Insurance consumption in Italy: a sub-regional panel data analysis

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Abstract

We analyze the consumption of life and non-life insurance across 103 Italian provinces in 1996-2002. We assess the determinants of insurance consumption, in the light of the empirical literature and the distinctive features of our country, trying to explain the underdevelopment of the South as regards this sector. Among the benefits of using sub-regional data on insurance expenditure, one seems to us particularly relevant. Since loadings on life insurance contracts tend to be uniform across regions of the same country, an important limitation of cross-country analyses, i.e. the difficulty of observing prices in this market, may be alleviated. On the other hand, a sub-regional analysis raises issues of cross-sectional dependence, either due to common nationwide and/or regional factors or to spatial proximity. We assess cross-sectional dependence in different ways: we employ a recent joint test for random effects, serial and spatial correlation (Baltagi, Song, Jung and Koh 2007) and the CD and CD(p) tests for, respectively, global or local cross-sectional dependence by Pesaran (2004). Where appropriate, we explore the possibility of a characterization of sectional dependence based on geographic proximity through panel models including both spatial and serial dependence in the error terms, which we estimate by maximum likelihood through new procedures written in the R language. Insurance turns out to depend on economic development and some demographics, as expected, but also on trust, the rule of law and borrowing conditions. Life insurance is negatively correlated with education, supporting the view that better education fosters financial risk taking.

*We thank: Roger Bivand for kind advice; Yves Croissant for fruitful collaboration; all R developers for their effort. Computations have been performed by R ([28]), in particular using the plm package for econometrics of panel data and the spdep spatial econometrics package ([6]). ML spatial panel estimators have been programmed *ex novo* in R and are forthcoming on the CRAN site. This paper has been prepared combining R and LaTeX in a dynamic statistical document through the Sweave utility for reproducibility of the results, according to the principles of literate statistical practice ([26]).

Contents

1 Introduction

In this paper we analyze the consumption of insurance in Italy's 103 *provinces* (corresponding to NUTS-3 regions) in the period 1996-2002. We consider both the life and non-life classes, excluding mandatory motor TPL.

The importance of insurance in the Italian economy is diversified both at the sectoral and geographic level. The non-life insurance sector is underdeveloped by European standards, with the exception of motor TPL business, and the situation hasn't changed much from the early Nineties to date, with overall penetration on GDP stagnant. Life insurance penetration, on the contrary, has increased fivefold over the observation period, driven by substantial changes in distribution and product mix. Regional differences, though, have remained striking for both classes and relatively stable. In a nutshell, both insurance density and penetration are much lower in the Southern part of the country.

We aim at describing the different levels of development in the Italian insurance market at the provincial level and assessing the determinants of insurance consumption, in the light of the empirical literature on the subject and of the strong regional heterogeneity in economic and socio-demographic characteristics which is a well-known feature of our country.

Our work is introduced by presenting some relevant facts of the Italian insurance sector. We proceed sketching the main results in insurance demand theory, focusing on which are expected to be the main drivers of consumption and realizing that some are difficult to observe. A brief survey of existing empirical literature highlights data limitations to joint modeling of supply and demand and provides a further basis for selecting the relevant information set. Microdata also give evidence of spatial heterogeneity of some kind, in that the behaviour of residents in southern Italy is often found significantly different from the rest. We address the further methodological question of what we mean by insurance consumption and which measures have been proposed in the literature and by practitioners; we define the two macroclasses of insurance we will concentrate upon, life and non-life excluding mandatory motor third party liability. Then we give some stylized facts about the Italian insurance market, observing the underdevelopment of the non-life (non-motor) class by European standards and the rapid development and reshuffling of distribution channels in the life sector. We highlight the composition of both classes in order to assess the prevailing economic motives of purchase.

Next, an analysis of heterogeneity of Italian territory at large and from the point of view of insurance consumption is followed by visual assessment and formal tests for spatial dependence in the response variables as well as in the explanatory ones. High differentiation and strong spatial dependence among neighbouring regions are found both for insurance consumption and for the relevant drivers.

We estimate random effects panel models of life and non-life insurance consumption, controlling for the various plausible deviations from the standard setting: serial correlation, heteroskedasticity and cross-sectional correlation. We use a general framework, which allows for random effects, serial and cross-sectional correlation. Based on Baltagi et al.'s conditional LM statistic, we test for spatial correlation first. Where it is excluded (non-life model), we proceed estimating three specifications that are, in different ways, robust w.r.t. serial correlation and various kinds of heteroskedasticity, obtaining results that are

		Total	Life	Non-Life	Motor	Non-Motor
1	United Kingdom	13.3	9.1	4.2	1.3	2.9
2	France	9.3	6.0	3.2	1.1	2.1
3	Italy	7.5	4.9	2.6	1.6	1.0
4	Germany	6.9	3.2	3.7	1.1	2.6
5	Spain	5.6	2.4	3.2	1.4	1.8

Table 1: Insurance consumption in Europe as % of GDP, 2003

rather similar from the three approaches. Where spatial correlation is present, we incorporate it into the model specification, estimating the general model with random effects and both serial and spatial correlation in the idiosyncratic error by iterative maximum likelihood. We discuss the issue of cross-sectional dependence within a different framework, by means of Pesaran's ([24]) CD and CD(p) tests, finding results consistent with our previous analysis but also further clarifying the nature of the dependence found. We conclude by discussing the results of estimation.

2 Some stylized facts about the Italian insurance market

2.1 Non-Life

The Italian non-life insurance market is still underdeveloped with respect to those of the main European countries (as we can see in table 1). The penetration ratio (premiums/GDP) of the non-motor business is lower than those of the other four big economies (Germany, France, United Kingdom and Spain). The class is dominated by MTPL, accounting for more than a half of non-life business. Its penetration is higher than in the rest of Europe both because of the high number of vehicles on the road and because of the steady, cost-driven increase in tariffs of the last years. Non-mandatory classes, on the contrary, are far less developed, with total penetration less than half that of our major European partners.

The composition of non-MTPL non-life is balanced, with property as the leading class, at 12 percent of total non-life revenue, and non-mandatory motor, general liability and accident between 8 and 9 percent. As Focarelli, Savino and Zanghieri ([13]) note, Health insurance is most underdeveloped with respect to the rest of Europe, despite high private health expenditure. Marine, aviation and transit and credit and suretyship, both at little above 2 percent, play a minor role (Table 2).

There is no data available on the share of personal and commercial lines in the revenues of every class, but according to common wisdom this is quite balanced, maybe slightly biased towards personal lines, in property; balanced in accident and health, with comparatively few but huge collective contracts purchased by the firms; and definitely leaning towards the commercial side in liability insurance.

Non-life insurance in Italy is mostly distributed through tied agents, collect-

	Class	Premiums	Share
1	Accident	2760	8.1
2	Health	1509	4.4
3	Motor other risks	3062	9.0
4	Marine aviation transit	766	2.2
5	Fire	2038	6.0
6	Other damage to property	2158	6.3
7	Motor TPL	17622	51.5
8	General TPL	2798	8.2
9	Credit and suretyship	787	2.3
10	Others	711	2.1
11	Total Non-life	34212	100.0

Table 2: Composition of Non-Life insurance

ing about 85 percent of revenues (see Table 3)[1]. The remainder is sold through brokers and, with lesser shares, through bank counters and direct channels (telephone, Internet). The direct channel still accounts only for about 3 percent of total revenues, though its importance is steadily increasing.

	Channel	2000	2001	2002	2003
1	Tied agents	88.3	87.3	86.2	84.8
2	Brokers	6.5	7.4	7.6	7.8
3	Direct	1.7	1.9	2.6	3.3
4	Company staff	2.7	2.6	2.7	3.0
5	Banks	0.7	0.8	0.9	1.1
6	Financial promoters	0.2	0.1	0.1	0.1

Table 3: Distribution channels of Non-Life insurance

2.2 Life

The development of Italian life insurance in the last years has been spectacular, driven by the explosion of *bancassurance*, the use of bank counters as a distribution channel, and the development of new types of contract besides the traditional ones. Unit- and index-linked contracts in fact flourished during the stockmarket boom of the late Nineties, pushed through the bank channel together with other financial products, their distinction with the latter becoming even more blurred. Later on, with the bursting of the stockmarket bubble, the product mix again shifted towards policies with capital guarantees of some form; in the meantime, a new player, the Italian Post Office, which had been a provider of very traditional, low-return and riskless savings accounts, entered the life market reconverting its many salespoints to the sale of financial products, including life policies, quickly gaining a significant market share and prompting

[1]Data are comprehensive of MTPL.

another shuffle in the market (see Table 4[2]).

Nowadays the banks' share in the distribution of life policies (Table 5) is steady at 50 percent of premiums, while the Post Office is quickly gaining ground at the expense of tied agents. Financial promoters and company staff hold a minor and quite steady slice. The strategies of the supply side play a major role in driving revenues of one channel over the other or those of life insurance over competing financial products from the same groups.

	Class	Premiums	Share
1	Class1	27740	28.6
2	Class3	26560	27.4
4	Class5	8335	8.6
5	Class6	128	0.1
6	Total Life	62780	64.7
7	Total Life + Non-Life	96992	100.0

Table 4: Composition of Life insurance

	Channel	2000	2001	2002	2003
1	Tied agents	25.6	22.1	20.3	18.1
2	Brokers	0.9	0.9	0.9	0.7
3	Post	2.1	4.6	5.1	7.2
4	Company staff	8.4	8.1	8.5	10.3
5	Banks	51.9	53.4	51.5	52.4
6	Financial promoters	10.6	10.8	13.6	10.8
7	Others	0.1	0.1	0.2	0.5

Table 5: Distribution channels of Life insurance

Italian life insurance is therefore a far less stable market than non-life. It has also recently become a much bigger one, at 4.9 percent of GDP against 2.6 percent of non-life in 2003, after lagging behind for many years. Most of the revenues come from endowment and annuities, either guaranteed or linked, while term life plays a residual role and long term care and dread disease policies are almost negligible. The vast majority of business is believed to belong to personal lines, though important collective policies are often sold to the firms. Thus, from an economic point of view, the relevant framework is that of saving theory.

3 Theoretical and empirical aspects of insurance consumption

The economic rationale behind life and non-life insurance is much different; so are theoretical models of consumption. Purchasing non-life insurance, a cus-

[2]Classes are reported according to the Italian classification; they correspond approximately to traditional endowment and annuities (plus term life, accounting for less than 3 percent of total) in class 1, unit- and index-linked policies in class 3, capitalization (life-independent endowment) in class 5, pension plans in class 6.

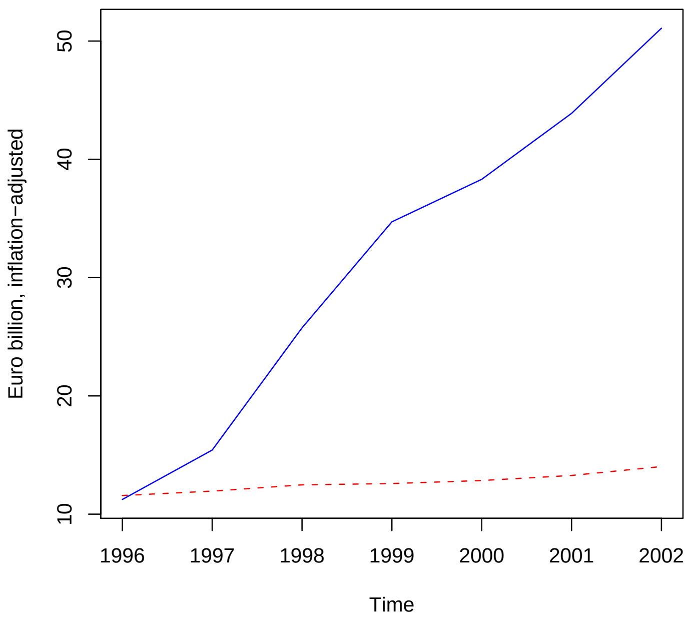

Figure 1: Evolution of Italian insurance, Life (solid) and Non-Life (dashed), 1996-2002

tomer buys an indemnity for future losses against paying a fixed price, the premium, today, thus transferring future wealth from an uncertain to a certain state. Theoretical models of non-life insurance demand, starting from the seminal paper of Mossin ([23]), predict that for a given level of risk exposure insurance demand is increasing with risk aversion, probability of loss and total wealth (even though whether the propensity to insure (i.e., the desired coverage as a percentage of the wealth at stake) should increase or not, depends on the behaviour of risk aversion). Moreover, while (by Mossin's Theorem) full coverage is optimal under the fair actuarial price, the degree of coverage decreases with the loadings (Schlesinger, in [10]). The effect of uncertainty of non-insurable wealth is less clear-cut. Guiso and Jappelli ([15]) find that background uncertainty about income has a positive effect on the decision to insure, which becomes less evident as wealth increases. Under the condition of risk-aversion decreasing with wealth, Falciglia ([12]) shows that higher market interest rates lead to a shrinking in insurance demand[3].

As far as commercial business is concerned, little-to-medium sized firms can be expected to behave similarly to households regarding the motivations of the insurance purchase. Large firms, on the contrary, might want to bear some risks by themselves, self-insuring through capital reserves, or transfer them through financial markets. Big firms also have contracting power in negotiating premium rates. Firm size could therefore matter.[4]

In the words of Villeneuve (in [10]) "life insurance serves to guarantee a periodic revenue or a capital to dependents of the policyholder (the spouse, the children, sometimes the parents or any other person) in case of his death (term life), or to himself, in case he survives". Thus, while the primary rationale behind the purchase of term life lies with the bequest motive, buying an endowment policy[5] or an annuity is mainly an investment choice, and is therefore best viewed as a problem of saving and asset allocation. In the unifying framework first developed by Yaari ([31]) and Hakansson ([17]), the demand for life insurance is attributed to a person's desire to bequeath funds to dependents and provide income for retirement. Beck and Webb ([5]) synthesize it as follows: "the consumer maximizes lifetime utility subject to a vector of interest rates and a vector of prices including insurance premium rates. This framework posits the demand for life insurance to be a function of wealth, expected income over an individual's lifetime, the level of interest rates, the cost of life insurance policies (administrative costs), and the assumed subjective discount rate for current over future consumption." In the case of term life, of course, also of the number, personal characteristics and preferences of the beneficiaries (see the extension of this scheme by Lewis ([20]), that is, in most cases, of family composition.

When trying to put theories at the test, many variables need to be proxied because of data limitations. Empirical studies identify some observable counterparts to total wealth, risk exposure, probability of loss and risk aversion. Wealth, when not observable, is generally proxied by means of income; so is risk

[3]The explanation lies with the so-called "inverted economic cycle" of insurance, in which one pays first, then, in the event of loss, receives his dues. Not insuring gives an opportunity-gain to invest the spared amount of the premium on financial markets, which increases along with the prevailing rates of return.

[4]See Yamori ([32]), Hoyt and Khang ([18]) and Main ([21]).

[5]An endowment policy actually has an important term life component (it entitles the beneficiaries to payment of its face value upon death of the insured); the main scope of the cover, nevertheless, is saving.

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 ([7]). Loss ratios of previous periods 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 [8] and the discussion in [7]).

Summaries of the existing empirical literature can be found in [7] (property-casualty), [13] (health), [5] and [22] (life). We will focus on the practical implications of previous studies on the preliminary choice of the set of variables to be included in the model.

Cross-country comparisons by Grace and Skipper and Browne, Chung and Frees find a positive relationship between non-life insurance demand and income, literacy, religion and the type of legal system. For the life class, Beck and Webb ([5]) add inflation and the degree of development of the banking sector. Education, young dependency ratio, life expectancy and size of social security do not prove significant in this setting.

Studies on microdata (usually household income or consumer expenditure surveys) have emerged in recent years, both in Italy and abroad, focusing mostly on the probability of purchasing an insurance policy (see, e.g., [29], [27]). The Italian reality has been analyzed in a number of recent papers drawing on data from the Bank of Italy's Survey on Household Income and Wealth (SHIW).

Guiso and Jappelli ([15]) find that the effect of household resources, expected income, income risk, self-employment, education and urbanization on the decision to purchase casualty insurance is positive and significant, while that of age is non-linear and family size is not significant. They also find that macroregional dummies for North and South are, respectively, significantly positive and negative. Their results are quite similar for the amounts insured, but the role of age, macroregional dummies and education is weaker. Focarelli, Savino and Zanghieri ([13]) investigate separately the probability of buying health and other kinds of non-life insurance (excluding mandatory motor TPL). They find evidence of positive effects from income, financial wealth, education and residence in the North or Centre for both classes, while age is not significant. Male, self-employed and homeowners are more likely to have property-liability-casualty insurance, while managers are more likely to have both.

Prosperetti ([25]), in what is to our knowledge the only disaggregated analysis so far on the Italian insurance market, decomposes non-life insurance into personal and commercial lines and into the main subcategories (liability, fire, theft, accident and health). He estimates cross-section models for insurance penetration in each and finds significant effects from (among demand side drivers) per capita consumption or income and, for some classes, from added value composition (shares of agriculture and industry) and firm size. He also includes (as supply side drivers) the structure of distribution (shares of big-, medium- and small-sized agencies and of brokers) and finds positive correlation between agency size and insurance penetration.

As far as life insurance is concerned, Michielin and Billari ([22]) analyze term life and pension insurance in the same probit fashion, finding that the decision to buy pensions policies is positively influenced by income, residence in the North (and, to a lesser extent, in the Centre) and, in a non-linear way, by age; term life purchase is positively correlated with family size, education, self-employment, income and home ownership, while urbanization and macroregion of residence are deemed insignificant. Cannata, Menegato and Millo (in [9]) analyze possession of term life and endowment policies. They find evidence of positive correlation of term life ownership with income and number of children, while the coefficients for age, number of family members excluding children, financial wealth and residence in the South are significantly negative; for endowment policies, the effect of income, education and marriage are positive; of children and other family members, not significant; of age, residence in the South and, notably, (other forms of) financial wealth, negative.

4 Methodology and data issues

Insurance data pose an inherent limitation to joint estimation of a supply and demand system. As Schlesinger (in [10]) 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. Our strategy is to enter the drivers of supply and demand in a single-equation relationship for insurance consumption in each of the two sectors.

4.1 The price issue

In general terms, the difficulty of (defining and) observing the "price" of insurance coverage, a key limitation of cross-country studies, may be overcome if average policy loadings are uniform across the observational units, as might be reasonably assumed in the case of regions belonging to the same country, but not in that of cross-country studies. This is rather plausible for the life sector, while regional price differences could still play a role in some non-life branches, where the price structure is indeed locally differentiated. When omitted, this price structure could reflect in spatial dependence in the error terms deriving from omitted variables bias.

Most of the Italian market is dominated by comparatively few big nationwide players (the market share of the first five groups is over 60 percent both in life and in non-life), thus, in our regional perspective, we take the view of insurance providers as price-makers, ready to provide as much coverage as demanded at the given price. Subject to this, and according to current tarification practice, insurance prices are determined principally by cost factors. Price proxies related to costs, notably the loss ratio, are often used in empirical work on non-life insurance (although there have been other solutions: Browne, Chung and Frees ([7]), in a cross-country comparison perspective, suggest proxying insurance prices by the market share held by foreign insurers). For reasons of data availability, we resort to the aggregated loss ratio for the Property sector[6], which accounts for roughly one half of total non-life revenue, as a proxy for the total non-life loss ratio.

[6] We define the property sector as Motor fire and theft, Fire and General property.

4.2 The unobserved heterogeneity issue

Roughly speaking, the main determinants of insurance demand that have been outlined above can be divided into individual- or system- specific. Disposable income, wealth, age, education, type of employment, family composition and the like fall into the individual factors. Legal system, social security system, tax system, demographics, inflation, return on financial investments, exchange rate and so on fall into the system factors.

The features of the social security system, e.g., play a major role in explaining life insurance: countries with extensive public coverage for old age use to have higher levels of life premium income. An inflation-ridden past history depresses public trust in traditional savings products, such as many kinds of life policies ([5]). Religious beliefs, as shown by Grace and Skipper ([14]) and Browne and Kim ([8]), are a key determinant of the low insurance consumption in many countries.

It is therefore difficult to disentangle the effects related to the national characteristics from those of income, age and the like, especially as the levels of per-capita income, the age structure of the population, the level of education, the degree of development of the financial system and so forth tend to go together through the stages of development of a country. Multicollinearity, due to the high correlation among explanatory variables, as more developed countries tend to have both higher income and life expectancy as well as a more developed financial system and so forth, makes parameter identification difficult.

We believe a regional study may help shed some light on the determinants of insurance consumption at the individual-specific level in an homogeneous environment as regards system-specific ones. Italy, a developed country that has nevertheless become a case study in regional (relative) underdevelopment, provides an ideal testing environment.

On the supply side, e.g., Beck and Webb ([5]) identify "the human and information resources" needed for pricing and portfolio management among possible limiting factors for insurance supply, but at the regional level insurance policies are sold by the same big nationwide players, where these functions are centralized.

"Short" panel data, characterized by a large cross-sectional dimension and a short temporal one, can help in this respect. In fact some panel studies of the determinants of insurance have emerged in the last decade (e.g., [5], [7], [11]). In spite of that, a range of methodological problems arise also in cross-country panel studies. Adding more countries to the panels means adding to the heterogeneity, in a sense incurring into the incidental parameters problem: in fact, as the geographical scope of the analysis widens, more determinants should be estimated, or more probably accounted for through fixed effects. More parsimonious random effects specifications, based on the assumption of a random draw of every country from a "homogeneous" population, are in fact often rejected by diagnostic tests (see Beck and Webb ([5]), where the RE spec is accepted only on the subgroup of developing countries). On the other side, adding to the time dimension raises issues of dynamic behaviour of the series considered, particularly as economic variables in levels tend to be nonstationary. This is not much of a concern in our case, as data numerosity in the time dimension is rather limited. On the other hand, estimation of a fixed effects model, which relies exclusively on temporal variability, becomes problematic in this setting.

Summing up: considering that the focus of our analysis is mainly in explaining provincial differences, so that we want to retain some cross-sectional variability to be exploited in estimation, and that some of our regressors of interest are time-invariant, a fixed effects analysis is not an option. A pure random effects model, on the converse, is inconsistent if there is any unobservable heterogeneity correlated with the regressors, which is rather likely in our case. A feasible technique, somehow intermediate between fixed and random effects, is to add subgroup dummies, usually on a geographic basis, such as "belonging to Latin America", or on a development-level one (see [30], page 288). We include subgroup dummies at two different levels, macroregional and regional, which amounts to the inclusion of, respectively, 5 and 20 fixed effects, in order to capture that part of the unobservable heterogeneity that might be correlated with the regressors. If the behaviour of the model doesn't change substantially between the two cases, we will take this as evidence in favour of the robustness of our specification.

4.3 Controlling for spatial effects

There are also some downsides to our approach to be considered. Some of them can (and shall) be addressed through spatial econometrics techniques.

Georeferentiation enriches the dataset with the information on the relative position of the data collection units, allowing detection and characterization of spillover effects and more generally a parsimonious characterization of dependence, e.g. when the latter is regularly decaying with distance. On the other hand, the regional scale of the analysis also brings some drawbacks and requires some caution. 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 salespoint location even if they are actually insuring risks spread over a wider territory. Furthermore, 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 centre, 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, but also in any case when the location of salespoint is different from the actual location of the insured.

More generally, premium data are subject to a problem which is typical in spatial analysis, the so called *aggregation bias*, due to the arbitraryness of administrative boundaries with respect to the geographic dimension of economic phenomena (see [1]). (Negative) local spatial correlation in error terms may arise if there are such cross-border spillovers. Global forms of spatial correlation can be due to the omission of spatially diffuse relevant regressors, which may reflect in a spatial structure in the errors and can be modelled including either a spatial autoregressive term in the error process or a spatially lagged dependent variable.

4.4 Measuring insurance consumption

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. Further measures specific to the life sector have been suggested ([5]). Unlike Prosperetti ([25]), 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.

A potentially important omission in the data is the relative price level, which according to common wisdom is rather diverse across Italy. Unfortunately there are no cross-sectional data available on regional purchasing power parities, but only time series of price indexes. Should it turn out to be important, the omitted purchasing power variable, which is likely to be spatially correlated, would show up in the form of spatial dependence in the residuals. The alternative measure of insurance consumption, the premiums to GDP ratio, does not suffer from this drawback as the purchasing powers get lost in the normalization. Therefore we estimated the models also w.r.t. this measure as a robustness check, finding much similar results.

5 The data

Data on insurance premiums are collected on a regional basis by ISVAP, the Italian insurance Authority, divided into three categories: life, compulsory third party liability, the vast majority of which regarding motor vehicles, (henceforth MTPL) and other non-life. While MTPL is a homogeneous class, both life and other non-life comprise very different kinds of policies. We have already given a description of the relative importance of each class in the aggregate (see Tables 2 and 4). We do not consider MTPL as, being a mandatory cover, it does not fit into the theoretical scheme sketched above[7]; we focus on the other two macroclasses, life and non-MTPL non-life (henceforth, non-life tout court).

5.1 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 macroregions. Macroregions divide the 20 NUTS2 Italian regions (*regioni*) into 5 aggregates: North-West, North-East, Centre, South and Islands.

6 The model

As observed above, we specify both models, life and non-life, as single-equation relatonships, relating insurance density to the relevant drivers for the supply and the demand side. Variables will be expressed in logs except for ratios.

[7]The decision to purchase an MTPL policy is a consequence of that of buying a car, thus the appropriate drivers of consumption have to be assessed differently.

In the model specification for the non-life sector we include: real GDP per capita, which accounts both for income and the general level of economic activity; real bank deposits per capita, employed, as often occurs, as a proxy for wealth; average number of family members, accounting for family composition; percentage of people with second-grade schooling or more[8]; density of inhabitants per square Km, as a proxy for risk conditions[9]; judicial system inefficiency, measured as years needed for settling a civil case[10]; survey results to the question "do you trust other Italians?" from the World Values Survey, 1999 wave [11]; share of value added, agricultural sector (originally included as the complements (industry and services sectors' shares), which always passed the test for equality of the relative parameters); density of insurance agencies per 1000 inhabitants, a supply-side variate inversely related to the opportunity cost of searching for a suitable insurance policy; loss ratio, property sector, as a proxy for the loss ratio of the non-motor sector as a whole (unavailable), included as a price variable with a one year lag; real interest rate on borrowing, supposed to reflect both the opportunity-cost of insuring against self-insuring (in the sense of Falciglia, [12]) and liquidity constraints.

The Life model obviously excludes loss ratios, substitutes real GDP per capita with real disposable income per capita and adds: the number of bank counters per 1000 inhabitants, representative of the pervasiveness of bancassurance distribution; the old dependency ratio, as ratio of people over 65 years old to people of working age, and the young dependency ratio, as ratio of people under 15 years old to people of working age. The first of the latter two is included in order to test whether life insurance behaves, on aggregate, according to the life cycle hypothesis, with cohorts in their working age saving and older ones dissaving. The expected effect is therefore negative. The young dependency ratio should account for the purchase of life policies aimed at protection of one's dependents (in this case, sons) in case of death and all those endowment policies providing lump sums or annuities to children at the time of enrolling in higher education, so we expect it to have a positive effect.

The information set consists of an excerpt for the years 1996-2002 from the GeoStarter 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. Insurance data, in particular, are provided by Isvap, the Italian regulatory body. The lack of data for some regressors reduces the available timespan to 1998-2002 for the non-life sector and to 1996-2001 for the life sector.

A list of names of the regressors included in the models follow. Whether they have been logged or not will be apparent from the model results tables: as a general rule, though, all variables are in logs except for ratios. All monetary variates are expressed in real terms using 2000 as the base year. In the Non-Life model:

[8]This is collected at regional level.

[9]Urbanization is also often used for this purpose (see [7] and references therein).

[10]This indicator comes from the database of [16] and is relative to 1999, thus it is included as a time-invariant variable; the variability over time should be almost negligible with respect to the high cross-sectional variance.

[11]This (like the previous one) is included as a time-invariant variate both due to unavailability of other waves and in the belief that such attitudes would show scant variability over a six- or seven-year horizon.

rPILproc i.e. real GDP per capita

rdepproc real bank deposits per capita

numcompfam average number of family members

istruz percentage of people with second-grade schooling or more

den density of inhabitants per square Km

inef judicial system inefficiency

trust survey results to the question ”do you trust other Italians?”

vaagr share of value added, agricultural sector

agproc density of insurance agencies per 1000 inhabitants

lrpro.1 loss ratio, property sector, lagged one year

rirs real interest rate on borrowing

The Life model substitutes real GDP per capita with

rYdproc real disposable income per capita

and adds

sport.pop the number of bank counters per 1000 inhabitants

odeprat old dependency ratio

ydeprat young dependency ratio

7 Local disparities and the development of Italian insurance

Italy is well known to be in many respects a heterogeneous country. Italian regions are highly differentiated both from the social, cultural and demographic point of view and from the more strictly economic one. The age structure of the population leans towards the older classes in the North-West and the Centre-North, while the residents in central North and the South are youngest. The structure of the family is also very differentiated: the average number of members of a family goes from 2 in Trieste to over 3 in Naples, constantly decreasing with latitude. Per capita income is highest in the North and the capital, lowest in the South, with all kinds of nuances in between (Table 6). Indicators of economic development like, e.g., registered cars per capita are similarly distributed, but with a higher concentration in the North-West and Centre-North than in the north-East. Unemployment is dramatically high in the South and rather low in most regions of the North and part of the Centre. The North is most industrialized, even though the share of industry in the productive tissue of the land is high also in most of the Centre, with the notable exception of Rome and its surroundings. Services, most notably touristic ones, dominate in the Islands and are important in the South as a whole.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Gini
Inhab./Km2	37.0	104.1	172.4	244.9	254.9	2647.0	0.46
Family size	2.0	2.4	2.6	2.6	2.8	3.1	0.05
Perc. aged 65+	12.1	17.1	19.1	19.5	21.9	25.3	0.09
Disp. income	8.2	10.7	14.0	13.4	15.4	18.8	0.12
Prem.p.c., life	157.2	330.1	573.9	595.7	767.6	1573.0	0.26
Prem.p.c., nonlife	49.0	91.4	202.5	194.4	272.7	534.9	0.30
Prem./GDP life	1.8	3.3	4.0	4.3	4.9	10.5	0.18
Pr./GDP nonlife	0.5	0.9	1.4	1.4	1.8	2.9	0.22

Table 6: Distribution across NUTS3 regions and inequality measures of some characteristics of Italian territory, 2000

Insurance consumption is no exception. All of the last 20 regions in the overall ranking, both in the life and non-life classes, come from the South and Islands; all but three (in non-life) and one (in life) of the first 20 are northern regions.

A comparison with the other commonly used measure of insurance consumption shows that the situation is little changed by considering insurance penetration[12]. In other words, at a first glance heterogeneity in insurance consumption doesn't seem to be only due to difference in available resources, as the average propensity to buy insurance out of one's income is almost as differentiated.

7.1 Spatial dependence analysis

Besides high macroregional differentiation, insurance penetration shows a high degree of spatial correlation[13].

Moran plots (see Figures 2 and 3, colour codes are: blue for the South, light blue for the Islands, green for the Centre, red for the North-East and black for North-West) show an evident cluster of low-density regions highly correlated with their neighbours, but the same applies to most observations. Influential outliers (indicated by a different symbol and labeled by their Istat code) also situate in the positive correlation sector, exception made, in the life class, for some relatively low-density regions with high-density neighbourhoods (Aosta, Trento, Rovigo and Lodi). In the non-life class Rome is a notable outlier in the second sector, that is, it is much more developed than its neighbourhood.

The situation is much alike as far as the explanatory variables are concerned. Moran plots (we report those for disposable income and average family members, see Figures 4 and 5) clearly indicate spatial dependence. More formal statistical tests (Table 7, data relative to the year 2000) confirm the visual impression.

In the following we try to assess whether the local disparities in explanatory factors are sufficient in explaining local variability; whether macroregional

[12] Here, given the consumption-orientation of the analysis, we employed a slightly different measure of insurance penetration, normalizing on disposable income instead of GDP.

[13] Tests and diagnostic plots for spatial correlation as well as spatial models are based on a spatial weights matrix constructed according to the principle of queen contiguity (that is, regions are considered neighbours if they share a common border or vertex; see [19]). According to common practice, the matrix has been row-standardized. Reggio Calabria and Messina, divided by the Messina Strait, have been considered contiguous.

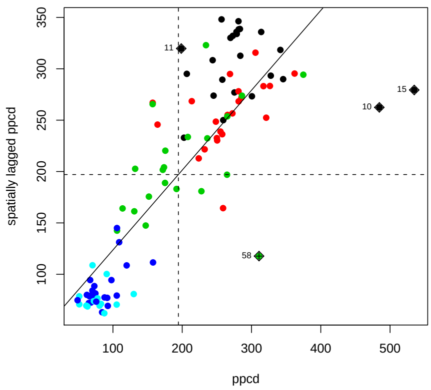

Figure 2: Moran plot of Non-Life insurance density

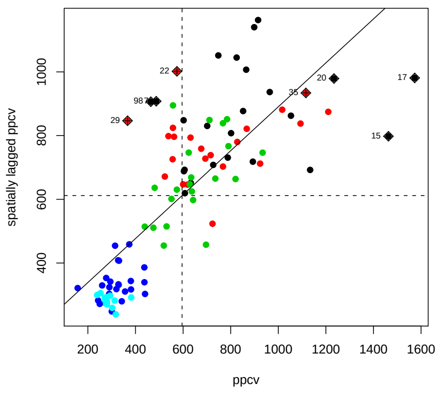

Figure 3: Moran plot of Life insurance density

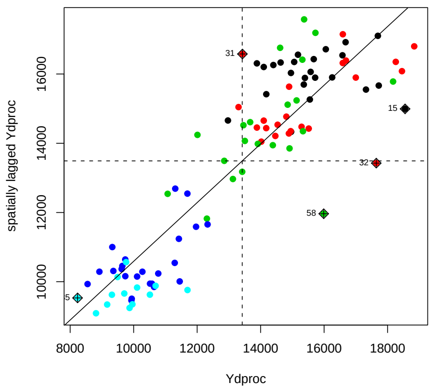

Figure 4: Moran plot of per-capita income

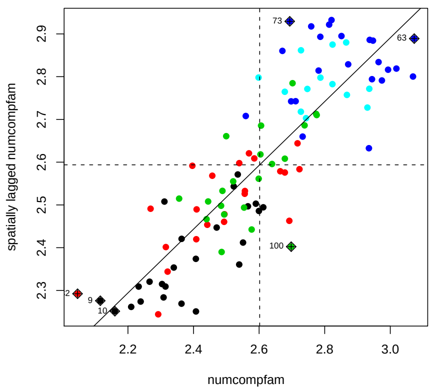

Figure 5: Moran plot of average number of family members

	Moran's I	P-value	Geary's C	p-value
ppcd	11.48	0.00000	-10.21	0.00000
ppcv	10.24	0.00000	-8.67	0.00000
Ydproc	12.45	0.00000	-11.60	0.00000
depproc	8.69	0.00000	-6.65	0.00000
numcompfam	11.00	0.00000	-10.79	0.00000

Table 7: Spatial dependence tests

dummies are needed to account for spatial heterogeneity; and whether spatial effects are significant, and should enter a model specification.

Consistent with the idea that insurance covers are complicated and little-understood goods, that the Italian market is underdeveloped with respect to the overall economic development of the country, at least as far as the non-life sector is concerned, and that the different degree of insurance penetration throughout the Italian territory may be due to unobservable, spatially correlated factors as well as to (observable) differences in resources and needs, we expect to find some evidence of global spatial effects. If, on the contrary, the non-spatial specification were able to fully account for the observed variability, this would bring evidence in favour of the view that less developed regions are such simply because of budget constraints and lower insurance needs. This would not rule out the possibility of local spatial effects due to aggregation biases of some kind: for example, due to the overlapping of administrative boundaries with operational areas of the sales force or any other kind of cross-border purchase.

8 Model estimation and results

We start the econometric analysis estimating by ML a RE model with first-order autocorrelated errors on a balanced panel data-set covering the time periods 1998-2002 and 1996-2001 for the non-life sector and life sector respectively. Besides the regressors outlined above, all models contain macroregional (regional[14]) and time fixed effects.

As observed, including (macro-)regional fixed effects, a sort of middle ground between FE and RE analysis, is a way of dealing with regressor-related heterogeneity while retaining most of the efficiency of a random effects estimator. The limited time dimension of our study also allows to include time dummies to capture the effects of global shocks, while retaining a comfortable number of degrees of freedom[15].

Based on the residuals of the random effects, AR(1) errors model, we proceed testing for spatial correlation in the general LM framework of Baltagi et al. ([4]), carrying out the one-dimensional conditional test for spatial error dependence

[14]The results for a specification where 18 regional fixed effects are included instead of the 5 macroregional ones, not reported, are quite similar and can be obtained from the authors upon request.

[15]We are therefore assuming that the inclusion of (macro)-regional and time effects does make the residual individual effect to be uncorrelated with the regressors. One further restrictive hypothesis our model rests upon is that all regressors be strictly exogenous, which is needed for consistency of the RE estimator.

(labeled C.1) for the null of no spatial correlation, assuming both first-order serial correlation of the errors and random effects.

The results are based on the spatial weights matrix W used in the spatial dependence analysis. The test statistic for the non-life specification is $LM = 0.49$ (p-value: 0.4856); for the life model it is $LM = 5.09$ (p-value: 0.024). Hence we conclude that spatial correlation is not relevant in our non-life model specification, while it is present in the errors of the model for the life sector.

Next, we test for serial correlation in the residuals.

For the non-life model, given the absence of spatial correlation, we run (the one-sided version of) Baltagi and Li's test for AR(1)/MA(1) residuals conditional on random effects ([3]) which finds strong evidence of serial correlation ($Z = 4.85$, p-value=$6.3e-07$).

For the life model, we test for serial correlation in the general LM framework of Baltagi et al. ([4]), carrying out the one-dimensional conditional test for serial correlation in error terms (labeled C.2) for the null of no serial correlation, assuming both spatial correlation and random effects.

The resulting test statistic is $LM = 131.21$ (p-value: 0). Hence we conclude that serial correlation is indeed present in both models, and that while the non-life model can be based on the (already estimated) specification with random effects and serial correlation, the life sector will need a model with random effects and both serial and spatial correlation in idiosyncratic errors.

The ML estimates for the random effects panel data model with AR(1) errors for the non-life sector are reported below (Table 8)[16]. As far as first-order serial correlation is concerned, the estimated value is 0.54[17].

As the standard RE panel data estimator is inefficient but still consistent in case of serial correlation and heteroskedasticity, we present also the estimates for this model, reporting White-Arellano corrected standard errors (see e.g. [2]). Moreover, in our small T, large N context, a less restrictive approach can be applied (see [30]), i.e. the general feasible GLS estimator, which allows for *time-varying* variances and arbitrary serial correlation of the errors, provided that the unrestricted errors covariance matrix is constant across individuals. The general feasible GLS estimates are reported in Table 9 for the non-life sector.

Standard RE estimates with White-Arellano robust standard errors for the non-life sector are reported in Table 10.

We observe that GDP and wealth, as expected, are important determinants of insurance consumption. Family numerosity plays a weak role, with a negative but not significant coefficient, and so does schooling. Population density, on the contrary, proves positive and significant, supporting the claim that it is a good proxy for risk conditions.

Legal system inefficiency, which plagues many of Italy's regions, has a significantly negative impact on insurance: bad enforcement of property rights negatively affects people's willingness to commit to long-term contracts, as already found by [16] analyzing financial services. Trust, on the contrary but probably for the same reasons, is an important positive determinant of insurance. The density of agencies plays a role as well, reducing the cost of searching

[16]Dependent variables for all models are henceforth always log of non-life and, respectively, life premiums per capita.

[17]A structural a-priori reason to suspect the presence of serial correlation is the existence of pluriannual contracts.

	Value	Std.Error	t-value	p-value	
(Intercept)	−0.9570	1.0369	−0.9229	0.3566	
log(rPILproc)	0.2857	0.0916	3.1183	0.0020	**
log(rdepproc)	0.1587	0.0435	3.6481	0.0003	***
log(numcompfam)	−0.1485	0.1596	−0.9306	0.3526	
istruz	0.0027	0.0034	0.8061	0.4207	
log(den)	0.0691	0.0243	2.8489	0.0046	**
inef	−0.0450	0.0170	−2.6512	0.0094	**
trust	0.5348	0.1654	3.2325	0.0017	**
vaagr	−0.0068	0.0040	−1.7137	0.0874	.
agproc	0.2836	0.1383	2.0510	0.0409	*
lrpro.1	0.0096	0.0165	0.5857	0.5584	
rirs	−0.0125	0.0067	−1.8586	0.0638	.
d99	0.0032	0.0133	0.2375	0.8124	
d00	0.0278	0.0185	1.4999	0.1344	
d01	0.0587	0.0225	2.6075	0.0095	**
d02	0.0756	0.0289	2.6124	0.0093	**
NO	0.2095	0.0574	3.6527	0.0004	***
NE	0.1302	0.0577	2.2576	0.0262	*
SU	−0.4812	0.0718	−6.7022	0.0000	***
IS	−0.5195	0.0802	−6.4775	0.0000	***

Table 8: ML with AR(1) errors, non-life

for insurance policies, consistently with the view that insurance is a complicated good to which a proper consultancy can add value[18].

The price variable is deemed insignificant. We take this as some support for the view that price elasticity of non-life insurance in Italy is rather low, but another possible explanation is that loss ratios of the property sector (though it accounts for almost one half of non-motor revenue) be a poor proxy for insurance prices as a whole.

Lastly, passive interest rates are significantly negatively related with insurance consumption: liquidity constraints and the cost of borrowing are a restraining factor for the Italian firms and households with respect to the decision to insure, as self-insurance becomes the more attractive if credit is expensive.

Regarding the life model, from the above tests it is apparent that spatial correlation of the errors has to be taken into account as well, together with serial correlation and individual effects. Therefore we resort to estimating a model with the above features by maximum likelihood[19].

To our knowledge, estimation of such a model hasn't been documented in the literature yet. The general framework for maximum likelihood estimation of spatial models with arbitrary heteroskedasticity and covariance structures has nevertheless been outlined by Anselin ([1]) and can be made operational by

[18]However, this result could be misleading due to the potential rejection of the strict exogeneity assumption. Notice that if a variation in insurance consumption gives rise to variations in the density of agencies in the future, then this variable should be considered predetermined.

[19]It must be stressed that in this case the RE and GGLS models aren't appropriate any more, so the above robustness check against different forms of error heteroskedasticity will not be feasible and our results will have to rest upon a homoskedasticity assumption.

	Estimate	Std. Error	t value	Pr(>|t|)	
(intercept)	−3.5823	0.9761	−3.6701	0.0003	***
log(rPILproc)	0.5294	0.0992	5.3352	0.0000	***
log(rdepproc)	0.2685	0.0452	5.9341	0.0000	***
log(numcompfam)	−0.2197	0.1643	−1.3372	0.1818	
istruz	−0.0003	0.0033	−0.0865	0.9311	
log(den)	0.0555	0.0177	3.1428	0.0018	**
inef	−0.0384	0.0118	−3.2556	0.0012	**
trust	0.3664	0.1169	3.1330	0.0018	**
vaagr	−0.0080	0.0042	−1.9330	0.0538	.
agproc	0.4112	0.1409	2.9181	0.0037	**
lrpro.1	0.0174	0.0200	0.8706	0.3844	
rirs	−0.0195	0.0077	−2.5192	0.0121	*
d99	0.0044	0.0145	0.3054	0.7602	
d00	0.0410	0.0193	2.1250	0.0341	*
d01	0.0702	0.0235	2.9839	0.0030	**
d02	0.0812	0.0298	2.7207	0.0067	**
NO	0.1648	0.0409	4.0270	0.0001	***
NE	0.0766	0.0409	1.8727	0.0617	.
SU	−0.3357	0.0551	−6.0897	0.0000	***
IS	−0.3883	0.0617	−6.2969	0.0000	***

Table 9: GGLS, non-life

specifying the relevant error covariance.

In deriving the C.1 conditional LM test for spatial correlation under both random effects and serial correlation (see Section 8), Baltagi, Song, Jung and Koh ([4]) give the expressions for the error covariance matrix, its inverse and determinant for the full model (see Appendix A).

Maximization of the likelihood gives the results in Table 11, where $phi = \frac{\sigma_\mu^2}{\sigma_e^2}$.

The stronger evolutionary dynamics of the life sector with respect to the non-life sector is evident from the estimates of the time-varying intercepts. As predicted by theory, life insurance depends on disposable income, whereas bank deposits turn out be insignificant, probably because they are not a good proxy for wealth. Regional life insurance consumption is also directly proportional to the average number of family members, coherently with the view of life insurance as a means to protect one's dependents, whereas the sign of the education variable is relatively unexpected. Actually, the effect of education on insurance has been debated, as some researchers see it as positively related to risk aversion, others to the willingness and the capacity to manage risks. The explanation could be that better educated people are able to better diversify their portfolios, holding a greater variety of (possibly riskier) assets, thus reducing the slice of safe assets, such as life insurance.

The role of judicial inefficiency is much weaker, consistently with the lesser amount of litigation involving life contracts with respect to non-life ones, while trust is again a positive driver, as for [16].

Bank counters' density plays no role, while the density of agencies is very important, contrary to the current trend towards the preminence of bancassur-

	Estimate	Std. Error	t value	Pr(>|t|)	
(intercept)	−1.2128	0.9453	−1.2829	0.2001	
log(rPILproc)	0.3544	0.0871	4.0684	0.0001	***
log(rdepproc)	0.1563	0.0387	4.0391	0.0001	***
log(numcompfam)	−0.2551	0.1539	−1.6571	0.0981	.
istruz	−0.0004	0.0032	−0.1142	0.9091	
log(den)	0.0653	0.0204	3.2019	0.0015	**
inef	−0.0432	0.0142	−3.0463	0.0024	**
trust	0.4909	0.1391	3.5297	0.0005	***
vaagr	−0.0070	0.0038	−1.8596	0.0635	.
agproc	0.3314	0.1323	2.5043	0.0126	*
lrpro.1	0.0056	0.0194	0.2894	0.7724	
rirs	−0.0176	0.0073	−2.4242	0.0157	*
d99	0.0013	0.0141	0.0947	0.9246	
d00	0.0305	0.0181	1.6859	0.0924	.
d01	0.0614	0.0218	2.8168	0.0050	**
d02	0.0749	0.0281	2.6658	0.0079	**
NO	0.1973	0.0483	4.0824	0.0001	***
NE	0.1161	0.0485	2.3949	0.0170	*
SU	−0.4543	0.0623	−7.2949	0.0000	***
IS	−0.5017	0.0698	−7.1921	0.0000	***

Table 10: RE, non-life

ance in distribution. It seems that tied agents are still a very important force in shaping the market.

Based on a rather loose interpretation of the life cycle theory, we expected the share of older age cohorts, who are expected to be dissaving, to play a negative role: they turn out to be uninfluent instead, while the share of the young has a positive effect, again consistently with the view of life insurance as a primary mean of protection for one's dependents.

8.1 Do regressors account for spatial dependence?

In the previous section we have based the non-life insurance consumption analysis on a static RE panel data model with AR(1) errors and we have found that, while insurance premiums are strongly spatially correlated (see section 7), the one-dimensional conditional LM test for spatial error correlation proposed by Baltagi et al. ([4]) favours the hypothesis of no residual spatial correlation. Therefore from this point of view we might conclude that the observed spatial pattern of non-life insurance has properly been accounted for by means of observables.

On the contrary, the same test provides evidence that some spatial correlation remains in the residuals of the life insurance model even after controlling for observables. It will be interesting to better assess the magnitude and nature of this correlation starting from a different perspective.

In order to further investigate the issue, in this section we consider an alternative specification based on a dynamic panel data model. Firstly, we employ

	coef	se	z	pz	
(Intercept)	−8.8869	2.6939	−3.2989	0.0010	***
log(rYdproc)	1.1908	0.2910	4.0927	0.0000	***
log(rdepproc)	0.1277	0.0875	1.4591	0.1445	
log(numcompfam)	0.6662	0.4053	1.6436	0.1003	
vaagr	−0.0103	0.0072	−1.4220	0.1550	
odeprat	0.0003	0.0080	0.0345	0.9725	
ydeprat	0.0260	0.0121	2.1457	0.0319	*
istruz	−0.0181	0.0073	−2.4895	0.0128	*
inef	−0.0176	0.0225	−0.7823	0.4340	
trust	0.3188	0.2264	1.4084	0.1590	
sport.pop	0.0070	0.1973	0.0353	0.9718	
agproc	0.7181	0.2032	3.5344	0.0004	***
d97	0.3070	0.0269	11.4299	0.0000	***
d98	0.7519	0.0378	19.9135	0.0000	***
d99	1.0910	0.0471	23.1788	0.0000	***
d00	1.2886	0.0581	22.1726	0.0000	***
d01	1.3752	0.0716	19.2071	0.0000	***
NO	0.0502	0.0876	0.5732	0.5665	
NE	−0.1049	0.0867	−1.2095	0.2265	
SU	−0.4943	0.1211	−4.0816	0.0000	***
IS	−0.4839	0.1393	−3.4724	0.0005	***
phi	0.2346	0.0462	5.0806	0.0000	***
rho	0.4054	0.0436	9.3056	0.0000	***
lambda	0.2842	0.0493	5.7694	0.0000	***

Table 11: ML with RE, serial and spatial correlation, life

Pesaran's ([24]) CD test for global spatial dependence in order to assess the degree up to which the regressors in our maintained specification are able to control for spatial correlation.

The standard CD test is based on an average (across the sectional dimension) of sample estimates of the pairwise correlations of residuals of the separate (timewise) regressions for every sectional unit:

$$CD = \sqrt{\frac{2T}{N(N-1)}}(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}); \quad \hat{\rho}_{ij} = \frac{\sum_t e_{it}e_{jt}}{(\sum_t e_{it}^2)^{1/2}(\sum_t e_{jt}^2)^{1/2}}$$

The CD test is asymptotically standard Normal distributed under the null of no cross-sectional correlation.

Separate regressions are infeasible here because we have more regressors than time periods, thus we revert to a version based on fixed effects residuals, which is valid subject to the validity of the slope homogeneity constraint. The CD test relies upon the hypothesis of serially uncorrelated residuals, thus in order to eliminate first-order serial correlation we include the lagged dependent variable, in addition to the original time-variant regressors[20].

[20]While fixed effects estimators are inconsistent for fixed T in dynamic panel data models,

Interestingly, while for the AR(1) panel data model with only fixed effects and time dummies for the non-life sector we obtain a CD statistic of 8.42, thus rejecting the null at any significance level, for the full model we get -0.68, with p-value of 0.4934. So the non-life AR(1) model shows evidence of global cross-sectional dependence which is satisfactorily accounted for by the covariates in the complete model. On the contrary, for the life sector the CD statistic on the purely autoregressive model is -1.66 (p-value: 0.0971) and that for the full model is -0.81 (p-value: 0.4175), so even the simple AR(1) model doesn't show any strong evidence of global cross-sectional dependence in the errors.

A variant of the CD test, called $CD(p)$ test, takes into account an appropriate subset of "neighbouring" cross-sectional units to check the null of no cross-sectional dependence against the alternative of *local* cross-sectional dependence, i.e. dependence between neighbours only. To do so, the pairs of neighbouring units are selected by means of a binary proximity matrix. In the original paper, a regular ordering of observations is assumed, so that the m-th cross-sectional observation is a neighbour to the $(m-1)$-th and to the $(m+1)$-th; nevertheless extending the $CD(p)$ test to irregular lattices is straightforward. A binary proximity matrix is employed as a selector for discarding the correlation coefficients relative to pairs of observations that are not neighbours in computing the CD statistic. The test is defined as

$$CD(p) = \sqrt{\frac{T}{\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} w(p)_{ij}}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} w(p)_{ij} \hat{\rho}_{ij} \right)$$

where $w(p)_{ij}$ is the (i,j)-th element of the p-th order proximity matrix, so that if h,k are not neighbours, $w(p)_{hk} = 0$ and $\hat{\rho}_{hk}$ gets "killed"; this is easily seen to reduce to formula (14) in Pesaran (cit.) for the special case considered in that paper.

Testing on first-order local instead of global correlation, the results are similar for the non-life model but different for the life one: while for the AR(1) panel data model with only fixed effects and time dummies we obtain a CD(1) statistic of 4.36 for the non-life model and 9.19 for the life model, thus rejecting the null of independence at any significance level, for the full models we obtain respectively the values of -0.71 and 7.22, with p-values of 0.4758 for the non-life and 0 for the life model.

Figure 6 depicts the behaviour of the CD(p) test on the full model as the order p of the proximity matrix grows, until converging to the global CD test value. The local nature of the correlation is apparent from the loss in significance as correlations between more distant pairs of observations are taken into account.

Therefore, summing up, also with this dynamic model specification we conclude that the regressors included successfully explain the spatial correlation observed in non-life insurance premiums. In the life model, on the converse, the spatial correlation is of local nature (i.e., between neighbouring areas); and part of it remains unexplained even after controlling for observable covariates.

Pesaran ([24], Section 6) shows that the CD test continues to hold also in this context, as long as the disturbances are symmetrically distributed.

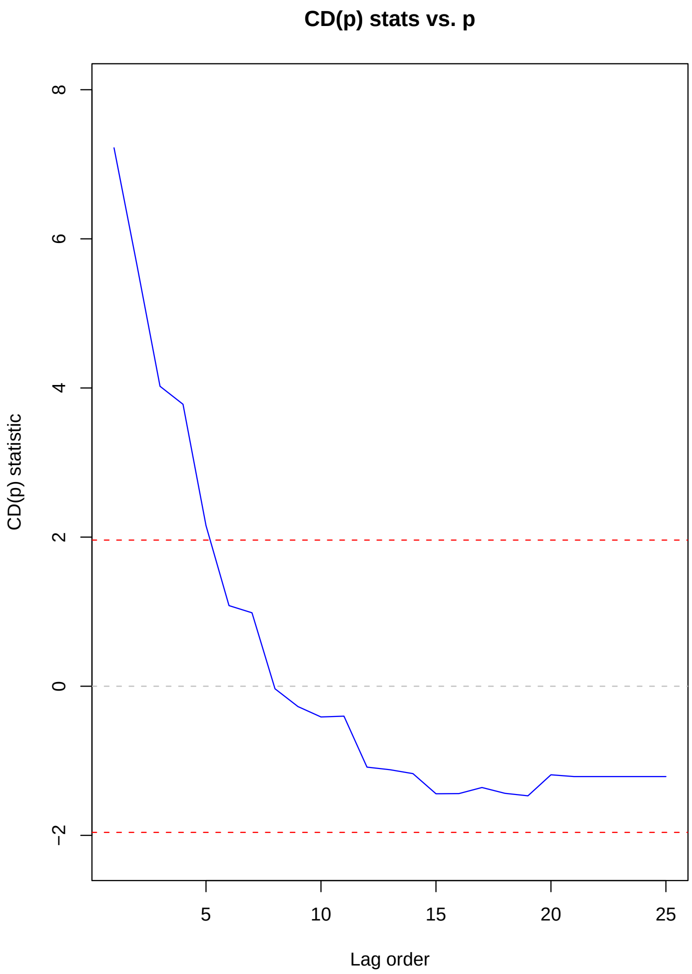

Figure 6: Recursive CD(p) plot, life, full model

9 Conclusions

In this paper we approach the empirical investigation of insurance consumption from a new perspective, an intermediate one between existing cross-sectional studies on countries and microdata analyses on household income, wealth and consumption surveys. Data availability for insurance premiums limits the analysis to the provincial (i.e. NUTS3) aggregation level. As far as lines of business are concerned, only macroclass level data are available: total life insurance, compulsory third party liability and other, non-mandatory non-life. We do not consider the second class because mandatory insurance asks for a different theoretical framework, so we concentrate on life and non-mandatory non-life.

In accordance with existing literature, we find a significant and positive influence of disposable income (GDP) on insurance consumption in the life (non-mandatory non-life) class. Life insurance is proportional to the number of family members and to the share of the young on the active population, coherently with the view of life insurance as protection. Interestingly, the sign of the education variable is negative, which might be related to better portfolio diversification for the well-educated. The role of judicial inefficiency is strongly negative on non-life; much weaker for life. Trust is a positive driver for both. These findings highlight the importance of a healthy social environment and of the correct enforcement of property rights on the development of the financial sector. High interest rates are found to depress non-life insurance consumption, arguably by raising the cost of borrowing and thus the opportunity-cost of insuring against self-insuring. Lastly, the density of agencies is very important, highlighting the value of advice in the purchase of a rather complicated contract as often are insurance policies.

Data limitations, both inherent the very nature of the insurance product and due to current statistical practice by the relevant bodies, are binding. Regional data may be useful in this respect, by eliminating that part of the heterogeneity that is associated with "sistemic" differences in countries and possibly allowing efficient random effects estimation of the relationships of interest. Dealing with such data, though, the spatial perspective should always be controlled for, as they raise further methodological issues with respect to panels or cross-sections of countries.

Appendix A: Maximum likelihood estimation of the SEM-AR-RE model

Baltagi, Song, Jung and Koh ([4]) derive the expressions for the error covariance matrix, its inverse and determinant for the model where errors are the sum of an individual, time-invariant component and an idiosyncratic one which is spatially autocorrelated and has serial correlation in the remainder:

$$\begin{aligned} & y = X\beta + u \\ & u = (\imath_T \otimes \mu) + \epsilon \\ & \epsilon = \lambda(I_T \otimes W)\epsilon + \nu \\ & \nu_t = \rho\nu_{t-1} + e_t \end{aligned} \tag{1}$$

We follow their simplifying notation, denoting:

$$\begin{aligned} & \alpha = \sqrt{\tfrac{1+\rho}{1-\rho}} \\ & d^2 = \alpha^2 + (T-1) \\ & V_\rho = \tfrac{1}{1-\rho^2} V_1 \\ & V_1 = \begin{bmatrix} 1 & \rho & \rho^2 & \dots & \rho^{T-1} \\ \rho & 1 & \rho & \dots & \rho^{T-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{T-1} & \rho^{T-2} & \rho^{T-3} & \dots & 1 \end{bmatrix} \end{aligned}$$

so $cov(u) = \Sigma$ and its inverse and determinant can be expressed as

$$\begin{aligned} & \Sigma = \phi(J_T \otimes I_N) + V_\rho \otimes (B'B)^{-1} \\ & \Sigma^{-1} = V_\rho^{-1} \otimes (B'B) + \tfrac{1}{d^2(1-\rho)^2}(V_\rho^{-1} J_T V_\rho^{-1}) \otimes [[d^2(1-\rho)^2\phi I_N + (B'B)^{-1}]^{-1} - B'B] \\ & |\Sigma| = \sigma_e^{-2NT}|T\phi(A'A)^{-1} + (B'B)^{-1}| \cdot |(B'B)^{-1}|^{T-1} \end{aligned}$$

and the likelihood is:

$$\begin{aligned} logL = & -\tfrac{NT}{2}2\pi - \tfrac{NT}{2}ln\sigma_e^2 + \tfrac{N}{2}ln(1-\rho^2) - \tfrac{1}{2}ln|d^2(1-\rho)^2\phi I_N + (B'B)^{-1}| \\ & + (T-1)ln|B| - \tfrac{1}{2\sigma_e^2}u'\Sigma^{-1}u \end{aligned}$$

This likelihood can be maximized by the two-step method outlined in ([1]), alternating between maximization of the concentrated likelihood w.r.t. (ϕ, ρ, λ) and GLS estimation of β given the former.

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