BUSINESS CYCLE AND MOTOR INSURANCE PROFITABILITY: EVIDENCE FOR ITALY

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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.

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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[1].

[1] 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[2]. 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[3].

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[4] (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

[2] See, for example Yip e Kelvin (2005) on frequency and Ayuso et al. (2007) on severity.
[3] See also Cummins and Phillips (2000) and Hun Seog (2010), chapter 15.
[4] 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[5], (4) can be solved for the return on equity to get

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

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

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

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.

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

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.

[5] 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[6]. 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:

- <u>Price liberalization.</u> In 1994 the system of state planned rates for MTPL was dismantled following the EU Single Market Directive.
- <u>Reforms to the traffic laws</u> ("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)
- <u>Direct compensation (2007):</u> 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.
- <u>Change in the "Bonus malus"[7] system (2007).</u> 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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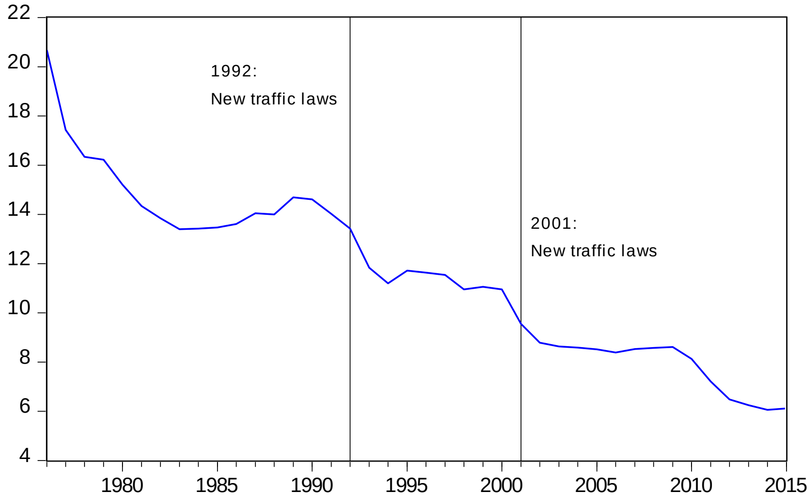
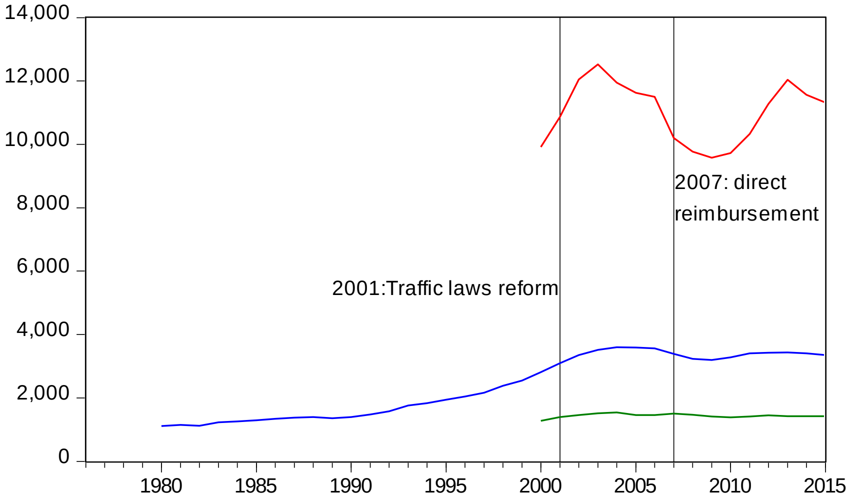
[6] The use of lagged value of losses tries also to account for incurred but not reported claims, which can be paid years after they have been sustained.
[7] No fault

Figure 1: Motor Third Part Liability Insurance

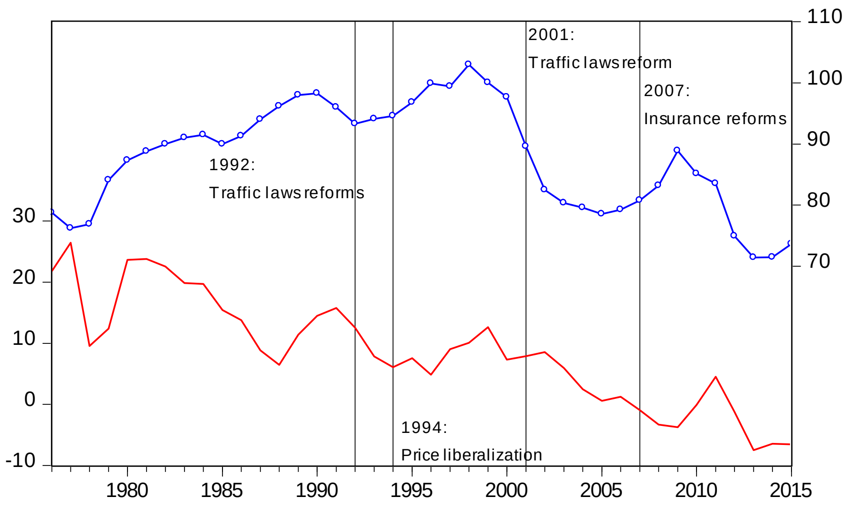
MTPL Claim Frequency



MTPL: Average cost of claims (euros, 2000 prices)



MTPL: Undervriwting Cycle



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[8] 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[9]), 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[10]. 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[11].
- An identity relating total claims (L) with frequency (FR), average cost (AC) and the stock of vehicles in circulation (VE) treated as exogenous[12].

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.

[8] 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.
[9] Computed as the price of gasoline and diesel fuel, weighted by consumption
[10] Price indexes for spare parts and car repair are available only from 1999.
[11] 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).
[12] 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[13] 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 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.

[13] 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

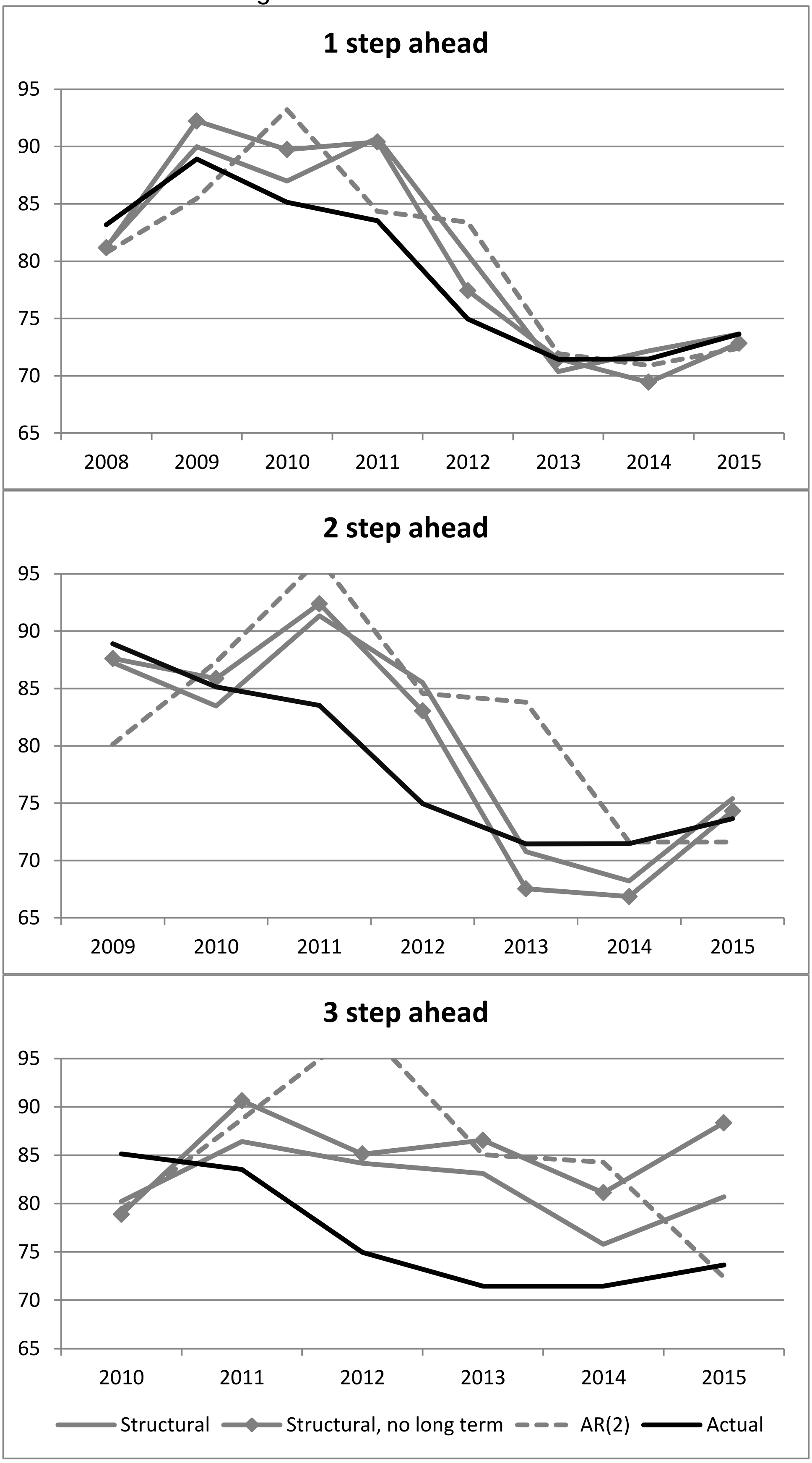
	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
1-year ahead						
Baseline	**3.423**	**2.435**	**3.043**	**2.964**	**0.021**	0.784
In difference	3.432	2.767	3.382	3.317	0.021	**0.782**
AR(2)	4.434	3.190	3.963	3.850	0.028	1.004
2-year ahead						
Baseline	5.241	**3.909**	**5.018**	**4.842**	0.033	1.319
In difference	**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.

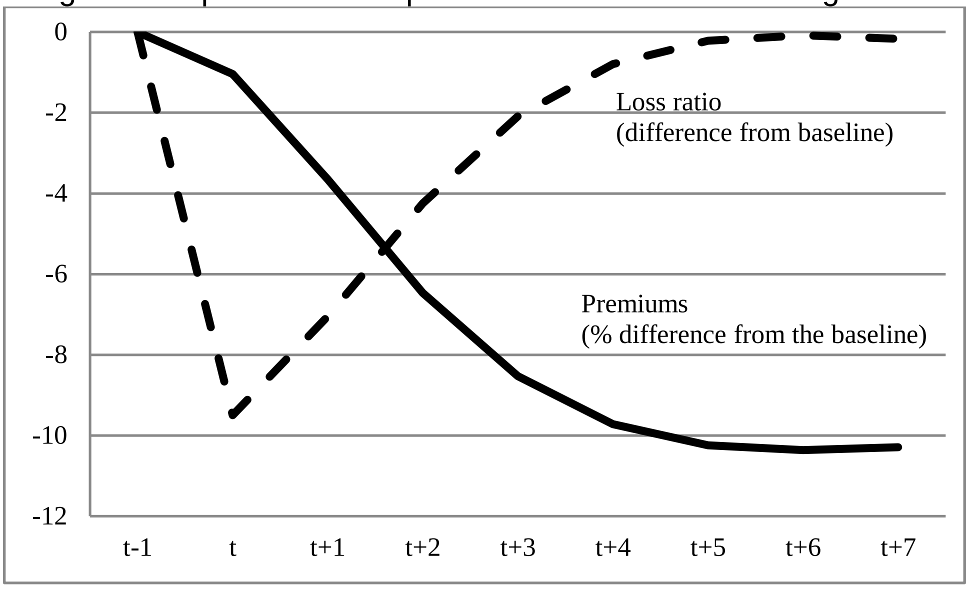
Figure 2: Loss ratio forecasts



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[14] 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.

[14] 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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