### 1.4.1 Similarity Matrix estimation

The claim is that two individuals are likely to belong to the same peer and therefore possibly influence each others' choices if they live close, they are observed in two not–too–distant points in time and they share some household's characteristics. Further on, a short physical distance is considered a prerequisite for peer membership.

Given these assumptions similarity between agents $h$ and $n$, $d_n^h$, follows a lexicographic order and it is computed as follows:

1. Two individuals are assumed not to belong to the same peer if they live in different States, or in the same State but in two cities with different population size, or if one is observed before 1997 and the other after that date. Therefore, pairs of individuals $h$, $n$ with those characteristics have similarity $d_n^h$ equal to 0.

2. Otherwise, if $h$ and $n$ live in the same State in two cities with the same population–size and they are both observed either before 1997 or after that date, $d_n^h$ is equal to a matching similarity measure constructed as follows:

   - A set of 0/1 dummy variables is created starting from the following variables: Family composition, 5 years–wide age class of household head, race, marital status, origin (ancestry) of household head, highest educational attainment, presence of children younger than 18 in the family, gender.
   - the index is equal to

$$d_n^h = \frac{\sum 1\text{–}1 \text{ matches}}{\# \text{ of } 0/1 \text{ dummies}}$$

Finally this similarity measure has no direction by construction therefore $d_n^h \equiv d_h^n$ and as previously explained it is re–parametrized in order to have $d_n^n = 0$ (zeros on the diagonal).

[6] An imprecise measure is a measure that is correct up to a certain level, as home–work place traveling distances up to city detail but not beyond. A mis–measurement is a truly incorrect distance, as a transformation applied to true distances

This procedure provide an estimate of similarities that is by construction imprecise: the physical distance information are quite poor if compared with other datasets used in social–interactions empirical literature (eg Topa (2001)). The matching similarity identifies individuals living in two equally big cities (possibly the same city) in the same State. Note also that matching similarities are considered as exogenous and given in the successive steps of the procedure.

In order to check that these similarities didn't simply capture State, population size and year effects, an OLS regression of $\pi_n^h$ on the full set of year, state and population dummies, plus their interactions is run. Results [7] shows that interactions' parameters are significantly different from zero, suggesting that similarities are more informative than a simple set of dummies.

### 1.4.2 Equation–by–Equation estimation

The demand system is non–linear, but each equation in (1.18) is linear conditional on $a(\boldsymbol{p}, \boldsymbol{z})$ and $b(\boldsymbol{p}, \boldsymbol{z})$. The second step uses this conditional linearity to estimate the model without imposing the cross–equation restrictions (1.4) but allowing for within–equation ones (1.16) and (1.3). $a(\boldsymbol{p}, \boldsymbol{z})$ is approximated with an household–level Stone price Index. $b(\boldsymbol{p}, \boldsymbol{z})$ is set equal to 1. As already explained this choice reduces the rank of the demand system to 2 according to Lewbell's definition.

Two endogeneity issues have to be addressed: first, total expenditure $\ln m^h$ and $(\ln m^h)^2$ are endogenous along the $i$ dimension, i.e. they are endogenous due to the contemporaneous allocation of total expenditure to different goods by each household. Second, in each equation describing the budget share of good $i$, mean budget share $\bar{w}_i^h$ is endogenous along the $h$ dimension, meaning it's endogenous due to the contemporaneous choice of the $H$ households of each good. These issues can be solved using a proper Instrumental Variables' procedure: endogeneity of total expenditure can be treated with standard 2SLS, the Generalized Spatial 2SLS (GS2SLS) proposed by Kelejian and Prucha (1998) is needed to account for endogeneity of mean budget shares. The resulting procedure requires that $\ln m^h$ and $(\ln m^h)^2$ are regressed on the exogenous variables and their predicted values are used as instruments. Earning from labor, which may be considered a natural instrument, is not used since it is potentially endogenous: labor force participation decision (as employment's sector) is used as a conditioning factor and results are coherent with Browning and Meghir (1991) thus rejecting separability. We will see that $\ln m^h$ will be instrumented with functions of

[7] which are not reported but are available upon request

the family size. Then GS2SLS is applied instead of the standard two step procedure to account for endogeneity of $\bar{w}_i^h$. GS2SLS is itself an iterative procedure. To see the basic steps and to underline the fact that endogeneity is along the $h$ dimension, rewrite demand for good $i$ (1.18) in matrix notation:

$$\begin{aligned} \boldsymbol{w}_i^h &= X^h\boldsymbol{\beta} + \phi_i \Pi \boldsymbol{w}_i^h + \boldsymbol{u}_i^h \\ \boldsymbol{u}_i^h &= \rho \Pi \boldsymbol{u}^h + \boldsymbol{\epsilon}_i^h \end{aligned} \tag{1.21}$$

This is written as a spatial autoregressive model, where $\boldsymbol{w}^h$ is the $H \times 1$ vector of observation on expenditure share on good $i$; $X^h$ is the $H \times K^*$ matrix that contains observations on the exogenous variables in $Z^h$, total expenditure and squared total expenditure, prices, $\bar{w}_j^h$, $\forall j \neq i$[8]. $\Pi$ is treated as a $H \times H$ matrix of known constants, $\rho$ and $\phi_i$ are scalar spatial autoregressive parameters.

Now rewriting model (1.21) as[9]

$$\begin{aligned} \boldsymbol{w}_i &= D\boldsymbol{\eta} + \boldsymbol{u}_i \\ \boldsymbol{u}_i &= \rho \Pi \boldsymbol{u}_i + \boldsymbol{\epsilon}_i \end{aligned} \tag{1.22}$$

where $D = (X, \Pi \boldsymbol{w}_i)$, $\boldsymbol{\eta} = (\boldsymbol{\beta}', \phi_i)'$, $\epsilon \sim IID(0, \sigma^2)$. The model can furthermore be transformed into

$$\boldsymbol{w}_i^*(\rho) = D^*(\rho)\boldsymbol{\eta} + \boldsymbol{\epsilon}_i \tag{1.23}$$

where $\boldsymbol{w}_i^*(\rho) = \boldsymbol{w}_i - \phi_i \Pi \boldsymbol{w}_i$, $D^*(\rho) = D - \rho \Pi D$. The estimation procedure is based on three steps:

- compute a 2SLS estimator for $\boldsymbol{\eta}$ in (1.22), $\hat{\boldsymbol{\eta}}$, using instruments for $\Pi \boldsymbol{w}_i$ chosen within the matrix $(\Pi X, \Pi\Pi X)$, in particular $\Pi Sex, \Pi age, \Pi Famsize$, and instruments for $\ln m^h$ and $(\ln m^h)^2$. Total expenditure is instrumented with the log of family size and its second power;
- use $\hat{\boldsymbol{\eta}}$ to estimate $\hat{\rho}$ and $\hat{\sigma}^2$ with GMM[10]
- use $\hat{\rho}$ and $\hat{\sigma}^2$ to compute $\boldsymbol{\eta}_{KP}$, a feasible 2SLS of $\boldsymbol{\eta}$ in (1.23) and its variance–covariance matrix $\hat{V}(\boldsymbol{\eta}_{KP})$. With a bit of algebra, the Kelejian and Prucha (1998) feasible 2SLS estimator can be rewritten as a standard 2SLS procedure over a set of transformed variables following (1.23):

[8] All the mean budget shares $\bar{w}_j^h$ $\forall j \neq i$ are considered as exogenous in $i$th budget share equation. Therefore the set of variables in $X^h$ changes for each equation. The overall set of regressors doesn't change preserving adding up, since in the $i$th equation $\bar{w}_i^h$ is instrumented.

[9] indexes $h$ are omitted

[10] details on moment conditions are in Kelejian and Prucha (1998)

Table 1.1: Zero occurencies

| | **freq.** | **%** |
|---|---|---|
| ALH | 5,317 | 45.18 |
| ALO | 5,282 | 44.88 |
| FDH | 4 | 0.03 |
| FDO | 597 | 5.07 |
| CLO | 791 | 6.72 |
| UND | 2,135 | 18.14 |
| GAS | 788 | 6.70 |
| OTH | 2 | 0.02 |

1. Pre–multiply each element of the first equation in (1.21) by $(I - \hat{\rho}\Pi)$
2. Run the usual 2SLS procedure on the transformed variables. Then, $(I - \hat{\rho}\Pi)\Pi\boldsymbol{w}_i$, $(I - \hat{\rho}\Pi)\ln m$ will be instrumented as in the first step.

As already noted Conley (1999) proves that if $\Pi$ is an imprecise but non mis–measured matrix of similarities GS2SLS lead to consistent estimates. Note also that thinking to (1.21) in terms of spatial structure deliver us the general properties of the model at hand: Anselin (1988) proves that while neglecting the presence of $\Pi\boldsymbol{u}^h$ in (1.21) lead to an efficiency loss, not considering social interactions, i.e. the presence of $\Pi\boldsymbol{w}_i$, would imply inconsistency of the estimates.

The system is estimated for 8 consumption categories: Alcohol at home (ALH), Alcohol out (ALO), Food at Home (FDH), Food out (FDO), Clothing excluding underwear (CLO), Underwear (UND), Motor Fuel (GAS), other non durables (OTH). Some of those consumption categories have a relevant presence of zero expenditures among the 11,769 observations (see Table 1.1).

Given the type of aggregates chosen, these zero occurrences are likely to correspond to purchase infrequency[11]. As pointed out by Blundell et al. (1993) it means that there is a conceptual difference between consumption and expenditure: the latter is not simply the empirically measured counterpart of the former. This difference affects both the dependent variables in the

[11] There may be undetected data quality problems: the under garments figure seems unreasonable given that data are year–level aggregates.

demand system and total consumption, arising a potential measurement error problem due to omitted variables. Nevertheless the estimation procedure removes the issue: budget shares are all treated as endogenous and therefore total expenditure is instrumented.

### 1.4.3 Estimation results

But for gasoline and other goods, the other consumption aggregates are chosen to check whether social interactions have different marginal effects on goods with a different visibility. Alcohol demand is maintained despite the particularly high zero occurrences because of its relevance from a tax policy point of view. OTH is omitted from the estimation to satisfy adding–up. Prices are monthly US–wide price indexes series for each category (OTH price is the overall price index) referring to the last month of each yearly observation. Base year is 2000. All indexes are then divided by OTH price to impose homogeneity. Because of two–stage budgeting hypothesis occupation is not instrumented: job–market participation is considered non–separable from overall consumption in the first stage, but when households have to decide about consumption allocation the job–market decision is already taken, and therefore it's predetermined with respect to budget shares' allocation. The same reasoning goes through for durables. Table 1.2 reports estimates obtained after the first step of the Kelejian and Prucha (1998) GS2SLS procedure for the own mean budget shares parameters for the first six consumption categories.

Estimated parameters are generally significantly different from 0, and they varies significantly across different types of goods and between visible and non–visible goods of the same type. Magnitude of parameters are relatively high compared to other demographics and conditioning factors (see full estimation results in the appendix). The main result of this paper is the significance of 5 out of 7 parameters reported in the previous table: social interaction and visibility together do matter in consumption choices. $t$-statistics in the table can be interpreted as tests of the null of separability of the social interactions conditioning factor and consumption goods' allocation: separability is rejected in five equations out of seven.

Parameters do not provide only a separability tests, they have an economic meaning per se: visibility itself seems to be relevant: estimates are different within pairs ALH/ALO, FDH/FDO, CLO/UND[12]. Clothing is positive and significant while underwear is not, Food Out has a parameter six

[12]Pairs of consumption categories are similar but for visibility, but it cannot be tested whether differences in $\phi$ are due only to visibility.

Table 1.2: Social interactions parameters' estimates

| **Visible goods** | | | | **Non visible goods** | | |
|---|---|---|---|---|---|---|
| FDO | $\phi_{FDO}$ | 0.0678 | | FDH | $\phi_{FDH}$ | 0.0147 |
| FDO | std.err | 0.019 | | FDH | std.err | 0.038 |
| FDO | t–stat | 3.52 | | FDH | t–stat | 3.83 |
| CLO | $\phi_{CLO}$ | 0.0667 | | UND | $\phi_{UND}$ | 0.0150 |
| CLO | std.err | 0.026 | | UND | std.err | 0.030 |
| CLO | t–stat | 2.52 | | UND | t–stat | 0.49 |
| ALO | $\phi_{ALO}$ | 0.0496 | | ALH | $\phi_{ALH}$ | -0.0638 |
| ALO | std.err | 0.042 | | ALH | std.err | 0.024 |
| ALO | t–stat | 1.18 | | ALH | t–stat | -2.67 |
| GAS | $\phi_{GAS}$ | -0.0677 | | | | |
| GAS | std.err | 0.030 | | | | |
| GAS | t–stat | -2.25 | | | | |

times the Food at Home one, intuitively a less visible category. In these cases common–sense is supported by previous results by Heffetz (2004), who ranked the same aggregates in terms of visibility. Alcohol at Home is significant and negative while Alcohol Out is not. Heffetz (2004) ranks ALH as more visible than ALO. Anyway, the model specifies social interactions as a conditioning factor, thus the lack of a full preferences' characterization do not allow to interpretation result beyond what is suggested by common sense. The same reasoning goes through for the negative sign of the gasoline parameter.

The effect of other demographics is in general the expected one, and as Browning and Meghir (1991) we reject separability of labor supply decision: tests $F$ on the joint significance of occupation dummies reject separability.

Turning the attention to income elastities (table 1.3), as expected alcohol is an inferior good while clothing and food are normal good. Gasoline's negative sign is couterintuitive. This result together with the one on gasoline's social interaction parameter may signal data problem on fuel expenditures.

Price parameters, and therefore uncompensated price elasticies are almost never significant. Year dummies are inclueded in the regression, thus taking into account exogenous shocks affecting overall price level. Price elasticites should take into account differences across price series, which turn out to be quite low in the data. This is due to the fact that in order to have price indexes coherent with the consumption categories aggregation, it was possible to use only US–wide price indexes, thus reducing heterogeneity across

Table 1.3: Income elasticities

| **Variable** | **Coefficient** | **(Std. Err.)** |
|---|---|---|
| ALH | -8.988 | 5.650 |
| ALO | -8.893† | 5.315 |
| FDO | 1.922 | 2.096 |
| FDH | 4.598∗ | 1.364 |
| CLO | 13.658∗ | 2.814 |
| UND | 14.610∗ | 5.609 |
| GAS | -18.744∗ | 5.941 |

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 1.4: Compensated price elasticities

| **equations** | **prices** | | | | | | |
|---|---|---|---|---|---|---|---|
| | ALH | ALO | FDO | FDH | CLO | UND | GAS |
| ALH | -18.759 | -31.759 | -18.952 | -71.610 | 7.825 | 11.741 | -49.719 |
| | (6.61) | (4.279) | (5.784) | (3.622) | (3.262) | (2.464) | (1.539) |
| ALO | -21.173 | 37.044 | -113.304 | 45.476 | -27.622 | 10.125 | 70.445 |
| | (4.69) | (6.966) | (6.585) | (3.853) | (3.342) | (2.818) | (1.776) |
| FDO | 4.414 | 0.840 | 0.180 | -14.030 | 11.284 | 0.875 | -6.840 |
| | (2.54) | (2.884) | (4.495) | (2.499) | (2.275) | (1.676) | (0.992) |
| FDH | 0.092 | 1.132 | 0.062 | 0.642 | 0.339 | -0.009 | -0.402 |
| | (1.626) | (1.935) | (2.62) | (2.115) | (1.57) | (1.057) | (0.709) |
| CLO | 0.680 | 1.543 | -8.462 | 8.405 | -6.760 | 0.076 | 14.767 |
| | (2.402) | (2.849) | (3.939) | (2.431) | (3.621) | (1.696) | (1.06) |
| UND | -2.509 | 6.628 | -1.531 | -55.576 | 15.583 | 0.119 | -12.964 |
| | (2.704) | (3.582) | (4.821) | (2.807) | (2.98) | (5.92) | (1.419) |
| GAS | 0.117 | 0.514 | -0.200 | -1.048 | 0.383 | 0.119 | -0.250 |
| | (2.523) | (3.51) | (4.716) | (2.812) | (3.005) | (1.894) | (6.126) |

std.deviations in parenthesis

Table 1.5: $\rho$ estimates

| | | | |
|---|---|---|---|
| CLO | 0.0108 | UND | 0.0323 |
| FDO | -0.005 | FDH | 0.0289 |
| ALO | 0.0277 | ALH | 0.0113 |
| GAS | 0.0266 | | |

prices. Compensated price elasticites (Table 1.4) are generally significant. Concentrating first on food and apparel equations, substitutability and complementarity are the expected ones: food and alcohol are complements, food at home and food out are substitutes (though the cross elasticity is positive but not significant on the Food Out equation), clothing and underwear are complements. Food, underwear and fuel own price elasticites are not significantly different from zero, which is not suprising since they are necessary goods. Clothing has a negative and significant own price elasticity, which again is in line with the theory. Alcohol equations' elasticities seem unreasonably high: this is likely to be driven by purchase infrequency (see Table 1.1).

The whole discussion on estimation results until now was based on first step results. This is correct since they are consistent, but if residuals are correctly modelled in (1.22), they are not efficient. The magnitude of $\rho$'s estimates, the spatial autoregressive parameters on unobservables, suggests that residuals structure changes with the type of good (see table 1.5).

Some of the estimates of social interactions parameters as well as demographics marginal effects change sign and magnitude moving to the 2SLS estimates on the transformed variables. Their significance as well as for other estimates in each equation is reduced. Given that the sample size is reasonably high, this evidence is unlikely to be driven by a better small sample behavior of the efficient estimates. We implicitly assumed in (1.22) that the weights matrix of the spatial autoregressive term and the one of $u$ were the same, but this need not to be true: unobserved characteristics may depend on peers' $u$s in a different way from expenditure shares. If this is true, $\Pi$ on the second equation of (1.22) should be substituted with a different weighting matrix. While on expenditure shares economics gives a guidance to build the weights matrix, there's no way to know the exact structure of the weights matrix on unobservables. Anselin (1988) points out that a wrong choice of such a matrix would lead to inconsistent results. Thus, it is reasonable to limit the interpretation of the results to the first stage 2SLS regressions, that even if inefficient are consistent.

Table 1.6: Over–identifying restrictions' validity

| | equations | | | | | | |
|---|---|---|---|---|---|---|---|
| | **ALH** | **ALO** | **FDO** | **FDH** | **CLO** | **UND** | **GAS** |
| J–statistic | 0.644 | 47.906 | 13.396 | 3.196 | 1.243 | 1.597 | 1.296 |
| $\chi^2_{(2)}$ p–value | 0.7248 | $< 10^{-4}$ | 0.0012 | 0.2023 | 0.5372 | 0.4499 | 0.5230 |

Table 1.7: Hausman test

| | equations | | | | | | |
|---|---|---|---|---|---|---|---|
| | **ALH** | **ALO** | **FDO** | **FDH** | **CLO** | **UND** | **GAS** |
| F–statistic | 6.77 | 7.58 | 2.81 | 11.61 | 11.09 | 10.35 | 106.29 |
| $F_{(3,11707)}$ p–value | 0.0001 | $< 10^{-4}$ | 0.0379 | $< 10^{-4}$ | $< 10^{-4}$ | $< 10^{-4}$ | $< 10^{-4}$ |

regression–based Hausman test

### 1.4.4 IV diagnostics

The usual diagnostics for IV estimation applies. Tests for the validity of over–identifying restrictions is carried on using the Hansen J–statistic.

Instruments are valid in five equations out of seven, both on first and third step estimated equations (table 1.6 reports tests on first step estimates). Further on, instruments are in general relevant: they are significantly different from zero in the first stage regressions, instruments chosen for total expenditure are significant in $\ln m^h$ and $(\ln m^h)^2$ equations while they are not on the mean budget share's one. Vice versa for instruments chosen for $\Pi \boldsymbol{w}_i$[13].

The proposed procedure is robust to two potential biases: endogeneity of total expenditure and of social interactions. Standard Hausman tests can be applied: the null of exogeneity of the instrumented variables is always rejected (see table 1.7 for first stage results).

### 1.4.5 Minimum Distance estimation

The final step consists in applying a minimum distance estimator to $\hat{\boldsymbol{\eta}}$ obtained by the equation by equation estimation. The cross–equation restrictions (Slutsky matrix symmetry) can be expressed as

[13]first stage regressions are not reported

$$\boldsymbol{\eta} - \boldsymbol{S\theta} = \mathbf{0} \tag{1.24}$$

Where $\eta$ is an $r \times 1$ dimensional vector while $\theta$ is $q \times 1$, with $r > q$. Symmetry restrictions are all linear. As in GMM estimation, to impose those restrictions OMD chooses $\boldsymbol{\theta}_{OMD}$ as to minimize

$$Q(\boldsymbol{\theta}) = [\hat{\boldsymbol{\eta}} - \boldsymbol{S\theta}]'\hat{V}(\hat{\boldsymbol{\eta}})^{-1}[\hat{\boldsymbol{\eta}} - \boldsymbol{S\theta}] \tag{1.25}$$

The three steps procedure has an implicit assumption on the parameters' space at the equation–by–equation estimation step: parameters on different equations are assumed to be uncorrelated, therefore $V(\hat{\boldsymbol{\eta}})$ is block–diagonal. Cross–equation restrictions refer only to prices' parameters $\gamma_{ij}$, this implies that but for $\hat{\gamma}_{ij}$ equation–by–equation estimates and their standard errors are the final estimates. Therefore, considering only the seven consumption categories (remember OTH is omitted for adding–up), $r = 49$ while $q = 28$, the number of unique elements of a $7 \times 7$ symmetric matrix. Further on, $\gamma_{ij}$ do not depend on $\tilde{w}_i^h$, therefore also the marginal effects on mean budget shares are unchanged after OMD estimation.

The minimized value of the objective function, $Q(\boldsymbol{\theta}_{OMD})$ is asymptotically distributed as a central $\chi^2$ with $r - q$ degrees of freedom. This provides a test for Slutsky symmetry[14]. The test accepts Slutsky symmetry ($Q(\boldsymbol{\theta}_{OMD}) = 18.7105$, p–value=0.6037). Given the linearity of (1.24) the estimate of Covariance matrix of OMD is:

$$\hat{V}(\boldsymbol{\theta}_{OMD}) = H\left(S'\hat{V}(\hat{\boldsymbol{\eta}})^{-1}S\right)^{-1} \tag{1.26}$$

Where $H = 11769$ is the sample size. As for the unrestricted estimates, most of $\hat{\theta}_{ij}$ are non–significant, and this drives the Slutsky symmetry test. Complete restricted estimates of prices' parameters matrix $\Gamma = [\gamma_{ij}]$ are reported in the appendix.

## 1.5 Conclusions

The aim of this paper was to assess whether consumption choices depend on social interactions. To do so Social Interactions were introduced in a Quadratic Almost Ideal Demand System as a conditioning factor. The novelty of the paper is in the estimation procedure: social interactions are captured with mean budget shares, that depend on probability of peer membership and visibility of each good. Peer membership identification is a major

[14] Proof of asymptotic properties of OMD estimators can be found in Cameron and Pravin K. Trivedi (2005) and in Ferguson (1958)

econometric issue once estimation is not performed with natural experiment or ad–hoc data sets. In this paper it is achieved constructing a similarity index, which measures the probability of belonging to the same peer for each couple of observations. This formulation allows to re–write each budget share equation as a Spatial Autoregressive model in order to adapt tools taken from the Spatial Econometrics literature: the endogeneity of mean budget shares that arises from the reflection problem is tackled using a Generalized Spatial 2SLS procedure.

Results support the initial hypothesis that social interactions are relevant in consumption allocation. Further on, they suggest a non–trivial role for visibility of different goods.

Future research should address two open issues which limit interpretation of estimation results: first, in this linear–in–means model pure social interaction and visibility are not separately identifiable. Second, in the literature there isn't a model that provides a structural characterization of preference dependence on social interactions and visibility. Another related field is the empirical investigation of an intertemporal consumption model with social interactions.

# Appendix

## A Codebook and Descriptive Statistics

| Var name | Variables description |
|---|---|
| ALH | alcoholic beverages for home use |
| ALO | alcoholic beverages at restaurants, bars, cafeterias, cafes, etc |
| FDO | dining out at restaurants, drive-thrus, etc, excl. alcohol; incl. food at school |
| FDH | food and nonalcoholic beverages at grocery, specialty and convenience stores |
| CLO | clothing and shoes, not including underwear, undergarments, and nightwear |
| UND | underwear, undergarments, nightwear and sleeping garments |
| GAS | gasoline and diesel fuel for motor vehicles |
| OTH | Other non durables expenses |
| CAR | the purchase of new and used motor vehicles such as cars, trucks, and vans |
| JWL | jewelry and watches |
| HSE | rent, or mortgage, or purchase, of their housing; |
| | home furnishings and household items; |
| | homeowners insurance, fire insurance, and property insurance |
| TOTEXP | total expenditure |
| p ALH | Alcoholic beverages at home price index |
| p ALO | Alcoholic beverages away from home price index |
| p FDO | Food away from home price index |
| p FDH | Food at home price index |
| p CLO | Apparel price index |
| p UND | Women's apparel (underwear prices are not available 1993-1996) price index |
| p GAS | Motor fuel price index |
| p OTH | All items price index |

| **Var name** | **Variables description** |
|---|---|
| h ALH | log price ALH-log price OTH |
| h ALO | log price ALO-log price OTH |
| h FDO | log price FDO-log price OTH |
| h FDH | log price FDH-log price OTH |
| h CLO | log price CLO-log price OTH |
| h UND | log price UND-log price OTH |
| h GAS | log price GAS-log price OTH |
| stone | $\sum_{\{X=ALH,ALO,FDO,FDH,CLO,UND,GAS\}} X \ln(X)$ |
| IYEAR 1994 | year dummy |
| IYEAR 1995 | year dummy |
| IYEAR 1996 | year dummy |
| IYEAR 1997 | year dummy |
| IYEAR 1998 | year dummy |
| IYEAR 1999 | year dummy |
| IYEAR 2000 | year dummy |
| IYEAR 2001 | year dummy |
| IYEAR 2002 | year dummy |
| IQTR 2 | quarter 2 dummy |
| IQTR 3 | quarter 3 dummy |
| IQTR 4 | quarter 4 dummy |
| IREGION 2 | North Central dummy |
| IREGION 3 | South dummy |
| IREGION 4 | West dummy |
| IOCCUP1 2 | Technical, sales, and administrative support occupations dummy |
| IOCCUP1 3 | Service occupations dummy |
| IOCCUP1 4 | Farming, forestry, and fishing occupations dummy |
| IOCCUP1 5 | Precision production, craft, and repair occupations dummy |
| IOCCUP1 6 | Operators, fabricators, and laborers dummy |
| IOCCUP1 7 | Armed forces dummy |
| IOCCUP1 8 | Self-employed dummy |
| IOCCUP1 9 | Not working dummy |
| IOCCUP1 10 | Retired dummy |
| SEX REF | Sex of reference person |
| AGE REF | age of reference person |
| YR EDREF | year of education reference person |
| IMARITAL1 2 | Widowed dummy |
| IMARITAL1 3 | Divorced dummy |
| IMARITAL1 4 | Separated dummy |
| IMARITAL1 5 | Never married dummy |
| PERSLT18 | "Number of children less than 18 " |
| PERSOT64 | Number of persons over 64 in CU |
| IREF RACE 2 | Black |
| IREF RACE 3 | American Indian, Aleut, Eskimo |
| IREF RACE 4 | Asian or Pacific Islander |
| m ALH | mean budget share of ALH |
| m ALO | mean budget share of ALO |
| m FDO | mean budget share of FDO |
| m FDH | mean budget share of FDH |
| m CLO | mean budget share of CLO |
| m UND | mean budget share of UND |
| m GAS | mean budget share of GAS |
| m OTH | mean budget share of OTH |
| lnx | $\log TOTEXP - stone$ |
| lnx2 | $(\log TOTEXP - stone)^2$ |

| | Estimation Subsample | | | | US–wide sample | |
|---|---|---|---|---|---|---|
| | **mean** | **sd** | **min** | **max** | **mean** | **sd** |
| ALH | 169.4168 | 323.9644 | 0 | 9689 | 156.0034 | 305.6665 |
| ALO | 148.1916 | 349.6133 | 0 | 8596 | 137.3304 | 328.3154 |
| FDO | 1496.894 | 1924.96 | 0 | 54991 | 1410.301 | 1766.066 |
| FDH | 3946.552 | 2184.401 | 0 | 22452 | 3787.429 | 2100.249 |
| CLO | 810.556 | 1061.452 | 0 | 33948 | 801.5828 | 1021.236 |
| UND | 138.5562 | 199.0201 | 0 | 2964 | 137.63 | 196.3205 |
| GAS | 1176.581 | 933.4128 | 0 | 9270 | 1172.394 | 925.0178 |
| OTH | 2.57E+07 | 3.96E+07 | 0 | 1.06E+09 | 11044.81 | 8904.229 |
| CAR | 3223.62 | 7905.023 | 0 | 95580 | 3278.012 | 8008.563 |
| JWL | 168.4439 | 1900.58 | 0 | 210000 | 148.0257 | 1271.566 |
| HSE | 5398478 | 1.31E+07 | 0 | 5.07E+08 | 3728.37 | 4086.647 |
| TOTEXP | 28370.56 | 20634.27 | 707.9996 | 743532.3 | 27190.09 | 19419.9 |
| p ALH | 99.06309 | 4.604702 | 90.89744 | 105.641 | | |
| p ALO | 98.36219 | 7.944797 | 82.3299 | 110.7195 | | |
| p FDO | 98.52624 | 6.234391 | 86.00479 | 107.7153 | | |
| p FDH | 98.59102 | 5.979608 | 84.1852 | 106.0734 | | |
| p CLO | 102.4084 | 3.366371 | 93.61198 | 107.571 | | |
| p UND | 105.9989 | 5.466155 | 92.67873 | 118.8631 | | |
| p GAS | 98.71063 | 13.41501 | 74.24512 | 130.373 | | |
| p OTH | 99.134 | 6.049358 | 85.95972 | 107.4052 | | |
| h ALH | 0.0000973 | 0.0168857 | -0.0223212 | 0.0579662 | | |
| h ALO | -0.0092608 | 0.0216242 | -0.0502381 | 0.0312734 | | |
| h FDO | -0.0062909 | 0.0066385 | -0.021008 | 0.0055633 | | |
| h FDH | -0.0054863 | 0.008038 | -0.0208597 | 0.0149212 | | |
| h CLO | 0.0338519 | 0.0876056 | -0.1308093 | 0.2179918 | | |
| h UND | 0.0675184 | 0.10364 | -0.1408286 | 0.3083668 | | |
| h GAS | -0.0115424 | 0.1079955 | -0.2719941 | 0.2138472 | | |
| stone | 2.497275 | 0.7220481 | 0.0668289 | 4.423194 | | |
| IYEAR 1994 | 0.0697169 | 0.2546783 | 0 | 1 | 0.0757231 | 0.2645582 |
| IYEAR 1995 | 0.0647422 | 0.2460789 | 0 | 1 | 0.0719397 | 0.2583916 |
| IYEAR 1996 | 0.032301 | 0.1768045 | 0 | 1 | 0.033804 | 0.1807268 |
| IYEAR 1997 | 0.1103559 | 0.3133439 | 0 | 1 | 0.1111995 | 0.3143833 |
| IYEAR 1998 | 0.109375 | 0.3121201 | 0 | 1 | 0.1131186 | 0.316742 |
| IYEAR 1999 | 0.1144899 | 0.3184165 | 0 | 1 | 0.117231 | 0.3216997 |
| IYEAR 2000 | 0.1625561 | 0.3689731 | 0 | 1 | 0.1545716 | 0.3615008 |
| IYEAR 2001 | 0.1566704 | 0.3635025 | 0 | 1 | 0.1515284 | 0.3585681 |
| IYEAR 2002 | 0.1619254 | 0.3683953 | 0 | 1 | 0.1525977 | 0.3596042 |
| IQTR 2 | 0.2383688 | 0.4261008 | 0 | 1 | 0.2442221 | 0.4296309 |
| IQTR 3 | 0.2378083 | 0.425756 | 0 | 1 | 0.2391501 | 0.4265704 |
| IQTR 4 | 0.2698991 | 0.4439227 | 0 | 1 | 0.2744071 | 0.4462212 |
| IREGION 2 | 0.1617152 | 0.3682023 | 0 | 1 | 0.2673338 | 0.4425741 |
| IREGION 3 | 0.2397001 | 0.4269154 | 0 | 1 | 0.33878 | 0.4733014 |
| IREGION 4 | 0.3462024 | 0.4757753 | 0 | 1 | 0.1927622 | 0.3944733 |
| IOCCUP1 2 | 0.1403447 | 0.3473565 | 0 | 1 | 0.1390267 | 0.3459792 |
| IOCCUP1 3 | 0.1122478 | 0.3156821 | 0 | 1 | 0.1133105 | 0.3169763 |
| IOCCUP1 4 | 0.0073571 | 0.0854602 | 0 | 1 | 0.00817 | 0.0900192 |
| IOCCUP1 5 | 0.0519198 | 0.221873 | 0 | 1 | 0.0533242 | 0.2246822 |
| IOCCUP1 6 | 0.0818386 | 0.2741282 | 0 | 1 | 0.0947498 | 0.2928731 |
| IOCCUP1 7 | 0.0044142 | 0.0662952 | 0 | 1 | 0.0032625 | 0.0570259 |
| IOCCUP1 8 | 0.0349636 | 0.183694 | 0 | 1 | 0.0395065 | 0.1947994 |
| IOCCUP1 9 | 0.0985846 | 0.298114 | 0 | 1 | 0.1012474 | 0.3016602 |
| IOCCUP1 10 | 0.2282791 | 0.4197382 | 0 | 1 | 0.2136258 | 0.4098712 |
| SEX REF | 1.430143 | 0.4951133 | 1 | 2 | 1.432433 | 0.4954205 |
| AGE REF | 51.36848 | 17.06942 | 17 | 94 | 50.8984 | 16.92091 |
| YR EDREF | 13.82112 | 2.813901 | 0 | 18 | 13.70314 | 2.809938 |

| | Estimation Subsample | | | | US–wide sample | |
|---|---|---|---|---|---|---|
| | **mean** | **sd** | **min** | **max** | **mean** | **sd** |
| IMARITAL1 2 | 0.1219871 | 0.3272824 | 0 | 1 | 0.1206032 | 0.32567 |
| IMARITAL1 3 | 0.1340387 | 0.3407058 | 0 | 1 | 0.1321727 | 0.3386831 |
| IMARITAL1 4 | 0.0298487 | 0.1701756 | 0 | 1 | 0.0279644 | 0.164873 |
| IMARITAL1 5 | 0.1387332 | 0.34568 | 0 | 1 | 0.1363674 | 0.343183 |
| PERSLT18 | 0.7101317 | 1.131586 | 0 | 10 | 0.7067032 | 1.108377 |
| PERSOT64 | 0.3805353 | 0.6572266 | 0 | 4 | 0.3587389 | 0.6448471 |
| IREF RACE 2 | 0.1053111 | 0.3069646 | 0 | 1 | 0.115257 | 0.3193362 |
| IREF RACE 3 | 0.0058156 | 0.0760406 | 0 | 1 | 0.007512 | 0.0863468 |
| IREF RACE 4 | 0.0557035 | 0.2293562 | 0 | 1 | 0.0325977 | 0.1775836 |
| m ALH | 0.1526445 | 0.1480501 | 0.0002917 | 0.6559903 | | |
| m ALO | 0.118248 | 0.1004168 | 0.000288 | 0.4505704 | | |
| m FDO | 1.222685 | 1.146591 | 0.0045779 | 5.28772 | | |
| m FDH | 3.911378 | 3.657658 | 0.0235374 | 16.5382 | | |
| m CLO | 0.6206222 | 0.5814182 | 0.0016867 | 2.735063 | | |
| m UND | 0.1158841 | 0.1091201 | 0.0003363 | 0.5074397 | | |
| m GAS | 1.085815 | 1.054143 | 0.0055939 | 4.869476 | | |
| m OTH | 9.659403 | 8.539694 | 0.0612457 | 39.68477 | | |
| lnx | 7.558408 | 0.9215498 | 3.685857 | 11.09327 | | |
| lnx2 | 57.97873 | 14.35368 | 13.58554 | 123.0606 | | |

## Equation–by–equation estimation results: first stage GS2SLS procedure

Estimation results after the first GS2SLS stage: estimates are consistent but not corrected by spatial structure on the error term

Table 1.8: ALH equation, first step

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_ALH | -0.064** | (0.024) |
| lnx | -0.063** | (0.024) |
| lnx2 | 0.004** | (0.002) |
| m_ALO | 0.054** | (0.015) |
| m_FDO | 0.004† | (0.002) |
| m_FDH | 0.003** | (0.001) |
| m_CLO | 0.001 | (0.003) |
| m_UND | -0.044** | (0.012) |
| m_GAS | -0.003* | (0.001) |
| m_OTH | 0.000 | (0.000) |
| h_ALH | -0.048 | (0.034) |
| h_ALO | -0.043 | (0.045) |
| h_FDO | 0.099 | (0.084) |
| h_FDH | 0.020 | (0.036) |
| h_CLO | 0.006 | (0.024) |
| h_UND | -0.002 | (0.014) |
| h_GAS | 0.003 | (0.004) |
| _IYEAR_1994 | 0.001 | (0.001) |
| _IYEAR_1995 | 0.000 | (0.002) |
| _IYEAR_1996 | 0.000 | (0.002) |
| _IYEAR_1997 | 0.001 | (0.002) |
| _IYEAR_1998 | 0.001 | (0.003) |
| _IYEAR_1999 | 0.000 | (0.003) |
| _IYEAR_2000 | 0.001 | (0.003) |
| _IYEAR_2001 | 0.001 | (0.004) |
| _IYEAR_2002 | 0.001 | (0.004) |

*Continued on next page...*

*... table 1.8 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| _IQTR_2 | 0.000 | (0.001) |
| _IQTR_3 | 0.000 | (0.000) |
| _IQTR_4 | 0.000 | (0.001) |
| POPSIZE | 0.000† | (0.000) |
| _IREGION_2 | -0.002** | (0.000) |
| _IREGION_3 | 0.002** | (0.001) |
| _IREGION_4 | 0.002** | (0.000) |
| _IOCCUP1_2 | 0.001† | (0.000) |
| _IOCCUP1_3 | 0.001† | (0.000) |
| _IOCCUP1_4 | 0.003* | (0.002) |
| _IOCCUP1_5 | 0.002** | (0.001) |
| _IOCCUP1_6 | 0.001* | (0.001) |
| _IOCCUP1_7 | -0.003** | (0.001) |
| _IOCCUP1_8 | -0.001 | (0.001) |
| _IOCCUP1_9 | 0.000 | (0.000) |
| _IOCCUP1_10 | 0.001 | (0.000) |
| SEX_REF | -0.002** | (0.000) |
| AGE_REF | 0.000** | (0.000) |
| YR_EDREF | 0.000† | (0.000) |
| _IMARITAL1_2 | 0.000 | (0.001) |
| _IMARITAL1_3 | 0.002** | (0.001) |
| _IMARITAL1_4 | 0.001 | (0.001) |
| _IMARITAL1_5 | 0.001* | (0.001) |
| _IREF_RACE_2 | 0.000 | (0.000) |
| _IREF_RACE_3 | 0.000 | (0.002) |
| _IREF_RACE_4 | -0.004** | (0.001) |
| PERSLT18 | -0.001** | (0.000) |
| PERSOT64 | 0.000 | (0.000) |
| NFEM | -0.001** | (0.000) |
| CAR | -0.048** | (0.013) |
| JWL | -0.036* | (0.015) |
| HSE | -0.021** | (0.005) |
| Intercept | 0.245** | (0.087) |

Significance levels : † : 10% * : 5% ** : 1%

Table 1.9: ALO equation, first step

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_ALO | 0.050 | (0.042) |
| lnx | -0.029 | (0.019) |
| lnx2 | 0.002 | (0.001) |
| m_ALH | -0.015 | (0.019) |
| m_FDO | 0.003 | (0.003) |
| m_FDH | 0.001† | (0.001) |
| m_CLO | 0.001 | (0.003) |
| m_UND | -0.016 | (0.011) |
| m_GAS | -0.003 | (0.003) |
| m_OTH | -0.001* | (0.000) |
| h_ALH | -0.077 | (0.050) |
| h_ALO | 0.084† | (0.044) |
| h_FDO | 0.014 | (0.089) |
| h_FDH | 0.083* | (0.034) |
| h_CLO | 0.017 | (0.024) |
| h_UND | 0.015 | (0.014) |
| h_GAS | 0.010* | (0.004) |

*Continued on next page...*

*... table 1.9 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| _IYEAR_1994 | 0.000 | (0.001) |
| _IYEAR_1995 | -0.001 | (0.002) |
| _IYEAR_1996 | -0.001 | (0.002) |
| _IYEAR_1997 | -0.001 | (0.002) |
| _IYEAR_1998 | -0.001 | (0.003) |
| _IYEAR_1999 | -0.002 | (0.003) |
| _IYEAR_2000 | -0.001 | (0.003) |
| _IYEAR_2001 | -0.001 | (0.004) |
| _IYEAR_2002 | 0.000 | (0.004) |
| _IQTR_2 | -0.001* | (0.001) |
| _IQTR_3 | 0.000 | (0.000) |
| _IQTR_4 | -0.002** | (0.001) |
| POPSIZE | -0.001* | (0.000) |
| _IREGION_2 | -0.001† | (0.001) |
| _IREGION_3 | 0.000 | (0.000) |
| _IREGION_4 | 0.000 | (0.000) |
| _IOCCUP1_2 | -0.001 | (0.000) |
| _IOCCUP1_3 | -0.001 | (0.000) |
| _IOCCUP1_4 | -0.002** | (0.001) |
| _IOCCUP1_5 | 0.000 | (0.001) |
| _IOCCUP1_6 | -0.001 | (0.001) |
| _IOCCUP1_7 | -0.001 | (0.001) |
| _IOCCUP1_8 | -0.001** | (0.000) |
| _IOCCUP1_9 | -0.002** | (0.000) |
| _IOCCUP1_10 | -0.001† | (0.000) |
| SEX_REF | -0.002** | (0.000) |
| AGE_REF | 0.000** | (0.000) |
| YR_EDREF | 0.000** | (0.000) |
| _IMARITAL1_2 | 0.000 | (0.000) |
| _IMARITAL1_3 | 0.002** | (0.000) |
| _IMARITAL1_4 | 0.001 | (0.001) |
| _IMARITAL1_5 | 0.003** | (0.001) |
| _IREF_RACE_2 | -0.003** | (0.001) |
| _IREF_RACE_3 | -0.002* | (0.001) |
| _IREF_RACE_4 | -0.002** | (0.000) |
| PERSLT18 | -0.001** | (0.000) |
| PERSOT64 | 0.000 | (0.000) |
| NFEM | -0.001** | (0.000) |
| CAR | -0.008 | (0.010) |
| JWL | 0.009 | (0.010) |
| HSE | -0.003 | (0.004) |
| Intercept | 0.132† | (0.071) |

Significance levels : † : 10% $*$ : 5% $**$ : 1%

Table 1.10: FDO equation, first step

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_FDO | 0.068** | (0.019) |
| lnx | 0.017 | (0.064) |
| lnx2 | -0.002 | (0.004) |
| m_ALH | 0.005 | (0.026) |
| m_ALO | -0.032 | (0.034) |
| m_FDH | 0.002 | (0.002) |
| m_CLO | -0.015† | (0.009) |
| m_UND | 0.060 | (0.037) |

*Continued on next page...*

*... table 1.10 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_GAS | -0.020** | (0.008) |
| m_OTH | -0.007** | (0.002) |
| h_ALH | -0.102 | (0.116) |
| h_ALO | -0.180 | (0.137) |
| h_FDO | 0.254 | (0.253) |
| h_FDH | -0.081 | (0.109) |
| h_CLO | -0.019 | (0.078) |
| h_UND | -0.003 | (0.047) |
| h_GAS | 0.006 | (0.012) |
| _IYEAR_1994 | 0.004 | (0.004) |
| _IYEAR_1995 | 0.000 | (0.006) |
| _IYEAR_1996 | 0.004 | (0.008) |
| _IYEAR_1997 | 0.004 | (0.008) |
| _IYEAR_1998 | 0.005 | (0.009) |
| _IYEAR_1999 | 0.005 | (0.009) |
| _IYEAR_2000 | 0.003 | (0.010) |
| _IYEAR_2001 | 0.004 | (0.012) |
| _IYEAR_2002 | 0.003 | (0.012) |
| _IQTR_2 | 0.000 | (0.002) |
| _IQTR_3 | -0.002 | (0.001) |
| _IQTR_4 | -0.001 | (0.002) |
| POPSIZE | -0.001† | (0.000) |
| _IREGION_2 | 0.001 | (0.002) |
| _IREGION_3 | 0.002 | (0.001) |
| _IREGION_4 | 0.000 | (0.001) |
| _IOCCUP1_2 | -0.002 | (0.001) |
| _IOCCUP1_3 | -0.008** | (0.001) |
| _IOCCUP1_4 | -0.010* | (0.004) |
| _IOCCUP1_5 | -0.004* | (0.002) |
| _IOCCUP1_6 | -0.005** | (0.002) |
| _IOCCUP1_7 | 0.000 | (0.006) |
| _IOCCUP1_8 | -0.005* | (0.002) |
| _IOCCUP1_9 | -0.013** | (0.001) |
| _IOCCUP1_10 | -0.007** | (0.002) |
| SEX_REF | -0.008** | (0.001) |
| AGE_REF | 0.000* | (0.000) |
| YR_EDREF | 0.002** | (0.000) |
| _IMARITAL1_2 | -0.005** | (0.002) |
| _IMARITAL1_3 | 0.000 | (0.001) |
| _IMARITAL1_4 | -0.001 | (0.002) |
| _IMARITAL1_5 | 0.002 | (0.002) |
| _IREF_RACE_2 | -0.011** | (0.001) |
| _IREF_RACE_3 | -0.015** | (0.004) |
| _IREF_RACE_4 | -0.001 | (0.003) |
| PERSLT18 | -0.003** | (0.000) |
| PERSOT64 | -0.004** | (0.001) |
| NFEM | -0.001** | (0.001) |
| CAR | -0.016 | (0.035) |
| JWL | 0.193** | (0.041) |
| HSE | -0.045** | (0.012) |
| Intercept | 0.034 | (0.233) |

Significance levels : † : 10% $*$ : 5% $**$ : 1%

Table 1.11: FDH equation, first step

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_FDH | 0.015** | (0.004) |
| lnx | 0.346** | (0.125) |
| lnx2 | -0.021* | (0.009) |
| m_ALH | 0.115* | (0.046) |
| m_ALO | -0.064 | (0.047) |
| m_FDO | -0.050** | (0.011) |
| m_CLO | -0.025$^{\dagger}$ | (0.015) |
| m_UND | -0.064 | (0.067) |
| m_GAS | 0.023* | (0.010) |
| m_OTH | -0.001 | (0.002) |
| h_ALH | -0.197 | (0.206) |
| h_ALO | 0.085 | (0.254) |
| h_FDO | -0.266 | (0.470) |
| h_FDH | 0.103 | (0.201) |
| h_CLO | 0.099 | (0.142) |
| h_UND | -0.123 | (0.083) |
| h_GAS | -0.022 | (0.023) |
| _IYEAR_1994 | -0.009 | (0.007) |
| _IYEAR_1995 | -0.018 | (0.012) |
| _IYEAR_1996 | -0.025$^{\dagger}$ | (0.014) |
| _IYEAR_1997 | -0.031* | (0.014) |
| _IYEAR_1998 | -0.030$^{\dagger}$ | (0.016) |
| _IYEAR_1999 | -0.033* | (0.016) |
| _IYEAR_2000 | -0.034$^{\dagger}$ | (0.018) |
| _IYEAR_2001 | -0.042* | (0.021) |
| _IYEAR_2002 | -0.051* | (0.022) |
| _IQTR_2 | 0.005 | (0.003) |
| _IQTR_3 | 0.000 | (0.003) |
| _IQTR_4 | 0.001 | (0.003) |
| POPSIZE | 0.000 | (0.001) |
| _IREGION_2 | 0.005$^{\dagger}$ | (0.003) |
| _IREGION_3 | -0.007** | (0.003) |
| _IREGION_4 | -0.005* | (0.002) |
| _IOCCUP1_2 | 0.006** | (0.002) |
| _IOCCUP1_3 | 0.022** | (0.003) |
| _IOCCUP1_4 | 0.039** | (0.009) |
| _IOCCUP1_5 | 0.015** | (0.003) |
| _IOCCUP1_6 | 0.019** | (0.003) |
| _IOCCUP1_7 | 0.000 | (0.007) |
| _IOCCUP1_8 | 0.009** | (0.003) |
| _IOCCUP1_9 | 0.045** | (0.003) |
| _IOCCUP1_10 | 0.024** | (0.003) |
| SEX_REF | 0.004** | (0.002) |
| AGE_REF | 0.000 | (0.000) |
| YR_EDREF | -0.007** | (0.000) |
| _IMARITAL1_2 | 0.013** | (0.003) |
| _IMARITAL1_3 | 0.016** | (0.003) |
| _IMARITAL1_4 | 0.026** | (0.005) |
| _IMARITAL1_5 | 0.025** | (0.003) |
| _IREF_RACE_2 | 0.014** | (0.003) |
| _IREF_RACE_3 | 0.008 | (0.009) |
| _IREF_RACE_4 | 0.012** | (0.004) |
| PERSLT18 | 0.012** | (0.001) |
| PERSOT64 | 0.004* | (0.002) |
| NFEM | -0.001 | (0.001) |
| CAR | -0.255** | (0.070) |
| JWL | -0.757** | (0.083) |
| HSE | -0.212** | (0.026) |

*Continued on next page...*

*... table 1.11 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| Intercept | -1.085* | (0.457) |

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 1.12: CLO equation, first step

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_CLO | 0.067* | (0.027) |
| lnx | 0.314** | (0.078) |
| lnx2 | -0.021** | (0.005) |
| m_ALH | -0.018 | (0.018) |
| m_ALO | 0.005 | (0.019) |
| m_FDO | -0.001 | (0.004) |
| m_FDH | 0.001 | (0.001) |
| m_UND | -0.061 | (0.076) |
| m_GAS | 0.001 | (0.004) |
| m_OTH | -0.004** | (0.001) |
| h_ALH | 0.026 | (0.084) |
| h_ALO | -0.064 | (0.102) |
| h_FDO | 0.220 | (0.196) |
| h_FDH | 0.030 | (0.083) |
| h_CLO | -0.077 | (0.060) |
| h_UND | 0.036 | (0.035) |
| h_GAS | 0.006 | (0.009) |
| _IYEAR_1994 | 0.001 | (0.003) |
| _IYEAR_1995 | 0.003 | (0.005) |
| _IYEAR_1996 | 0.002 | (0.006) |
| _IYEAR_1997 | 0.003 | (0.006) |
| _IYEAR_1998 | 0.003 | (0.006) |
| _IYEAR_1999 | 0.002 | (0.007) |
| _IYEAR_2000 | 0.001 | (0.007) |
| _IYEAR_2001 | -0.002 | (0.009) |
| _IYEAR_2002 | -0.004 | (0.009) |
| _IQTR_2 | 0.000 | (0.001) |
| _IQTR_3 | 0.001 | (0.001) |
| _IQTR_4 | 0.000 | (0.001) |
| POPSIZE | -0.001 | (0.000) |
| _IREGION_2 | 0.000 | (0.001) |
| _IREGION_3 | 0.002 | (0.002) |
| _IREGION_4 | -0.002 | (0.001) |
| _IOCCUP1_2 | -0.003** | (0.001) |
| _IOCCUP1_3 | -0.005** | (0.001) |
| _IOCCUP1_4 | 0.000 | (0.003) |
| _IOCCUP1_5 | -0.003* | (0.001) |
| _IOCCUP1_6 | -0.004** | (0.001) |
| _IOCCUP1_7 | -0.001 | (0.003) |
| _IOCCUP1_8 | -0.002 | (0.002) |
| _IOCCUP1_9 | -0.005** | (0.001) |
| _IOCCUP1_10 | -0.004** | (0.001) |
| SEX_REF | 0.000 | (0.001) |
| AGE_REF | 0.000 | (0.000) |
| YR_EDREF | 0.001** | (0.000) |
| _IMARITAL1_2 | 0.001 | (0.001) |
| _IMARITAL1_3 | 0.000 | (0.001) |
| _IMARITAL1_4 | 0.003† | (0.002) |
| _IMARITAL1_5 | 0.002 | (0.001) |

*Continued on next page...*

*... table 1.12 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| _IREF_RACE_2 | 0.004** | (0.001) |
| _IREF_RACE_3 | -0.005† | (0.003) |
| _IREF_RACE_4 | 0.001 | (0.001) |
| PERSLT18 | 0.004** | (0.000) |
| PERSOT64 | -0.002** | (0.001) |
| NFEM | 0.000 | (0.000) |
| CAR | 0.115** | (0.043) |
| JWL | 0.270** | (0.051) |
| HSE | 0.004 | (0.014) |
| Intercept | -1.123** | (0.285) |

Significance levels : † : 10% $*$ : 5% $**$ : 1%

Table 1.13: UND equation, first step

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_UND | 0.015 | (0.030) |
| lnx | 0.040* | (0.016) |
| lnx2 | -0.003* | (0.001) |
| m_ALH | -0.007 | (0.004) |
| m_ALO | 0.002 | (0.005) |
| m_FDO | 0.000 | (0.001) |
| m_FDH | 0.000 | (0.000) |
| m_CLO | 0.001 | (0.005) |
| m_GAS | 0.000 | (0.001) |
| m_OTH | 0.000 | (0.000) |
| h_ALH | 0.025 | (0.021) |
| h_ALO | 0.021 | (0.026) |
| h_FDO | 0.025 | (0.049) |
| h_FDH | -0.002 | (0.020) |
| h_CLO | 0.003 | (0.015) |
| h_UND | 0.002 | (0.009) |
| h_GAS | 0.002 | (0.002) |
| _IYEAR_1994 | 0.000 | (0.001) |
| _IYEAR_1995 | 0.001 | (0.001) |
| _IYEAR_1996 | 0.001 | (0.001) |
| _IYEAR_1997 | 0.001 | (0.001) |
| _IYEAR_1998 | 0.001 | (0.002) |
| _IYEAR_1999 | 0.001 | (0.002) |
| _IYEAR_2000 | 0.001 | (0.002) |
| _IYEAR_2001 | 0.001 | (0.002) |
| _IYEAR_2002 | 0.001 | (0.002) |
| _IQTR_2 | 0.000 | (0.000) |
| _IQTR_3 | 0.000 | (0.000) |
| _IQTR_4 | 0.000 | (0.000) |
| POPSIZE | 0.000 | (0.000) |
| _IREGION_2 | 0.000 | (0.000) |
| _IREGION_3 | 0.000† | (0.000) |
| _IREGION_4 | 0.000 | (0.000) |
| _IOCCUP1_2 | 0.000 | (0.000) |
| _IOCCUP1_3 | 0.000 | (0.000) |
| _IOCCUP1_4 | 0.002† | (0.001) |
| _IOCCUP1_5 | 0.000 | (0.000) |
| _IOCCUP1_6 | 0.000 | (0.000) |
| _IOCCUP1_7 | 0.000 | (0.001) |
| _IOCCUP1_8 | 0.000 | (0.000) |

*Continued on next page...*

*... table 1.13 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| _IOCCUP1_9 | 0.001$^{\dagger}$ | (0.000) |
| _IOCCUP1_10 | 0.000$^{\dagger}$ | (0.000) |
| SEX_REF | 0.001** | (0.000) |
| AGE_REF | 0.000** | (0.000) |
| YR_EDREF | 0.000 | (0.000) |
| _IMARITAL1_2 | 0.000 | (0.000) |
| _IMARITAL1_3 | 0.000$^{\dagger}$ | (0.000) |
| _IMARITAL1_4 | -0.001* | (0.000) |
| _IMARITAL1_5 | -0.001$^{\dagger}$ | (0.000) |
| _IREF_RACE_2 | 0.001$^{\dagger}$ | (0.000) |
| _IREF_RACE_3 | 0.001 | (0.002) |
| _IREF_RACE_4 | -0.001$^{\dagger}$ | (0.000) |
| PERSLT18 | 0.001** | (0.000) |
| PERSOT64 | 0.000 | (0.000) |
| NFEM | 0.000 | (0.000) |
| CAR | 0.012 | (0.009) |
| JWL | 0.025** | (0.009) |
| HSE | 0.001 | (0.003) |
| Intercept | -0.143* | (0.059) |

Significance levels : $\dagger$ : 10% $*$ : 5% $**$ : 1%

Table 1.14: GAS equation, first step

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_GAS | -0.068* | (0.030) |
| lnx | -0.829** | (0.276) |
| lnx2 | 0.059** | (0.019) |
| m_ALH | 0.016 | (0.041) |
| m_ALO | -0.167** | (0.064) |
| m_FDO | 0.009 | (0.012) |
| m_FDH | 0.009$^{\dagger}$ | (0.005) |
| m_CLO | -0.011 | (0.016) |
| m_UND | -0.091 | (0.075) |
| m_OTH | 0.007* | (0.003) |
| h_ALH | -0.168 | (0.197) |
| h_ALO | 0.174 | (0.244) |
| h_FDO | -0.097 | (0.457) |
| h_FDH | -0.062 | (0.197) |
| h_CLO | 0.213 | (0.144) |
| h_UND | -0.031 | (0.082) |
| h_GAS | 0.015 | (0.021) |
| _IYEAR_1994 | -0.002 | (0.007) |
| _IYEAR_1995 | 0.000 | (0.011) |
| _IYEAR_1996 | 0.001 | (0.013) |
| _IYEAR_1997 | 0.005 | (0.014) |
| _IYEAR_1998 | 0.001 | (0.015) |
| _IYEAR_1999 | -0.001 | (0.016) |
| _IYEAR_2000 | 0.006 | (0.017) |
| _IYEAR_2001 | 0.012 | (0.021) |
| _IYEAR_2002 | 0.010 | (0.022) |
| _IQTR_2 | -0.008* | (0.004) |
| _IQTR_3 | -0.005$^{\dagger}$ | (0.003) |
| _IQTR_4 | -0.007$^{\dagger}$ | (0.004) |
| POPSIZE | 0.004** | (0.001) |
| _IREGION_2 | 0.009** | (0.003) |

*Continued on next page...*

*... table 1.14 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| _IREGION_3 | 0.005* | (0.002) |
| _IREGION_4 | 0.010** | (0.003) |
| _IOCCUP1_2 | 0.014** | (0.003) |
| _IOCCUP1_3 | 0.013** | (0.003) |
| _IOCCUP1_4 | 0.004 | (0.008) |
| _IOCCUP1_5 | 0.016** | (0.003) |
| _IOCCUP1_6 | 0.023** | (0.004) |
| _IOCCUP1_7 | -0.004 | (0.009) |
| _IOCCUP1_8 | 0.013** | (0.004) |
| _IOCCUP1_9 | -0.001 | (0.003) |
| _IOCCUP1_10 | 0.002 | (0.003) |
| SEX_REF | -0.001 | (0.002) |
| AGE_REF | -0.001** | (0.000) |
| YR_EDREF | -0.002** | (0.000) |
| _IMARITAL1_2 | -0.005 | (0.003) |
| _IMARITAL1_3 | 0.008** | (0.003) |
| _IMARITAL1_4 | 0.000 | (0.005) |
| _IMARITAL1_5 | 0.000 | (0.003) |
| _IREF_RACE_2 | 0.000 | (0.002) |
| _IREF_RACE_3 | 0.022** | (0.008) |
| _IREF_RACE_4 | -0.009* | (0.004) |
| PERSLT18 | -0.007** | (0.001) |
| PERSOT64 | 0.000 | (0.002) |
| NFEM | -0.001 | (0.001) |
| CAR | -0.601** | (0.153) |
| JWL | -0.581** | (0.161) |
| HSE | -0.267** | (0.048) |
| Intercept | 3.053** | (1.003) |

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

## Equation–by–equation estimation results: third stage GS2SLS procedure

Final equation by equation estimation results: estimates are efficient, i.e. corrected by spatial structure on the error term

Table 1.15: ALH equation, final estimates

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_ALH | -0.004 | (0.042) |
| lnx | -0.039 | (0.024) |
| lnx2 | 0.003† | (0.002) |
| m_ALO | 0.012 | (0.026) |
| m_FDO | 0.005† | (0.003) |
| m_FDH | 0.001 | (0.001) |
| m_CLO | 0.001 | (0.005) |
| m_UND | -0.054* | (0.022) |
| m_GAS | -0.001 | (0.003) |
| m_OTH | -0.001 | (0.000) |
| h_ALH | -0.042 | (0.032) |

*Continued on next page...*

*... table 1.15 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| h_ALO | -0.046 | (0.043) |
| h_FDO | 0.088 | (0.080) |
| h_FDH | 0.005 | (0.034) |
| h_CLO | 0.008 | (0.023) |
| h_UND | -0.006 | (0.014) |
| h_GAS | 0.002 | (0.004) |
| _IYEAR_1994 | 0.001 | (0.001) |
| _IYEAR_1995 | 0.000 | (0.002) |
| _IYEAR_1996 | 0.000 | (0.002) |
| _IYEAR_1997 | 0.000 | (0.002) |
| _IYEAR_1998 | 0.000 | (0.003) |
| _IYEAR_1999 | -0.001 | (0.003) |
| _IYEAR_2000 | 0.000 | (0.003) |
| _IYEAR_2001 | 0.000 | (0.003) |
| _IYEAR_2002 | 0.000 | (0.004) |
| _IQTR_2 | 0.000 | (0.001) |
| _IQTR_3 | 0.000 | (0.000) |
| _IQTR_4 | 0.000 | (0.000) |
| POPSIZE | 0.000 | (0.000) |
| _IREGION_2 | -0.001$^{\dagger}$ | (0.001) |
| _IREGION_3 | 0.000 | (0.001) |
| _IREGION_4 | 0.001$^{\dagger}$ | (0.001) |
| _IOCCUP1_2 | 0.001 | (0.000) |
| _IOCCUP1_3 | 0.001$^{\dagger}$ | (0.000) |
| _IOCCUP1_4 | 0.003* | (0.002) |
| _IOCCUP1_5 | 0.002** | (0.001) |
| _IOCCUP1_6 | 0.001* | (0.001) |
| _IOCCUP1_7 | -0.002** | (0.001) |
| _IOCCUP1_8 | -0.001 | (0.001) |
| _IOCCUP1_9 | 0.000 | (0.000) |
| _IOCCUP1_10 | 0.001$^{\dagger}$ | (0.000) |
| SEX_REF | -0.002** | (0.000) |
| AGE_REF | 0.000** | (0.000) |
| YR_EDREF | 0.000 | (0.000) |
| _IMARITAL1_2 | 0.001 | (0.001) |
| _IMARITAL1_3 | 0.002** | (0.001) |
| _IMARITAL1_4 | 0.001 | (0.001) |
| _IMARITAL1_5 | 0.002** | (0.001) |
| _IREF_RACE_2 | 0.000 | (0.000) |
| _IREF_RACE_3 | 0.000 | (0.001) |
| _IREF_RACE_4 | -0.003** | (0.001) |
| PERSLT18 | -0.001** | (0.000) |
| PERSOT64 | 0.000 | (0.000) |
| NFEM | -0.001** | (0.000) |
| CAR | -0.036** | (0.014) |
| JWL | -0.026$^{\dagger}$ | (0.013) |
| HSE | -0.018** | (0.005) |
| CONSTANT | 0.159$^{\dagger}$ | (0.090) |
| Intercept | 0.000 | (0.000) |

Significance levels : $\dagger$ : 10% $\quad *$ : 5% $\quad **$ : 1%

Table 1.16: ALO equation, final estimates

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_ALO | -0.050 | (0.047) |

*Continued on next page...*

*... table 1.16 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| lnx | -0.025 | (0.019) |
| lnx2 | 0.001 | (0.001) |
| m_ALH | 0.028 | (0.022) |
| m_FDO | 0.011** | (0.004) |
| m_FDH | 0.001 | (0.001) |
| m_CLO | 0.009† | (0.005) |
| m_UND | -0.037* | (0.017) |
| m_GAS | -0.008** | (0.003) |
| m_OTH | -0.001 | (0.000) |
| h_ALH | -0.078 | (0.050) |
| h_ALO | 0.082† | (0.044) |
| h_FDO | 0.020 | (0.090) |
| h_FDH | 0.076* | (0.034) |
| h_CLO | 0.020 | (0.024) |
| h_UND | 0.014 | (0.014) |
| h_GAS | 0.009* | (0.004) |
| _IYEAR_1994 | 0.001 | (0.001) |
| _IYEAR_1995 | 0.000 | (0.002) |
| _IYEAR_1996 | -0.001 | (0.002) |
| _IYEAR_1997 | -0.001 | (0.002) |
| _IYEAR_1998 | -0.002 | (0.003) |
| _IYEAR_1999 | -0.002 | (0.003) |
| _IYEAR_2000 | -0.002 | (0.003) |
| _IYEAR_2001 | -0.002 | (0.004) |
| _IYEAR_2002 | 0.000 | (0.004) |
| _IQTR_2 | -0.001* | (0.001) |
| _IQTR_3 | 0.000 | (0.000) |
| _IQTR_4 | -0.002** | (0.001) |
| POPSIZE | -0.001** | (0.000) |
| _IREGION_2 | -0.001† | (0.001) |
| _IREGION_3 | 0.000 | (0.001) |
| _IREGION_4 | 0.000 | (0.000) |
| _IOCCUP1_2 | -0.001 | (0.000) |
| _IOCCUP1_3 | -0.001 | (0.000) |
| _IOCCUP1_4 | -0.002** | (0.001) |
| _IOCCUP1_5 | 0.000 | (0.001) |
| _IOCCUP1_6 | -0.001 | (0.001) |
| _IOCCUP1_7 | -0.001 | (0.001) |
| _IOCCUP1_8 | -0.002** | (0.000) |
| _IOCCUP1_9 | -0.002** | (0.000) |
| _IOCCUP1_10 | -0.001† | (0.000) |
| SEX_REF | -0.002** | (0.000) |
| AGE_REF | 0.000** | (0.000) |
| YR_EDREF | 0.000** | (0.000) |
| _IMARITAL1_2 | 0.001 | (0.001) |
| _IMARITAL1_3 | 0.002** | (0.001) |
| _IMARITAL1_4 | 0.001† | (0.001) |
| _IMARITAL1_5 | 0.004** | (0.001) |
| _IREF_RACE_2 | -0.003** | (0.000) |
| _IREF_RACE_3 | -0.003* | (0.001) |
| _IREF_RACE_4 | -0.002** | (0.001) |
| PERSLT18 | -0.001** | (0.000) |
| PERSOT64 | 0.000 | (0.000) |
| NFEM | -0.001** | (0.000) |
| CAR | -0.003 | (0.010) |
| JWL | 0.014 | (0.010) |
| HSE | -0.001 | (0.004) |
| CONSTANT | 0.121† | (0.070) |

*Continued on next page...*

*... table 1.16 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| Intercept | -0.002 | (0.001) |

Significance levels : † : 10% * : 5% ** : 1%

Table 1.17: FDO equation, final estimates

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_FDO | -0.550** | (0.195) |
| lnx | 0.026 | (0.089) |
| lnx2 | -0.002 | (0.006) |
| m_ALH | 0.184** | (0.067) |
| m_ALO | 0.701** | (0.238) |
| m_FDH | -0.016** | (0.006) |
| m_CLO | -0.004 | (0.012) |
| m_UND | 0.014 | (0.054) |
| m_GAS | 0.164** | (0.058) |
| m_OTH | 0.051** | (0.019) |
| h_ALH | -0.018 | (0.159) |
| h_ALO | -0.279 | (0.197) |
| h_FDO | -0.088 | (0.379) |
| h_FDH | 0.044 | (0.158) |
| h_CLO | -0.140 | (0.115) |
| h_UND | -0.002 | (0.065) |
| h_GAS | -0.009 | (0.018) |
| _IYEAR_1994 | -0.003 | (0.006) |
| _IYEAR_1995 | -0.012 | (0.009) |
| _IYEAR_1996 | -0.010 | (0.011) |
| _IYEAR_1997 | 0.007 | (0.011) |
| _IYEAR_1998 | -0.008 | (0.012) |
| _IYEAR_1999 | -0.010 | (0.013) |
| _IYEAR_2000 | -0.015 | (0.015) |
| _IYEAR_2001 | -0.020 | (0.018) |
| _IYEAR_2002 | -0.023 | (0.019) |
| _IQTR_2 | 0.003 | (0.002) |
| _IQTR_3 | -0.004† | (0.002) |
| _IQTR_4 | 0.002 | (0.002) |
| POPSIZE | 0.004* | (0.002) |
| _IREGION_2 | 0.038** | (0.012) |
| _IREGION_3 | 0.001 | (0.002) |
| _IREGION_4 | -0.011** | (0.004) |
| _IOCCUP1_2 | -0.003 | (0.002) |
| _IOCCUP1_3 | -0.010** | (0.002) |
| _IOCCUP1_4 | -0.005 | (0.005) |
| _IOCCUP1_5 | -0.009** | (0.003) |
| _IOCCUP1_6 | -0.007** | (0.002) |
| _IOCCUP1_7 | 0.014 | (0.009) |
| _IOCCUP1_8 | -0.007* | (0.003) |
| _IOCCUP1_9 | -0.015** | (0.002) |
| _IOCCUP1_10 | -0.008** | (0.002) |
| SEX_REF | -0.008** | (0.001) |
| AGE_REF | 0.000 | (0.000) |
| YR_EDREF | 0.003** | (0.000) |
| _IMARITAL1_2 | -0.010** | (0.003) |
| _IMARITAL1_3 | -0.001 | (0.002) |
| _IMARITAL1_4 | 0.001 | (0.003) |
| _IMARITAL1_5 | 0.011** | (0.003) |

*Continued on next page...*

*... table 1.17 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| _IREF_RACE_2 | -0.014** | (0.002) |
| _IREF_RACE_3 | -0.013* | (0.006) |
| _IREF_RACE_4 | 0.060** | (0.019) |
| PERSLT18 | -0.003** | (0.001) |
| PERSOT64 | -0.005** | (0.001) |
| NFEM | -0.002* | (0.001) |
| CAR | -0.038 | (0.051) |
| JWL | 0.239** | (0.056) |
| HSE | -0.043* | (0.017) |
| CONSTANT | -0.328 | (0.342) |
| Intercept | 0.270 | (0.190) |

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 1.18: FDH equation, final estimates

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_FDH | 0.015 | (0.017) |
| lnx | 0.397* | (0.168) |
| lnx2 | -0.024* | (0.012) |
| m_ALH | 0.168† | (0.102) |
| m_ALO | -0.094 | (0.085) |
| m_FDO | -0.052** | (0.019) |
| m_CLO | 0.007 | (0.032) |
| m_UND | -0.102 | (0.169) |
| m_GAS | 0.015 | (0.025) |
| m_OTH | -0.002 | (0.005) |
| h_ALH | -0.183 | (0.208) |
| h_ALO | 0.102 | (0.255) |
| h_FDO | -0.277 | (0.474) |
| h_FDH | 0.113 | (0.203) |
| h_CLO | 0.105 | (0.144) |
| h_UND | -0.129 | (0.084) |
| h_GAS | -0.020 | (0.023) |
| _IYEAR_1994 | -0.009 | (0.007) |
| _IYEAR_1995 | -0.017 | (0.012) |
| _IYEAR_1996 | -0.027† | (0.014) |
| _IYEAR_1997 | -0.032* | (0.014) |
| _IYEAR_1998 | -0.030† | (0.016) |
| _IYEAR_1999 | -0.032* | (0.016) |
| _IYEAR_2000 | -0.034† | (0.018) |
| _IYEAR_2001 | -0.042† | (0.021) |
| _IYEAR_2002 | -0.051* | (0.023) |
| _IQTR_2 | 0.005 | (0.003) |
| _IQTR_3 | 0.000 | (0.003) |
| _IQTR_4 | 0.000 | (0.003) |
| POPSIZE | 0.001 | (0.001) |
| _IREGION_2 | 0.006† | (0.004) |
| _IREGION_3 | -0.006† | (0.003) |
| _IREGION_4 | -0.002 | (0.003) |
| _IOCCUP1_2 | 0.006* | (0.002) |
| _IOCCUP1_3 | 0.022** | (0.003) |
| _IOCCUP1_4 | 0.038** | (0.009) |
| _IOCCUP1_5 | 0.016** | (0.003) |
| _IOCCUP1_6 | 0.019** | (0.003) |
| _IOCCUP1_7 | 0.000 | (0.007) |

*Continued on next page...*

*... table 1.18 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| _IOCCUP1_8 | 0.008* | (0.003) |
| _IOCCUP1_9 | 0.044** | (0.003) |
| _IOCCUP1_10 | 0.024** | (0.003) |
| SEX_REF | 0.004** | (0.002) |
| AGE_REF | 0.000 | (0.000) |
| YR_EDREF | -0.007** | (0.000) |
| _IMARITAL1_2 | 0.015** | (0.004) |
| _IMARITAL1_3 | 0.017** | (0.003) |
| _IMARITAL1_4 | 0.027** | (0.005) |
| _IMARITAL1_5 | 0.026** | (0.004) |
| _IREF_RACE_2 | 0.015** | (0.003) |
| _IREF_RACE_3 | 0.008 | (0.009) |
| _IREF_RACE_4 | 0.014** | (0.005) |
| PERSLT18 | 0.012** | (0.001) |
| PERSOT64 | 0.003$^{\dagger}$ | (0.002) |
| NFEM | -0.001 | (0.001) |
| CAR | -0.229* | (0.092) |
| JWL | -0.736** | (0.095) |
| HSE | -0.204** | (0.031) |
| CONSTANT | -1.279* | (0.614) |
| Intercept | 0.001 | (0.002) |

Significance levels : $\dagger$ : 10% $*$ : 5% $**$ : 1%

Table 1.19: CLO equation, final estimates

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_CLO | 0.038 | (0.025) |
| lnx | 0.249** | (0.065) |
| lnx2 | -0.017** | (0.004) |
| m_ALH | -0.014 | (0.020) |
| m_ALO | 0.009 | (0.026) |
| m_FDO | -0.003 | (0.005) |
| m_FDH | 0.000 | (0.001) |
| m_UND | 0.022 | (0.071) |
| m_GAS | 0.001 | (0.004) |
| m_OTH | -0.002* | (0.001) |
| h_ALH | 0.017 | (0.077) |
| h_ALO | -0.059 | (0.092) |
| h_FDO | 0.229 | (0.177) |
| h_FDH | 0.021 | (0.075) |
| h_CLO | -0.067 | (0.053) |
| h_UND | 0.036 | (0.031) |
| h_GAS | 0.007 | (0.008) |
| _IYEAR_1994 | 0.001 | (0.003) |
| _IYEAR_1995 | 0.003 | (0.004) |
| _IYEAR_1996 | 0.002 | (0.005) |
| _IYEAR_1997 | 0.003 | (0.005) |
| _IYEAR_1998 | 0.003 | (0.006) |
| _IYEAR_1999 | 0.002 | (0.006) |
| _IYEAR_2000 | 0.001 | (0.007) |
| _IYEAR_2001 | -0.002 | (0.008) |
| _IYEAR_2002 | -0.003 | (0.009) |
| _IQTR_2 | 0.000 | (0.001) |
| _IQTR_3 | 0.000 | (0.001) |
| _IQTR_4 | 0.000 | (0.001) |

*Continued on next page...*

*... table 1.19 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| POPSIZE | -0.001 | (0.000) |
| _IREGION_2 | 0.000 | (0.001) |
| _IREGION_3 | 0.000 | (0.001) |
| _IREGION_4 | -0.002* | (0.001) |
| _IOCCUP1_2 | -0.003* | (0.001) |
| _IOCCUP1_3 | -0.005** | (0.001) |
| _IOCCUP1_4 | -0.001 | (0.003) |
| _IOCCUP1_5 | -0.003* | (0.001) |
| _IOCCUP1_6 | -0.004** | (0.001) |
| _IOCCUP1_7 | -0.002 | (0.003) |
| _IOCCUP1_8 | -0.002 | (0.001) |
| _IOCCUP1_9 | -0.005** | (0.001) |
| _IOCCUP1_10 | -0.004** | (0.001) |
| SEX_REF | 0.000 | (0.001) |
| AGE_REF | 0.000 | (0.000) |
| YR_EDREF | 0.001** | (0.000) |
| _IMARITAL1_2 | 0.001 | (0.001) |
| _IMARITAL1_3 | 0.000 | (0.001) |
| _IMARITAL1_4 | 0.003 | (0.002) |
| _IMARITAL1_5 | 0.002 | (0.001) |
| _IREF_RACE_2 | 0.005** | (0.001) |
| _IREF_RACE_3 | -0.005$^{\dagger}$ | (0.003) |
| _IREF_RACE_4 | 0.001 | (0.001) |
| PERSLT18 | 0.003** | (0.000) |
| PERSOT64 | -0.002** | (0.001) |
| NFEM | 0.000 | (0.000) |
| CAR | 0.079* | (0.036) |
| JWL | 0.244** | (0.044) |
| HSE | -0.006 | (0.012) |
| CONSTANT | -0.889** | (0.236) |
| Intercept | 0.001 | (0.003) |

Significance levels : $\dagger$ : 10% $*$ : 5% $**$ : 1%

Table 1.20: UND equation, final estimates

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_UND | 0.079 | (0.067) |
| lnx | 0.057** | (0.021) |
| lnx2 | -0.004** | (0.001) |
| m_ALH | -0.003 | (0.012) |
| m_ALO | 0.007 | (0.009) |
| m_FDO | -0.001 | (0.002) |
| m_FDH | -0.001 | (0.001) |
| m_CLO | -0.011 | (0.012) |
| m_GAS | 0.001 | (0.002) |
| m_OTH | 0.000 | (0.000) |
| h_ALH | 0.029 | (0.022) |
| h_ALO | 0.022 | (0.027) |
| h_FDO | 0.016 | (0.052) |
| h_FDH | 0.000 | (0.021) |
| h_CLO | 0.000 | (0.016) |
| h_UND | 0.003 | (0.009) |
| h_GAS | 0.002 | (0.002) |
| _IYEAR_1994 | 0.000 | (0.001) |
| _IYEAR_1995 | 0.001 | (0.001) |

*Continued on next page...*

*... table 1.20 continued*

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| _IYEAR_1996 | 0.001 | (0.001) |
| _IYEAR_1997 | 0.001 | (0.002) |
| _IYEAR_1998 | 0.001 | (0.002) |
| _IYEAR_1999 | 0.001 | (0.002) |
| _IYEAR_2000 | 0.001 | (0.002) |
| _IYEAR_2001 | 0.001 | (0.002) |
| _IYEAR_2002 | 0.001 | (0.002) |
| _IQTR_2 | 0.000 | (0.000) |
| _IQTR_3 | 0.000 | (0.000) |
| _IQTR_4 | 0.000 | (0.000) |
| POPSIZE | 0.000 | (0.000) |
| _IREGION_2 | 0.000 | (0.001) |
| _IREGION_3 | 0.000 | (0.000) |
| _IREGION_4 | 0.000 | (0.000) |
| _IOCCUP1_2 | 0.000 | (0.000) |
| _IOCCUP1_3 | 0.000 | (0.000) |
| _IOCCUP1_4 | $0.002^{\dagger}$ | (0.001) |
| _IOCCUP1_5 | 0.000 | (0.000) |
| _IOCCUP1_6 | 0.000 | (0.000) |
| _IOCCUP1_7 | 0.000 | (0.001) |
| _IOCCUP1_8 | 0.000 | (0.000) |
| _IOCCUP1_9 | 0.000 | (0.000) |
| _IOCCUP1_10 | 0.000 | (0.000) |
| SEX_REF | 0.001** | (0.000) |
| AGE_REF | $0.000^{\dagger}$ | (0.000) |
| YR_EDREF | 0.000 | (0.000) |
| _IMARITAL1_2 | 0.000 | (0.000) |
| _IMARITAL1_3 | -0.001* | (0.000) |
| _IMARITAL1_4 | $-0.001^{\dagger}$ | (0.000) |
| _IMARITAL1_5 | -0.001 | (0.000) |
| _IREF_RACE_2 | 0.001 | (0.000) |
| _IREF_RACE_3 | 0.001 | (0.002) |
| _IREF_RACE_4 | 0.000 | (0.001) |
| PERSLT18 | 0.002** | (0.000) |
| PERSOT64 | 0.000 | (0.000) |
| NFEM | 0.000 | (0.000) |
| CAR | $0.021^{\dagger}$ | (0.011) |
| JWL | 0.032** | (0.012) |
| HSE | 0.003 | (0.004) |
| CONSTANT | -0.204** | (0.078) |
| Intercept | 0.000 | (0.000) |

Significance levels : $\dagger$ : 10% $*$ : 5% $**$ : 1%

Table 1.21: GAS equation, final estimates

| Variable | Coefficient | (Std. Err.) |
|---|---|---|
| m_GAS | -0.082* | (0.034) |
| lnx | -0.610** | (0.187) |
| lnx2 | 0.044** | (0.013) |
| m_ALH | 0.072 | (0.054) |
| m_ALO | $-0.125^{\dagger}$ | (0.065) |
| m_FDO | -0.006 | (0.013) |
| m_FDH | 0.011* | (0.005) |
| m_CLO | -0.003 | (0.025) |
| m_UND | 0.049 | (0.096) |

*Continued on next page...*

*... table 1.21 continued*

| **Variable** | **Coefficient** | **(Std. Err.)** |
|---|---|---|
| m_OTH | 0.005$^{\dagger}$ | (0.003) |
| h_ALH | -0.112 | (0.158) |
| h_ALO | 0.146 | (0.196) |
| h_FDO | -0.150 | (0.369) |
| h_FDH | -0.024 | (0.158) |
| h_CLO | 0.167 | (0.114) |
| h_UND | -0.029 | (0.066) |
| h_GAS | 0.013 | (0.017) |
| _IYEAR_1994 | -0.002 | (0.006) |
| _IYEAR_1995 | -0.001 | (0.009) |
| _IYEAR_1996 | -0.001 | (0.011) |
| _IYEAR_1997 | 0.003 | (0.011) |
| _IYEAR_1998 | 0.003 | (0.012) |
| _IYEAR_1999 | 0.002 | (0.013) |
| _IYEAR_2000 | 0.007 | (0.014) |
| _IYEAR_2001 | 0.012 | (0.017) |
| _IYEAR_2002 | 0.010 | (0.018) |
| _IQTR_2 | -0.006* | (0.003) |
| _IQTR_3 | -0.004$^{\dagger}$ | (0.002) |
| _IQTR_4 | -0.005$^{\dagger}$ | (0.003) |
| POPSIZE | 0.005** | (0.001) |
| _IREGION_2 | 0.005$^{\dagger}$ | (0.003) |
| _IREGION_3 | 0.005* | (0.002) |
| _IREGION_4 | 0.008** | (0.003) |
| _IOCCUP1_2 | 0.012** | (0.002) |
| _IOCCUP1_3 | 0.012** | (0.002) |
| _IOCCUP1_4 | 0.005 | (0.007) |
| _IOCCUP1_5 | 0.015** | (0.003) |
| _IOCCUP1_6 | 0.020** | (0.003) |
| _IOCCUP1_7 | -0.001 | (0.007) |
| _IOCCUP1_8 | 0.012** | (0.003) |
| _IOCCUP1_9 | -0.002 | (0.002) |
| _IOCCUP1_10 | 0.002 | (0.002) |
| SEX_REF | -0.001 | (0.001) |
| AGE_REF | -0.001** | (0.000) |
| YR_EDREF | -0.002** | (0.000) |
| _IMARITAL1_2 | -0.005 | (0.003) |
| _IMARITAL1_3 | 0.007** | (0.002) |
| _IMARITAL1_4 | 0.000 | (0.004) |
| _IMARITAL1_5 | 0.000 | (0.002) |
| _IREF_RACE_2 | -0.003 | (0.002) |
| _IREF_RACE_3 | 0.017* | (0.007) |
| _IREF_RACE_4 | 0.000 | (0.003) |
| PERSLT18 | -0.006** | (0.001) |
| PERSOT64 | -0.001 | (0.002) |
| NFEM | -0.001 | (0.001) |
| CAR | -0.484** | (0.105) |
| JWL | -0.492** | (0.118) |
| HSE | -0.233** | (0.034) |
| CONSTANT | 2.246** | (0.681) |
| Intercept | -0.001 | (0.002) |

Significance levels : $\dagger$ : 10% $*$ : 5% $**$ : 1%

## OMD estimates of prices' parameters

| | ALH | ALO | FDO | FDH | CLO | UND | GAS |
|---|---|---|---|---|---|---|---|
| ALH | -0.043 | | | | | | |
| | (0.03) | | | | | | |
| ALO | -0.048 | $-0.092^{*}$ | | | | | |
| | (0.031) | (0.79) | | | | | |
| FDO | 0.069 | 0.042 | -0.195 | | | | |
| | (0.064) | (0.074) | (0.260) | | | | |
| FDH | 0.005 | $0.080^{*}$ | -0.007 | 0.232 | | | |
| | (0.033) | (0.032) | (0.120) | (0.188) | | | |
| CLO | -0.003 | 0.012 | -0.062 | -0.032 | -0.031 | | |
| | (0.019) | (0.020) | (0.120) | (0.050) | (0.031) | | |
| UND | 0.002 | 0.018 | -0.004 | -0.015 | 0.007 | -0.001 | |
| | (0.011) | (0.012) | (0.032) | (0.020) | (0.013) | (0.008) | |
| GAS | 0.001 | $0.008^{*}$ | -0.001 | -0.001 | -0.005 | 0.000 | 0.013 |
| | (0.003) | (0.003) | (0.014) | (0.015) | (0.005) | (0.002) | (0.009) |

std errors in parenthesis. ** 5% significance level

# Chapter 2

# Does Social Capital reduce moral hazard? A network model for non–life insurance demand

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The present chapter shows the results achieved and the discussions jointly had by my coauthor and me, but the final form as a chapter is due to me alone for the purpose of this thesis. This means that I am the only responsible for every linguistic or mathematical error and imprecision.

## abstract

We study the effect of moral hazard involved in non market contracts on the demand for marketed contracts. We extend the Arnott and Stiglitz model on the coexistence of market and non–market insurance to allow for the presence of Social Capital as a determinant of the severity of moral hazard in informal contracts. We provide a rigorous definition of Social Network and Social Capital by means of an equilibrium concept typical of the Network literature. Such a formal approach gives us a clear guidance for measuring Social Capital and validate the model on empirical data. The model is estimated on a panel dataset, supporting our claim that Social Capital increases the demand for non–life insurance. We test for the presence of spatial correlation, and

conclude that the the spatial structure of demand for non–life insurance contracts is determined by the spatial distribution of Social Capital.

## 2.1 Introduction

Social Capital is a concept not limited to sociology: during the last 20 years it spread out and has been used across almost all social sciences. Despite such a great interest and huge amount of research on it, it's still a suggestive word that reminds of many different but related research fields, rather than a precise concept. Further on, the study of social capital has a lot to do with Italy: the seminal book by citePutnam:93 about democracy and institutions' efficiency across Italy is a source of overwhelming empirical evidence on the relevance of social capital in Italian social life. Focusing on economics, recently Guiso et al. (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 results on this relation.

Our question is whether it matters also on individual choices about insurance expenditure. In particular, we are interested in demand for non–life insurance contracts. While life insurance can be assimilated to pension funds and other financial assets in terms of economic rationale - it's an investment which gives a return - for non–life insurance things are different. Households buy a non–life insurance contract to avoid the risk of suffering losses in some future state of the world: they pay a fixed price (the premium) to transfer money from a future uncertain state of the world to a certain one. Arnott and Stiglitz (1991) set up a model where together with market insurance, individuals can enter in non–market mutual insurance contracts. In their model the role played by non market insurance is related to peer monitoring: if informational asymmetry between the insurer and the customer still holds in non–market contracts, they are dysfunctional and non–market insurance displaces market contracts reducing social welfare. Vice versa, if individuals can observe other individuals' effort, non–market contracts are welfare enhancing since they provide extra insurance coverage at the market price set by the insurance company. What they call peer monitoring is actually the severity of moral hazard in non–market agreements. We will investigate the relation between moral hazard involved in non market insurance contracts and demand for market insurance. We will also formally link moral hazard and social capital, concluding that social capital itself increases the aggregate demand for insurance. A careful definition of Social Capital and its role in the model allows us to test our conclusions empirically.

Previous studies on Italy leave space for such a model. Millo and Lenzi (2005) found that the Italian insurance market exhibits spatial heterogeneity and spatial correlation at the province level even after controlling for a number of demographics. If heterogeneity in the diffusion of insurance contracts is due to differences in the degree of Social Capital, it is reasonable to think that its diffusion does not follow administrative province boundaries: therefore, our explanation is coherent with the presence of spatial correlation at the province level. The social capital interpretation is suggestive also for another reason: Durlauf and Fafchamps (2004) point 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 (mainly catholic) 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 elder people assistance or scholarships are some examples.

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 yet in the literature because of computational difficulties. Based on the comprehensive treatment of Elhorst (2001), 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 second section describes the economic model. The following one extends it to provide a formal definition of Social Capital and to include it as a determinant of the demand for market insurance. Such an extension will be done within a Network approach. Before going to empirical validation of our model we describe the dataset. The fifth section is dedicated to the definition of an empirical measure for Social Capital. The sixth part describes the estimation procedure and results. In the seventh section we carry on the analysis of the spatial structure of the model. Conclusions are drawn in the final section.

## 2.2 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 effect of moral hazard and therefore - as we will see in the next section - of Social Capital on the demand for market insurance.

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 $w$, the damage caused by the accident $d$. Individuals pay a premium $\beta$ and receive a net payout $\alpha$ in case the accident occurs. Utility has the following form:

$$\begin{aligned} EU^M &= (1-p(e))U(w-\beta) + p(e)U(w-d+\alpha) - e \\ &= (1-p(e))u_0 + p(e)u_1 - e \end{aligned} \tag{2.1}$$

$EU^M$ is well behaved (increasing and strictly concave) and separable, meaning in both the 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 the clients to augment their effort at accident avoidance, i.e. $d-\alpha > \beta$, meaning that the ordering of states of the world in terms of utility is not altered: the wealth reduction in the "good" state of the world, $\beta$, must be lower than the wealth reduction in the "bad" state, $d-\alpha$. This equilibrium is stable only if clients purchase no additional insurance. Such a condition must be enforceable by the insurer. This exclusivity condition is not far from what happens in the real world: insurance companies cannot force their clients to buy just one contract, but they ask them to reveal which other contracts they have covering the same risk, and in 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 one of them has an accident and the other doesn't, the latter will transfer $\delta$ to the former. Each of them realizes that the extra insurance will pay out if they have an accident and their partner doesn't, therefore their expected utility changes:

$$\begin{aligned} EU_i^{NMO} &= (1-p(e_i))(1-p(e_j))U(w-\beta) + p(e_i)p(e_j)U(w-d+\alpha) \\ &\quad + (1-p(e_i))p(e_j)U(w-\beta-\delta) \\ &\quad + p(e_i)(1-p(e_j))U(w-d+\alpha+\delta) \\ &\quad - e_i \\ &= (1-p(e_i))(1-p(e_j))u_0 + p(e_i)p(e_j)u_1 \\ &\quad + (1-p(e_i))p(e_j)u_2 + p(e_i)(1-p(e_j))u_3 - e_i \end{aligned} \tag{2.2}$$

Individuals maximize their utility considering $\alpha$ and $\beta$ and therefore the contract's price $q = q(\alpha, \beta)$ as fixed: they perceive that if they enter a mutual contract they can buy extra insurance at the market price $q$. They choose $\delta$, which is the premium but also the payoff of the non–market agreement. Further on each of them considers her partner as rational and assumes she will choose the level of effort which maximizes her own utility.

If each individual does not observe the others' effort, the exclusivity provision cannot be enforced: each client pays an extra premium $\delta$ if the partner has an accident and he doesn't, while he receives an extra payoff $\delta$ in the opposite case. It is optimal for them to reduce the effort while the insurance company is still offering the same contract. This is a partial equilibrium result since it doesn't consider the reaction of insurance companies to agents' behavior. 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. Individual's expected utility, $EU^{NMU}$, is lower than without non–market insurance.

Vice versa, the authors show that if individuals can observe perfectly each other's effort, it is optimal for them to provide non market insurance up to full coverage to augment the risk sharing opportunity. Individuals choose $\delta$ 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: as in the previous case, $e_i = e_j \Rightarrow p(e_i) = p(e_j)$. Then, (2.2) simplifies to

$$EU^{NMO} = (1-p)^2 u_0 + p^2 u_1 + p(1-p)(u_2 + u_3) - e \tag{2.3}$$

The utility maximizing non–market agreement is $\delta^* = (d - \alpha - \beta)/2$, which brings coverage up to full insurance. Furthermore, substituting $u_2$ and $u_3$ in (2.3) and taking the derivative it can be proved that expected utility is increasing in $\delta$ between 0 and the utility–maximizing $\delta^*$.

Up to now we poited out that the presence of non–market agreements with perfect peer monitoring unanbigously reduces risk, since it augments the coverage available to individuals. Without peer monitoring this risk reduction induces individuals to reduce effort, thus displacing the insurance company, which is not able anymore to enforce a positive level of effort. The effort reducing effect of the extra coverage is present even with perfect peer monitoring, but it is contrasted by the absence of moral hazard: therefore a positive value of $\delta$ implies a positive level of $e$. Furthermore, from first order conditions, it is relatively easy to prove that the effort is not only positive but also increasing in $\delta$ between 0 and the optimal level $\delta^*$ as long as $p(e) < \frac{1}{2}$[1]. This is due to the fact that as $\delta$ 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** *Given the contract offered by the insurance company $q = q(\alpha, \beta)$, if $p < \frac{1}{2}$ at equilibrium (i.e. if $\delta = (d - \alpha - \beta)/2$), the effort–increasing effect of peer monitoring is higher than the effort–reducing effect of extra coverage.*

The insurance company won't be displaced: it maximizes its expected utility with respect to $\beta$ and $\alpha$ under the zero profit condition $\alpha = \frac{1-p}{p}\beta$ and assuming that individuals maximize their own utility (i.e., $e = e^*$ and $\delta = \delta^* = (d - \alpha - \beta)/2$).

We can now prove that non–market agreements are welfare enhancing, i.e. $EU^M < EU^{NMO}$. From (2.1) and (2.3),

$$\begin{aligned}(1-p)u_0 + pu_1 - e &< (1-p)^2 u_0 + p^2 u_1 + p(1-p)(u_2 + u_3) - e \\ u_0 + u_1 &< u_2 + u_3 \\ u_0 - u_2 &< u_3 - u_1 \\ u(w-\beta) - u(w-\beta-\delta) &< u(w-d+\alpha+\delta) - u(w-d+\alpha)\end{aligned} \tag{2.4}$$

The inequality holds since utility is strictly concave and $\beta < d - \alpha$ due to moral hazard between the market insurer and clients. Such a result holds also once heterogeneity among individuals is introduced. Insurers offer different contracts based on observed characteristics of individuals such as age or marital status and on past statistics as loss ratios in a particular region[2]. What they are not able to do, due to information asymmetry, is to offer different contracts based on individual effort. The result by Arnott and Stiglitz tells us is that if the probability of accident occurrence is small, for any contract offered $\alpha, \beta$ and for any positive level of non–market coverage $\delta$ up to $\delta^*$, individual expected utility is higher than without non market agreements:

$$E_j^{NMO}[U|\boldsymbol{X}_j] > E_j^M[U|\boldsymbol{X}_j] \tag{2.5}$$

where $\boldsymbol{X}_j$ is a vector of observable individual characteristics, $EU^{NMO}$ is expected utility with non market contracts and perfect peer monitoring, $EU^M$ is expected utility with only market insurance.

[1]Such a condition is reasonable: individuals want to insure against events with high losses $d$ but small probability $p$

[2]the loss ratio for a type of accident is the ratio between claims paid and premium income.

Up to now we briefly outlined the main results of Arnott and Stiglitz (1991). We need a further step: while the authors were interested in the welfare effects of non–market agreements, we want to investigate how the demand for insurance changes if non market agreements are available. While a thorough investigation of properties of the demand function given a general utility is beyond the scope of the paper, we can 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 reasonable and usual assumption in the applied literature on insurance.

First of all, we can assume that insurance firms discriminate on the basis of all observable characteristics of agents and thus conditional on a set of demographics $\boldsymbol{X}$ potential client differ only by their effort. Thus, the following results can be thought of as valid for an homogeneous population or, given a population in which individuals differ along the dimension of $\boldsymbol{X}$ and of effort, the same results are all conditional on $\boldsymbol{X}$. Then for the remaining of the section we assume without loss of generality that individuals are all identical.

Drowing from the analytical treatment of moral hazard models in Arnott and Stiglitz (1988), it can be proved that:

**Proposition 2** *If expected utility function is separable, i.e. it falls in the class*

$$EU = (1 - p(e))U(w) + p(e)U(w - d) - e$$

*and if disutility of effort is event independent, the effort is measured by the disutility it causes, utility of consumption $U(\cdot)$ is event independent and*

$$\lim_{e \downarrow 0} \frac{(\partial p/\partial e)^3}{\partial^2 p/\partial e \partial e} > -\infty$$

*then demand for insurance decrease with the price of insurance and increase with effort.*

From the differentiation of the first–order conditions of the individual's effort choice problem the proposition can be proved to hold but for discontinuity points in the price–consumption line, which is the locus of utility maximizing linear contracts, i.e. contracts in which $q = \frac{\beta}{\alpha}$.

A sufficient condition for this line to be everywhere continuous is convexity of indifference curves. The last assumption of the proposition fullfil this requirement: the limit condition implies that $p$ is not too responsive to the effort $e$ (i.e., $p'$ is low) and the curvature is high enough (i.e. $p''$ is high) at any point $(\alpha, \beta)$. An example of such a $p(e)$ is $p(e) = \bar{p} - e^{\gamma}$, where $\gamma > \frac{1}{2}$: if individual put no effort on accident avoidance $p(e) = \bar{p}$, then the probability of suffering a wealth loss $d$ is decreasing with a power function of the effort.

Thus we restricted the utility function of individuals. The next step is to set conditions on strategies available to the other players, i.e. the insurance companies. First, we restrict contracts offered to be linear, i.e. $q = \frac{\beta}{\alpha}$. Market insurance contracts are exclusive, meaning that agents can sign just one contract with one insurance firm to cover a given risk. Further more, insurance market is competitive and companies set the price in order to make zero profit. Therefore at equilibrium

$$q = \frac{\beta}{\alpha} = \frac{p(e)}{1 - p(e)}$$

Separability, convexity of indifference curves, linear pricing and zero profit characterize equilibria. 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. Thus, for the sake of simplicity we concentrate on internal solutions, i.e. on equilibria characterized by positive insurance $(\beta > 0, \alpha > 0)$ and zero profits.

Proposition 2 states that insurance demand depends on effort $e$ and insurance price $q$, which are the choice variables respectively of agents and firms. If non–market agreements are not available, agents choose $e = \tilde{e}$ to maximize their expected utility considering $\tilde{q}$ as given. On the other hand firms internalize 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 which do not involve moral hazard, equilibrium effort and price changes. Agents consider the price offered $q^*$ as given, but they can choose not only $e$, but also the extra coverage characterizing the informal agreement $\delta$. We just saw that at equilibrium agents will agree upon $\delta^* = (d - \alpha^* - \beta^*)/2$ such that they reach full insurance. Arnott and Stiglitz result reported in proposition 1 states that if $p < \frac{1}{2}$ the equilibrium effort $e^*$ is higher than the effort agents would have put without non market agreements, given $q^*$. As without non market agreements, insurance firms anticipate agents' choices $e^*, \delta^*$ in order to set the price $q^*$.

Therefore, we can conclude that:

**Proposition 3** *Given $\alpha > 0, \beta > 0$, if there exists an equilibrium without non market agreements $E_0$ and one with non market agreements and no moral hazard involved in those agreements $E_1$; if $p < \frac{1}{2}$; if the insurance company can offer only linear contracts and if assumptions of proposition 2 hold, then demand for market insurance in $E_1$ is higher than in $E_0$*

The proof is straightforward: if $E_0$ and $E_1$ exist and $p < \frac{1}{2}$ holds than proposition 1 holds and the effort level $e$ in $E_1$ is higher than in $E_0$[3]. Since price is linear $q = \frac{\beta}{\alpha}$ is fixed. Then, since assumptions of proposition 2 hold, $q$ is fixed and $e$ is higher in $E_1$, market insurance demand is higher when informal contracts (without moral hazard involved in them) are available.

Proposition 3 deliver us an empirical implication about insurance demand only if the insurance company do not observe informal agreements, or if anyway it doesn't internalize it when setting the price $q$. If this is not the case $E_0$ and $E_1$ cannot exist at the same time: being $E_0$ the starting equilibrium, once informal insurance become available, the insurance firm would change $q$ in order to account for $\delta$.

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 the level of effort to put on it but they must respect the contract. In other words, we assume that $i$ will transfer $\delta^*$ to $j$ everytime $j$ has an accident and $i$ doesn't, without deviations. Given the informal nature of the agreement this assumption may not be innocuous. A possible extention to relax it could be to consider $\delta$, the transfer on which $i$ and $j$ agree upon, as uncertain, and rewrite the model in terms of expected $\delta$. Our claim is that such an extension would complicate the expression of expected utility and the algebra stemming from it, while the main implications of the model would not change.

There is still something to do in order to achieve a testable implication: we would like to discriminate peers of individuals endowed with non–market agreements and to measure the severity of moral hazard within those communities. Moral hazard depend on peer monitoring, i.e. on reciprocal observability of the effort but also on the duration of the partnership, the level of trust between individuals entering the agreement, the severity of punishment when deviating from an agreement, the power of reputation and social pressure: in one word, the severity of moral hazard depends on the stock of social capital a community is endowed with.

## 2.3 A network–based definition of Social Capital

As already pointed out in the introduction, there isn't a clear–cut definition of Social Capital. It is an elusive concept that declines into particular mean-

[3]Note that we have to assume existence of those equilibria since linear pricing lead always to an equilibrium, but it could involve $\alpha = 0$ or $\beta = 0$.

ings depending on the context where it is used. Social Capital is a suggestive idea, but in order to have a testable model we need to formalize this concept. Durlauf and Fafchamps (2004) point out as a common feature of many definitions of Social Capital 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 that enter a non market insurance agreement with a given $\delta$ can choose in each period whether to put an effort $e_{NMU}$, which is the one with moral hazard in the Arnott Stiglitz framework, or $e^{NMO}$, effort without moral hazard. If expected utility is decreasing in the effort, such a game is a Repeated Prisoner's dilemma. From (2.2),

$$\begin{aligned}\frac{\partial EU^i}{\partial e_i} &= \big[-(1-p(e_j))u_0 + p(e_j)u_1 \\ &\quad - p(e_j)u_2 + (1-p(e_j))u_3\big]p'(e_i) - 1 \\ &= \left[(u_3-u_0)(1-p(e_j) + (u_1-u_2)p(e_j)\right] p'(e_i) - 1\end{aligned} \tag{2.6}$$

which is decreasing in $e_i$ if $\beta + \delta < d - \alpha - \delta$, i.e. the total cost of insurance, $\beta + \delta$ must be lower than the loss suffered when the accident occurs. If this condition holds (together with $p(e) < \frac{1}{2}$), the game rewritten in strategic form with expected utilities as payoffs is of the Prisoner's dilemma type (see figure 1). Since marginal utility is decreasing in the (own) effort, for individual $i$ we can write

$$EU_{ij}^H = EU(e_i = e_{NMU}, e_j = e^{NMO}) > EU_{ij}^{NMO}$$

$$EU_{ij}^L = EU(e_i = e^{NMO}, e_j = e_{NMU}) < EU_{ij}^{NMU}$$

| | | Player $j$: $e^{NMO}$ | Player $j$: $e_{NMU}$ |
|---|---|---|---|
| Player $i$ | $e^{NMO}$ | $EU_{ij}^{NMO}, EU_{ji}^{NMO}$ | $EU_{ij}^L, EU_{ji}^H$ |
| | $e_{NMU}$ | $EU_{ij}^H, EU_{ji}^L$ | $EU_{ij}^{NMU}, EU_{ji}^{NMU}$ |

Figure 2.1: the non–market insurance game in strategic form

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 $N = \{1, 2, \dots, n\}$ where each pair of interacting agents $i, j$ is involved in an infinite repetition of the described game. Players' connecting decision is captured by a directed graph $\vec{g} \subset N \times N$, where each directed link $(i, j) \in \vec{g}$ is player $i$ decision to connect with player $j$. Suppose now that every linking decision lead 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*

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

*and for any player $i$ the set of her neighbors 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 information spread around the network only gradually. To be specific, at each round before playing $i, j$ share information about their behavior with their neighbors, i.e. whether they deviated from the cooperative strategy. To sustain a cooperative equilibrium it's also necessary that each agent adopts a strategy that punish defiance: $i$ force herself to play a trigger strategy, i.e. she will switch to defection with $j$ as soon as she knows $j$ deviated with some of her neighbors. More formally, for any agent $i$ the strategy $s^g = (s_1^g, \ldots, s_n^g)$ is of the following type:

1. first, player $i$ chooses whether to start her interaction with $j$ putting effort $e^{NMO}$ (which is to cooperate) or to put effort $e_{NMU}$;

2. in the following rounds, she reacts immediately to the news $j$ did not start with $e^{NMO}$ with some $k \in N_j$ switching irreversibly to $e_{NMU}$ in her game with $j$.

In order to give a definition of an equilibrium, some additional notation is needed: $\pi_i(s^g)$ is the overall payoff 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 starts 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, the two players have incentives to sustain the cooperative equilibrium, i.e.*

$$\forall (i, j) \in g \quad \pi_i(s_C^g) \geq \pi_i(s_D^g)$$

The connection of this definition with the Social Capital literature is clear once the PSN is characterized in terms of cohesiveness. Let define

**Definition 3 (i–excluding distance)** *$d^i(j,k)$, the i–excluding distance between $j$ and $k$ is the shortest path joining $j$ and $k$ which 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 $i$.*

Then

**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 $\nu_{ik} = EU_{ik}^{NMO} - EU_{ik}^{L}$ Then, $g$ is a PSN if and only if for all $(i,j) \in g$*

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

Proof of proposition 1 is in the appendix and follows the one in Vega–Redondo (2006). 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 neighborhood $N_i$;
- Stability is more likely in *cohesive* networks, i.e. in networks with small excluding distances $d^i(j,k)$.

It is also clear that, since payoffs are uncertain, the level of volatility in the model is inversely related with stability. Given this formalization,

**Definition 4 (Social Capital)** *The stock of Social Capital of the network $g$ is the* density[4] *of $g$.*

Going back to the first part of the model, we showed that demand for market insurance is affected by non–market insurance agreement if they do not involve moral hazard. In a pairwise stable network agents have no incentives to reduce the effort, i.e. moral hazard is inversely related to network stability. Therefore, from definition 4 the empirical implication of the model is that demand for market insurance depend on Social Capital. Further on, as Vega–Redondo pointed out cohesiveness is network counterpart of Coleman's concept of closure of a Social Network. We have a second empirical implication: demand for market insurance is related to network closure.

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

## 2.4 Demographics and insurance data

In order to identify 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 it 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; urbanization has also been suggested for this purpose (Browne et al. (2000)). Loss ratios[5] have also been suggested as a proxy for the probability of loss. 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 (see Browne and Kim (1993), Grace and Skipper (1991) and the discussion in Browne et al. (2000)).

### 2.4.1 Controlling for supply side variables

We stated in section 2 that an insurance company has a 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 can't 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 a non–trivial problem: as Schlesinger (in Dionne (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 usually only observe 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 at all, is therefore far from being obvious. We cannot observe the amounts insured, therefore inclusion of medium premium rates, which would probably be best, is ruled out. We resort therefore to the loss ratio, as e.g. in Esho et al. (2001), observing that the role of this

[5] Loss ratios are defined as the ratio of claims incurred to premiums earned.

index as a proxy for market riskiness could lead to some ambiguity. Due to unavailability of data on losses for the non-life market as a whole, we include the aggregate loss ratio for the property sector only (Fire, Motor non-TPL, Other material loss).

Lastly, given the importance of tied agents in the distribution of insurance products (this channel did account in 2000 for 88.3 of non-life premium volume)[6], the number of agencies per capita has been included as a supply-side driver, inversely related to the opportunity-cost of searching for insurance covers.

Our dataset consists mainly of an excerpt for the years 1998-2000 from the Geo-Starter database provided by Istituto Tagliacarne, an institution inside SiStaN (the Italian national statistical system). It provides both first-hand data and an organized collection of data from various institutional sources. Data on insurance premiums, in particular, are collected on a provincial basis by ISVAP, the Italian insurance Authority, divided into three categories: life, compulsory third party liability, the vast majority of which regarding 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.

### 2.4.2 Measuring insurance consumption

As noted above, we are only able to observe the equilibrium value of insurance consumption, and neither the quantity nor the price of insurance. Furthermore, measuring insurance consumption across administrative regions of different economic and demographic "size" requires resorting to some kind of relativization. Two common normalized measures are used in the literature as well as among practitioners: insurance penetration, defined as the ratio of insurance premiums on GDP, measures the importance of the insurance sector with respect to the total economy; insurance density, defined as premiums per capita, measures average per capita expenditure. We focus henceforth on premiums per capita. In the same fashion, all variables subject to a size bias in the information set have been normalized with respect to the relevant benchmark.

### 2.4.3 Locational issues

Premium data are registered according to the location of sales point as communicated by the companies. Besides the inevitable aggregation bias due

[6]Including motor TPL.

to the arbitrarinesses of administrative boundaries with respect to the geographic dimension of economic phenomena (see Anselin (1988)), some important additional biases may arise if the location of sales point is different from the actual location of the insured.

First, mostly for big contracts negotiated by brokers but also for some distribution agreements, e.g., in bancassurance, some big units, usually located in an important industrial or financial center, are accountable for all business nationwide. This happens, for example, for marine insurance premiums collected by business units located in the main harbours for customers located and doing business elsewhere, or for some nationwide salesmen network whose business goes through a single agency, typically located at the company headquarters.

Second, collective policies purchased by the firms as a 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.

### 2.4.4 Administrative boundaries in Italy

In the following, we refer to the Italian administrative units called *province*, corresponding to level 3 in the NUTS (Nomenclature of Territorial Units for Statistics) classification by Eurostat, using the generic name of regions, and to the classification used by Istat, the Italian statistical office, when speaking of macro-regions. Macro-regions divide the 20 NUTS2 Italian regions (*regioni*) into 5 aggregates: North-West, North-East, Centre, South and Islands.

## 2.5 How to measure Social Capital?

In the third section 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 sociological concept.

Our definition suggests a somewhat natural way to measure Social Capital effect: as we stated in the previous section, what matters is social capital endowment and closure of Social Networks. Since we have province level data, we want to measure the density and cohesiveness of social networks characterizing each province. We are not the first to try to measure closure with this kind of data: Goldin and Katz (1998) based their empirical measure of Social Capital intensity directly on Coleman's definition of closure. They have a dataset on schooling and some economic variables on Iowa, USA in 1915. The detail is at county level, comparable to Italian provinces. Their measure was the proportion of 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.

As they did, we want to measure closure of social networks with the dimension and isolation of communities. Goldin and Katz's measure can be replicated for our data, but it's not sufficient to identify isolated communities: in 1915 Iowa the overall population density was very low, therefore living in a small village meant at the same time living kilometers far away from other towns. Nowadays Italy on the contrary is characterized by a very high population density. This means that living in a small town doesn't necessarily mean living in an isolated place. An example is the Po valley in northern Italy: towns can be really small, below 1000 inhabitants, but they often happen to be one beside another with no free land in the middle. This means that the percentage of population living in small towns alone does not necessarily identify isolated communities. Therefore, our claim is that the degree of closure of social networks characterizing an Italian province is identified by the percentage of population living in towns with less than 1000 citizens (pupop1000), but also by other three variables. The first two are the fraction of province's hill territory (percsup.c) and the fraction of mountainous territory (percsup.m), which should control for 'Po valley' effect. The third variable controls for a different potential source of cohesiveness: a province where people are mainly involved in agriculture could be expected to be a closed community (in the Coleman sense), either for cultural reasons or for common working interests. Such an effect is captured by the fraction of territory devoted to agriculture (percsup.agr), which in this context seems more meaningful and coherent with our definition of social capital than the pure Goldin and Katz measure. Those variables seems to be informative, i.e. they do not simply follow a North–South gradient:

| pupop1000 | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| North West | 0.3158 | 0.5512 | 0.7080 | 0.6492 | 0.7805 | 0.8443 |
| North East | 0 | 0.1183 | 0.4085 | 1.6490 | 2.0880 | 13.780 |
| Centre | 0 | 0.4006 | 0.7385 | 1.6300 | 1.6120 | 14.430 |
| South | 0 | 0 | 1.936 | 2.901 | 2.612 | 20.520 |
| Islands | 0 | 0 | 0.2445 | 2.0190 | 1.9270 | 12.670 |

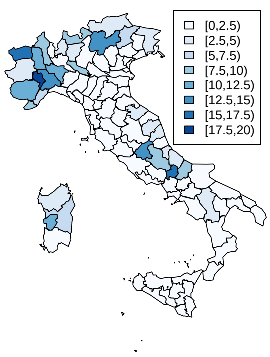
| percsup.m | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| North West | 0 | 9.078 | 44.960 | 43.180 | 64.310 | 100 |
| North East | 0 | 0 | 24.540 | 29.170 | 40.200 | 100 |
| Centre | 0 | 7.080 | 31.680 | 31.020 | 42.480 | 85.320 |
| South | 0 | 3.990 | 29.730 | 32.120 | 54.200 | 100 |
| Islands | 0 | 0 | 11.100 | 16.860 | 30.680 | 66.300 |

| percsup.c | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| North West | 0 | 6.503 | 18.700 | 25.240 | 38.250 | 97.290 |
| North East | 0 | 0 | 20.380 | 23.120 | 35.910 | 100 |
| Centre | 0 | 47.310 | 65.500 | 60.580 | 74.140 | 100 |
| South | 0 | 32.100 | 52.950 | 47.590 | 60.980 | 80.910 |
| Islands | 33.700 | 53.520 | 65.200 | 64.610 | 73.880 | 86.970 |

| percsup.agr | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| North West | 0.0684 | 0.1911 | 0.3766 | 0.4254 | 0.6884 | 0.9101 |
| North East | 0.1173 | 0.4370 | 0.6626 | 0.5735 | 0.7328 | 0.8843 |
| Centre | 0.1717 | 0.4133 | 0.5166 | 0.5035 | 0.6147 | 0.7603 |
| South | 0.2202 | 0.5632 | 0.6638 | 0.6372 | 0.7545 | 0.9197 |
| Islands | 0.3158 | 0.5512 | 0.7080 | 0.6492 | 0.7805 | 0.8443 |

Figure 2.2: geographical distribution of pupop1000 and agricultural land

pupop1000




percsup.agr

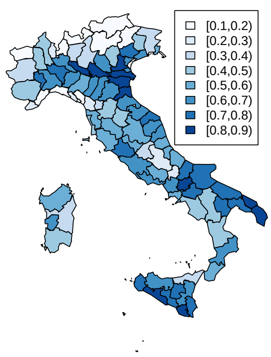
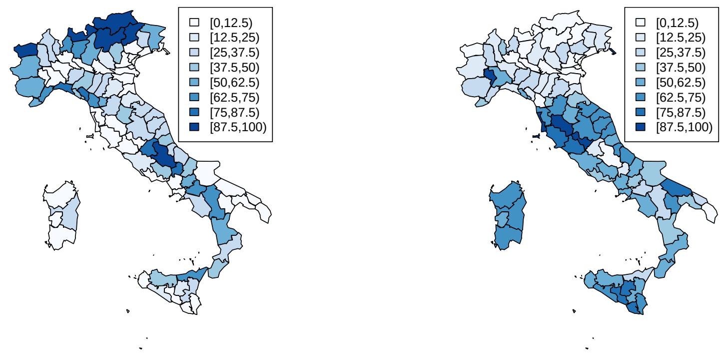


Figure 2.3: geographical distribution of mountainous and hill territory

percsup.m percsup.c




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 quite probably on geographic proximity.

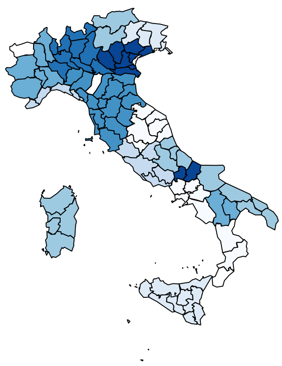
Moral hazard may well depend also on global interaction effects. To be specific, it may depend on a trust feeling towards others by individual not necessarely induce by direct linking, but based on general experience, prejudice, culture and so on. If global interactions have a role in explaining moral hazard and therefore insurance demand, a measure of them must be included among the regressors in order to have an unbiased estimate of local social interaction effects, since global and local interactions are likely to be correlated. To measure global interaction, we follow Guiso et al. (2004) using an index derived from a question in the "World Value Survey", run in Italy in 1999. The question asked was

> “Using the responses of 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 them, nor distrust, (2) Do not trust them very much, (1) Do not trust them at all”

The answers to the "World Value Survey" are published aggregated at regional level. This could generate a potential collinearity problem with the macro–areas dummies, nevertheless Trust index values don’t seem to follow exactly a north–south gradient:

| trust | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---|---|---|---|---|---|---|
| North West | 3.172 | 3.313 | 3.313 | 3.316 | 3.371 | 3.371 |
| North East | 3.132 | 3.22 | 3.352 | 3.302 | 3.386 | 3.398 |
| Centre | 3.068 | 3.11 | 3.185 | 3.239 | 3.351 | 3.351 |
| South | 3.029 | 3.091 | 3.244 | 3.201 | 3.247 | 3.625 |
| Islands | 3.172 | 3.172 | 3.172 | 3.191 | 3.236 | 3.236 |

Figure 2.4: geographical distribution of Trust



## 2.6 Model estimation and results

Our dataset is a balanced panel: we have 103 observations (one for each province) observed over three years, from 1998 to 2000. A pooled OLS is likely to be inefficient, since the IID hypothesis on the error terms is usually inappropriate in panel data settings. Once the longitudinal dimension of the dataset 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 a province's territory, which is clearly invariant. Even excluding these regressors, many other variables have a low variability across years and within each province[7], which would reduce the efficiency of a FE estimator.

### 2.6.1 The panel model

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

$$y_{it} = \boldsymbol{X}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it} \quad i = 1, \ldots, 103;\ t = 0, \ldots, 2 \tag{2.7}$$

where $\boldsymbol{X}$, $\nu_i$ and $\epsilon_{it}$ are independent of each other and both uncorrelated with the explanatory variables. $y_{it}$ is the log of non–life insurance premiums per capita in province $i$ in year $1998 + t$.

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

$$\begin{array}{rcll} \mathrm{Var}(\xi_{it}) & = & \sigma_\nu^2 + \sigma_\epsilon^2 & \\ \mathrm{Cov}(\xi_{it}, \xi_{is}) & = & \sigma_\nu^2 & \forall t \neq s \\ \mathrm{Cov}(\xi_{it}, \xi_{js}) & = & 0 & \forall t \neq s, i \neq j \end{array}$$

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

$$\begin{array}{c} H_0 : \sigma_\nu^2 = 0 \\ H_1 : \sigma_\nu^2 > 0 \end{array}$$

Assuming normality of the errors, a parsimonious testing strategy can be based on the Lagrange Multiplier principle: the OLS model is estimated and then maintained, while it is compared to 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 together with some refinements. We run the King and Wu modification, which is distributed as a standard normal[8]. The result of the test is 0.8895, with p–value equal to 0.1869, thus not providing any evidence in favor of the random effects model.

Relaxing the assumption of "well behaved" residuals (see (2.9) and (2.10) below), another test for the RE hypothesis feasible in short panels is given in Wooldridge (2002). This is based on estimation of ${\sigma_\nu}^2$ from the upper triangle of the $N$ empirical $\Omega$ blocks given by the outer product of the residuals vectors

[7] See the summary table in the appendix.

[8] This is a locally mean most powerful refinement of the usual Breusch–Pagan $\chi^2$ 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 and Pagan test strongly rejects the null.

$\tilde{v}_i = (\tilde{v}_{i1}, \ldots, \tilde{v}_{iT})$. The result of the test is 5.4713, with p–value smaller than $10^{-7}$, this time favoring the random effects model. As RE estimators remain consistent under the OLS specification, we proceed estimating an RE model.

### 2.6.2 The random effects model

Under the RE specification, homoskedasticity in both $\nu_i$ and $\epsilon_{it}$ and no serial correlation in $\epsilon_{it}$, the variance-covariance matrix of the errors becomes

$$V = \sigma_\nu{}^2(I_N \otimes \boldsymbol{i}_T\boldsymbol{i}'_T) + \sigma_\epsilon{}^2(I_N \otimes I_T) \tag{2.8}$$

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

$$V = I_N \otimes \Omega \tag{2.9}$$

where

$$\Omega = \begin{bmatrix} \sigma_\epsilon^2 + \sigma_\nu^2 & \sigma_\nu^2 & \ldots & \sigma_\nu^2 \\ \sigma_\nu^2 & \sigma_\epsilon^2 + \sigma_\nu^2 & \ldots & \vdots \\ \ldots & & \ddots & \sigma_\nu^2 \\ \sigma_\nu^2 & & & \sigma_\epsilon^2 + \sigma_\nu^2 \end{bmatrix} \tag{2.10}$$

Observations regarding the same province share the same $\nu_i$ effect, thus the relative errors are autocorrelated, with $Corr(v_{is}v_{it}) = \frac{\sigma_\nu^2}{(\sigma_\epsilon^2+\sigma_\nu^2)}$. Ordinary least squares estimates for $\beta$ in model (2.7) are therefore inefficient, though consistent. Generalized least squares (GLS) are the efficient solution if $\Omega$ is known. Various feasible GLS procedures exist drawing on consistent estimators of $\Omega$.

The standard approach to RE panels is to assume both (2.9) and (2.10). In "large N" panels a less restrictive approach is possible, termed *general FGLS* estimator (GGLS) Wooldridge (2002), which allows for arbitrary *intra-group* heteroskedasticity and serial correlation of errors, i.e. inside the $\Omega$ covariance blocks, provided that these remain the same for every individual. For the sake of robustness, we try out both estimators. Results are much alike; GGLS are reported in the appendix.

## 2.7 Spatial structure

As observed while describing insurance data, there are good reasons to think that non–life insurance activity may not follow provincial administrative boundaries. For example, the latter may overlap with operational areas of the sales force, or there may be any other kind of cross-border purchase. 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 dataset.

In econometric applications, proximity between data points in space is usually characterized by means of a *proximity matrix*, say, $W$, containing a measure of proximity for every pair of data points and, by convention, setting the diagonal to zero. Hence a *spatial lag operator* is defined such that $Wy$, the *spatial lag* of $y$, stands for "the values of $y$ at *neighboring* locations"[9]. Anselin (1988) warns about the relevant consequences on estimation (and, to a lesser extent, on testing) of the choice of $W$. Here we resorted to a proximity matrix where each entry $w_{ij}$ is the inverse of coordinates' distance between province $i$ and $j$, with a cut–off point at 250km (i.e., any $w_{ij} < 1/250$ is set equal to 0). This has been row-standardized, so that the spatial lag of $y$, $Wy$, is simply the weighted average of values of $y$ at neighboring locations.

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

$$y = \rho W y + X\beta + \epsilon \tag{2.11}$$

and the *spatial error* (SEM) model:

$$\begin{aligned} y &= X\beta + e \\ e &= \lambda W e + \epsilon \end{aligned} \tag{2.12}$$

The consequences on estimation of omitting the lagged dependent variable are inconsistency and biasness of parameter estimates. Neglecting a spatial error structure has less serious consequences: estimates, while still consistent, are inefficient. Therefore, we concentrated our analysis on a SAR extension of our panel random effects model. Following Elhorst (2001), stacking the data as one cross section for every point in time and assuming $\epsilon \sim IID$, the panel RE version of (2.11) becomes

$$y = \rho(I_T \otimes W)y + X\beta + (i_T \otimes \nu) + \epsilon$$

where the variance covariance matrix of $(i_T \otimes \nu) + \epsilon$ is a block matrix where each block corresponds to a point in time $t$ and has the same structure as $V$ defined in the previous section. Results are reported in Table 1.

[9] See Anselin (1988), Ch.3, for a classic treatment.

Table 2.1: panel RE spatial autoregressive model estimates

| | coef | se | z | pz |
|---|---|---|---|---|
| log(Ydproc) | 1.1881 | 0.1726 | 6.8852 | 0.0000 |
| log(dep/pop) | 0.0780 | 0.0482 | 1.6186 | 0.1055 |
| I(pop25.54/popover60) | 0.2101 | 0.1225 | 1.7148 | 0.0864 |
| I(va/1000) | 0.0033 | 0.0013 | 2.5465 | 0.0109 |
| u | −0.0006 | 0.0018 | −0.3628 | 0.7168 |
| qexport | 0.0517 | 0.0818 | 0.6311 | 0.5279 |
| I(va.serv/va) | 0.3525 | 0.4452 | 0.7917 | 0.4285 |
| I(va.indutot/va) | 0.4285 | 0.4462 | 0.9604 | 0.3368 |
| I(den/1000) | 0.1037 | 0.0568 | 1.8264 | 0.0678 |
| numcompfam | 0.0335 | 0.1082 | 0.3098 | 0.7567 |
| lrpro | 0.0157 | 0.0212 | 0.7379 | 0.4606 |
| log(ag/pop) | 0.1238 | 0.0500 | 2.4743 | 0.0134 |
| inef | −0.0509 | 0.0129 | −3.9396 | 0.0001 |
| dum98 | −0.0718 | 0.0116 | −6.2073 | 0.0000 |
| dum99 | −0.0226 | 0.0091 | −2.4876 | 0.0129 |
| NO | 0.0534 | 0.0601 | 0.8889 | 0.3741 |
| NE | 0.0917 | 0.0539 | 1.7009 | 0.0890 |
| SU | −0.2414 | 0.0606 | −3.9818 | 0.0001 |
| IS | −0.2606 | 0.0711 | −3.6650 | 0.0002 |
| trust | 0.4787 | 0.1397 | 3.4257 | 0.0006 |
| pupop1000 | 0.1165 | 0.0371 | 3.1360 | 0.0017 |
| percsup.m | 0.0027 | 0.0012 | 2.2276 | 0.0259 |
| percsup.c | 0.0009 | 0.0009 | 1.0260 | 0.3049 |
| percsup.agr | 0.0727 | 0.1469 | 0.4950 | 0.6206 |
| pupop1000:percsup.m | −0.0012 | 0.0003 | −3.5274 | 0.0004 |
| pupop1000:percsup.c | −0.0005 | 0.0001 | −3.2824 | 0.0010 |
| pupop1000:percsup.agr | −0.0909 | 0.0398 | −2.2827 | 0.0224 |
| rho | 0.0908 | 0.0293 | 3.0979 | 0.0019 |

Social Capital effects are not completely absorbed by equilibrium prices: supply side proxies (in particular $\log(ag/pop)$) do have a positive effect but three out of four Social Capital proxies have positive and significant coefficients' estimates. Trust is positive and significant as well, confirming the role of global interactions. About spatial structure, as we expected non–life insurance demand exhibits spatial correlation: $\rho$ is positive and significant. Significance of the interaction parameters suggests for a non–linear dependence on our Social Capital proxies. Therefore we computed marginal effects for Social Capital variables.[10].

| | eff.marg. | se | t-ratio | p-value |
|---|---|---|---|---|
| pupop1000 | 0.0086 | 0.0041 | 2.0802 | 0.0384 |
| percsup.m | −0.0010 | 0.0010 | −1.0164 | 0.3103 |
| percsup.c | −0.0007 | 0.0007 | −0.9369 | 0.3496 |
| percsup.agr | −0.2181 | 0.1227 | −1.7766 | 0.0767 |

Marginal effect of pupop1000, which was the only one interacted with all the other Social Capital variables, is positive and significant, even if reduced in magnitude. Given these results, we investigated the relation between Social Capital and spatial correlation in the dependent variable.

### 2.7.1 Social Capital and spatial effects

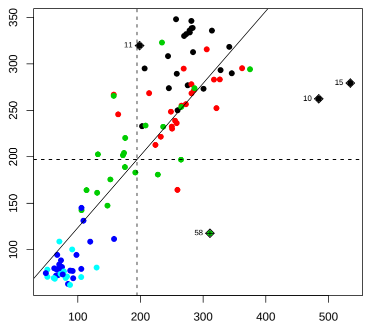
As for non–life insurance demand, Social Capital may not follow administrative boundaries and may exhibit a spatial structure. A first evidence in this direction comes from the moran plots of non–life insurance and the social capital variables we chose (see figure 5).

Moran's I statistic is a spatial correlation measure. In this case the proximity matrix is a row–standardized dichotomic matrix: Moran's I statistic thus boils down to the regression coefficient of the variable of interest over its spatial lag (see Anselin (1988)). The Moran plot is the relative scatter plot, where on the x–axis there is the variable of interest and on the y–axis its spatial lag. The straight line is the OLS estimated one. Therefore graphs show that both the variable of interest (ppcd, which are log premium per capita) and the social capital variables exhibit spatial correlation. Moran's I statistics gives the same indication if a distance–based $W$ is used. What we expected than is that since the empirical implication of our model is a causal relation between Social Capital and insurance demand, such a causality should reflect in the spatial structure as well.

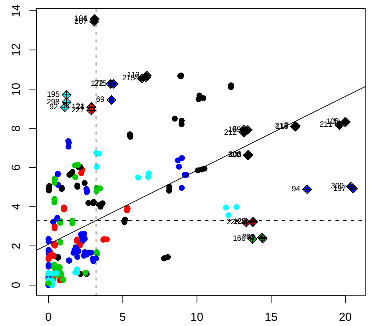
[10]Marginal effects are computed over the mean of the relevant variable.

Figure 2.5: Moran plots

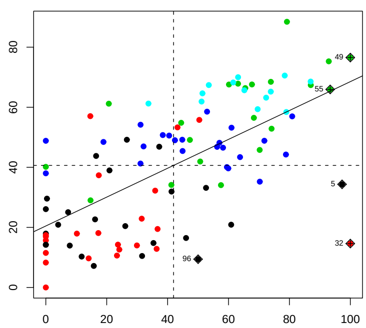
ppcd



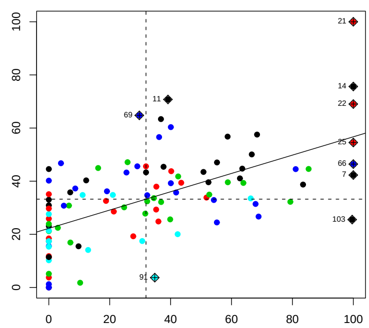
pupop1000



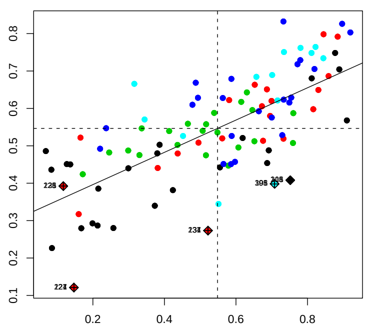
percsup.c



percsup.m



percsup.agr



Colors' legend:

- black = North-West
- red = North-East
- green = Center
- blue = South
- light blue = Islands

To test it, we repeated the panel SAR estimation for a model which do not include Social Capital variables, and compared the magnitude of the spatial correlation coefficient:

| | coef | se | z–stat | p–value |
|---|---|---|---|---|
| $\rho$ w/o Soc. Cap | 0.1730 | 0.0314 | 5.5138 | $< 10^{-4}$ |
| $\rho$ with Soc. Cap | 0.0908 | 0.0293 | 3.0979 | 0.0019 |

Results of these tests are in line with the causal relation implied by the model: a panel model without social interactions effects exhibits a significant Spatial autocorrelation structure ($\rho \neq 0$). Augmenting the model with social capital variables almost halves the spatial correlation coefficient, meaning that Social Capital has a positive marginal effect on non–life insurance demand, and its spatial structure accounts for a large part of insurance demand's spatial structure.

### 2.7.2 Robustness checks

Anselin (1988) points out the possible bias introduced by a wrong choice of the proximity matrix $W$. We performed a robustness check employing one binary contiguity matrix[11] and two different distance-based matrices: the first based on the inverse of road travelling distance, the second on the inverse of the euclidean distance between the geographic coordinates of capital cities in each province. The results of the two alternative distance-based specifications are much alike given the same cut–off point, as they are choosing different cut–off points:

Once the model is estimated with the 0/1 matrix there is no evidence of spatial dependence regardless of the presence or not of the Social Capital variables[12]. Nevertheless given the problem at hand such a proximity matrix seems to us less reasonable than a distance based one: provinces' extensions varies a lot, and so do travelling costs and Social Capital: a 0/1 matrix do not accounts for such an heterogeneity.

A SAR model gives consistent estimates, but if there is unexplained spatial correlation in the error term these estimates may not be efficient. To account for that we would need a sort of spatial ARMA model, accounting both for the autoregressive spatial component and the spatial error one. In our case we would need a panel version of such a model, which is still an open issue in the spatial econometric literature. Therefore, as a first test

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

[12] results are not reported but are available upon request

Table 2.2: $\rho$ coefficient by cutoff point

| KM | coef | se | z | pz |
|---|---|---|---|---|
| 50 | 0.0657 | 0.0201 | 3.2670 | 0.0011 |
| 75 | 0.0903 | 0.0205 | 4.3981 | 0.0000 |
| 100 | 0.1036 | 0.0214 | 4.8310 | 0.0000 |
| 125 | 0.1128 | 0.0224 | 5.0254 | 0.0000 |
| 150 | 0.1194 | 0.0233 | 5.1199 | 0.0000 |
| 175 | 0.1286 | 0.0246 | 5.2193 | 0.0000 |
| 200 | 0.1112 | 0.0262 | 4.2418 | 0.0000 |
| 225 | 0.0937 | 0.0278 | 3.3760 | 0.0007 |
| 250 | 0.0908 | 0.0293 | 3.0979 | 0.0019 |

we estimated a panel SEM (spatial error model) without the autoregressive component. Elhorst (2001) suggests the following specification:

$$y = X\beta + (i_T \otimes \mu) + e$$

$$e = \lambda(I_T \otimes W)e + \epsilon$$

We report estimates of $\lambda$ with proximity matrices with different cut–offs:

Table 2.3: $\lambda$ coefficient by cutoff point

| KM | coef | se | z | pz |
|---|---|---|---|---|
| 50 | −0.1966 | 0.1323 | −1.4858 | 0.1373 |
| 75 | −0.2188 | 0.1682 | −1.3011 | 0.1932 |
| 100 | −0.2907 | 0.2198 | −1.3224 | 0.1860 |
| 125 | −0.3650 | 0.2637 | −1.3842 | 0.1663 |
| 150 | −0.4398 | 0.2936 | −1.4982 | 0.1341 |
| 175 | −0.4626 | 0.3172 | −1.4584 | 0.1447 |
| 200 | −0.4956 | 0.3403 | −1.4563 | 0.1453 |
| 225 | −0.5312 | 0.3545 | −1.4982 | 0.1341 |
| 250 | −0.5358 | 0.3690 | −1.4520 | 0.1465 |

$\lambda$ is never significant, thous providing evidence in favour of efficiency of the SAR specification we chose.

## 2.8 Conclusions

We started from Arnott and Stiglitz model on the co–existence of marketed and non–marketed insurance contracts, concentrating on implications on the demand function. We extended tghe model to allow for Social Capital as a potential explanatory variable. We chose a network approach: non–market agreement are described as strategic decisions of agents playing a prisoners' dilemma type of game with their neighbors. Each of them adopt a trigger strategy to punish neighbors deviating from the cooperative equilibrium in any game they are involved. Such a behavior lead to a Pairwise Stable Equilibrium which is more likely the higher the level of Social Capital embedded in the Social Network. Here comes the first contribution of our paper: the network approach we chose provide us with a formal definition of Social Capital, which is crucial to obtain a clear testable model. The empirical part is carried out on a province–level Italian dataset provided by Istituto Tagliacarne. We carefully built 4 proxies for Social Capital and controlled for global interactions effect. We estimated a Spatial autoregressive RE panel model, and our testable implication, which was of a positive marginal effect for Social Capital on demand for market non–life insurance, is confirmed. Further on, we are able to explain a large part of the spatial correlation found by Lenzi and Millo on the very same dataset by means of the spatial structure of our new explanatory variables.

# Appendix

## A Proof of proposition 1

The normalized payoff functions in case $i$ cooperates with $j$ is

$$\begin{aligned}\pi_i(s_C^g) &= \sum_{k\in N_i}\left\{(1-\eta)\sum_{\tau=0}^{\infty}\eta^{\tau}EU_{ij}^{NMO}\right\}\\ &= \sum_{k\in N_i}EU_{ij}^{NMO}\end{aligned}$$

while if $i$ deviates her anticipated payoff is

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

Therefore, the stability condition

$$\pi_i(s_C^g) \geq \pi_i(s_D^g)$$

Can be rewritten as

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

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

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

$$EU_{ij}^{NMO} + \sum_{k\in N_i/\{j\}}\eta^{d^i(j,k)}\left[\eta EU_{ik}^{NMO} + (1-\eta)\nu_{ik}\right] \geq (1-\eta)EU_{ij}^{H} \qquad (2.13)$$

Which is in the form of proposition 1.

## A Variables' description and descriptive statistics

**Ydproc** disposable income per capita

**pop25.54/popover60** ratio of people aged 25-54 to people aged over 60

**inef** indicator of juridical system inefficiency: average duration of civil trials

**den/1000** population density, inh. per sq. Km (scaled by a factor of 1000)

**va.indutot/va** share of industry on value added

**va.serv/va** share of services on value added

**u** unemployment rate

**qexport** share of export on total value added

**numcompfam** average number of family members

**lrpro** loss ratio of the property sector

**trust** trust indicator as defined by the World Values Survey (see above)

**pupop500** share of population living in towns with less than 500 inhabitants

**percsup.m** share of mountainous territory

**percsup.c** share of hill territory

**percsup.agr** share of the land devoted to agriculture

**dep/pop** bank deposits per capita

**va/1000** total value added (scaled by a factor of 1000)

**ag/pop** ratio of number of agencies over province's population

A table with some descriptive statistics follows.

| | Min. | 1st Qu. | Median | Mean | 3rd Qu. | Max. |
|---:|---:|---:|---:|---:|---:|---:|
| log(Ydproc) | 9.00 | 9.27 | 9.54 | 9.47 | 9.63 | 9.84 |
| I(pop25.54/popover60) | 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 |
| I(den/1000) | 0.04 | 0.10 | 0.17 | 0.24 | 0.26 | 2.66 |
| I(va.indutot/va) | 0.11 | 0.21 | 0.28 | 0.28 | 0.33 | 0.46 |
| I(va.serv/va) | 0.52 | 0.63 | 0.68 | 0.68 | 0.74 | 0.85 |
| u | 1.71 | 5.01 | 7.55 | 10.90 | 16.14 | 33.16 |
| qexport | 0.01 | 0.09 | 0.20 | 0.20 | 0.30 | 0.63 |
| numcompfam | 2.05 | 2.46 | 2.61 | 2.62 | 2.78 | 3.15 |
| trust | 3.03 | 3.17 | 3.25 | 3.26 | 3.35 | 3.63 |
| pupop1000 | 0.00 | 0.30 | 1.38 | 3.20 | 3.28 | 20.52 |
| percsup.m | 0.00 | 0.00 | 30.68 | 31.92 | 52.43 | 100.00 |
| percsup.c | 0.00 | 17.25 | 42.40 | 41.95 | 63.14 | 100.00 |
| log(dep/pop) | 1.35 | 1.78 | 2.20 | 2.11 | 2.38 | 3.09 |
| I(va/1000) | 1.27 | 4.21 | 6.22 | 10.04 | 10.18 | 112.10 |
| lrpro | 0.25 | 0.43 | 0.49 | 0.52 | 0.59 | 1.82 |
| percsup.agr | 0.07 | 0.38 | 0.59 | 0.55 | 0.73 | 0.92 |
| log(ag/pop) | −8.98 | −8.01 | −7.73 | −7.83 | −7.62 | −7.32 |
| pupop1000:percsup.m | 0.00 | 0.00 | 28.90 | 158.40 | 121.10 | 1666.00 |
| pupop1000:percsup.c | 0.00 | 0.00 | 35.85 | 107.50 | 104.00 | 1949.00 |
| pupop1000:percsup.agr | 0.00 | 0.18 | 0.56 | 1.41 | 1.53 | 15.07 |

# C Full estimation results

## C.1 Random Effects panel estimation results without spatial correction

| | coef | se | t | pt |
|---:|---:|---:|---:|---:|
| (Intercept) | −7.232032 | 1.720103 | −4.204418 | 0.000035 |
| log(Ydproc) | 1.156512 | 0.165342 | 6.994670 | 0.000000 |
| I(pop25.54/popover60) | 0.268546 | 0.119293 | 2.251143 | 0.025149 |
| inef | −0.051496 | 0.011580 | −4.447068 | 0.000013 |
| NO | 0.045594 | 0.055319 | 0.824209 | 0.410520 |
| NE | 0.084450 | 0.049043 | 1.721975 | 0.086174 |
| SU | −0.255475 | 0.054661 | −4.673777 | 0.000005 |
| IS | −0.288996 | 0.064639 | −4.470903 | 0.000011 |
| dum98 | −0.094306 | 0.012889 | −7.316894 | 0.000000 |
| dum99 | −0.036897 | 0.009717 | −3.797031 | 0.000179 |
| I(den/1000) | 0.102903 | 0.051126 | 2.012731 | 0.045097 |
| I(va.indutot/va) | 0.405786 | 0.442339 | 0.917366 | 0.359738 |
| I(va.serv/va) | 0.368092 | 0.434076 | 0.847990 | 0.397165 |
| u | −0.000067 | 0.001900 | −0.035110 | 0.972017 |
| qexport | 0.022075 | 0.092149 | 0.239558 | 0.810848 |
| numcompfam | 0.016147 | 0.109742 | 0.147132 | 0.883133 |
| trust | 0.510440 | 0.125794 | 4.057747 | 0.000064 |
| pupop1000 | 0.134755 | 0.033928 | 3.971815 | 0.000091 |
| percsup.m | 0.002976 | 0.001112 | 2.676534 | 0.007876 |
| percsup.c | 0.000725 | 0.000772 | 0.938466 | 0.348811 |
| log(dep/pop) | 0.167496 | 0.051477 | 3.253771 | 0.001278 |
| I(va/1000) | 0.002882 | 0.001207 | 2.386959 | 0.017650 |
| lrpro | 0.014176 | 0.023118 | 0.613210 | 0.540234 |
| percsup.agr | 0.117385 | 0.134327 | 0.873875 | 0.382933 |
| log(ag/pop) | 0.167453 | 0.054103 | 3.095078 | 0.002166 |
| pupop1000:percsup.m | −0.001326 | 0.000303 | −4.377530 | 0.000017 |
| pupop1000:percsup.c | −0.000477 | 0.000135 | −3.522188 | 0.000499 |
| pupop1000:percsup.agr | −0.114299 | 0.036413 | −3.138982 | 0.001876 |

### C.2 Spatial lag model (SAR) without Social Capital variables

| | coef | se | z | pz |
|---:|---:|---:|---:|---:|
| log(Ydproc) | 1.2750 | 0.1751 | 7.2838 | 0.0000 |
| log(dep/pop) | 0.0791 | 0.0487 | 1.6237 | 0.1044 |
| I(pop25.54/popover60) | 0.1969 | 0.1209 | 1.6281 | 0.1035 |
| I(va/1000) | 0.0027 | 0.0013 | 2.0554 | 0.0398 |
| u | −0.0003 | 0.0018 | −0.1422 | 0.8870 |
| qexport | 0.0869 | 0.0830 | 1.0465 | 0.2953 |
| I(va.serv/va) | 0.3667 | 0.4342 | 0.8446 | 0.3983 |
| I(va.indutot/va) | 0.5049 | 0.4444 | 1.1360 | 0.2560 |
| I(den/1000) | 0.0727 | 0.0550 | 1.3227 | 0.1859 |
| numcompfam | 0.0522 | 0.1065 | 0.4899 | 0.6242 |
| lrpro | 0.0138 | 0.0213 | 0.6492 | 0.5162 |
| log(ag/pop) | 0.1299 | 0.0507 | 2.5615 | 0.0104 |
| inef | −0.0392 | 0.0134 | −2.9309 | 0.0034 |
| dum98 | −0.0657 | 0.0118 | −5.5488 | 0.0000 |
| dum99 | −0.0178 | 0.0093 | −1.9169 | 0.0553 |
| NO | 0.1239 | 0.0503 | 2.4616 | 0.0138 |
| NE | 0.0723 | 0.0486 | 1.4888 | 0.1365 |
| SU | −0.2233 | 0.0636 | −3.5088 | 0.0004 |
| IS | −0.1792 | 0.0732 | −2.4485 | 0.0143 |
| trust | 0.2481 | 0.1337 | 1.8555 | 0.0635 |
| rho | 0.1730 | 0.0314 | 5.5138 | 0.0000 |

### C.3 Spatial error model (SEM) with Social Capital variables

| | coef | se | z | pz |
|---|---|---|---|---|
| log(Ydproc) | 1.2240 | 0.1722 | 7.1073 | 0.0000 |
| log(dep/pop) | 0.0738 | 0.0461 | 1.5992 | 0.1098 |
| I(pop25.54/popover60) | 0.2046 | 0.1210 | 1.6905 | 0.0909 |
| I(va/1000) | 0.0032 | 0.0013 | 2.4845 | 0.0130 |
| u | −0.0013 | 0.0018 | −0.7136 | 0.4755 |
| qexport | 0.0426 | 0.0817 | 0.5216 | 0.6020 |
| I(va.serv/va) | 0.3719 | 0.4409 | 0.8435 | 0.3989 |
| I(va.indutot/va) | 0.4555 | 0.4431 | 1.0281 | 0.3039 |
| I(den/1000) | 0.1033 | 0.0572 | 1.8073 | 0.0707 |
| numcompfam | 0.0542 | 0.1068 | 0.5074 | 0.6119 |
| lrpro | 0.0131 | 0.0206 | 0.6343 | 0.5259 |
| log(ag/pop) | 0.1223 | 0.0468 | 2.6144 | 0.0089 |
| inef | −0.0527 | 0.0130 | −4.0540 | 0.0001 |
| dum98 | −0.0778 | 0.0106 | −7.3466 | 0.0000 |
| dum99 | −0.0250 | 0.0080 | −3.1192 | 0.0018 |
| NO | 0.0691 | 0.0601 | 1.1498 | 0.2502 |
| NE | 0.1031 | 0.0540 | 1.9105 | 0.0561 |
| SU | −0.2682 | 0.0609 | −4.4028 | 0.0000 |
| IS | −0.2868 | 0.0716 | −4.0067 | 0.0001 |
| trust | 0.5257 | 0.1406 | 3.7396 | 0.0002 |
| pupop1000 | 0.1216 | 0.0374 | 3.2511 | 0.0011 |
| percsup.m | 0.0027 | 0.0012 | 2.1617 | 0.0306 |
| percsup.c | 0.0008 | 0.0009 | 0.9142 | 0.3606 |
| percsup.agr | 0.0476 | 0.1474 | 0.3227 | 0.7469 |
| pupop1000:percsup.m | −0.0012 | 0.0003 | −3.6655 | 0.0002 |
| pupop1000:percsup.c | −0.0005 | 0.0002 | −3.3669 | 0.0008 |
| pupop1000:percsup.agr | −0.0949 | 0.0401 | −2.3684 | 0.0179 |
| lambda | −0.5358 | 0.3690 | −1.4520 | 0.1465 |

### C.4 Spatial error model (SEM) without Social Capital variables

| | coef | se | z | pz |
|---|---|---|---|---|
| log(Ydproc) | 1.3459 | 0.1757 | 7.6594 | 0.0000 |
| log(dep/pop) | 0.0787 | 0.0469 | 1.6793 | 0.0931 |
| I(pop25.54/popover60) | 0.2073 | 0.1205 | 1.7208 | 0.0853 |
| I(va/1000) | 0.0024 | 0.0013 | 1.7754 | 0.0758 |
| u | −0.0010 | 0.0018 | −0.5502 | 0.5822 |
| qexport | 0.0826 | 0.0832 | 0.9929 | 0.3208 |
| I(va.serv/va) | 0.4062 | 0.4320 | 0.9403 | 0.3470 |
| I(va.indutot/va) | 0.5533 | 0.4435 | 1.2475 | 0.2122 |
| I(den/1000) | 0.0758 | 0.0558 | 1.3570 | 0.1748 |
| numcompfam | 0.0765 | 0.1059 | 0.7221 | 0.4702 |
| lrpro | 0.0116 | 0.0208 | 0.5577 | 0.5771 |
| log(ag/pop) | 0.1391 | 0.0477 | 2.9190 | 0.0035 |
| inef | −0.0420 | 0.0136 | −3.0877 | 0.0020 |
| dum98 | −0.0792 | 0.0109 | −7.2395 | 0.0000 |
| dum99 | −0.0238 | 0.0083 | −2.8802 | 0.0040 |
| NO | 0.1650 | 0.0508 | 3.2510 | 0.0011 |
| NE | 0.0946 | 0.0491 | 1.9265 | 0.0540 |
| SU | −0.2769 | 0.0645 | −4.2929 | 0.0000 |
| IS | −0.2276 | 0.0743 | −3.0635 | 0.0022 |
| trust | 0.3258 | 0.1357 | 2.4011 | 0.0163 |
| lambda | −0.5162 | 0.3665 | −1.4086 | 0.1589 |

# Chapter 3

# Social interaction effects in an inter–generational model of informal care giving

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The present chapter shows the results achieved and the discussions jointly had by my coauthor and me, but the final form as a chapter is due to me alone for the purpose of this thesis. This means that I am the only responsible for every linguistic or mathematical error and imprecision.

## abstract

We study jointly the health perception of the elderly and the care giving decision of their adult children. Social interactions play a crucial role: elder parents' health perception depends on relations with household members. On the other hand adult children make their care giving decisions strategically, meaning that each of them considers his siblings' decision. We find empirical evidence which support this claim using the 2004 wave of the SHARE survey. We estimate social interaction effects by means of methods taken from the spatial econometric literature. Health perception relation with care giving depends on the determinants of adult children's decision to care: Parents' health may be modelled as a common good for parents and children; the latter's decision may be driven by bequest motives or by pure altruism and/or

cultural values. We test implications of the model thanks to the unique features of the SHARE dataset: it is trans–national, allowing to control for cultural and institutional differences, it contains information on health status of over–50 Europeans and details on their social and intergenerational relations.

## 3.1 Introduction

Aging is one of the main concerns in most European Countries. While this process is the result of scientific development and improved economic living conditions, it rises several policy issues. First of all, pension systems are under revision in many countries, in order to be sustainable in societies with a shrinking labor force compared to an expanding number of retired people. Health care, and in particular long term care systems must adapt to this changing society as well. This is the focus of our paper: we are interested in the relation between formal and informal care, and in the strategic behavior of care–givers and care–receivers. This is a relevant topic from a policy perspective: institutions can change the cost and availability of formal care. Nevertheless the overall impact of different settings depend on the relation between formal and informal care provision. As an example: reducing the cost for formal care may reduce or increase the supply of informal one, depending on whether those services are substitutes or complements. Further, caring is a time–consuming activity which is not necessarily compatible with a full time occupation, thus time devoted to informal care and labor force participation are negatively related. we will formalize all these relations in a game–theoretic setting. In a nutshell: the amount of care provided by non co–residing siblings can be thought of as the equilibrium output between the supply and the demand for informal care in the 'family market'. This is not new in the literature, and such an output has been obtained from a bargaining process (Pezzin and Steinberg Schone (1999)). We will follow an alternative approach based on a non–cooperative game among altruistic players. Our aim is to study both sides of the market, devoting a particular attention to interactions among family members. Care supply has already been studied as an endogenous choice on the labor decisions of siblings, in particular to explain gender differences in labor market participation and wages (Ettner (1995), Ettner (1996), Wolf and Soldo (1994), Crespo (2007)). Usually the focus is not on care giving choices, which at most are considered as endogenous factors in the labor market decision. In the present paper we turn our attention to the care giving choice itself, controlling for endogenous labor supply. Such an approach allows us to concentrate on the strategic interaction among siblings: the choice to allocate hours to parent's care depend crucially on the same choice done by brothers and sisters.

Demand for health care depends on the health status of the elders. A structural model of the demand side is beyond the scope of the paper. Health status can be thought as the output of an accumulation process (Grossman (1972)). In such a setting, demand for informal care as well as for publicly provided health care services can be though of as an input in the health capital production function. Anyway, we are focusing on people older than 50: at that age, the accumulation process can be considered as finished: even if healthy behavior, such as not smoking or a proper diet still improve objective health, important inputs in the health accumulation function as income, education, living arrangement depend on choices that can safely be assumed to be predetermined. Our focus then turns to a subjective measure of health, which is self reported perceived health.

Measuring perceived health is not the same as measuring objective health (see Jurges (2005) for a detailed discussion on health measures in SHARE). The self–perception of health status entails objective health conditions, but also individual preference or general attitude, social and family network determinants and cultural differences (Reher (1998); Silverstein and Bengtson (1997), Collins (2004)). Then, we claim that self reported health is a measure of well–being, not only a measure of physical health corrected by individual and sociological country differences. This is coherent with the World Health Organization[1] definition of health:

> [...] a state of complete physical, mental and social well–being and not merely the absence of disease or infirmity

The paper is structured as follows: the next section outlines the economic model; the third one describes the SHARE dataset. Next we move to the econometric specification and estimation procedure. Fifth section reports and comments on the results, conclusions are drawn in the last section.

## 3.2 The Economic model

We model the caring decision as a one–shot non cooperative game among parents, $P_1, P_2$, and their children, $S_1, S_2, \ldots, S_n$. Children choose how much time to spend caring for their parents, $I_1, \ldots, I_n$ and how much to spend in leisure, $L_1, \ldots, L_S$. Parents can choose how much of their income to buy formal care hours, $F$, but they can also transfer (or commit to transfer inthe

[1]Constitution of the World Health Organization, Geneva 1946

future) an amount of money to their children as a bequest, $B$. Further on, they can choose how to split such a bequest amongst their children: $\beta$ stands for the sharing rule applied by parents. Following Sloan et al. (1997), we chose not to model caring decisions as a cooperative game since in such a model players should face an infinite number of periods. We think this assumption is unrealistic: parent's death is an event that can't be neglected in caring choices.

Children's help is provided to parents' households, thus as a starting point we assume there is a single parent. We will discuss in the following section what decision rules among parents are consistent with our model and the relevance of the single parent assumption. Children are all equal and have the same strategies, thus we can assume without loss of generality there are just two of them. Again, we will discuss at lenght implications of this simplifying assumption.

Parent and sons are altruistic: children are worried about their parents' health, while $P$ utility depend on children's utility derived from consumption. Formally, $P, S_1, S_2$ face the following maximization problems:

$$
\begin{array}{ll}
P\text{'s problem:} & \\
\max_{F,B,\beta} & \left\{U^Q(Q) + U^I(I_1) + V^C(C_1) + U^I(I_2) + V^C(C_2)\right\} \\
\text{s.t.} & \begin{array}{l} Q = F + I_1 + I_2 \\ p^F F + B \leq Y^P \end{array}
\end{array}
\tag{3.1}
$$

Where $p^F$ is the market price for formal care, $C_i$ is $i$th son's consumption and $Y^P$ is income. We model the decision process as a one–shot game, thus there are no savings and current and permanent income coincide. Parent's utility function is assumed to depend only on care and not on other goods' consumption. This is equivalent to assume separability of care from all other available goods in $P$'s utility.

$$
\begin{array}{ll}
S_i \text{ problem: } \max\limits_{I_i, L_i} & \left\{U^Q(Q) + V^C(C_i)\right\} \\
\text{s.t.} & \begin{array}{l} Q = F + I_i + I_{-i} \\ Y^i + B_i(\beta) = C_i \\ Y^i = \omega(T - L_i - I_i) \\ L_i + I_i \leq T \\ L_i \geq 0 \\ I_i \geq 0 \end{array}
\end{array}
\tag{3.2}
$$

$\omega$ is market wage and $T$ is total available time. Such a model is similar to Bernheim et al. (1985) (assuming additively separable utility functions) and to Sloan et al. (1997) (assuming no income sharing and no cooperation within the family), but it considers as endogenous the labor force participation decision. The total amount of care, $Q$, is a public good (partly) produced within the family. Child $i$'s utility is concave, first increasing and then decreasing in $I_i$. $U^P$ has the same shape, but it depends also on the additional terms $U^I(I_i)$: these term allows us to formalize the idea that $P$ attaches a higher a value to informal care per se, while $S_i$ is indifferent on the type of care his parent receives as long as the amount $Q$ is provided. Formally, these assumptions can be expressed in terms of utility's first derivatives:

$$\frac{\partial U^Q}{\partial Q} > 0; \quad \frac{\partial U^I}{\partial I} > 0; \quad \frac{\partial V^C}{\partial C} > 0$$

the shape of $U^S$ and $U^P$ together with positiveness of first derivatives implies that

$$\mathrm{argmax}_{I_i} U^P > \mathrm{argmax}_{I_i} U^S \tag{3.3}$$

$U^S$ depends on $F$ only through the public good $U^Q$. Then,

$$\frac{\partial U^S}{\partial F} = \frac{\partial U^S}{\partial U^Q} \cdot \frac{\partial U^Q}{\partial Q} \cdot \frac{\partial Q}{\partial F} = \frac{\partial U^Q}{\partial Q} > 0$$

Which implies that $S$ utility function is always increasing in parent's choice variable $F$: if $P$ do not commit to transfer any bequest $B$, children actually choose $I_S$ independently of their parent's choice of $F$. Thus without bequest $i$th child's maximization problem can be rewritten as

$$S_i \text{ problem: } \max_{I_i, L_i, C_i} \quad \left\{ U^Q(Q) + V^C(C_i) \right\}$$
$$\text{s.t.} \quad \begin{array}{l} Q = F + I_i + I_{-i} \\ C_i = Y^i = \omega(T - L_i - I_i) \\ L_i + I_i \leq T \\ L_i \geq 0 \\ I_i \geq 0 \end{array} \tag{3.4}$$

Absence of a bequest implies that $P$ do not participate to the game between children: parent's choice of $F$ can only increase children utilities, thus $S_1$ and $S_2$ decide regardless of $P$'s provision of formal care. In this setting child $i$ utility is always positively affected by $I_{-i}$: $i$'s sibling informal care augment the public good enjoyed by $i$ at no price. Thus child $i$ either does not react to a positive $I_{-i}$, or his supply of informal care is crowded out, since

$I_{-i}$ substitutes $I_i$ and $i$ can re–allocate part of his resources to consumption. Thus each child take parent and siblings decisions as given and maximize

$$\begin{array}{ll} \max\limits_{I_i,L_i} & \left\{U^Q(\bar{F}+I_i+\bar{I}_{-i})+V^C(\omega(T-L_i)-\omega I_i)\right\} \\ & L_i+I_i \leq T \\ \text{s.t.} & L_i \geq 0 \\ & I_i \geq 0 \end{array} \tag{3.5}$$

Non–negativity constraints are imposed since corner solutions are not ruled out, i.e. $i$ can choose to work all his available time or to spend it all providing care. The Kuhn–Tucker conditions are

$$-\omega\frac{\partial V^C}{\partial C}-\lambda_1+\lambda_2 = 0 \tag{3.6}$$

$$-\omega\frac{\partial V^C}{\partial C}+\frac{\partial U^Q}{\partial Q}-\lambda_1+\lambda_3 = 0 \tag{3.7}$$

$$\lambda_1(T-L_i-I_i) = 0 \tag{3.8}$$

$$\lambda_2 L_i = 0 \tag{3.9}$$

$$\lambda_3 I_i = 0 \tag{3.10}$$

Together with

$$\lambda_1 \geq 0; \quad \lambda_2 \geq 0; \quad \lambda_3 \geq 0$$

The Kuhn–Tucker multipliers $\lambda_1$, $\lambda_2$ and $\lambda_3$ can be interpreted respectively as the opportunity costs of working, leisure and informal care. Solving the maximization problem we get the optimal allocation of time by each son: $i$ allocates always all his time in the activity characterized by the lower opportunity cost. Further more, any optimal allocation involving informal care (i.e., if $I_i > 0$) does not involve leisure, since its opportunity cost is certainly higher than the informal care's one: $I_i$ and $L_i$ have the same cost in terms of forgone wages (i.e. they enter in the same way in $V^C$), but $I_i$ has also a utility increasing effect since it increases $U^Q$, the altruistic part of $U^S$. Then regardless of $\lambda_1$, $\lambda_2 < \lambda_3$ and therefore we obtain an internal solution only if working and providing care have the same opportunity cost, i.e. if $lambda_1 = \lambda_2$.

As we already stated $P$ do not enter the game since he can't influence $I$'s choices with $F$, thus $P$'s maximization is:

$$\begin{aligned} \max_{F} \quad & \left\{U^Q(F+\bar{I}_i+\bar{I}_{-i})+U^I(\bar{I}_i)+U^I(\bar{I}_{-i})+V^C(\bar{C}_i)+V^C(\bar{C}_{-i})\right\} \\ \text{s.t.} \quad & p^F F \leq Y^P \end{aligned} \tag{3.11}$$

Since $U^Q$ is always increasing in $F$, the optimal choice for $P$ is to allocate all his resources to $F$: $\bar{F} = Y^P/p^F$.

Those allocations are Pareto efficient, i.e. neither the sons nor the parent can modify their choice in such a way that either $P$, $S_1$ or $S_2$ are better off without reducing someone else's utility. Nevertheless since $P$ prefers informal to formal care whatever is the choice of $I$ by his sons, $U^P$ as a function of $I_i, I_{-i}$ is never maximized. This result motivates the introduction of strategic bequest as in Bernheim et al. (1985): $P$ can 'substitute' formal care with informal one committing to transfer a bequest to his sons. The new maximization problems are:

$$\begin{aligned} \max_{F,B,\beta} \quad & \left\{U^Q(F+\bar{I}_i+\bar{I}_{-i})+U^I(\bar{I}_i)+U^I(\bar{I}_{-i})+V^C(\bar{C}_i)+V^C(\bar{C}_{-i})\right\} \\ \text{s.t.} \quad & p^F F + B_i(\beta) + B_{-i}(\beta) \leq Y^P \end{aligned} \tag{3.12}$$

$B_i$ depends on $\beta$: the parents chooses how much to transfer to his sons, but also how to split it between them.

$$S_i \text{ problem: } \max_{I_i, L_i} \quad \left\{U^Q(Q)+V^C(C_i)\right\}$$
$$\text{s.t.} \quad \begin{array}{l} Q = \bar{F} + I_i + \bar{I}_{-i} \\ Y^i + \bar{B}_i(\bar{\beta}) = C_i \\ Y^i = \omega(T - L_i - I_i) \\ L_i + I_i \leq T \\ L_i \geq 0 \\ I_i \geq 0 \end{array} \tag{3.13}$$

The effect of the transfer $B_i$ on $i$'s decision depend crucially on the sharing rule adopted by $P$. If $B_i > 0$, but the sharing rule is such that $B_i$ does not depend on $-i$'s choice (i.e. on care provided by siblings, $I_{-i}$), the bequest does not alter the effect of siblings' choices about care provision on $i$'s choice. Then in this case the only effect of the bequest $B_i > 0$ is that it relaxes $i$'s budget constraint, but it does not change the Kuhn–Tucker conditions and the relative prices of working, leisure and informal care: if the opportunity cost of $I_i$was higher then the one of working, bequest cannot induce the children to provide informal care. Nevertheless, if in equilibrium without bequest $\bar{I}_i > 0$, $P$ can obtain extra care and therefore increase his utility transferring $B$ to his child. The starting point is that $\bar{I}_i > 0$ implies that either the opportunity cost of providing care is lower or it is equal to the one of working. In the first case, $P$ substitutes formal with informal care: he will buy $F^* = (\bar{F} - \delta)$ and induce $i$ to allocate $I_i^* = \bar{I}_i + \delta$, where $\delta = B/p^F$. The new allocation does not alter $i$'s utility: $U^Q$ is unchanged since $Q$ is the same; $V^C(C_i)$ is unchanged as well since the cost of the extra $I_C$ is balanced by $B_i$. Parent's utility $U^P$ increases since $\forall I \; \partial U^I/\partial I > 0$. Vice versa, if shadow prices are equal and therefore we start from an internal solution $(0 < \bar{I}_i < T)$, the $U^P$ growth due to a higher level of $I_i$ and/or $C_i$ does not necessarily compensate the parent's utility loss due to the income reduction $-B_i$. This is due to the fact that since players choose simultaneously $P$ is not able to induce $i$ to use $B_i$ to maximize $P$'s utility: $i$ will use the extra income to augment his consumption if his marginal utility $\partial V^C/\partial C_i > \partial U^Q/\partial I_i$, vice versa he will increase the informal care provision. In other words, the children will provide an extra amount of $I$ only if the altruisti motivation will prevail. Then we make the same assumption Bernheim et al. (1985) did: Parent selects the transfer subsequent to the child's choice of $I_i$. Since the transfer we are talking about is a bequest, this seems reasonable: the model involves just one period, results do not change with expected inter–vivos transfers[2]. Thus, given the timing of the decision and the fact that opportunity costs of working and providing care are the same, $i$ anticipates $P$'s transfer and allocate $B_i$ to extra care as in the corner solution's case.

This result does not necessarily lead to a global maximum for $P$: if his budget constraint is binding, he could be unable to provide $B_i$ up to the point that maximizes $U^P(I)$. Results changes if $P$ splits the overall bequest among his children proportionally to the care provided by each of them: $P$ can set $\beta$ in such a way he extracts an additional amount of informal care from each son at the same price as before. In the previous paragraphs the child had a 'monopoly' over $B_i$: $i$ sets the price for the extra care at the level that maximizes his utility (i.e. the transfer $B_i$ that leaves his utility unaltered compared to the non–bequest case). The presence of siblings can reduce $i$'s market power over the bequest. In order to clarify this point, remeber we are assuming (without loss of generality) that there are two children. Bernheim et al. (1985) shows that if $\beta$ assigns shares $B_i$ proportional to $I_i/I_1 + I_2$, then in equilibrium both $I_1$ and $I_2$ are greater or equal than without bequest. We now want to extend this result considering $L_i$ as endogenous. Let's call $I_i^*$ the informal care supplied by $i$ at equilibrium without bequest. The sharing

[2]On the empirical part we will consider both expected bequest and past inter vivos transfers, but the latter are not included amongst the Parent's choice variables

rule is the following: if both $S_1$ and $S_2$ provide a level of care which is higher or equal than $I_i^*$, each one will receive a bequest proportional to the relative amount of care provided:

$$B_i = \frac{I_i}{I_1 + I_2}$$

On the other hand, if one or both of them will provide an amount $I_i < I_i^*$, the whole amount $B$ will be given to the 'most generous child':

$$\exists i : I_i < I_i^* \Rightarrow B_i = \begin{cases} B & \text{if } I_i > I\_i \\ 0 & \text{if } I_i < I\_i \\ 0 & \text{if } I_i = I\_i < \min_i I_i^* \end{cases}$$

This is an application of the Rotten Kid theorem which Bernheim et al. (1985) prove to hold with exogenous labor supply decision. In order to show that the result holds also in our model, we rewrite the Kuhn–Tucker conditions:

$$\begin{aligned} -\omega \frac{\partial V^C}{\partial C} - \lambda_1 + \lambda_2 &= 0 & (3.14) \\ \left(\frac{\partial B}{\partial I_i} - \omega\right) \frac{\partial V^C}{\partial C} + \frac{\partial U^Q}{\partial Q} - \lambda_1 + \lambda_3 &= 0 & (3.15) \\ \lambda_1 (T - L_i - I_i) &= 0 & (3.16) \\ \lambda_2 L_i &= 0 & (3.17) \\ \lambda_3 I_i &= 0 & (3.18) \end{aligned}$$

Then, since $\partial B / \partial I_i > 0$, from the first two conditions it's easy to see that the opportunity cost of informal care $\lambda_3$ is still larger than the opportunity cost of leisure $\lambda_2$ and the difference $(\lambda_3 - \lambda_2)$ increases with respect to the case of no bequest. Then $\lambda$'s ordering is unchanged, which means that the bequest sharing rule does not alter the effect of the labor participation choice on the informal care one and Bernheim et al. (1985) still holds. What does change is the role of $I_{-i}$ on $S_i$ choice: while without such a sharing rule child $i$ utility is always positively affected by $I_{-i}$, now it has also a negative effect, since $B_i$ is decreasing in $I_{-i}$. Then if the strategic bequest motive is valid (and only in this case), an increase in $I_{-i}$ could have a positive marginal effect on $i$'s supply of informal care.

### 3.2.1 Relaxing the assumptions: one child, two parents

We assumed at the beginning of this section that there are at least two children. With a single child and no bequest, the altruistic feature of child's utility finction (can) lead to a positive provision of informal care, regardless of parent's choice of $F$. While it's meaningless speaking about sharing rules in this case, still $P$ can induce an higher provision of $I$ with respect to the 'altruistic' level committing to transfer a positive $B$ to his child. From a welfare perspective, the presence of more than one child has the same effect as moving from a monopoly to an oligopoly: children - given the bequest amount and the sharing rule - compete á la Cournot on quantities of informal care to be sold to the unique client, the parent. Equilibrium characteristics are the usual one of Cournot–Nash outcomes, in particular the total amount $I_1 + I_2$ supplied is larger than in monopoly.

In other words the amount of informal care provided by each child depends crucially on the bargaining power of the parent. If there is only one child, $P$ can increase the level of informal care only transferring part of his disposable income to his child. If there are two (or more) children he can make them compete for the bequest obtaining an extra amount of care from them. Nevertheless, if there is no bequest, there are no gains moving from one to a higher number of children. From the son's point of view what matters is the sharing rule: without bequest or if the bequest share is fixed, there is basically no interaction among children: each one can maximize his own utility on his own time allocation and their choices are not altered by the presence of siblings. This is not true if the bequest amount depends on the relative supply of informal care. In this case an increase in $I_{-i}$ increases $U^Q$ but reduces $B_i$: $i$ must take it into account once he maximizes $U_i^S$.

The effect of the presence of a spouse depends on how parent's household decision process is modelled. A first choice (the so–called 'unitarian' model) is to assume that individuals have the same preferences and therefore the household as a whole can be considered the elementary decision unit with its own unique utility function. This approach is not fully satisfactory. An appealing alternative are models of 'collective' utility: they are characterized by two different utility functions and some decision rule to split resources. Chiappori (1992) provides a common framework for those models. In particular, coherently with the previous sections, we assume individuals to be altruistic: the father's utility depends on his own care consumption and on his partner's utility. The decision rule can be thought of as a two–stage procedure: first, parents share their income and informal care provided by the children, then each of them optimally chooses his or her own consumption. Chiappori (1992) result is that with collective utility functions any allocation that respect this process is Pareto efficient. Which particular allocation is reached depends on the shape of each parent's utility. Within this framework a very simple utility specification is consistent with saving choices (see

Browning (2000) for details on the model and Alessie et al. (2006) for an application). As long as children are altruistic toward parents' household as a whole, any collective utility is consistent with the model developed in the previous sections. We just need to assume that informal care is supplied to the parent's household and not to each member separately; bequest to children is a different good from bequest to the surviving spouse and parents have a common budget constraint to abide by.

### 3.2.2 Empirical implications

The economic model gives us a number of empirical implications. In particular, we have three features to test on children choices: first, endogeneity of labor supply decision in informal care; second, the interactions among children when choosing how much time to devote to caring; third, the relevance of the strategic bequest motive in children's choices.

While the first point is clear, some words should be spent on the following two points, which are related. If the bequest motive is purely altruistic, or in general if expected bequest do not depend on children's behavior, parent's expected bequest or potential future transfers should have no role on children decision. Further, each child $i$ enjoys the public good made up of formal care and informal care provided by each of his siblings. Therefore $i$'s help either is not affect by his siblings' help, or it is crowded out by them. A complementary relationship is not consistent with such an explanation. Vice versa if the bequest motive is strategic, the marginal effect of parent's expected bequest on informal care choice should be positive and informal care of each child can be in a complementarity relation, but there cannot be crowding out. Thus we can discriminate among bequest motives estimating the marginal effect on $i$'s informal care supply of other sibling's help.

On the parent's side, the main hypothesis is that informal care increases utility derived from care. We can go further: the whole model holds also if parent's utility depends only on total informal care (i.e. $U^I(I_1)+\cdots+U^I(I_n)$ can be replaced by $U^I(I_1+\cdots+I_n)$). Thus, we can test whether parents attach a different value to each child or if they value informal care independently on the giver.

## 3.3 The SHARE dataset

We use data from the Survey of Health, Ageing and Retirement in Europe (SHARE[3]). It collects cross-national interdisciplinary data on socio–economic characteristics, health status, family and social networks of persons aged 50 and over. SHARE provides details about respondent's health and about the provision of formal and informal care to the elderly people. Moreover the survey contains specific information about individual and household income and about real and financial assets. SHARE dataset has a number of characteristics that fits our problem very well. First of all, the survey collects two different types of health status measures: self-reported perceived health and objective measures of health. In the physical health module individuals are asked to self report their current health status. Two scales are allowed: the European and the American version of the so–called 'perceived health[4]'. On the other hand, there are many variables that give us an objective measure of health: we consider two generated variables. The first describes the number of limitations with activities of daily living (ADL[5]). The second describes the number of chronic diseases reported by each individual[6]. We use both the subjective and the objective measures in our analysis: we claim that

[3]This paper uses data from release 2 of SHARE 2004. The SHARE data collection has been primarily funded by the European Commission through the $5^{th}$ framework programme (project QLK6-CT-2001-00360 in the thematic programme Quality of Life). Additional funding came from the US National Institute on Ageing (U01 AG09740-13S2, P01 AG005842, P01 AG08291, P30 AG12815, Y1-AG-4553-01 and OGHA 04-064). Data collection in Austria (through the Austrian Science Foundation, FWF), Belgium (through the Belgian Science Policy Office) and Switzerland (through BBW/OFES/UFES) was nationally funded. The SHARE data collection in Israel was funded by the US National Institute on Aging (R21 AG025169), by the German-Israeli Foundation for Scientific Research and Development (G.I.F.), and by the National Insurance Institute of Israel. Further support by the European Commission through the 6th framework program (projects SHARE-I3, RII-CT-2006-062193, and COMPARE, CIT5-CT-2005-028857) is gratefully acknowledged. For methodological details see Börsh-Supan and Jürgens (2005).

[4]Respondent is initially randomised to answer to the European or to the American scale of the self-perceived health. At the end of the health module the respondent answers to the same question, but on the other scale so that we collect both measures for each respondent . The European scale is: 1 Very good, 2 Good, 3 Fair, 4 Bad and 5 Very bad. American scale is: 1 Excellent, 2 Very good, 3 Good, 4 Fair and 5 Poor

[5]Six activities are included: dressing, walking, bathing or showering, eating, getting in and out of bed and using the toilet

[6]The variable corresponds to the followings diseases: hearth attack, high blood pressure or hypertension, high blood cholesterol, a stroke or cerebral vascular disease, diabetes, chronic bronchitis or emphysema, asthma, arthritis, osteoporosis, cancer or malignant tumour, stomach or duodenal ulcer, Parkinson disease, cataracts and hip fracture or femoral fracture

'perceived health' is a measure of well–being that depends not only on the objective health status, but also on social supports and interactions between parents and children. In other words, we use perceived health as a measure of utility derived from caring, while controlling for objective health. This is not the only advantage of using SHARE: the dataset provides information on all our choice variables, hours of informal care, hours of payed job, formal care and expected bequest. Informal care is measured in hours of care received from every children of the respondent per week. SHARE reports three types of help: personal care, help in housekeeping and paperwork. Most of the hours of help provided falls in the second category. There is a wide heterogeneity across different Countries (see table 1): while Central and Northern Countries are those with the higher level of care, Southern ones are those were among those who provide care there is the higher share devoted to personal care. This second feature is in line with different institutional arrangements: Northern Countries, which have the most generous elders' support system, are those where children devote less time to personal care. Unfortunately the sample size do not allow us to exploit the differences among those three types of help: we are going to use the aggregate number of help hours across the three types of help. Thus, cross–country comparison, which is one of the main potentials of SHARE, will mix up institutional settings with cultural differences (see Reher (1998) for a discussion on North–South differences in family ties).

The second choice variable we need is hours of payed job, which are not directly surveyed in SHARE. Nevertheless this does not mean we do not have any information: we know whether each child does work or not, and if he/she works full time or part time. We used CESIFO tables on the average collectively agreed normal annual working time by Country (EIRO data) and on the part–time average hours of work as a percentage of full–time hours (OECD data) to build the working hours variable we need. Parent's first choice variable is formal care. Again, we have three measures of it: hours per week of professional nursing care, hours received of paid domestic help and number of weeks in which the respondent received meals on wheels. Even if we faced the same problem as with informal care data (i.e. too few observations to evaluate each type of help separately), we were not able to aggregate them due to the different units of measure. Thus we included the three variables separately despite the low number of observations.

Last but not least SHARE allows us to build a proper measure of expected wealth: individuals are asked whether they expect to leave more than 50.000 euros as a bequest. Conditional on this first question, they are asked whether they expect to leave any bequest, or if they expect to leave more than 150.000 euros. Using these answers we built an expected bequest measure. Thus, we

Table 3.1: Types of Informal and Formal Care

| | SE | DK | NL | DE | BE | FR | AT | CH | IT | ES | GR | Obs |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Informal care | | | | | | | | | | | |
| personal care | 13 | 11 | 6 | 20 | 19 | 14 | 22 | 1 | 19 | 31 | 23 | 179 |
| % | 4.89 | 5.58 | 5.00 | 6.87 | 9.36 | 11.76 | 11.06 | 1.82 | 19.19 | 41.33 | 11.27 | 9.97 |
| housekeeping | 235 | 179 | 83 | 266 | 186 | 90 | 172 | 41 | 67 | 58 | 136 | 1513 |
| % | 88.35 | 90.86 | 69.17 | 91.41 | 91.63 | 75.63 | 86.43 | 74.55 | 67.68 | 77.33 | 66.67 | 82.77 |
| paperwork | 54 | 27 | 47 | 96 | 53 | 63 | 59 | 24 | 52 | 41 | 133 | 649 |
| % | 20.30 | 13.71 | 39.17 | 32.99 | 26.11 | 52.64 | 29.65 | 43.64 | 52.53 | 54.67 | 65.20 | 35.50 |
| hours of help per week (hours>0) | 1.93 | 2.74 | 2.12 | 4.80 | 5.73 | 10.82 | 5.73 | 3.86 | 17.65 | 14.62 | 7.21 | |
| | Formal care | | | | | | | | | | | |
| nursing care | 41 | 87 | 85 | 45 | 411 | 559 | 60 | 3 | 46 | 110 | 2 | 1449 |
| % | 1.35 | 5.10 | 2.86 | 1.53 | 10.84 | 17.72 | 3.23 | 0.30 | 1.82 | 4.79 | 0.07 | 5.14 |
| hours per week | 8.34 | 9.31 | 7.88 | 14.11 | 4.25 | 3.50 | 28.65 | 1.00 | 4.52 | 2.66 | 30.50 | |
| paid domestic help | 131 | 166 | 262 | 46 | 375 | 219 | 59 | 10 | 68 | 94 | 3 | 1433 |
| % | 4.30 | 9.72 | 8.80 | 1.56 | 9.89 | 6.94 | 3.17 | 1.00 | 2.70 | 4.09 | 0.10 | 5.09 |
| hours per week | 6.27 | 2.35 | 4.44 | 14.54 | 5.35 | 9.86 | 11.85 | 8.50 | 15.65 | 12.60 | 22.33 | |
| meals on wheels | 39 | 46 | 33 | 42 | 61 | 34 | 38 | 0 | 0 | 4 | 0 | 297 |
| % | 1.28 | 2.69 | 1.11 | 1.43 | 1.61 | 1.08 | 2.04 | 0.00 | 0.00 | 0.17 | 0.00 | 1.05 |
| # of weeks | 16.73 | 27.31 | 19.53 | 20.47 | 19.38 | 21.67 | 29.39 | 0.00 | 0.00 | 3.75 | 0.00 | |

Informal Care givers % refers to children who give help. Formal Care givers % to all sample have the 'perfect' measure: we do not have to rely on current wealth to infer expected bequest, thus the variable we use is exogenous by construction.

The last characteristic of SHARE we have to consider is that the data potentially provides information on three generations: respondents, their children and their parents. We focus on respondents and their children since health measures are available only for respondents. This choice may induce a bias: the sampling scheme is based on the respondents, thus results on respondent's children decision may not be representative for the whole children population. As far as we know the only author that tackled this issue in SHARE is Crespo (2007), who uses SHARE to analyse the role of informal care activity on female labor supply. She exploits information on both samples, finding qualitatively similar results.

## 3.4 The Econometric specification

Before going to the specification of the econometric model we set up to test the empirical implications, some words must be spent on a hidden assumption of the model: throughout the previous sections we didn't discuss the living arrangement choice of the children. Whether the child co–resides with his parents or not does change his caring choices. Living arrangements of the elderly has been previously studied by Börsh-Supan et al. (1988); Börsh-Supan et al. (1993) relate it to wealth and health while Alessie et al. (2006) relate it to saving choices. In the present paper we assume living arrangement to be predetermined with respect to the caring choice. This is clearly a simplifying assumption, nevertheless it is not unreasonable: the hypothesis is that living arrangement depend on marriage, education or early job market decisions, which can be safely considered as predetermined when individuals decide how to allocate time to elders' care. Co–residing children are on average younger than thirty years old, much less than non cohabiting ones[7]. Further on, they tend to help less. This difference in the two subsample may be due to the fact that cohabiting children still have to decide about their adult life living arrangement and, at the same time, they have younger parents which do not need care. Thus descriptive statistics provide indirect support to our assumption.

The main objective of the empirical analysis is to estimate simultaneously how children allocate time to informal care, $IC_i$ and paid work $WT_i$, together with the effect on their parents' utility, $Ph$. The system of simultaneous equations we want to estimate is therefore the following:

[7]descriptive statistics are reported in the appendix

$$
\begin{array}{rcl}
Ph & = & \beta_{1,1}IC_1 + \beta_{1,2}IC_2 + \beta_{1,3}IC_3 + \beta_{1,4}IC_4 + \\
 & & +\beta_{1,5}Ph_{SP} + X\boldsymbol{\beta}_{1,6} + X_P\boldsymbol{\beta}_{1,7} + u_1 \\
IC_1 & = & \gamma_2 \sum_{i\neq 1} IC_i + X\boldsymbol{\beta}_{2,6} + X_{IC}\boldsymbol{\beta}_{2,8} + \beta_{2,9}WT_1 + u_2 \\
\vdots & & \vdots \\
IC_4 & = & \gamma_5 \sum_{i\neq 4} IC_i + X\boldsymbol{\beta}_{5,6} + X_{IC}\boldsymbol{\beta}_{5,8} + \beta_{5,9}WT_4 + u_5 \\
WT_1 & = & \beta_{6,1}IC_1 + X\boldsymbol{\beta}_{6,6} + X_{WT}\boldsymbol{\beta}_{6,14} + u_6 \\
\vdots & & \vdots \\
WT_4 & = & \beta_{9,1}IC_4 + X\boldsymbol{\beta}_{9,6} + X_{WT}\boldsymbol{\beta}_{9,14} + u_9
\end{array}
\tag{3.19}
$$

Where $X$ is a matrix of $n$ observation over $k_X$ exogenous variables common to all equations (as an example country dummies), $X_P, X_{IC}, X_{WT}$ are exogenous variables which appear only on the parent's equation, informal care equations and working hours equations respectively. $Ph_{SP}$ is the health status of the spouse. Since each spouse enters the sample, $Ph_i$ is the dependent variable for the $i$th observation, while it is $Ph_{SP}$, a regressor, for the $i$th spouse observation. Then, we assume $u_{1,i}, u_{1,j}$ to be correlated if $i, j$ belong to the same household.

The economic model imposes restrictions on the system which allow us to estimate the parameters in several steps:

1. First, the labor force participation choice of child $i$ is endogenous only for $i$'s informal care choice. In terms of system (3.19), $WT_i$ appears as a regressor only on $IC_i$, while the only endogenous regressor in each $WT_i$ equation is $IC_i$. Then if we assume $\boldsymbol{u}$ to be IID up to the household level, we can use the usual two step procedure: we instrument $WT_i$ with years of education and number of children, then we plug $\hat{WT}_i$s predictions in $IC_i$ equations:

$$
\begin{array}{rcl}
Ph & = & \beta_{1,1}IC_1 + \beta_{1,2}IC_2 + \beta_{1,3}IC_3 + \beta_{1,4}IC_4 + \\
 & & +\beta_{1,5}Ph_{SP} + X\boldsymbol{\beta}_{1,6} + X_P\boldsymbol{\beta}_{1,7} + u_1 \\
IC_1 & = & \gamma_2 \sum_{i\neq 1} IC_i + X\boldsymbol{\beta}_2, 6 + X_{IC}\boldsymbol{\beta}_2, 8 + \beta_{2,9}\hat{WT}_1 + u_2 \\
\vdots & & \vdots \\
IC_4 & = & \gamma_5 \sum_{i\neq 4} IC_i + X\boldsymbol{\beta}_{5,6} + X_{IC}\boldsymbol{\beta}_{5,8} + \beta_{5,9}\hat{WT}_4 + u_5
\end{array}
\tag{3.20}
$$

2. In each $IC_i$ equation informal care provided by $i$'s siblings ($IC_j$s) enter only through $\sum_{j\neq i} IC_j$. From an economic point of view, this is so since what matters on each child's decision is the aggregate supply of

care by his siblings. Endogeneity problem is still there since $\sum_{j \neq i} IC_j$ is a function of endogenous regressors. In order to solve it we can use the fact that children ordering is exogenous: children ordering is descending in age. Then, $IC_i \ \forall i$ can be thought of as sampled from the same population. This fact allows us to stack $IC_i$, $WT_i$ and all the demographics in $X$ which refers to each child. The last four equations of (3.20) can be rewritten as:

$$IC = \gamma \Pi IC + X\boldsymbol{\beta}_{2,6} + X_{IC}\boldsymbol{\beta}_{2,8} + \beta_{2,9}\hat{WT} + u_2 \tag{3.21}$$

Where $[\pi]_{ij} = 1$ if $i \neq j$ and $i, j$ are siblings.

Equation (3.21) is linear in means and the endogeneity of $\Pi IC$ is due to the so called 'reflection problem' (see Manski (1993)): $IC$ appears on both sides of the equation. We can use spatial econometrics methods to estimate $\gamma$: Kelejian and Prucha (1998) suggest a GMM estimator, which has been used in a simultaneous equations setting in Pasini (2006). Since we assume $u_2$ to be IID, the GMM estimator turns out to be equal to a 2SLS estimator with instruments for $\Pi IC$ chosen among $\Pi X$ and $\Pi X_{IC}$.

We have an additional problem at this step: a high number of children do not provide any help. Thus data are clearly censored and they may suffer of a sample selection problem. Therefore we estimate each equation with a Heckman twostep procedure (see Vella (1998) for a general discussion on models with sample selection), where individuals first choose whether to help or not, then they choose how much time to spend caring[8]. Consistently with the dependent variable, the total number of other siblings helping enters the set of first stage regressors, while the total number of hours provided by other siblings enter the second stage.

3. The previous step's result can be used again as a preliminary step: we obtain predicted value of $\Pi \hat{IC}_i$ and we use it to estimate the parameters in the first equation of (3.19)

Standard errors should be computed taking into account this procedure. We didn't want to impose further structure on the distribution of the $\boldsymbol{u}$ vector and at the same time we were worried to account for potential heteroskedasticity. Therefore, we used non parametric bootstrapping to obtain

[8]We chose not to use ML estimate because endogeneity of $WT$ makes convergence hard to get

standard errors and p–values both at the second and at the last step. We can safely bootstrap on each step separately thanks to the simple residuals vector of the reduced form of (3.20).

## 3.5 Empirical Results

Results of the 'children' part of the estimation procedure are reported in the appendix, i.e. the Heckman estimates of children's choice, where three variables are treated as endogenous: in the first stage probit, hours of payed job and the number of siblings helping; in the second stage linear regression, hours of payed job and the total number of hours provided by other siblings.

The two main findings are that labor force participation effect is significant and negative on both stages, while social interaction's effect is significant only on the decision to care, but not on the care's intensity. Since both hours of work and social interaction parameters are instrumented, it's crucial that the chosen instruments are valid and relevant. All the instruments pass a Hansen J-test of over-identification run on the two stages separately (J–stat on first stage, 6.387, p–value 0.2704. J–stat on second stage, 11.059 p–value 0.0502). Years of education and number of children of each child are relevant and they have the expected signs on first stage regressions. Both $\Pi hourshelp$ and $\Pi childhelp$ are instrumented with the sums over the gender dummy, age, proximity, year of education and a dummy for not being married. Instruments are relevant on both first stage regressions. Further, instruments are chosen appropriately: those supposed to instrument work hours are not significant on the social interaction first stage equations, and vice versa[9]. Hausman test rejects exogeneity of other children's care variables and hours of work: test statistic is 136.55, the p–value lower than $10^{-7}$. Last thing to check about the estimation procedure is the relevance of sample selection: the Mills' $\lambda$ is significant at 5% level.

Sign and significance suggest that informal care provided by each child and informal care of the other siblings are substitutes. This last finding is particularly relevant: interaction among children are significant and their magnitude is not negligible: an additional sibling helping induce a reduction of 10.6% on the probability of providing help, thus determinaning a large fraction of the selection. The sign is reversed on the second stage equation. Among those who helps (i.e., we consider the marginal effect on the observed sample), an additional child helping implies 9.03 more hours spent providing care. This may be due to the fact that once a child decide to help, the amount of time spent helping depend on parent's health status, other things

[9] first stage equation results are again reported in the appendix

being equal. The effect of an additional hour of payed work is quite small, and its significance is strongly related with the gender dummy. Hours of payed job coefficient is significant at 10% and negative in the choice equation, confirming that working and helping are substitutes. The sign is oddly reversed on the second stage, but it's no more significant. This is due to the correlation with gender, which is positive and significant at the second stage: gender is a major determinant of labor force participation, thus it's likely that the two dummies capture related phenomena. This is confirmed by the fact that in a preliminary version of the paper we used gender as an instrument for labor force participation and payed work hours coefficient in both stages were negative and strongly significant.

Substitutability among children's help together with non–significance of expected bequest rejects the hypothesis of strategic bequest motive for care.

Country dummies[10] are in general significant. Signs are all negative in the selection equation, i.e. on the decision whether to help or not, coherently with the descriptive statistics' evidence. Marginal effects on the care intensity equation (thus corrected by the selection mechanism) have signs which are coherent with sociological explanations as in Reher (1998) and with institutional differences: Northern countries (Sweden, Denmark and The Netherlands) have lower intensity compared to Germany, southern Countries (Italy, France, Greece and Spain) a positive one. Signs of other Central European Countries are mixed. Nevertheless the non significance of many Country dummies in the second stage warn to interpret these results with caution.

Other controls have the expected sign: the provision of care depends positively on the number of parent's health diseases, on gender and age of the son. Single children provide more help than those who have siblings, and there's a positive and significant relation between care and proximity of children from parent's house: the nearest child helps more than the child who lives far from parents. Parent's household income reduce the probability of helping, and can be interpreted as a proxy for formal care (note that formal care variables turn out to be poorly significant, maybe for a quasi-collinearity reason similar to the gender/hours of work one). Money gifts and support from parents towards children induce a higher probability of providing care. This transfer cannot be confused with expected bequest: in our model bequest or trasfers used as a mean to induce a higher provision of care by parents must take place after care provision.

Table 5 reports the results of the second part of the estimation procedure: 2SLS estimates of the perceived health status of parent for both scales. Remeber that perceived health (and well beig) scales are such that the higher

[10] Germany is the excluded one

the dependent variable, the worse is health (and well being). The perceived condition worsen for older parents while is better for more educatated. As expected, there is a high positive correlation between the self–reported health and the objective health, both in terms of ADL and chronic diseases. We control for formal care–giving, for household income and expected bequest. With respect to income and wealth, the perception of health condition is better the higher the family income. The main result is that there is a negative effect of informal care–giving, which is significant with both the european and the US scale: after controlling for objective health, parent's status is better off when children help him. Furthermore, we tested whether parents value informal care from each child differently: we re–run the perceived health equation dividing help from each child and tested whether the parameters were equal or not. We accepted the test with the EU scale while we reject with the US one. These results do not allow us to get a clear conclusion. Nevertheless the significance of the total informal care provision supports the hypothesis that parents value informal care more than formal one.

About other explanatory variables, spouse's perceived health has a positive marginal effect, while the effect of the spouse's objective health is negative. This result provide indirect evidence on our claim that perceived health is a well–being measure: individual satisfaction grows with the spouse's one (which fits with an altruistic utility function), while the objective health effect may account for a 'comparison' effect: if the spouse suffer of chronic diseases, the individual tend to value more his relatively healthier status. Country dummies are all negative, again in line with the observation that a large fraction of children who help are from Germany.

Further on, our claim is that perceived health, $Ph_i$, is a good measure of utility derived by care consumption. SHARE provide us also a direct measure of well being, i.e. a measure of subjective overall satisfaction. Since subjective perception of well being and health status are logically and empirically positively correlated, as a robustness check we repeat our analysis on the well being measure, and we find qualitatively similar results with a lower significance, thus supporting the idea that perceived health is a more precise measure of satisfaction derived from health. The second possible objection to our choice of perceived health as a well being measure is the reverse: it may simply capture health status, with no link to well being perception. If this was the case, once controlling for objective measures of health and differences in response scales (captured by country dummies), other determinants of individual utility should not be significant. We showed that this is not the case, thus confirming that self reported health is not just another measure of health status.

## 3.6 Conclusions

We developed a model for the interaction among parents and their children facing caring decisions. Children decide how to allocate time to payed work, informal care to their parents and leisure. Decision is taken strategically, i.e. each child's choice depends on his siblings' behavior. The main finding for this first part of the model is that time devoted to informal care by child $i$ and child $j$ are substitutes. Parents' utility depends both on formal care bought on the market and informal care provided by his children. Parents value informal care more than children do, therefore at any equilibrium they would like to induce children to increase informal care supply. We tested for bequest as a possible mean for parents to induce such extra supply by children. Estimation results do not support the strategic bequest motive, therefore once the interaction effect among children is controlled for, then positive and heterogeneous informal care provision is due to altruism and sociological and cultural attitudes. Further on, we do not find evidence of substitutability of formal and informal care. While the first result is useful to understand the dynamic of choices within households, the second one provides an important policy implication: formal care is not an instrument to improve labor force participation. As an example, consider a mother of a baby that also has to take care of an elder disabled parent. We claim that her reservoir wage depends on both types of care, but the State cannot reduce it by providing formal care for the elderly.

We used self reported health as a measure of well being: after controlling for formal care and objective health status, such a measure is still informative and captures parent's utility derived from care consumption. This has a relevant empirical implication: the good news are that we can extract more information than just health conditions from subjective questions, the bad news are that, once we rely on those measures instead of objectively measured health, results may be biased.

# Appendix

## A Estimation results and Descriptive statistics

Table 3: First stage 2SLS regressions

| | hours of job | | other's help | | other's hours of help | |
|---|---|---|---|---|---|---|
| years of education | 0.658 | *** | -0.001 | * | -0.016 | |
| | (0.034) | | (0.001) | | (0.015) | |
| # of children | -1.290 | *** | -0.000 | | -0.124 | |
| | (0.103) | | (0.002) | | 0.045 | |
| other children's gender | -0.305 | ** | -0.000 | | 0.241 | *** |
| | (0.145) | | (0.003) | | (0.063) | |
| other children's age | -0.011 | ** | 0.002 | *** | 0.016 | *** |
| | (0.005) | | (0.000) | | (0.002) | |
| other's single condition | -0.892 | *** | -0.009 | *** | -0.019 | |
| | (0.160) | | (0.005) | | (0.069) | |
| other years of education | 0.062 | *** | -0.001 | ** | -0.048 | *** |
| | (0.017) | | (0.000) | | (0.007) | |
| other proximity | -0.921 | *** | 0.024 | *** | 0.584 | *** |
| | (0.195) | | (0.004) | | (0.084) | |

Table 4: Two-stage Heckman with endogenous regressors

| | Second stage | | | First stage | | |
|---|---|---|---|---|---|---|
| | hours of help | | | help from child | | |
| | m.eff | coeff | | m.eff | coeff | |
| hours of work | 0.180 | 0.117 | | -0.001 | -0.009 | ** |
| | | (0.167) | | | (0.005) | |
| # siblings helping | | | | -0.106 | -1.053 | *** |
| | | | | | (0.305) | |
| hours of help from other siblings | 9.038 | 1.796 | | | | |
| | | (1.351) | | | | |
| gender | 4.130 | 3.939 | ** | -0.003 | -0.028 | |
| | | (1.761) | | | (0.048) | |
| age | -0.030 | 0.170 | ** | 0.003 | 0.029 | *** |
| | | (0.081) | | | (0.002) | |
| single | 3.249 | 2.176 | * | -0.015 | -0.156 | *** |
| | | (1.256) | | | (0.033) | |
| Austria | 0.612 | -0.136 | | -0.010 | -0.109 | ** |
| | | (1.080) | | | (0.055) | |
| Sweden | -0.372 | -0.252 | ** | -0.023 | -0.273 | *** |
| | | (1.085) | | | (0.049) | |
| The Netherlands | -0.693 | -3.728 | *** | -0.033 | -0.441 | *** |
| | | (1.348) | | | (0.061) | |
| Spain | 8.330 | 1.822 | | -0.052 | -0.946 | *** |
| | | (3.900) | | | (0.073) | |
| Italy | 11.593 | 6.250 | | -0.047 | -0.777 | *** |
| | | (4.100) | | | (0.068) | |
| France | 5.525 | 1.583 | | -0.040 | -0.573 | *** |
| | | (2.624) | | | (0.062) | |

Table 4: Two-stage Heckman with endogenous regressors

| | Second stage | | | First stage | | |
|---|---|---|---|---|---|---|
| | hours of help | | | help from child | | |
| | m.eff | coeff | | m.eff | coeff | |
| Denmark | -0.406 | -0.053 | | 0.005 | 0.051 | |
| | | (1.241) | | | (0.055) | |
| Greece | 2.629 | -0.050 | | -0.030 | -0.390 | *** |
| | | (1.391) | | | (0.056) | |
| Switzerland | -0.664 | -2.749 | | -0.024 | -0.303 | *** |
| | | (1.838) | | | (0.080) | |
| Belgium | 1.574 | -1.672 | | -0.036 | -0.472 | *** |
| | | (1.680) | | | (0.055) | |
| # adl | -0.939 | 0.374 | | 0.019 | 0.191 | *** |
| | | (1.033) | | | (0.022) | |
| # spouse's adl | 2.302 | 2.788 | | 0.007 | 0.071 | *** |
| | | (2.817) | | | (0.023) | |
| hours of nursing care | -0.062 | -0.029 | | 0.000 | 0.005 | |
| | | (0.150) | | | (0.003) | |
| hours of paid professional help | 0.052 | 0.052 | | 0.000 | 0.000 | |
| | | (0.283) | | | (0.002) | |
| weeks received meals-on-wheels | -0.071 | 0.011 | | 0.001 | 0.012 | *** |
| | | (0.028) | | | (0.002) | |
| proximity | 7.054 | 9.280 | *** | 0.033 | 0.323 | *** |
| | | (2.946) | | | (0.050) | |
| only child | 1.945 | 2.208 | * | 0.004 | 0.038 | |
| | | (1.206) | | | (0.053) | |
| expected bequest | -0.583 | -0.540 | | 0.001 | 0.006 | |
| | | (0.465) | | | (0.012) | |
| # of chronic diseases | | | | 0.009 | 0.091 | *** |
| | | | | | (0.010) | |
| # of spouse's chronic diseases | | | | 0.000 | 0.004 | *** |
| | | | | | (0.000) | |
| household income | | | | -0.005 | -0.052 | *** |
| | | | | | (0.008) | |
| household wealth | -0.080 | -0.007 | | -0.001 | -0.013 | *** |
| | | (0.101) | | | (0.003) | |
| financial transfers | -1.743 | 0.961 | | 0.018 | 0.165 | *** |
| | | (1.146) | | | (0.036) | |
| costant | | -15.793 | * | | -1.774 | *** |
| | | (9.240) | | | (0.226) | |
| sample size | 26,867 | | | | | |
| uncensored obs | 1,828 | | | | | |
| $\lambda$ | 6.582 | ** | | | | |
| | (2.771) | | | | | |

Note: bootstrapped standard errors robust in parentheses.
(*) Significant at 10%. (**)Significant at 5%. (***)Significant at 1%
Germany is the excluded country

Table 5: Perceived health equation

| | EU scale | | US scale | | Well-being | |
|---|---|---|---|---|---|---|
| age | 0.004 | *** | 0.006 | *** | -0.004 | |
| | (0.001) | | (0.001) | | (0.001) | |
| gender | -0.005 | | 0.021 | | 0.022 | * |
| | (0.012) | | (0.014) | | (0.012) | |
| years of education | -0.022 | *** | -0.025 | *** | -0.006 | *** |
| | (0.002) | | (0.002) | | (0.002) | |
| partner | -0.207 | *** | -0.311 | *** | -0.578 | *** |
| | (0.027) | | (0.034) | | (0.030) | |
| Austria | -0.144 | *** | -0.246 | *** | -0.044 | * |
| | (0.027) | | (0.032) | | (0.024) | |
| Sweden | -0.326 | *** | -0.687 | *** | -0.071 | *** |
| | (0.025) | | (0.027) | | (0.002) | |
| The Netherlands | -0.264 | *** | -0.307 | *** | -0.263 | *** |
| | (0.023) | | (0.028) | | (0.022) | |
| Spain | -0.168 | *** | -0.225 | *** | -0.107 | ** |
| | (0.031) | | (0.034) | | (0.032) | |
| Italy | -0.087 | *** | -0.154 | *** | 0.133 | *** |
| | (0.027) | | (0.031) | | (0.027) | |
| France | -0.248 | *** | -0.214 | *** | 0.115 | ** |
| | (0.023) | | (0.027) | | (0.025) | |
| Denmark | -0.301 | *** | -0.553 | *** | -0.339 | |
| | (0.028) | | (0.033) | | (0.024) | |
| Greece | -0.317 | *** | -0.322 | *** | -0.046 | |
| | (0.024) | | (0.027) | | (0.024) | |
| Switzerland | -0.365 | *** | -0.343 | *** | -0.130 | * |
| | (0.032) | | (0.040) | | (0.031) | |
| Belgium | -0.308 | *** | -0.341 | *** | -0.100 | *** |
| | (0.023) | | (0.025) | | (0.021) | |
| # adl | 0.298 | *** | 0.287 | *** | 0.099 | *** |
| | (0.014) | | (0.013) | | (0.014) | |
| # spouse's adl | -0.009 | | 0.000 | | 0.022 | |
| | (0.014) | | (0.016) | | (0.014) | |
| spouse's perceived health | 0.150 | *** | 0.162 | *** | 0.292 | *** |
| | (0.012) | | (0.011) | | (0.016) | |
| # of chronic diseases | 0.249 | *** | 0.293 | *** | 0.045 | *** |
| | (0.005) | | (0.005) | | (0.005) | |
| # of spouse's chronic diseases | -0.042 | *** | -0.051 | *** | -0.003 | |
| | (0.006) | | (0.007) | | (0.005) | |
| help from children | -0.005 | *** | -0.008 | *** | -0.004 | ** |
| | (0.001) | | (0.001) | | (0.002) | |
| hours of nursing care | 0.002 | | 0.003 | * | 0.002 | ** |
| | (0.003) | | (0.002) | | (0.001) | |
| hours of paid professional help | 0.002 | | 0.003 | | -0.001 | |
| | (0.002) | | (0.002) | | (0.002) | |

Table 5: Perceived health equation

| | EU scale | | US scale | | Well-being | |
|---|---|---|---|---|---|---|
| weeks received meals-on-wheels | 0.002 | | 0.001 | | 0.001 | |
| | (0.002) | | (0.002) | | (0.001) | |
| household income | -0.012 | *** | -0.016 | *** | 0.013 | *** |
| | (0.004) | | (0.006) | | (0.005) | |
| household wealth | -0.007 | *** | -0.005 | ** | -0.002 | |
| | (0.002) | | (0.002) | | (0.002) | |
| expected bequest | -0.026 | *** | -0.037 | *** | -0.025 | *** |
| | (0.005) | | (0.006) | | (0.005) | |
| only child | 0.050 | *** | 0.057 | *** | 0.042 | *** |
| | (0.013) | | (0.015) | | (0.013) | |
| costant | 2.583 | *** | 3.262 | *** | 2.581 | *** |
| | (0.101) | | (0.123) | | (0.105) | |
| sample size | 16248 | | 16242 | | 10323 | |

Table 6: Sample characteristics of care-giving children

| | SE | DK | NL | DE | BE | FR | AT | CH | IT | ES | GR |
|---|---|---|---|---|---|---|---|---|---|---|---|
| # of observations (tot 26867) | 3,597 | 1,761 | 2,523 | 2,508 | 3611 | 2624 | 1832 | 945 | 2471 | 2270 | 2725 |
| % co–residing | 5.95 | 5.57 | 12.72 | 10.41 | 15.59 | 13.61 | 11.30 | 13.76 | 34.80 | 30.62 | 33.61 |
| | | | | | | | | | | | |
| average age: | | | | | | | | | | | |
| co–residents | 21.87 | 23.50 | 23.14 | 26.59 | 25.52 | 24.00 | 29.54 | 23.48 | 28.70 | 29.62 | 25.66 |
| non co-resident | 37.36 | 37.82 | 36.03 | 38.13 | 37.63 | 37.15 | 38.69 | 37.82 | 38.54 | 38.79 | 38.43 |
| | | | | | | | | | | | |
| working hours: | | | | | | | | | | | |
| men | 30.99 | 29.07 | 30.86 | 30.30 | 30.03 | 27.97 | 33.65 | 36.51 | 30.94 | 32.59 | 30.49 |
| women | 25.84 | 23.10 | 21.73 | 22.28 | 25.61 | 23.98 | 25.39 | 25.79 | 21.36 | 22.38 | 20.81 |
| | | | | | | | | | | | |
| years of education | 12.42 | 13.85 | 13.19 | 14.52 | 11.36 | 12.56 | 12.66 | 13.46 | 11.74 | 10.69 | 12.74 |
| number of children | 1.23 | 1.24 | 0.94 | 0.98 | 1.14 | 1.12 | 1.08 | 0.93 | 0.81 | 0.93 | 0.83 |
| single (%) | 33.53 | 49.12 | 38.92 | 46.05 | 34.89 | 48.93 | 46.29 | 52.06 | 43.18 | 40.79 | 48.51 |
| | | | | | | | | | | | |
| Proximity to parents (%): | | | | | | | | | | | |
| same building | 0.50 | 0.68 | 0.48 | 7.54 | 1.02 | 0.69 | 8.52 | 3.17 | 7.49 | 3.30 | 9.28 |
| less than 1 km | 8.59 | 7.50 | 10.74 | 8.81 | 12.85 | 8.00 | 11.52 | 8.99 | 12.71 | 21.06 | 11.71 |
| less than 5 km | 16.24 | 15.11 | 24.02 | 16.95 | 20.83 | 12.12 | 17.90 | 14.81 | 14.12 | 13.88 | 11.34 |
| less than 25 km | 22.02 | 25.55 | 22.00 | 20.57 | 27.31 | 20.12 | 22.54 | 25.08 | 14.20 | 11.94 | 12.51 |
| less than 100 km | 17.60 | 22.32 | 16.69 | 13.60 | 15.51 | 16.43 | 12.77 | 17.88 | 6.48 | 7.36 | 4.59 |
| less than 500 km | 18.71 | 18.80 | 10.82 | 15.15 | 4.26 | 13.99 | 11.08 | 11.32 | 3.04 | 6.17 | 10.02 |
| more than 500 km | 10.40 | 4.49 | 2.54 | 6.98 | 2.63 | 15.05 | 4.37 | 4.97 | 7.16 | 5.68 | 6.94 |
| | | | | | | | | | | | |
| only child (%) | 7.53 | 7.95 | 6.42 | 15.03 | 12.13 | 11.01 | 13.86 | 8.78 | 11.41 | 8.50 | 9.54 |
| help to parents (%) | 7.40 | 11.19 | 4.76 | 11.60 | 5.62 | 4.54 | 10.86 | 5.82 | 4.01 | 3.30 | 7.49 |
| help from daughter | 40.23 | 41.12 | 49.17 | 54.30 | 55.67 | 57.98 | 53.77 | 61.82 | 63.64 | 65.33 | 57.84 |

# Conclusion

The message of this dissertation is that social interactions matter. I present three economic models that share the common feature that they account for the simultaneous and inter–dependent choices of reference group members. In the first chapter a demand system with social interactions is presented. The model allows individual allocations to depend on reference group average behavior. Empirical evidence confirm this dependence: social interaction effect is large and its magnitude varies with the visibility of each good. In the second chapter I study market insurance demand when individuals can enter non–market agreements with their peers. The theoretic model implies that moral hazard involved in informal agreements decreases with the density and cohesiveness of the social network each individual is part of, and therefore insurance demand grows with the stock of social capital. The model is tested on Italian data, confirming the role of social capital. Further on, it explains part of the spatial correlation among provinces in premia per capita. The last chapter sets up a game theoretical model to study how adult children choose how much time to spend caring for their parents. Results confirm that children behave strategically: the more other children help, the less each child provide care to their parents.

Throughout the chapters estimation is carried on with a new procedure that relies on tools taken from the spatial econometrics literature. Such an approach solves the issues arising from Manski's reflection problem as other methods do but has the advantage of being applicable to population–wide datasets: this is not true for maximum likelihood estimation. The method do not depend on the particular application chosen: The three chapters differ substantially on this point, underlining the second advantage of the proposed procedure: it can be applied on any context in which social interactions are potentially relevant and agents can be represented as points on a $N$–dimensional lattice. Thus, the possible research directions stemming from the present work are both applied and methodological. As an example, a potentially interesting application are asset allocation problems: market participation decision may well depend on social interactions. The procedure can be used in other fields as well, i.e. in models that assess the determinants of crime, or how expectations on educational attainments arise among others. Further on, the method is applicable to models of strategic behavior that do not relate directly to individual social interactions. As an example it could be used to model firms' choices with respect to oligopolistic and cartel behavior, or to merge and acquisitions.

From a methodological point of view, it would be interesting to extend the results to account for endogenous peer formation. In the proposed procedure the reference group may be unknown, but it must be fixed along time and exogenous: relaxing these assumptions could lead to a promising empirical counterpart to the the growing theoretic literature on network formation.

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