DISCUSSION PAPER SERIES

No. 3444

FIRM SIZE DISTRIBUTION: TESTING THE 'INDEPENDENT SUBMARKETS MODEL' IN THE ITALIAN MOTOR INSURANCE INDUSTRY

Luigi Buzzacchi and Tommaso Valletti

INDUSTRIAL ORGANIZATION

CE PR

Centre for Economic Policy Research

www.cepr.org

FIRM SIZE DISTRIBUTION: TESTING THE 'INDEPENDENT SUBMARKETS MODEL' IN THE ITALIAN MOTOR INSURANCE INDUSTRY

Luigi Buzzacchi, Politecnico di Torino
Tommaso Valletti, Imperial College and CEPR

CEPR Discussion Paper No. 3444

July 2002

ABSTRACT

Firm Size Distribution: Testing the 'Independent Submarkets Model' in the Italian Motor Insurance Industry*

This Paper tests the presence of multiple independent submarkets in the Italian motor insurance industry. Independence is motivated by administrative boundaries among provinces and by further locational reasons. We find that the independence effects are sufficient to induce a minimum degree of inequality in the size distribution of firms once submarkets are aggregated. These results are consistent with the predictions of Sutton (1998). At the submarket level, some degree of inequality can be explained by a model of equilibrium price dispersion based on costly consumer search. Our findings show that Sutton's limiting approach and an approach based on a game theoretical analysis of an industry are good complements when the industry is made of several independent submarkets.

JEL Classification: D40, G22 and L11
Keywords: independent submarkets, insurance companies, price dispersion and size distribution of firms

Luigi Buzzacchi
Politecnico di Torino
Corso Duca degli Abruzzi 24
10129 Torino
Italy
Email: luigi.buzzacchi@polimi.it

Tommaso Valletti
Imperial College
Management School
53 Prince's Gate
Exhibition Road
London
SW7 2PG
Tel: (44 20) 7594 9215
Fax: (44 20) 7523 7685
Email: t.valletti@ic.ac.uk

For further Discussion Papers by this author see: www.cepr.org/pubs/new-dps/dplist.asp?authorid=143786

For further Discussion Papers by this author see: www.cepr.org/pubs/new-dps/dplist.asp?authorid=145352

Submitted 16 June 2002

1.   Introduction

The notion of "market definition" is crucial to any work in Industrial Economics. When economists try to understand the way firms interact, with the aim of giving theoretical answers to positive or normative questions, they would start by positing demand functions that define the relevant market(s) where firms compete. In principle, one could try to split an industry into smaller and smaller subindustries, until a break in the chain of substitutes is found. In this way, one would be left with a certain group of subindustries each containing groups of products with a low degree of substitutability between groups and a high degree of substitutability within groups. Taking this argument to its extreme and logical conclusion, the question arises as to what kind of effects one could expect to find once an industry is made of many submarkets, all independent of each other. In particular, should we expect to find in a market a certain number of identical firms, each of whom has entered roughly the same submarkets? Or, conversely, should we expect to find inequality in the size distribution of firms because there are bigger firms that have entered relatively more submarkets?

These questions lie at the core of a sizeable literature on the growth of firms that started long ago with the work of Robert Gibrat. Gibrat proposed a "law of proportionate effect", stating that the rate of growth of a firm, relatively to its market size, is a random variable, independent of the firm's current size. Thus bigger firms should grow faster and the firm size distribution should follow a log-normal distribution. Later research used more sophisticated stochastic models in order to generalise Gibrat's results. Yet in the end, no distribution or families of distributions could be used across industries with some degree of general validity (see Sutton, 1997, for a review of the literature).

The question of the appearance of unequal distributions of firm size is posited again in a new form and answered in Sutton (1998). Sutton does not look for "the" family of distributions that data should fit, rather he looks for a "bound" on the form of size distribution. The problem is addressed by developing a theory of submarkets that are independent in the sense that each firm's profit function is additively separable into the contributions of the firm's profits in different submarkets. A high number of submarkets means that there are many entry opportunities to be filled by firms, some of whom may be operating in many other submarkets, and some of whom may enter the industry for the very first time. Sutton shows that when the number of submarkets is sufficiently large, strategic considerations become less important than statistical effects. In particular, by introducing a simple "Symmetry Principle", that specifies that there is an equal treatment with respect to all

potential entrants to each submarket,[1] Sutton finds that the size distribution of firms in the industry (at the aggregate level) has to be greater than the following "lower" bound:

(1) $C_k \geq k/N[1 - \ln(k/N)]$

where C_k is the k-firm concentration ratio and N is the total number of firms in a market. Hence there is a <u>minimum</u> degree of inequality in firm size that, in graphical terms, implies that the Lorenz curve constructed with data for a certain market has to be more skewed than the limiting value given by the right-hand side of eq. (1).[2]

While independence effects operate over many submarkets and give predictions on the structure one could expect to find in the overall market, strategic effects are predominant within each submarket. From a theoretical point of view, very little can be said in general on the structure of individual submarkets. Sutton's model is generally elusive (and willingly so) on what should happen at the submarket level.[3] Hence a game-theoretical approach that takes into account the peculiar features of the industry in question has an obvious edge when the researcher turns to the analysis at the micro level.

The purpose of this paper is to show how Sutton's limiting approach and one based on a game theoretical analysis of an industry are good complements when the industry is made of several independent submarkets. In a nutshell, we want to argue that Sutton's approach is the way to go when a "top down" analysis of an industry is done, i.e. the data at the researcher's disposal are at a very aggregate level of observation. On the other hand, a "bottom up" analysis applied to a properly defined market should be based - when possible - on a reasonable game theoretical model.

We want to test the complementarity between the "independent submarkets model" and a game theoretical model in the Italian motor insurance industry, which represents an

---

[1] When a new opportunity opens up in a given submarket, there may be different types of firms: some firms may be already active in that submarket, some may be entirely new, and some may be active in other submarkets but not in the current one. The Symmetry Principle states that any two firms that have not yet entered a particular submarket will follow identical strategies in that submarket. On the other hand, the Symmetry Principle does not impose any restriction on the strategies of firms that are already active in that submarket.

[2] Sutton (1998) provides some empirical evidence from the US cement industry. The bound on the inequality of firm size distribution has been recently tested by other authors. Walsh and Whelan (2001) consider the Irish food and drink industry, where submarkets are defined in terms of consumers' tastes rather than geographical location. The locational dimension is crucial in de Juan (1999), who uses data from the Spanish retail banking market. See also Asplund (1999) for a related analysis of the Swedish driving schools market.

[3] Under special circumstances, some restrictions can be placed on the size distribution in a submarket. Sutton (1998) argues that a maximally fragmented structure with firms of similar same size should arise in models with symmetric product differentiation (and symmetric costs) when price competition is weak and products are close substitutes. These models are particularly appropriate when there are overlapping submarkets, for instance when firms are supplying customers in different geographical regions.

ideal setting. In the first place, there are administrative boundaries such that every vehicle has to be insured in the province where the owner is resident. Since there are 103 provinces in Italy, this immediately gives us an idea of the minimal amount of submarkets that are present. Clearly, provinces are of very different sizes, hence we cannot expect every province to contain the same number of submarkets. On the other hand, demographics show a big variance across provinces and we can try to understand which provinces should contain more or less submarkets. We show that most provinces exhibit a degree of inequality of market shares that is quite high, and that may be consistent with the hypothesis of having many submarkets within each province.

Another interesting feature of this industry in Italy that can be exploited for empirical purposes is that the majority of premiums are collected via tied agents, while other sales structures are of negligible importance. Tied agents dominate the distribution system in the non-life segment, and in particular in the motor business where the share of tied sales outlets is estimated to be well above 90%. The number of agencies (branches) in each province therefore provides excellent information on the points of presence of a company. Notice how, according to Sutton's analysis, a firm grows by collecting 'opportunities': there is a logical correspondence in our case with firms' growth via the opening of a new agency.

We also have evidence of a trait that is quite typical of the insurance industry: products are fairly homogenous (we analyse the third-party motor liability segment), still there is considerable price dispersion. If one knew the boundaries of the relevant market, one could apply a well-structured model of strategic interaction among the companies competing in that market. Indeed, there are established game theoretic models that obtain equilibrium price dispersion due to consumer costly search. Such models already derive some degree of inequality in market shares that could in principle explain the picture at the broad provincial level. Importantly, the model we employ also implies that inequality within a submarket has to stay below an "upper" bound.

We derive a set of tests to compare the "top down" with the "bottom up" approach. The independent submarkets model would predict a *minimal* level of the degree of inequality among firms' shares, while the game theoretic model we select would predict a *maximal* level. As an 'acid' test we can then compare the degree of inequality at various levels of observation: national, regional, provincial, etc. We find that while models of strategic interaction may have a lot to say about the equilibrium properties of a submarket that coincides with the level of small and medium sized towns, at a more aggregate level independence effects are the main force behind the overall picture that may have very little

resemblance with what happens at the submarket level. Hence, from a more theoretical point of view, our results confirm that the novel analysis conducted by Sutton (1998) on the degree of firm size inequality is a good line of attack to address the problem of the growth of firms when the level of observation is quite aggregate. In particular, the mechanism at work is not due to aggregation effects *per se*, rather it reflects the larger companies' operation over several geographic regions. At a more practical level, our analysis illustrates the importance of independence effects in undertaking any market structure analysis. Policy makers should be very careful when using indicators of market power, such as the Herfindhal index, when the "right" level of market definition is not addressed properly.

The remainder of the paper is organised as follows:

- In section 2 we give a brief description of the industry (more data can be found in Appendix 1).

- In section 3 we propose a game theoretic model to describe strategic interaction at the micro (i.e., submarket) level. We adapt a model taken from Carlson and McAfee (1983) that predicts price dispersion and an upper bound on the degree of inequality within a given submarket (the details of the model are in Appendix 2). This model is a complement to Sutton's analysis since it puts the emphasis on strategic interaction, in the absence of independence effects.

- The empirical results are contained in sections 4 and 5. We show that while a more structured equilibrium model like the one we employ has predictive power at the level of some smaller provinces and towns, such a model cannot explain the inequality that emerges at a broader level within most provinces where, we claim, many submarkets are present and independence effects are already taking place. As the number of submarkets increases, strategic effects become less important than independence effects. Since our analysis supports the idea that the observed skewed distributions of firms is due to the emergence of various independent opportunities, we then show in section 5 that the degree of inequality in the firm size distribution is related to characteristics such as the population living in an area, its density, and the flows of commuters.

- In the final section we briefly summarise our findings and argue that the skewness in the firm size distribution that we have found is not just an Italian phenomenon but is also observed in many European countries.

2. Firm size distribution in the Italian motor insurance industry

The insurance industry is typically divided into two quite separate businesses: Life and Non-Life. The former includes a variety of pension schemes and investment activities, while the latter concerns motor insurance, accident and health, fire, theft, general liability and credit. Their weight in the Italian insurance business is relatively similar: for instance in 1998, total premiums were 111,278 billion lira (approximately £35 billion), 50.8% collected in Life insurance and 49.2% in the Non-Life segment.

In this paper we concentrate on the Non-Life business: in particular, the Motor Insurance segment is the class that represents the bulk of direct premiums collected (58% in 1998). Finally, the Motor Liability class has the major influence on the Motor segment (82% in 1998; and 48% of the entire Non-Life business). In Italy, the legal system imposes the obligation of drawing up certain insurance policies and the most widespread compulsory insurance is by far Motor Liability: every vehicle has to be insured.

What makes this especially interesting for our purposes is that a vehicle has to be insured within a particular administrative area. Italy is divided into 20 Regions and 103 Provinces: vehicles are registered in a province, hence a policy has to be bought in the same province. Since the majority of vehicles are privately-owned cars, the province of residence of a (potential) car owner is an excellent proxy for the maximum dimension of an independent submarket. Car-owners can be perfectly discriminated on the basis of their residence and they must insure according to the policy designed by a company for that particular province.

Within a province, the motor insurance industry has a further and very strong spatial dimension.[4] Such a spatial nature thus reinforces the first, broad cut deriving from the administrative boundaries and the sales system becomes fundamental to explain the size distribution of insurance companies. In Italy, the majority of premiums is written through agents (89% of total Life and Non-Life) and the preponderance is even more striking in the Non-Life business (in the Life segment financial advisors and bank counters are increasingly important). In the Motor Liability class, the companies that used exclusive agents collected 97.5% of total premiums and they relied almost solely on such a distribution system.

---

[4] Insuring a car is an activity that typically occurs once a year and a contract is tacitly renewed unless a three-month notice is given. Other contacts are expected should an accident occur, thus increasing "transportation" costs. Moreover, information among consumers is very disperse: there is virtually no advertising done by companies, and prices can be collected only by directly contacting a company. Sales over the phone or over the Internet are extremely small in Italy (see Appendix 1). Motor Liability prices have also been regulated until 1994 and many customers are still not very aware of the potential gains that could be made by searching for better tariffs within a province. As a result, a customer is likely to patronise only those companies that operate in the neighbourhood of the area where he lives and/or works: any other place, even in the same province, would be too far away and the unknown price would not justify a longer trip. In section 3 we examine in details the role played by consumer search costs.

We have collected data for all tied agents present in Italy in 1998 in every province (there was a total of 15,044 branches; see Appendix 1 for details). The number of agencies that each insurance company has in a given territory gives an indication of its points of presence and it is the proxy we use for market shares. Every time an "opportunity" opens in some area, a new agency is also likely to be opened. The independence between opportunities in the Motor Liability segment, both spatial and administrative, provides an ideal setting in which to empirically examine the validity of Sutton's independent submarkets model.

To make a case for the "independent submarkets model", we also need to be sure that profit functions are additively separable *across* submarkets. This would not be the case, for instance, when firms concentrate their R&D efforts in some regions but sell their products all over the country, or when national advertising is relevant. In the Italian motor insurance industry both advertising and R&D outlays are irrelevant. Of course, there may be effects deriving from economies of scale and from risk pooling *within* submarkets, but these would have a much smaller impact across submarkets.[5]

Figure 1 shows the industry Lorenz curve constructed using the number of agencies each company has. Such a curve satisfies Sutton's lower bound given by eq. (1). We have also drawn a second Lorenz curve, using total premiums rather than agencies. As it can be seen, the two curves are not different from each other.[6]

[Figure 1 – Lorenz curves (national level)]

This first, broad picture would seem to confirm the limiting distribution in aggregate. Since our aim is to test the null hypothesis of the independent submarkets model being the driving mechanism of the size distribution, in the next section we formulate an alternative hypothesis, namely that a game theoretic model valid for this particular industry can explain the distribution of market shares.

---

[5] To be sure, the theory of Sutton requires the weaker assumption of "approximate" independence (Sutton, 1998, p. 293-294). In our context, approximate independence has an appealing interpretation. While profit functions may not be additive say between every 2 or 3 adjacent local submarkets, the degree of dependence becomes attenuated as the distance between submarkets increases and would disappear for distant ones. In other words, if a particular company is affected by an unusual number of accidents in Palermo, this is extremely unlikely to affect the performance of the same company in Milan.

[6] The degree of inequality in firm size distribution can be described numerically using the Gini coefficient. In figure 1, Gini is 58.96% if premiums are used and 61.93% if agencies are used (as a reference point, the Gini corresponding to Sutton's bound is 49.97%). We performed the Kolmogorov-Smirnov test to see whether the two alternative measures could produce significant differences in the degree of inequality and we rejected with a

3. Consumer search and firm size inequality

In the previous section we have argued that the degree of firm size inequality at the national level can be explained by the presence of independent submarkets, at most as large as a province. What drives the distribution of market shares within a province, or, more generally, at a more disaggregate level of observation?

The motor insurance policy that we examine is compulsory and a rather homogenous product, making the premiums charged by different companies directly comparable. The data at our disposal show that there is a significant amount of price dispersion among the premiums. Hence, a model of strategic interaction at the level of each submarket should be able to explain equilibrium price dispersion that, in turn, can generate unequal market shares. Our focus in this section is precisely to apply a plausible strategic model to the motor insurance market.

We directly rely on a rather well known literature on price dispersion and consumer costly search, which can generate asymmetric firm sizes. In particular, we employ here the results of the model developed by Carlson and McAfee (1983) (hereafter CM). This model deals with a homogenous product when consumers must search among alternative offers and firms differ in their costs. We find this model particularly appealing for a number of reasons. Firstly, it was proposed having the insurance market as a reference point. Search costs are important in the motor insurance industry and customers in practice get quotes from companies only by visiting a branch, without knowing the price *ex ante*.[7] Secondly, CM has already been tested previously by Dahlby and West (1986) in a province of the Canadian automobile insurance market. Thirdly, the model has direct implications in terms of the size distribution of firms within a submarket that is the main interest of our analysis.[8]

---

confidence above 99% the hypothesis that the two curves are drawn from different distributions. Data on premiums collected by individual firms within a given area are not publicly available.

[7] We want to stress that the hypothesis of product homogeneity for third-party compulsory liability is not stringent in our view. Of course, companies may differentiate by selling also other insurance products. However, compulsory third-party liability represented 82% of the total motor insurance market in Italy in 1998 (the total includes fire, theft, comprehensive, etc.; the average for the EU is 61%; see Meyer, 2001). The characteristics of product homogeneity and consumer costly search have been used frequently in the insurance literature, e.g., Dahlby and West (1986), Schlesinger and von der Schulenburg (1993).

[8] Model selection is of course a very delicate exercise. We cannot claim we have adopted the "right" model, however we can dismiss some other potential candidates. Any model without cost asymmetries would be very unlikely since it would not generate the observed price dispersion, at least as the number of firms becomes large. A standard model of horizontal differentiation with consumer transport costs (think of the Salop circle) is also not very appealing for two reasons. Given that firms differ in their costs, it is not clear where firms should be placed around the circle, at an equal or unequal distance from each other, which would make the model cumbersome. Also, in a such a model consumers *know* all the prices posted by firms, while in practice they do not and decide to buy a policy after a certain number of searches, which is more in line with the model employed here. It is also important to mention that cost asymmetries among firms (such as administrative and sales expenses) are documented by several industry reports (e.g. ISVAP, 2000).

In Appendix 2, we manipulate and extend CM's results to obtain testable implications, in particular with respect to the degree of firm size inequality in a submarket. We obtain the following predictions:

- Inequality test: the degree of firm size inequality in a submarket j, as measured by the coefficient of variation of market shares (CV_j), depends positively on the number of firms (n_j), negatively on the population served (m_j) and negatively on the range of consumer search costs (T_j):

(2) $CV_j = CV(n_j, m_j, T_j)$
                    +, -/0, -

- Entry test: when the number of firms is endogenised, it depends positively on m_j and T_j:

(3) $n_j = n(m_j, T_j)$
                +/0, +

- Under some assumptions on the distribution of firms' costs, the reduced-form equation for CV_j obtained from eq. (2) and eq. (3) depends only on m_j and T_j in a negative way.
- Finally, we can place an *upper* bound to the predicted coefficient of variation in submarket j. When province-specific and firm-specific cost factors are additive, such bound depends only on the standard deviation of firm-specific costs (σ_α) and on the range of consumer search costs in submarket j:

(4) $CV_j \leq \overline{CV}_j = \sigma_\alpha / 2T_j$.

While all the algebra is relegated in Appendix 2, we can provide some intuition for the results. In CM model, consumers know the distribution of prices and search with equal probability among n firms, using a sequential search strategy. If a low-price firm raises its prices, it would lose some market share since customers would have less incentive to search, looking for the cheapest offers. In equilibrium, prices reflect somehow the marginal costs, hence the most efficient firm is also the cheapest. This generates price dispersion with an associated dispersion of market shares.

Comparative statics described by eq. (2) are quite interesting. As the number of firms increases, all prices decline, which is a reasonable result. However, the prices of the most expensive firms decline relatively less compared to the price of the cheapest rivals. This is because, as n increases, anyone firm has a lower probability of being sampled. Hence consumers would search less at the 'old' prices, which would be particularly detrimental to the cheapest firms. Since consumers are induced to search if they can expect some gain, it is precisely the cheapest firms that have to reduce their prices relatively more than the more expensive rivals if they want to keep their market shares. This effect produces an increase in dispersion of the distribution of prices, and hence of market shares, explaining why the coefficient of variation of market shares increases with n.

The other effects in eq. (2) are less intricate to grasp. For a given number of firms, there is no effect on CV from the size of the market (m) if there are constant returns to scale, while the effect is negative if there are decreasing returns that penalise the biggest firms, hence compressing the dispersion of quantities. Finally, if the range of search costs (T) increases, the main effect is that people would search less and market shares get closer; on the contrary when search costs are low all the price differences are magnified and are reflected in an increased dispersion of market shares. Comparative statics given by eq. (3) are natural to interpret: there are higher profits, attracting more firms into the market, when search costs are high, and when the size of the market is big.

4. Empirical analysis

We have shown two effects that can generate some degree of inequality of firm sizes in different areas. Take a province. If each province contains several independent submarkets, mainly due to geographic reasons, then we should expect the Lorenz curve to become skewed, in line with Sutton's reasoning. This effect should be more pronounced as more independent opportunities emerge, and a good proxy for the number of opportunities is the province population (strongly correlated with the number of vehicles). Hence a simple prediction of Sutton's model is that, as long as each province contains many submarkets, then an index of firm size inequality should be positively related to the province population. However, within each submarket, a model of strategic interaction based on consumer search costs can also explain some degree of inequality. In this case, firm size inequality should not be positively correlated to population. Independence and strategic effects generate opposite predictions.

Our interest in this section is two-fold: we would like to understand what may constitute a reasonable size for a proper submarket and, at the same time, we seek to identify

what main mechanism is driving the size distribution of firms at a certain level of observation (e.g., national, regional, provincial).

Take again the case of provinces. It is natural to assume that a province is the highest aggregation level that may let a single submarket emerge. We show in the analysis below that this never happens, and a province already contains many submarkets. Provinces are very different in their demographics and physical characteristics: population varies from 90,000 to almost 4 million; area varies from 212 square km to 7,520 square km. If more submarkets are already contained within a given province, then some independence process should occur also at the province level. A similar reasoning can be applied to other levels of observation. In particular, each province has an administrative capital, which is typically the biggest town in the province (there are only 2 exceptions out of 103). If we are prepared to assume that people living in the capital town subscribe to policies in the same town, perhaps this is then a good level of observation to apply Carlson and McAfee, while Sutton's independence effects would not have much to say at that level. Anticipating our results, we consider appropriate to identify a submarket with small capital towns (with a population below 70,000 inhabitants).

The strategy in our empirical analysis is the following:

1. We first draw the Lorenz curves at various levels of observation to see if inequality described by eq. (1) holds.
2. We then conduct a complementary test to see if the observed level of dispersion of market shares can be explained by CM.
3. CM model is also tested against predictions given by eq. (2) and eq. (3).
4. The basic workings of Sutton's independence model are further assessed.

4.1   Results

Figure 2 reports the Lorenz curves at the province level. Some, but not all, of the provincial Lorenz curves lie below Sutton's bound. It is immediate to think that as population grows, more profitable opportunities should arise, causing more skewness in the Lorenz curve (population is strongly correlated with the number of vehicles, $\rho = .93$; see Appendix 1). In fact, by adopting a cut-off level of 1,000,000 inhabitants, the number of curves above the bound in figure 2 would be much smaller. However, even in that case, there would be some significant outliers.

Figure 3 draws the Lorenz curves constructed at the level of each capital town. The subgroup of towns with a population below 70,000 inhabitants is drawn in the lower panel;

this subsample will be called 'small capital towns' in the remainder.[9] Virtually all the Lorenz curves of the subgroup of small capital towns lie below the limiting curve, supporting the initial view that small towns are rather well-defined submarkets, with smaller towns containing only a few opportunities. On the other hand, the Lorenz curves of the 10 biggest cities (with population above 300,000 people) lie above the bound. Of course there are also other effects: for instance people living in towns other than the capital could well be working in the biggest town and buy their insurance there, hence the population outside the main town could help explain the size distribution of the main town itself.

[Figure 2 – Lorenz curves (province level)]
[Figure 3 – Lorenz curves (capital town level)]

We have also constructed Lorenz curves for the agencies at the regional level, and for the agencies outside the provincial capital. These curves are not reported here for space limitations, but they prove to be systematically more skewed than the curves for the provinces, and for the capitals respectively. This is consistent with the view that regions contains more submarkets than provinces, and that areas outside capital towns may contain more submarkets than the corresponding capital town if it is the case that more submarkets arise when a certain population is dispersed rather than concentrated in the same place.

We now take the alternative hypothesis and investigate if inequality is driven by price dispersion *à la* CM rather than by independence effects. CM model should be able to generate, up to some extent, the observed *levels* of inequality. The theoretical model tells that observed inequality in a submarket should fall below the upper bound given by eq. (4) that depends on T and on σ_α, where the latter is estimated at 185,000 lira (approx. £60). Figure 4 reports the CM theoretical upper bound as a function of the range of search costs and compares it with the actual distribution of the coefficient of variation of market shares at various levels of observation. In each panel, the coefficient of observation is on the horizontal axis. The continuous curve (right scale, 000's lira) represents the upper bound described by eq. (4), re-written as $T_j \leq \sigma_\alpha / 2CV_j$. In each panel, there is also the distribution of the

---

[9] This cut-off level comprises 40 towns and it emerges somewhat naturally from the distribution of capital towns since there is a gap between it and the next relevant group of cities that would include populations of 100,000 inhabitants. In our view, and as it will become clearer in the remainder, these towns corresponds as a first approximation to "proper" submarkets. Its order of magnitude is also not too different from the size of 5-10,000 used by de Juan (1999) in her analysis of the Spanish retail banking market if one considers that there are repeated visits to a bank made in a year, while branches of an insurance company are typically visited not more than a couple of times per year.

observed coefficients of variation at various levels of observation (frequencies are on the left scale). The levels of observation, from highest to lowest are: regions,[10] provinces, provincial areas excluding capital towns, provincial capital towns, small provincial capital towns. In principle, one could estimate the range of search costs at every level of observation (region, province, capital, etc.) from demand equations estimated at that level. We run these regressions (available on request) but our results were not particularly good, so we prefer to follow a more conservative approach. In our regressions we found a plausible range of search costs between 150,000 lira and 500,000 lira. We stick to the lowest estimated value, which would represent an upper range of search costs of approximately 22% of the premium paid.[11] The sequence of histograms is instructive. First of all, in line with the previous figures, coefficients of variation are higher when there are more submarkets. Regions are followed by provinces, then by provincial areas not including the capital town, by capital towns, and finally coefficient are lowest for small capital towns. Secondly, even when adopting the most stringent threshold for the range of search costs, it is clear that most of the *observed* coefficients of variation generally violate the *predicted* upper bound based on the model of strategic interaction among firms. This is evident for regions (all the regions violate the bound), provinces (90% violate the bound), areas outside capital towns (73%) and capital towns (66%). On the other hand, in the subsample of small capital towns, 58% of the observation would not violate the upper bound predicted by CM.

The coefficient of variation associated to Sutton's limiting distribution is approximately 1 (the precise value depends on the number of firms). Figure 4 shows that many regions and provinces, and also some capital towns, already exceed such lower bound, suggesting that the overall picture that is observed at those levels is better explained by independence effects rather than by a story based on strategic interaction. It should also be said that Sutton's result is asymptotic, i.e. inequality should be above the bound when there is a sufficiently high number of submarkets, which may not occur in some provinces and/or towns of medium size.

[Figure 4 – Predicted and observed coefficients of variation]

---

[10] Regions are included to show the effects from aggregation at a higher level of observation. Regions are also well-defined administrative areas that may be of interest in their own, given their geographic proximity and cultural homogeneity.

[11] These values are of the same order of magnitude as those estimated by Dahlby and West (1986). They found a plausible upper range for search costs of approximately 60$, corresponding to 30-50% of the premium paid,

Small capital towns are then good candidates for sample where the degree of firm size inequality is consistent with strategic effects. To confirm this, we first took the variance of premiums at the national level and we tested whether the various provinces had a variance significantly different from the national variance.[12] A χ^2 test could not reject additivity in most of the provinces.[13]

Given that additivity was not rejected, we then tested the predictions on the coefficient of variation given by equations (2) and (3). We run two regressions using the SURE methodology to take into account that the errors in the two regressions are correlated and hence we could get more efficient estimates than with separate regressions. Table I reports the results obtained at the capital town level.

Regression	ALL CAPITAL TOWNS		SMALL CAPITAL TOWNS	
	Eq. (2)	Eq. (3)	Eq. (2)	Eq. (3)
CONSTANT	0.149	29.02	0.259	17.38
	(1.35)	(44.90)**	(1.97)*	(6.54)**
NCOMP	0.018		0.012	
	(4.74)**		(2.22)**	
POP	0.229	14.62	0.331	187.65
	(2.81)**	(8.98)**	(0.17)	(3.86)**
SEARCH	2.278	-377.38	-14.593	-120.33
	(0.41)	(2.61)**	(2.07)**	(0.59)
R^2	46.18	43.91	28.01	31.28
ADJUSTED R^2	44.55	42.79	22.01	27.56
F	28.32	39.14	4.67	8.42

Dependent variable eq. (2): coefficient of variation of market shares
Dependent variable eq. (3): number of companies
t-statistics in parenthesis
* Significant at the 5% level
** Significant at the 1% level

Table I – Regression results: testing the search model

The set of regressions corresponding to the columns "all capital towns" shows mixed results with respect to the theoretical predictions. While the number of companies (NCOMP) has the impact on the coefficient of variation predicted by eq. (2), the opposite is true for the population served (POP). At the same time, the population has a positive effect on entry, as expected, however the range of consumer search costs (SEARCH) has a negative and

---

according to different customer classes, in 1980. Given that search costs are linked to the opportunity cost of time, their values are in line with our findings for 1998.

[12] In Appendix 2 we show that that if cost factors are additive in their firm-specific and province-specific components, then the variance of prices (after a small adjustment to take into account the number of companies in a market) should be the same for all markets.

[13] The test is available on request. Additivity was not rejected in 80% of the provinces at the 1% confidence level, 68% at the 5% confidence level and 64% at the 10% confidence level. This result also allowed us to infer

significant effect on entry, in contrast with eq. (3). Moreover, we do not find the expected negative impact of SEARCH on the coefficient of variation.[14]

On the other hand, when we run the regressions at the level of small capital towns, results are much more in line with the theoretical predictions. The impact of NCOMP, POP and SEARCH on the coefficient of variation is fully consistent with eq. (2). The only result clashing with eq. (3) is the effect of SEARCH on the number of firms, which is found not to be significant, while it should have a positive impact. We have also done similar regressions at the level of the whole province, and outside capital towns. Results (not reported here) give little support to the theory of search costs applied to those levels, especially when the samples are not split and include both small and big areas. On the other hand, results are better when they are obtained for subsamples of relatively smaller areas.

In summary, our analysis indicates that the predictions of the model of strategic interaction based on consumer search perform in a satisfactory way when they are applied to proper submarkets, corresponding to towns of limited size. In fact, CM performs quite well at the level of small capital towns that represent a reasonable order of magnitude for a submarket in this industry. On the contrary, this theory does not perform particularly well when it is applied to bigger towns or provinces, that is to say in those cases where it is likely that we are not dealing with a single submarket. In bigger towns, we expect that there are already many submarkets, and this is also true at the province level or in rural areas outside capital towns. Independence effects should be at work in those areas, thus diluting strategic effects. In general, when the data at our disposal already include many submarkets, the observed skewed distributions of market shares should then reflect the emergence of independence rather than strategic effects alone. This logic applies both to provinces and big towns: it is not plausible to analyse them as a single submarket.

Finally, we provide a last test for Sutton's hypothesis. Given that considerable firms' asymmetries are already present in each province, the degree of inequality at the national level could then simply derive from the aggregation of the various provinces.

By looking at the raw data (see Appendix 1), we immediately realise that on average each province contains only a half of the total number of operators. Moreover, some

---

the variance of firm-specific costs from the variance of prices, obtaining a standard deviation for costs of 185,000 lira. This is the value used to draw the limiting curve in the left panel of figure 4.

[14] The variable SEARCH was constructed as the inverse of the density of agencies in a capital town (agencies per head). When we run the regressions at the province level, or outside capital towns, we used the inverse of the geographic density of agencies in a territory (agencies per square km). In the latter case, results would not be affected by using the alternative indicator agencies per head and per square km.

companies are 'national', in the sense that they sell policies in virtually every province, while some other companies are 'regional' and they operate only in specific areas.[15]

We can dismiss the hypothesis that smaller firms are systematically smaller: it can well be the case that a company with a small overall share, has a big local share in some provinces. In figure 5 we report the distribution of market shares at various levels of observations (whole country, regions, provinces, areas outside capital towns, capital towns, small capital towns) for the two groups of companies, 'national' and 'regional' ones, *conditional* on the number of markets they are present. As with figure 4, we believe that the sequence of panels is instructive. The distribution of market shares of 'national' companies (white histograms) is not particularly affected by the level of observation: Italy, regions, provinces, areas outside capital towns, and capital towns show distributions that are remarkably similar. On the contrary, the distribution of 'regional' companies is crucially affected by the level of observation. All the regional companies have a national market share below 1%, but there are a few who might have a share between 2 and 4% at the regional level, an so forth: the distribution of black histograms shifts to the right going to lower levels of observation. Finally, in small capital towns, it is still true that 'national' companies are bigger on average than 'regional' ones ('national' companies have an average of 4.0% market share in the small capital towns where they are present, while 'regional' companies have an average share of 2.8% of the markets where they operate). The advantages of the 'national' companies can be explained for instance by economies of scope in the sale of other insurance and financial products. However the two distributions that are totally different at the national or at the provincial level, become quite similar within small capital towns.[16]

The overall picture that emerges from this analysis is that the degree of inequality observed at the national or provincial level derives from some companies operating everywhere rather than some companies being systematically bigger. The skewed national distribution is due to the fact that they have picked up "opportunities" all over the country.

[Figure 5 - Distribution of market shares for 'national' and 'regional' firms]

---

[15] The total sample of companies divides itself quite naturally into two different groups. If we define as 'national' a company that operates in at least 70% of the total number of provinces and as 'regional' a company that is present in at most 50% of the provinces, then 27 out of 61 companies would be 'national', and the remaining 34 would be 'regional'. 'National' companies have a total of 13,568 branches and an average provincial share of 3.6%. 'Regional' companies have 1,476 branches and an average provincial share of 1.2% where they are present. 'Regional' companies are typically clustered in neighbouring provinces.

[16] The average number of firms (branches) that are present in 'small capital towns' is 26 (38). Hence we are not presenting data at a level so disaggregated that it is obvious to find a few firms of roughly equal size.

		Level of observation					
		Nation	Region	Province	Extra cap. town	Capital town	Small cap. town
	N. of observations (i)	1	20	103	103	103	40
A	Gini(i) < Gini(Sutton, N_i) SD(i) < SD(Sutton, Ni)	No No	6/20 1/20	88/103 83/103	96/103 90/103	95/103 89/103	40/40 39/40
B	Refuse H_0: SD(i) > SD(Sutton, N_i) [F-test, 95%]	No	1/20	15/103	6/103	33/103	22/40
C	Refuse H_0: SD(i) > SD(Sutton, N_i) [Brown-Forsythe's test, 95%]	No	0/20	1/103	0/103	17/103	9/40
D	CV(i) > CV(CM, N_i)	Yes	20/20	93/103	75/103	68/103	17/40
E	Refuse H_0: CV(i) > CV(CM, N_i) [χ^2-test, 95%]	Yes	18/20	69/103	57/103	40/103	3/40
F	Main mechanism at work	Sutton	Sutton	Sutton	Sutton	Mixed/ CM	CM

Table II - A summary: top down versus bottom up

Table II provides a recapitulation of our analysis. The table shows whether the observed size distribution at a certain level of observation can be compatible with either Sutton's approach (rows A, B and C) or with CM's model (rows D and E). Row A compares the observed Gini coefficient in a certain area *i* with the Gini coefficient predicted by Sutton's model in an area that contains the same number of firms N_i as those present in area *i*. Row A contains a simple count of the observations that lie below (i.e., violate) the theoretical lower bound. For instance, 6 regions out of 20 lie below Sutton's predicted bound. In the same row A we also report a similar comparison on standard deviation (SD), since on the latter distribution we can conduct same statistical analysis. This is done in row B, where we test the null hypothesis that the observed distribution has a standard deviation significantly bigger than Sutton's predicted standard deviation. For instance, we can reject the null only in 1 out of 20 regions with a confidence interval of 95%. Put it differently, we can reject statistically only in 1 out 20 regions the idea that regions are made of many independent submarkets. The tests in row B are sensitive to the assumption that the data are drawn from an underlying normal distribution, which we also tested. Since normality was rejected in some cases, we used Brown-Forsythe's test statistic centred at the median (reported in row C) that is robust under non-normality: as predicted by the literature, results are similar but somewhat more conservative. We also conducted non-parametric tests (Kolmogorov-Smirnov test, Moses rank-like test) that produced almost identical results.

Row D counts how many times the observed coefficient of variation of market shares in a certain area *i* exceeds the limiting coefficient of variation that would be predicted by CM's model, in a market where σ_α = 185,000 lira and T = 150,000 lira, as in the previous analysis. For instance, all the regions exceed (i.e., violate) the predicted upper limit. In row E we

conduct a statistical test on the observed distribution of the coefficient of variation. For instance, in 18 out 20 regions we can exclude statistically that they have a coefficient of variation that lies below CM's bound. In other words, in 18 out 20 regions we can reject the idea that regions represent a single submarket where CM's theoretical model is at work.

Row F reports our conclusions about the main mechanism at work at a certain level of observation, based on the results that we have discussed throughout the entire section. The firm size distribution in Italy at the level of a) the whole country, b) regions, c) provinces and e) provincial areas outside capital towns is driven by Sutton's independent submarkets. There are a few outliers where the number of opportunities is fairly small such that independence effect do not show up (these are typically small provinces, and even one region – Valle d'Aosta – that contains a single province), but these outliers do not change the overall picture. On the other hand, small capital towns represent well-defined submarkets where Carlson and MacAfee's game theoretical model has a good predictive power in terms of the firm size distribution and its comparative statics. Finally, capital towns present a mixed picture, since they both contain small towns where CM's model is applicable, and very large towns where independence effects prevail.

5.   A final look at independence effects

Since the foregoing analysis supports the idea that towns and provinces may already contain many submarkets, we have performed some additional simple regressions in order to understand what may lead to the emergence of independent opportunities. We have regressed the Gini coefficient of a market,[17] calculated according to three different levels of aggregation (whole province, capital towns only, whole province without capital towns), against various variables. The results for some OLS regressions are reported in table III. They all investigate the same idea: the more opportunities arise, the more important independence effects should become, producing higher degrees of inequality and higher Gini coefficients.

Most of the variance of the Gini coefficient of a certain area is explained by the population in the same area (regression A). This is reasonable: the greater the number of people, the more opportunities arise. The same result can be obtained by putting vehicles in place of population, since they are strongly correlated with each other. We have included as a

---

[17] We have chosen to use Gini coefficients here since they are related in a natural way to the Lorenz curves we have shown in the initial figures 1-3; results would not change in any significant way by using coefficients of variation instead. The Gini coefficient for a population of x_i observations, $i = 1, …, n$ with average $\bar{x}$ is defined as $Gini = \sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j| / (2\bar{x}n^2)$.

regressor also the square of the population (regression B). Results indicate that opportunities do not arise linearly with the population: once a new person appears, that individual will represent a new opportunity for low levels of population (assuming that, at first, people will be scattered all over the place), but eventually a new person will appear in the same place where other people have already appeared, and this does not give the same rise in opportunities. In other words, 10 cars to be insured in 10 different places sufficiently distant from each other may support 10 independent opportunities, while the same 10 cars at the very same location represent fewer opportunities (in the limit they could even belong to only one independent submarket). This finding is reinforced by the fact that people are not distributed uniformly over a territory, rather they aggregate in some places.[18]

Regression C at the province level also includes premiums per capita. We should first remark that this regression has the same explanatory power as a regression that uses total premiums only (not reported in the table). This is hardly surprising, but since we do not have total premiums at a more disaggregated level, we have reported such a regression for better comparisons with regressions at the level of capital towns and outside them.[19] Finally, notice that we have done additional regressions at the provincial level (not reported in the table), including an area variable and the frequency of accidents, in order to test respectively if geographic dispersion and the riskiness of a market could explain Gini coefficients. Neither of these variables turned out to be significant. In particular, the frequency of accidents was never relevant also when we turned the analysis to the level of capital towns and areas outside them,[20] while the geographic variable did have some impact, as we discuss below.

In the regressions at the levels of capital towns and outside them, we have also included the residual population, to indicate that there could be interaction between areas in the presence of people's mobility (think of commuters). The results show a significant positive effect on the Gini of the capital towns of the population living outside and not

---

[18] An analysis of the estimated coefficients from regressions B and C, reveals that a peak for the Gini coefficient is reached for levels of the population above 2.6 million inhabitants, after which Gini would *decrease* with further increases in the population. However, virtually all the provinces have lower levels of population, hence Gini is increasing everywhere with the population (at a decreasing rate). The only 3 outliers out 103 provinces would be the provinces of Rome, Milan and Naples.

[19] The variable premiums per capita represents a measure of the attractiveness of a market. Premiums per capita are in fact higher in richer provinces. In Italy, richer provinces are typically in the North and in the Centre, as opposed to poorer Southern regions. The latter are also typically the riskier markets, in the sense that more cases of fraud are reported by companies.

[20] This result is remarkable given the emphasis that many practitioners place on the frequency of accidents as a measure of risk and potential frauds. If one plots the frequency of accidents against Gini (say at the level of capital towns to get rid of other spatial effects), a spurious positive relationship would be found since it would simply reflect size effects. Bigger towns have more vehicles and also more "opportunities", and more accidents are likely to occur in an area where lots of vehicles circulate than in a deserted area. Hence while the frequency of accidents may have an impact on the *level* of prices, it does not seem to affect the distribution of firm size.

viceversa. This makes sense, because there are many reasons why some categories of people regularly go to the capital town (typically the most important town), where they can subscribe their policies, thus giving rise to new opportunities, while the reverse is less likely.

	PROVINCE			CAPITAL TOWN	OUTSIDE CAPITAL TOWN	
Regression	A	B	C		A'	B'
CONSTANT	0.347 (36.68)**	0.284 (22.01)**	0.166 (7.27)**	0.060 (2.68)**	0.069 (1.86)	0.044 (1.17)
PROVINCE POP.	0.104 (9.17)**	0.283 (9.44)**	0.286 (11.02)**			
(PROV. POP.)^2		-0.053 (6.30)**	-0.055 (7.55)**			
CAP. TOWN POP.				0.583 (9.92)**	0.081 (0.89)	0.085 (0.95)
(CAP. TOWN POP.)^2				-0.176 (8.13)**	-0.041 (1.22)	-0.040 (1.22)
POP. OUT. CAP. TOWN				0.259 (7.05)**	0.341 (5.25)**	0.395 (7.03)**
(POP. OUT. CAP. TOWN)^2				-0.119 (6.88)**	-0.098 (3.27)**	-0.116 (4.39)**
PREMIUMS PER CAPITA			0.342 (5.92)**	0.292 (5.19)**	0.422 (4.72)**	0.452 (5.11)**
AREA					0.009 (1.71)	
AREA* DLD						0.011 (2.76)**
R^2	45.4	60.9	71.1	81.5	53.9	55.9
ADJUSTED R^2	44.9	60.1	70.2	80.5	51.0	53.2
F	84.04	77.92	81.28	85.22	18.68	20.32

Dependent variable: Gini coefficient
t-statistics in parenthesis
* Significant at the 5% level
** Significant at the 1% level

Table III – Firm size inequality in submarkets: regression results

Outside capital towns, we also tested whether a geographic dimension of the market such as its area could help to explain the aggregation process. We tested this with a slight twist, including a dummy (DLD) that takes a value of 1 in areas with low population density and 0 otherwise.[21] Results indicate that area has a positive and significant impact on Gini only in areas outside the capital towns that are not densely populated (see regression B'). This is coherent with the fact that the product in question has a strong locational feature: given an amount of vehicles to be insured, there are more independent opportunities when they distributed over a wide territory. However, there is a scale effect: once density is high enough, then the area effect is not relevant anymore and population alone is the main explanatory

variable. This is in line with what we said before on "urbanisation", i.e. the tendency of people to aggregate in some specific places.

All the regressions also show that premiums per capita are positively significant when they are included as regressors. Premiums per capita are correlated with various measures of wealth and development of a province (higher premiums are asked for more expensive vehicles that are typically insured in wealthier areas, where there is also a higher number of vehicles per capita). Higher premiums correspond to more opportunities, and the positive relationship with the degree of inequality is confirmed in all the regressions we run.

We make a final remark. Regressions for capital towns include *all* towns, big and small. This may seem to contradict our view about the applicability of CM to small towns. We argued in the previous section that firm size inequality in small towns is driven by strategic effects. However – in line with Sutton's spirit – we have included them as well since the overall picture should be driven by independence effects, prevailing over strategic ones.[22]

To summarise, the empirical evidence confirms that the aggregation process of different independent submarkets can explain the degree of inequality in the firm size distribution. Higher Gini coefficients are found as more opportunities arise, where the number of opportunities can be reasonably represented by total premiums or by the population size when data on premiums are not available. Opportunities do not arise linearly, capturing the idea that populations are not uniformly distributed over a territory, rather there are relevant agglomeration features (there are more opportunities in 10 towns with a population of 100,000 inhabitants than in a single big city with 1 million people). The "spatial" dimension of submarkets is also further testified by a geographic variable (only below certain density levels) and by the explanatory power of the population living outside the capital town on the Gini of the capital town, related to a very typical effect of flows of commuters.

6.   Concluding remarks

This paper has tested the role of independent submarkets as a determinant of firm size distribution, along the lines of the theory recently proposed by Sutton (1998). We have conducted the test in the Italian motor insurance industry, exploiting its interesting features:

- It is divided into 103 independent administrative areas;
- Within each area, location of companies is the most important parameter;

---

[21] Low density is defined as less than 150 inhabitants per square kilometre; using this threshold, 71 out of the 103 provincial areas outside the capital town would be defined as "low density".

- Firms are typically present in multiple areas.

At the submarket level, we have found that some degree of inequality can be explained by a reasonable model of equilibrium price dispersion based on costly consumer search. However, strategic effects alone cannot explain the observed levels of inequality in each province, supporting the hypothesis that independence effects are already at work within each province. Once submarkets are aggregated, distributions are very unequal, thus offering evidence in favour of the "bounds" approach proposed by Sutton. The main mechanism at work derives from the operations of several large insurance companies over various submarkets and this mechanism places a constraint on data that overrides the details of strategic interaction at the submarket level. Moreover, we have investigated further what could determine the numerosity of independent opportunities that arise in each province.

In general, if a researcher is able to identify a submarket at the "right" level, then a model based on strategic interaction that captures the relevant features of the industry in question would be very informative. For instance, in this paper we made a case for applying a consumer search cost model in small provincial capital towns. However, data at our disposal would under many circumstances include many submarkets, generating pictures that reflect independence effects as the number of submarkets increases. In this paper, we showed how the information contained in an index of inequality calculated at the level of big cities (e.g. Milan or Rome) would reflect the aggregation of various more or less independent submarkets that include different areas within the same city and commuters that may live outside. Independence effects operates across these submarkets that are very difficult to identify, but their effect shows up in the observed degree of inequality of firm sizes. Figure 6 gives a visual summary of the ideas discussed in this paper. Shaded areas indicate hypothetical "proper" submarkets, while the thick borders indicate the data at the researcher's disposal. In some circumstances (case (1)) the two notions coincide: that is where game theory can be nicely at work (CM in our case, applied to small towns). Often, on the other hand, the unit of observation will contain already many submarkets that are difficult to identify. This is case (2), where a town contains three submarkets, one of whom is partially made of commuters. In this case independence effect will start to emerge. By using data at an even higher level of observation, they become predominant: this is case (3) in the figure.

The skewed distribution found at the national level does not seem to be a phenomenon limited to Italy. Using a different source of data (Swiss Re, 1996), we have information on

---

[22] To confirm this, if we run two separate regressions for small and for big capital towns, then the subsample of big capital towns would deliver similar results (with slightly stronger effects), while the subsample of small

concentration indices of insurance companies in the Non-Life business in different European countries. Since we do not have the total number of companies, we cannot draw the aggregate Lorenz curve for each market. However, we have data for the 5-firm, 10-firm and 15-firm concentration indices (measured on premiums), so we can perform in every country the conditional test proposed by Sutton (1998). According to the theory, for a fixed $k \leq m$ and a certain value C_m for the m-firm concentration ratio, the actual k-firm concentration ratio should lie above the following bound:

(5) $C_k \geq k / N_m [1 - \ln(k / N_m)]$

where N_m is the solution of:

(6) $C_m = m/N_m [1 - \ln(m/N_m)]$

Figure 7 plots a scatter diagram of C_5 versus C_{15}. The solid curve corresponds to the fragmented equilibrium (slope = 1/3), while the dotted bound has been derived solving recursively eq. (6) with respect to N_m using $m = 15$ and a grid of values of C_m between 0 and 1, and then plugging every resulting value of N_m into the expression for the bound (eq. (5) with $k = 5$). All the data points lie very neatly above the bound. We have also repeated the exercise with C_{10} versus C_{15} (not reported here), always confirming the conditional prediction.

We have not addressed the problem of firm dynamics at all in this paper, despite the fact that it is central to the size distribution of firms. It would be very interesting to see what happens when independent markets have reached different levels of maturity and development (i.e., young versus old markets). In particular, the question of whether firms that are present at the national level are also older firms or whether companies with a strong regional vocation remain such over time or try to capture opportunities elsewhere, is a valuable one. These are questions that we plan to investigate in the future.

[Figure 6 – Submarkets and levels of observation]
[Figure 7 – Testing the conditional prediction at the European level]

---

capital towns would not support the hypothesis of independent submarkets.

Bibliography

ANIA, 1999, *Italian Insurance in 1998 – Annual Report*, Rome

Asplund, Marcus, 1999, "On the Size Distribution of Firms and Markets," mimeo, Stockholm School of Economics

Barla, 2000, "Firm Size Inequality and Market Power," *International Journal of Industrial Organization* 18(5): 693-722

Carlson, John A. and R. Preston McAfee, 1983, "Discrete Equilibrium Price Dispersion," *Journal of Political Economy* 91(3): 480-493

Dahlby, Bev and Douglas S. West, 1986, "Price Dispersion in an Automobile Insurance Market," *Journal of Political Economy* 94(2): 418-438

ISVAP, 2000, *L'Assicurazione RC Auto in Italia: Analisi e Proposte*, Rome

de Juan, Rebecca, 1999, "The Independent Submarkets Model: An Application to the Spanish Retailing Banking Market," mimeo, Fundacion Empresa Publica, Madrid

Meyer, U., 2001, "Third Party Motor Insurance in Europe: Comparative Study of the Economic-Statistical Situation", in Bund der Fersicherten, *Car Insurance Tariffs Project*, Final Report, Henstedt-Ulzburg

Schlesinger, H. and J.-M. von der Schulenburg, 1993, "Consumer Information and Decisions to Switch Insurers," *Journal of Risk and Insurance* 60(4): 591-615.

Sutton, John, 1997, "Gibrat's Legacy," *Journal of Economic Literature* 35: 40-59

Sutton, John, 1998, *Technology and Market Structure*, MIT Press, Cambridge (MA)

Swiss Re, 1996, "Deregulation and Liberalization of Market Access: the European Insurance Industry on the Threshold of a New Era in Competition," *sigma*, n. 7

Walsh, Patrick Paul and Ciara Whelan, 2001, "The Role of Taste Niches in Modelling Market Structure: An Application to Carbonated Soft Drinks," WP01/13, Centre for Economic Research, University College Dublin

Appendix 1

The Italian Motor Insurance Industry: firms included in the sample.
The empirical work in this paper is based on an original database that comprises the geographic distribution system of 61 companies over 103 provinces. In total, 15,044 tied agencies were identified using two different sources: the biggest companies report their distribution system on their web sites, while the remaining agencies were collected using the telephone directories of all the Italian provinces. Agencies within each province were further subdivided according to whether they were or not in the capital town of the province. Using some random samples, we also checked that the two sources did not produce significant discrepancies (the telephone directories of 1998 report information collected at the end of 1997, while websites are usually updated at various points in time – in our case between the end of 1998 and early 1999).

In 1998 there were 97 insurance companies authorised to offer contracts in the Italian Motor insurance business. These companies collected total premiums amounting to 27,897 billion lira (22,932 for Motor Liability and 4,964 for other damages). Premiums are mainly collected through tied agents: this phenomenon is true at the European level, and exceptionally high in Italy (Swiss Re, 1996). Alternative sales systems include brokers, independent agents, direct sales, and distribution channels that are destined to become increasingly important such as banks, phone sales and Internet sales. Out the total population of 97 companies, in 1998, 6 companies sold only over the phone and over the Internet (0.6% of total premiums), 4 companies used only bank branches (0.1%) and 66 sold almost exclusively via tied agents (97.4% of total premiums). The remaining 21 companies (1.9% of total premiums) sold exclusively through the remaining channels (independent agents, brokers, direct sales).

We concentrate our study only on those companies selling via tied agents, both because it is the dominant channel and because it is the channel that exhibits the clearest locational dimension. While phone sales and sales through bank branches compete against tied agents, this would not be true for the other distribution systems that are devoted to satisfy companies' needs (think of brokers, re-insurance – i.e. the way companies pool major risks). Overall the exclusion of firms not relying on tied agents does not seem particularly problematic.

Out of the remaining 66 companies, 5 had particular agreements such that the same distribution system was shared with other companies that belonged to the same group. In these cases we have merged the firms and considered them as a single entry. As a result our relevant population is made of 61 companies.

Summary statistics.
Table 1 contains the descriptive statistics relative to the 103 Italian provinces. Additional information has been taken from the Italian Insurers Association (ANIA, 1999). Table 2 reports the correlation matrix between the exogenous variables involved.

It should be noticed that the Gini coefficient is on average below the Gini coefficient associated to Sutton's bound (0.5), but there are provinces with values above it, suggesting that aggregation effects are already working at the provincial level. On average, in every province half of the total number of companies is present with at least one agency. This average does not imply that all the companies have the same presence over the territory: almost one half of the companies attempts to pick opportunities all over the country, while the remaining half has branches only in selected provinces.

	Mean	Standard deviation	Min	Median	Max
Number of branches (province)	146	160	27	106	1,181
# companies (province)	33	6	18	33	56
# companies (capital town)	30	7	17	30	54
# companies (outside capital town)	22	8	2	23	42
Total premiums collected (L. billion)	197	251	20	128	1,664
Average premium (L. thousand)	704	90	548	694	1,140
Market share (national)	1.64	2.13	0.02	0.66	10.63
Herfindhal (province)	5.47%	1.49%	3.68%	5.11%	14.29%
Herfindhal (capital town)	5.37%	1.46%	3.50%	5.04%	16.50%
Herfindhal (outside capital town)	9.45%	7.42%	4.11%	7.06%	50.00%
Gini coefficient (province)	0.41	0.10	0.14	0.40	0.63
Gini coefficient (capital town)	0.30	0.11	0.10	0.30	0.64
Gini coefficient (outside capital town)	0.35	0.11	0.00	0.37	0.61
CV of market shares (province)	0.86	0.25	0.34	0.83	1.69
CV of market shares (capital town)	0.73	0.26	0.30	0.68	1.50
CV of market shares (outside capital town)	0.75	0.27	0	0.75	1.75
Population in the province (million)	0.56	0.62	0.09	0.38	3.80
Population in the capital town (million)	0.17	0.32	0.02	0.09	2.65
Population outside the capital town (million)	0.39	0.36	0.03	0.28	2.43
Area (sq. km.)	2,925	1,750	212	2,562	7,520
Provincial density (inhabitants per sq. km.)	244	334	37	173	2,669
Provincial density outside the capital town (inhabitants per sq. Km.)	163	211	26	130	1,775
Inhabitants per branch (thousand)	3.87	1.32	2.16	3.39	8.03
Premiums per capita (L. million)	0.34	0.09	0.15	0.37	0.52
Motor vehicles (million)	0.09	0.10	0.00	0.06	0.72
Frequency of accidents (number of accidents/vehicles insured)	10.10%	2.01%	6.36%	9.69%	18.24%
Average accident's cost (L. million)	4.48	1.10	2.29	4.40	8.11

Table 1. Summary statistics for 103 Italian provinces

Cap. town pop.	Prov. pop.	Pop. out. cap.	Premiums collected	Motor vehicles	Branches	Premiums per capita	Area	Density (outside capital)	Frequency of accidents	Average accident's cost	
1.00	0.89	0.64	0.90	0.81	0.87	0.15	0.16	0.45	0.49	–0.08	Cap. town pop.
	1.00	0.92	0.96	0.93	0.93	0.09	0.23	0.69	0.53	–0.09	Prov. population
		1.00	0.83	0.86	0.81	0.01	0.25	0.78	0.47	–0.09	Pop. out. Capital
			1.00	0.96	0.98	0.29	0.19	0.58	0.39	0.03	Premiums collected
				1.00	0.97	0.28	0.23	0.57	0.33	0.04	Motor vehicles
					1.00	0.28	0.22	0.54	0.33	0.02	Branches
						1.00	–0.17	0.05	–0.23	0.59	Premiums per capita
							1.00	–0.24	–0.06	–0.16	Area
								1.00	0.47	–0.02	Density (outside capital)
									1.00	–0.49	Frequency of accidents
										1.00	Average accident's cost

Table 2. Correlation matrix

There is a very strong correlation of Gini coefficients measured according to alternative definitions of submarkets. The correlation matrix is not reported here for the sake of brevity, on the other hand we believe it is of some interest to report the correlation matrix between various measures of market structure (table 3). There is a positive correlation between Gini and the number of firms, while the degree of inequality in size distribution is not related monotonically to a classic measure such as the Herfindhal index. This is consistent with what one could expect from the independent submarkets model that predicts a positive relationship between number of firms and their degree of inequality, while there is a non monotonic relationship between the latter and the Herfindhal index. When there are a few opportunities, in fact, there will be a few companies of similar size, resulting in high Herfindhal indices but low Gini. On the other hand, in big provinces, it is likely that many opportunities are to be filled by companies: if such opportunities are more or less independent, statistical aggregation should give a picture where many companies of very different sizes coexist (high Gini and Herfindhal indices).[23]

Province			Capital town			Outside capital town			
Gini	# companies	Herfindhal	Gini	# companies	Herfindhal	Gini	# companies	Herfindhal	
1.00	0.70	-0.04	1.00	0.75	0.03	1.00	0.66	-0.43	Gini
	1.00	-0.03		1.00	0.03		1.00	-0.71	# companies
		1.00			1.00			1.00	Herfindhal

Table 3. Correlation matrix between Gini and concentration indices

Price data.

We employ price data in order to estimate: a) consumer search costs and b) the variance of firm-specific costs (see Appendix 2). The summary statistics reported in Table 1 under the heading "average premium" refer to the prices charged by 44 companies out of the total of 61, for which information on prices is available (such companies represent 95% of the whole market).[24] Price discrimination is a widespread phenomenon in the motor insurance industry and firms can charge different prices according to the province, the type of vehicle, and some characteristics of the owner (such as age, sex, and job). Given these problems, we have decided to consider the price charged to an important segment of the market, namely a middle-aged male, with a petrol car of average power, rated in the best premium class of the "bonus/malus" system. Price data in Table 1 refer to the distribution of average prices charged by the same company over the various provinces. If we consider the distribution of prices charged by various companies within a given province, prices would vary between a minimum of 497,000 lira and a maximum of 1,011,000 lira, with a standard deviation of 123,000 lira. We also have the complete price lists in 14 provinces: in these provinces we re-ran the econometric analysis considering a weighted average of the premiums charged by a company to 19 different categories, without affecting the results reported in the main text.

---

[23] Another classic measure of inequality is the coefficient of variation (CV) of market shares. It can be shown that the relationship between the Herfindhal index (H) and CV is given by $H = (1 + CV^2)/n$, where n is the number of firms. Hence H is negatively related to n but positively related to CV that, in turns, may vary positively with n if the independence effect applies. This decomposition shows clearly the respective contributions of the number of firms and the firm size distribution to the Herfindhal index. Barla (2000) uses a model with capacity constraints to examine the relation between size inequality and market power and tests it in the US airline industry.

[24] "Average premium" need not be confused with "Premium per capita" in Table 1. The latter was constructed dividing total premiums collected by all companies in a certain province by the province population (such information exists, while premiums collected at the provincial level by each company are not publicly available).

Appendix 2

Carlson and McAfee's model of equilibrium price dispersion.
In the model of CM, consumers search with equal probability among n firms that post different prices. Consumers differ in their cost of search, and the distribution of such costs determines the optimal stopping rule (i.e. the number of searches that they must make until they find a certain price).

Firms face demands that are a function of the distribution of consumers' costs of search and the arguments in those functions depend on the prices set by all n firms. In case the distribution $G(c)$ of search costs c is uniform ($G(c) = c/s$, $0 \leq c \leq T$), then the demand function for the generic firm i ($i = 1, \ldots, n$) simplifies to (see CM, eq. (12), page 488):

(a) $$\frac{x_i}{m/n} = 1 - \frac{p_i - \overline{p}}{T}$$

where $\overline{p} = \sum_{i=1}^{n} p_i / n$ is the average price, T is the range of search costs, and $1/s$ is the density (the total number of buyers is then $m = T/s$). Firm i's market share, relative to the average number of customers insured, varies inversely with the deviation between firm i's premium and the average premium. Notice how an increase in price results in a loss of market share; however this effect is diluted as the number of firms increases. Other things being equal, as n goes up, consumers search less, hence market shares are less responsive to differences in prices. Also notice how market shares are inversely related to T. If search costs are high, consumer search less for a given distribution of prices, and market shares tend to be more similar. Finally, observe how the estimation of eq. (a) (demand equation) allows to quantify the inverse of T from the estimated coefficient of the deviation between firm i's price and the average price.

Clearly, in order to sustain a persistent distribution of dispersed prices, firms need to be different in some respect. CM develop their model with the assumption that there are cost differences among firms, and they obtain the equilibrium prices when firms have quadratic cost functions (Dahlby and West, 1986, provide a more general treatment). In particular, if the cost function of firm i takes the form $C_i(x_i) = \alpha_i x_i + \beta x_i^2$, $\beta \geq 0$, CM obtain (see their eq. (18), page 488):

(b) $$p_i = \alpha_i + \frac{(1+\gamma)n}{n-1}[T + K(\overline{\alpha} - \alpha_i)]$$

where $K = (n-1)/(2n-1+\gamma n) < 1$, $\gamma = 2m\beta(n-1)/Tn^2$. Recalling eq. (a), equilibrium quantities simplify to:

(c) $$x_i = \frac{m}{n}[1 - K(\alpha_i - \overline{\alpha})/T]$$

Finally, in order for firms not to make losses, it must be that the square bracket in eq. (b) is positive for every firm, including the least efficient one (firm n):

(d) $$\alpha_n - \overline{\alpha} \leq T/K$$

Direct manipulation of eq. (c) gives the following values for the coefficient of variation of market shares and its limit as n grows large (σ_α is the standard deviation of costs):

(e) $\quad CV_x = K\sigma_\alpha / T$

(ebis) $\quad \lim_{n \to \infty} CV_x = \sigma_\alpha / 2T$

From eq. (b) we can obtain the following effect on prices due to an increase in the number of firms:

(f) $\quad \dfrac{\partial p_i}{\partial n} = -\dfrac{1 + (n-1)\gamma}{(n-1)^2}[T + K^2(\bar{\alpha} - \alpha_i)]$

Since from condition (d) $T + K(\bar{\alpha} - \alpha_i) \geq 0$ and $K < 1$, a fortiori the square bracket in the last expression has to be positive: all prices decline with n, but relatively more so for the cheapest firms. Before trying to derive testable predictions, it is useful to sign the following derivatives (equality signs are relevant when there are constant returns to scale, i.e. $\beta = \gamma = 0$):

$$\partial K / \partial n > 0, \partial^2 K / \partial n^2 < 0$$
(g) $\quad \partial K / \partial T \geq 0, \partial^2 K / \partial T^2 \leq 0$
$$\partial K / \partial m \leq 0, \partial^2 K / \partial m^2 \geq 0$$

We are now in a position to analyse the effects on the equilibrium size distribution of a change in one of the variables. We distinguish between two cases, according to whether the number of firms is exogenous or endogenous. If entry is fixed somehow exogenously, then:

number of firms: $\quad \partial CV_x / \partial n > 0$

range of search: $\quad \partial CV_x / \partial T < 0$

population: $\quad \partial CV_x / \partial m \leq 0$

When n is endogenous, then condition (d) with an equality sign represents the free entry condition. As a result we have two equations, one for entry and one for the coefficient of variation. Notice how the RHS of eq. (d) is decreasing in n while the LHS is increasing in n under a mild condition: $\partial(\alpha_n - \bar{\alpha}) / \partial n \geq 0$ (satisfied by most standard distributions). Comparative statics over the entry condition give:

(h)
$$\partial n / \partial m = \dfrac{-T/K^2 \cdot \partial K / \partial m}{\partial(\alpha_n - \bar{\alpha}) / \partial n + \partial K / \partial n \cdot T / K^2} \geq 0; |\partial n / \partial m| \leq -\partial K / \partial m \cdot \partial n / \partial K$$

$$\partial n / \partial T = \dfrac{T/K^2(K/T - \partial K / \partial T)}{\partial(\alpha_n - \bar{\alpha}) / \partial n + \partial K / \partial n \cdot T / K^2} > 0; |\partial n / \partial T| \leq K/T \cdot \partial n / \partial K$$

The total effect on the coefficient of variation of a change in an exogenous variable y is $dCV_x / dy = \partial CV_x / \partial y + \partial CV_x / \partial n \cdot \partial n / \partial y$. Given our previous results it is immediate to show that in a reduced-form equation when n is endogenous: $dCV_x / dm \leq 0, dCV_x / dT < 0$.

These results are valid in a single market. If costs differ across provinces, then the cost function of firm i in province j should become: $C_{ij}(x_{ij}) = \alpha_{ij}x_{ij} + \beta x_{ij}^2$. If province-specific and firm-specific cost factors are additive, then $\alpha_{ij} = \alpha_i + \alpha_j$, where the first component can be thought as the firm-specific cost of administering a policy and the second component is the pure loss cost from insuring a car in a province. Under this interpretation, the cost difference between two firms with the same ranking and insuring the same number of cars does not depend on the province. The predictions of the model can then be extended to the province level:

(i) $\qquad CV_{xj} = K_j\sigma_{\alpha j}/T_j = K_j\sigma_\alpha/T_j$

where σ_α is the standard deviation of the firm-specific components. A similar manipulation of eq. (b) would also lead to the following expression for the variance of prices at the level of market j:

(j) $\qquad \sigma_{pj}^2 = K_j^2\sigma_\alpha^2$

which can be further approximated by observing that as n becomes large, then γ tends to 0 and the factor K_j simplifies to $(n_j - 1)(2n_j - 1)$, which is in turn close to ½. Since we have data on the variance of prices at the province level, eq. (j) is the base of our test of additivity in the cost function.

Figure 1 - Lorenz curves in the Italian motor insurance industry
(national level)

Legend:
- Sutton's bound
- Agencies
- Total premiums
- equal-sized firms
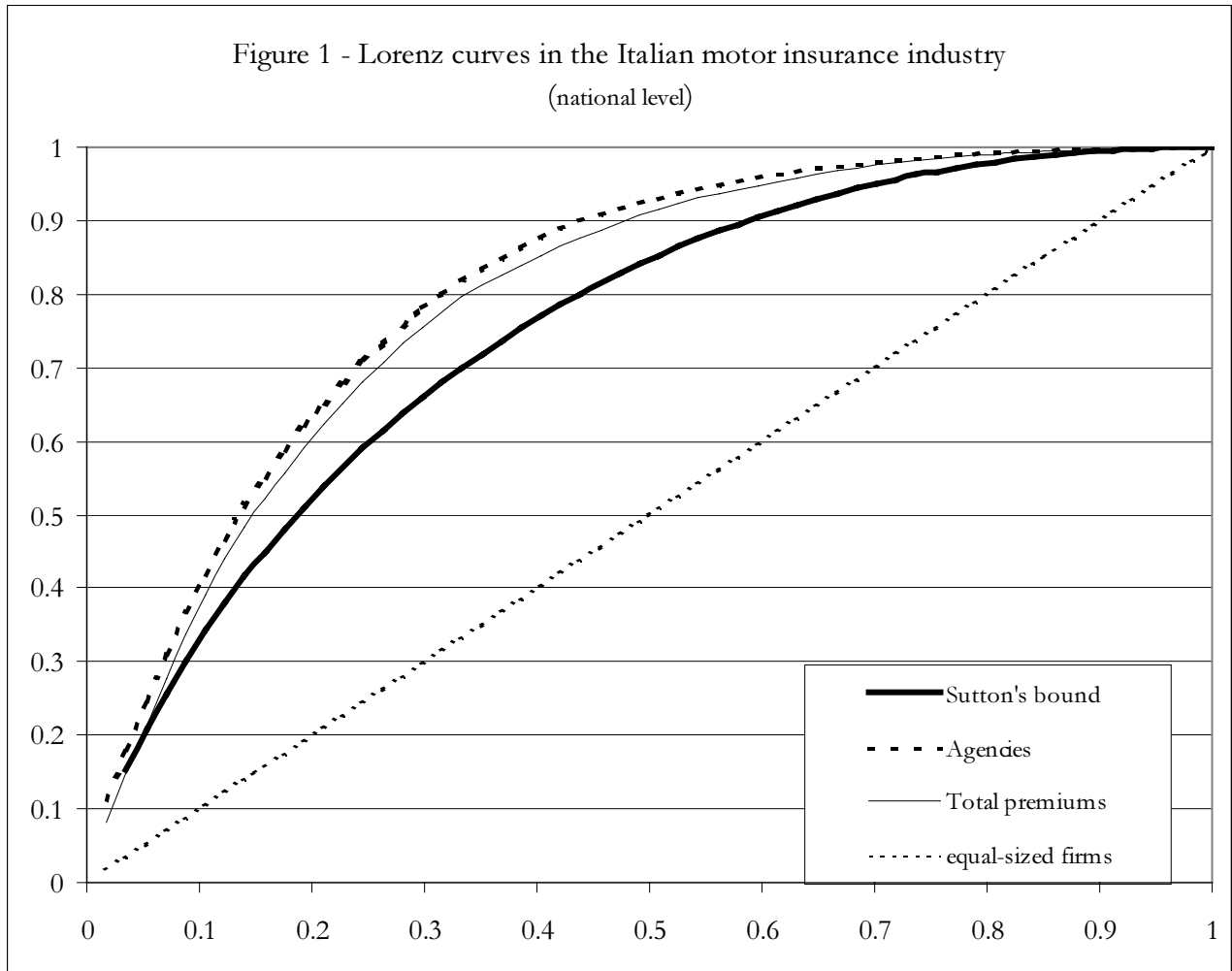
Figure 2 - Lorenz curves for the Italian motor insurance industry
(province level)
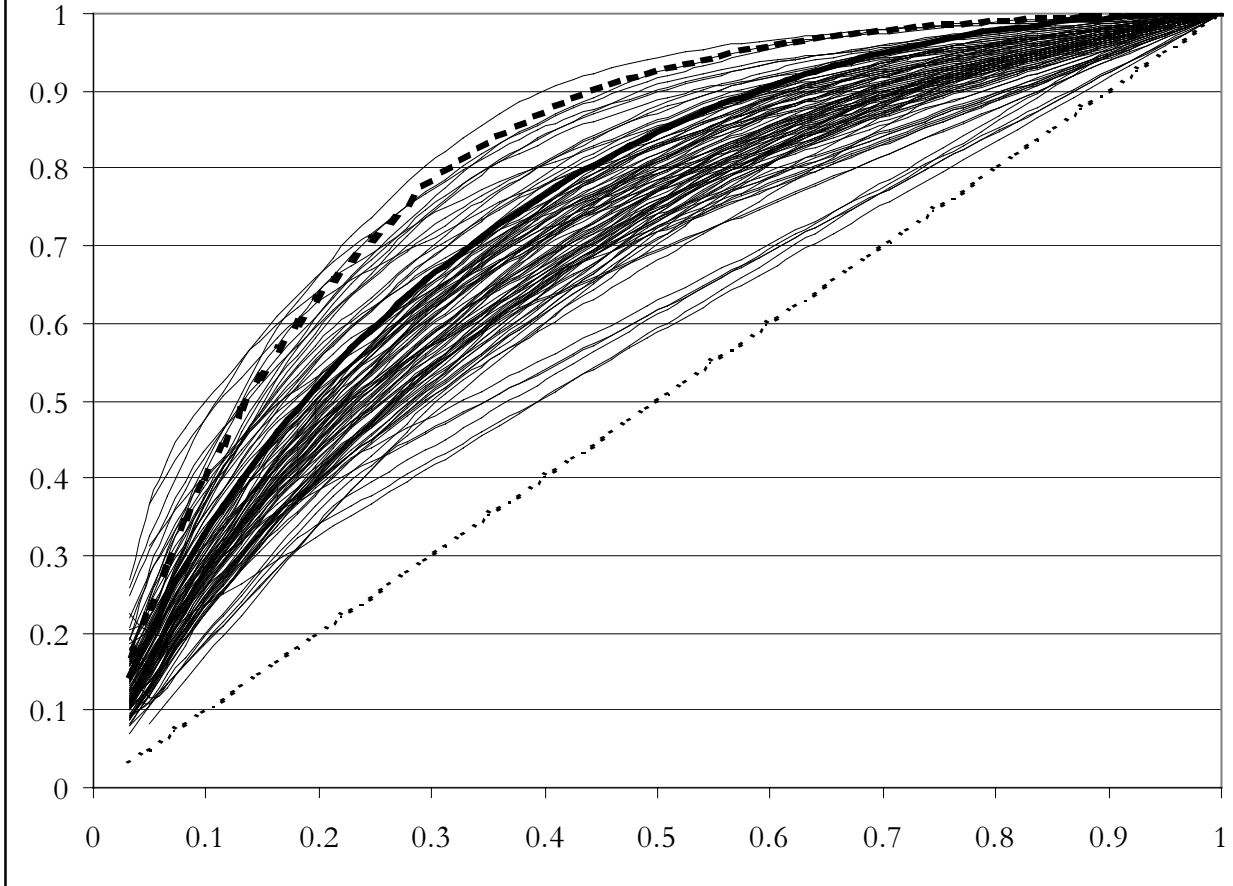
Figure 3a - Lorenz curves for the Italian motor insurance industry (large capital town level - 63 observations)
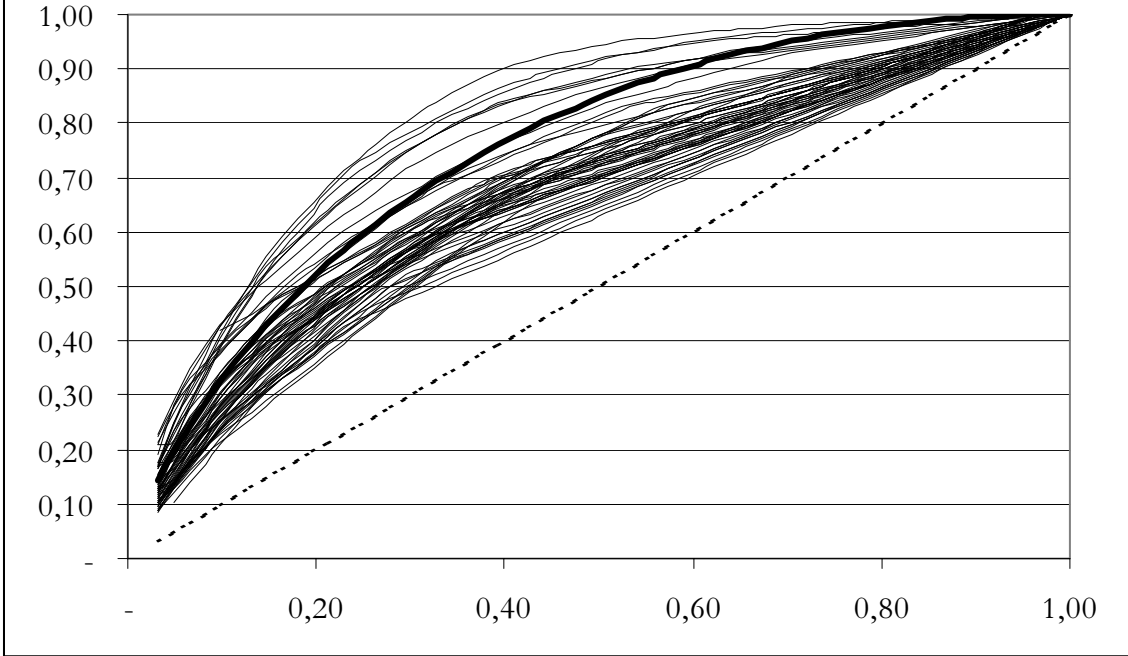
Figure 3b - Lorenz curves for the Italian motor insurance industry (small capital town level - 40 observations)
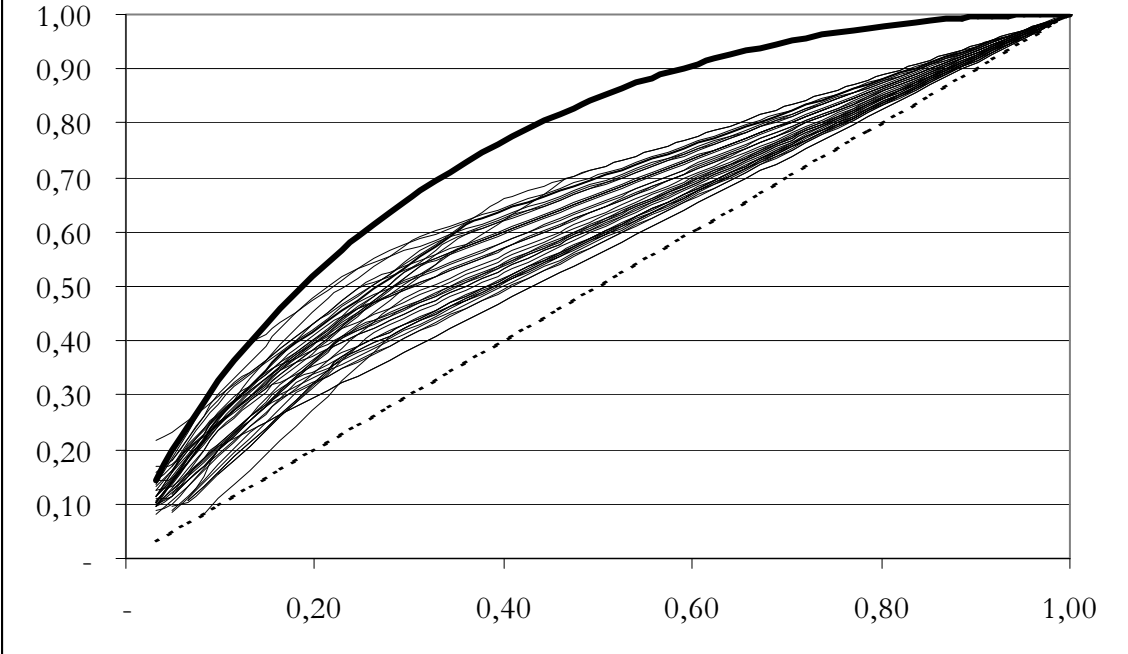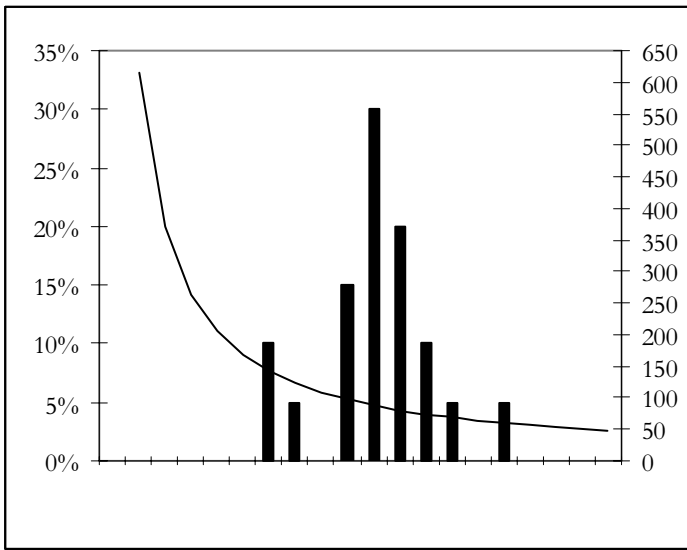
regional level (average CV = 1.06)
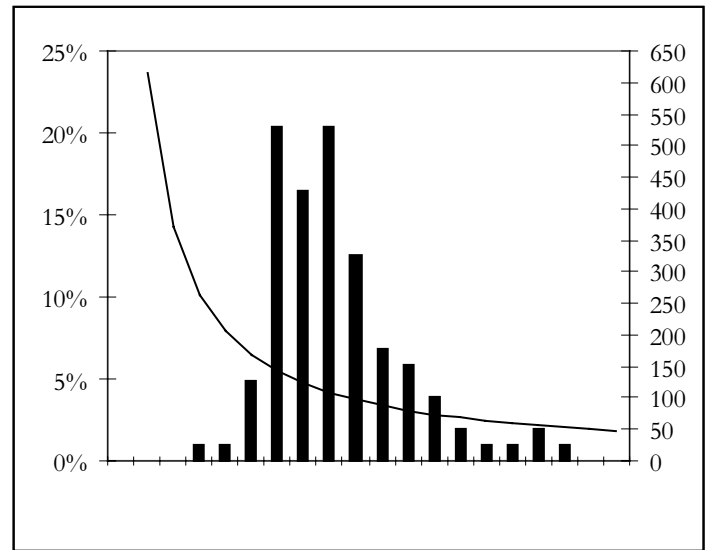
provincial level (average CV = 0.87)
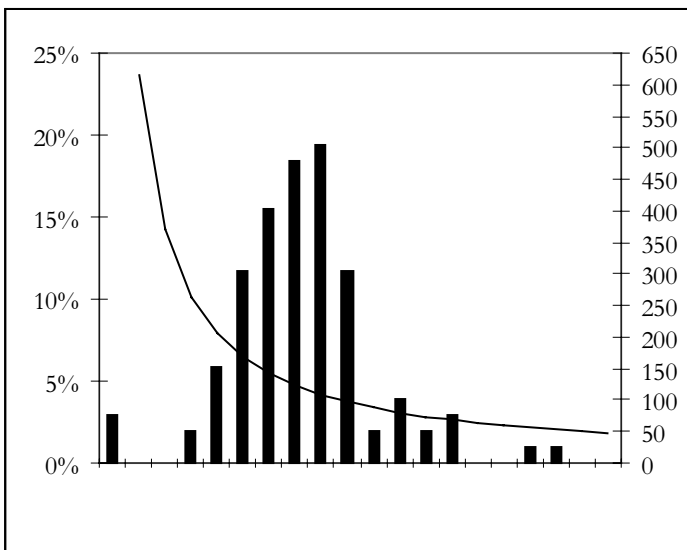
extra capital town level (average CV = 0.77)
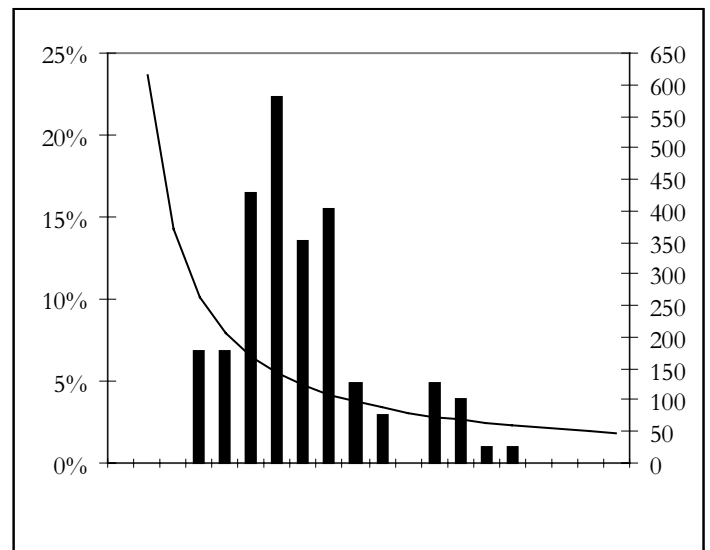
capital town level (average CV = 0.72)
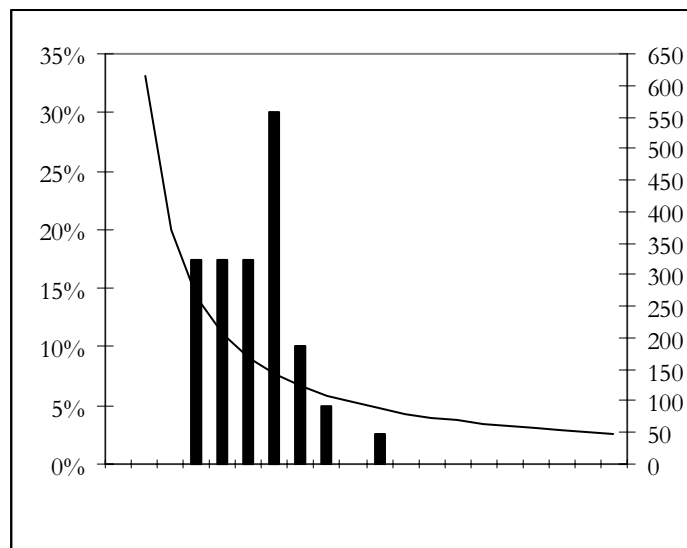
small capital town level (average CV = 0.57)

Figure 4 – Predicted and observed coefficients of variation
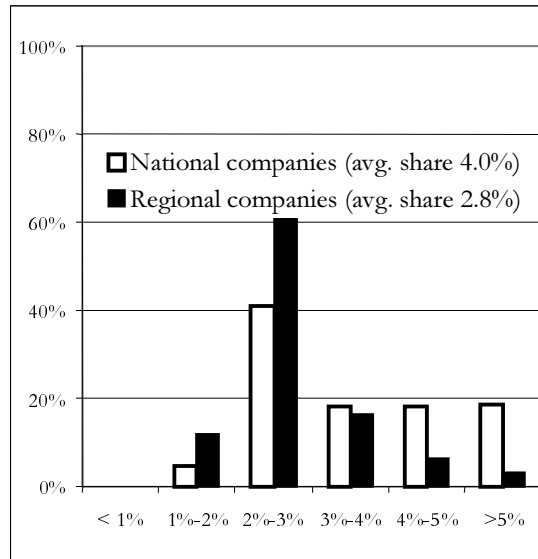
33
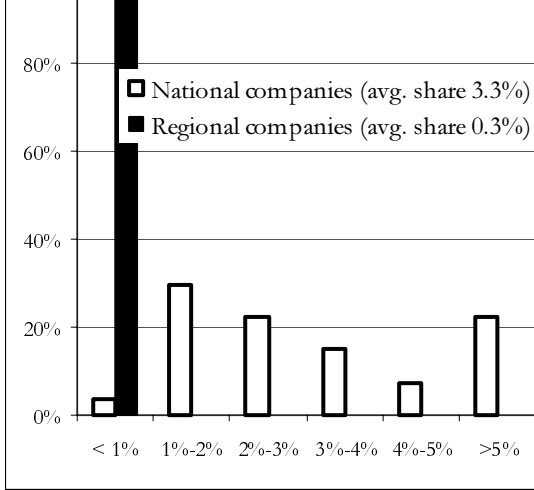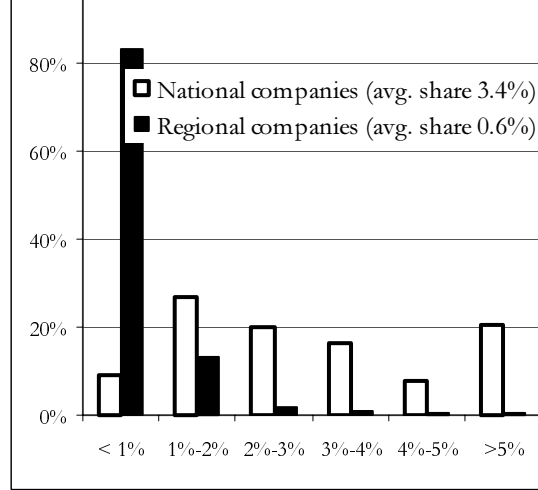
(national level)

(regional level)
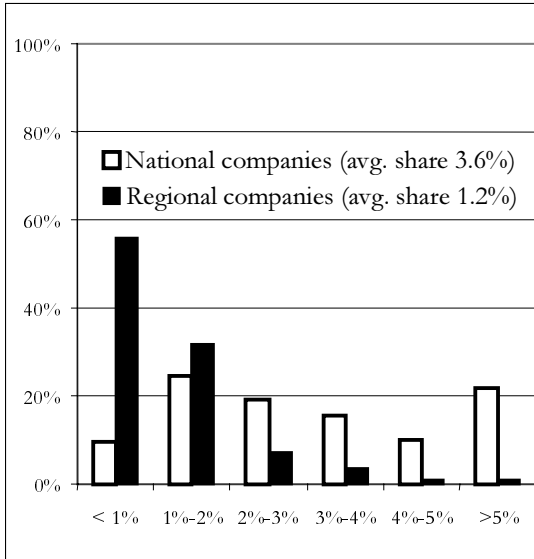
(provincial level)
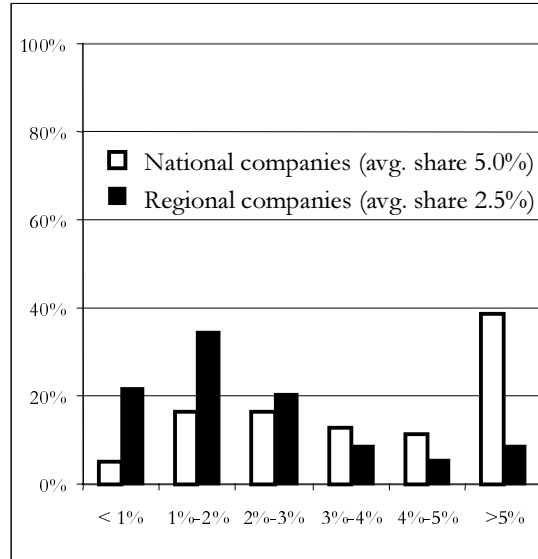
(extra capital town level)
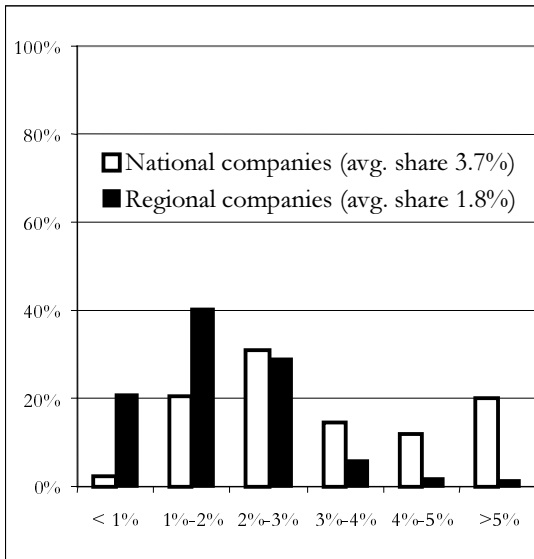
(capital town level)

(small capital town level)

Figure 5 – Distribution of market shares for 'national' and 'regional' firms

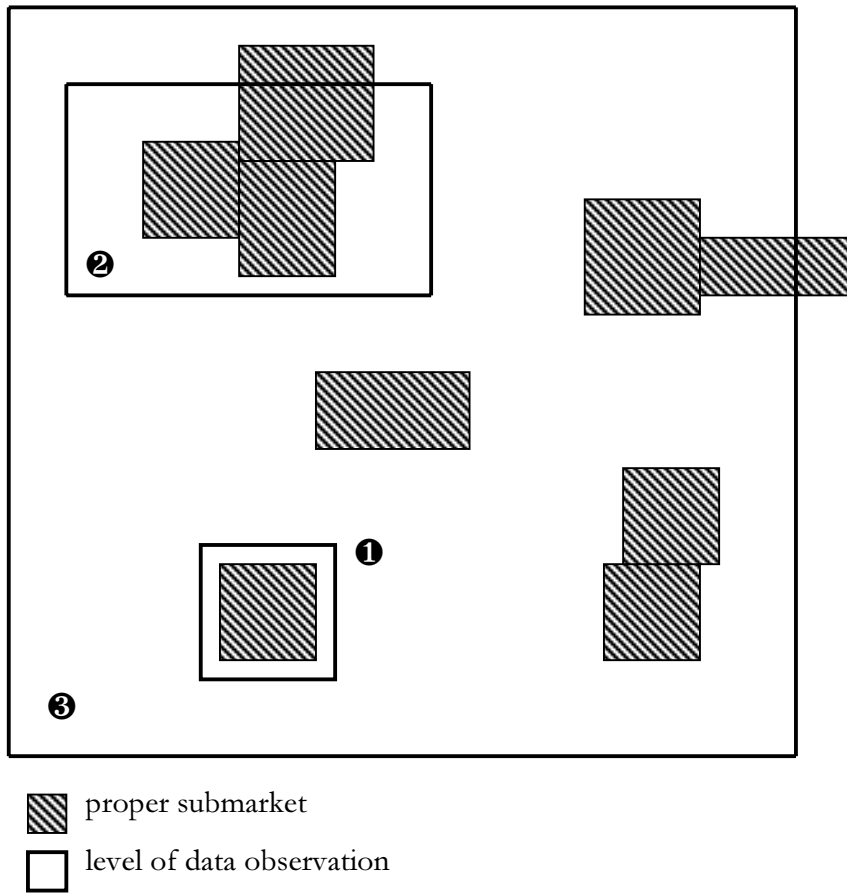proper submarket

level of data observation
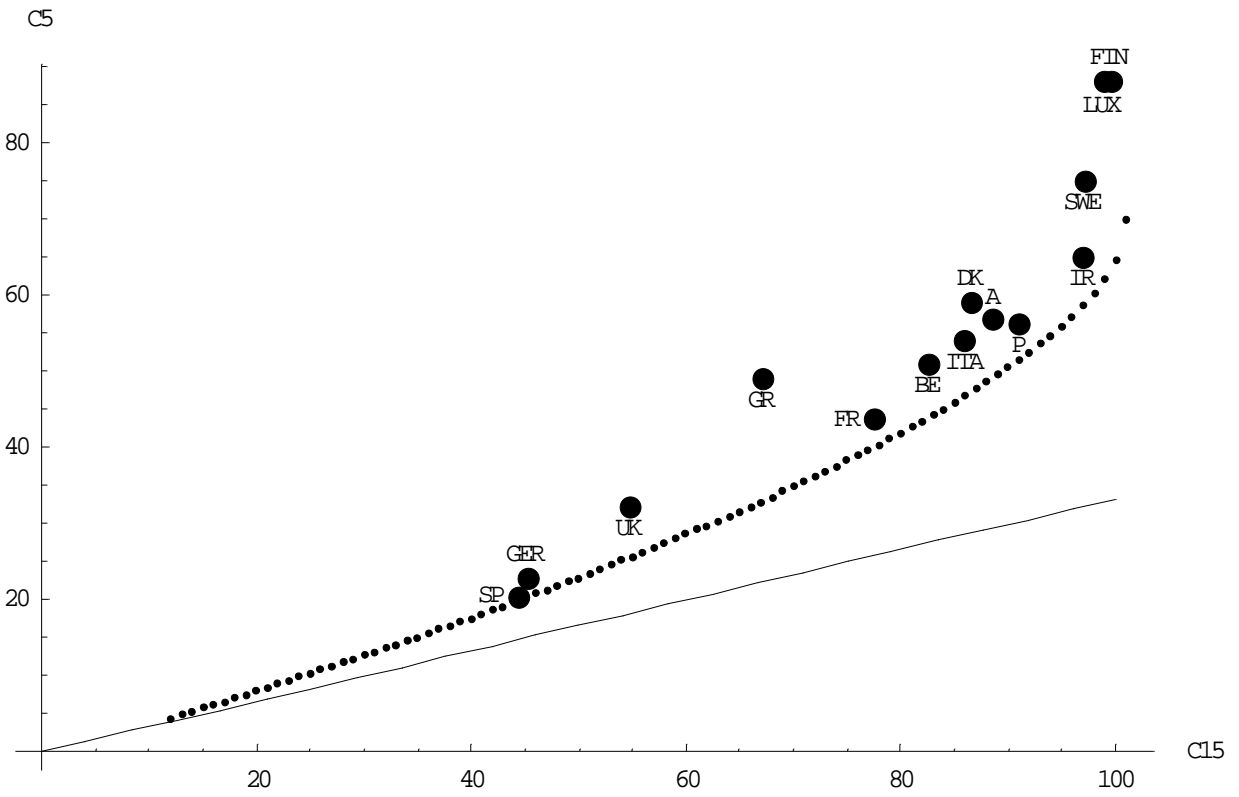
Figure 6 – Submarkets and levels of observation

Figure 7 – Testing the conditional prediction at the European level