Alma Mater Studiorum – Università di Bologna

DOTTORATO DI RICERCA IN

Economia

Ciclo 30°

Settore Concorsuale: 13/A1 Economia Politica

Settore Scientifico Disciplinare: SECS-P/01 Economia Politica

Essays in Applied Insurance Economics

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Esame finale anno 2018

TABLE OF CONTENTS

ABSTRACT 3

WHAT CAUSES INSURANCE FRAUD? EVIDENCE ON MOTOR THIRD PART LIABILITY IN ITALIAN PROVINCES 6

THE VALUE AND PRICE OF A “TOO-BIG-TO-FAIL” GUARANTEE IN THE INSURANCE INDUSTRY 32

BUSINESS CYCLE AND MOTOR INSURANCE PROFITABILITY 66

ABSTRACT

The papers included in this thesis deal with a few aspects of insurance economics that have seldom been dealt with in the applied literature.

In the first paper "What causes insurance fraud? Evidence on Motor Third Party Liability in Italian Provinces" I apply for the first time the tools of the applied economics of crime to study the determinants of frauds, using data on Italian provinces. I find a negative correlation between frauds and economic development. The contributions to the literature are manifold:

- I show that the price of insuring has a positive correlation with the propensity to defraud
- Social norms constraint fraudulent behavior, but their strength is severely curtailed in economic downturns
- On the methodological side, I apply a simple extension of the Random Coefficient model, which allows for the presence of time invariant covariates and asymmetries in the impact of the regressors.

The second paper, "The Value and Price of a "Too-Big-to-Fail-Guarantee in the Insurance Industry", assesses how and to what extent the evolution of macro prudential regulation of insurance companies has been reflected in their equity prices. To this end I employ a standard event study methodology, deriving the definition of the "control" and "treatment" groups from what is implied by the regulatory framework. The main results are:

- Markets care about the evolution of the legislation, and their perception has shifted from a first positive assessment of a possible implicit "too big to fail" subsidy to a more negative one related to its price in terms of stricter capital requirement
- The size of this phenomenon is positively related to leverage, size and on the geographical location of the insurance companies

The third paper, "Business Cycle and Motor Insurance Profitability" introduces a novel methodology to forecast non-life insurance premium growth and profitability as function of macroeconomic variables. It adapts the simultaneous equation framework traditionally used for macroeconometric models to some items of the technical account of the Italian motor third party business, employing a simple theoretical model of insurance pricing to derive a long term relationship between premiums, claims expenses and short term rates. The model is shown to provide a better forecast of premiums and profitability compared with the single equation specifications commonly used in applied analysis.

Gli articoli inclusi in queste tesi si occupano di aspetti dell'economia dell'assicurazione raramente trattati dalla letteratura empirica.

Nel primo articolo , "What causes insurance fraud? Evidence on Motor Third Party Liability in Italian Provinces" *si applicano per la prima volta gli strumenti dell'economia applicata del crimine per studiare le determinanti delle frodi assicurative, utilizzando dati sulle province italiane. SI trova una correlazione negativa tra frodi e sviluppo economico. I contributi alla letteratura sono molteplici:*

- *Si mostra come il costo di assicurarsi ha una correlazione positiva con la propensione a frodare.*
- *Il Comportamento fraudolento è limitato dalle norme sociali, ma la loro forza è indebolita severamente in caso di recessione.*
- *Dal punto di vista metodologico, si applica una semplice estensione del modello Random Coefficient, che permette di impiegare regressori fissi nel tempo e di tenere conto dell'impatto asimmetrico delle variabili esplicative.*

Il secondo articolo, "The Value and Price of a "Too-Big-to-Fail-Guarantee: Evidence from the Insurance Industry" *valuta come e in che misura l'evoluzione della regolamentazione macroprudenziale delle compagnie di assicurazione si è riflessa nel prezzo delle loro azioni. A tal fine si utilizza una metodologia event study, derivando la definizione dei gruppi di "controllo" e "trattamento" dalle implicazioni dal quadro normativo. I principali risultati sono:*

- *Il mercato finanziario reagisce all'evoluzione della legislazione, e la sua percezione è cambiata da una prima valutazione positiva di un possibile sussidio implicito a una più negativa, a causa del suo costo in termini di requisiti patrimoniali più severi*
- *L'intensità del fenomeno è maggiore per le compagnie con più indebitate, più grandi, e dipende dalla loro localizzazione geografica.*

Il terzo articolo, "Business Cycle and Motor Insurance Profitability: Evidence for Italy" *presenta una nuova metodologia per prevedere la crescita dei premi di assicurazione danni la profittabilità del settore in funzione di variabili macroeconomiche .Lo schema ad equazioni simultanee tradizionalmente usato per i modelli macroeconometrici viene adattato ad alcune voci del conto economico del settore auto italiano, impiegando un semplice modello teorico di pricing dell'assicurazione danni per derivare una relazione di equilibrio tra premi, costi dei sinistri premi e tassi a breve termine. Si mostra come il modello fornisce dei premi che della profittabilità previsioni più accurate rispetto alle specificazioni a equazione singola utilizzate nelle letteratura applicata.*

WHAT CAUSES INSURANCE FRAUD? EVIDENCE ON MOTOR THIRD PART LIABILITY IN ITALIAN PROVINCES

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November 30, 2017

This paper seeks to explain the large differences in the incidence of motor insurance fraud between Italian provinces. The econometric analysis highlights the role of the variability in per capita income and strength of social norms common to other types of crimes. Moreover the differences in the average cost of purchasing this mandatory cover are shown to affect the propensity to defraud. Finally, cyclical fluctuations in the labor market have an effect, both directly and by weakening the deterrent power of social norms.

JEL Classification: G22, A13

Keywords: Non–life Insurance, Frauds, Crime, Social Capital

*I wish I to thank the participants to the 2015 Ph.D Forum at the University of Bologna, and in particular Matteo Cervellati, Lucio Picci and Paolo Vanin for their comments . All errors are my own.

1. INTRODUCTION

In this article I apply the tools of the economic analysis of crime to a very specific form of offense: fraud in motor third part liability (MTPL) insurance, a compulsory cover for all drivers in most countries. The empirical analysis of crime has normally focused on property crimes in which there are normally no prior relationships between the perpetrators and the victim. In the case of insurance fraud, a contractual relationship exists (in the case of MTPL insurance, a very specific and standardized one), and the terms of the contract may play some role in the propensity to breach it. The first contribution of this paper is then the analysis of the impact of the contract terms (more specifically, the cost of the insurance policy) on the propensity to cheat. The second one is the assessment of the impact of the business cycle on the propensity to defraud, not just directly but also via the effect on the strength of the social norms that should act as deterrent. I focus on Italy because of its large diversity in social and economic conditions and the extreme variability of insurance prices. The econometric analysis uses aggregate data on provinces but employs a panel specification that can disentangle the effects of cross-unit variability from those due to cyclical fluctuations. The empirical analysis of insurance fraud is not a new field, but this is, to my knowledge, the first time the tools on the economics of crime are applied to aggregate data and consider explicitly the insurance contract terms.

The main results can be summarized as follows: first of all, the terms of the insurance contract, approximated by the average price paid by motorists, matter in explaining the incidence of fraud. Average premium has a strong explanatory power, especially when it is instrumented using determinants of insurance pricing not related to frauds; this highlights the role of perceived fairness of a financial contract and the level of trust in the financial institutions issuing it. Secondly, social norms play a deterrent role, but their strength is significantly lessened when economic conditions worsen, in particular after the 2008/09 recession. Additionally, and in line with evidence on the determinants of crime rates, the economic environment matters, both in terms of "structural" differences in per capita income across provinces and of cyclical changes in the unemployment rate.

The results are relevant first of all for the insurance industry and the regulators: a reduction in the overall level of costs and possibly, in its variability across provinces may be helpful in combating frauds, which are responsible for a non-negligible part of compensation costs which, in turn, are to a large extent passed onto policyholders. Moreover the estimates of the impact of the business cycle on frauds can be useful for insurance company to predict the evolution of the incidence of fraud. However, some of the implications of the results go beyond insurance. Firstly, it documents empirically that the terms of a financial contract may provide an incentive to breach it. Secondly, it shows that the impact of social norms on criminal activity is not time invariant, but it is affected by the business cycle.

The paper is structured as follows: Section 2 defines insurance fraud, in Section 3 I sketch the model that serves as background for the empirical analysis and describe the possible role of the perceived fairness of the insurance price and of social interactions. Section 4 has a quick review of the economic literature and the following one describes the data on frauds, as a preliminary to the econometric analysis, shown in Section 6. The results are presented in section 7 and their robustness to spatial correlation and different measures of the strength of social norms are shown in section 8. Section 9 concludes.

2. Defining Insurance Fraud

Insurance fraud is a form of ex-post moral hazard that involves the manipulation of information in order to unduly benefit from insurance protection: it can entail either the making up of a non-existing claim or the exaggeration of the damages sustained in a true accident. Fraudsters take advantage of the promise made by the insurer to pay losses in some circumstances defined when signing the contract. This kind of crime, therefore, occurs within the context of a contractual relationship linking the insurer and the policyholder. As a consequence, the decision to invent or exaggerate an accident can be seen as an (extreme) economic response to the terms of the contract; the potential importance of the contract characteristics sets frauds apart from other forms of consumer dishonesty, such as shoplifting.

Insurance fraud has been characterized as a "crime without victims". Due to mutualization, the extra costs due to fraud, if not detected and recovered, are passed to a large extent onto all policyholders. This does not create any significant of harm to any of them individually, possibly leading to policyholders' underestimation of the severity of the offense. Moreover, if the concept of risk-pooling is poorly understood, people may be led to think that fraudsters steal the insurers' money and non that belonging to policyholders. This may lead to a high tolerance to fraud and a consequent reduction of the moral costs attached to committing it, especially in areas where premiums are high (not necessarily due to frauds) or in response to a large increase in premiums.

The analysis in this paper deals with fraud in Motor Third Part Liability Insurance (Responsabilità Civile Auto e Natanti, in Italian), a mandatory cover against damages caused to other vehicles and persons while driving. In this line of business insurers have the obligation to provide a binding quote to any driver who asks for it, regardless of her driving history. Ratemaking must adhere to several regulatory requirements on, for example, deductibles and level and modes of compensation. Moreover compensations for bodily injuries (which account for nearly 70% of total paid to claim-holders) are to a large extent dictated by the law and are often decided after a trial. As a consequence, in this line of business insurers cannot adopt many of the contract features designed to prevent frauds like pricing out unwanted customers or setting a high a level for deductible; therefore, the costs related to being caught are one of the few leverages that can be used to reduce the extent of fraud.

3. Drivers of fraud: economic conditions, contract terms and social capital

My analysis follows the standard framework for the economic analysis of crime dating back to the seminal works of Becker (1968), Allingham and Sandmo (1972) and Ehrlich (1973). The decision to file a fraudulent claim is considered as the outcome of a rational choice based on the comparison of the utility gains of a successful attempt with the cost the fraudsters may incur if fraud is detected. As shown by a large body of empirical literature, the business cycle and in particular its impact on the unemployment rate are key drivers of this trade off[1]

[1] See, for example Raphael and Winter-Ebmer (2001), and Gould et al., 2002.

I extend the analysis in two directions and focus on:

- The impact on the price of the insurance contract and its perceived "fairness" on the propensity to defraud
- The strength of social norms, and in particular whether it is correlated with the business cycle

3.1 CONTRACT TERMS

I consider claim falsifications related to a well identified and highly standardized insurance contract[2], for which I have aggregate price information at the provincial level that can be used to build a direct link with the measure of fraud. On average, in Italy every year only around 6% of vehicles undergo an accident covered by MTPL policies; therefore it is fair to say that the price each policyholder pay is the only feature that matters to the large majority of them as very few are exposed to other characteristics of the contract (the speed of response, quality of the reparation, etc.). MTPL insurance in Italy is one of the most expensive in Europe[3] and the differences across provinces are very large indeed, as shown by table 1, which shows the annual premium paid by three types of drivers, as published by IVASS, the industry regulator.

Table 1: Average premium by types of male driver in 2012, euros

	1	2	3
Aosta	1746	336	431
L'Aquila	2397	473	607
Milan	2601	505	649
Bologna	3174	650	835
Rome	3187	677	869
Bari	3407	792	1025
Naples	3734	1221	1580

Source: IVASS

1) 18 year old, top Bonus Malus (BM) class, with a 1300cc gasoline car
2) 40 year old, lowest BM class, with a 1300cc gasoline car
3) 55 year old, lowest BM class, with a 1900cc diesel car

One of the hypotheses I want to test is whether this large differences in prices maps into the incidence of fraud. There can be several reasons for that: policyholders living in a province with a higher claims frequency can think that the price they pay for this mandatory cover is too high even though it is fairly priced from an actuarial point of view, moreover the perceived "unfairness" of the price paid for a mandatory cover can be enhanced by a poor understanding of the workings of non-life insurance. Van Wolferen (2014) uses experiments to show that people think about non-life insurance as a financial investment (as suggested by Kunreuther et al. (2013)); when they do not incur in an accident, and therefore receive no compensation, policyholders might feel that the money spent for the premium is wasted, increasing their tolerance to fraud[4].Changing company is

[2] When subscribing an MTPL contract, the driver can choose between only two or three options regarding the limit to coverage (the minimum of which is set by law) and the deductible

[3] Differences with respect to other European countries are due to a much higher claims frequency and a higher level of compensation. Similarly differences across provinces mirror a large variation if frequency and in the incidence of accidents with bodily injuries, see, for example ANIA (various issues)

[4]Insurance fraud may also be seen also as an example of "negative reciprocity". A growing strand of theoretical and experimental literature, surveyed in Fehr and Gachter and Fehr (2000) and Schmidt (2006) shows that consideration and expectation on how other agents behave are important drivers of individual

not yet a very popular option. According to the regulator, in 2014 only 15,2% of policyholder switched to another insurer, despite the substantial savings that can be achieved: those who changed companies saw their premium decrease by almost 22% as opposed to the 5% experienced by those who did not move(see IVASS, 2015). This may be due to poor information, which may lead motorists to see the cost for this mandatory cover as a tax rather than the price of a financial product and possible react accordingly, by defrauding or fail to insure[5] .

3.2 SOCIAL CAPITAL

According to IVASS, on average only slightly more than 2% of the accidents believed by the insurers to be fraudulent are actually reported to the judiciary (IVASS, 2013). Therefore, the probability of undergoing a trial if caught defrauding is extremely low. Insurers are forbidden by law to refuse to insure a driver who accepts the quote proposed, and efforts to price away riskier drivers by charging very high premiums are often punished by the regulator. Given the relatively overall low incidence of fraud, some other kind of punishment may be at work as deterrent. One particular candidate is the existence of civic norms: these will increase the (non-pecuniary) opportunity cost of defrauding, given the guilt and shame it would provoke. The strength of informal networks, arising for example in small communities may magnify this effect by means of social sanctions such as ostracism for those known as an insurance fraudsters. Starting from the seminal work of Putnam (1993) the impact of civic norms and associations (grouped together under the somehow loose heading of "social capital") on various aspects of social life has been studied at large. Italy has been the subject of quite a lot of analyses, due to the wide and persistent differences in indicators of social capital across provinces. Guiso et al. (2004), based on a large household survey, find that various measures of social capital show a strong correlation with individual financial choices. In areas with higher social capital people tend to rely more on banks for financial transactions, holding less cash and being involved in less informal lending, and invest in more sophisticated financial products. Working with aggregate data at the provincial level Millo and Pasini (2010) show that social capital increases the demand for non-life insurance. The relationship between social capital, the strength of networks and various forms of criminal activity in Italy has been studied by Buonanno et al. (2009) and Buonanno et al. (2012), using data at the province level. They find that civic norms (proxied by blood donation, electoral turnover and participation to charitable associations) and networks affect negatively property crimes; moreover, crime is lower when social interactions are denser, e.g. when a large share of population lives in small towns[6].

Most of the empirical analysis on the nexus between social capital and financial transactions is either based on cross-section regressions or include social capital as a time-invariant explanatory variable. However, it may well be that, when faced with extremely large adverse shocks (i.e. a

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behavior Agents often deviate from purely self-interested behavior in a reciprocal manner: in response to friendly actions or expected intentions, people are much nicer and cooperative than predicted by the self-interest model(positive reciprocity); conversely, after a hostile actions/intentions they are frequently much more nasty (negative reciprocity). The evidence indicates that these attitudes are important for bilateral negotia-tions, for the enforcement of social norms, for understanding the functioning of markets and economic incentives. More recently Kline et al. (2014) provide evidence from experiments and the World Value Survey that deviations from meritocracy are related to a higher propensity towards self-serving dishonesty.

[5] According to ANIA, in 2014 8.7% of vehicles in use did not carry a valid insurance, with a peak of over 13% in the Southern regions

[6] More specifically, they use as regressors he share of people living in center with less of 2000 inhabitants or in towns with more than 250,000.

surge in the unemployment rate), individuals may find social norms less binding and therefore, committing small offenses like insurance fraud more acceptable; I seek to assess whether and to what extent the large drop in economic activity and employment in 2008 and 2009 affected the deterrent impact on social capital on the propensity to defraud[7].

4 Literature Review

Most of the theoretical literature on insurance fraud[8] aims at either finding the contract, expressed in terms of premium, compensation and deductible which minimizes the incentive to defraud or to derive the optimal level of (costly) monitoring by the insurer, ignoring what drives the decision to defraud.

On the empirical side, a rapidly increasing stream of literature utilizes individual claims data and run GLM models using as covariates the features of the policy (deductible, kasko, etc...), the details of the policyholder (age, sex, number of years with the same insurer, etc.) and information on the accident (period of the day, type of road, witnesses), to construct models able to flag suspicious claims[9].

However, the impact of the environmental variables and the business cycle, which this paper is focused on, is not considered in detail: the geographic location of the accidents is normally dummied out and the use of cross section data by construction neglects the impact of the business cycle. One exception is the paper by Dionne and Wang (2013) on Taiwan: they add to a standard probit model time dummies and find a statistically significant positive relationship between the probability of a claim being fraudulent and cyclical downturns.

A very few papers use aggregate data for US states. Cummins and Tennyson (1996) use a cross section of data for 29 US states: lacking data on the incidence of frauds, they proxy ex-post moral hazard in motor insurance by the ratio of bodily injury claims in the total. They find a positive and significant correlation with a tolerant attitude to insurance fraud in the state, measured by a survey, the percentage of people without health insurance and with the urbanization rate. They find similar results for the share of sprain and strain claims (one of the easiest to fake injuries) over bodily injury claims. Tennyson (1997) provides an in-depth analysis of the survey data mentioned above. It turns out that over 20% of respondents find fraud at least "probably" acceptable. Overall individual attitude to fraud has a strong correlation with that expressed by people living in the same state, hinting at some environmental factors like to ones I review in this paper playing a role. Moreover, a negative attitude towards the insurance industry in general has a positive correlation with the attitude to fraud. Finally, Goel (2014) uses a cross-section of 31 US states and finds that insurance frauds convictions are inversely related to convictions for corruption and to higher public expenditure on crime fighting, while state level insurance regulation is generally not significant. He interprets the results as better institutions having a negative impact on the propensity to defraud and of substitution in enforcement resources. Moreover, fraud convictions are inversely correlated with per capita income and positively to the urbanization rate.

[7] Stevenson and Wolfers (2011) find that, during the Great Recession, countries that experienced the largest rise in unemployment also show the largest drop in public confidence and trust towards national government and the financial sector.
[8] A comprehensive and up-to-date survey can be found in Picard (2014).
[9] See, for example the analysis on Spanish motor insurance carried out by Artìs, Ayuso and Guillém (2002) and Caudill, Ayuso and Guillém (2005).

5. THE DATA

This article uses data on the number of MTPL claims reported as fraudulent by the insurance companies for each Italian province, and communicated to the regulator for statistical purposes: data are annual and range from 2000 and 2011, the last year for which they have been published. It is not possible to distinguish the percentage of frauds involving bodily injuries. Reported frauds may or may not have become part of a trial (most of them were not). In this way they are immune from the underreporting bias which affects other data on crime.

However, there is not a common methodology, agreed by all the insurance companies or imposed by the regulator, to assess whether a claim is truthful or false. Normally, each claim is automatically analyzed via an algorithm, and given a score. Suspect claims are then reported to local units for more in-depth searches based on standard criteria. However, these criteria may vary across companies (but not across provinces) and this may lead to some potential bias in the data as market shares of companies are not homogeneous across provinces. The econometric methodology used in this paper seeks to minimize this potential bias.

Figure 1: MTPL: Fraudulent claims ad % of the total

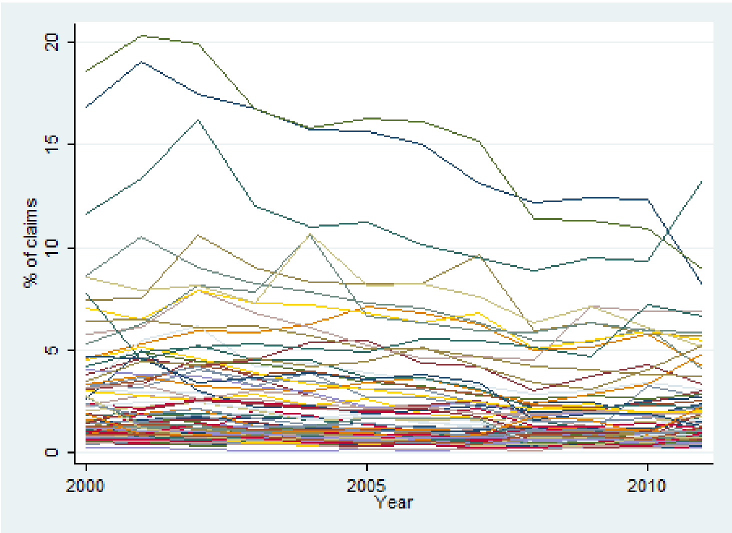


Figure 1 shows the share of fraudulent claims on the total by province, between 2000 and 2011. In most of the provinces frauds account for less than 5% of total accidents, but there are a few outliers showing an incidence in excess of 10%, with a marked downward trend.

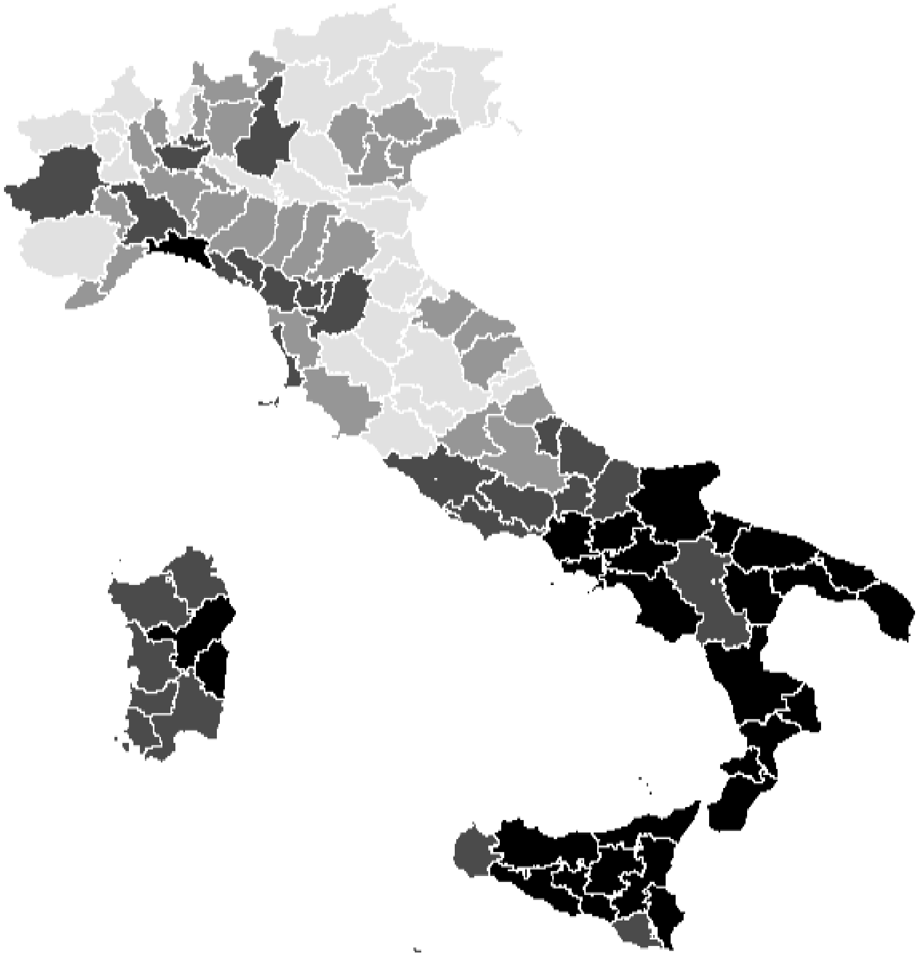
A further evidence of the polarization of the phenomenon is provided by the decomposition of the variance, shown in table 2. Most of the variability is across provinces; nevertheless the standard deviation across time is non-negligible, being equal to roughly one third of the mean.

Table 2: Incidence of fraud in MTPL insurance: variance decomposition

	Mean	Std. Dev.
Overall	2.139	2.769
Between		2.680
Within		0.742

As shown by Figure 2, the highest incidence of fraud is concentrated into a few neighboring provinces in the South and Sicily.

Figure 2: MTPL: Geographic distribution of fraud incidence (2000-2011 average)



6. The Econometric Model

The econometric analysis aims at quantifying how the incidence of insurance fraud, measured as (the log of) the number of fraudulent claims per 100,000 people is affected by:

• The economic environment: I will consider both the differences across provinces in per capita GDP and unemployment rate and their deviations from the long term province mean, to assess whether fraudulent activity is related to structural differences in income and the extent to which it reflects business cycle fluctuations[10] .

• Social capital and networks: I test whether non-pecuniary costs of committing frauds, which have been shown to be significant in explaining property crime, matter for insurance fraud as well. I employ standard measures of social capital and network strength. In the baseline specification a time-invariant effect is assumed and subsequently I shall assess whether the strength of civic

[10] As far as the unemployment rate is concerned, the focus on a very specific type of crime and the use of data at the provincial level should minimize the aggregation bias in the relationship between unemployment and crime first illustrated by Chiricos (1987).

norms has been affected by busyness cycle fluctuations and, in particular by the severe downturn that the economy experienced in 2008 and 2009.

• The price of insurance: In order to test whether a higher cost of insuring increases the propensity to defraud I use as a regressor the average MTPL premium in the provinces, lagged one year, as the price paid on the last policy renewal is the only piece of information on the contract available when deciding to commit a fraud (MTPL contracts are annual). The possible endogeneity of the variable is dealt with by using Instrumental Variables.

In addition to these variables I use a list of proxies for factors which may facilitate fraudulent activity, such as the relative (in)efficiency of the judiciary, the presence of organized crime, and road congestion. Additionally, based on the evidence on individual claims, I add a proxy for the average age of vehicles, i.e. the share of vehicles older than four years in the total stock. Table 3 summarizes the explanatory variables and shows whether they are time invariant or not.

Table 3: Explanatory variables

	Time Invariant ?
Economic conditions	
Per capita GDP	No
Unemployment Rate	No
Socio-demographic factors	
Adult population by age class	No
Crime and judicial system	
Days for a 1st degree sentence	Yes
Index of organized crime	Yes
Social capital and networks	
Blood donations per 1000 adults	Yes
% living in small towns	Yes
% living in large cities	Yes
Tolerance to fraud	
Average MTPL premium	Yes
Vehicle parc	
% of new vehicles	No
Vehicle per square mq	No

The nature of these variables raises a series of issues:

1. It is not possible to rule completely out that the criteria to identify a fraudulent are homogeneous across provinces; this would call for a Fixed Effect estimator...

2. ..however, some of the explanatory variables are time invariant, requiring a Random Effect estimator.

3. Average premiums are likely to be endogenous; in terms of compensation paid or reserved, fraudulent claims account for around 2% of the total, but in some provinces they make for nearly 15% of the total. The correlation between fraud incidence measured on the number of claims and on the sums paid is 97%, hinting at frauds playing a non-negligible role in the costs borne by insurers and reflected in premiums in some areas where the phenomenon is more widespread. Moreover, average premiums are calculated by dividing the premium amount by the stock of registered vehicles. This may be badly measured, as sometimes vehicles no longer in circulation are not canceled and during the period considered there was not any direct linkage between the

databases containing the lists of the insured and registered vehicles: the potential measurement error of the variable strengthen the case for instrumental variables

4. There could be spatial correlation in the dependent variable, possible due to social and cultural factors not fully captured by the regressors or, more trivially, by the fact that fraudsters can operate also in other (possibly neighboring) provinces.

The first three issues are dealt with in the baseline estimation, while the fourth is considered as a robustness test.

6.1 *Description of the data*

Table 4 and 5 show the summary statistics and the correlation between the variables on which I focus my analysis on. There appears to be a large (cross sectional) variability between them; the correlation between frauds and the most important explanatory variables, with the notable exception of average premiums, are in line with what hypothesized in Section 4.

Table 4: Summary statistics

	Mean	Std. Dev	Min	Max
Frauds	0.001	0.001	0.000	0.018
P.C. GDP (euro '000)	18.292	4.880	8.921	33.503
Unempl. Rate	8.380	5.768	1.340	32.440
Org. Crime	2.065	1.490	0.383	8.500
Jud. Efficiency	2.848	0.829	1.425	5.882
Blood donations	0.383	0.146	0.120	0.850
% in small towns	9.703	9.687	0.000	42.559
% in large cities	5.154	14.491	0.000	69.505
Avg. Premium (euro '000)	0.367	0.059	0.169	0.656

6.2 *Model Specification*

In order to employ simultaneously time varying and invariant regressors I use a version of the RE specification originally proposed by Mundlak (1978), the Within-Between model illustrated in detail by Bell and Jones (2015). Consider a standard RE specification:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 z_i + (u_i + e_{it}) \qquad (1)$$

It requires that covariates be independent of residuals.

$$Cov(x_{it}, u_i) = 0, Cov(x_{it}, e_{it}) = 0 \qquad (2)$$

This assumption is seldom met by data, leading researchers to discard Random Effects in favor of the Fixed Effects specification in which time invariant covariates are averaged out. This endogeneity often arises from the fact that time varying covariates are treated as single process, whereas in fact they can be decomposed in a "between" component, which does not vary with time, and a "within" one

$$x_{it} = x_i^B + x_{it}^W \qquad (3)$$

Table 5: Cross-correlation table

	Frauds	P.C. GDP (euro '000)	Unempl. Rate	Org. Crime	Jud. Efficiency	Blood donations	% in small towns	% in large cities	Avg. Premium (euro '000)
Frauds	1								
P.C. GDP (euro '000)	-0.542	1							
	(0.000)								
Unempl. Rate	0.636	-0.797	1						
	(0.000)	(0.000)							
Org. Crime	0.405	-0.483	0.565	1					
	(0.000)	(0.000)	(0.000)						
Jud. Efficiency	0.360	-0.590	0.573	0.421	1				
	(0.000)	(0.000)	(0.000)	(0.000)					
Blood donations	-0.450	0.621	-0.576	-0.421	-0.463	1			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
% in small towns	-0.261	-0.012	-0.146	-0.247	-0.137	-0.060	1		
	(0.000)	(0.671)	(0.000)	(0.000)	(0.000)	(0.006)			
% in large cities	0.246	0.139	0.098	0.147	-0.056	0.034	-0.279	1	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.119)	(0.000)		
Avg. Premium (euro '000	-0.086	0.472	-0.423	-0.283	-0.237	0.304	-0.323	0.140	1
	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Note = significance level in brackets

$$x_i^B = \frac{1}{T}\sum_{t=0}^{T} x_{it}$$

$$x_{it}^W = x_{it} - x_i^B$$

The specification in (1) assumes that within and between effects are equal; the variance that is not accounted for will end up in the error term, leading them to be correlated with the regressor.

The proposed alternative uses both components of the time-varying regressors, in order to account for both the impact of the difference across units and of the cyclical fluctuation around the mean

$$x_{it} = \beta_0 + \beta_1(x_{it} - \bar{x}_i) + \beta_2\bar{x}_i + \beta_3 z_i + (u_i + e_{it}) \quad (4)$$

$$\bar{x}_i = \frac{1}{T}\sum_{t=0}^{T} x_{it}$$

The response of fraud to the business cycle or to change in the insurance cost need not be symmetric. Mocan, Billups and Overland (2005) develop a model in which, if an individual commits a crime during a cyclical downturn, her legal human capital decreases due to for, example bad reputation, whereas the criminal one appreciates, and this may make it difficult for her to switch back to a legitimate activity when the economy recovers; this leads to hysteresis, whereby the reduction in criminal activity during booms are smaller than its increase in downturns. Similarly, Calvo-Armengol, Verdier and Zenou (2007) show that, when a person engages in a criminal activity when his peers commit crimes too, she finds it difficult to go back to the labor market. Mocan and Bali (2010) test this proposition using aggregate data on US states and individual data for all those born in Philadelphia in 1958. They find that year-on-year increase in the unemployment rate have a large, in absolute value, impact on the diffusion of several types of crime than an improvement in the labor market. I extend the Within-Between specification including in the model both positive and negative deviations of per capita GDP and unemployment from their long term mean, to see whether the business cycle has an asymmetric impact on the propensity to defraud.

The specification has then two endogenous regressors, the province mean of the average premiums and the deviations from it. I assume that premiums are set in using backward looking expectations and use the lagged values[11] of a few determinants of claims frequency and severity impacting compensation costs, and therefore premiums, without affecting the propensity to defraud, namely:

• The incidence of fatal accidents: compensations for deaths are extremely costly and fatal accidents are very unlikely to have been made up

• The average rainfall in the province, affecting both the frequency and sever-ity of true accidents. Note that the dependent variable used in the ratio of fraudulent claims on population. Had I used the ratio on total claims this instrument would not have been valid.

• Fuel consumption per vehicle, a proxy for the intensity of vehicles' use, and therefore of the likelihood of an accident; in principle this should affect just true accidents, as the decision of commit a fraud does not depend on how intensive is car usage.

[11] at (t-2), then

• The share of national highways in the total, excluding motorways[12]. Accidents in non-urban road have four times the number of fatalities than those occurring elsewhere. Fraudsters choose where to stage a fake accident, so the percentage of non-urban road is most likely to matter just for true claims.

I use two lags of the first three variables to account for smooth adjustment of premiums to changes in compensation costs[13]. In order to test the validity of the instruments I employ four tests:

• A standard F test for the significance of the excluded instruments in the two first-stage regression

• The Kleibergen-Paap (2006) for underidentification with potentially non i.i.d errors: it is a test of whether the excluded instruments are cor-related with the endogenous regressors

• The Angrist-Pischke (AP) first-stage F tests of weak identification of the individual endogenous regressor, i.e. to check whether the excluded in-struments are only weakly correlated with the endogenous regressors, see Angrist and Pischke (2009), pp. 217-18.

• The standard J-test for overidentification

7 RESULTS

7.1 BASELINE SPECIFICATION

In Table 6 I show the result of the baseline specification: the first column has just the economic determinants, then the measures of organized crime, court efficiency, social capital and networks are added, and finally the full model including premiums is estimated by GLS and by 2SGLS.

Frauds are more widespread in poorer provinces, in those where social cap-ital is lower and where people are more concentrated in large cities; this is consistent with the evidence on other types of crime. Moreover, fluctuations in the unemployment rate affect the propensity to defraud asymmetrically, in accordance with the hysteresis hypothesis. Finally, cross sectional differences in the long-term mean of the average premiums are positively correlated with frauds, but increases in premiums over time do not lead to a higher incidence of fraud.

[12] Motorways accidents occurring in a given province are not very likely to involve only vehicles registered in that province

[13] The most widely used time series model used to measure premium fluctuations in non-life insurance premiums, initially proposed by Lamm-Tennant and Weiss (1997) regress the percentage change in premiums on two own lags and at least the first and second lag of the ratio between compensation paid and premiums

Table 6: Estimation results: baseline specification

	(1)	(2)	(3) Full Model	(4) Full Model-IV
GDP above mean	-0.202	-0.176	-0.320	-0.504
	(0.581)	(0.584)	(0.525)	(0.462)
GDP below mean	0.292	0.274	0.452	0.642
	(0.682)	(0.681)	(0.645)	(0.591)
GDP, mean	-0.206	-0.912	-1.646***	-2.666***
	(0.633)	(0.556)	(0.508)	(0.736)
Unemp. rate above mean	0.0479***	0.0485***	0.0595***	0.0743***
	(0.0178)	(0.0180)	(0.0188)	(0.0270)
Unemp. rate below mean	-0.0193	-0.0199	-0.0178	-0.0156
	(0.0129)	(0.0128)	(0.0129)	(0.0121)
Unemp. rate, mean	0.0858***	0.0335	0.0232	0.00789
	(0.0294)	(0.0338)	(0.0304)	(0.0245)
Organized crime		-0.0574	-0.0255	0.0190
		(0.0356)	(0.0331)	(0.0400)
Days(/365) for a 1st degree sentence		0.0737	0.0796	0.0873
		(0.0777)	(0.0592)	(0.0557)
Blood donations per 10,000 inhabitants		-0.880**	-0.913**	-0.965***
		(0.412)	(0.419)	(0.324)
living in small villages		-0.0196***	-0.0111*	0.000221
		(0.00674)	(0.00626)	(0.00849)
living in large cities		0.0127***	0.0115***	0.00978***
		(0.00303)	(0.00290)	(0.00294)
Deviation deom avg. premium			0.601*	1.329
			(0.317)	(1.141)
Avg. premium, mean			2.171***	5.135***
			(0.393)	(1.768)
Observations	824	824	824	824

Standard errors in parentheses
Dependent Variable: number of MTPL fraudulent claims per 10,0000inhabitants. Robust and province-clustered standard errors
Additional Regressors, not shown: share of population aged 20 to 40 and over 65, vehicles per squared km, share of vehicles over 4 years old, macroregional dummies
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of the first stage regression are presented in table 7; the validity of the excluded instruments is confirmed.

Table 7: 1st stage results

	Deviation	Mean
Fatal acc. (-1)	0.005**	-0.001
	(0.000)	(0.001)
Fatal acc. (-2)	0.007***	0.002*
	(0.000)	(0.001)
Rainfall(-1)	0.013	0.008*
	(0.014)	(0.004)
Rainfall(-2)	0.033***	-0.004
	(0.008)	(0.005)
Fuel cons.(-1)	0.026*	0.009
	(0.010)	(0.006)
Fuel cons.(-2)	0.01	0.014*
	(0.013)	(0.007)
Share of Nat. routes	-0.177	0.319***
	(0.123)	(0.061)
Std. Errors in brackets		
Tests on the instrumens		
F-test	4.13	3.79
	(0.002)	(0.003)
AP F-test	21.57	17.80
	(0.000)	(0.000)
KP underid. Test	20.68	
	(0.004)	
Hansen J	3.733	
	(0.202)	

7.2 SOCIAL CAPITAL OVER THE BUSINESS CYCLE

In what follows I test whether changes in economic conditions, and especially the large contraction in GDP and employment occurred between the second half of 2008 and the end of 2009, affect the strength of social norms. I use two alternative methods. Firstly I augment the baseline model with the interaction of blood donation with time dummies having value 1 from 2008 or 2009 on or the positive and negative deviation of per capita GDP and the unemployment rate. The use of time dummies assumes implicitly that the impact of the crisis is the same for all provinces, whereas the interaction with the deviations allows for the fact that, due to the large differences across provinces in the structure of the employment, the crisis had initially a larger impact on the areas where the share of private sector employment, especially in the manufacturing sector, was higher. These areas broadly overlap with those featuring the highest levels of the proxies for social capital (see Cartocci, 2007).

Table 8: Estimation results: donations interacted

	(1)	(2)	(3)	(4)	(5)
blood…	-0.965***	-1.168***	-1.157***	-0.934***	-0.951***
	(0.324)	(0.365)	(0.358)	(0.347)	(0.324)
…& post 2008 dummy		0.399***			
		(0.140)			
…& post 2009 dummy			0.517***		
			(0.181)		
…& GDP above mean				-3.826	
				(2.772)	
…& GDP below mean				-6.323*	
				(3.716)	
…& unemp. above mean					0.234***
					(0.0650)
…& unemp. below mean					0.0814
					(0.0635)
N	824	824	824	824	824

Dependent Variable: number of MTPL fraudulent claims per 10,0000 inhabitants. Robust and province-clustered standard errors
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 shows that the crisis, and especially the drop in employment reduced the deterrence provided by social capital. For example, looking at column (3), the elasticity with respect to blood donation is -1.168 before 2009 and becomes -1.17+0.399=-0.769, with a 35% fall, afterwards. By the same token, in Column (4), When per capita GDP is 5% below the (province) long-term average, the elasticity of social capital is -0.934 -6.323 x (-0.05) = -0.618; when the unemployment rate is 1 percentage point above the (province) long-term average, the elasticity of social capital is -0.959 + 0.240 x 1 = -0.719 (Column (5)).

Alternatively, I estimate the baseline model splitting the sample in four nonoverlapping two-year periods; it appears that after the large drop in employment in 2008-9 social capital no longer exerted any influence on the propensity to defraud.

Table 9: Estimation results: sub periods

	(1) 2004-2005	(2) 2006-2007	(3) 2008-2009	(4) 2010-2011
GDP, mean	-1.442*	-2.037***	-0.908	-1.581**
	(0.833)	(0.744)	(0.971)	(0.774)
Blood donations	-1.016**	-1.312***	-0.426	-0.283
	(0.459)	(0.426)	(0.583)	(0.400)
Observations	206	206	206	206

Dependent Variable: number of MTPL fraudulent claims per 10,0000inhabitants. Robust and province-clustered standard errors
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8 Robustness Tests

8.1 Spatial Correlation

The inclusion of social capital is meant to capture some cultural factors that may explain why the highest incidence of insurance frauds is concentrated in a few neighboring provinces. However, the measures of social capital are imper-fect and may miss some other cultural traits specific to some areas. Moreover, ignoring spatial correlation in the variable may bias the estimates or make them inconsistent[14]. In order to test whether the results of the baseline model are robust to spatial effects, I reestimate the model adding a spatial lag. I use two different weighting matrices: a contiguity matrix and one with the inverse of the distance between each province's capital. The spatial leg is instrumented, as it is customary, with the weighted average of the explanatory variables, using each matrix in turn. Table 10 compares the baseline model with the two spatial lag specifications. There are basically no differences as far as the main outcome is concerned. Moreover, proximity is shown to play a role in explaining propensity to defraud over and above the measures of social capital and network strength, whereas distance does not. There can be several explanations for that. First of all, and rather trivially, fraudsters may operate not just in the province where the vehicles are registered but also in neighboring ones. Additionally, the cultural traits helping explain fraudulent behavior may be due less to geographical characteristics related to distance than to other cultural and historical factors, such as belonging to a city state in the Middle age, or living in a province which formed part of the State of the Church or the Kingdom of the Two Sicilies. Guiso et al. (2013) show that a large part of the differences in the endowment of social capital across Italian provinces can be traced back to the political institutions prevailing in the Middle Ages and, in some cases further back in time to the Pre-Roman period.

[14] Several papers have analyzed the spatial dimension of criminal activity, for example Zenou (2003), Glaeser et al. (1996).

Table 10: Estimation results: Spatial lag model

	(1)	(2)	(3)
lag(proximity)		0.146***	
		(0.0529)	
lag(distance)			0.00933
			(0.0172)
GDP above mean	-0.504	-0.404	-0.274
	(0.462)	(0.465)	(0.435)
GDP below mean	0.642	0.702	0.390
	(0.591)	(0.597)	(0.561)
GDP, mean	-2.666***	-2.257***	-2.277***
	(0.736)	(0.657)	(0.672)
Unemp. rate above mean	0.0743***	0.0840***	0.0542**
	(0.0270)	(0.0278)	(0.0244)
Unemp. rate below mean	-0.0156	-0.0157	-0.0205*
	(0.0121)	(0.0122)	(0.0115)
Unemp. rate, mean	0.00789	0.00943	0.0116
	(0.0245)	(0.0228)	(0.0230)
Organized crime	0.0190	0.0148	0.00119
	(0.0400)	(0.0369)	(0.0369)
Days(/365) for a 1st degree sentence	0.0873	0.0819	0.0789
	(0.0557)	(0.0519)	(0.0524)
Blood donations per 10,000 inhabitants	-0.965***	-0.878***	-0.943***
	(0.324)	(0.303)	(0.306)
% living in small villages	0.000221	0.000581	-0.00502
	(0.00849)	(0.00798)	(0.00767)
% living in large cities	0.00978***	0.00863***	0.0101***
	(0.00294)	(0.00281)	(0.00277)
Deviation from avg. premium	1.329	1.817	0.261
	(1.141)	(1.172)	(0.984)
Avg. premium, mean	5.135***	4.605***	3.874**
	(1.768)	(1.592)	(1.571)
Observations	824	824	824

Dependent Variable: number of MTPL fraudulent claims per 10,0000inhabitants. Robust and province-clustered std. errors

Additional Regressors, not shown: share of population aged 20 to 40 and over 65, vehicles per squared km, share of vehicles over 4 years old, macroregional dummies

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8.2 Alternative Definitions of Social Capital

In the baseline regression I use blood donation, which is one of most common indicator of social capital: the altruism implied by giving blood is often considered the outcome of strong civic norms and engagement. However these are multi-faceted phenomena than may not be captured by a single indicator: moreover differences in blood donations across provinces can be due also to other factors, such as demography (people older than 65 cannot donate). Therefore, as a robustness check I consider other indicators of social capital[15], which may measure other dimensions of social capital, in particular I consider:

• Turnouts to referendums: I average the participation rate in the two ref-erenda that took place in 1999 and 2001. Referenda are on well identified issues with national importance and voting is not mandatory; a high rate of participation can then be interpreted as a sign of engagement in public issues, the outcome of strong networks.

• Participation to sport clubs: Members of sport club per 1,000 persons. One may think of these groups as channels through which values and trust are learnt and shared.

• Daily newspapers sold: number of daily newspapers sold per 1,000 persons. Reading a newspaper can be seen as an investment in the knowledge of public affairs, leading to larger involvement in collective action and public life. Putnam (2000) found that people who regularly read newspapers are more likely to vote, volunteer more frequently for community projects, visit friends more frequently, and build tighter relationships with their neighbors. The results (Table 11) show that the impact of social capital remains signif-icant regardless of the way it is measured.

[15] Data are taken from Cartocci (2007) [10]

Table 11: Estimation results: Alternative measures of social capital

	(1)	(2)	(3)	(4)
GDP above mean	-0.614	-0.490	-0.607	-0.500
	(0.541)	(0.520)	(0.537)	(0.509)
GDP below mean	0.787	0.617	0.759	0.656
	(0.713)	(0.685)	(0.709)	(0.674)
GDP, mean	-2.818***	-2.455***	-2.873***	-2.526***
	(0.811)	(0.793)	(0.834)	(0.776)
Unemp. rate above mean	0.0820**	0.0735**	0.0816**	0.0744**
	(0.0326)	(0.0312)	(0.0317)	(0.0303)
Unemp. rate below mean	-0.0132	-0.0153	-0.0137	-0.0142
	(0.0134)	(0.0129)	(0.0134)	(0.0128)
Unemp. rate, mean	0.00749	0.00839	0.0189	0.0201
	(0.0254)	(0.0253)	(0.0270)	(0.0257)
Organized crime	0.0254	0.00577	0.0544	0.0222
	(0.0432)	(0.0424)	(0.0492)	(0.0435)
Days(/365) for a 1st degree sentence	0.0879	0.0896	0.0604	0.0808
	(0.0585)	(0.0572)	(0.0645)	(0.0601)
Blood donations	-0.963***			
	(0.338)			
Avg. turnout at referenda		-0.0225**		
		(0.00938)		
Members of charities/ 1000 people				
Participation to sport clubs				-0.0985
				(0.0724)
Newspapers sold/1000 people			-0.00631***	
			(0.00237)	
% living in small towns	0.00259	-0.000189	0.00930	0.00386
	(0.00992)	(0.00966)	(0.0104)	(0.00957)
% living in large cities	0.00938***	0.00926***	0.00823**	0.00731*
	(0.00324)	(0.00316)	(0.00351)	(0.00377)
Deviation from avg. premium	1.809	1.351	1.848	1.442
	(1.621)	(1.550)	(1.554)	(1.497)
Avg. premium, mean	5.666***	4.885**	7.007***	5.016**
	(2.051)	(2.015)	(2.358)	(2.007)
Observations	824	824	824	824

Dependent Variable: number of MTPL fraudulent claims per 10,0000inhabitants. Robust and province- clustered std. errors

Additional Regressors, not shown: share of population aged 20 to 40 and over 65, vehicles per squared km, share of vehicles over 4 years old, macroregional dummies

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

9. CONCLUDING REMARKS

Some of the results of this paper have general implications, not restricted to insurance. First of all it is shown that the business cycle may affect the incidence of fraud over and above the impact on pecuniary incentives. Morality -at least as far as a relatively minor offense like insurance fraud is concerned-appears to depend on economic conditions, especially when the labor market is buffeted by a large negative shock like the large recession that hit the economy starting in the second half of 2008. This can be both the effect of economic necessities partially trumping moral values and the consequence of a reduction in the trust towards the financial sectors documented in other studies. It would be interesting to test whether social capital has the same time varying impact on other, more harmful, forms of crime.

The other original contribution of the paper is showing that, other things being equal, contract terms affect the propensity to cheat; making up or inflating claim is more widespread in provinces where the average premium paid is higher (because of reasons other than fraud). The impact the perceived costs and benefits of a contract on the incentive to cheat may be explored in other areas and provide important insight on the relationship between, for example, the perceived quality of public services and the incidence of tax evasion.

Thirdly, the impact of economic fluctuations on frauds is asymmetric: propensity increases when unemployment goes up but is not reduced by improvements in the labor market: this is consistent with some sort of hysteresis that features in other theoretical and empirical analyses. Additionally, the analysis developed in this paper has shown that motor insurance fraud is in many ways, a crime like the others: it is more widespread in poorer areas, as it probably works as a structural supplement or replacement to labor income, and its diffusion is higher in provinces where civic values are weaker and a larger share of population lives in large cities where the indirect enforcement provided by informal networks is less tangible.

The findings of this paper are relevant for the insurance industry. First of all, reducing the costs of MTPL insurance can provide a non-negligible help in fighting frauds. A discussion on the extent of competition and profit margins in the Italian motor insurance industry is obviously beyond the scope of this paper; however any measure reducing the cost of protection, by for example cutting administration or legal costs might help curb frauds. Reducing the level of compensation (which account for 70% of the costs borne by insurers to provide cover) would be in theory a more effective alternative, but it could backfire. It would entail curbing and standardizing the entitlements prescribed by law to those suffering bodily injuries and controlling more tightly the expenditure on car reparations (by, for example, obliging drivers to have their cars repaired in some specific garages), and this may raise among policyholders the feeling of being exploited by the insurance, possibly increasing the propensity to defraud.

APPENDIX

Table A1: Variable Description and data sources

Variable	Description	Source
Frauds	Number of fraudulent MTPL claims	IVASS
Vehicles	Number of registered motor vehicles	ISTAT
Premiums	Total MTPL premiums collected in the province	IVASS
GDP	Per capita nominal GDP in the province	ISTAT
CPI	Consumer Price Index for the province	ISTAT
Unemployment	Unemployment Rate in the province	ISTAT
Population aged 20-40	Total population between 20 and 40 in 2001	ISTAT
Population aged 60 or more	Total population aged 60 or more	ISTAT
Judicial Efficiency	Years needed to get to a first degree sentence in the court located in the province, average between the 2000 and 2007 data	ISTAT
Organized Crime	Incriminations for criminal association per 100K inhabitants, 2000--2005 average	ISTAT
Blood donations	Blood donations per 10K inhabitants, 2002	Ministry of Health
Referenda turnout	Average turnout at the 1999 and 2011 referenda	Ministry of Interior
Sport clubs	Number of members of sport clubs per 10K inhabitants	Cartocci(2007)
Newspaper diffusion	Daily newspapers bought per 10K inhabitants, 2001-2 average	ISTAT
% in small towns	% of population living in villages with less than 2000 inhabitants, 2001	ISTAT
% in big cities	% of population living in cities with morethan 250K inhabitants, 2001	ISTAT
Fatal accidents	Share of fatal road accidents in the total	ISTAT
Rainfall	Annual rainfall in the province	ISTAT
Fuel consumption	Per vehicle consumption	ACI
Share of National routes	% of national routes in the total (in Kilometers)	ISTAT

ACI: Automobile Club ISTAT: National Institute for Statistics IVASS: Insurance Regulation Authority

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THE VALUE AND PRICE OF A "TOO-BIG-TO-FAIL" GUARANTEE IN THE INSURANCE INDUSTRY

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20th October 2017

This paper analyzes the impact of the evolution of the regulation dealing systemically important insurance groups, using an event study methodology. The results show that investors were able to detect which companies were to be designated well ahead of the publication of the list. Most importantly, after an initial positive reaction, consistent with the expectation of a "too-big-to-fail" implicit subsidy, the disclosure on how the capital charges for systemic insurers would be calculated led to sizeable negative abnormal returns for the entities concerned. Leverage plays a key role in driving investors' reaction; more leveraged entities experience higher abnormal returns when the expectation of a TBTF guarantee arises and lower ones when information on the size of the capital charges is revealed.

JEL Classification: G20, G22, G23, G28

Keywords: Insurance Companies, Systemic Risk, Global Systemically Financial Institutions, TBTF, Too-Big-to-Fail, Capital Requirements

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* I wish to thank Dario Focarelli the participants to the 44th Seminar of the European Group of Risk and Insurance Economists, to the Goethe University 2016 Workshop on systemic Risk in insurance the 2016 Ph.D Forum at the University of Bologna, in particular Giacomo Calzolari. All errors are my own.

1. INTRODUCTION AND MOTIVATION

In 2008, the biggest bailout in history prevented the failure of a large insurance company, AIG. This was coupled, in Europe, with substantial amounts of public money being used to rescue and recapitalize financial conglomerates with sizeable insurance activities. Despite AIG paying back bailout funds in the following years, concluding repayments in 2012, this has raised the question of whether insurance companies can become an important source of systemic risk and, if so, which entities should be regulated and how. Since 2012, international regulators have proposed a new framework aimed at identifying and regulating Global Systemically Important Insurers (G-SIIs). This framework foresees stricter oversight of accounts and practices, the requirement for the designated companies to prepare a plan allowing an orderly resolution of the entity in case of severe distress and, above all, envisages an additional capital requirement to which G-SIIs will be subjected, the Basic Capital Requirement (BCR).

This paper seeks to assess how financial markets have reacted to the introduction of this regulation between the end of 2011 and the end of 2015. In particular, I try to gauge to what extent insurance companies designed as systemically important, or those who may be so in the future, enjoy a “too-big-to-fail” (TBTF) premium and/or whether the imposition of additional capital requirements has been perceived as burden. In order to distinguish with precision which entities are liable to fall under the new measures I explore the different layers of regulation recently proposed for domestically and internationally active insurance groups. Following what is being done for other components of the financial industry (especially banks) I use a time-tested event study methodology.

The results show that this regulation does matter to investors, as the key steps of the regulation were accompanied by statistically significant abnormal returns for the equity of the entities affected. Investors were able to identify which companies would be designed as G-SII a year and a half before the official designation, and the positive reaction to the extension of the framework for systemically important banks to insurance companies can be thought as the perception of a valuable “too- big-too-fail” implicit guarantee, in line with what was found in similar studies on the banking sector. However, when details emerged, after the formal designation, on what arguably is the most important policy measure, the Basic Capital Requirement, G-SIIs experienced negative abnormal returns, which can be seen as a gauge of the price of the TBTF guarantee. This interpretation is corroborated by the fact that both the first–positive-effect and the second-negative-effect are stronger for more leveraged entities.

The overall impact of the regulation so far is not very large, slightly below what found for banks. Considering the group of G-SIIs, the cumulated abnormal return of the events, when they are statistically significant, is 0.58%. The -0.18% return differential with respect to a group of large multinational insurers which are not designated as systematic indicates that, so far, the price of the TBTF guarantee is perceived as slightly higher than its value. These findings, along with the results of the responsiveness of abnormal results to company characteristics, can hopefully inform the debate on the regulation and provide support for the next stages.

In Section 2 I briefly describe the cases of public bailouts of insurance companies during the 2007/8 financial crisis and sketch the new regulatory framework for global insurers that is being developed. Section 3 illustrates the differences between the banking and insurance business, the merits and limitations of capital-based regulation applied to insurance intermediaries and the evidence available so far on the TBTF premium in insurance. Section 4 summarises the methodology utilised. The results are shown in Section 5 and discussed in Section 6. Section 7 concludes.

1. THE INSURANCE SECTOR, THE FINANCIAL CRISIS AND THE NEW REGULATION

The insurance sector was not spared by the global financial crisis and some groups had to be bailed out by governments or central banks. Towards the end of 2008, as a consequence of the rapidly escalating losses on its CDS portfolio, AIG, one of the largest insurers in the world, had to be bailed out by the US government. In September 2008 the Federal Reserve recapitalized AIG for USD 85 billion, in exchange for 79.9% of AIG equity; one year later, escalating uncertainty over the future of the company forced the Fed to pledge another USD 37.8 billion. This amounted to the largest bailout in history. On top of that, AIG was forced to sell part of its insurance business. More specifically, the amount disbursed to support AIG reached USD 184.6 billion in April 2009. In return, AIG paid interest plus dividends on the received funding and US Treasury obtained a 92% ownership share in the company. As of December 14, 2012, the government assistance for AIG concluded. All Federal Reserve loans were repaid and the Treasury sold all of the common equity obtained through the support (Webel, 2013).

During the subprime crisis, other large US insurance companies, in addition to AIG, received public bailout funds through the TARP scheme, many others applied for it and others benefited from capital relief because of ad hoc regulatory changes. Many of them came under distress as the large losses in their investment portfolio, coupled with long-term guarantees to policyholders, quickly eroded their capital base. Others, writing financial guarantees to other firms, were unable to pay the claims related to the defaults of mortgage-backed securities. Finally, several life insurers qualified for public bailout because of their status as bank holding companies[16].

In Europe, public support was given to the insurance subsidiaries of banks (such as RBS in the UK and Fortis in Belgium) and, to three large Dutch financial conglomerates: ING, Aegon and SNS Reaal. Within the framework of a Europe-wide financial plan, €30 billion were made available to prevent a liquidity shortfall; €14 billion were actually used.

Regulators have started responding to the problems that surfaced in 2007/8 within a wider framework for the regulation of insurance activity at the global level. The measures aim to target two issues: 1) how to regulate large and complex groups operating under different jurisdictions and 2) how to mitigate the contribution of the insurance sector to financial systemic risk. The focus of this paper is on the latter set of measures.

In order to respond to the growing complexity of the global insurance business[17] the body in charge of coordinating insurance regulation internationally, the International Association of Insurance Supervisors (IAIS) has drafted a framework of globally accepted principles framing the supervisory activity, called Insurance Core Principles (ICPs). This is a set of principles and standards intended to help local supervisors design and implement a more effective supervision. These principles,

[16] Schwarcz & Schwarcz (2014)
[17] See Schoenmaker, Osterloo, & Winkels (2008) for a description on how the globalisation of the insurance industry is changing the structure of large multinational groups, leading to the centralisation of some activities. Cummins & Venard (2007) provide some fitting examples of the tension between the existence of a global structure and the need to comply to strict national regulation and market practice.

which are not mandatory, are to be applied to any insurance company, on both a legal entity and group-wide level, in an attempt to cover all aspects of the regulatory activity, from the powers of the supervisor, to the set-up of the risk management framework and to the prevention of fraud and money laundering[18] .

The ICPs have then been extended to create the Common Framework for the Supervision of International Insurers (ComFrame), a set of requirements specifically focused on the group-wide supervision of internationally active insurance groups (IAIGs): an IAIG is an entity which writes premiums in at least three jurisdictions, with at least 10% of them outside the home market, and which has total assets of at least USD 50 billion or gross written premiums of at least USD 10 billion, based on a three-year average. No distinction is made either between primary insurers and reinsurers or among pure life or P&C insurers and composite entities. The IAIS has so far refrained from publishing a list of the IAIGs, the number of which should be around 50 worldwide, according to press estimates. A crucial feature of the ComFrame is the provision of an additional capital charge to be applied to large international insurance groups; the details on how this capital charge will operate are to be disclosed in late 2016.

In addition to the ComFrame, new regulation is being drafted in order to minimise the contribution of the insurance industry to systemic risk. The starting point is of course to assess which parts of the insurance business may be a source of systemic risk. A discussion of what in the insurance business constitutes a source of systemic risk is clearly beyond the scope of this paper, and in-depth analysis of the issue can be found in several recent surveys[19].

In May 2011 the IAIS presented its thinking on the matter, and sketched the possible regulatory responses (IAIS, 2011). First of all, the IAIS states that traditional insurance activity is not a source of systemic risk, as it entails underwriting risks that are (i) idiosyncratic (ii) not correlated with each other (iii) not influenced by the business cycle.

However, as shown by the AIG case, insurance groups can contribute to systemic risk via non-traditional activities, which have rapidly increased in size and scope. In life insurance, the existence of financial guarantees on capital and, above all, minimum guaranteed returns attached to many products complicate the risk profile with respect to standard, pure risk, products. The collapse in asset prices or yields may leave some insurers unable to pay the guaranteed returns, leading potentially to insolvency; the exposure of life insurers to the same asset classes can lead rapidly to contagion. Other problems could come from non-insurance activities such as trade in derivatives, used to hedge assets returns. In non-life insurance, systemic risk is restricted to very specific lines of business, such as the supply of credit protection in the form of credit insurance, credit guarantees and derivatives (especially CDS).

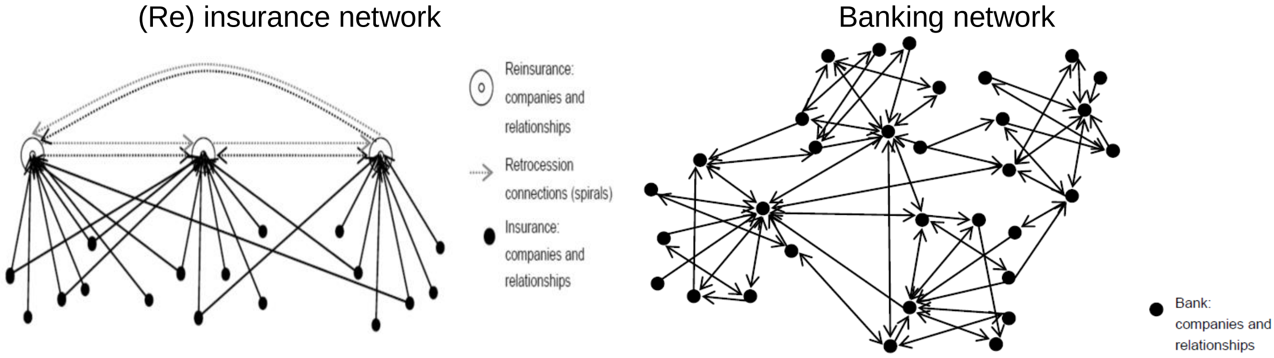
The IAIS argues that, given the overall small size of non- traditional insurance, the potential contribution to systemic risk by the industry should be limited. However, other considerations, related to the size of the entities and their geographical reach must be taken into account. Insurers are large institutional investors, holding large positions in fixed income securities; therefore a main source of risk is linked to large drops in bond prices, not to mention defaults.

While systemic risk can arise due to the linkages between insurers and banks, the connections within the industry are much less a case for concern. As shown in Figure 1, there are profound differences in the way insurance companies and banks are interconnected. The banking networks allow for the possibility of distress in an entity to spread quickly to the rest of the industry, as shown by the freeze in the European interbank market in 2009 and 2011.

[18] See IAIS (2011) for a detailed list of the areas of application
[19] See, among many others, Eling and Pankoke (2014), Cummings and Weiss (2013) and Geneva Association (2010).

In insurance, on the other hand, the structure is normally highly hierarchical. There are almost no linkages among primary insurers; therefore, there is not a network comparable to the interbank market. Risks in the insurance sector are redistributed by reinsurance companies; they receive risks from insurers and may share part of it with other reinsurers via retrocessions. he insurer-reinsurer relationship can have non-negligible implications for systemic risk, according to IAIS[20]. The reinsurance market appears to be highly concentrated, and this leads to a strong interconnection between reinsurers and primary insurers ceding business to them. In principle the failure of a reinsurer may create problems as several contracts may be cancelled, leaving insurers without protection for tail risks, since contracts are very specific and difficult to be rewritten quickly.

Figure 1: Insurance and banking networks compared



Source: Radice (2010)

Based on the considerations outlined above, IAIS has set up a framework to designate which insurance groups are systemically important (IAIS, 2011), and devised specific policy measures for them (IAIS, 2012a). The designation was based on a set of indicators related to:

- Size: the importance of an entity increases with the amount of services provided; however a large size is also a “prerequisite for effective risk pooling and diversification
- Global activity: the extent of international activity is a proxy of the negative externalities that distress may generate
- Interconnectedness: interlinkages with other institutions may give rise to systemic risk
- Non-traditional and non-insurance (NTNI) activities: activities such as investing substantially in the bond market or entering into derivative contracts are thought to be the biggest potential sources of systemic risk
- Substitutability: the difficulty of replacing the services provided by an institution in distress increases its systemic importance

This indicators-based methodology was complemented by soft information on specific features of the companies and their products, gathered through interviews with national supervisors.

On July 18th 2013 nine insurance groups were designed as systemically important (Global Systemically Important Insurers, G-SIIs). There were five European companies, Allianz (Germany), AXA (France), Assicurazioni Generali (Italy), Aviva and Prudential (UK), three from the US, AIG, MetLife and Prudential Financial, and a Chinese one, Ping An. In November 2014 the designation for these groups was confirmed, with no additions to the list. It changed in October 2015, with Generali being replaced by the Dutch insurer Aegon.

[20] For a completely opposite view see Kessler (2013)

Together with the first list, a set of policy measures for G-SIIs was decided. It includes the following[21]:

- Systemically important insurers will be subjected to a more intensive and coordinated supervision, on top of the other requirements determined by national (and supranational, in case of EU insurers) authorities. Moreover, plans to restrict non-traditional and non-insurance businesses and separate them from the mainstream activities may be envisaged.
- Increased resolvability of groups or parts of them, in order to improve the supervisor's ability to resolve an entity in distress, minimising the impact on the rest of the financial system and the taxpayer's exposure to the risk of loss. G-SII are required to present a plan detailing how to handle the restructuring in case of failure
- Higher Loss Absorbency (HLA): a higher level of capitalisation will be required given the risk G-SIIs pose to the global financial system. The initial step is constituted by a Basic Capital Requirement (BCR). The BCR is to be calculated using a factor based approach using risk weights related to different areas of activities, and applied on a group wide basis[22]. This will be replaced at some point by a Global Insurance Capital standard (ICS), which will be applied to all IAIGs.

The resolution plans were submitted to the regulator during the summer 2014 and, after a discussion begun in October 2013, in November 2014 the model to calculate the BCR was presented. The details on the HLA were published in October 2015. From 2019, G-SIIs will be required to hold a level of capital no lower than the BCR. Figure 2 summarises the different layers of regulations and the types of companies affected by each of them.

The new regulatory framework creates three groups of insurers:

1) Those that are too small or focused on just one market to be subjected to the ComFrame
2) The IAIGs that will have to adopt the ComFrame
3) A subset of the IAIGs, determined on an annual basis, deemed to be systemically important, to which the G-SII regulation will apply

It follows that insurers belonging to group 1 will never be subjected to the G-SII regulation, whereas those in group 2 may be. In the empirical exercise I will exploit this fact to assess the impact of the evolution of the regulation on the equity prices of different groups of companies.

Figure 2: The regulatory framework

Type of Entity:	**Legal Entity**	**Group**	**IAIGs**	**G-SIIs**
	Supervisory requirements and actions			
1st Tier: Insurance Core Principles	ICPs applied to legal entities only	ICPs applied to legal entities and groups		
2nd Tier: ComFrame			ComFrame	
3rd Tier: G-SIIs Package				G-SIIs package

Source: Adapted from IAIS (2013)

[21] For a quick presentation of the measures see IAIS (2014b)
[22] The details on how it is to be computed can be found in IAIS (2014a)

The process of identifying the systemically important insurers has so far spanned over four years. These are the most salient events, which will be considered in the empirical analysis.

1) November 15th, 2011: The IAIS publishes a document on the relationship between insurance activity and systemic risk (IAIS, 2011) and sets a list of which activities undertaken by insurance groups can be a source of systemic risk. It contains also the first, tentative, list of policy measures to be taken in order to mitigate the contribution of the insurance industry to systemic risk.
2) January 10th 2012: The Financial Stability Board (FSB), the international body in charge of regulating the whole financial system, announces that the supervisory framework for systemically important financial institution will be extended to global systemically important insurance companies and other types of financial institutions[23]. No details are provided on how or when this would be done and how to define systemically important insurers.
3) May 31st, 2012: IAIS releases its proposed assessment methodology for the identification of G-SIIs.

   According to the Financial Times (Masters & Gray, 2012)

   "Some 48 insurance groups in 13 countries are being targeted by global regulators for possible designation as "systemically important", a label that could lead to higher capital requirements and limits on business lines."

4) July 18th 2013: The list of G-SIIs is published, together with the revised list of policy measures.
5) December 16th 2013: The IAIS publishes, for public consultation, the proposed methodology for the calculation of the Basic Capital Requirement to be applied to GSII.
6) October 5th 2015. The details of the Higher Loss Absorbency Requirement for Global Systemically Important Insurers are published[24]. The IAIS paper stipulates how the extra capital requirement needed on top of the BCR are to be calculated.
7) November 3rd 2015.The G-SII list is updated, with Assicurazioni Generali being replaced by Aegon

2. THE ROLE OF CAPITAL AND THE "TOO-BIG-TO FAIL" PREMIUM

Investors' assessment on the measure is likely to be driven to a large extent by the result of the trade-off between the expectation of a "too-big-to-fail" premium enjoyed by systemically important insurers and its cost, in terms of higher administrative charges and above all, higher and costlier capital requirements.

The G-SIIs' regulation is based on a blueprint taken from banking prudential regulation, in which capital buffers clearly play a key role. However, this can be different, given the specificities of the two industries. While banks and (life) insurers share the role of channelling savers' funds into investment and of large investors in financial markets, major differences emerge in several respects (Thimann, 2015). For the purpose of this analysis the most important ones are about the role of debt and capital, and therefore leverage.

[23] See http://www.financialstabilityboard.org/2012/01/meeting-of-the-financial-stability-board-in-basel-on-10-january/
[24] See IAIS, 2015

Insurers, being pre-funded, do not need to issue much debt and, crucially, do not do that to finance core activities[25]. Financial assets are acquired using the insurance premiums already earned, and not issuing additional liabilities. Therefore, while a higher capital charge will slow down asset accumulation and leverage in bank, the same will not happen in insurance, as the size of the asset size is mostly determined by the amount of premiums written.

As explained in Plantin & Rochet (2007), Chapter 4, in the traditional insurance business, capital serves as a buffer. If the proceeds from the sale of assets (which can take a long period and be conducted smoothly given the high liquidity of most assets) is not enough to cover all the claims, capital is used to pay the remaining claims, and only if it is depleted the claimholders suffer losses. It works somehow in the same way as the deductible in a non-life insurance contract. Therefore, for insurers "raising capital […] means that there are (even) more assets available to cover the liability stream […], but such additional capital will be consumed, if at all, at the end of the process and has no crisis prevention or stabilisation function" (Thimann, 2015, page 376).

Additionally, bail in is built in in most of the traditional life contracts as a participation to the gains (or losses) of the financial portfolios where their premiums are invested. This works as an additional buffer on top of capital. Unit-linked contracts with no guarantees on the amount invested entail would be, by definition, bailed in by policyholders[26].

In non-life insurance, the policyholder's claim to be compensated is guaranteed by the law regardless of the return from the investment of provisions. Policyholders are protected by the imposition of very prudent provisioning criteria, strong constraints on the asset classes in which provisions can be invested and/or by the requirement to hold extra capital over and above the technical provisions. As such, in these lines of business, a bail in is ruled out.

Therefore, as far as the bulk of the business is concerned, the specificity of insurance may call into question the usefulness of capital surcharges as systemic risk mitigating tool; as a consequence, it may be argued that any new regulation that increases surcharges may be perceived simply as an additional cost and investors may react negatively to news of their introduction.

Another crucial issue is whether insurers can be considered "too-big-too-fail", thus raising the expectations of a public bailout in case of distress. As pointed out by Schwarcz & Schwarcz (2014), most of the U.S. insurers that received government support as a consequence of the 2007/8 crisis were not "too-big-to-fail" in terms of size, but experienced distress due to the strong exposure to the mortgage backed securities (both as liabilities for the companies writing credit insurance and as assets for life insurers) and the strong interconnections with other parts of the financial markets. The same applies for Europe, where it was mostly the banking and asset allocation arms of financial conglomerates that led to the distress which triggered the bailout.

[25] Normally debt is issued for M&A operations or to acquire fixed assets.

[26] However, the existence of guarantees on the premiums invested and of minimum return of course changes the conclusion. In this case an adequate level of capital woks as a buffer against adverse changes in the price and yields of financial assets. Recently, Berdin & Gründl (2015) develop a stylised model of a German life insurance companies and show that, in a scenario of prolonged low interest rate, quite a large number of companies with an insufficient level of capitalisation would run the risk of going bust as the yield on investment remains below the guaranteed returns for a prolonged period

Thus, it may be argued that the bailout was caused mostly by the activity undertaken by some insurers rather than by their size or core business. However, given the evidence on AIG and the large Dutch conglomerates presented in Section 2, one could argue that, in case of other crises, large insurers could benefit from public bailout given:

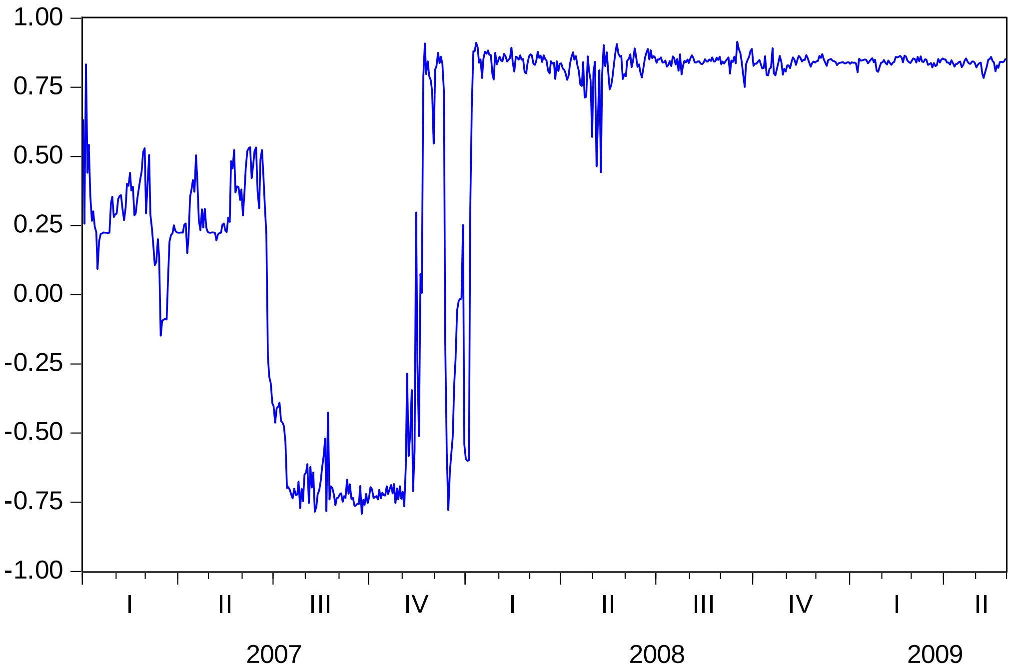
- The role they play in providing long term savings to large number of people and the fact that the failure of a life insurer could lead to loss of confidence in the industry as a whole
- The weight of their investment in some asset classes (for example, government and sovereign bonds); distress could trigger a fire sale of assets leading to potentially destabilising effects on prices. However, the extent of the sales may be limited by the ALM strategy aimed at reducting the maturity mismatch.
- The possibility that large losses in policyholder wealth due to the financial distress of an insurer and or the plunge in its equity price may propagate to other parts of the financial markets, undermining the confidence in the whole system. Figure 3 plots the dynamic correlation between the prices of CDS of ING and Aegon's debt. The unfolding of the subprime crisis in the final months of 2007 led to a spike in the correlation between the perceived default risks.

According to the regulator, two main arguments supported the intervention (IAIS, 2011):

- Large losses in the investment portfolios of the insurance business led to a drop in solvency ratio; the ensuing chaos in financial markets exposed the banking arms to severe liquidly problems, preventing the access to market to restore the capital buffers of the insurance business.
- In a conglomerate, the loss of confidence in the banking or insurance sector may have propagated to the other sectors, and then to the rest of the financial system.

All this suggest that the existence and size of the TBTF premium is something that has ultimately to be assessed empirically.

Figure 3: Dynamic Conditional Correlation* between CDS prices: ING and Aegon



*Computed using the Dynamic Conditional Correlation approach presented in Engle (2002).

The impact on the new regulation on systemically important financial institutions (SIFIs) on the banking sector is the subject of a few recent papers[27]. Less has been written so far concerning insurance.

The consequences of the AIG crisis and subsequent bailout on stock prices are studied by Safa, Hassan, & Maroney (2013). They analyse the impact of the most important events related to the insurer's near bankruptcy, assessing the extent of the contagion to other parts of the US financial industry. They find that the announcement of the first bailout had a positive effect on insurers' equity price; in the day following the announcement average prices were 4% higher than what was projected by a factor model. However, immediately after the second bailout, stocks were 7% down with respect to the same benchmark. Equity prices of banks, brokers and savings and loans institutions show the same pattern. According to the authors, this indicates that, initially, the bailout was welcomed by market, but the later realisation that the crisis was persisting and a new capital injection was needed depressed the valuations. Moreover, the authors try to test whether the Federal Reserve perceived AIG as too big to fail. They estimate a factor model for financial intermediaries' stock prices and introduce dummies for the period after the disclosure of large losses by AIG and before the first bailout ("crisis period") and for that including the two bailouts ("post-crisis period"). If AIG was perceived as too big to fail, stock returns would have discounted an intervention by the Fed and the dummy for the crisis period would have been positive. Conversely, the dummy for the post crisis period would be negative. The estimated coefficients, albeit having the expected sign, are not significant and this leads the authors to conclude against the "too big to fail" hypothesis.

Dewenter & Riddick (2016) study the impact of several events on equity prices of the eight of the nine insurers that have been named as systemic and a "control" sample of other 22 entities with similar characteristics. They consider the first AIG bailout and a few steps of the evolution of the G-SII regulation. They find that, adding the reactions to these events, designated firms enjoyed, on average, a "Too-Big-To-Fail" premium of roughly 10% with respect to the other entities considered. Moreover, the find that in the G-SII sample, positive abnormal returns in several events are positively correlated with companies' leverage and standard measures of systemic risk constructed using equity prices. This reinforces the authors' view of the existence of a TBTF guarantee. Their analysis reaches three main conclusions:

[27] For example, Bongini, Nieri, & Pelagatti (2015) study whether the release of information concernng the methodology to identify SIFI, the list of designated banks and the new capital requirements had different impacts on the affected banks from that on non-designated banks. All in all, they find that the market reaction to the announcement was not very strong, slighly negative but very diverse according to the banks'characteristics (level of capitalisation, retail versus investment banks, etc.). Mixed but very weakly negative results are found by Kleinov et al. (2015): interestingly, they find that the announcement of the banks designed as systemic leave their stock prices unchanged, and interpret this find as a sign that investors were able to predict the outcome of the designation process. Moenninghoff et al. (2015) find that, overall, the new regulation has a negative impact on the banks affected, which is however mitigated by the positive effect of the official designation. They also find that such a positive reaction may be linked to the expectation of a "too-Big-to-Fail" guarantee, which is exacly what the new regulation is meant to avoid. Schäfer, Schnabel, & Weder di Mauro, 2015 use event studies to analyse the impact of other reforms enacted after the subprime crisis in the US and Europe finding that overall, they reduce bailout expectations at the expense of lower equity returns.

"[…] first, […] equity investors conclude that the potential benefits of the TBTF guaranty outweigh potential compliance costs for the designated firms, with stock prices rising an average 11.7% across the eight announcements, corresponding to an economically significant net increase in G-SII market value of $17.2 billion. The equity gains are not associated with a perceived fall in default probability, but are associated with an increase in implied asset risk of approximately 15%, and with a 2.5% abnormal loss to bondholders. These results are consistent with investor expectations that protected firms will increase asset risk in response to the moral hazard created by protection against default, and with investor expectations that bondholders will bear more risk and higher losses if the firm does fail, even with the G-SII protection. Second, we find that other large non-designated insurance firms do not, on average, enjoy any net benefits or costs from the new regulatory regime[…] consistent with the market recognizing that these firms fall outside of the TBTF umbrella. Third, we find that investors identified the likely candidates for G-SII designation very early in the process, with most of the net benefit embedded in stock prices a year before the final announcement of specific names" (Dewenter and Riddick, 2016 p. 32).

Using a slightly different methodology in terms of estimation, choice of events, and considering both a much larger sample of securities and a different, regulation based, criterion to select the "control" group, I reach somewhat different conclusions.

In the remainder of the paper I will seek to provide an empirical test of the following hypotheses:

1) The G-SII regulation is not considered important and therefore the new pieces of information have a neutral impact on stock returns
2) The new regulation does have an impact, the sign of which derives from the balance of two effects
    a. The new regulation, and especially the stricter capital requirements, may make insurers safer, reducing their cost of equity and propping up returns. At the same time, being designated as systemic implies the expectation of some sort of public guarantee: in this sense "systemic" can be read as "too big to fail" and implies an indirect subsidy which boosts returns upon designation announcements.
    b. The higher costs and burden entailed by the new regulation offset the perceived TBTF benefits, leading to negative response of stock prices to any announcement

4. METHODOLOGY

The methodology used for this event study closely follows the standard one described in Campbell, Lo, and MacKinlay (1997) and surveyed more recently in Kothari & Warner (2007). For each company and announcement I estimate a simple market model using 88 observations ending three days before the event date; the sample length corresponds to four months of transactions and seeks to strike a balance between the need to have enough information to get sound parameter estimates and to minimise the probability of the estimates being contaminated by other events, an issue that is particularly relevant given the large volatility stock markets experienced in 2011-2012.

As a regressor I use the national market index for the county where the company is listed, following the results of Campbell, Cowan, & Salotti (2010). While such a choice might be questionable in an analysis of the banking sector, given the weight credit institutions have on the stock markets in some countries, the issue is much less relevant for insurers, the capitalisation of which is much smaller. My preferred measure of abnormal returns is computed over the event day (or first trading day after that if the event happens during the weekend or on a bank holiday) and the next, in order to account for differences in the time zones and lagged perception of the implications of the regulatory actions.

I use the daily returns of all the insurers stocks included in the Datastream World Insurance index that were continuously traded between June 2011 and November 2015. I exclude brokers and analyse separately the impact on the six largest reinsurance companies in the world as a robustness check, as their prudential supervision related to systemic risk is not tackled by the measures under analysis[28]. With this, I have a list with 121 securities, which can be found in Appendix A.

Then I consider different subsamples of insurers and test whether, on average, the event produced statistically significant abnormal returns and then if they were different across subgroups, using some parametric and non-parametric tests.

Since I consider the same set of events for all the securities, the assumption of absence of cross section correlation (needed to aggregate abnormal returns) is not met. Therefore, in order to test whether the Cumulative Average Abnormal Returns (CAAR) of each subgroup is different from zero I employ the parametric test introduced by Bohemer, Musumeci & Poulsen (1991) and modified by Kolari & Pynnonen (2010), which adjusts the variance of the standardised CAAR taking into account both serial correlation and cross section correlation across securities' abnormal returns; this latter issue can also be potentially a serious problem in case of concurrent events affecting a subset of insurers, such as, for example, a development in the Eurozone debt crisis.

I cross-check the results with those of a non-parametric test, the Generalised Sign Test explained in Cowan (1992). The whole procedure is explained in Appendix B. To test whether the difference between two groups is significantly different from zero I employ a simple t-test and a (non-parametric) Wilcoxon rank-sum test. Additionally, I check for the existence of other events that may have influenced insurers' stock prices in the dates analysed, using event study papers related to the period under analysis[29] and the Financial Times website. I do not find any significant event that can confound the results.

As a robustness check, I consider the results obtained from two alternative models. Firstly, I consider a larger window, covering two days before and after the event, to account for possible leaks and a slower reaction to the news. Then I re-estimate the market models using for each security a global stock market index (the Morgan Stanley Global Index), as done in other recent multi-country event studies[30].

In order to test the significance of the average stock price response to the regulatory announcements, I split the sample in two ways. First of all, I take the full sample of insurance companies and form a subset of entities which meet the IAIG criteria Data on total assets are taken from Worldscope, and I look into company statements to determine the geographical scope of the

[28] The decision on the list of global systemically important reinsurers and the policy measures was scheduled for July 2014 but has been delayed.
[29] Altavilla, Giannone, & Lenza (2014), Stracca (2013), Gagnon, Raskin, Remache, & Sack (2011)
[30] For example Schäfer, Schnabel, & Weder di Mauro (2015). Securities prices are converted into US dollars in order to avoid spurious volatility due to exchange rate fluctuations.

activity. I was able to identify 38 entities meeting the IAIG criteria of size and geographical diversification: adding to them the six global reinsurers the final number is not too far away from the "around 50 insurers" affected by the regulation declared by IAIS. The remaining companies are grouped into the "Other" category. Then, within the IAIG sample, I consider the nine insurers designated as G-SII in 2013 and those not designated. For the latest event I modify the group in accordance with the 2015 revision of the list. As an alternative, I just focus on the IAIGs and group them according to the region where they are headquartered, creating three groups: EU-based, US-based and those located in the rest of the world.

Subsequently, I consider just the sample of IAIGs, and focus on the performance of the individual securities trying to assess which characteristics explain the size of the abnormal returns in selected events. Given the very small number (38) of data points I focus on just size, a proxy for the weight of non-insurance activity and a measure of leverage. As emphasized by Bongini, Nieri, & Pelagatti (2015) concerning banks, it is likely that less capitalised entities would benefit more from being perceived as "too-big-to-fail" and suffer more from the obligation to raise capital levels.

5. Results

Table 1 details the results of the tests on cumulative returns, comparing the IAIGs that were designated as systemically important, the other IAIGs, and the other companies. The CAAR is reported in the fourth column, followed by the values of respectively the Kolari and Pynnonen (KP) test and the Generalised Sign Test (GST).

The seventh column has the differences between the CAAR for the G-SIIs group and the others, and then the p-values of the t-test on the difference and that of the Wilcoxon rank sum test.

The disclosure of the activities that the IAIS thinks are sources of systemic risks (Event 1) in November 2011 followed the publication (In July 2011) of the criteria used to define an IAIG. Therefore, investors were, in principle, already able to identify the type of companies liable to be targeted by the new regulation. Large, international insurers show negative and statistically significant abnormal returns on average, while companies too small and local do not record any significant abnormal return. At this stage, investors do not seem to be able to pick which companies would have been identified: the average CAAR of the G-SII group is lower than that of the group of the non-designed ones, but the difference is not significantly different from zero.

A clear distinction between the subgroups also appears in the reaction to the following event, the FSB announcement of the extension to insurers of the regulation for systemically important institutions. Here, an explicit connection is made for the first time to the regulation coming into force for banks and that for insurance that begins to be planned. Investors appear now to be able to distinguish among IAIGs, and the group of G-SII enjoys a large and significant positive return (2.94%), which translates into a 1.08% extra-return over the other IAIGs and a 2.62% over non IAIGs.

The FSB statement lacks any detail on how the specific regulation for insurance was to be framed, and therefore the results can be rationalised as the expectation of some form of guarantee linked to the systemically important status or the possibility to be designated as such. In line with some evidence for the banking sector and the findings of Dewenter & Riddick (2016), this can be interpreted as the value of the implicit "too-big-to-fail-guarantee", conditional on the information available on the event date.

The presentation of the methodology to be employed to identify a G-SII (Event 3) does not appear to be related to any significant difference in the average returns, even though the CAAR for the SIIs group is negative and statistically significant. This can be interpreted as investor having already guessed which companies would have been designated and adjusting their valuation accordingly. This view seems to be confirmed by the fact that the formal designation itself (Event 4) is not met by statistically significant abnormal returns.

On the contrary, when details emerge on the most important policy measure, the Basic Capital Requirement for G-SIIs (Event 5), a clear distinction shows up. The insurers that are subjected from the beginning to the new capital requirements experience a statistically significant -0.8% CAAR and the other insurers (non-IAIGs) have a statistically significant -0.6%, but the other IAIGs (non-G-SIIs) show no significant abnormal returns. The difference between designated and non-designated IAIGs amounted to a statistically significant -1.26%. These results, being related to an estimate of the capital burden designated insurers will incur, can be interpreted as the perceived cost of the “too-big-to-fail guarantee”.

The negative performance of the insurers that do not meet the IAIG criteria may be rationalised as the realisation by investors that these entities would not be covered by the regulation mitigating systemic risk, but may still suffer from a systemic event for which they may not be ready[31]. In other words, the results of Event 5 show that being outside the “club” of IAIGs has some costs, but being inside it and having to face systemic risk related charges is not a free lunch either and entails a significant stock market penalisation.

Finally, the addition of new, more detailed information on how the HLA is calculated (Event 6) does not seem affect the three groups in a significant way.

Table 2 presents the results of the analysis for the IAIGs only, which are grouped according to the location of the their headquarters: European Union (EU), United States (US) and rest of the world (ROW). This splitting is meant to capture the impact of the differences in the regulatory regimes with which the new framework will coexist. It must be noted, however, that the response of the ROW group is never significantly different from zero as long as the parametric tests are considered; the large heterogeneity in the regulatory frameworks is probably responsible for the large variability of the abnormal returns.

The methodology proposed by the IAIG to identify systemically important insurers (Event 3) is viewed by investors as more damaging for European concerns than for US ones, whereas the difference with those in the rest of the world is not significantly different from zero. When the single most important measure is tackled -- the discussion of the details of the calculation of the BCR (Event 5) -- it is the US group that records a negative differential with respect to the EU-based insurers.

The publication of the HLA calculation details has a negative impact on large US-based insurers, but the difference with respect to entities based elsewhere is not statistically significant.

In order to assess the robustness the results, especially as far as the ability of investors to pick which companies would have been affected by the new measures, it may be useful to compare the

[31] As an additional robustness check I split the small insurers’ sample according to HQ location, finding no significant differences.

behaviour of primary insurers versus that of reinsurers. To this end, I add to the sample the six reinsurers that match the IAIGs criteria[32].

Table 3 presents the result of the split between IAIGs, other insurers and large reinsurers. Concerning the first event, the absence of any statistically significant CAAR for the insurance group and the difference with respect to IAIGs' abnormal returns confirm the view that the information provided by the IAIS paper was enough to enable investors to determine which companies were liable to be affected by the new regulation. The same applies for Event 2; moreover, the slightly negative CAAR for reinsurers is an indication that investors ruled out any form of TBTF premium benefitting reinsurers. The positive CAAR posted in event 3 may be interpreted as an indication of investors reacting to the realisation that reinsurers were (temporarily) "off the hook" as far as systemic risk regulation was concerned.

The results of the robustness tests are reported in Appendix C. The results obtained using a single global index in the market model are in line with that of the baseline model far as the size and significance of the events are concerned. On the contrary, moving from a two-day to a much larger five-day window gives more volatile results, as expected.

Summing up, some of the regulatory announcements had a non-negligible impact on insurers' stock prices. The first official documents by the IAIS mentioning systemic risk depressed the valuation of IAIGs, but then, when the FSB suggested that insurance and banks could somehow be "lumped" together as far as systemic risk regulation was concerned, IAIGs experienced positive abnormal returns. Additionally, investors appear to be able to distinguish the insurers most likely to be designated, well ahead of the formal designation. The information provided by the IAIS in its methodological paper seems to have been enough to enable investors to pick those which would have been designated, despite the fact that investors have a much narrower information set than the regulators.

Finally, I utilise the information on the change in the SII list that occurred in November 2015 (Event 7) to get an overall assessment of how financial markets value the "systemic" status. Using a SUR model, I regress the returns of Generali and Aegon stocks on their home market index, the STOXX index for financial services (to control for industry specific shocks) and three time dummies for the day when the new list was announced, and the day before and after. I use a sample spanning 85 days before the event and three after it[33]. It turns out that the only significant time dummy is the one for Generali on the event day: the coefficient is 1.07 with a t-statistic of 1.93, indicating a positive, but not very statistically significant positive effect of being removed from the SII list. The fact that Aegon equity price does not seem to be affected by the event may indicate that firm characteristics matter for the assessment of the implications of the new regulation.

[32] They are QBE (Australia), Swiss RE (Switzerland), SCOR (France), Munich Re and Hannover RE (Germany). Berkshire Hataway was excluded as, while listed as a reinsurer, it is in fact a large conglomerate.
[33] The sample includes event 6, so I dummy it out

Table 1: Cumulative average abnormal returns, G-SIIs, other IAIGs and other insurers

Event	Date	Description		CAAR	KP§	GST§	Diff. Vs. SII	p-val.	Wilcoxon§
1	November 15th 2011	The IAIS publishes a document on the relationship between insurance activity and systemic risk, and sets a list of which activities undertaken by insurance groups can be a source of SR	SII	-1.31	0.02**	0.06**			
			Non-SII	-1.08	0.08*	0.00***	-0.23	0.35	0.46
			Other	0.36	0.14	0.43	-1.67	0.01***	0.02***
2	January 10th 2012	The FSB announces that the supervisory framework for systemically important financial institutions will be extended to global systemically important insurance companies and other types of financial institutions.	SII	2.94	0.13	0.00***			
			Non-SII	1.86	0.28	0.00***	1.08	0.11	0.08*
			Other	0.32	0.22	0.01***	2.62	0.00***	0.00***
3	May 31st, 2012	The IAIS releases its proposed assessment methodology for the identification of G-SIIs	SII	-0.23	0.03**	0.04**			
			Non-SII	-0.24	0.36	0.45	0.01	0.50	0.42
			Other	0.05	0.01***	0.01***	-0.28	0.34	0.11
4	July 18th 2013	The list of G-SIIs is published, together with the list of policy measures	SII	-0.20	0.26	0.30			
			Non-SII	0.19	0.24	0.11	-0.39	0.18	0.33
			Other	-0.15	0.45	0.39	-0.05	0.41	0.47
5	December 16th 2013	The IAIS releases the public consultation document on the calculation of the basic capital requirements to be imposed on G-SIIs	SII	-0.82	0.00***	0.01***			
			Non-SII	0.44	0.20	0.31	-1.26	0.00***	0.04**
			Other	-0.61	0.00***	0.00***	-0.21	0.21	0.22
6	October 3th 2015	The details of the HLA are published	SII	-0.13	0.21	0.17			
			Non-SII	0.26	0.41	0.25	-0.74	0.14	0.18
			Other	-0.23	0.28	0.17	0.10	0.46	0.47

§p-values. Significant at ***1% **5% *10%

Table 2: Cumulative average abnormal returns, IAIGs split by geography

Event	Date	Description		CAAR	KP§	GST§	Diff. Vs. EU	p-val.	Wilcoxon§
1	November 15th 2011	The IAIS publishes a document on the relationship between insurance activity and systemic risk, and sets a list of which activities undertaken by insurance groups can be a source of SR	EU	-1.07	0.08	0.00***			
			US	-1.33	0.03	0.02**	0.26	0.34	0.15
			ROW	-1.08	0.48	0.07*	0.01	0.50	0.37
2	January 10th 2012	The FSB announces that the supervisory framework for systemically important financial institutions will be extended to global systemically important insurance companies and other types of financial institutions.	EU	2.20	0.09	0.44			
			US	2.49	0.37	0.15	-0.29	0.49	0.20
			ROW	1.37	0.44	0.00***	0.83	0.15	0.28
3	May 31st, 2012	The IAIS releases its proposed assessment methodology for the identification of G-SIIs	EU	-1.57	0.16	0.00***			
			US	0.86	0.23	0.19	-2.42	0.03***	0.12
			ROW	0.14	0.38	0.36	-1.70	0.09*	0.28
4	July 18th 2013	The list of G-SIIs is published, together with the list of policy measures	EU	0.29	0.33	0.03**			
			US	0.28	0.19	0.15	0.01	0.50	0.28
			ROW	-0.29	0.39	0.34	0.58	0.19	0.26
5	Dec. 16th 2013	IAIS releases the public consultation document on the calculation of the basic capital requirements to be imposed on G-SIIs	EU	0.30	0.35	0.03**			
			US	-0.62	0.11	0.01***	0.92	0.01***	0.01***
			ROW	0.43	0.46	0.50	-0.13	0.50	0.34
6	October 3th 2015	The details of the HLA are published	EU	0.13	0.45	0.41			
			US	-0.16	0.05**	0.02**	0.29	0.46	0.28
			ROW	0.07	0.13	0.20	0.06	0.41	0.28

§p-values. Significant at ***1% **5% *10%

Table 3: Cumulative average abnormal returns, insurers and reinsurers

Event	Date	Description		CAAR	KP§	GST§	Diff. Vs. IAIGs	p-val.	Wilcoxon§
1	November 15th 2011	The IAIS publishes a document on the relationship between insurance activity and systemic risk, and sets a list of which activities undertaken by insurance groups can be a source of SR	IAIGs	-1.13	0.07*	0.00***			
			Other	0.36	0.14	0.43	-1.49	0.00***	0.00***
			Reins	0.76	0.24	0.10*	-1.89	0.05**	0.12*
2	January 10th 2012	The FSB announces that the supervisory framework for systemically important financial institutions will be extended to global systemically important insurance companies and other types of financial institutions.	IAIGs	2.11	0.27	0.00***			
			Other	0.32	0.22	0.01***	1.79	0.00***	0.00***
			Reins	-0.60	0.00***	0.08*	2.71	0.07*	0.04**
3	May 31st, 2012	The IAIS releases its proposed assessment methodology for the identification of G-SIIs	IAIGs	-0.23	0.22	0.20			
			Other	0.05	0.01***	0.01***	-0.28	0.26	0.18
			Reins	0.61	0.18	0.00***	-0.84	0.15	0.28
4	July 18th 2013	The list of G-SIIs is published, together with the list of policy measures	IAIGs	0.10	0.37	0.14			
			Other	-0.15	0.45	0.39	0.25	0.25	0.12
			Reins	0.82	0.11	0.01***	-0.72	0.24	0.26
5	Dec. 16th 2013	IAIS releases the public consultation document on the calculation of the basic capital requirements to be imposed on G-SIIs	IAIGs	0.15	0.47	0.19			
			Other	-0.61	0.00***	0.00***	0.76	0.00***	0.01***
			Reins	-0.06	0.25	0.36	0.21	0.12	0.36
6	October 3th 2015	The details of the BCR are published	IAIGs	0.21	0.40	0.33			
			Other	-0.23	0.28	0.17	0.44	0.13	0.09*
			Reins	-0.53	0.14	0.33*	0.74	0.13	0.21

§p-values. Significant at ***1% **5% *10%

In order to investigate this issue I then consider the sample of the IAIGs, i.e., all the companies that at some point may be affected by the regulation and regress the CAAR for the most significant events (1, 2, and 5) on size, gearing and the importance of non-insurance activity. Moreover for event 5, I also a dummy for the entities headquartered in the US, in order to gauge how investors assess the compatibility with the global framework being developed and the existing national regulation. This is relevant in light of the expected developments in prudential regulation: the Solvency II regime, coming into force for all EU-based companies in 2016 foresees a risk based capital weighting scheme, whereas US companies will stick to the risk weighting scheme.

Consider first the results for events 1 and 2 reported in Table 4 (first and second columns). They show that size is positively related to CAAR for both events and that Event 2 extra returns have a positive correlation with company's gearing.

If the positive abnormal returns are interpreted as an expectation of a TBTF guarantee, this accrues, as expected, to larger entities and those that, being more leveraged, would be more in need of a public bailout. The relative size of non-policyholders' liability is not statistically significant.

Consider then the third column, which shows the same model (plus the dummy for US insurers) applied to Event 5. It appears that size is no longer correlated with the response. Interestingly, in event 5, the relationship with gearing remains significant but switches sign: more leveraged firms may need extra efforts to raise capital to meet the BCR and this seems to be priced in in their stocks. On top of that, companies being based in the US have a stronger penalty, possibly suggesting a more difficult compatibility between the BCR and the local solvency regime.

Table 4: Determinants of Abnormal Returns in selected events

Dep. Var: CAR	Event 1	Event 2	Event 5
Constant	-10.42	-11.74	0.14
	[-2.46]*	[-2.46]*	[0.04]
Total asset (log)	0.57	0.59	0.10
	[2.11]*	[2.19]*	[0.51]
Debt/capital	-0.04	0.07	-0.03
	[-1.38]	[2.52]*	[-2.41]*
Non policyholder liabilities	-1.06	1.59	-1.51
	[-1.16]	[0.79]	[-1.44]
Headquartered in the US			-1.40
			[-2.98]**
Observations:	38	38	38
Adj.R-squared:	0.11	0.28	0.32
F-statistic:	1.47	4.37	3.93
Prob(F-stat):	0.24	0.01	0.01

Significant at ***1% **5% *10%

6. DISCUSSION

Some of the steps in the development of the regulation did cause significant abnormal returns in insurers' equity prices. In order to calculate the total impact I add across events the abnormal returns, considering just the case when they are statistically significant at least at the 10% for both the both the Kolari-Pynnonen and the Generalised Sign Test . Considering the group of G-SIIs, I take events 1, 2,3 and 5: the cumulated abnormal return is 0.58%. The difference with respect to non-designated IAIGs is statistically significant only in events 2 and 5: summing them I get -0.18%. Finally, the difference over non-IAIGs, considering events 1 and 2, is 0.95%.

The first conclusion that can be drawn is that the perceived value of the TBTF guarantee related to being designated (or initially perceived by investors as) systemically important is relatively small, less than 0.6%. However, the difference with respect to IAIGs not having this status is slightly negative. This contrasts sharply with the nearly 12% (10.3% considering only the statistically significant responses) TBTF premium estimated by Dewenter & Riddick (2016), which consider a different set of events and put together the reaction to the first AIG bailout and only some of the steps of the G-SII regulation process. Some of the differences may be due to the choice of the events: in particular their analysis stops at the designation of the G-SIIs, while mine includes the publication of the details of the Basic Capital Requirement. More important, however, is the fact that their "control" group put together IAIGs which can be at some point designated as systemic with large, but just domestically focused entities which will never be designeted.

It is, however, important to notice the quite large difference with respect to the group of smaller companies which do not meet the IAIG criteria, suggesting that, possibly, some form of implicit guarantee could come from the ComFrame regulation.

However, the process of regulating the sources of systemic risk in insurance is at a realtively early stage compared with that of the banking sector and therefore the sum of the impacts may not, at present, be very informative. What matters more is the effect of the additional information provided by the events.

Considering the G-SIIs group, only the - rather vague - statement by the FSB on the extension of the framework for G-SIFI to insurance was met by positive abnormal returns. The following steps, i.e the releases of the details on how to identify SIIs (event 3) and, crucially, how to calculate the BCR (event 5), were accompanied by negative abnormal results. This is likely to indicate a pessimistic revision of the investors' assessment of the impact of the new regulation on insurers' profitability. However, the extra information provided by the details on the HLA calculation and the revision of the SII list was not considered relevant by financial market.

The revision in expectations also appears in the results of the regressions of the CAAR for events 2 and 5 on companies' size and, crucially, gearing. When the FSB declared that the systemic risk framework would also encompass insurers, the benefit in terms of extra returns was larger for bigger and more leveraged insurers, consistent with the TBTF premium hypothesis. However, once the details of the measures, and in particular the calculation of the BCR were known, size no longer mattered[34] and more geared insurers experienced larger negative abnormal returns, consistent with the view that the new measures represented a higher cost for firms as they will have to recapitalise. Bongini, Nieri & Pelagatti (2015) find a similar result for banks.

[34] This is consistent with the view that size is an imperfect indicator of systemic risk for banks and insurance, as shown by the low correlation between asset-prices based measures of systemic risk and the size of the individual entities. See for example, Adrian & Brunnemeier, 2016.

7. CONCLUSION

This paper has sought to assess whether and to what extent financial market priced the different phases of the evolution of the macroprudential framework for insurance companies.. The new regulation matters to investors, as some of the key steps were accompanied by statistically significant abnormal returns and investors seem to have understood which entities would have been designated as systemically important well ahead of the publication of the list. The size of the abnormal returns and their evolution over time, suggest that investors' opinions on the regulation have turned to moderately pessimistic once the details on the capital standards were enounced. Overall, the impact is not very strong, in line with what found recently by similar studies on banks. Gearing is an important driver of the results. Its correlation with the cumulative results was positive upon the announcement of the extension of the SIFI status to insurers before turning negative when investors were able to estimate the cost of being systemically important in terms of capital requirement. This is again consistent with an evolution of market perception from an initial expectation of a TBTF premium to a more pessimistic assessment of the costs and burdens related to the new regulation, especially for US-based entities.

APPENDIX A: INSURERS CONSIDERED

INTERNATIONALLY ACTIVE INSURANCE GROUPS (IAIGS)

	Name	Country	Assets 2010 YE (USD '000)
Designated as G-SII in 2013 and 2014	AVIVA	UNITED KINGDOM	591820229
	ALLIANZ	GERMANY	881697289
	AXA	FRANCE	1037518855
	ASSICURAZIONI GENERALI	ITALY	597900960
	PING AN INSURANCE	CHINA	169752469
	PRUDENTIAL	UNITED KINGDOM	419755352
	AMERICAN INERNATIONAL GROUP	UNITED STATES	683443000
	METLIFE	UNITED STATES	730906000
	PRUDENTIAL FINANCIAL	UNITED STATES	539854000
Non Designated	AGEAS (EX-FORTIS)	BELGIUM	142342814
	MANULIFE FINANCIAL	CANADA	406783811
	POWER FINANCIAL	CANADA	138358244
	SUN LIFE FINANCIAL	CANADA	203583257
	MAPFRE	SPAIN	64569551
	CNP ASSURANCES	FRANCE	451545437
	AEGON (designated in 2015)	NETHERLANDS	472167398
	TOKIO MARINE HOLDINGS	JAPAN	188605816
	MS&AD INSURANCE GP.HDG.	JAPAN	82463115
	SONY FINANCIAL HOLDINGS	JAPAN	65482398
	SAMSUNG FIRE & MAR.IN.	KOREA (SOUTH)	23830851
	LEGAL & GENERAL	UNITED KINGDOM	524189226
	STOREBRAND	NORWAY	69243952
	VIENNA INSURANCE GROUP	AUSTRIA	55359872
	OLD MUTUAL	UNITED KINGDOM	313392987
	RSA INSURANCE GROUP	UNITED KINGDOM	33035621
	BALOISE-HOLDING AG	SWITZERLAND	63711969
	SWISS LIFE HOLDING	SWITZERLAND	143526673
	ZURICH INSURANCE GROUP	SWITZERLAND	324302899
	STANDARD LIFE	UNITED KINGDOM	239761143
	SHIN KONG FINL.HLDG.	TAIWAN	64623125
	ACE	SWITZERLAND	82586000
	AFLAC	UNITED STATES	101039000
	CHUBB	UNITED STATES	50151000
	GENWORTH FINANCIAL	UNITED STATES	111295000
	TRAVELERS	UNITED STATES	104688000
	EULER HERMES GROUP	FRANCE	7404483
	HISCOX	BERMUDA	5733282
	XL GROUP	BERMUDA	44879826

OTHER INSURERS

Name	Country	Assets 2010 YE (USD '000)
ARCH CAP. GP.	BERMUDA	15770792
CINCINNATI FINL.	UNITED STATES	15095000
AMP	AUSTRALIA	82476410
CHALLENGER	AUSTRALIA	17090611
INSURANCE AUS. GROUP	AUSTRALIA	18735042
ADMIRAL GROUP	UNITED KINGDOM	2279765
AMLIN	UNITED KINGDOM	9237019
BEAZLEY	IRELAND	4946640
PORTO SEGURO ON	BRAZIL	8055497
SUL AMERICA UNT	BRAZIL	6509969
E-L FINANCIAL	CANADA	13554996
FAIRFAX FINL.HDG.	CANADA	30314468
INDL.ALL.IN. & FINL.SVS.	CANADA	32792659
INTACT FINANCIAL	CANADA	11811103
CATLIN GROUP	BERMUDA	11806000
CHESNARA	UNITED KINGDOM	7438861
NUERNBERGER BETS.	GERMANY	31840050
WURTTEMBERGISCHE LEB.	GERMANY	41505319
ALM BRAND	DENMARK	9200129
TOPDANMARK	DENMARK	11039415
TRYG	DENMARK	9511345
GRUPO CATALANA OCCIDENTE	SPAIN	11686722
APRIL	FRANCE	1895465
CATTOLICA ASSICURAZIONI	ITALY	25941756
MEDIOLANUM	ITALY	46911913
UNIPOL GRUPPO FINANZIARI	ITALY	73506545
VITTORIA ASSICURAZIONI	ITALY	3547104
MAX INDIA	INDIA	2908440
RELIANCE CAPITAL	INDIA	5716623
T & D HOLDINGS	JAPAN	139563228
JARDINE LLOYD THOMPSON	UNITED KINGDOM	1984725
CHINA TAIPING IN.HDG.	HONG KONG	19630869
CHINA LIFE INSURANCE 'H'	CHINA	206608264
PICC PROPERTY & CLTY.'H'	CHINA	29341125
SAMSUNG FIRE & MAR.IN.	KOREA (SOUTH)	23830851
HYUNDAI MARINE & FIRE IN.	KOREA (SOUTH)	10186551
DONGBU INSURANCE	KOREA (SOUTH)	13263737
LANCASHIRE HOLDINGS	UNITED KINGDOM	2576600
STOREBRAND	NORWAY	69243952
NOVAE GROUP	UNITED KINGDOM	2325611

Other Insurers (Continued)

Name	Country	Assets 2010 YE (USD '000)
UNIQA INSU GR AG	AUSTRIA	39775884
SCB LIFE ASSURANCE	THAILAND	2013043
DISCOVERY	SOUTH AFRICA	1796183
LIBERTY HOLDINGS	SOUTH AFRICA	31916917
MMI HOLDINGS	SOUTH AFRICA	NA
SANLAM	SOUTH AFRICA	48291979
SANTAM	SOUTH AFRICA	2185363
HELVETIA HOLDING N	SWITZERLAND	36315515
SCHWZ.NATIONAL-VERSICH.- GESELL.	SWITZERLAND	7519112
VAUDOISE 'B'	SWITZERLAND	10979703
ST.JAMES'S PLACE	UNITED KINGDOM	41212786
ANADOLU HAYAT EMEKLILIK	TURKEY	3631081
CHINA LIFE INSURANCE	TAIWAN	20430356
FUBON FINL.HLDG.	TAIWAN	108426390
SHIN KONG FINL.HLDG.	TAIWAN	64623125
AMERICAN FINL.GP.OHIO	UNITED STATES	32454000
ASSURED GUARANTY	BERMUDA	19247554
ASSURANT	UNITED STATES	26320588
ARTHUR J GALLAGHER	UNITED STATES	3350800
AXIS CAPITAL HDG.	BERMUDA	16373125
BROWN & BROWN	UNITED STATES	2400814
CNA FINANCIAL	UNITED STATES	54690000
CNO FINANCIAL GROUP	UNITED STATES	31060200
HCC INSURANCE HDG.	UNITED STATES	9064082
HARTFORD FINL.SVS.GP.	UNITED STATES	314621000
LINCOLN NATIONAL	UNITED STATES	193824000
MARKEL	UNITED STATES	10762326
MARSH & MCLENNAN	UNITED STATES	14105000
OLD REPUBLIC INTL.	UNITED STATES	15837400
PROGRESSIVE OHIO	UNITED STATES	21150300
PROTECTIVE LIFE	UNITED STATES	47562786
PARTNERRE	BERMUDA	23349411
EVEREST RE GP.	BERMUDA	18258870
RENAISSANCERE HDG.	BERMUDA	8138278
TORCHMARK	UNITED STATES	16159762
UNUM GROUP	UNITED STATES	57307700
W R BERKLEY	UNITED STATES	17463055
WILLIS GROUP HOLDINGS	UNITED KINGDOM	15840000
WHITE MOUNTAINS IN.GP.	BERMUDA	14034400
ALLEGHANY	UNITED STATES	6354552

APPENDIX B: METHODOLOGY

First consider an 88-day estimation window [$T_{0,}$ T_1], ending three days before the event and estimate the following model

$$r_{it} = \alpha + \beta r_{Mt} + u_{it} \quad \text{(A1)}$$

The abnormal returns are computed in the event window ($T_{2,}$ T_3) as

$$ar_{it} = r_{it} - \hat{\alpha} + \hat{\beta} r_{Mt} \text{ (A2)}$$

Then they are cumulated over the event window of days ranging from T_2 and T_3, encompassing the event day, as

$$CAR_i(T_2, T_3) = \sum_{t=T_2}^{T_3} ar_{it} \text{(A3)}$$

The BMP test considers first the cumulative returns standardized for an estimate of their standard deviation

$$SCAR_i(T_2, T_3) = CAR_i(T_2, T_3)/S_{CAR_i(T_2,T_3)} \quad \text{(A4)}$$

Where the standard deviation is corrected for the serial dependence that arises in successive prediction errors based on the same parameter estimates as follows

$$S_{CAR_i(T_2,T_3)} = \sqrt{\left(\frac{1}{(T_1-T_0)} \sum_{t=T_0}^{T_1} ar_{it}^2\right)\left\{(T_3 - T_3) * \left[1 + \frac{(T_3-T_2)}{(T_1-T_0)} + \frac{\left(\sum_{t=T_2}^{T_3} r_{Mt} - (T_3-T_2)\overline{r_M}\right)^2}{\sum_{t=T_0}^{T_1}(r_{Mt} - \overline{r_M})^2}\right]\right\}} \quad \text{(A5)}$$

where $\overline{r_M}$ is the mean of the market return over the estimation sample.

Then the statistics on the cross-section of the N companies belonging to a group is derived as

$$Z = \frac{\sum_{n=1}^{N} SCAR_n(T_2, T_3)}{\sqrt{N} S_{SCAR}} \text{(A6)}$$

where

$$S_{SCAR} = \sqrt{\left[\frac{1}{N-1} \sum_{n=1}^{N} \left(SCAR_n(T_2, T_3) - \frac{1}{N} \sum_{n=1}^{N} SCAR_n(T_2, T_3)\right)^2\right]} \qquad \text{(A7)}$$

Z is asymptotically distributed as a standard normal.

However, the BMP test assumes that individual securities are uncorrelated in the cross section, which may not be the case when the event date is the same for all companies. Kolari & Pynnonen (2010) devise a modification of the BMP statistics in order to account for cross-section correlation. The statistics they propose is the following

$$Z_{BMP-KP} = Z_{BMP}\sqrt{\frac{1-\bar{p}}{1+(1+N)\bar{p}}} \qquad \text{(A8)}$$

where $\bar{p}$ is the average cross-sectional correlation coefficient of the residuals of the estimated equation (i.e. the abnormal returns in the estimation period). This statistic is again asymptotically normally distributed under the null hypothesis of no effect.

In the generalised sign (GS) test the null hypothesis is that, within a group, the share of returns having positive sign in the event window is equal to the fraction expected to have that sign, based on the estimation window. For example, considering positive returns

$$\hat{p} = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{((T_1-T_0))}\sum_{t=T_0}^{T_1} S_{nt}\,, \quad S_{nt} = \begin{cases} 1 \; if \; u_{nt} > 0 \\ 0 \; otherwise \end{cases} \qquad \text{(A8)}$$

The test statistics is based on the normal approximation of a binomial distribution with parameter $\hat{p}$ and reads

$$Z = \frac{N_0 - N\hat{p}}{\sqrt{[N\hat{p}(1-\hat{p})]}} \qquad \text{(A9)}$$

where N_0 is the number of securities in the group having on average positive residuals in the estimation windows.

In order to test for negative signs, substitute negative for positive in the definition of S_{nt} and N_0.

Appendix C: Robustness Checks

Table A1: Market model with common world index

	Event	1	2	3	4	5	6
SII	CAAR	-1.24	3.29	0.81	0.41	-0.90	0.14
	BMP-KP	0.12	0.07*	0.10*	0.26	0.03**	0.37
	GST	0.16	0.00**	0.36	0.11	0.02**	0.32
Non SII	CAAR	-1.02	1.67	0.80	0.18	0.35	0.88
	BMP-KP	0.07*	0.29	0.48	0.17	0.24	0.16
	GST	0.04**	0.00***	0.03**	0.07*	0.12	0.06**
OTHER	CAAR	-0.19	0.65	0.89	-0.25	-0.72	0.33
	BMP-KP	0.45	0.06*	0.06**	0.37	0.00***	0.47
	GST	0.29	0.02**	0.00***	0.38	0.00***	0.45
SII-Non SII	dCAAR	-0.22	1.62	0.01	0.23	-1.25	-0.74
	p-value	0.40	0.02**	0.50	0.34	0.01***	0.14
	Wilcoxon	0.44	0.03**	0.50	0.45	0.05***	0.20
SII-Other	dCAAR	-1.05	2.64	-0.08	0.66	-0.18	-0.19
	p-value	0.01***	0.00***	0.34	0.41	0.21	0.35
	Wilcoxon	0.02**	0.00***	0.11	0.47	0.22	0.28
EU	CAAR	-0.75	2.25	1.39	1.02	0.43	1.22
	BMP-KP	0.35	0.31	0.27	0.08*	0.33	0.02**
	GST	0.18	0.03**	0.27	0.10*	0.03**	0.01**
US	CAAR	-1.25	2.24	-0.27	0.23	-0.63	-0.79
	BMP-KP	0.11	0.43	0.22	0.30	0.16	0.00***
	GST	0.00***	0.38	0.17	0.01	0.05**	0.02**
ROW	CAAR	-1.40	1.71	0.76	-0.81	0.16	1.02
	BMP-KP	0.50	0.45	0.48	0.40	0.44	0.01**
	GST	0.04**	0.02**	0.21	0.28	0.25	0.02**
EU-US	dCAAR	0.50	0.00	1.67	0.79	1.06	2.01
	p-value	0.22	0.50	0.04**	0.02**	0.01***	0.01**
	Wilcoxon	0.08*	0.20	0.05**	0.04**	0.01***	0.07*
EU-ROW	dCAAR	0.65	0.54	0.63	1.83	0.27	0.19
	p-value	0.22	0.26	0.23	0.01***	0.34	0.39
	Wilcoxon	0.01***	0.03**	0.01***	0.01***	0.00***	0.04**

Table A1: Market model with common world index (continued)

	Event	1	2	3	4	5	6
IAIGs	CAAR	-1.07	2.04	0.80	0.24	0.06	0.79
	BMP-KP	0.08*	0.27	0.35	0.22	0.48	0.25
	GST	0.03**	0.00***	0.04**	0.05**	0.42	0.01**
Other	CAAR	0.05	0.77	0.53	-0.33	-0.76	0.33
	BMP-KP	0.45	0.06*	0.06*	0.37	0.00***	0.47
	GST	0.29	0.02**	0.00***	0.38	0.00***	0.45
Reinsurers	CAAR	0.96	-0.36	1.66	1.04	-0.20	0.74
	BMP-KP	0.15	0.00***	0.08*	0.08*	0.29	0.36
	GST	0.34	0.07*	0.00***	0.02**	0.38	0.28
IAIGs-Other	dCAAR	-1.12	1.27	0.27	0.57	0.82	0.46
	p-value	0.01***	0.01***	0.32	0.09*	0.01***	0.18
	Wilcoxon	0.02**	0.01***	0.32	0.02**	0.01***	0.16
IAIGs-Reins	dCAAR	-2.03	2.40	-0.86	-0.80	0.26	0.27
	p-value	0.03**	0.06*	0.13	0.22	0.41	0.36
	Wilcoxon	0.26	0.14	0.37	0.33	0.44	0.32

Table A2: [-2, 2] Window

	Event	1	2	3	4	5	6
SII	CAAR	-1.48	3.43	-0.22	-0.30	0.32	-0.43
	BMP-KP	0.00***	0.05**	0.04**	0.22	0.20	0.22
	GST	0.01***	0.01***	0.15	0.45	0.41	0.17
Non SII	CAAR	-1.06	2.33	-0.66	0.25	0.32	0.33
	BMP-KP	0.14	0.17	0.23	0.19	0.34	0.38
	GST	0.01***	0.02**	0.05**	0.05*	0.11	0.24
OTHER	CAAR	-0.34	-0.20	-0.22	-0.07	-0.10	-0.90
	BMP-KP	0.28	0.00***	0.38	0.35	0.03**	0.05*
	GST	0.02**	0.02**	0.07*	0.23	0.14	0.00***
SII-Non SII	dCAAR	-0.42	1.10	0.44	-0.55	0.00	-0.76
	p-value	0.25	0.16	0.31	0.16	0.50	0.25
	Wilcoxon	0.19	0.03**	0.07*	0.40	0.18	0.46
SII-Other	dCAAR	-1.14	3.63	0.00	-0.23	0.42	
	p-value	0.00***	0.00***	0.14	0.31	0.10*	
	Wilcoxon	0.03**	0.01***	0.33	0.36	0.13	
EU	CAAR	-0.16	-0.66	0.30	0.00	0.27	0.83
	BMP-KP	0.33	0.01***	0.34	0.39	0.21	0.23
	GST	0.46	0.00***	0.02***	0.10	0.04**	0.04**
US	CAAR	-1.93	1.92	0.72	1.14	-0.79	-0.64
	BMP-KP	0.01***	0.45	0.03**	0.03**	0.14	0.00***
	GST	0.00***	0.00***	0.02**	0.14	0.23	0.00***
ROW	CAAR	-1.23	1.65	-1.50	-0.50	0.87	-0.44
	BMP-KP	0.50	0.44	0.48	0.43	0.49	0.46
	GST	0.00***	0.17	0.42	0.00***	0.13	0.39
EU-US	dCAAR	1.26	1.76	-1.18	-1.18	1.36	1.47
	p-value	0.09*	0.18	0.19	0.02**	0.05*	0.08*
	Wilcoxon	0.11	0.21	0.35	0.13	0.01***	0.17
EU-ROW	dCAAR	0.56	2.03	1.04	0.46	-0.30	0.67
	p-value	0.30	0.08*	0.14	0.26	0.36	0.13
	Wilcoxon	0.01***	0.03**	0.18	0.38	0.00***	0.22

Table A2: [-2, 2] Window (continued)

	Event	1	2	3	4	5	6
IAIGs	CAAR	-1.16	2.59	-0.56	0.12	0.32	0.15
	BMP-KP	0.12	0.16	0.15	0.32	0.33	0.49
	GST	0.00***	0.00***	0.02**	0.14	0.19	0.44
Other	CAAR	-0.31	-0.16	-0.24	-0.10	-0.16	-0.90
	BMP-KP	0.28	0.00***	0.38	0.35	0.03**	0.05*
	GST	0.02**	0.02**	0.07*	0.23	0.14	0.00***
Reinsurers	CAAR	0.62	-2.92	-1.80	0.26	0.59	-2.05
	BMP-KP	0.36	0.05	0.04	0.29	0.07	0.03**
	GST	0.34	0.08	0.11	0.01	0.02	0.08*
IAIGs-Other	dCAAR	-0.85	2.75	-0.32	0.22	0.48	1.05
	p-value	0.01***	0.01***	0.15	0.34	0.03**	0.05*
	Wilcoxon	0.00***	0.10*	0.00***	0.00***	0.24	0.11
IAIGs-Reins	dCAAR	-1.78	5.51	1.24	-0.14	-0.27	2.20
	p-value	0.17	0.07*	0.14	0.45	0.40	0.05*
	Wilcoxon	0.44	0.10*	0.20	0.44	0.49	0.13

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BUSINESS CYCLE AND MOTOR INSURANCE PROFITABILITY

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November 28, 2017

This article presents a structural model of the Italian motor third party insurance sector, introducing an innovative methodology to analyze and forecast premium dynamics and underwriting profitability. Long and short-run relationships between the macroeconomic environment and claims average cost and frequency are estimated using a standard time-series methodology and a specification for premiums is then obtained using the relationship between premium, claims and the risk free rate implied by several insurance pricing model. The resulting simultaneous equations model is shown to have better forecasting performance with respect to the standard approaches used to measure underwriting cycles.

JEL Classification: C51, C53, G20

Keywords: Non-Life Insurance, Underwriting cycle, Forecasting

* I wish to thank Roberto Menegato and Roberto Cannata of Assicurazioni Generali and the participants to the 2017 Ph.D Forum at the University of Bologna. Silvia Santarossa tested a simplified version of this model for her Master thesis at the University of Trieste, under my supervision. I thank her for the patience. All errors are my own.

1. INTRODUCTION

Predicting the non-life insurance underwriting cycle, i.e. the evolution of profitability over time, is a key issue for industry practitioners, regulators and academics. Protracted periods of soft market, when protection is available at low prices, are associated with low profitability and possibly a higher insolvency rate among insurers. On the other hand, the price policyholders pay in certain lines of business, especially the mandatory ones, is a very sensitive issue regulators routinely face.

Modelling the underwriting cycle is one of the most important task non-life actuaries perform and over the last three decades insurance economist have joined in the effort. The standard econometric model used to forecast profitability features a simple autoregressive structure for the variable of interest (the ratio between losses and premiums or the growth rate of premiums), at times complemented by lagged values of macroeconomic variables. No attempt is made to model the relationship between macroeconomic aggregates and claims frequency or costs, in order to build a causation chain running from the business cycle to insurance profitability. The present paper attempts to fill this gap, using aggregate data for the largest non-life line of business in the Italian market, Motor Third Party Liability (MTPL) and standard time series analysis. The aim of the paper is to introduce an innovative yet easy to implement framework companies and regulator can apply to forecast premium and profitability dynamics and to do scenario analysis for those lines of business, such as motor, where the business cycle heavily influences claims. This richer setting is shown to produce better forecasts of both premiums and profitability compared with traditional models.

The article is structured as follows. Section 2 first provides a brief review of the economic theories of the underwriting cycle and then summarizes their econometric applications. Section 3 introduces the new modelling approach. As a background for the econometric estimation, section 4 reviews the most important legislative and regulatory changes which have affected the Italian motor insurance market over the last forty years, which are susceptible to having affected the evolution of claims and premiums. Section 5 details the model estimation, first testing for the presence of long term relationships between insurance and macroeconomic variables and then modelling the short term dynamics. In section 6 I compare the forecasting ability of three models: the one estimated in Section 5, one that explicitly considers claim dynamics but does not take into account the long term relationships and the standard approach to underwriting cycles modelling, assessing their accuracy for both premium growth and profitability. The results are discussed in Section 6, together with some suggested extensions of the model. Section 7 concludes.

2. THE UNDERWRITING CYCLE: THEORY AND MEASUREMENT

The underwriting cycle in property and casualty insurance can be described as

“the alternance of soft market periods, where price and profitability are stable or falling and coverage is readily available to consumers, and subsequent hard market periods, where prices and profits increase abruptly and less coverage is available” (Harrington, Niehaus e Yu, 2013)

Insurers receive the payments from customers before incurring the costs, therefore they have to set the premium level based on an expectation of future claims and adjusting for the past forecasting errors or for large, unpredictable shocks, like a major weather event. The evolution of claims (caused mostly by factors exogenous to the insurance market, with the notable exception of changes in regulation) and the following adjustments in premiums determines the cycle.

The underwriting cycle is normally analyzed by studying the dynamics of the loss or combined ratio (the ratio of respectively claims paid and claims plus expenses to premiums collected). The inversion of the production cycle typical of the insurance industry plays a key role in shaping profitability dynamics. The seminal model is the one proposed by Venezian (1985), which concludes that cycles are created by how insurers set prices. Studying the US industry, he posits that insurers set prices based on a naïve extrapolation, as past claim costs are used to project future ones. Typically, he found that the last three years of data for claims are used to project them to up to two years into the future, and then premiums are set according to this forecast: this in itself is enough to generate cyclical patterns (of around six years of length) for the combined ratio.

Cummins and Outreville (1987), refine this model, laying the foundation for the most widely used specification. They set up a rational expectation pricing model and show that, even if insurers can optimally forecast future claims, specific contract features, reporting lags, delayed data availability and staggered contracts generate frictions which are fully responsible for the cycle. They find that the best approximation for the dynamics is an AR(2) model and derive the following empirical specification, estimated with annual data.

$$LR_t = \alpha + \beta_1 LR_{t-1} + \beta_1 LR_{t-2} + \beta_3 D_t + \varepsilon_t \quad (1)$$

Where LR is the loss ratio and D a set of time dummies. Moreover the existence of a cycle requires the following restrictions on the coefficients

$$\beta_1 > 0, \beta_2 < 0, \beta_1^2 + 4\beta_2$$

And the length of the cycle is calculated as $P = 2\pi / cos^{-1}\left(\frac{\beta_1}{2\sqrt{-\beta_2}}\right)$

This specification has been widely used to study the behavior of different line of business in one market and across countries (see for example Meier (2006) or Meier e Outreville (2010)). This type of literature find strong evidence for the AR(2) specification and cycle length varying between 4.5 and 7 years, depending on countries and lines of business.

This model is further developed by Lamm-Tennant and Weiss (1997), which suggest a slightly more sophisticated specification capable of better accommodating country or line of business-specific features. Moreover, and most importantly, they model premium growth rather than the loss or the combined ratio, allowing for more flexibility in the response of premiums to past claim evolution. They estimate the following model:

$$\Delta P_{it} = \alpha + \sum_{q=1}^{Q} \beta_q \Delta P_{it-q} + \sum_{n=1}^{N} \gamma_q X_{t-n} + \sum_{m=0}^{M} \delta_m D_{t-m} + \varepsilon_t \quad (2)$$

Where the vector X contains macroeconomic variables and lagged measures of claims growth or insurance profitability.
This model too has been extensively used to analyses premium evolution over time and for different lines of business and to measure the length of the underwriting cycle[35].

[35] For example Chen, et al. (1999) apply the methods proposed by Cummins and Outreville (1987) and Lamm-Tennant and Weiss (1997) to several Asian and European countries, finding evidence for the validity of both type of modelling.

However this somehow mechanistic approach to the cycle has attracted criticism. Boyer, Jacquier and Van Der Noorden (2012) perform a througut testing of the AR(2) specification applied to US data, finding that parameters are estimated very imprecisingly and that this type of model has a poor forecasting performance, and eventually argue against the existence of fixed length and measurable cycles. This point is further stressed by Boyer and Owadally (2015). After a meta analysis of the papers on the subject publshed over the last 30 years they conclude that “the evidence supporting the existence of underwriting cycles is misleading” and therefore argiung that insurance profitability cannot be predicted using standard econometric tools. Their criticism is the starting point of this paper, which however uses a standard econometric setting to improve the forecasting performance of the AR(2) specification.

Recently, Bruneau e Sghaier (2015) have recovered the AR(2) model using a more sophisticated econometric setting and aggregate data on the French Property and Casualty industry between 1963 to 2008. They show that the standard AR(2) specification works when capacity, defined as the ratio between financial capital to premium, is low, while when capital constraints are not binding the combined ratio is found to be related to lagged stock market. Moreover, capitalization is related to past inflation. They conclude that this evidence points to the need for solvency rules to take into account of the financial cycle when setting the capital requirements.

A few papers have tackled the issues of the long term relationships among insurance and financial variables. The most detailed application (and closest in spirit to the analysis presented below) is the one by Lazar and Denuit (2011). They consider the aggregate US Property and Liability sector and, using different econometric techniques, document that premiums have a positive long run relationship with losses and GDP and a negative one with short-term real interest rates. Looking at several developed economies, Bruneau et al.(2009) found long term relationships and strong evidence of nonlinearity in the adjustment to equilibrium between non-life premiums and financial variables: in particular, they found a positive relationship with the stock exchange and a negative one with short term interest rates.

The last two papers uncover statistical facts and in the latter case, relate them to financial pricing models but do not seek to provide any explanation on the linkages between the business and underwriting cycle. Importantly, no structural explanation is provided for the positive relationship between the business cycle and premium dynamics.

3. MODELLING CLAIMS AND PREMIUMS TOGETHER

This paper attempts to reproduce with time series econometric tools what non-life actuaries routinely do in order to price contracts: getting an estimate of the costs the company is expected to incur over the duration of the contract and set its price accordingly. Therefore, I first derive a forecast for claims, based on macroeconomic variables and then relate it to premiums using a simple pricing model.

I use aggregate 1976 to 2015 annual data for the Italian MTPL line of business, for which series on claims frequency and the average cost of claims are available. They are related to overall losses by the following identity

$$LO_t = FR_t * AC_t * STOCK_t$$

With LO, total losses paid to claimholders, FR claims frequency, AC average costs and STOCK the number of insured vehicles.

On the claim side, when individual data are available frequency and severity are generally modelled jointly using information such as age, gender, type of car, etc.,. with cross section models. Count data or logistic specifications normally employed[36]. Of course these models are of little use in estimate the aggregate behavior over time, and in the specification I simply assume that

- The probability of having an accident (frequency) is related to on how intensively vehicle are used, which is in turn a function of economic activity and the cost of fuel. I also consider the technological improvement in vehicles which has increased their safety. Moreover, driving behavior is also influenced by rules and therefore I take into accounts the evolution of traffic laws.
- The severity is assumed to be a function of the labor costs in the repairing sectors and of the quality of the stock of vehicles, with a larger share of newer ones leading to higher costs. Admittedly the choice of variables does not consider bodily injuries. During the period considered, their costs were by and large decided in courts, with large differences across provinces. However, the overall good fit of the model shows that the covariates chosen are sufficient. I consider also the evolution of the traffic laws.
- For premiums, I consider as regressors the evolution of claims and the short term interest rate. This choice is motivated by several theories of non-life insurance premiums: from the simplest one, in which premiums reflect the discounted value of expected losses, plus expenses and a risk premium, to the extension of the CAPM model to the non-life insurance business, first introduced by Cooper (1974), described below[37].

Premiums for period t are collected in t-1 and pays for losses at t (whose amount is clearly not known at t-1). Insurer's net income (Y) is the sum of underwriting income (U), derived from the insurance activity, investment income (I) derived from investing premiums between collection and claims payment. We have then

$$Y_t = U_t + I_t \qquad (1)$$

Underwriting income is the difference between premiums earned[38] (P), losses (L) and expenses (S). Assuming that administrative expenses and commissions to intermediaries (s) are proportional to premiums we have.

$$U_t = P_t - L_t - S_t = (1-s)P_t - L_t \qquad (2)$$

This can be redefined as

$$U_t = r_t^U P_t \,, r_t^U \equiv \frac{U_t}{P_t} = \frac{[(1-s)P_t - L_t]}{P_t} \qquad (3)$$

Where r_t^U is the underwriting return.

Total return, which equals the return on equity, is then

$$Y_t = U_t + I_t = r_t^U P_t + r_t^A A_t = r_t^E E_t \qquad (4)$$

Where A is total asset r_A return on asset, r_E the return on equity and E equity

[36] See, for example Yip e Kelvin (2005) on frequency and Ayuso et al. (2007) on severity.
[37] See also Cummins and Phillips (2000) and Hun Seog (2010), chapter 15.
[38] I abstract here from reinsurance activity, which plays a minor role in motor lines

Using the balance sheet identity $A_t = R_t + E_t$, and under the simplifying assumption that insurers' liability are just composed of loss reserves and equity[39], (4) can be solved for the return on equity to get

$$r_t^E = r_t^U \frac{P_t}{E_t} + r_t^A \left(\frac{P_t}{E_t} \frac{R}{P_t} + 1 \right) \qquad (5)$$

Using the CAPM formula and taking expectations, the returns on equity and assets can also be written as

$$Er_t^E = r_t^f + \beta_E \left(Er_M - r_t^f \right) \quad (6)$$

$$Er_t^A = r_t^f + \beta_A \left(Er_M - r_t^f \right) \quad (7)$$

Combining (5), (6) and (7), and solving for the expected underwriting return I get

$$Er_t^U = -\frac{P_t}{E_t} r_t^f + \beta_U \left(Er_M - r_t^f \right) \ (8)$$

From the definition of underwriting return shown in (3), taking expectations and assuming that the underwriting risk premium $\beta_U \left(Er_M - r_t^f \right)$ is constant and equal to B I get an equilibrium relationship for the level of premiums.

$$P_t = \frac{EL_t}{\left[(1-s) + r_t^f - B \right]} \qquad (9)$$

Therefore this simple model posits a positive relationship between premium and expected losses and a negative one with the risk free rate.

Of course, there are shortcomings in both the theoretical model and the application.

- First of all the model shares all the known limitations of the standard CAPM, but as suggested by Cummins and Phillips (2000) the extension to multi-factor models should be straightforward. This is left for future research.
- Secondly, the Insurance CAPM is a one-period model, and in principle it is not suitable for long-term insurance contracts: however, given that MTPL contracts are by law annual this is probably a minor nuisance in the present context.
- Additionally, theoretical and empirical analysis have shown that default risk, and more broadly capitalization can play an important role in pricing (see for example, Cummins and Danzon, 1997), and CAPM pricing does not take into account these factors. However, the impact of capitalisation on pricing is more likely to be seen when considering individual firms, due to idiosycratic choices in terms of market positioning and pricing and overall efficiency. The overall level of capitlisation is (should be) kept in check by regulation and should not affect average prices.
- A more damaging (at least theoretically) objection is that while CAPM assumes that assets are tradable (Hun Seog 2010, chp. 15), while motor insurance liabilities are mottly not tradable given the limited use of reinsurance.

However all these objections must be weighted against the intuitive nature of the model and its ability to fit the data relatively well.

[39] Debt issuance is very limited in non-life insurers, and normally used just for M&A activity.

Based on the observation of actual ratemaking, I assume that insurers have partially adaptive expectations, i.e. they set prices based on average between the expected level of claims in the current and next year and on what happened in the previous one, as they try to smooth out large fluctuations in claims (due, for example of particularly bad weather) in order not to have too much volatility in premiums. In the empirical application I set as expected claims their average[40]. Therefore expectations are, at least partially rational (model consistent) in the spirit of Cummins and Outreville (1987).

During the period I consider, the Italian motor insurance market went to some regulatory reforms which affected pricing ad need to be considered in the empirical model. They are summarized in the following section, along the changes in the traffic laws.

4. Key Reforms to traffic Laws and MTPL insurance Regulation

Motor Third Party Liability (MTPL) insurance, is not only the largest non-life line in Italy accounting for over 40% of total non-life premiums, but also, being this cover mandatory, the most heavily regulated. Moreover, claim dynamics is clearly affected by the impact of the road safety legislation. The most important are the following:

- Price liberalization. In 1994 the system of state planned rates for MTPL was dismantled following the EU Single Market Directive.
- Reforms to the traffic laws ("Codice della Strada") enacted in 1992 and 2001, with the most important provisions coming into force over the following years, including
    - Stricter speed limits (1992) and steeper penalties for drunk driving
    - Change in penalty system (2001). A new system penalty system for traffic offence was introduced. Each driver receives twenty "points", which are lost in case of offences. If all points are lost the license is revoked.
    - Mandatory installation of ABS on all new vehicles (2001)
- Direct compensation (2007): in case of damages to the vehicles and small bodily injuries, the claimant is refunded by the company with which she is insured. This company will in turn receive from the one covering the responsible of the accident a fixed reimbursement, based on the historical average cost of claims. The measure is aimed at controlling claim costs and speeding up and simplifying settlement.
- Change in the "Bonus malus"[41] system (2007). Each driver is allocated to a class according to its past claims history: after two year without accident she moves to a lower risk class. From 2008 on all persons living in the same household were allowed take the class of its less risky member, with a corresponding decline in premium paid (for example a driver in their 20s took the risk class of her parents). This led to a large migration of drivers into the two lowest risk classes and a corresponding fall in premiums. However, as premiums no longer reflected the true risk, the deterioration in technical results led to a repricing over the following two years.

Figure 1 plots claims frequency, the average cost and two measures of the underwriting cycle, the loss ratio (total compensations as share of premiums) and the growth rate of premiums alongside the time of the key reforms.

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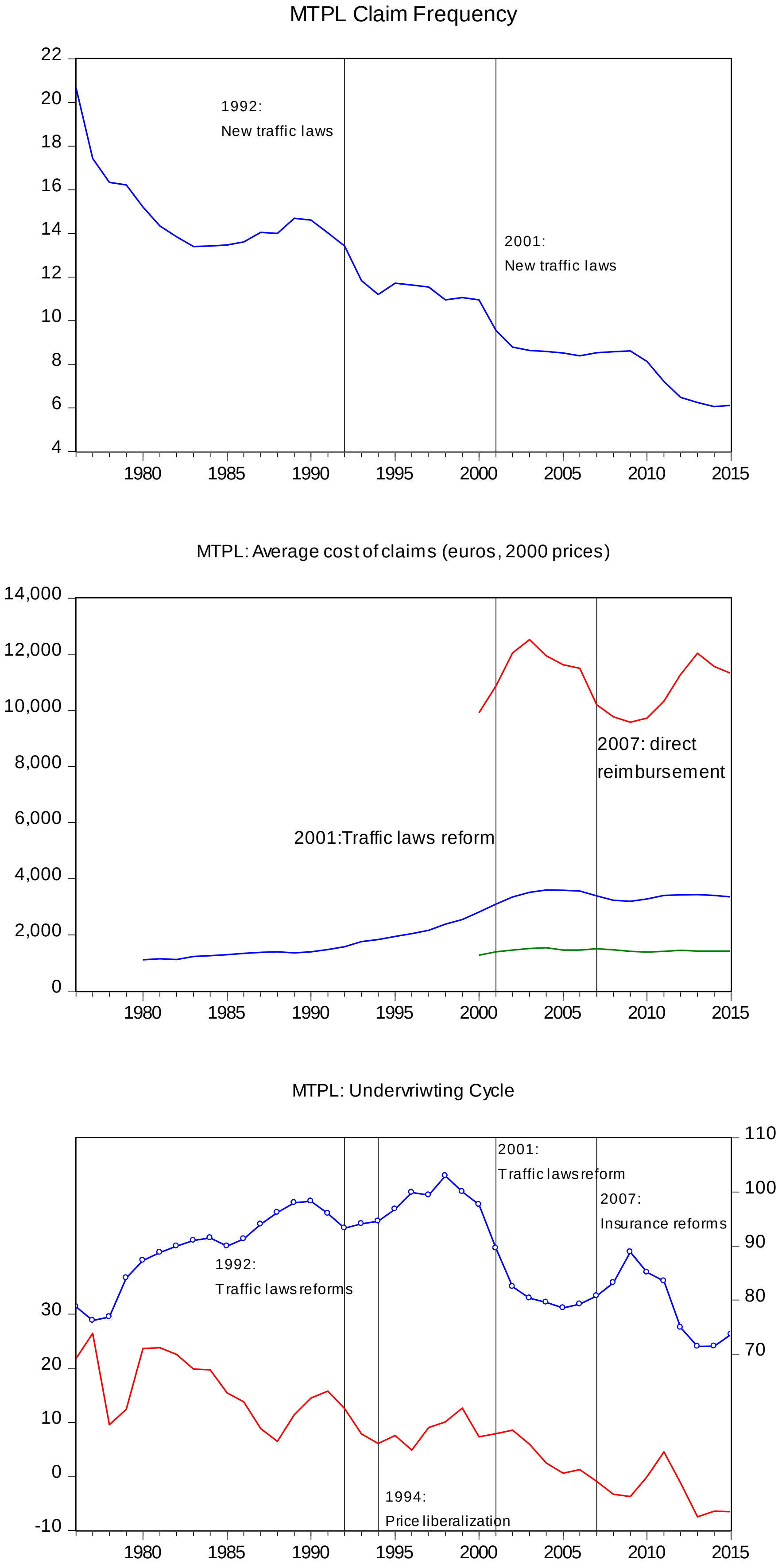
[40] The use of lagged value of losses tries also to account for incurred but not reported claims, which can be paid years after they have been sustained.
[41] No fault

Figure 1: Motor Third Part Liability Insurance



5. MODEL STRUCTURE, DATA, AND ESTIMATION METHOD

In order to model premiums and losses I employ a standard simultaneous equations approach, whose use is widespread in macroeconomics but has enjoyed only a limited popularity in finance[42] The empirical model used for the simulations consists of three estimated equations and an identity (see table 7 for a detailed representation of the model and the alternative ones used in the forecast comparison):

- An equation for claims frequency: here I relate frequency to economic activity (real GDP) as a proxy for car usage, its cost (the real price of fuels[43]), a linear trend, capturing technological progress increasing vehicle security and (just possibly) better driving skills. The 1992 and 2001 traffic law reforms are considered in the form of two step dummies. Only the latter is statistically significant.
- An equation for the average cost of claims (deflated by CPI). Ideally one would model separately bodily injuries and vehicle damages as the former are often compensated after a court sentence; in the period considered each court (and sometimes judge) had its own way to assess the extent of the compensation. However, the breakdown is available only from 2000. I take real wages as a proxy for the gauge used to settle bodily injuries compensation and the labor costs needed for repairing and a proxy for the average quality of the vehicle stock, constructed as the share of vehicles less than four year old in the total, under the implicit assumption that newer cars are more costly to repair[44]. I also consider the dummies for the 2001 traffic laws reforms and for the 2007 introduction of direct compensation. Based on the results of the AIC tests, I retained a model with a just linear trend.
- An equation for premiums (expressed in real terms and divided by the stock of vehicles), as a function of the yield on 3-month government bonds and the moving average of total losses (real, per vehicle). In the short term equation I added the output gap, to test the cyclical properties of the markup[45].
- An identity relating total claims (L) with frequency (FR), average cost (AC) and the stock of vehicles in circulation (VE) treated as exogenous[46].

As an initial step the order of integration of the insurance variables is established using a standard Augmented Dickey Fuller test, allowing for a break. The results (shown in Appendix A) point to all processes being I(1), with some less clear cut results for frequency especially when a specification including a linear trend is considered.

[42] See Dreger and Marcellino (2007) for a macroeconomic example, Casolaro and Gambacorta (2004) for a model of the Italian banking system and Cummins (1973) for an early application of simultaneous equations models to life insurance.
[43] Computed as the price of gasoline and diesel fuel, weighted by consumption
[44] Price indexes for spare parts and car repair are available only from 1999.
[45] The relationship between demand fluctuations and oligopoly was first explored theoretically by (Rotheberg & Saloner, 1986). For a macroeconomic angle on the relationship between the business cycle and price markups see, for example Galí, Gertler, & López-Salido (2000), Blanchard (2008) and Nekarda and Ramey (2013).
[46] A simple model, relating macroeconomic variables to vehicle registrations and cancellations, thus capable to project the size of the stock can be easily appended, but it is not the focus of this paper.

Given the evidence of nonstationary in the insurance variables, the model consists of a set of three equations specified as error correction models, in which short term fluctuation depend also (and crucially) on the deviation of the past value of the dependent variables from its equilibrium value.

Therefore I look for long term relationship between the variables. There are several possible options for testing for their existence and modelling them. I chose the methodology developed by Pesaran et al. (2001). I prefer it over others for several reasons:

- Monte Carlo simulations have shown that it delivers more reliable results in terms of exsitence of cointegrating vectors whan the sample is short (Haug, 2002). However, as a robustness check, I consider also the result of a Dynamic OLS estimation (Stock e Watson, 1993).
- It does not restrict all the series to be I(1) and this is relevant given the mixed evidence on claims frequency
- It allows some flexiblity in the choice of the lag structure of the dependent variable and the covariates (as opposed to the Johansen-Joselius VAR methodology or Stock and Watson's DOLS)

Finally, once the existence of long term relationships is established, a standard ECM specification is estimated separatedly for each variable in order to assess the model properties. Finally, the three equations are estimated jointly with standard three step least squares to produce the model.

5.1 Long term relationships

Tables 1 to 3 present the results of the ARDL estimation: the long term coefficients[47] for the covariates and the results of the bound tests and the coefficient on the error correction term which measures the speed of the adjustment toward the equilibrium after a shock. The asymptotic critical values are provided alongside the finite sample ones proposed by Narayan (2004). The F-statistic is well above the I(1) bound indicating that the hypothesis of no long run relationship is strongly rejected. Moreover, the signs of the covariate are in line with expectations.

As a robustness check I estimate the same models using Stock and Watson (1993) Dynamic OLS, and test for cointegration using the Engle and Granger and Philips and Oularis tests. The results, shown in Appendix B, confirm the evidence of the expected long run relationships.

[47] Note that the coefficients for static regressors (like to step or level dummies introduced to account for legislative reforms) are not computed. They are duly introduced in the short term specification.

TABLE 1: Long run relationship
Dependent variable: claim frequency
Sample 1976 – 2015

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Real fuel prices (log)	-0.019	0.008	-2.349	0.026
Real GDP (log)	0.090	0.021	4.197	0.000
Linear Trend	-0.001	0.000	-3.025	0.005

Serial Correlation: 0.003 [0.99] Heteroskedasticity: 1.220 [0.323]

Cointegrating vector
EC = FR_RCA - (-0.019*LOG(RPCARB) + 0.090*LOG(GDPR) -0.001*t)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	8.637513	5%	3.88	4.61
K	2	1%	4.99	5.85
		Finite Sample: n=40		
Actual Sample Size	40	5%	4.36	4.61
		1%	5.98	6.973

TABLE 2: Long run relationship
Dependent variable: Average cost of claims (deflated with CPI)
Sample 1976 – 2015

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Real wages (log)	1.705	0.839	2.031	0.053
% of <4 year old cars	0.061	0.018	3.278	0.090
Linear Trend	0.076	0.031	2.441	0.022

Serial Correlation: 1.206 [0.314] Heteroskedasticity: 1.229 [0.290]

Cointegrating vector
EC = Log(RAC) - (1.705*LOG(RWAGE) + 0.061*LOG(%NEWC) -0.076*t)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	6.400	5%	3.88	4.61
		1%	4.99	5.85
K	2			
		Finite Sample: n=40		
Actual Sample Size	40	5%	4.36	4.61
		1%	5.98	6.973

TABLE 3: Long run relationship
Dependent variable: Average real unt premiums
Sample 1976 – 2015

Variable	Coeff.	Std. Error	t-Statistic	Prob.
T-Bill Rate	-0.026	0.007	-3.389	0.002
ClaimsAverage	0.873	0.055	15.872	0.000
Constant	-0.027	0.051	-0.526	0.603

Serial Correlation: 1.214 [0.313] Heteroskedasticity: 1.430 [0. 232]

Cointegrating vector
EC = Log(RUPR) - (--0.026*TBOT + 0.873*LOG(RUCL) -0.027)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	4.96437	5%	3.1	3.87
K		1%	4.13	5.00
			Finite Sample:	
Actual Sample Size	40		n=40	
		5%	3.435	4.26
		1%	4.77	5.855

5.2 *Short Term Dynamics*

The three equations do not have endogenous regressors, as the business cycle and interest rate are not affected by the dynamics of the motor insurance market, so the short term dynamics can be estimated simply via OLS applied to individual equations. However, for robustness system 3SLS estimation is performed too and the results (which are not markedly different from the OLS ones) are used to build the simulation model.

Tables 4 to 6 present the results and some specification tests. A few comments are in order. Firstly the error correction terms are in all the three cases correctly signed and statistically significant, adding to the evidence of the cointegration analysis: however their magnitude is rather low, indicating quite a slow return to equilibrium after a shock. The strength of the short term impact of the covariates varies across equations. It appears quite strong in the frequency equation and much less so in the claim equation. Tighter traffic laws seem to have played a role in reducing both claims frequency and severity and direct compensation contributed to lower claim costs. The premiums equation has some interesting features. First of all, the specification tests lead to an AR(3) structure, indicating, together with the relatively low value of the coefficient associated to the error correction term, a rather high level of persistence in the series. Moreover, premiums are shown to adapt quite quickly to changes in claims growth and there is an evidence of procyclical markup over compensation costs. Finally, the 2007 reform of the way MTPL contracts are priced was effective in lowering premiums.

TABLE 4: Short Term relationship
Dependent Variable: Claim frequency (annual change) D_FR
Method: Least Squares
Date: 08/07/17 Time: 16:43
Sample (adjusted): 1977 2015
Included observations: 39 after adjustments
HAC std. errors & covariance

Variable	Coeff	Std. Error	t-Statistic	Prob.
Constant	-6.343	2.136	-2.969	0.006
Change in frequency (-1)	0.238	0.122	1.952	0.061
Fuel price growth	-0.013	0.005	-2.309	0.029
Real GDP growth	0.139	0.043	3.254	0.003
Error Correction term (-1)	-0.217	0.075	-2.910	0.007
Traffic laws dummy	-1.667	0.368	-4.534	0.000
2009 dummy	0.823	0.370	2.223	0.035

Adjusted R-squared	0.718	Mean dependent var	-0.259
S.E. of regression	0.340	S.D. dependent var	0.489
F-statistic	7.092	Durbin-Watson stat	2.128
Prob(F-statistic)	0.000	RESET[1] p-val.	0.652
Serial correlation, p-val.	0.217	Hetersch., p-val	0.965198

TABLE 5: Short Term relationship
Dependent Variable: Average cost (annual % change)
Method: Least Squares
Sample (adjusted): 1977 2015
Included observations: 38 after adjustments
HAC std errors & covariance

Variable	Coeff	Std. Error	t-Statistic	Prob.
Constant	0.106	0.031	3.441	0.002
Avg. Cost growth(-1))	0.424	0.168	2.531	0.018
Avg. Cost growth -2))	0.182	0.105	1.740	0.094
D(% of <4 year old vehcles)	0.545	0.281	1.942	0.064
Error correction term	-0.058	0.029	-2.008	0.056
2001 Traffic laws dummy	-0.043	0.014	-2.982	0.006
Direct Refund dummy	-0.053	0.007	-7.195	0.000

Adjusted R-squared	0.737	Mean dependent var	0.066
S.E. of regression	0.0260	S.D. dependent var	0.050
F-statistic	15.479	Durbin-Watson stat	1.714
Prob(F-statistic)	0.000	RESET[1] p-val.	0.091
Serial correlation, p-val.	0.280	Heterosch., p-val	0.324

TABLE 6: Short Term relationship
Dependent Variable: Real premiums per vehicle (% growth)
Method: Least Squares
Sample (adjusted): 1977 2015
Included observations: 38 after adjustments
HAC std errors & covariance

Variable	Coeff	Std. Error	t-Statistic	Prob.
Real premium growth(-1)	0.376	0.169	2.223	0.035
Real premium growth(-2)	0.131	0.115	1.148	0.261
Real premium growth(-3)	-0.159	0.084	-1.906	0.067
Real claims growth	0.440	0.153	2.884	0.008
D(T-bill rate)	-0.005	0.002	-1.992	0.057
Output Gap	0.005	0.002	2.065	0.049
Error Correction Term(-1)	-0.266	0.082	-3.244	0.045
Insurance reform dummy	-0.047	0.006	-7.241	0.000

Adjusted R-squared	0.878	Mean dependent var	0.041
S.E. of regression	0.022	S.D. dependent var	0.062
Serial correlation, p-val		Durbin-Watson stat	2.135
Heterosch., p-val		RESET[1] p-val.	0.732

5. *FORECASTING PERFORMANCE*

Once the statistical properties of the model are assessed, it is possible to answer to the key question of the paper, i.e. whether modelling explicitly losses leads to a better forecasting of premium dynamics and profitability. I evaluate the model presented above based on its capability to forecast premium growth and the loss ratio one to three year ahead. To this end I estimate it and the alternative ones first between 1976 to 2008 and produce an out of sample forecast, then I add one year and repeat the process.

As far as premium growth is concerned I compare the prediction of the structural model with:

1) The structural model, estimated without considering the log term relationship: Clements and Hendry (1995) have shown that a bad speficiation of the long term relationship may lead to less accurated forecasts compared with a simple model in differences.
2) A single equation model for premium growth based on Lamm-Tennant and Weiss (1997), i.e. a AR(2) model with added regressors like the short term rate the output gap, lagged values of the loss ratio and the dummies for the legislative reforms. At any date the added regressors and their lags are chosen as to minimize RMSE.
3) A single equation AR(2) model for the loss ratio, augmented by the dummy for the insurance market and traffic laws reforms.

Table 7 summarizes the models I compare.

TABLE 7: forecasting models

Model A: Structural model with long term relationships

$$D(FR_t) = \alpha^1 + \sum_{i=1}^{I} \beta_i^{11} D(FR_{t-i}) + \sum_{j=0}^{J} \beta_j^{12} dlog\big(GDPR_{t-j}\big) + \sum_{p=0}^{P} \beta_p^{13} dlog(\,RPF_{t-p}) + \delta^1(FR_{t-1} - FR^*_{t-1}) + \theta^1 D_t^{Traffic}$$

$$\begin{aligned} Dlog(AC_t/P_t) = \alpha^2 \\ &+ \sum_{i=1}^{I} \beta_i^{21} dlog(AC_{t-i}/P_{t-i}) + \sum_{j=0}^{J} \beta_j^{22} dlog(LC_{t-i}/P_{t-i}) + \sum_{i=0}^{I} \beta_i^{23} d(VQ_{t-i}) \\ &+ \delta^2\big(log(AC_{t-1}/P_{t-1}) - \log(AC_{t-1}/P_{t-1})^*)\big) + \theta^2 D_t^{Traffic} \end{aligned}$$

$$\begin{aligned} Dlog\left(\frac{PR_t/P_t}{STOCK_t}\right) = \alpha^3 \\ &+ \sum_{i=1}^{I} \beta_i^{31} dlog\left(\frac{PR_{t-i}/P_{t-i}}{STOCK_{t-i}}\right) + \sum_{i=-1}^{I} \beta_i^{32} dlog\left(\frac{LO_{t-i}/P_{t-i}}{STOCK_{t-i}}\right) + \sum_{i=0}^{I} \beta_i^{33} d(TB3_{t-i}) + \sum_{q=0}^{Q} \beta^{34} YGAP_{t-q} \\ &+ \delta^3\left(log\left(\frac{PR_{t-1}/P_{t-1}}{STOCK_{t-1}}\right) - \left(\frac{PR_{t-1}/P_{t-1}}{STOCK_{t-1}}\right)^*\right) + \theta^3 D_t^{Ins} \end{aligned}$$

$$LO_t = FR_t * AC_t * STOCK_t$$
$$LR_t = 100 * \frac{LO}{PR}$$

“*”Indicates the long term value of the variable, given by the cointegrating vector

Model B: Structural model with no long term relationships

$$D(FR) = \alpha^1 + \sum_{i=1}^{I} \beta_i^{11} D(FR_{t-i}) + \sum_{j=0}^{J} \beta_j^{12} dlog\big(GDPR_{t-j}\big) + \sum_{p=0}^{P} \beta_p^{13} dlog(\,RPF_{t-p}) + \theta^1 D_t^{Traffic}$$

$$Dlog(AC/P) = \alpha^2 + \sum_{i=1}^{I} \beta_i^{21} dlog(AC_{t-i}/P_{t-i}) + \sum_{j=0}^{J} \beta_j^{22} dlog(LC_{t-i}/P_{t-i}) + \sum_{i=0}^{I} \beta_i^{23} d(VQ_{t-i}) + \theta^2 D_t^{Traffic}$$

$$\begin{aligned} Dlog\left(\frac{PR_t/P_t}{STOCK_t}\right) &= \alpha^3 + \sum_{i=1}^{I} \beta_i^{31} dlog\left(\frac{PR_{t-i}/P_{t-i}}{STOCK_{t-i}}\right) + \sum_{i=-1}^{I} \beta_i^{32} dlog\left(\frac{LO_{t-i}/P_{t-i}}{STOCK_{t-i}}\right) + \sum_{i=0}^{I} \beta_i^{33} d(TB3_{t-i}) + \sum_{q=0}^{Q} \beta^{34} YGAP_{t-q} \\ &+ \theta^3 D_t^{Ins} \end{aligned}$$

$$LO_t = FR_t * AC_t * STOCK_t$$
$$LR_t = 100 * \frac{LO}{PR}$$

Model C: Lamm-Tennant (1997)

$$\begin{aligned} Dlog\left(\frac{PR_t/P_t}{STOCK_t}\right) &= \alpha^{PR} + \sum_{i=1}^{I} \beta_i^{PR} dlog\left(\frac{PR_{t-i}/P_{t-i}}{STOCK_{t-i}}\right) + \sum_{i=0}^{I} \beta_i^{LO} dlog(GDPR_{t-i}) + \sum_{i=0}^{I} \beta_i^{TB} d(TB3_{t-i}) + \sum_{q=1}^{Q} \theta_q^{LR} \frac{LO_{t-q}}{PR_{t-q}} \\ &+ \theta^{TR} D_t^{Traffic} + \theta^{IN} D_t^{Ins} \end{aligned}$$

Model D: AR(2) for the Loss Ratio

$$LR_t = \alpha^{LR} + \sum_{i=1}^{2} \rho_i\, LR_{t-i} + +\theta^{TR} D_t^{Traffic} + \theta^{IN} D_t^{Ins}$$

Insurance market variables:
FR: claims Frequency, AC: average cost of claims, PR: MTPL premiums, LO: total claims expenditure, LR: Loss Ratio
Macroeconomic/Financial Variables:
GDPR: Real GDP, RPF: fuel prices deflated by CPI, P: CPI , VQ: share of less than 4our year old cars in the total (proxy for vehicle quality) , STOCK: registered vehicles, TB3: yield on 3 month government bills, YGAP: Output gap
Dummies:
$D^{Traffic}$: dummies for the 1992 and 2001 traffic law reforms. D^{Ins}: Step dummies for the 2007 direct remburement regulation and the 2008 Bonus malus reform

Tables 8 and 9 compare the 1 to 3 year ahead forecasts for the premium level and the loss ratio. Given the relatively short sample I measure the performance using simple metrics like RMSE or Theil's Us, as other metods like the Diebold and Mariano's one are too data intensive.

Table 8: forecast comparison for premium levels
The numbers in bold indicate the best performance according to the measure

	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
1-year ahead						
Baseline	586189.9	**436361.3**	**2.611**	**2.566**	0.018	0.628
In difference	**530422.8**	488855.7	2.939	2.935	**0.016**	**0.584**
AR(2)	685722.4	607267.1	3.610	3.595	0.021	0.805
2-year ahead						
Baseline	1043428	**878705.7**	**5.500**	**5.319**	**0.030**	1.240
In difference	**996896.9**	948557	5.821	5.835	0.031	**1.210**
AR(2)	1741983	1462634	8.794	8.652	0.053	1.995
3-year ahead						
Baseline	1685560	**1264462**	8.274	**7.802**	0.051	2.066
In difference	**1469476**	1264579	**7.736**	7.833	**0.046**	**1.684**
AR(2)	2617916	2311133	14.573	14.101	0.079	2.981

Table 9: forecast comparison for the loss ratio
The numbers in bold indicate the best performance according to the measure

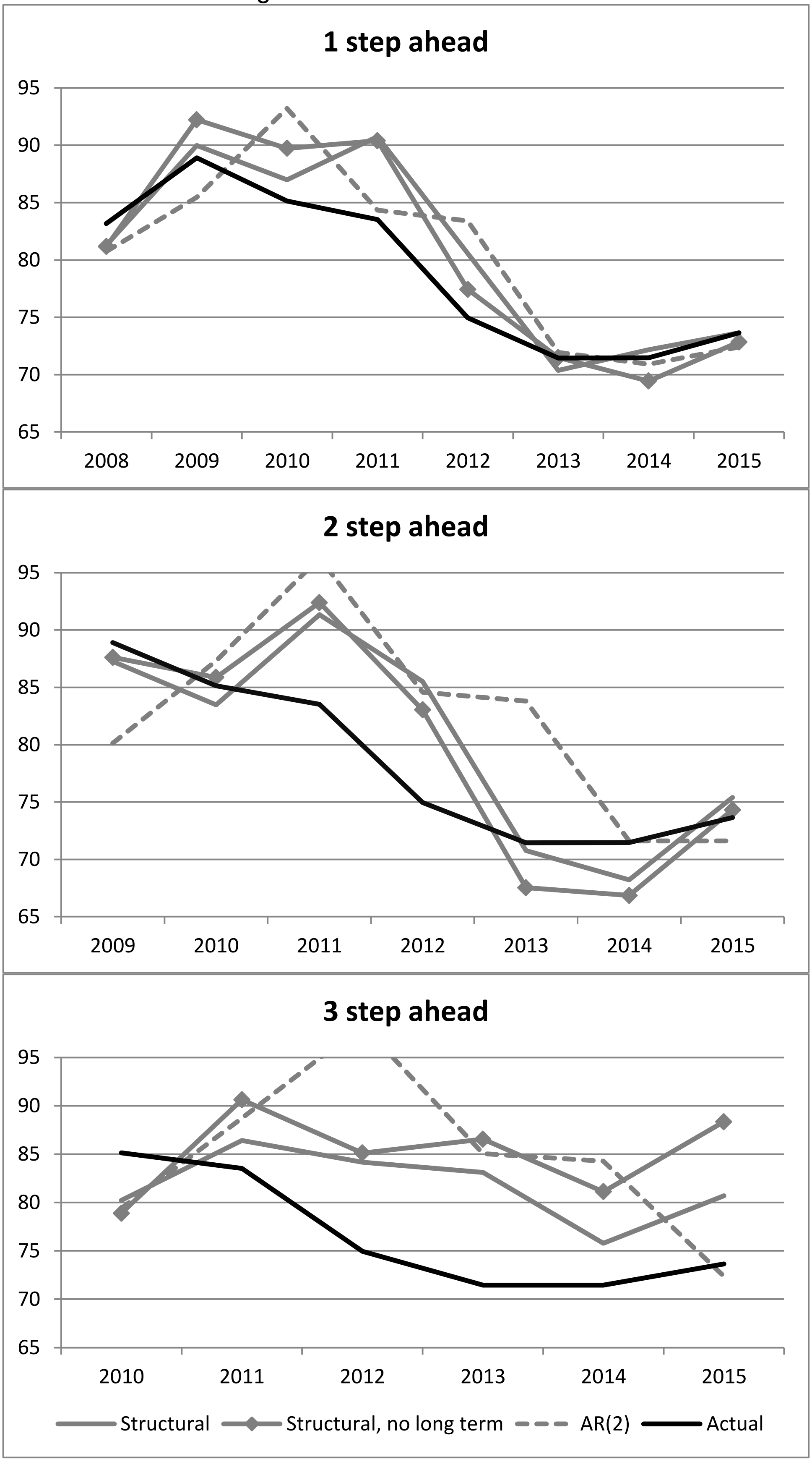
	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
1-year ahead						
Baseline	**3.423**	**2.435**	**3.043**	**2.964**	**0.021**	0.784
In difference	3.432	2.767	3.382	3.317	0.021	**0.782**
AR(2)	4.434	3.190	3.963	3.850	0.028	1.004
2-year ahead						
Baseline	5.241	**3.909**	**5.018**	**4.842**	0.033	1.319
In difference	**5.119**	4.023	5.221	5.119	**0.032**	**1.314**
AR(2)	8.402	6.839	8.687	8.299	0.052	2.017
3-year ahead						
Baseline	**7.331**	**6.686**	**8.924**	**8.516**	**0.046**	**1.907**
In difference	11.038	10.502	14.011	13.074	0.068	2.962
AR(2)	12.651	10.348	13.828	12.612	0.078	3.247

RMSE: Root Mean Squared Error,
MAE: Mean Absolute Error,
MAPE: Mean Absolute Percentagne Error,
SMAPE: Synthetic Mean Absolute Percentagne Error

A full model with premiums and claims responding to macro variable is superior to a model with just premiums, while the evidence of the usefulness of the long term relationship is less clear cut. What stands out is that including a projection of current and one step ahead losses in the equation for premium, growth improves the forecasting performance.

Figure 2 compares the forecasts for the Loss ratio at different horizons, showing how the structural model is better capable of spotting the turning points in profitability.

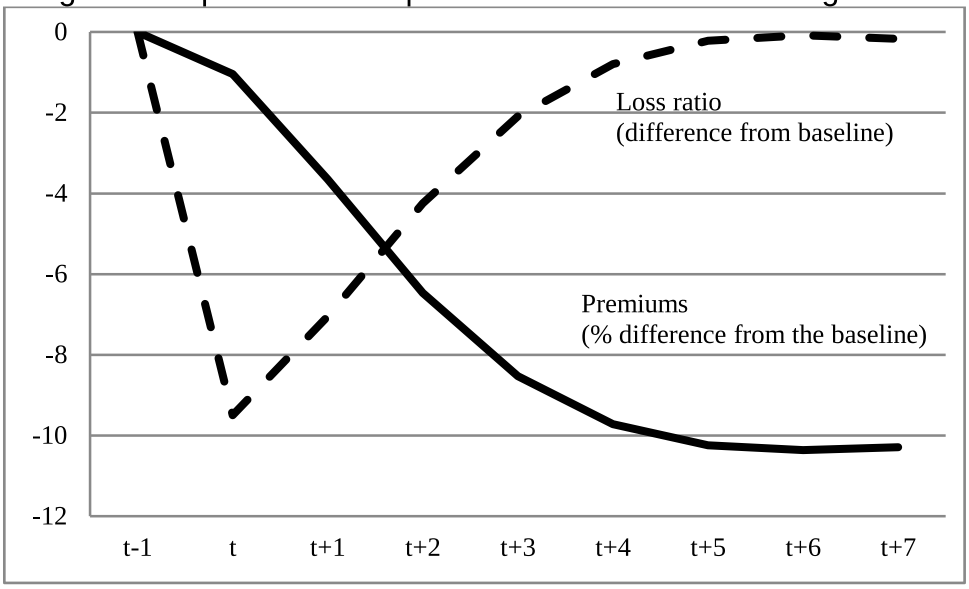
Figure 2: Loss ratio forecasts



6. Discussion

The model just shown can be used to forecast the evolution of premiums and of profitability given a set of macroeconomic projections and to conduct simple scenario analyses on how fast the motor insurance market reacts to shocks. For example, Figure 3 shows the impact of a 10 percent permament and unanticipated decrease in average claims costs, highlighting a relatively slow path of premium adjustement.

Figure 3: impact of a 10% permanent decrease in average costs



Of course this modelling framework is not exempt from drawbacks.

The use of aggregate data may hamper the identification of important factors such as the ongoing change in the market structure, as it is likely that, for example concentration affects the premium markup. The same applies to distribution channels, as far as the impact of online sales is concerned.

Another possible improvement in the model, which was prevented in this paper by the absence of data, could be to consied also stock variables (like insurance provisions and capital) in the model. Bruneau, et al. (2009) show that, for the French non-life sector as a whole, the loss ratio has a stable relationship with the degree of capitalization in the industry. This could be very useful to assess the impact of very large shocks and, in line with what proposed by Bruneau and Sghaier (2015), to integrate macroeconomic conditions into the asessment of capital requirements, using a framework with a detialed description of how shocks are transmitted from the technical account to the balance sheet.

The absence of good long term series on administrative expenses and commissions prevented the modelling of the combined ratio, which is in principle straightforward, as a long term relationship between these expenses and wages/prices is likely. This could be useful for assesing to what extent and at which hspeed changes in non-claims related expenses are passed through to consumers. In principle the model could be further expanded to arrive to a full fledged model of the technical accounts of a specific line of business. This modelling approach appears particularly suitable for line of business that are higly responsive to the business cycle, like motor. A useful extension would be to other quantitatively important lines like home insurance.

This framework could be applied on company data, resultin in an important tool for planning and stress tests. At the same time this approach could be used by insurance and competition regulators to monitor and project profitability and overall soundness of different non life lines of business.

In terms of model specification, another important issue would be to use the cointegration framework to assess to what exent the adjustment of premium to losses is nonlinear[48] or asymmetric, i.e. whether premiums converge to the long term equilibium values faster when they start below or above that or whether the speed adjustment depend on macroeconomic or financial conditions.

Finally, the model illustrated in the paper has also something to say about whether cycles exists or not and ther length can be measured. Most of the evidence in favor or against fixed length cycles is based on reduced form equations for the loss ratio. The modelling approach outlined in this paper innovates on the subject by investigating separately the determinants of the loss ratio and shows that a cyclical pattern emerges as a reaction of the system to external shock, and the speed of adjustment to the equiibrium plays a key role. This weakens the case for regular underwiting cycles.

7. Conclusion

This paper presents a framework for the modelling of premium and profitability dynamics in motor insurance. It builds on the existing applied literature on the underwriting cycle and introducing an explicit modelling of claims frequency and average costs. The resulting simultaneous equation model, applied to the Italian MTPL line of business, is shown to provide more accurate forecasts for premium growth and the loss rate with respect to standard single equation specifications.

The methodology could be extended fruitfully by applying panel cointegration techniques. The influence of the business cycle on the technical account could be analyzed at different levels for example:

- Using data on companies it is in principle possible to assess the speed at which individual entities respond to shocks and to spot common patterns in pricing not necessarily justified by the evolution of claims.
- With data at the local level, to assess the extent of within country mutualization
- A breakdown by line of business could inform about cross sector subsidizing.

This is left for future research.

[48] See Fredj et al. (2009) for evidence of non-linearity between non-life premiums and GDP based on a cointegration framework

APPENDIX A: UNIT ROOT TESTS

Without breaks

Levels	Constant p-value*	Constant & Trend p-value*
Frequency	0.7366	0.0561
Real Average Cost	0.6026	0.4682
Real Unit Premiums	0.4719	0.9989

1st Difference	Constant p-value*	Constant & Trend p-value*
Frequency	0.0057	0.0290
Real Average Cost	0.0997	0.2023
Real Unit Premiums	0.1167	0.0713

With Breakpoint

Level	Constant		Constant & Trend	
	p-value*	Break Date	p-value*	Break Date
Frequency	0.7591	2000	0.0407	1992
Real Average Cost	0.0769	1990	0.8908	1999
Real Unit Premiums	0.0630	2009	>.99	1998

*Vogelsang (1993) asymptotic one-sided p-values.

1st Difference	Constant		Constant & Trend	
	p-value*	Break Date	p-value*	Break Date
Frequency	0.106	1993	0.3083	1993
Real Average Cost	0.2663	2004	0.1077	1997
Real Unit Premiums	<0.01	2004	0.0259	1999

*Vogelsang (1993) asymptotic one-sided p-values.

APPENDIX B: ALTERNATIVE COINTEGRATION TEST (DOLS)

Frequency
Dependent Variable: FR_RCA
Method: Dynamic Least Squares (DOLS)
Sample (adjusted): 1980 2014
Included observations: 35 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Real fuel prices (log)	-0.021	0.013	-1.600	0.122
Real GDP (log)	0.099	0.021	4.707	0.000
Constant	-1.218	0.299	-4.063	0.001
Linear Trend	-0.001	0.000	-2.278	0.032
Driving license reforms	-0.028	0.004	-6.902	0.000
Traffic code reforms	-0.020	0.003	-6.020	0.000

P-values	Engle-Granger	Phillips-Ouliaris
Tau-statistic	0.980	0.303
z-statistic	0.383	0.272

Average claims cost
Dependent Variable: log(AC/CPI)
Method: Dynamic Least Squares (DOLS)
Sample (adjusted): 1980 2014
Included observations: 35 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Real wages (log)	1.465	0.411	3.561	0.001
% of <4 year old cars	0.036	0.013	2.718	0.101
Constant	-0.739	1.152	-0.641	0.526
Linear Trend	0.049	0.014	3.529	0.001

P-values	Engle-Granger	Phillips-Ouliaris
Tau-statistic	0.706	0.868
z-statistic	0.444	0.844

Average premium
Dependent Variable: log(RPR/STOCK)
Method: Dynamic Least Squares (DOLS)
Sample (adjusted): 1980 2014
Included observations: 35 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
T-Bill Rate	-0.016	0.009	-1.709	0.100
Average claim	0.837	0.079	10.595	0.000
Constant	-0.083	0.071	-1.174	0.252
MTPL insurance reform	-0.069	0.051	-1.334	0.194

P-values	Engle-Granger	Phillips-Ouliaris
Tau-statistic	0.148	0.511
z-statistic	0.153	0.443

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