A by-line analysis of insurance fraud*

Preliminary and incomplete: please do not quote

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Abstract

We investigate the determinants of the share of insurance frauds over total claims in four different lines of property-liability insurance across 103 Italian provinces and five years. Fraud is framed in terms of rewards and both formal and social costs of crime; either are related to the characteristics of the local socioeconomic system and of the local insurance market. Results are different across lines; fraudulent behaviour in some lines turns out to be more frequent in poorer areas and during weak phases of the economic cycle, or among the younger and less educated, in accordance with the general literature on crime. Some support is also found for the controlling role of social capital, through social sanctions, on fraudulent behaviour. There is no evidence of any effect of the density of territorial units (inspectorates and claim handling units of insurers) on fraud frequency.

1 Introduction

Insurance fraud is a widespread problem; it has nevertheless always been particularly acute in Italy, where fraudulent claims have long been inflating loss payments. The costs of frauds have historically played an important role in taking the tariffs of the Italian motor insurance sector, both third party liability (henceforth MTPL) and damage to vehicles (henceforth Motor Hull) towards high levels when compared with neighbouring European States. A number of initiatives have been enacted by the Italian Insurance Association (ANIA) and the local supervisory body (then IsVAP) in order to curb the phenomenon. Among the latter, in order to improve knowledge of the local dimension of the issue, a yearly survey was started in 1992 and carried on through two decades

*Research assistance by Tommaso Bortolotti is gratefully acknowledged. The paper has benefited greatly from discussions with our colleagues at the Research Dept. of Generali; nevertheless all final choices, and hence all errors and omissions, are our. All the computations in the paper are done inside the R open-source environment for statistical computing (R Core Team, 2014), generally using the *plm* add-on package for panel data econometrics. This paper has been prepared as a dynamic document with the *Sweave* utility (Leisch, 2002) according to the principles of literate statistical practice.

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by IsVAP to assess the number and importance of fraud in four insurance lines (MTPL, Motor Hull, Fire, Property other than fire), for each of the 95 - then 103 - Italian provinces.

One interesting feature of the dataset is that claims are labeled "fraudulent" based only on internal assessments by the claim handling departments, regardless whether the company then chose to deny the indemnity and possibly prosecute the claimant. Therefore the data can be considered independent from the influence of external factors, which can be substantial, on the decision to deny indemnification and/or to denounce the supposed fraud to the police.[1] There is of course an element of human judgment in this subjective labeling. A random effects model should appropriately account for any systematic bias in the average assessment of suspicious claims by claim handlers in a particular province. For some years, up to 2002, the published data were comprehensive of the number of structures present on the territory: agencies, subagencies and inspectorates. Total premiums and claims for the above lines were also reported until 2002, allowing to control for the overall profitability of the line in each province.

We draw on the data from 1998 (the year data start to be observed on the new set of 103 provinces) to 2002 (end of full reporting, only percentages of fraudulent claims are disclosed from 2003 onwards) to build a homogeneous panel dataset, augmented with sociodemographic, economic and environmental variables.

We assess the determinants of the aggregate percentage of fraudulent claims in a province, as determined by the above procedure, in the light of a simple economic model of the individual decision to commit an insurance fraud. Our conclusions from aggregate data cannot of course be taken to bear on the determinants of individual behaviour (so called *ecological fallacy*) but they can nevertheless shed some light on the larger scale determinants of insurance fraud in a given region, and on the efficacy of the insurer's presence on the territory as a deterrent measure.

Besides the econometric results, the descriptive analysis of these rich and detailed, yet little known, data is in itself a novelty and a value added of our paper.

Insurance fraud – especially in what we will henceforth collectively call "Motor lines" (Motor TPL and Motor own damage, or Hull) as opposed to the "Property lines", Fire and Theft/Other damage to property – shows the characteristics associated in the empirical literature with petty crimes: it is spatially correlated. This spatial correlation is consistent with imitation behaviour which often emerges as a distinctive feature of petty crimes as opposed to the most serious criminal offences, like rape and murder, which are usually characterized as being independent of the behaviour of neighbours. Nevertheless, we find a notable exception in the behaviour of Fire insurance, which does not show any sign of spatial effects after controlling for the observable determinants. Together with the large average size of fraudulent claims, and with the high risk of collateral damage associated with arson, this makes Fire frauds stand out as a particularly serious kind of insurance crime.

[1] Anecdotal evidence collected by the authors includes adventurous stories from the claim handling departments about managing the pressure from dangerous social groups while denying suspect claims. One of the best-known ones has it that as a claimant, to reinforce his plea, took out a pistol and put it on the desk, the claims settler did so too.

2 The crime literature and the determinants of insurance fraud

In the words of Cohen and Felson (1979), fraud is made possible by three factors: a supply of offenders; available targets; and the absence of controls. There are a number of psychological characteristics correlated with fraud offending, but following Graycar (in Duffield and Graboski, 2001), "opportunities and guardianship provide more scope for fraud control".

The economic analysis of crime, by which criminal behaviour is investigated in terms of a rational choice between the rewards and the costs of engaging in criminal activity, has been effectively started by Becker (1968). Departing from previous attempts at characterizing fraudsters as "anthropologically different", he framed the choice to commit fraud as a rational one. He modeled the decision process in terms of a choice under uncertainty, the utility of committing a crime depending on (monetary or nonmonetary) rewards from committing crime, the punishment if convicted, the probability of conviction; and on the other income available independently from the criminal activity (see the comprehensive literature review by Buonanno, 2003, from which we widely borrowed).

The economic analysis of insurance fraud follows in these same footsteps, with consideration for some peculiarities. Insurance fraud may involve policyholders mis-, i.e. over-, reporting their losses, or reporting accidents that never occurred; but also inflating the claim by inflicting further damages, or hiding relevant information when stipulating a policy (see Picard, 2013). Auditing costs, in the form of state verification, become central, be they either through costly state verification (the insurer has to incur a cost for verifying the actual state of the claim) or through costly state falsification (the insured incurs a cost for hiding the actual state of the claim from the insurer). In the following we will approach the individual decision to engage in insurance fraud in terms of a simple model of rewards and costs, in the line pioneered by Becker (1968), tracing the determinants of these rewards and costs to the characteristics of the local market and territory in order to explain the aggregate incidence of fraud on total claims. Next to the determinants of rewards and costs, bearing directly on the probability of conviction and on the seriousness of the sanction, we will control for total income and a number of other features which have been shown to affect criminal behaviour in general: unemployment, income inequality, education, age (in particular youth) (Buonanno, 2003, 3 to 6).

Crime and social sanction Next to formal sanctions (conviction), following a more recent literature on crime and social interactions pioneered by Glaeser et al (1995) (see Buonanno, 2003, 7) we will consider another potentially important nonmonetary element of the cost of engaging into crime: the social sanction.

Social interactions have been shown by Glaeser et al (1995) to affect crime rates for less serious crimes, as is the case of insurance fraud, and not for violent crimes like murder and rape. In their view, committers of (petty) crimes can be influenced by their neighbourhood through a positive peer effect, as Glaeser et al (1995, p.508) put it: "one agent's decision to to become a criminal positively affects his neighbor's decision to enter a life of crime". In this case, crime rates of the neighbourhood differ from what would be predicted solely by local sociodemographic characteristics and the additional effect of the peer group shall be taken into consideration.

From the opposite perspective, the presence of strong social ties in the neighbourhood can restrain potential offenders by another mechanism, in a sense mirroring the imitation effect. A social sanction in the form of disapproval, exclusion or even forms of retaliation (Buonanno et al, 2012, Introduction) may be imposed on those members of the neighbourhood who are notoriously involved in criminal activities and provide an effective disincentive to doing so.

The deterrent effect of social ties is discussed extensively in Buonanno et al (2009) and Buonanno et al (2012). They derive the result that the social sanction is important in property crime, but not in violent crime; which is in accordance with Glaeser et al (1995). This speaks in favour of the relevance of social ties in the analysis of insurance fraud, which sure is perceived as a petty crime. Again, in their work Italian provinces are chosen as an ideal testbed because of the rich variance in social, demographic and economic characteristics.

Education Some negative correlation between the level of education and criminal activity is a well established empirical fact (one for all Lochner and Moretti, 2004).

Groot and van den Brink (2010) find that the probability of comitting a number of violent and non-violent crimes (from shoplifting to assault) decreases with the years of education; with the notable exception of tax fraud, a typical white-collar crime. There are many competing explanations for this stylized fact.

Education may shift preferences by influencing moral standards and values in ways that are not clearly explained by economic theory (Soares, 2004). For example, education can increase self-control and restraint.

Another view traces the deterrent effect of education back to the ability to figure out future scenarios, by which better educated people should be more able to foresee the future consequences of their actions (Borghans et al, 2008; Beraldo et al, 2013).

A similar explanation involves the degree of time preference, the better educated being expected to have not only a clearer view of the future consequences of their actions but also a longer time horizon. In both cases, low education can be seen as increasing the discount factor which individuals apply to the possible consequences of engaging in illegal activities.

The opportunity cost of engaging in criminal activity is yet another candidate: the higher educated tend to earn more, hence detracting time from non-criminal activities is more costly; conviction can also negatively affect current and future earnings from legitimate activities (see for example the wage equation in Grogger, 1998, Table 4).

Because of both this indeterminacy and of its obvious empirical significance, even when not explicitly included in the theoretical model education is generally believed to influence criminal activity and added as a control variable to most empirical analyses of crime (see, e.g. Dills et al, 2008, Table 2).

Age Age, and young age in particular, is widely regarded as another determinant of crime rates: "Young, unskilled men commit most crimes" (Gould et al, 2002). In particular, high crime rates are associated with the combination of youth and unemployment, or with bad job market conditions at large. The association between youth crime and the local labour market conditions has been framed by Grogger (1998); he focuses on property crime. Interestingly, he explains (part of) the well known racial differentials between crime rates in the US in terms of racial differences between marginal wage rates: people facing lower marginal wages

Moreover, according to Grogger (1998) wages also explain the tendency of crime to decline with age: which takes us to the role of income as an opportunity cost of criminal activity.

Income

> [A] decline in the wage offer increases the relative payoff of criminal activity, thus inducing workers to substitute away from the legal sector towards the illegal sector. In addition, a lower wage offer may produce an income effect by increasing the need to seek additional sources of income in possibly less desirable and more dangerous ways. A lower wage also reduces the opportunity cost of serving time in prison.

(Gould et al, 2002) More in particular, "crime rates are found to be significantly determined by both the wages and unemployment rates of less educated males" (Gould et al, 2002, Conclusions). Also, reputational sanctions are positively correlated with the wage (Lott 1992 cited in (Gould et al, 2002).

Macroeconomic datasets have often drawn a different picture; yet, even if at first consideration economic development seems positively associated to crime rates, Soares (2004) has shown how, after controlling for reporting bias, the actual effect of it is to reduce crime rates: an explanation which is much more consistent with economic theory.

Heterogeneity Cornwell and Trumbull (1994) highlight the importance of accounting for individual heterogeneity; from a methodological point, therefore, of using panel data with some kind of individual effect. In this sense, Guiso et al (2000) justify their resorting to provincial data within one country with the need to draw on a sample that be homogeneous with respect to the basic characteristics of the socio-economic system: law, currency, language and so forth. This is crucial in avoiding the extreme collinearity that often plagues cross-country regressions (see the discussion in Millo and Carmeci, 2011).

Peer monitoring and social capital The severity of the social sanction incurred by fraudsters is, as observed, a product of the likelihood of any fraudulent behaviour being observed by the severity of the social sanction associated with a fraudster's stigma. The former will be correlated to the intensity of the social ties, through which monitoring takes place; the latter will in turn depend on the social capital endowment of the local community. The two will merge into the expected value of the social sanction, so that although individually unidentified their combined effect will be approximated by any valid measure of social capital.

The literature on social capital has developed strongly during the last decade, together with measurement issues for this somewhat elusive concept. Some generally accepted proxies have emerged. To approximate the expected value of the social sanction connected to committing an insurance fraud, we resort on some variables which have become standard in the social capital literature, perhaps most prominently employed in Guiso et al (2000) seminal paper.

These are: voter turnout at non-mandatory elections between 1946 and 1987[2] (*sc1*), anonymous blood donations (*sc2*) and *trust* in fellow citizens, as measured by the World Values Survey (Guiso et al, 2000, Appendix, Table A1); moreover, we consider the voter turnout at more recent referenda: in 1995 and 2001.

Spatial correlation and peer effects Glaeser et al (1995) find that the reference social groups for auto theft and larceny, crimes comparable to insurance fraud, are over 200 in size. This can well cross provincial boundaries at the first-neighbour level.

Different spatial specifications can account for the different effects, in particular a spatial lag is appropriate for processes where the engagement of neighbours has a direct bearing on one's own action.

3 Data and descriptive analysis

As observed in the Introduction, the IsVAP database allows to characterize "actual" aggregate fraud rates, free from underreporting bias, across four different lines of business. A descriptive analysis highlights the profound differences between the typical fraudulent claims.

We focus on two main indicators: the frequency of fraudulent claims over the total and the share of monetary rewards from fraudulent claims over total indemnities.

3.1 Frequency of fraud

At national level, in the last year of the sample (2002) which we take as a specimen here, over five million claims were filed; the vast majority of them, 3.4 million, in the MTPL sector, of which 111614 (3.28 percent of the total) were considered fraudulent. Frequency of fraud went from fractions of a percentage point in many provinces to a staggering maximum of 19.9 percent in Naples. Five provinces, concentrated in Campania and Apulia, crossed the 10 percent mark.

The Motor Hull total claims were 750000, 1.44 percent of them (i.e., 10777) fraudulent. Frequency crossed the 10 percent mark only once (Brindisi) and 6 times the 5 percent one, again in the same regions. Massa Carrara, in Tuscany, fell little short at 4.23.

Other property originated 623199 claims, of which 0.53 percent fraudulent. Only two provinces crossed the 4 percent mark.

Fire originated 314325 claims, 1222 (0.39 percent) fraudulent. Fraud frequency, much below 1 percent in most of Italy, reached 6 percent in two provinces of Calabria; yet the share of the costs due to fraud were much higher, with a record 62 percent in Caserta.

In the following tables, the usual summary statistics are reported for the whole population (across every year) and for each line, both for the relative

[2] Voting used to be mandatory in Italy, with the exception of referenda

frequency of fraud and (next paragraph) for the percentage cost of fraudulent claims over the total.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
MTPL	0.13	0.66	1.01	2.16	2.44	20.34
M Hull	0.00	0.43	0.82	1.68	1.79	67.00
Fire	0.00	0.21	0.41	0.96	1.13	36.00
Oth Prop	0.00	0.18	0.36	0.61	0.69	31.00

3.2 Average cost/severity

The cost of the average fraudulent claim was higher than the average claim cost in three lines out of four. Motor Hull had the smallest average claim cost in the four lines considered, at 1600 euro. The average fraudulent claim was 1.6 times that, at 2500 euro.

The average claim cost in Other property was slightly less than 2000 euro; the average fraudulent claim more than double this figure, at 4300 euro and 2.2 times the former. There was a slight negative correlation between the relative dimension of the fraudulent claim (with respect with the general average cost) and the frequency of fraud.

The average claim cost in Fire was little over 3700 euro; the average fraudulent claim, at a staggering 37000 euro, was 10 times the former. Correlation between the relative dimension of the fraudulent claim and the frequency of fraud was negligible.

By contrast, the average cost of the fraudulent claim in MTPL, at under 3000 euro, was slightly less (0.8) than the average claim cost, which was little short of 3500. The distribution of relative costs of the fraudulent claim was very even, suggesting that the fraudulent MTPL claim, unlike, say, that of Fire, is very "typical" in size with respect to rightful ones.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
MTPL	0.09	0.62	0.96	1.94	2.29	14.77
M Hull	0.00	0.76	1.41	2.20	2.79	34.71
Fire	0.00	0.26	1.00	3.76	3.62	64.50
Oth Prop	0.00	0.23	0.52	1.22	1.25	41.35

3.3 Geographical distribution and spatial correlation

From a cross-sectional viewpoint, it is interesting to compare the average frequencies, in order to spot whether there are geographical clusters, or even a geographic gradient, over the observation period. From casual observation of the maps in the four panels of 1, the tendency of southern provinces to have higher fraud frequency is quite evident, although with different degrees of variance within macroregions: while the motor-related lines in the first row of the figure are more uniform, the property-related ones show both higher variability and a less pronounced gradient from North to South.

The same considerations can be made regarding the share of indemnities from fraudulent claims over the total claim cost in 2, the Campania-Apulia and

Figure 1: Maps of average fraud frequency for MTPL (top left), Motor Hull (top right), Fire (bottom left) and Other damage to property (bottom right), 1998-2002. Darker is higher.

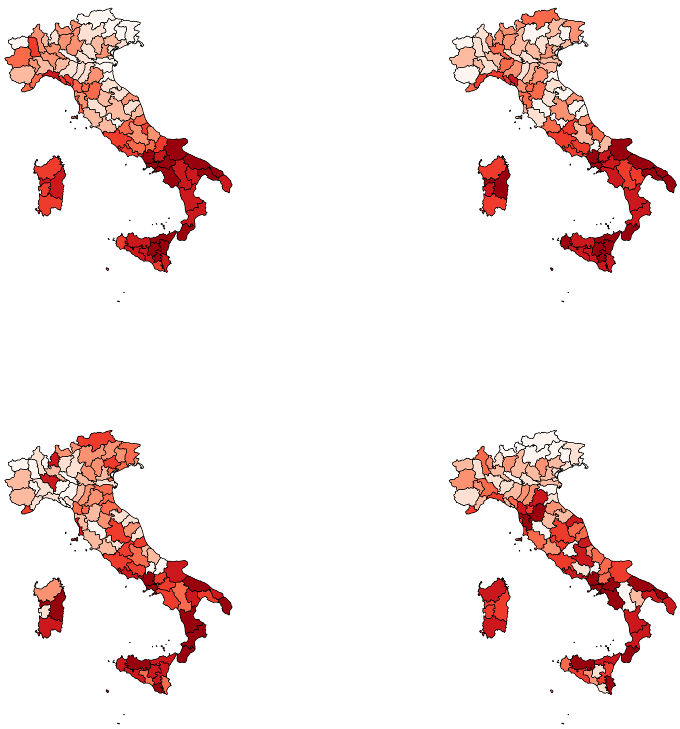

Figure 2: Maps of average fraud severity for MTPL (top left), Motor Hull (top right), Fire (bottom left) and Other damage to property (bottom right), 1998-2002. Darker is higher.

	Min.	Italy	Max.	Gini	Moran	
rPILproc	10051.70	17564.85	28650.07	0.14	11.63	***
inef	1.44	3.79	8.32	0.20	7.29	***

Table 1: 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
rPILproc					
inef					

Table 2: Macroregional averages, year 2000

Calabria-Sicily axes consistently darker than the rest in motor-related lines and, to a certain extent, also in property-related ones; but here, again, with higher variability and a number of darker areas scattered in the Centre and North of the country, in particular in the North-East for Fire insurance.

4 Economic model

Let the net return on fraud be defined as the economic return minus the sum of monetary and nonmonetary costs associated with the frauding activity.

The gross return is given by the insurance payment R, which is conditional on not being caught. Let p be the probability of being caught; the expected value of the gross return is then $R(1-p)$.

In the following we make the simplifying hypothesis that the reported loss be total. The cost of frauding can then be divided into:

- insurance premium
- actual cost for loss of the insured asset, if any: L
- additional costs incurred from the loss of the insured asset (interruption of the economic activity, deductibles etc.);

all the former incurred with probability 1

- explicit costs of punishment C, incurred with probability p and discounted by a subjective factor r_1
- social sanction S from engaging in fraudulent activity incurred with probability s and discounted by a subjective factor r_2

Notice that the latter is incurred with a probability s that does not necessarily match that of being caught and prosecuted formally, but instead depends on the visibility of fraud to peers. In turn, the cost of being seen as a fraudster will depend on the social stigma associated with fraud, which can be substantial or negligible depending on the local culture of the relevant community.

Quite obviously, in order to enact an insurance fraud one must first purchase an insurance policy. The cost of insuring can even be substantial with respect to the face value of the fraud enacted, or even exceed it, as e.g. can be the case

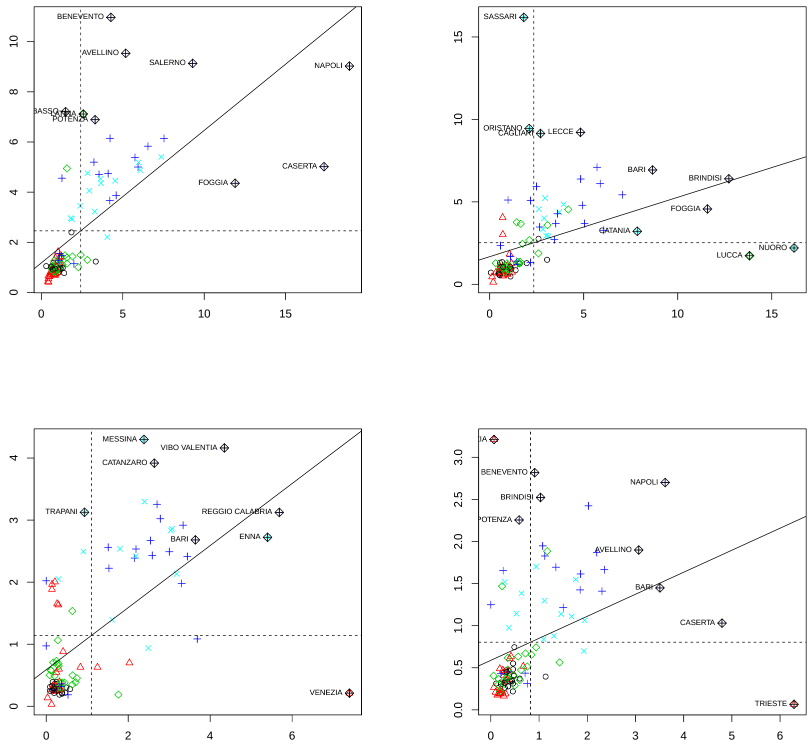

Figure 3: Moran plots (each variable plotted against its spatial lag)

in the (very common) micro-frauds on fake accidents with small motorcycles. In accordance with tarification practice, we approximate the insurance premium per unit of cover with the inverse of the realized, or *ex-post*, loss ratio $1/lr$, so that the total premium paid on R is R/lr. Again in accordance with standard tarification practice, we consider the lagged value of the loss ratio; which has the added benefit of being predetermined with respect to the current year's fraud level.[3]

The expected net return from insurance fraud is then

$$E(F) = R(1-p)/lr - L - \frac{p}{1+r_1}C - \frac{s}{1+r_2}S,$$

which may be expressed in relative terms as the net return on each unit of false claim $E(F)/R = (1-p)/lr - L/R - \frac{p}{1+r_1}C/R - \frac{s}{1+r_2}S/R$: this will depend positively on the ratio of the probability of not being caught on the loss ratio for the given insurance line; and negatively on the ratio of actual to reported loss, on the ratio of the expected formal punishment to reported loss – as perceived through the individual discounting factor– and, analogously, on the ratio of expected social sanction to reported loss, again subjectively discounted.

On the basis of the above model, we formalize our hypotheses as follows:

H1: **Income** from legitimate activities is an opportunity cost for the prospective fraudster; i.e., insurance fraud is bound to be more frequent in low-income regions

H2: The **unit price of insurance** is a deterrent to fraud

H3: The possibility of **formal sanctions** is a deterrent to fraud

H4: A dense network of **local structures**, enhancing

H5: Fraud is more likely to happen in **densely populated** areas

H6: **Young age** is positively associated with fraud frequency

H7: **Education** is a deterrent to fraud

H8: Insurance fraud acts as **informal welfare** during economic downturns

H9: **Social stigma** is perceived as a cost and therefore the endowment of social capital of a region is a deterrent to fraud

H10: Frauds are driven by imitation/**herd behaviour**

H11: The **macroregion**al differences within Italy can be satisfactorily explained out by the above, vs. some macroregion shows consistently higher/lower incidence of frauds, conditional on all the controls

4.1 Observable proxies

In the following we approximate the relevant quantities with observable aggregate proxies.

[3] An alternative would be to consider the loss ratio *net* of frauds, but it is unclear whether the fraudulent claims are or are not taken into account in tariff setting.

Probability of detection Insurance fraud is an offence which is very unlikely to be detected (and prosecuted) directly by the police, perhaps with the exception of borderline cases resulting in extensive collateral damage or loss of life, as may happen with arson, or with fake road accidents gone bad. For the overwhelming majority of frauds, detection will rely crucially on auditing by the insurance provider. The probability of being caught p will hence depend on the effectiveness of the auditing facilities of insurers. The auditing capacity can be approximated by the density of the territorial network of inspectorates and local claim handling points.

The probability of detection might also depend on population density. In principle it can both be conjectured that either a denser population enhances monitoring by reducing distances, or that it makes it easier for one's criminal behaviour to go unnoticed. Glaeser and Sacerdote (1996) have addressed the causes of the higher incidence of crime in big cities and ultimately explained most of this effect in terms of the fact that families there are much less intact; and, but with a lower weight, by the lower probabilty of arrest. Hence the role of population density is ambiguous a priori; but if anything, we might expect it to make frauds easier rather than more difficult.

Formal punishment In theory, using a national dataset of provinces makes the value of the formal sanction in case of fraud uniform. Nevertheless, there may be systematic differences in the behaviour of local courts which can be accounted for by means of individual effects. Moreover, the actual formal punishment C will depend on the quality of law enforcement. In this respect, we consider a widely used index of judicial (in)efficiency: the days to completion of a civil trial (Guiso et al, 2000) (for an application to insurance demand see Millo, 2010).

Social sanction The likelihood of incurring the social sanction will in turn be related to the intensity of peer monitoring. This can be hypothesized to grow with both the density of population and that of social ties. It must be considered, though, that fraud might be easier to perform in densely populated areas, and that this last effect might even dominate the former. Controlling for peer monitoring through social capital variables should be more appropriate and can assist us in separating the two effects.

The social stigma associated with being considered a fraudster may in turn be tentatively proxied with the endowment of social capital of a province. We therefore consider a measure of social capital as a proxy for the expected social sanction sS, although we are thus not in a position to identify the separate contribution of monitoring efficiency vs. sanction severity.

Subjective discount factors The perception of the possibility of future punishment is here proxied through the education level of the individual, under the hypothesis that better educated persons are able to better frame future outcomes.

Insurance price As discussed, the price of insurance is a cost to be incurred in order to file a fake claim. The realized, *ex-post* unit price of insurance can be proxied by the inverse of the loss ratio.

Economic climate The relative expected value of the fraud $E(F)$ will depend on the price level within each province; the expected utility of it on the income level of the prospective fraudster: under the usual concavity assumptions, it will be proportionally higher at lower levels of total wealth. The income distribution would therefore be relevant; in its absence, average per capita income and the unemployment rate are to be considered.

Income and unemployment will also account for the opportunity costs incurred by frauding: business interruption, alternate transportation costs and the like. The higher the level of economic activity, the higher the opportunity costs; the higher the share of the unemployed, the lower.

Income usually enters insurance demand models with a strongly positive expected sign, as proxying for the total insurance needs of the economic system. Considering the incidence of fraudulent claims over the total, frauds are here made relative to the total amount of coverage, so that the actual amount of insurable wealth can be excluded from the model, and income taken to account only for the above features. Hence the expected sign is negative.

Unemployment is also customarily used as a proxy for the economic cycle. In this sense, being more volatile in time than average per capita income, it can serve the purpose of signalling strong and weak phases of the economy, as famously done by Munnell and Cook (1990).

The explanatory variables to be included in the model are therefore the following (in parentheses the expected sign of the effect).

- \- income
- \- inverse loss ratio
- \+ judicial system inefficiency
- \- number of agencies/inspectorates
- ? population density
- \- age
- \- schooling
- \+ unemployment rate
- \- social capital

5 Results

In the following we present the results of estimation.

In the light of controlling for both idiosyncratic characteristics of territory and the possibility of a random bias affecting claim handlers in each province, we adopt a random effects specification including an individual, time invariant random effect 'c_i.[4] The possibility of correlated heterogeneity is handled at

[4]A fixed effects analysis is infeasible because of the scant or null time variation of some regressors, most notably of our measures of social capital.

macroregional level, with the addition of five macroregional dummies for North-West, North-East, Centre, South and Islands, as suggested in **?**, p.288 and done in Millo and Carmeci (2011, 2015).[5]

The specification

$$f_{it} = \alpha_i + \beta_i X_{it} + c_i + u_{it}$$

is augmented with time dummies to control for common variation over time, and with alternative measures of social capital.

Lastly, spatial lags in the dependent variable or in the errors are controlled for in a complete specification:

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

where y is the $nT \times 1$ response vector, X a $nT \times k$ matrix of regressors and ν is the $nT \times 1$ vector of autocorrelated error terms, all stacked by year and then province; 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. W is a binary contiguity matrix with ones corresponding to neighbouring provinces, zeros elsewhere, the row sums being standardized to one. μ is a $n \times 1$ vector of individual random effects with elements $\mu_i \sim i.i.d.N(0, \sigma^2_\mu)$; and I_T, $\imath_T$ respectively a $T \times T$ identity matrix and a $T \times 1$ vector of ones; ν_t and e_t are $n \times 1$ vectors. 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_t. The error terms ϵ, ν and e_t are normally distributed and X, μ and e_t are assumed to be mutually independent. As observed, this specification is meant to control for individual heterogeneity (ϕ), for serial error correlation deriving from the persistence in time of idiosyncratic shocks (ψ), and for two possible kinds of spatial diffusion processes: in the dependent variable (λ) and in the idiosyncratic shocks (ρ). As a variance ratio, ϕ is constrained to be positive.

After starting from the above encompassing model, in the following Table 3 we will present our preferred reduced specification for each line, and comment on the results of the latter.

6 Discussion and conclusions

We have approached the subject of insurance fraud from an empirical, aggregated perspective, drawing on a detailed provincial dataset. This viewpoint complements the more common analyses on individual datasets, linking the frequency of fraudulent behaviour in a territorial unit with the economic and sociodemographic characteristics of the same and the density of the local presence of insurers.

[5] It must be observed that adding macroregional dummies for the South can be seen as controlling for its supposedly lower endowment of social capital, see Guiso et al (2000), hence such addition can be conjectured to weaken the evidence in favour of the inclusion of the social capital controls.

	MTPL	V2	MHull		Fire		Property	
(Intercept)	25.427	***	22.102	***	57.306	***	17.315	**
	(5.318)		(5.583)		(14.594)		(5.408)	
income	-0.14	*	-0.084		-0.168		0.074	
	(0.056)		(0.066)		(0.204)		(0.075)	
price	-0.663	*	-0.19		-0.454		-0.056	
	(0.299)		(0.124)		(0.372)		(0.118)	
judicial	0.047		-0.034		0.044		2.429	
	(0.116)		(0.127)		(0.322)		(5.034)	
structures	-0.718		-5.721		8.821		0.45	
	(3.696)		(4.126)		(13.715)		(0.408)	
density	2.1	***	0.5		0.157		-0.104	
	(0.389)		(0.424)		(1.113)		(0.076)	
age	-0.18	*	-0.187	*	-0.826	***	-0.128	**
	(0.077)		(0.08)		(0.203)		(0.043)	
education	-0.118	**	-0.095	*	-0.001		0.044	
	(0.039)		(0.04)		(0.115)		(0.037)	
unemployment	0.05	*	0.029		0.392	***	-2.4	*
	(0.023)		(0.027)		(0.1)		(1.163)	
trust	-2.913	*	-2.028		-5.655	.	0.238	
	(1.172)		(1.25)		(3.188)		(0.397)	
Spatial lag	no		0.125	*	no		no	
Spatial error	0.321	***	no		no		no	

Table 3: Model specifications by line.

While our findings cannot be taken to bear directly on individual behaviour (so-called *ecological fallacy*), nevertheless they can prove useful in assessing the average outcomes of a territorial unit.

All that said, at the aggregate level Motor frauds confirm the typical characteristics of petty crimes. Motor TPL fraud is consistently associated with regions with lower personal income and densely populated areas, where their limited claims can hope to go unnoticed through the multitude of small accidents happening every day. Perhaps due to the very high cost of MTPL policies in "problematic" areas, the unit price of insurance seems to be another deterrent to fraud. [6] Judicial inefficiency mostly has the expected positive sign, but is never significant. The coefficient of education is consistent across Motor specifications and significant, while it is not significant for Property lines.

Consistently with common knowledge, there is some evidence that MTPL fraud tends to be committed by younger and less educated people, and in more densely populated areas. Unemployment is another positive predictor, signalling the effect of the business cycle.

Motor Hull fraud is consistently, albeit weakly, associated with low per capita income across all models; and, even strongly, with young age and low education,

[6]It must be observed that MTPL cover is mandatory, so it will in all likelihood be in place already unless one buys a new car for provoking false accidents, which is highly implausible. This line of reasoning, nevertheless, does not consider the substantial share of uninsured cars cruising across Italy; in theory, one might well insure a previously uninsured car prior to making up a fake accident. Premiums on previously uninsured cars, however, are usually very high as a consequence of the bonus-malus system.

although we stress once more that these aggregate data cannot be translated back onto individual behaviours. Unemployment is also positively and consistently associated with Motor Hull fraud, testifying its intensification during the bad turns of the economic cycle. We notice how this latter coefficient barely changes with the introduction of time dummies, accounting for national comovements, testifying the relationship to the local economic situation. The effects of all four social capital measures are consistently negative, although insignificant; thus providing weak evidence of the deterrent effect of social norms. The sharpest result from the Motor Hull model is instead the strong negative effect of inspectorates' density: it seems that those provinces endowed with a rich network of the latter do a better job in controlling fraudulent behaviours in this line of business.

As for fire, fraudulent claims are more common in provinces where a younger population prevails, and most of all they are strongly associated with negative phases of the economic cycle, as witnessed by the highly significant positive coefficient of unemployment, thus validating the common knowledge notion from the insurance world, that arson be often considered as a way to convert illiquid assets into liquidity, the insurer being forced into acting as a "lender of last resort" by individuals or small firms in trouble. The significantly positive dummy for the North-East, famously endowed with small enterprises, brings anothe piece of evidence in this respect.

By contrast, social norms and stigma do seem to play a weak role, which is consistent with a less frequent crime of often bigger scope, often enacted by commercial firms.

The different proxied for social capital we employ deliver overall consistent results, testifying their appropriateness and confirming previous literature on the general influence of peer monitoring and social sanction on crime.

In the perspective of the economic literature on crime in general, the insensitivity of Fire fraud to social capital variates, combined with the findings on the relatively large value of fraudulent Fire claims, perhaps enacted by means of arson, characterizes Fire fraud as a more serious instance in the overall panorama of insurance fraud as a petty crime, and speaks for a different approach also in controlling and deterring it.

All three models for the above lines share a reasonably good fit: about 30 percent for MTPL and around 20 percent for the other two.

The provincial distribution of frauds in the Other damage to property line of insurance is more difficult to describe in our framework, perhaps due to the extreme heterogeneity. Model fit is under 10 percent, and the only really sharp result is the positive effect of population density. Age and education both have the expected negative sign, and are weakly significant. Social capital measures are sometimes negative and significant, as expected, but some other times not. The density of the inspectorates' network is never significant, and consistently has the wrong sign.

The main messages we draw from this piece of research are that insurance frauds in the four different lines considered have much different characteristics and are driven by different environmental attributes, e.g. MTPL fraud being more directly linked with the general level of economic development while Fire fraud tends to be much bigger in scope and related to bad swings of the economic cycle. The controlling role of social norms and the fear of the social sanction also shows up from our data, confirming the findings of the general literature

	MTPL	MHull	Fire	Property
H1: income	*			
H2: price	*			
H3: judicial				
H4: structures				
H5: density	***			
H6: (young) age	*	*	***	**
H7: education	**	*		
H8: "welfare"	*		***	*
H9: social stigma	*		.	
H10: imitation		*		
H11: macroregion		NE, CE		SO, CE

Table 4: Synthesis of findings by research hypotheses

on crime, but only for some lines.

Perhaps the only tendency common to all four lines of business considered is the link between fraud and young age, as predicted by much of the previous literature; the prevalence of fraud between lesser educated people, by contrast, can be spotted in our data as regards the Motor lines, but does not show for the two Property lines.

We bring no evidence that fraud be effectively curbed through a denser presence of local units of the insurance companies; nor does a better functioning judicial system, in the sense of speedier verdicts, significantly deter fraud.

Significant spatial effects are found only in the Motor models: in MTPL the spatial process at work is identified as a spatial error, i.e. it is likely to originate from measurement problems (administrative boundaries overlapping with the actual spatial dimension of the DGP) or from some omitted spatially correlated regressor; in Motor hull the spatial effect is instead identified as a spatial lag, i.e. as some evidence of imitation behaviour by which higher fraud incidence in one province increases the likelihood of fraudulent behaviour in neighbouring ones.

Lastly, the macroregional dummies are seldom significant. In particular, they are not in either of the Motor models. South and Centre (the baseline) have significantly higher fraud incidence, after controlling for the explanatory variables, in (non-Fire) Property, while the North-East is significantly higher in the Fire model, which is reasonable considering the prevalence of small and medium sized enterprises in that part of Italy. Despite many stereotypes on the Italian South, economic variables seem to explain away most of the regional idiosyncracies.

From a policy viewpoint, there seems to be little scope for intervention because the drivers of fraudulent behaviour seem to be beyond the control of both insurance companies and regulators. Still, the strong link between fraudulent behaviour and underdevelopment indicators like unemployment and illiteracy means that policies promoting education and public welfare are likely to lead to the very welcome side effect of mitigating insurance fraud, improving the efficiency and fairness of the industry.

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