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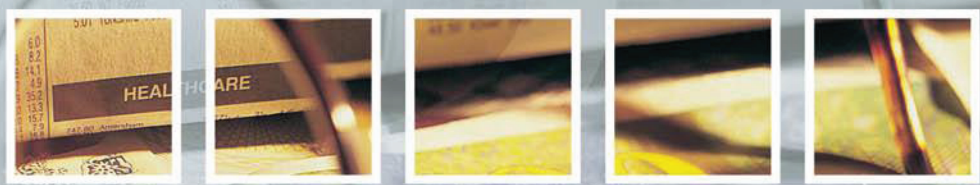
A Sub-Regional Panel Data Analysis of Life Insurance Consumption in Italy



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A sub-regional panel data analysis of life insurance consumption in Italy

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Abstract

We propose a different empirical approach to the long-standing research question on the determinants of life insurance development, together with new methodological tools, and apply both to the peculiar Italian situation. Our sub-regional panel sample has less unobserved heterogeneity than prior research on the determinants of aggregate life insurance consumption relying on large databases of countries, while retaining a fair amount of variance in observable characteristics, but it raises issues of cross-sectional dependence which combine with well-known issues of insurance data like serial correlation. We therefore employ a new spatial panel estimator allowing for regional heterogeneity, spatial and serial correlation.

Keywords: Life insurance, Regional data, Spatio-temporal correlation

1 Introduction

The aim of this study is twofold. From an analysis of the Italian life insurance market across a panel of Italy's *provinces* (i.e., NUTS2 regions) observed over six years we will assess the determinants of market development in the particular Italian case, characterized by an extremely uneven geographical distribution of insurance density; moreover, generalizing our findings, we will bring new evidence to the empirical literature on aggregate insurance demand. In this latter respect, we will pay special attention to some research questions which are still largely undecided, as those regarding the effect on life insurance purchases of some demographic characteristics: education, family size and number of young dependents (Zietz, 2003). Methodologically, we propose an innovative viewpoint: sub-regional data from within one country. We will describe both the advantages and the drawbacks of this empirical perspective and provide solutions for the associated issues through a first application of novel econometric modelling techniques.

Empirical research on the determinants of life insurance consumption has followed two main routes. One, based essentially on microdata from surveys on households, consumers, and various subsets of the population (students, married couples, retired people), has investigated life insurance demand from a microeconomic perspective, in the light of savings theory and in particular of the life-cycle hypothesis (see e.g. the recent contribution by Liebenberg *et al.* (2012) and the literature survey therein). The other main empirical perspective has been that of aggregate market development, usually drawing on cross-sections or panels of countries; in this latter case, the focus has usually been on the determinants of aggregate market turnover, sometimes labeled "demand" but perhaps more appropriately described as "consumption", as its observed values are the outcome of a market equilibrium between demand and supply.

Besides their interest to insurance scholars, practitioners and market players, aggregate approaches to the analysis of life insurance consumption find a broader motivation in policy issues pertaining to its role in the financial system and in the aims, scope and sustainability of the welfare state. The importance of insurance for economic growth has been extensively analyzed in the literature, both as a component of a broader financial system (King & Levine, 1993) and in a stricter sense, as in Outreville (1996) and Ward & Zurbruegg (2000). In particular, Arena (2008) has provided evidence of a causal link from the development of the life insurance market in a country to its economic growth. From the point of view of welfare, life insurance, serving 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, or to himself, in case he survives" (Villeneuve, 2000), in turn comprises two main different economic functions, defined by the two opposite "risks" related to uncertainty about the duration of human life: protection of dependents from the untimely death of the income earner, and protection of the lifetime income of the latter from the so-called "survival risk", i.e. living longer than the accumulated resources can provide for. Therefore life insurance has a role in supporting, or even substituting, public welfare. In fact, countries relying substantially on the private sector for the provision of old age benefits typically have very large life insurance revenues to GDP ratios, as is the case for Japan, the United Kingdom, Belgium or South Korea. A third function of life insurers is related to their role as institutional investors. As such, they help the efficient allocation of resources by investing the technical reserves associated with insurance activity. The financial component of life insurance is actually very important, because the time span of contracts is so long that the accumulated reserves reach substantial amounts.

The importance of insurance in the Italian economy is geographically very diverse. Unlike what happens with non-life insurance (see Millo & Carmeci, 2011), the Italian life insurance market as a whole is comparatively well developed by European standards, but striking regional differences persist, the South of the country being generally underdeveloped with respect to the North and Centre (see Figure 1, left panel). Moreover, life insurance density is highly correlated in space, with a striking similarity between clusters of nearby provinces (see Figure 1, right panel).

Given the important economic function life insurance performs, to investigate the determinants that lead to the current situation is a question of broad interest and scope, not limited to that of the insurance industry.

Our work is introduced by sketching the main results in insurance demand theory, focusing on which are expected to be the main drivers of consumption and discussing some observable proxies. 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. Discussing the limitations of cross-country aggregate studies, we motivate the choice of a

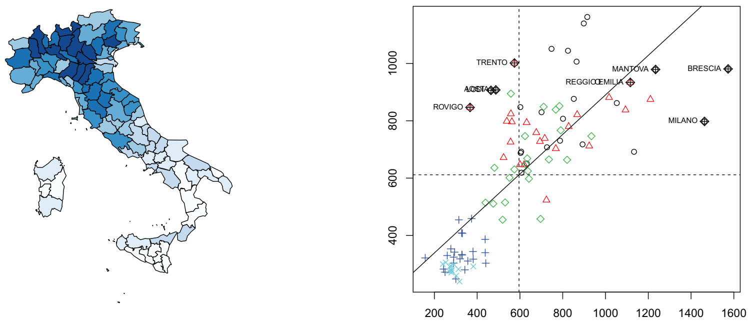

Figure 1: Map (left: darker is higher) and Moran plot (right: variable plotted against its spatial lag) of life insurance density in Italy. Data are euros per capita in the year 2000. Symbols and colour codes for macroregions are: ○ North-West; △ North-East; ◇ Centre; + South; × Islands.

sub-regional perspective as a means of eliminating some sources of variation that tend to overshadow all others and that are potentially prone to multicollinearity. Our sample of Italian provinces is homogeneous as regards systemic characteristics, yet it has enough variability to allow the identification of other determinants of insurance consumption. Moreover, some drivers that are problematic to define or observe can be safely omitted from the empirical analysis because they do not vary over provinces, and their time variation can be easily absorbed by time effects: life insurance prices, i.e. all kinds of policy loadings, which unlike what happens with non-life insurance are set at the national level; and financial returns on life insurance in force, which again derive from centralized financial management and do not change with the province where the policyholder resides.

We discuss the problems of heterogeneity in space and time and spatial and serial correlation which are likely to affect our sample. Assuming the coexistence of individual effects, serially and spatially correlated errors, we have to employ a novel estimator. Combining: the general analysis of Anselin (1988) on maximum likelihood estimation of spatial models; the work of Case (1991) on models with both spatially autoregressive errors and a spatially lagged dependent variable; and analytical results from Baltagi *et al.* (2007) on the coexistence of random effects, spatial and serial correlation in the errors, we propose a general specification encompassing all these features and we estimate it through a new algorithm for maximum likelihood estimation. Ex post, we find evidence of both spatial and serial correlation, as expected. Thanks to our encompassing specification we are able to discriminate between spatial correlation in the dependent variable and in the errors, only finding evidence of the latter, meaning that idiosyncratic shocks to insurance consumption propagate to neighbouring regions. The evidence of serial correlation is in turn consistent with previous literature (see Beenstock *et al.*, 1986).

Our results, while confirming that the diffusion of life insurance depends on economic development, per capita savings and demographic factors, reconcile to some extent the aggregate perspective with survey evidence. Regarding demography, unlike previous international studies (Beck & Webb, 2003) but in line with the theoretical predictions of Lewis (1989) and previous survey evidence (reviewed in Liebenberg *et al.*, 2012), we are able to document the positive influence of the ratio of young dependents. Also contrary to most results from the literature on international insurance development, but again in agreement with some microeconometric evidence (Duker, 1969; Anderson & Nevin, 1975; Auerbach & Kotlikoff, 1989), life insurance is negatively correlated with schooling, supporting the view that better education fosters financial risk taking. Moreover, we assess the importance of supply factors and of some environmental variables, finding that: the density of insurance agencies has a substantial positive effect but that of bank counters has none; and that the general level of trust is supportive of life insurance consumption, while the rule of law, unlike what happens in international samples (Ward & Zurbruegg, 2002) and the Italian non-life sector (see Millo & Carmeci, 2011), is not influent.

As for the reasons of the extremely uneven geographical distribution of life insurance density in Italy, the model successfully explains spatial correlation and macroregional heterogeneity within two clusters of macroregions: the Centre-North (North-West, North-East and Centre) on one side, and the South and Islands on the other. Nevertheless, an unexplained difference in outcomes remains between the two. A better explanation of the Italian "insurance divide" will be the subject for further work.

In the next section we review the literature in order to define the subject and then to sketch previous empirical findings providing the foundation for our work. In the third section we describe the dataset, review the model based on Beenstock *et al.* (1986) and discuss the reasons for expecting the presence of heterogeneity and correlation in space and time. The fourth section presents the random effects specification with spatially lagged dependent variable and serially and spatially correlated errors; then outlines the estimation method; lastly, discusses the results. The last section draws the conclusions.

2 Literature review

In the unifying framework first developed by Yaari (1965) and Hakansson (1969), the demand for life insurance is attributed to a person's desire to bequeath funds to dependents and provide income for retirement. In the case of term life, according to the extension of this scheme by Lewis (1989), it is also a function of the number, personal characteristics and preferences of the beneficiaries, that is, in most cases, of family composition.

The primary function of life insurance can therefore be characterized as "income" protection, meaning either "income of one's dependents" against premature death of the insured, or "lifetime income of the insured" in the case of lower earnings, e.g. after retirement. Beenstock *et al.* (1986) term the first *life protection* and the second *income protection*. They add another function which is typical of insurance: pure *saving*, the element not related to human life but only to the investment yield. These categories roughly correspond in standard practice to *term life*, *annuities and pensions* and *capitalization*, although distinctions are blurred in the life products that are actually sold. Most endowment policies sold in Italy, for example, have an important term life component, entitling the beneficiaries to payment of its face value upon death of the insured.[1]

	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 1: Composition of life insurance revenue by class in Italy, 2000. Classes are reported according to the Italian classification; they correspond approximately to traditional endowment and annuities plus term life in class 1, unit- and index-linked policies in class 3, capitalization (life-independent endowment) in class 5, pension plans in class 6.

A summary of the empirical approach can be found in Beck & Webb (2003) who synthesize the phenomenon 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."

The relevant literature is too vast to be summarized here: in his comprehensive review of the literature on insurance and economic growth, Outreville (2012) counts 85 papers "most of them examining the demand for life insurance". In the following we will only mention results that bear a direct relevance to our analysis.

Studies on microdata (usually household income or consumer expenditure surveys) from the international literature over the last 40 years are summarized in Table 1 of Liebenberg *et al.* (2012). While generally confirming the positive association with income, they weakly support the idea that life insurance consumption be declining with age but are inconclusive as regards the effect of education (often significant but with changing signs) or that of young dependents (mostly non significant).

Many cross-country comparisons find a positive influence from income and schooling (Beenstock *et al.*, 1986; Browne & Kim, 1993; Beck & Webb, 2003) and a negative effect of inflation (Beenstock *et al.*, 1986; Browne & Kim, 1993; Outreville, 1996; Ward & Zurbruegg, 2002; Feyen *et al.*, 2011). The positive income effect is undisputed in applied research. The expected effect of education on insurance purchases is less obvious, although most (Truett & Truett, 1990; Browne & Kim, 1993; Li *et al.*, 2007; Feyen *et al.*, 2011) see it as positively related to risk awareness (and hence to life insurance consumption). A different view, equally plausible and consistent with some empirical findings from survey data (Duker, 1969; Anderson & Nevin, 1975; Auerbach & Kotlikoff, 1989) but scarcely

[1]For an overview on the actual composition of life insurance sold in Italy, see Table1, whence it may be seen that there is no clear correspondence between the theoretical functions of life insurance and the classification.

considered in the literature on insurance development, relates education to the willingness and the capacity to manage risks (see also Outreville and Szpiro, unpublished, cited in Browne *et al.*, 2000). A puzzling result, by Browne & Kim (1993), is that although being a substitute for life insurance, social security expenditure is in turn positively correlated with it.

The related aspects of mean age of the population (Beenstock *et al.*, 1986; Truett & Truett, 1990), life expectancy (Beenstock *et al.*, 1986; Outreville, 1996) and old dependency ratio (Beck & Webb, 2003; Feyen *et al.*, 2011) have also been found positive and significant. Only two studies separate between young and old dependency ratios: Beck & Webb (2003), consistently with the positive effect of an ageing population, find a positive coefficient for the share of old dependents and a negative one for that of the young, while they are both positive in Feyen *et al.* (2011).

In general, and unsurprisingly, most characteristics of developed countries (wealth, high life expectancy, good education, monetary stability) tend to be associated with another feature of advanced economies: a well-developed life insurance sector. The issues posed by this multicollinearity and the way they have been dealt with will be discussed in the next paragraph.

The literature has also reserved little attention to another theoretically important determinant of life insurance purchases, what Beck & Webb (2003) call the "vector of interest rates": i.e., the rates of return on life insurance reserves and those of competing financial products as stocks, mutual funds and in particular safe activities as government and corporate bonds. Hence, as Outreville (2012, p.20) aptly observes, life insurance purchases should depend from the spread between the former and the latter. Unfortunately, the rates of return on life insurance reserves at country level are not readily observable and therefore the few studies considering interest rates have simply included (real) government bond yields (Outreville, 1996; Li *et al.*, 2007) or lending rates (Beck & Webb, 2003), finding conflicting results: either a positive (Beck & Webb, 2003), a negative (Li *et al.*, 2007) or no effect (Outreville, 1996). In this respect, we conclude that data problems have to date hindered researchers from correctly approaching an important determinant of life insurance consumption. The interest rates issue further motivates our subnational approach, which will be the subject of the next paragraph.

2.1 Motivating a subnational perspective

Studies on international insurance have recently been drawing on ever-bigger datasets, growing both in geographical scope and in the time dimension. While the latter may pose methodological problems (essentially concerning stationarity and spurious regression issues), the growth in geographical coverage has generally been considered a positive feature, as indeed it enriches the informative content of the given sample.

In this respect, though, the cross-country perspective raises big concerns as regards individual heterogeneity relating to institutional, regulatory, social and other factors which are generally unobservable or difficult to quantify and take into account. Moreover, a number of relevant indicators of development tend to go together and to be all higher in some countries, those who, in the words of Zingales (2003), "seem to be doing the right thing in many dimensions", having better legal enforcement, a higher level of trust, less corruption, a more efficient and independent judicial system and better developed financial markets, just as others (see the discussion in Outreville, 1990) are characterized by high inflation, low education, a prevalently agrarian workforce and a monopolistic insurance market. Thus, "[e]ach institution taken individually has a positive effect on economic growth. Yet there are too many (highly correlated) variables and too few countries to be able to reliably identify the effect": collinearity makes establishing statistical relationships difficult. Hence Guiso *et al.* (2004) analize the causal link between financial development and growth from a regional perspective, observing that the level of political, regulatory and financial integration reached within Italy can be considered an upper bound for that a set of countries will ever be able to attain. So in analyzing Italian data from a sub-regional perspective we are confident that the systemic factors will be as homogeneous as possible, while at the same time the variance of other regressors will be high.

Past studies in the insurance development literature have acknowledged the heterogeneity problem (Browne & Kim, 1993; Outreville, 1996; Beck & Webb, 2003; Li *et al.*, 2007) proposing the separation of developing from developed countries as a solution. Yet the homogeneity hypothesis, explicitly stated by Li *et al.* (2007), that focusing on OECD countries "avoids mixing different country characteristics and heterogeneous consumer demand" still seems overoptimistic to us. Some systemic characteristics, in fact, differ just as wildly within OECD countries as they do between these and the rest of the World. Some examples follow.

In the specific case of insurance, a major source of systemic differences between countries, which often "eats up" all the cross-sectional variability, are social security systems outsourcing old-age welfare to the private sector, which gives rise to the world's biggest life insurance markets in terms of penetration over GDP (South Africa, the United Kingdom, Japan and South Korea). In general, the features of the social security system play a major role in explaining life insurance: countries with extensive public coverage for old age use to have lower levels of life premium income, so that comparisons between countries with different social security systems is often not meaningful unless the heterogeneity is controlled for, e.g. by exploiting time variation in a panel setting, although the time variation is often very small with respect to the cross-sectional one.

An inflation-ridden past history, as, within Li *et al.* (2007)'s sample, in Turkey or Mexico, in turn depresses public trust in traditional savings products, such as many kinds of life policies: Outreville (1996), in an extensive study of life insurance markets in developing countries, considers the expected inflation rate and the presence of a monopolistic market structure and of barriers to entry of foreign competitors, unsurprisingly observing a negative effect (on inflation, see also Beck & Webb (2003) and the case of Brazil in Babbel (1981)).

Religious beliefs, as shown by Grace & Skipper (1991) and Browne & Kim (1993), are another key determinant of the low insurance consumption in many countries, especially Islamic ones. Browne & Kim (1993) find a positive relationship between life insurance consumption and income, literacy and the type of legal system. In turn, Ward & Zurbruegg (2002) find a positive influence of the rule of law in both an Asian and an OECD sample. Beck & Webb (2003) add also the degree of development of the banking sector, finding a positive effect on the subsample of developing countries. Possibly for the reasons given above (see also the discussion in Hussels *et al.* (2005)), education, young dependency ratio, life expectancy and the size of social security do not prove significant in their setting.[2]

Many of these influential factors have little or no time variability, therefore they cannot be included in a fixed effects analysis. If they are, as in Feyen *et al.* (2011), then estimation must omit individual fixed effects, subject to the very strong assumption that the variables included actually account for all of the individual heterogeneity. One modelling possibility, in such cases, is to introduce macroregional fixed effects together with individual random effects, as will be discussed later.

2.2 Consumption or demand: the role of supply

Some of the studies cited (Browne & Kim, 1993; Zietz, 2003; Li *et al.*, 2007) indifferently use the terms *consumption* and *demand* to indicate the total yearly premium volume of a market, while in our opinion, only the first term is adequate, as indicating an equilibrium market outcome resulting from the interplay of supply and demand. As a logical consequence of this imprecise wording, they estimate one reduced form equation, equating (per capita) premium volume to a number of explanatory regressors, then take the resulting coefficients as measures of the influence on insurance demand, which is not necessarily true unless supply is infinitely elastic at a given price, which seems a heroic assumption especially in a cross-country setting. Browne & Kim (1993, p. 620) actually devote some words to the possible effects of supply on price and, although declaring them "beyond the scope of the [...] study", include one price proxy in one of their equations.

To our knowledge, only Beenstock *et al.* (1986) and Outreville (1996) explicitly formalize a supply schedule, making it dependent on the cost and risk conditions faced by life insurance providers: interest rates, life expectancy; and either on market structure variables (financial development, market openness vs. monopolistic behaviour) as in Outreville (1996) or on the prices of substitute products, as in Beenstock *et al.* (1986). Beck & Webb (2003) in turn discuss the importance of including supply factors, and name some environmental characteristics (quality of human resources, property rights protection) as influencing the insurers' cost function.

Beck & Webb (2003), after observing the usual impossibility to observe price and quantity separately in insurance datasets, stress the importance of the missing price variable and adopt two solutions to account for it. The first is including a number of "supply-side factors that are likely to affect the ability of insurers to market and distribute policies cost-effectively: urbanizaton, monetary stability, bureaucratic quality, the rule of law, corruption and banking sector development". The second is to include country fixed effects in their panel analysis, so as to control for that part of the unobserved heterogeneity that is country-specific and time-invariant. Still, Beck & Webb (2003)'s solution is prone to the bias from omitted, time-variant regressors (and price can hardly be assumed time-invariant over 36 years) and limited by the fact that most of the assumed determinants of supply can also be thought to influence demand.

In our analysis we rather choose to start from the terse formalization in Beenstock *et al.* (1986), who explicitly model equilibrium revenue, the observ-

[2] More precisely, they are significant in the cross-section but are not in the panel sample.

able variable, as price times quantity eliminating the need for a problematic price proxy. Nevertheless, their model still considers the price of competing types of life coverage. In this respect, we observe that in a sub-regional setting the price of each life insurance product, measured as policy loadings and commissions, is cross-sectionally invariant, as the products sold are the same nationwide. Therefore only time variations must be accounted for, which are absorbed by time fixed effects. The same goes for the problematic interest rate spread between insurance reserves and market rates: insurers are nationwide players who invest on international markets, hence the polcyholder's region of residence makes no difference in this respect.[3]

3 Empirical setting

As anticipated, we take Beenstock *et al.* (1986)'s model as our reference. They analyze life insurance in 10 industrialized countries over 12 years (see also their companion paper on non-life Beenstock *et al.*, 1988).

They choose the model's regressors based on the decomposition into life protection, income protection and saving. A priori, they postulate that demand for life protection depends on life expectancy, parental dependency, age, the price of insurance, the general price level and the level of social security transfers received by the population; supply from insurance price, life expectancy, the real rate of interest, age and the price of pension products (because capacity-constrained insurers face a trade-off between supplying life or pension insurance). In their framework, the demand for pensions in turn depends on income, life expectancy, the price of pension policies, the general price level, parental dependency and social security payments; supply from prices of both insurance categories (for reasons given above), age and the real rate of interest. Lastly, supply of and demand for the saving element of insurance depend on aggregate saving and on a vector of interest rates.

We adopt their formalization, augmented by some significant variables from other studies, and purged of those invariant at national level. Personal disposable income has generally been proxied by means of GDP or GNP, a suboptimal solution due to data limitations (see the discussion in Browne & Kim, 1993, p.622). We directly observe aggregate disposable income *(ryd)*. We add bank deposits per capita *(rbankdep)* as a proxy for the stock of wealth.[4]. Including this together with the yearly flow of income, usually not an option in international databases, allows us to test the combination of two effects: that on life protection, which should be negative according to the theoretical prediction of Lewis (1989), and that on saving products, which should obviously be positive. We use three measures of dependency: young and old dependency ratio *(ydeprat, odeprat)*, the ratio of non-working-age people, respectively younger (under 14)

[3]The lending rate is the only observable financial yield to vary with the insured's province of residence. Although excluding it from the maintained model for lack of theoretical support, as a robustness check we added it to an alternative specification.

[4]We verified the appropriateness of deposits as a proxy for wealth drawing on a new database from the Bank of Italy (see Albareto *et al.*, 2007), comparing our data on bank deposits with their estimates of household wealth for the year 1998. On a per capita, cross-region basis, the correlation between bank deposits and real assets was 0.92, with financial wealth 0.80, both significantly positive at the 1 percent level. Province-level data are not available.

and older (over 65) divided by the labour force (15-64), are meant to control for young and old dependents; the female participation rate to the workforce *(partrate)* for dependent spouses. We consider social security payments *(socialsec)* as the sum of three different kinds of provisions: old age pensions *(ss.oldage)*, pensions to surviving spouses *(ss.surv)* and inability transfers *(ss.inab)*[5]. The general price level is unfortunately unobservable, as in Italy there are no comprehensive price statistics at provincial level. Yet the role of inflation in cross-country surveys is in distinguishing countries where a long history of inflation has permanently discouraged long-term commitments to saving products from those where it has not: in this respect we are confident that Italy's provinces can be considered homogeneous and the general price level discarded from our analysis. Regarding the price of insurance, although the focus is on equilibrium revenue, the price of pensions still enters the supply function of life protection suppliers and the reverse. In general, as Schlesinger (2000) notes, "it is often difficult to determine [even] 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". Here the difficulty of (defining and) observing the "price" of insurance coverage, a key limitation of cross-country studies, may be considered irrelevant as products are designed on a nationwide basis and therefore average policy loadings can be taken as uniform across provinces, if not for some possible composition effects. Both interest rates on saving products and the return rates insurers are able to obtain from investing their reserves are determined on a national or international basis, so that we can safely consider them cross-sectionally invariant in our setting.

In Beenstock *et al.* (1986)'s formalization, total premium income V for the three categories of life insurance products "life protection" (V_1), "pension plans" (V_2) and "saving" (S) can be expressed as $V = P_1Q_1 + P_2Q_2 + S$ where, according to the equilibrium solutions in their paper and considering our choice of regressors,

$$\begin{aligned}
&V_1 = F_1(ryd, family, odeprat, ydeprat, partrate, socialsec)\\
&V_2 = F_2(ryd, odeprat, socialsec)\\
&S = F_3(rbankdep)
\end{aligned}$$

plus the control variables. Like Beenstock *et al.* (1986), we are not able to observe the three components separately: see comments to Table 1 above. Therefore we will estimate one model for $V_1 + V_2 + S$ as a whole.

With respect to Beenstock *et al.* (1986)'s specification, we add two supply-side variables: the densities of the two main distribution channels, bank counters *(bankcount)* and insurance agencies *(agencies)*, over population (in thousands). Rather than by Beck & Webb (2003)'s finding on bank development, which regards developing countries, this inclusion is motivated by the widespread belief that life insurance be "sold rather than bought", meaning that the ability of salespeople is a powerful force in shaping demand (see Bernheim *et al.*, 2003). A different explanation could be that selling points density reduces the cost of searching for an appropriate policy: but the high standardization of life products and the diffusion of selling points are so high as to make the searching costs

[5] It is notorious that inability pensions are used as an improper state subsidy to some poorer parts of Italy by tacitly lowering requirements and controls, although both the economic and geographic dimensions of the phenomenon are unclear.

explanation less plausible.[6]

In this light we also add education, which might capture the degree of financial sophistication and risk awareness of the population, and the general level of trust based on survey data. Education is less likely to be relevant here as a measure of human capital in the insurers' production function, as claimed by Outreville (1996) and Beck & Webb (2003), considering that production takes place at the national level.

In the spirit of Hofstede (1995), we acknowledge the influence of cultural values in the purchase of insurance and the need to account for them, although in our more homogeneous setting this is probably mitigated. As noted in Ward & Zurbruegg (2000), the argument in Fukuyama (1995) that a higher level of trust facilitates economic transactions is readily applicable in insurance (see also de Meza *et al.*, 2010; Guiso, 2012). A survey-based measure of trust *(trust)* is therefore added to the model.

Finally, an index of judicial inefficiency *(inef)* is added, consistently with the findings of La Porta *et al.* (1998) on the influence of the legal environment on financial development and the specific results of Ward & Zurbruegg (2002) regarding Asian insurance markets (see also the discussion in Beck & Webb, 2003). The index is the average length of civil trials from Guiso *et al.* (2004).

3.1 Data description

We draw on Italian data collected at the provincial level over the years 1996-2001. In the following, we refer to the (then-) 103 Italian administrative units called *province*, corresponding to level 3 in the NUTS (Nomenclature of Territorial Units for Statistics) classification by Eurostat. We also refer to macroregions, which divide the territory into 5 aggregates: North-West, North-East, Centre, South and Islands. The dependent variable, Life insurance density in euro per capita, comes from the Italian regulatory body, Isvap. As observed, it takes much different values across Italian provinces, being generally lower in the South of the country. All of the last 20 regions in the overall ranking come from the South and Islands; all but one of the first 20 are northern regions. Besides high spatial differentiation, insurance density shows a high degree of spatial correlation[7], as shown by Figure 1.

The situation is much alike for most of the possible determinants of insurance consumption, although clustering is less apparent. Spatial dependence is confirmed by statistical tests (Moran and Geary, not reported). Summary statistics are reported in Appendix B, Tables 7 and 8.

The description and sources of the regressors included in the model can be found in Table 6. All monetary variates are expressed in real terms using 2000 as the base year by deflating them with the official national price index from Istat,

[6]Nowadays the banks' share in the distribution of life policies is steady at 50 percent of premiums, while the Post Office is 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.

[7]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, provinces are considered neighbours if they share a common border or vertex; see LeSage 1999). According to common practice, the matrix has been row-standardized. Reggio Calabria and Messina, divided by the Messina Strait, have been considered contiguous.

the Italian statistical institute; the sources cited are for the raw data; further calculations by the authors have employed population statistics from Istat.

3.2 Heterogeneity and correlation in space and time

Our setting poses a number of specification problems, mostly related to heterogeneity and dependence in time and space. To control for unobserved heterogeneity in space we add both macroregional fixed effects and provincial random effects. As Wooldridge (2002) notes, this is a sort of middle ground between FE and RE analysis, a way of dealing with regressor-related heterogeneity while retaining most of the efficiency of a random effects estimator. Anyway, adding provincial fixed effects would not be an option in this setting, where cross-sectional variability is the main focus of the study and some regressors are very persistent or even time-invariant altogether. The limited time dimension of our study also allows to include time dummies to account for time shifts of all those factors which have been omitted because they are cross-sectionally invariant, like policy loadings (the "price" of insurance) and investment returns.

As Beenstock *et al.* (1986) observe, serial correlation is very likely to be an issue in life insurance data because of the considerable slice of recurring payment policies, so that any shock to premiums in one given province and year is bound to persist in subsequent years, albeit with decreasing intensity. This time-decaying kind of serial correlation is different from, and may coexist with, the time-invariant error persistence given by individual error components: the first accounting, as observed, for the (limited) persistence of an innovation whose memory is eventually lost, the second for a permanent unobserved individual feature.

Spatial correlation can arise as a meaningful characteristic of the data generating process, if justified by the economic model, or as a specification and measurement problem, typically due to the so-called *aggregation bias*, "a mismatch between the spatial unit of observation and the spatial dimension of the economic phenomena under consideration" (Anselin & Bera, 1998, p.239), or to the omission of a spatially correlated regressor. It can be modeled as a spatial diffusion process in the dependent variable (spatial lag), whereby the outcome in each province influences those of neighbours, and/or in the errors (spatial error), meaning that idiosyncratic shocks in one place partly propagate in space towards neighbouring ones. In our case an influence of life insurance purchases in one province on neighbours is difficult to justify, while the spatial diffusion of shocks is a plausible hypothesis, as innovations in demand or supply will hardly follow the administrative boundaries according to which the data have been collected.

4 Specification and estimation

Beside the inclusion of macroregional and time fixed effects, the peculiar features of our problem require the estimation of a model with individual (provincial) random effects and both serial and spatial correlation in the idiosyncratic error. Moreover, the nature of the spatial correlation is unclear and therefore it is not possible to choose a priori between the two common specifications of *spatial lag* (where the dependent variable premultiplied by a spatial contiguity matrix is added to the right-hand-side regressors) and *spatial error*, where it is the idiosyncratic error term that is spatially lagged.

4.1 Specification

Case (1991) estimates a model nesting both spatial specifications in order to account for any possible source of spatial effects and, after estimation of the full model, discriminate via a Wald test. Building on the general approach of Anselin (1988) and on analytical results from Baltagi *et al.* (2007), we augment Case's specification with a time-autoregressive term in the remainder of the idiosyncratic error.

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

where y is the $nT \times 1$ response vector and X a $nT \times k$ matrix of regressors, both stacked by year and then cross-section; W is an $n \times n$ spatial weights matrix representing the relative position of units in geographical space, and as such assumed exogenous and time-invariant. More precisely, here W is a binary contiguity matrix with ones corresponding to neighbouring provinces, zeros elsewhere, standardized so that the row sums are all one.[8] μ is a $n \times 1$ vector ofindividual random effects; and I_T, $\imath_T$ respectively a $T \times T$ matrix and a $T \times 1$ vector of ones. As for the estimands, β is the vector of parameters of interest, λ and ρ the spatial autoregressive and spatial error coefficients, ψ the (time) autoregressive coefficient for the remainder error term ν. X, μ and e are assumed mutually independent.

As observed, this specification is meant to control for individual heterogeneity, for serial error correlation deriving from the persistence in time of idiosyncratic shocks, and for two possible kinds of spatial diffucion processes: in the dependent variable and in the idiosyncratic shocks.

4.2 Estimation

We estimate the specification in (1) by two-step maximum likelihood (ML) as detailed in Appendix A. Coefficient estimates are reported in Table 5 and will be discussed in the next section. As for the spatial lag and error covariance parameters (Table 3), the former turns out not significant while the spatial error parameter is significant and rather large, indicating a spatial diffusion process in the errors. Random effects and serial correlation are in turn, respectively, not significant and highly significant, pointing to time-decreasing error persistence rather than time-invariant individual effects. As for the time and macroregional fixed effects, the former are significant and almost linearly increasing, while

[8] Different choices for W are possible, and are common in the literature: especially distance based weights, where distance can be geographic or defined according to some economic measure. The choice of the contiguity matrix is one of the most controversial subjects in spatial econometrics (see Anselin, 1988, p.19). Binary contiguity has the advantage of simplicity, of imposing a minimum of a-priori structure and of making the interpretation of a spatial lag straightforward as the average value of neighbours; therefore (Anselin, 1988, p.21) it is often preferred for spatial error structures and in general where the focus is on testing for spatial effects rather than on precisely estimating a theoretically well defined spatial process.

of all the macroregional effects South and Islands turn out very similar, and much different from the rest of Italy. In general, estimation results indicate that neglecting spatio-temporal correlation would have led to inefficient estimation of the vector β of the parameters of interest; but, at the same time, they show some directions for admissible simplification of the model which will be pursued below.

	Estimate	Std. Error	z value	Pr(>|z|)
d97	0.3586	0.0276	13.0139	0.0000
d98	0.8632	0.0391	22.0861	0.0000
d99	1.2477	0.0488	25.5788	0.0000
d00	1.4638	0.0583	25.0982	0.0000
d01	1.5652	0.0683	22.9258	0.0000
NO	0.0986	0.0750	1.3146	0.1886
NE	-0.0928	0.0680	-1.3650	0.1723
SU	-0.5195	0.0905	-5.7431	0.0000
IS	-0.5415	0.1106	-4.8952	0.0000

Table 2: Time and macroregional fixed effects' estimates and diagnostics. Significance stars are: '.' = significant at 10 percent; '*' = 5 percent; '**' = 1 percent; '***' = 0.1 percent. Standard errors are based on the GLS step at optimal values of spatial and covariance parameters.

	Estimate	Std. Error	t-value	Pr(>|t|)
phi	0.3252	0.2817	1.1545	0.2483
psi	0.6826	0.0514	13.2711	0.0000
rho	0.3979	0.0960	4.1433	0.0000
lambda	-0.1560	0.1125	-1.3863	0.1657

Table 3: Error variance parameters (top) and spatial autoregressive coefficient (bottom). Significance stars are: '.' = significant at 10 percent; '*' = 5 percent; '**' = 1 percent; '***' = 0.1 percent. Standard errors are based on estimates of the numerical Hessian.

The model shows strong serial correlation in the errors (0.68), as expected, confirming the persistence of idiosyncratic shocks discussed above. By contrast the evidence of a random effects structure is weak: the variance of the individual error component, picking up that part of the heterogeneity not yet accounted for by macroregional fixed effects (see Millo & Carmeci, 2011, beginning of Section 6) is estimated at 33 percent of the idiosyncratic error variance and not significant. As for the spatial parameters, the Wald test for spatial lag versus spatial error correlation implicit in the encompassing model favours the second, which is significant and substantial (0.4), while the spatial lag coefficient is not significantly different from zero. This is evidence in favour of a diffusion process in the errors whereby idiosyncratic shocks propagate to a certain extent to neighbouring provinces; as expected, outcomes in one province do not seem to influence those of neighbours.

4.3 Discussion of estimation results

According to the diagnostics for the full model, the specification is to be reduced to a pooled model with spatial and serial correlation in the errors, and neither random effects nor a SAR term. The statistical admissibility of this reduction is supported by a joint likelihood ratio test ($\chi^2(2) = 2.86$, p-value=0.24). Estimation of this reduced specification yields slightly higher serial correlation (0.73) and lower spatial correlation (0.26) in the errors. Results for the coefficients in β are reported below in Table 5.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-7.9235	2.3020	-3.4420	0.0006
log(ryd)	1.3820	0.2185	6.3254	0.0000
log(rbankdep)	0.1946	0.0795	2.4471	0.0144
log(family)	0.2909	0.3530	0.8243	0.4098
odeprat	-0.0019	0.0062	-0.3046	0.7607
ydeprat	0.0220	0.0101	2.1708	0.0299
log(socialsec)	-0.0726	0.0720	-1.0086	0.3132
log(partrate)	-0.0623	0.1799	-0.3466	0.7289
log(school)	-0.6970	0.2358	-2.9562	0.0031
log(inef)	-0.0066	0.0574	-0.1155	0.9081
log(trust)	0.9469	0.5218	1.8146	0.0696
log(bankcount)	0.0010	0.0672	0.0143	0.9886
log(agencies)	0.1602	0.0735	2.1791	0.0293

Table 4: Model summary. Significance stars are: '.' = significant at 10 percent; '*' = 5 percent; '**' = 1 percent; '***' = 0.1 percent. Standard errors are based on the GLS step at optimal values of spatial and covariance parameters.

As expected, disposable income is a very significant positive driver of life insurance consumption, confirming all previous evidence: higher income flows lead to increased insurance purchases. We attribute this to both life protection and income protection products, for the reasons discussed above. An alternative specification substituting GDP for disposable income (see the discussion in Browne & Kim, 1993, p.622) confirms the positive result, although predictably yielding a much lower estimate for the elasticity. Fit statistics empirically support the theoretical preferability of disposable income and hence of model (0) as our maintained specification.

Our proxy for aggregate wealth, the per capita amount of bank deposits, is significantly positive too, a less obvious result. As observed, based on the model of (Lewis, 1989) wealth should exert a negative effect on life protection insurance (the well-endowed are better protected from loss of breadwinners' income risk) while according to Beenstock *et al.* (1986) it is positively related to saving products. Our analysis seems therefore to capture the effect of wealth on the saving-related part of life premiums, while not finding any evidence in favour of Lewis (1989)'s effect.

Social security expenditure, which should in theory substitute for income protection, is negative (contrary to what happens in cross-country comparisons) but not significant: the effect of public welfare seems statistically not discernible in a homogeneous setting, but shows the expected negative sign.

	m0		m1		m2		m3	
(Intercept)	-7.924	***	-2.456		-8.143	***	-1.313	
log(ryd)	1.382	***	-	-	1.634	***	1.464	***
log(rgdp)	-	-	0.786	***	-	-	-	-
log(rbankdep)	0.195	*	0.281	***	-	-	0.258	**
log(socialsec)	-0.073		-0.046		-0.075		-0.118	
log(family)	0.291		0.134		0.299		0.109	
odeprat	-0.002		0.008		-0.006		-	-
ydeprat	0.022	*	0.015		0.021	*	-	-
log(age)	-	-	-	-	-	-	-1.491	*
log(partrate)	-0.062		-0.133		-0.062		-0.277	
log(school)	-0.697	**	-0.806	**	-0.741	**	-0.785	**
log(inef)	-0.007		-0.001		-0.028		-0.006	
log(trust)	0.947	.	0.658		0.926	.	1.229	*
log(bankcount)	0.001		-0.041		0.043		-0.016	
log(agencies)	0.16	*	0.134	.	0.169	*	0.141	
logLik	335.4	-	326.8	-	332.5	-	178	-
obs	618	-	618	-	618	-	412	-
n	103	-	103	-	103	-	103	-
T	6	-	6	-	6	-	4	-

Table 5: Model comparison. Significance stars are: '.' = significant at 10 percent; '*' = 5 percent; '**' = 1 percent; '***' = 0.1 percent. Standard errors are based on the GLS step at optimal values of spatial and covariance parameters.

Regarding social security as a proxy for wealth, as used by Browne & Kim (1993), the availability of a better measure (bank deposits, see above) highlights its inappropriateness: the latter is, as observed, significant and positive just as one would expect, while social security retains its negative sign and a very similar value if bank deposits are removed from the model. We conclude that the hypothesis of social security as a substitute for private life insurance is consistent with, albeit only weakly supported by, our data; and that the use of social security as a proxy for wealth is unwarranted.

Regarding dependency indicators, the only significant one is the young dependency ratio: the presence of young dependents is associated with life insurance purchases, confirming the predictions of Lewis (1989). On the contrary, neither the share of the elderly nor the labour force participation rate or the average number of family members seem to play a role once we have controlled for the share of the young. The signs of the coefficients on family size and participation rate are, respectively, positive and negative, as expected, reflecting their correlation with the number of dependents, while old dependency is very close to zero. Hence, while providing evidence in favour of the life protection function theory of Lewis (1989), our data do not support the conjecture in Beck & Webb (2003, p.13) (the elderly are assumed to buy more of both life protection and savings products) neither the opposite, life-cycle type view (the elderly are dissaving). Again, this is in sharp contrast with international evidence in Beck & Webb (2003), where life insurance is directly related to the share of the old and inversely to that of the young.

A different approach (Beenstock *et al.*, 1986; Browne & Kim, 1993; Outreville, 1996) considers (average) age as a proxy for life expectancy. As the argument goes, *(a)* people expecting to live "longer" would be inclined to buy more annuities (income protection life insurance, in our framework) because they would earn benefits for a "comparatively longer" time (Beenstock *et al.*, 1986); or *(b)* people expecting to die "earlier than average" should buy more life protection insurance. Therefore average age should have a positive effect on the former, a negative one on the latter. At national aggregate level, we consider this reasoning a fallacy: insurance will typically be priced according to national mortality tables, i.e. to average life expectancy: so that annuities will be more expensive where people tend to live longer, life protection where life expectancy is shorter, offsetting the effect which is unsurprisingly never[9] found significant in empirical studies (see also Li *et al.*, 2007, p.641). Yet this reasoning might become relevant in our sub-regional setting (as it is *a fortiori* for individual data): if prices are set according to national average mortality, provinces (individuals) with longer life expectancy should actually find income protection products relatively cheap, and the opposite for life protection. Moreover, given the preponderance of annuities' revenue over that of life protection policies (see Table 1), if this theory holds we would expect the positive effect to prevail. Average age is therefore added to an alternative specification because of collinearity with dependency ratios. For the above reasons, we consider the negative and significant observed effect as due to negative correlation with the (omitted) share of young dependents. While it might also be seen as consistent with argument *(b)*, it sure is evidence against *(a)*.

Schooling in turn proves negative and significant at the 1 percent level. As observed, many (Truett & Truett, 1990; Browne & Kim, 1993; Li *et al.*, 2007; Feyen *et al.*, 2011) see education as positively related to risk awareness (and hence to life insurance consumption). Our evidence supports instead the minority view which relates education to the willingness and the capacity to manage risks, implying that better educated people are able to better diversify their portfolios, holding a greater variety of (possibly riskier) assets and thus reducing the slice of safe assets as life insurance.

As for the other controls, judicial inefficiency is insignificant. As this is the main distinctive character in an otherwise homogeneous legal environment, this finding contradicts the applicability of the general arguments of La Porta *et al.* (1998) to the life insurance case and of the specific findings of Ward & Zurbruegg (2002) to the Italian one. Moreover, this finding is strikingly dissimilar from the sharp negative effect of judicial inefficiency on non-life insurance in Millo & Carmeci (2011), which testifies the appropriateness of trial length as an efficiency measure. We conclude that property rights protection, and in general the rule of (civil) law, is no important determinant of life insurance purchases in an advanced democracy, the difference with respect to non-life being consistent with the lesser amount of litigation involving life contracts. Trust is a positive driver, as also found by Guiso (2012) for non-life insurance and by Guiso *et al.* (2004) for financial development at large.

As for supply controls, despite the current trend towards the preminence of bancassurance in life distribution, the density of bank counters is not significant at all.

[9]A partial exception is the reduced model in Outreville (1996, Table 3).

while that of insurance agencies proves an important positive factor, contrary to the current trend towards the preminence of bancassurance in life distribution. It seems that tied agents are still a very important force in shaping the market.

Lastly, as observed all relevant interest rates (both the financial yields on life insurance reserves and those of competing financial products) are invariant over provinces. The lending rate is the only observable financial yield to vary with the insured's province of residence. The reasons for including it in the model are unclear but, as its effect was positive and significant in Beck & Webb (2003), in order to control for the possibility that customers consider the spread between the interest rate on financing and the one thay can get from investing, we include the cost of borrowing, which shows considerable territorial variability, in an alternative specification (not reported). As expected, the estimated coefficient is not significant.

5 Conclusions

We approach the empirical investigation of life insurance consumption in Italy from a sub-regional perspective. The highest disaggregation level for which data are available is that of 103 provinces, which we observe over the years 1996-2001.

This setting allows analyzing some of the determinants of insurance development in an environment which is highly integrated in other respects (legal, religious, monetary, fiscal) and free from the systemic differences which may overshadow some relationships of interest in cross-country studies. Moreover, some specification issues (most notably, the measurement of insurance prices and financial yields) turn out to be irrelevant because there is no variation at the cross-sectional level, and the common time variation can be easily accounted for. Lastly, we are able to distinctly observe disposable income and a good proxy for wealth and savings (bank deposits), disentangling their effects instead of proxying for both through GDP or GNP as usually done in the literature.

An overview of the literature on insurance consumption provides the foundation for our model specification. Three economic functions of life insurance are discussed: protection of dependents in case of death, protection of one's own income stream in case of survival, and pure saving. Based on this, we identify appropriate explanatory variables and proceed to a descriptive analysis, showing evidence of spatial dependence and heterogeneity.

We discuss some methodological issues arising from considering data from observational units inside an integrated market instead than from different countries, i.e. spatial correlation, and from peculiar features of insurance, such as serial correlation. Together with the need to allow for individual random effects, these issues require a new maximum likelihood estimator for random effects panels with spatial lags, spatial and serial correlation, implemented elaborating on the work of Anselin (1988), Case (1991) and Baltagi *et al.* (2007).

Consistently with previous evidence, we confirm the positive influence of disposable income. Using bank deposits as a proxy for wealth, we identify a positive effect, which we see as related to the savings component of premiums; the latter possibly offsets the expected negative effect on life protection, which does not show up in the data. The ratio of young dependents to people of working age captures the need for life protection, while the substitution effect of social security payments, although showing the expected sign, is not significant.

The positive coefficient of the density of the distribution network and that of trust (as defined by Guiso *et al.* (2004)) point to important supply effects, to some extent validating the common wisdom that "insurance is sold, not bought". Lastly, and contrary to most previous research, the effect of the education level of the population turns out negative, a finding which we attribute to the role of education in fostering risk understanding and managing capabilities, driving customers towards riskier kinds of assets and away from the safe and moderate returns that characterize most life policies. In other words, better education seems to have been associated with disintermediation, reducing the perceived need for insurers' professional risk management and guarantees. Yet one must bear in mind that the timespan of our sample has seen a bullish stockmarket throughout. To which extent the experience of the subsequent ten years of recurring financial crises may have modified this attitude in the Italian public is an interesting subject for future research.

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Appendix A: Descriptive statistics

	Description	Source
ryd	Real per capita disposable income	Ist. Tagliacarne
rbankdep	Real bank deposits per capita	Bank of Italy
family	Average number of family members	Istat
odeprat	Old dependency ratio (over 65 to 15-64)	Istat
ydeprat	Young dependency ratio (under 14 to 15-64)	Istat
socialsec	Real per capita social security payments	Ist. Tagliacarne
partrate	Labour participation rate of people aged 15-64	Ist. Tagliacarne
bankcount	Bank counters per 1000 inhabitants	Bank of Italy
agencies	Density of insurance agencies per 1000 inhabitants	Isvap
school	Share of people with second-grade schooling or more	Istat
inef	Judicial inefficiency: years to settle a civil case	Guiso *et al.* (2004)
trust	Survey results to the question ”do you trust others?”	World Values Survey

Table 6: Description and sources of regressors

Appendix B (not meant for publication): Computational aspects

In this appendix we describe the estimation procedure in some detail. This is probably beyond the scope of the paper, and the subject of a dedicated paper currently under revision at a computational statistics journal too. As the relevant reference isn't available yet (and would also, if cited, identify of the authors of the present paper), we provide a synthetic treatment below.

	Min.	Italy	Max.	Gini	Moran	
ryd	8232.91	13420.02	18838.51	0.12	12.45	***
rbankdep	3878.30	8388.58	21981.67	0.20	8.69	***
family	2.05	2.60	3.07	0.05	11.00	***
odeprat	16.22	26.78	36.54	0.10	9.40	***
ydeprat	13.55	20.30	28.79	0.11	12.92	***
socialsec	1026.69	2103.23	6218.51	0.21	9.70	***
partrate	35.47	47.85	58.08	0.05	9.48	***
school	34.32	41.85	50.00	0.05	11.66	***
inef	1.44	3.79	8.32	0.20	7.29	***
trust	3.03	3.26	3.62	0.02	7.88	***
bankcount	0.22	0.52	1.01	0.20	11.81	***
agencies	0.13	0.38	0.59	0.15	11.92	***

Table 7: Summary statistics; range, inequality (Gini's coefficient) and spatial correlation tests (Moran's I) for the year 2000.

	N-W	N-E	Centre	South	Islands
ryd	15600.56	15559.07	14243.68	10396.13	9793.90
rbankdep	10201.66	10514.48	9088.06	5568.43	5303.25
family	2.39	2.48	2.58	2.85	2.79
odeprat	28.18	27.97	29.57	23.84	22.84
ydeprat	17.74	17.76	18.48	24.72	24.46
socialsec	2960.79	2369.16	2030.48	1497.97	1258.35
partrate	49.87	51.88	48.20	43.96	43.64
school	43.54	43.88	44.63	39.01	35.83
inef	2.89	2.86	3.71	5.14	4.76
trust	3.32	3.30	3.24	3.20	3.19
bankcount	0.61	0.71	0.54	0.31	0.36
agencies	0.45	0.45	0.42	0.28	0.26

Table 8: Macroregional averages, year 2000

ML estimation with a general error covariance matrix has been outlined in Magnus (1978) (see also Anselin *et al.*, 2007). If the error is distributed as $N(0,\Omega)$ then the log-likelihood is

$$logL = (C) - \frac{1}{2}ln|\Omega| - \frac{1}{2}e'\Omega^{-1}e \tag{2}$$

This provides a general framework for ML estimation of (1). Anselin (1988), the classic reference on spatial econometric model estimation by ML, outlines the general procedure for a model with spatial lag, spatial errors and possibly nonspherical residuals as follows. Let our model, in matrix notation, be

$$\begin{aligned} y &= \lambda W_1 y + X\beta + u \\ u &= \rho W_2 u + \eta \end{aligned} \tag{3}$$

with W_1, W_2 proximity matrices, $\eta \sim N(0,\Omega)$ and, in general, $\Omega \neq \sigma^2 I$.[10]

[10] Two special cases of this general model are often found in applied literature: if $\rho = 0$ one

Introducing the standard simplifying notation $A = I - \lambda W_1$ and $B = I - \rho W_2$, if there exists Ω such that $e = \Omega^{-\frac{1}{2}}\eta$ and $e \sim N(0, \sigma_e^2 I)$, and B is invertible, then $u = B^{-1}\Omega^{\frac{1}{2}} e$ and the model (3) can be written as $\Omega^{-\frac{1}{2}} B(Ay - X\beta) = e$ with e a "well-behaved" error. Making the estimator operational requires the transformation from the unobservable e to observables. Expressing the likelihood function in terms of y requires calculating the Jacobian of the transformation $J = det(\frac{\partial e}{\partial y}) = |\Omega^{-\frac{1}{2}} BA| = |\Omega^{-\frac{1}{2}}||B||A|$. These determinants are to be added to the log–likelihood, which becomes

$$logL = -\frac{N}{2} ln\pi - \frac{1}{2} ln|\Omega| + ln|B| + ln|A| - \frac{1}{2} e'e$$

where the difference w.r.t. the usual likelihood of the classic linear model is given by the Jacobian terms (which are 1 in that case, see Greene (2003), B.41). The likelihood is thus a function of β, λ, ρ and parameters in Ω. Scaling, without loss of generality, the overall errors' covariance as $B'\Omega B = \sigma_e^2 \Sigma$, this likelihood can be concentrated w.r.t. β and the error variance σ_e^2 substituting $e = [\hat{\sigma}_e^2 \Sigma]^{-\frac{1}{2}}(Ay - X\hat{\beta})$:

$$logL = -\frac{N}{2} ln\pi - \frac{N}{2} \hat{\sigma_e^2} - \frac{1}{2} ln|\Sigma| + ln|A| - \frac{1}{2\hat{\sigma_e^2}} (Ay - X\hat{\beta})'\Sigma^{-1}(Ay - X\hat{\beta}) \quad (4)$$

and a closed-form GLS solution for β and σ_e^2 is available for any given set of spatial (λ, ρ) and other parameters in the covariance matrix Σ:

$$\begin{array}{l} \hat{\beta} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}Ay \\ \hat{\sigma_e^2} = \frac{(Ay - X\hat{\beta})'\Sigma^{-1}(Ay - X\hat{\beta})}{N} \end{array} \quad (5)$$

so that a two-step procedure is possible which alternates optimization of the concentrated likelihood and GLS estimation.

A panel model with $N = n \times T$ observations can be described in this framework, with proximity matrices which, stacking observations by time, become $I_T \otimes W$, where W is the proximity matrix for a cross-section and $\otimes$ is the Kronecker product, so that e.g. the spatial filter on y becomes $A = I_{nT} - \lambda(I_T \otimes W_1)$. The distinctive features of a random effects panel with serially and spatially correlated errors concentrate in the errors' covariance matrix Σ. Introducing serial correlation in the remainder of the error term, together with spatial correlation and random effects, as in (1) and denoting $J_T = \imath\imath'$ where $\imath$ is a vector of ones, $\alpha = \sqrt{\frac{1+\psi}{1-\psi}}$, $d^2 = \alpha^2 + (T-1)$ and

$$V_\psi = \frac{1}{1-\psi^2} \begin{bmatrix} 1 & \psi & \psi^2 & \dots & \psi^{T-1} \\ \psi & 1 & \psi & \dots & \psi^{T-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \psi^{T-1} & \psi^{T-2} & \psi^{T-3} & \dots & 1 \end{bmatrix}$$

Baltagi *et al.* (2007) express the errors' covariance as $\Sigma = \phi(J_T \otimes I_N) + V_\psi \otimes (B'B)^{-1}\Sigma$ and its inverse and determinant as

$$\begin{array}{l} \Sigma^{-1} = V_\psi^{-1} \otimes (B'B) + \frac{1}{d^2(1-\psi)^2}(V_\psi^{-1} J_T V_\psi^{-1}) \otimes [[d^2(1-\psi)^2 \phi I_N + (B'B)^{-1}]^{-1} - B'B] \\ |\Sigma| = |d^2(1-\psi)^2 \phi I_N + (B'B)^{-1}| \cdot |(B'B)^{-1}|^{T-1}/(1-\psi)^N \end{array}$$

has the spatial autoregressive (SAR) model , while if $\lambda = 0$ the spatial (autoregressive) error (SEM) model. Both usually include the hypothesis of spherical errors: $\Omega_\eta = \sigma^2 I$.

Substituting (5) in (4) and optimizing the likelihood through the two-step procedure described above, we get the β parameter estimates reported in Table 5 and the spatial lag and error covariance parameters shown in Table 3. Standard errors are based on the GLS step, calculated at optimal values of λ, ϕ, ψ and ρ, for the βs and on the numerical estimates of the Hessian for λ and the parameters of the error covariance.

6 Appendix C (not meant for publication): Robustness checks

6.1 Coefficient stability

	1999-2001	V2	1998-2001		1997-2001		Full sample	
(Intercept)	-7.767584476	*	-7.560974155	**	-7.673612816	**	-7.9235425110	***
log(ryd)	1.537907467	***	1.464105365	***	1.407169495	***	1.3820390094	***
log(rbankdep)	0.266812294	*	0.282164780	**	0.245820547	**	0.1945874411	*
log(family)	0.248858175		0.219403667		0.265514215		0.2909266702	
odeprat	-0.001315976		-0.003437049		-0.002326482		-0.0018743559	
ydeprat	0.026035998	.	0.021021944	.	0.019378343	.	0.0219633521	*
log(socialsec)	-0.123580751		-0.125938858		-0.102916775		-0.0726272478	
log(partrate)	-0.328215996		-0.258366652		-0.115840826		-0.0623484642	
log(school)	-0.892555090	**	-0.819549858	**	-0.812124866	**	-0.6970110613	**
log(inef)	0.001777409		-0.004142098		0.010444789		-0.0066243976	
log(trust)	1.602553353	*	1.351767105	*	1.160183085	*	0.9468690911	.
log(bankcount)	-0.085325687		-0.046177634		-0.016790836		0.0009613859	
log(agencies)	0.134631870		0.145668304		0.140319745	.	0.1601601085	*

Table 9: Stability check of coefficients in time.

	1996-1998	V2	1996-1999		1996-2000		Full sample	
(Intercept)	-8.641923041	***	-9.251999825	***	-8.509825909	***	-7.9235425110	***
log(ryd)	1.231119920	***	1.384003493	***	1.281032450	***	1.3820390094	***
log(rbankdep)	0.247003479	**	0.184423753	*	0.191210600	*	0.1945874411	*
log(family)	0.204382276		0.295259626		0.353439622		0.2909266702	
odeprat	-0.006777274		-0.004904942		-0.004428612		-0.0018743559	
ydeprat	0.010944617		0.021523929	*	0.016316517		0.0219633521	*
log(socialsec)	-0.011199982		-0.035958995		-0.033810918		-0.0726272478	
log(partrate)	0.019347727		-0.116981598		-0.096556407		-0.0623484642	
log(school)	-0.279949651		-0.357038614		-0.307500258		-0.6970110613	**
log(inef)	-0.064496220		-0.068841096		-0.040852033		-0.0066243976	
log(trust)	0.876709533	.	1.228919977	*	1.081381783	*	0.9468690911	.
log(bankcount)	0.012622042		0.019368333		0.018882912		0.0009613859	
log(agencies)	0.134321490	.	0.166180911	*	0.120335836	.	0.1601601085	*

Table 10: Stability check of coefficients in time.

	Italy	V2	North		South	
(Intercept)	-7.9235425110	***	-8.242197923	**	-7.258605494	*
log(ryd)	1.3820390094	***	1.309320809	***	1.179497248	***
log(rbankdep)	0.1945874411	*	0.188841028	.	0.104476856	
log(family)	0.2909266702		0.114284797		0.614446420	
odeprat	-0.0018743559		0.002211223		-0.008608014	
ydeprat	0.0219633521	*	0.031554875	.	0.012130215	
log(socialsec)	-0.0726272478		-0.051615836		-0.269139377	*
log(partrate)	-0.0623484642		-0.053028448		0.005082605	
log(school)	-0.6970110613	**	-0.711137996	*	0.120932802	
log(inef)	-0.0066243976		0.046794776		-0.103472103	
log(trust)	0.9468690911	.	1.612083695	.	0.939185057	
log(bankcount)	0.0009613859		0.002426308		-0.086845742	
log(agencies)	0.1601601085	*	0.207078657	.	0.195499399	*

Table 11: Stability check of coefficients in space.