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

Giovanni Millo*, Giacomo Pasini†

This version: February 9, 2007

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.
JEL Classification: C21, D85, G22, Z13
Keywords: Insurance, Social Capital, Network stability, Spatial Panel data model

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

*Research Dept., Assicurazioni Generali SpA and University of Trieste. e–mail giovanni_millo@generali.com.

†Economics Dept., University of Venice and SSAV, School for Advanced Studies in Venice; corresponding author. Dipartimento di Scienze Economiche, Cannaregio 873 – 30121 Venice, Italy. Tel: +39 041 2349125; e–mail giacomo.pasini@unive.it; homepage: http://venus.unive.it/pasinigi. Authors wish to thank Agar Brugiavini, Stefano Magrini, Paolo Pin, and participants to seminars in Venice and Rimini for their useful comments.

than a precise concept. Further on, the study of social capital has a lot to do with Italy: the seminal book by Putnam [15] 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. [12] 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 [2] 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 show that the lower the level of moral hazard, the higher the aggregate 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. Lenzi and Millo [13] 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 [7] 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.

The paper is structured as follows: the second section describes Arnott and Stiglitz's [2] 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. Last section concludes.

2 The model

Arnott and Stiglitz [2] 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 β and receive a net payout α in case the accident occurs. Assuming a well behaved (increasing and strictly concave), separable and event–independent utility function, individuals maximize their expected utility

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

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, β, 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 δ 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:

$$
\begin{aligned}
EU_i^{NMO} &= (1-p(e_i))(1-p(e_j))U(w-\beta) + p(e_i)p(e_j)U(w-d+\alpha) \\
&\quad + (1-p(e_i))p(e_j)U(w-\beta-\delta) \\
&\quad + p(e_i)(1-p(e_j))U(w-d+\alpha+\delta) \\
&\quad - e_i \\
&= (1-p(e_i))(1-p(e_j))u_0 + p(e_i)p(e_j)u_1 \\
&\quad + (1-p(e_i))p(e_j)u_2 + p(e_i)(1-p(e_j))u_3 - e_i
\end{aligned}
\tag{2}
$$

Individuals maximize their utility considering α and β and therefore the contract's price q as fixed: they perceive that if they enter a mutual contract they can buy extra insurance at the market price q. They choose δ, 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 δ if the partner has an accident and he doesn't, while he receives an extra payoff δ 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 the individuals to provide non market insurance up to full coverage to augment the risk sharing opportunity. Individuals choose δ and e_i given $q(\alpha, \beta)$. Again each of them assume the peers entering non–market agreements are 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) simplifies to

$$
EU^{NMO} = (1-p)^2 u_0 + p^2 u_1 + p(1-p)(u_2+u_3) - e \tag{3}
$$

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 (3) and taking the derivative it's clear that expected utility is increasing in δ between 0 and the utility–maximizing δ^*. The key difference with the previous case is that since there is perfect peer monitoring there is no moral hazard in non–market agreements: therefore a positive value of δ implies a positive level of e. Furthermore, from first order conditions, it is easy to prove that the effort is not only positive but also increasing in δ between 0 and the optimal level δ^* as long as $p(e) < \frac{1}{2}$[1]. The effort is nevertheless lower than without non–market agreement since the coverage is now higher. The insurance company will react to the effort reduction but won't be displaced: it maximizes its expected utility with respect to β and α under the zero profit condition $\alpha = \frac{1-p}{p}\beta$ and assuming that individuals maximize their own utility (i.e., $e = e^*$ and $\delta = \delta^*$). Up to now we proved that with peer monitoring at the new equilibrium individuals will enjoy full coverage at the price of substituting part (but not all) of the coverage provided by a risk–neutral insurer with coverage from a risk averse one. We can go further: we can prove non–market agreements are welfare enhancing. We must show that $EU^M < EU^{NMO}$. From (1) and (3),

$$\begin{array}{rcl} (1-p)u_0 + pu_1 - e & < & (1-p)^2 u_0 + p^2 u_1 + p(1-p)(u_2+u_3) - e \\ u_0 + u_1 & < & u_2 + u_3 \\ u_0 - u_2 & < & u_3 - u_1 \\ u(w-\beta) - u(w-\beta-\delta) & < & u(w-d+\alpha+\delta) - u(w-d+\alpha) \end{array} \tag{4}$$

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 is crucial 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 α, β and for any positive level of non–market coverage δ up to δ^*, individual expected utility is higher than without non market agreements:

$$E_j^{NMO}[U|\boldsymbol{X}_j] > E_j^M[U|\boldsymbol{X}_j] \tag{5}$$

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.

Arnott and Stiglitz were interested in the welfare effects of non–market agreements. We want to investigate how the demand for insurance changes. Individual expected utility without any insurance contract is

$$E_j[U|\boldsymbol{X}_j] = (1 - p(e_j))U_j(w_j|\boldsymbol{X}_j) + p(e_j)U_j(w_j - d|\boldsymbol{X}_j)$$

In general, j is willing to buy insurance if

$$E_j[U|\boldsymbol{X}_j] < E_j^Y[U|\boldsymbol{X}_j]$$

where Y stands for M if only market insurance is available and $Y = NMO$ if there are also non–market agreements. The question is whether there exist 'marginal' js that are willing to buy market insurance only if non–market insurance is also provided.

Suppose non–market agreements are not available. If the insurer is able to discriminate clients' preferences toward insurance perfectly but for the unobserved effort, those marginal js cannot exist: the insurer can offer different contracts α_X, β_X to groups of homogeneous individuals clustering them on the basis of $\boldsymbol{X}$. If the insurance company is willing to sell any contract within a group, it offers a contract α_X, β_X such that everybody would maximize utility buying the available contract. In other words: within each group either nobody buys any coverage, or everybody does.

Things are different in the more realistic case in which the insurer is able to discriminate clients based on individual characteristics up to a certain level. This means that not all $x \in \boldsymbol{X}$ are observable by the insurer, that is forced to pool clients with different preferences together. At equilibrium the insurer offers a different contract α_X, β_X to each group such that

$$E_j^M[U|\boldsymbol{X}_j, \alpha_X, \beta_X] > E_j^M[U|\boldsymbol{X}_j, \alpha, \beta] \quad \forall(\alpha, \beta) \tag{6}$$

but since the different clients are pooled together α_X, β_X can't be optimal for everybody:

$$\exists j : \quad E_j[U|\boldsymbol{X}_j, \alpha_X, \beta_X] > E_j^M[U|\boldsymbol{X}_j, \alpha_X, \beta_X] \tag{7}$$

Now suppose non–market agreements are introduced: (5) is valid for any contract α, β, meaning that it holds also for α_X, β_X. Therefore, there is space for some j to be

$$E_j^{NMO}[U|\boldsymbol{X}_j, \alpha_X, \beta_X] > E_j[U|\boldsymbol{X}_j, \alpha_X, \beta_X] > E_j^M[U|\boldsymbol{X}_j, \alpha_X, \beta_X] \tag{8}$$

If the insurer takes into account the presence of the non–market agreements, the new optimal contract is α_X^*, β_X^* and

$$E_j^{NMO}[U|\boldsymbol{X}_j, \alpha_X^*, \beta_X^*] > E_j^{NMO}[U|\boldsymbol{X}_j, \alpha, \beta] \quad \forall(\alpha, \beta) \tag{9}$$

While by (6)

$$E_j^M[U|\boldsymbol{X}_j, \alpha_X, \beta_X] > E_j^M[U|\boldsymbol{X}_j, \alpha_X^*, \beta_X^*] \tag{10}$$

Then, since j satisfies (6) by (9) and (10) it satisfies also

$$E_j^{NMO}[U|\boldsymbol{X}_j, \alpha_X^*, \beta_X^*] > E_j[U|\boldsymbol{X}_j, \alpha_X^*, \beta_X^*] > E_j^M[U|\boldsymbol{X}_j, \alpha_X^*, \beta_X^*] \tag{11}$$

The implication of the model is therefore that if

- the insurer cannot perfectly discriminate individuals, and
- there is moral hazard between the insurer and clients while there is perfect peer monitoring within non–market agreements,

we should observe a (positive) marginal effect on demand for market insurance with the introduction of non–market agreements.

Nevertheless 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 level of peer monitoring within those communities.

It should be clear now that what Arnott and Stiglitz call peer monitoring is essentially the severity of moral hazard within the pair entering a non market contract. As the authors point out, the latter depends on reciprocal observability of the effort but also on the duration of the partnership, the level of trust between them, 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.

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 meanings 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 [7] 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 [16].

Suppose that pairs of individuals that enter a non market insurance agreement with a given δ 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),

$$\begin{aligned}\frac{\partial EU^i}{\partial e_i} &= \big[-(1-p(e_j))u_0 + p(e_j)u_1 \\ &\qquad - p(e_j)u_2 + (1-p(e_j))u_3\big]p'(e_i) - 1 \\ &= [(u_3-u_0)(1-p(e_j) + (u_1-u_2)p(e_j)]\, p'(e_i) - 1\end{aligned} \tag{12}$$

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 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 [16]: we have a finite population of agents $N = \{1, 2, \ldots, n\}$ where each pair of interacting agents i, j is involved in an infinite repetition of the described game. Players' 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 $s^g = (s^g_1, \dots, s^g_n)$ 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^g_C and s^g_D 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.*

$$\forall (i, j) \in g \quad \pi_i(s^g_C) \geq \pi_i(s^g_D)$$

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

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

Proof of proposition 1 is in the appendix and follows the one in Vega–Redondo [16]. 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[3] *of g.*

Going back to the first part of the model, we showed that demand for market insurance increases as moral hazard involved in non–market insurance falls. 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 is increasing in 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 higher in closed networks.

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 ([14]), 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. [4]). Loss ratios[4] 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 [5], Grace and Skipper [11] and the discussion in Browne et al. [4]).

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

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

4.1 Controlling for supply side variables

We stated in section 2 that an insurance company has a limited discriminating power, i.e. 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 [6]) 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 [9], observing that the role of this 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)[5], 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.

[5]Including motor TPL.

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.

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 to the arbitrarinesses of administrative boundaries with respect to the geographic dimension of economic phenomena (see Anselin [1]), 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.

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.

5 How to measure Social Capital?

In the third section we tackled one of the major problems pointed out by Durlauf and Fafchamps [7], 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 [10] 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

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

Figure 2: geographical distribution of pupop1000 and agricultural land

pupop1000 percsup.agr

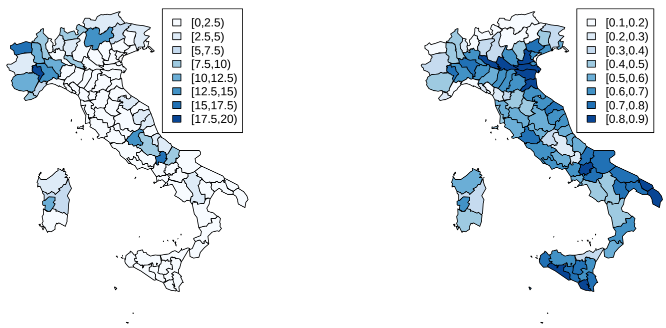
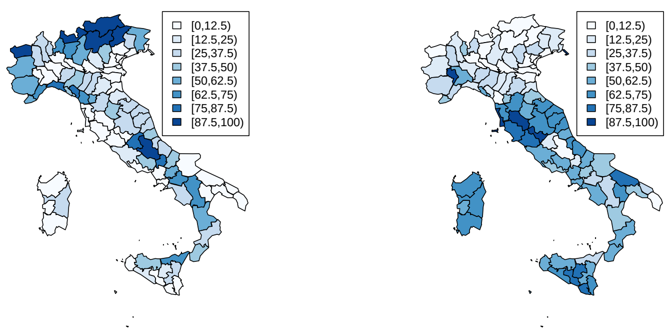


Figure 3: geographical distribution of mountainous and hill territory

percsup.m percsup.c



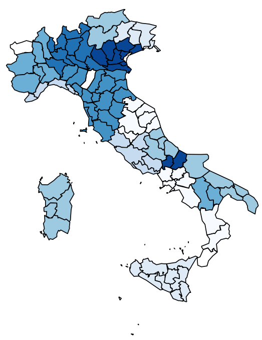
correlated. To measure global interaction, we follow Guiso, Sapienza and Zingales [12] using an index derived from a question in the "World Value Survey", run in Italy in 1999. The question asked was

> “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 4: geographical distribution of Trust



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[6], which would reduce the efficiency of a FE estimator.

6.1 The panel model

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

$$y_{it} = \boldsymbol{X}_{it}\boldsymbol{\beta} + \nu_i + \epsilon_{it} \quad i = 1, \ldots, 103; \; t = 0, \ldots, 2 \tag{13}$$

where $\boldsymbol{X}$, u_i and ϵ_{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 [3] 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[7]. The result of the test is 0.8895, with p–value equal to

[6] See the summary table in the appendix.

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

0.1869, thus not providing any evidence in favor of the random effects model.

Relaxing the assumption of "well behaved" residuals (see 15) and (16 below), another test for the RE hypothesis feasible in short panels is given in Wooldridge ([17]). This is based on estimation of ${\sigma_\nu}^2$ from the upper triangle of the N empirical Ω blocks given by the outer product of the residuals vectors $\tilde{v}_i = (\tilde{v}_{i1}, \ldots, \tilde{v}_{iT})$. 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.

6.2 The random effects model

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

$$V = {\sigma_\nu}^2 (I_N \otimes \boldsymbol{i}_T \boldsymbol{i}_T') + {\sigma_\epsilon}^2 (I_N \otimes I_T) \tag{14}$$

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

$$V = I_N \otimes \Omega \tag{15}$$

where

$$\Omega = \begin{bmatrix} \sigma_\epsilon^2 + \sigma_\nu^2 & \sigma_\nu^2 & \ldots & \sigma_\nu^2 \\ \sigma_\nu^2 & \sigma_\epsilon^2 + \sigma_\nu^2 & \ldots & \vdots \\ \ldots & & \ddots & \sigma_\nu^2 \\ \sigma_\nu^2 & & & \sigma_\epsilon^2 + \sigma_\nu^2 \end{bmatrix} \tag{16}$$

Observations regarding the same province share the same ν_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 β in model (13) are therefore inefficient, though consistent. Generalized least squares (GLS) are the efficient solution if Ω is known. Various feasible GLS procedures exist drawing on consistent estimators of Ω.

The standard approach to RE panels is to assume both (15) and (16). In "large N" panels a less restrictive approach is possible, termed *general FGLS* estimator (GGLS)[17], which allows for arbitrary *intra-group* heteroskedasticity and serial correlation of errors, i.e. inside the Ω 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.

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, Lenzi and Millo [13] 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"[8]. Anselin [1] 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:

$$y = \rho W y + X\beta + \epsilon \tag{17}$$

and the *spatial error* (SEM) model:

$$\begin{aligned} y &= X\beta + e \\ e &= \lambda W e + \epsilon \end{aligned} \tag{18}$$

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 [8], stacking the data as one cross section for every point in time and assuming $\epsilon \sim IID$, the panel RE version of (17) becomes

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

where the variance covariance matrix of $(i_T \otimes \mu) + \epsilon$ 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.

[8] See [1], Ch.3, for a classic treatment.

Table 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 two 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: ρ 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.[9].

	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.

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).

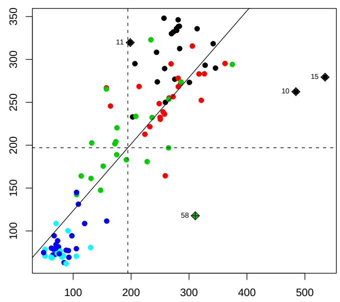
Moran's I statistic is a spatial correlation measure. In this case the proximity matrix is a row–standardized dichotomic matrix: Moran's I statistic thus boils down to the regression coefficient of the variable of interest over its spatial lag (see [1]). The Moran plot is the relative scatter plot, where 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 refle in the spatial structure as well.

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:

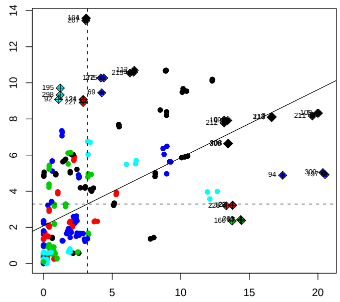
[9] Marginal effects are computed over the mean of the relevant variable.

Figure 5: Moran plots

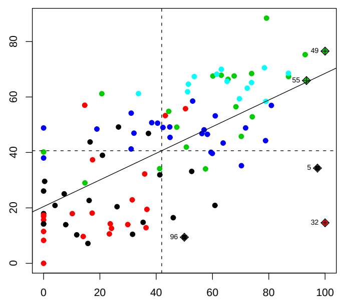
ppcd



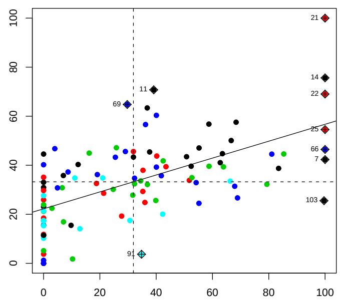
pupop1000



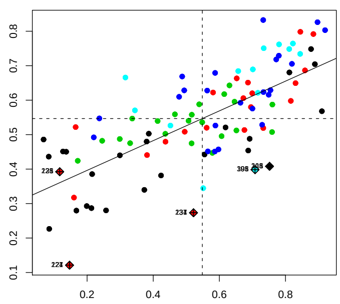
percsup.c



percsup.m



percsup.agr



Colors' legend:

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

	coef	se	z–stat	p–value
ρ w/o Soc. Cap	0.1730	0.0314	5.5138	$< 10^{-4}$
ρ 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.

7.2 Robustness checks

Anselin [1] 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[10] 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:

Table 2: ρ 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

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[11]. Nevertheless given the problem at hand such a proximity matrix seems to us less reasonable than a distance based one: provinces' extensions

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

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

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 we estimated a panel SEM (spatial error model) without the autoregressive component. Elhorst [8] suggests the following specification:

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

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

We report estimates of λ with proximity matrices with different cut–offs:

Table 3: λ 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

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

8 Conclusions

We started from Arnott and Stiglitz model on the co–existence of marketed and non–marketed insurance contracts. We extended it 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.

References

[1] L. Anselin. *Spatial Econometrics: Methods and Models.* Kluwer Academic Publisher, University of California, Santa Barbara, 1988.

[2] Richard Arnott and Joseph E. Stiglitz. Moral hazard and nonmarket institutions: Dysfunctional crowding out or peer monitoring? *The American Economic Review*, 81(1):179–190, March 1991.

[3] Badi H. Baltagi. *Econometric Analysis of Panel Data.* John Wiley & Sons, UK, 1995.

[4] M. Browne, J.W. Chung, and E. Frees. International property-liability insurance consumption. *The Journal of Risk and Insurance*, 67, N°1, 2000.

[5] M.J. Browne and K. Kim. An international analysis of life insurance demand. *The Journal of Risk and Insurance*, 60:617–634, 1993.

[6] G. Dionne. *Handbook of Insurance.* Kluwer Academic Publishers, Dordrecht Netherlands, 2000.

[7] Steven N. Durlauf and Marcel Fafchamps. Social capital. *NBER Working Paper series*, July 2004.

[8] J. Paul Elhorst. Panel data models extended to spatial error autocorrelation or a spatially lagged dependent variable. Technical report, 2001.

[9] N. Esho, R. Zurbruegg, A. Kirievsky, and D. Ward. Law and the determinants of property-casualty insurance. Technical report, Australian Prudential Regulation Authority, June 2001.

[10] Claudia Goldin and Lawrence F. Katz. Human capital and social capital: the rise of secondary schooling in america, 1910 to 1940. *NBER working paper series*, (6439), March 1998.

[11] M. Grace and H. Skipper. An analysis of the demand and supply determinants for non–life insurance internationally. Technical report, CR-MIR, Georgia State University, 1991.

[12] Luigi Guiso, Paola Sapienza, and Luigi Zingales. The role of social capital in financial development. *American Economic Review*, 94(3):526–556, June 2004.

[13] Giovanni Millo and Annapaola Lenzi. Regional heterogeneity and spatial spillovers in the italian insurance market. *Assicurazioni Generali Research Dept. Working Paper series*, 1, 2005.

[14] J. Mossin. Aspects of rational insurance purchasing. *Journal of Political Economy*, 79:553–568, 1968.

[15] Robert D. Putnam, R. Leonardi, and R. Nanetti. *Making Democracy Work: Civic Traditions in modern Italy.* Princeton University Press, Princeton, USA, 1993.

[16] Fernando Vega–Redondo. Building up social capital in a changing world. *Journal of Economic Dynamics & Control*, 30:2305–2338, 2006.

[17] J.M. Wooldridge. *Econometric analysis of cross-section and panel data.* MIT Press, 2002.

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

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

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

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

$$EU_{ij}^{NMO} + \sum_{k\in N_i/\{j\}}\eta^{d^i(j,k)}\left[\eta EU_{ik}^{NMO} + (1-\eta)\nu_{ik}\right] \geq (1-\eta)EU_{ij}^H \qquad (19)$$

Which is in the form of proposition 1.

B 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 GGLS 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