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Return Attribution Analysis of the UK Insurance Portfolios

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Abstract

We examine the attribution of premium growth rates for the five main insurance sectors of the United Kingdom for the period 1969-2005; in particular, Property, Motor, Pecuniary, Health & Accident, and Liability. In each sector, the growth rates of aggregate insurance premiums are viewed as portfolio returns which we attribute to a number of factors such as realized and expected losses and expenses, their uncertainty and market power, using the Sharpe (1988, 1992) Style Analysis. Our estimation method differs from the standard least squares practice which does not provide confidence intervals for style betas and adopts a Bayesian approach, resulting in a robust estimate of the entire empirical distribution of each beta coefficients for the full sample. We also perform a rolling analysis of robust estimation for a window of seven overlapping samples. Our empirical findings show that there are some main differences across industries as far as the weights attributed to the underlying factors. Rolling regressions assist us to identify the variability of these weights over time, but also across industries.

Keywords: Insurance Premiums, Monte Carlo Integration, Non-Negativity Constraints, Return Attribution, Sharpe Style Analysis

JEL Classifications: C1, C3, C5, E3, G2, G22.

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1. Introduction

The extensive literature on the evolution of insurance premiums in the context of economic theory, utilizes various forms of rational expectations, see for example Lamm-Tennant and Weiss (1997). More recently, the analysis has been extended in the context of option pricing theory, see for example Cummins (1988, 2000), Phillips et al (1998), Myers and Read (2001). The empirical literature has focused primarily on the existence of cycles in the insurance premiums, initially documented by Venezian (1985). The notion of a cycle is best described as a period of high premiums and profits, followed by periods of low premiums and profits. The former is a '*hard market*' in which one can hypothesize that many insurers enter the market and the latter a '*soft market*' in which a shortage of supply is observed (Niehans and Terry, 1993).

From a theoretical perspective, there are two main theoretical explanations behind the observed underwriting cycle: (i) the '*perfect markets - rational expectations*' hypothesis emphasizes the importance of expected future losses (claims) to explain current premiums (Cummins, 1988, and Cummins and Outreville, 1987), while the '*institutional rigidities*' hypothesis emphasizes the importance of losses, but it is the past losses that set current premiums (Venezian, 1985). (ii) the '*capital market imperfection*' hypothesis according to which current premiums are explained by past surplus (Winter, 1989, Gron, 1994, Cummins and Danzon, 1997). A synthesis of (i) and (ii) could accommodate the formation of cycles within a rational expectations framework and Lamm-Tennant and Weiss (1997) provide international evidence towards this direction. However, so far there are no empirical studies known to the authors originating from the application of option pricing or portfolio theory to insurance.

In this paper we intend to view insurance premiums from a factor portfolio attribution perspective, originating in Sharpe (1988, 1992). To this end, the growth rate of recorded aggregate net premium in an insurance sector is viewed as the return of the portfolio value formed

from the total number of insurance contracts. We shall use the Sharpe Style Analysis as it offers an effective representation of portfolio performance attribution; see Hall, Hwang and Satchell (2002) and Hwang and Satchell (2007). This is based on the simple idea that portfolio returns can be attributed to a number of investment style factors with coefficients of known sign. In the original form of Style Analysis the growth rate of recorded aggregate net premium in an insurance sector is viewed as the return of the portfolio value formed from the total number of insurance contracts. We shall use the Sharpe Style Analysis replicating the returns of the portfolio under assessment, thus style factor coefficients should sum to unity. In the present context in which we shall try to attribute the growth rate of net premiums, our factors data include realized net losses (that is net claims) and realized net expenses as the main attribution factors of our modelling. In addition, over the last decade or so, some new factors have been put forward to explain fluctuations over the premiums, e.g. Harrington and Danzon (1994) argue that premiums could be driven by competition. Based on this finding we also include a proxy of market power as a factor in our analysis. This is often linked to the capacity constraint hypothesis, in which premiums could be driven by lags in supply, see Gron (1994) and Cummins and Danzon (1997). In addition, net premiums are also attributed to the conditional expectations formed over both claims and expenses Venezian (1985), Fung, Lai, Patterson and Witt (1998), as well as on the conditionally expected variance of losses.

Given a sample of time series data for the aggregate net premiums and the corresponding factors for each sector, the framework of Sharpe Style Analysis forms a constrained linear regression problem without intercept. When only the equality constraint is imposed, where the sum of portfolio style weights sums to unity, the distribution of the least-squares estimator of the weights is known, so statistical testing for the weights readily is available. When linear *inequality* constraints are imposed to ensure that estimated portfolio weights lie within the economically

rational bounds, it is not possible to obtain a closed-form solution, thus Judge and Takayama (1966) proposed a modified simplex algorithm for an iterative solution of the inequality-constrained quadratic program. However, when there are more than two independent variables, it can be very difficult to obtain confidence intervals for the estimated betas. One could at most assess the superiority or inferiority of the solution vs. the maximum likelihood estimator using the results of Judge and Yancey (1986). To solve this problem, in this paper we adopt a Bayesian perspective to formally impose the inequality parameter restrictions, in the form of a prior probability density of the model parameters as in Christodoulakis (2003, 2007) and Kim et. al. (2003). The latter is then combined with the sampling information as captured by the likelihood function to provide the joint posterior density function of the model parameters. We then use Monte Carlo Integration (MCI) as proposed by Kloek and van Dijk (1978) and van Dijk and Kloek (1980) and further studied by Geweke (1986) to generate the posterior distribution. This methodology allows the computation of the posterior distribution of the parameters of interest and other functions, also enabling exact inference procedures that are difficult to treat in a least squares approach. We apply our methodology on annual aggregate UK data for five insurance sectors from 1969 to 2005.

The rest of this paper is organized as follows. In section 2 we review the specification of Style Analysis in a Bayesian context. In section 3 we describe the data set and in section 4 we present the empirical results. Finally, section 5 offers some concluding remarks.

2. Sharpe Returns-Based Style Analysis for Insurance

In this paper we are motivated by the work of William Sharpe (1988, 1992), who proposed the Style Analysis as a method to meaningfully attribute the evolution of portfolio value growth rates to a small set of factors satisfying a number of economic constraints. Technically,

the Style Analysis takes the form of a linear regression in which the value of each factor coefficient is constrained within its economically meaningful range and the sum of the coefficient values equals unity. For example, a portfolio employing long position investment strategies should attribute its return variation to factors with positive coefficients. However, standard unconstrained linear regressions often yield estimated factor coefficients with economically incorrect sign, whilst the factors' explanatory power may not be fully allocated to the respective parameters. If the sign of the factor coefficients is known from economic theory and/or empirical evidence, then implementation of Style Analysis will exhaustively attribute the variation of the dependent variable only to factors with a meaningful sign, whilst the remaining will be taking the value of zero, see for example Table 2 of Sharpe (1992). Our analysis for the UK insurance sectors involves six factors, namely, realized claims (C), conditionally expected claims (C^c), realized expenses (E), conditionally expected expenses (E^c), market power (MP) and the conditionally expected volatility of claims (V_c). In this respect, our analysis includes the two main theoretical hypotheses, that is '*rational expectations*' and '*capital markets imperfections*', and one could expect that these factors are linked to premiums with a non-negative coefficient, thus our parameter space will be constrained to reflect this knowledge.

Because of the presence of inequality-constrained parameters, the standard approach for their estimation involves a form of quadratic programming which yields estimates with unknown distribution, thus making their statistical testing impossible. It is this particular problem that led Sharpe to state that "when quadratic programming is employed, the (standard) assumptions that lie behind such tests are violated, making true out-of-sample tests the only reliable means of evaluating the efficacy of the approach", see Sharpe (1992) p. 8 and endnote 2. Our approach in this paper views these factor parameters from a Bayesian perspective and thus through the

derivation of their posterior distribution we offer direct inference procedures. In the following we shall describe our methodological framework using notation drawn from Christodoulakis (2007).

Our aggregate premium growth rate for any sector, Y , can be attributed to a finite number of style factors X such that

$$\begin{aligned}
 Y &= X\beta + U \\
 \text{s.t.} & \\
 \mathbf{1}'\beta &= 1 \text{ and } \beta \geq 0
 \end{aligned}
 \tag{1}$$

where Y is a vector of T observations of portfolio returns, that is the growth rate of premiums, X a matrix of T observations for K style factor returns, that is the growth rates of claims and expenses, β a vector of K style factor betas, $\mathbf{1}$ is a vector of units and $U \sim N(0, \sigma^2 I)$. The least squares estimation of β in the above model is derived from a constrained quadratic program. The solution under equality constraints is available in closed-form and its distributional properties known. When inequality constraints are imposed in addition, the solution requires iterative optimization, see Judge and Takayama (1966), but the distributional properties of the estimator are not known. Davis (1978) provides a solution for the latter problem which requires that one knows which constraints are binding, an implausible assumption for Sharpe style analysis.

One solution to that problem is to view the style regression from a Bayesian perspective and impose the parameter restrictions in the form of information encapsulated in the prior distribution. We first impose the equality constraint by restating model (1) in deviation form from the K -th style return

$$\begin{aligned}
Y^* &= X^* \beta^* + U^* \\
\text{s.t.} & \\
\mathbf{1}'\beta^* &\leq 1 \text{ and } \beta^* \geq 0
\end{aligned} \tag{2}$$

where β^* denotes a vector consisting of the first $K-1$ elements of β , the t -th elements of the new variables is $y_t^* = y_t - x_{K,t}$ and $x_{i,t}^* = x_{i,t} - x_{K,t}$, where $i = 1, \dots, K-1$ is the i -th column of X . Now β^* is a vector of $K-1$ elements and the K -th beta can be obtained from $1 - \mathbf{1}'\beta^*$. In our standard Bayesian framework β^* is formally treated as a random variable in population and all elements of X^* are independent of each other and of U , β^* and σ^2 . Then, by Bayes law the posterior density of β^* and σ^2 is given by the product of the likelihood function and the prior density for β and σ^2 . Following van Dijk and Kloek (1980) our prior is composed of an improper uninformative component regarding σ^2 and an informative one regarding β^* , which for style analysis captures our prior knowledge $\mathbf{1}'\beta^* \leq 1$ and $\beta^* \geq 0$. In particular, by independence we can write

$$\text{Prior}(\beta^*, \sigma^2) = \sigma^{-1} q(\beta^*) \tag{3}$$

where

$$q(\beta^*) = \begin{cases} 1 & \text{if } \mathbf{1}'\beta^* \leq 1 \text{ and } \beta^* \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

We then calculate the joint posterior density of β^* and σ^2 by combining the prior density and the likelihood function. Then, integrating out σ^2 , (see Christodoulakis (2007)), we can show that the posterior distribution of β^* is given by

$$\text{Posterior } (\beta^* | Y^*, X^*) \propto c \left[\lambda + \frac{(\beta^* - b)' X^{*'} X^* (\beta^* - b)}{\hat{\sigma}^2} \right]^{-\frac{1}{2}(\lambda + K - 1)} \times q(\beta^*)$$

where

(4)

$$c = \frac{\lambda^{\frac{\lambda}{2}} \Gamma \left[\frac{1}{2}(\lambda + K - 1) \right]}{\pi^{\frac{K-1}{2}} \Gamma \left[\frac{\lambda}{2} \right] \det(\hat{\sigma}^2 (X^{*'} X^*)^{-1})^{\frac{1}{2}}}$$

and $\Gamma(\cdot)$ is the gamma function, b is the least squares estimate of β , $\lambda = T - K + 1$ and $q(\beta^*)$ is an indicator variable which takes value 1 if all constraints hold and 0 otherwise. This is recognized as a truncated multivariate t density with mean zero, variance $\frac{\lambda}{(\lambda - 2)\hat{\sigma}^2} X^{*'} X^*$ and λ degrees of freedom.

Following the methodology proposed by Kloek and van Dijk (1978) and van Dijk and Kloek (1980), for any posterior density and any function $g(\cdot)$, the posterior expectation of $g(\beta^*)$ is given by

$$E(g(\beta^*) | Y^* X^*) = \frac{\int g(\beta^*) \text{Posterior}(\beta^* | Y^* X^*) d\beta^*}{\int \text{Posterior}(\beta^* | Y^* X^*) d\beta^*}$$

The empirical implementation of the above estimator can be performed using Monte Carlo procedures. This approach requires the establishment of a density function $I(\beta^*)$ from which we shall draw randomly sequences of β^* ; this is termed *importance function* and should approximate

the posterior density with implementable Monte Carlo properties. We can then calculate expectations using

$$E(g(\boldsymbol{\beta}^*) | \mathbf{y}^* X^*) = \int \left(\frac{g(\boldsymbol{\beta}^*) \text{Posterior}(\boldsymbol{\beta}^* | \mathbf{y}^* X^*)}{I(\boldsymbol{\beta}^*)} \right) I(\boldsymbol{\beta}^*) d\boldsymbol{\beta}^*$$

where the expectation is now taken over $I(\boldsymbol{\beta}^*)$. Practically, let $\boldsymbol{\beta}_1^*, \boldsymbol{\beta}_2^*, \dots, \boldsymbol{\beta}_N^*$ be a set of N random draws from $I(\boldsymbol{\beta}^*)$, then it can be shown that

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N \frac{g(\boldsymbol{\beta}_i^*) \text{Posterior}(\boldsymbol{\beta}_i^* | \mathbf{y}^* X^*)}{I(\boldsymbol{\beta}_i^*)} = E(g(\boldsymbol{\beta}^*) | \mathbf{y}^* X^*) \quad (5)$$

apart from a normalizing constant which can be calculated separately.

Naturally, for the implementation of our proposed approach we shall be generating multivariate t -distributed vectors $\boldsymbol{\beta}_i^*$. First, we estimate $\boldsymbol{\beta}_i^*$ by OLS and then derive the Cholesky factorization of the least squares covariance matrix such that

$$CC' = \hat{\sigma}^2 (X' X)^{-1}$$

which is in turn used to generate a $K-1$ vector s_i of independent standard normal random variables. Letter \mathbf{b} denotes the least squares estimate of $\boldsymbol{\beta}^*$, then the i -th replication of $\boldsymbol{\beta}_i^*$, $i = 1, \dots, N$, will be

$$\hat{\boldsymbol{\beta}}_i^* = \mathbf{b} + C s_i$$

which is thus drawn from a $(K-1)$ -variate normal density. We can now convert or simulated $\hat{\beta}_i^*$ to a t -distributed draw, by drawing a $\theta = \lambda$ vector q_i of independent standard normal variables and combining such that

$$\hat{\beta}_i^* = \mathbf{b} + C s_i \left(\frac{\theta}{q_i' q_i} \right)^{\frac{1}{2}} \quad (6)$$

Now it can be shown that $\hat{\beta}_i^*$ is a t -distributed variable with $\theta = \lambda$ degrees of freedom. The simulation process consistent with (4) is now described in three iterative steps:

- (a) for $i = 1$ generate $\hat{\beta}_i^*$ from (6)
- (b) set $\beta_i^* = \hat{\beta}_i^*$ if $\mathbf{1}' \hat{\beta}_i^* \leq 1$ and $\hat{\beta}_i^* \geq 0$ and go to (a) otherwise
- (c) repeat (a) and (b) for $i = 2, \dots, N$

It is now straight forward to estimate our unknown parameters by setting $g(\beta_i^*) = \beta_i^*$ and then using equation (5). Furthermore, it is possible to obtain estimates of higher moments of β^* or any other functions of interest in a similar manner. Contrary to the existing problems of least squares – based estimates, the proposed approach offers exact inference procedures as discussed in van Dijk and Kloek (1980), Geweke (1986) and Kim et al (2005). Furthermore, in a different context Lobosco and DiBartolomeo (1997) proposed a method using Taylor expansions, which unfortunately is valid only in the special case in which none of the true style coefficients reaches the bounds of zero or one.

3. UK Insurance Data

Our data set covers the period 1969-2005, is of annual frequency and has been collected from the Annual Reports of the Association of British Insurers³ (ABI thereafter) (2006) and for comparison from OECD (2005). It is comprised of figures for the five main UK insurance sectors, namely accident, liability, motor, pecuniary and property. The original variables included

³ For further information please refer to: <http://www.abi.org.uk/Subscription/SubscriptionDetails.asp?Year=2009>.

in the analysis are the net premiums (P), the net incurred claims (C), and the expenses (E). The net premiums refer to premium net of reinsurance ceded but gross of commission, and excluding premium tax insurance. ABI provides data labeled net premiums, gross premiums, and reinsurance ceded. We opt for using net premiums in line with previous research in the literature (Venezian, 1985, Winter, 1989, Gron, 1994, Cummins and Danzon, 1997). ABI defines claims as the situation when a policyholder or beneficiary seeks payment or settlement under the terms of an insurance policy. The net incurred claims represent insurance losses for the insurance companies and are the amounts paid during the year plus the amounts outstanding at the end of the year less amounts outstanding at the start of the year. Note that series for the net claims incurred figure are as shown in the revenue account tables of the representing firm, thus is net of reinsurance recoveries. The expenses represent all total costs incurred in the running of the business, including commission paid to sales staff as defined by ABI (2006b).⁴

Further to the above variables in the empirical part we opt to proceed to a parsimonious Sharp Style analysis that incorporate also expected claims (C^e), expected expenses (E^e). The theoretical justification of the inclusion of these variables is based on the hypothesis that predictions over claims and expenses could explain current premiums (Cummins and Outreville, 1987). Furthermore, this hypothesis argues that net premiums could also reflect the data collection lags, regulatory lags, and policy renewal lags if indeed rational expectations hold. As a result, net premiums should also be attributed upon expected future claims and expenses. However, the drawback of using forecasts is the underlying measurement errors (Niehaus and Terry, 1993) and if this is the case because of their correlation with past values, one could possibly correct by opting for the appropriate time series modelling. To this end, we apply time series analysis to

⁴ The authors would like to thank the Association of British Insurers and Professor Gerry Dickinson for providing part of the data. The principal data source comes from the Association of British Insurance (ABI) where they maintain a large collection of insurance statistics for the UK. Moreover, ABI provide us with all *UK Business Insurance Market Statistics* and the annual *Sources of Premium Income Book* (2006a).

obtain unbiased and efficient expectations for claims and expenses. Moreover, various ARMA-GARCH models are tested and chosen the ones with the best fit by applying Likelihood Ratios and the Akaike and Schwarz criteria⁵.

To account for uncertainty we opt for the conditionally expected volatility of claims (V_c), which as in the case of C^e and E^e , we utilise the same ARMA-GARCH. In the literature, it is quoted that there exist a positive relationship between uncertainty and premiums (Lai and Witt 1990, 1992). Moreover, uncertainty about losses would increase the variance of insurance premiums. This is particularly true when expectations about future uncertainty of losses are high then premiums would also be high *ceteris paribus*.

Lastly, we construct a variable to capture market power (MP) that is approximated by the market share of a particular insurance industry. This factor could assist accommodating the underlying disequilibrium between supply and demand. In case that competition is driven by premiums then the underwriting cycle could also be the outcome of competition. This phenomenon has also been considered as an irrational behaviour in order to maintain or gain market share (Harrington and Danzon, 1994). This would imply that an insurer's pricing would also contain information on the behaviour of competitors. However, Gron (1994), Winter (1994), and Cummins and Danzon (1997) have raised some criticism over the insurer's initiative to alter premiums, bringing forward the argument of capacity constraints on the supply side. Shocks to surplus affect the price and quantity of insurance supplied. This type of effect is primarily a short-run type of effect, while the current framework of Sharpe Style Analysis refers primarily to

⁵ We omit this analysis to save space but its details are available upon request. Our purpose is to obtain the one-step-ahead forecast for each variable. In spite of the availability of alternative econometric methodologies, the ARMA-GARCH class of models is general enough to capture adequately the autocorrelation properties of the data and provide projections for one-step-ahead horizon.

factors' attribution in the mid to long term. For discounting the series where appropriate we opt for the treasury note rates from the Bank of England.

4. Estimation by Monte Carlo Integration

In spite of the various theoretical works, see Phillips et al 1998 for a review, that have attempted to explain the insurance underwriting cycle, empirical studies have rather been inconclusive and have yet to offer insights over the main determinants of insurance premiums. Our methodology, following the Style Analysis, extends the literature towards the attribution of insurance premiums and also provides a suitable framework to examine the evolution of β 's over time. To this end, in addition to the full sample analysis, we also perform rolling regression analysis, which because of our Monte Carlo Integration estimation approach, can be applied for very small sample sizes. Essentially, the analysis that we follow is a rolling windows constrained regressions based on sliding set of sub-samples. For the purpose of this study, the underlying time variation of betas was estimated over a sub-sample of eight years duration identified as the average underwriting cycle, see Cummins (2000).

Next, we proceed to our analysis by applying the Monte Carlo Integration procedure as described above. To this end, we have set the number of simulation replications equal to 10^6 and have used GAUSS language as our computational platform, and we obtained the simulated realizations of our β s parameters using a multivariate t-distribution as an importance function that approximates the true posterior density function.

4.1 Estimation of betas over the full sample

We report our empirical results for the full sample of all five insurance industries in Table 1 below, whilst in Figure 1 we opt to graph the corresponding empirical posterior distributions for β 's for the representative industry of motor insurance, given its market size. The coefficients β_1 - β_6

represent weights of realized losses and expenses, market power, conditionally expected expenses and losses and conditional volatility of losses, respectively. In line with the methodology our estimated weights are always positive and sum to unity. Also, since the results are based on the empirical posterior density of the β^* vector all sampling moments of the posterior distribution are derivable. In particular, we report estimates of mean, median, standard deviation, skewness and kurtosis coefficients.

<<Table 1 about here>>

A first glance of the results shows that for the motor and property industry, the dominant weight is the conditionally expected volatility of losses, which projects the uncertainty of the historically realized losses. In detail, the weight of uncertainty for motor and property is 38 and 29 percent respectively. This result does not hold for the remaining industries, as for the liability and accident industry realized losses appear to count for 50 and 75 percent respectively of the growth rate of premiums, whilst for the pecuniary industry it is the realized expenses that play the dominant role, capturing 57 percent. These findings highlight some differences and similarities across industries and are in line with Lai and Witt (1990) and (1992), though Niehaus and Terry (1993) has highlighted the sensitivity of the results to measurement errors. Further, for the motor and property industry, that together captures 65% of the whole market in 2005, volatility in losses is of high importance due to the significance of risks attached to the general economic conditions for these industries along the lines first proposed by Fung et al. (1998) for the property insurance industry in the US. In particular, the oil-crisis present in our time-span could matter for the motor industry, thus the high weight of volatility, whilst the property industry is sensitive to country specific and/or global macroeconomic instabilities that are directly linked to mortgage default. In addition, the frequency and severity with respect claims are higher for motor and property (see

ABI, 2006). For the industries of liability and accident, the dominant weight of current losses could be anticipated due to the immediate nature of claims. This finding, in particular for liability insurance business, is similar to the one reported by Chen et al. (1999).

For the case of pecuniary industry, that involves mainly consequential and mortgage indemnity policies, operational costs, as discussed in Cummins and Outreville (1987) and Cummins and Danzon, (1997), are high as the signing of an insurance contract involves fees paid to expertise not commonly found within the premises of the industry, i.e. specialized legal advises. In effect, for pecuniary insurance contracts expenses appear to be the main driving force of premiums, implying that at periods that industry's expectation concerning expenses rise the premiums also tend to rise (Lai and Witt, 1990).

Overall, this discussion of the posterior mean of β s for the whole sample uncovers two pairs of industries with similar dominant weights, but also that indeed there are differences across the industries.

Specifically, for the motor industry, the coefficient corresponding to conditional expected losses (β_5) takes the value of 21 percent with jointly with the conditional volatility of losses (β_6) accounts for 59 percent of the weights. Thus, the first two conditional moments of losses together with the realized losses (β_1) of 16 percent, constitute together the dominant weight. Similar result is obtained for the property industry, though the weight of the realized loss is small, $\beta_1 = 0.08$. As shown above and in line with Lai and Witt (1992), for industries with high weights for conditionally expected volatility of losses also show high weights of the conditionally expected mean of losses. The realized and conditionally expected expenses have similar weights, moderate in magnitude and count together for 23 percent and 18 percent for motor and property industry respectively. Lastly, market power holds the least weight for motor industry, on average 2

percent. Close inspection of the associated statistics for standard deviations, skewness and kurtosis show that the empirical posterior distribution of the β (see Figure 1 in Annex) is non-normal, and it is highly unlikely to support a significant in magnitude weight of market power. This result reflects that indeed this market faces high competition. In contrast, our estimate for the property industry is 19 percent.

<<Figure 1 about here>>

For the liability industry, apart from the dominant weight of realized losses, the conditionally expected losses hold a 19 percent weight, whilst the combined weight of the remaining three factors is of moderate magnitude, 32 percent. Note, that although also for accident the dominant weight is realized losses, however, in contrast with liability industry, the combined weight of the remaining five factors is low and 26 percent.

For the pecuniary industry it is worth noting that as in the case of the property industry the weight of market power is not negligible, standing at 12 percent. This similarity is not surprising as pecuniary concerns also mortgage indemnity policies, that are closely linked to property industry. So in effect, these two industries could face similar competition conditions. Harrington and Danzon (1994), Gron (1994), Winter (1994), and Cummins and Danzon (1997) investigate the significance of market power and capacity constraint and argue that could be a main determinant of the underwriting cycle. The combined weight of the remaining three factors is 31 percent, with realized losses playing the primal role.

Moreover, our results clearly demonstrate that the coefficient of β_1 , that is the attribution to net incurred premiums due to losses, asserts the dominant impact on the premiums for the accident and liability insurance industries, justifying the case of no perfect foresight in the

insurance industry (Fung et al., 1998). Effectively the provided evidence partially supports the ‘*rational expectations*’ hypotheses in the long run, according to which expected claims/losses are used to set premiums (Mamatzakis and Staikouras, 2006). That is future losses in the form of net incurred claims drive premiums.

4.2 Rolling estimation of betas

In this section we perform a rolling analysis of overlapping small samples. We present the evolution of mean estimated⁶ values of coefficients graphically in Figure 2, so as to obtain insights for the dynamics of the underlying attributions. Overall, the results confirm the findings of the previous section. As in the case of the whole sample, all beta coefficients are highly non-normal exhibiting skewness and excess kurtosis, particularly negative skewness for the betas of the dominant style.

In detail, for the Motor industry the conditionally expected volatility of losses, that accounts for uncertainty along the lines proposed by Gron (1994), captures the dominant weight, in particular in the early seventies. This is not surprising given that the specific industry is sensitive to oil-price changes and the general macroeconomic conditions, so the oil-crisis in the seventies may have positively contributed to the growth rate of premiums. Uncertainty’s weight is lower but shows persistence to the remaining sub-samples. It is also worth noticing that at the sub-sample of 1978-1985, when uncertainty captures its lowest weights over all, the realized losses emerge as having the dominant weight. It could be that the high uncertainty in the early seventies caused the premiums to increase, whilst the rise induced by the realized losses took place with a lag. Once the weight of uncertainty falls to moderate levels the weight of realized losses also follow suit.

⁶ For reasons of space availability we do not present our estimates of the remaining statistics of the empirical posterior distributions, but these are available to the reader upon request.

<<Figure 2 about here>>

The weight of uncertainty is also substantial in magnitude for property and liability, though for the latter industry it appears that realized losses matter more as in Chen et al. (1999). For the property industry one could expect that volatility in expected losses is a major factor that determines premiums (Lai and Witt, 1990 and 1992), and this effect is enhanced at periods of major economic and financial imbalances that could reflect overheating in property prices, which characterized market conditions in UK in the sub-periods of the nineties and the 2000-2005. Indeed, the weight of loss conditional volatility is increasing over time with the exception of the 1986-1993 period of substantial house repossessions in the UK, where realized and expected losses and expenses mattered more.

The liabilities insurance industry, which concerns insurance over unanticipated losses in income or profit, exhibits a fluctuating and rather decreasing weight of loss conditional volatility over time which appears negatively correlated with the weight of realized losses. The remaining factors exhibit a relatively stable weight over time. However, for the liability and accident industry realized losses appear to capture the dominant weight.

For the case of pecuniary industry, operational costs exhibit an overall high weight as in the case of the whole sample and in Harrington and Danzon (1994) and Cummins and Danzon (1997). But the present dynamic analysis allows observing that this need not to be always the case, as in the periods 1978-1985 and 1982-1989 realized losses and during 1990-1997 the expected losses capture the dominant weight. It is also worth noticing that although market power captures low levels of weights in the remaining industries, for the pecuniary industry market power is of importance, in particular in the latter sub-samples, e.g. it captures a 34 percent weight in the period 1994-2001. This finding could reflect that over the early years the competitive

conditions in the specific industry could not significantly change but the effects of higher concentration become visible during the last decade.

Lastly, in the case of accident the dynamic analysis shows that realized losses capture the dominant weight, as in Mamatzakis and Staikuras (2006), though some variation over time exist. In particular, for the period 1986-1993 it is the expected rather than the realized losses that capture the dominant weight of attribution. In addition, expenses and market power get the second and third largest weight respectively, with the latest raising its weight over time.

5. Conclusions

For selected UK insurance industries we model the growth rates of premiums using the Sharpe (1988, 1992) Style Analysis. This is the first application of Style Analysis in the context of insurance and intends to attribute exhaustively the evolution of premiums growth rate to a limited number of factors with economically meaningful influence. Our estimation method departs from the least squares practice, which does not provide confidence intervals for style betas, and applies a Bayesian approach, providing the posterior distributions of beta coefficients.

Overall, the reported posterior means of β s for the whole sample uncovers two pairs of industries with similar dominant weights, but also that indeed there are differences across the industries. In particular, for the motor and property insurance industry what appears to matter is the weight of the conditionally expected loss and the conditionally expected volatility of losses, counting for 75 and 64 percent respectively. With respect to the property and pecuniary insurance industries we find that the weight of the market power weights higher on growth of premiums compared to the rest of the factors. For accident and liability the weight of realized losses dominates. The dynamic analysis provides further insights over the main determinants of the underwriting cycle in the short run. Overall, it appears that there is not a silver bullet that could

attribute net premiums, while this paper helps to identify the plurality of contributing factors to the net premiums over time and across industries.

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Table 1. The UK Insurance Industries, 1969-2005.

MOTOR INDUSTRY						
	β_1	β_2	β_3	β_4	β_5	β_6
Mean	0.16	0.12	0.02	0.11	0.21	0.38
Median	0.15	0.10	0.02	0.10	0.22	0.38
Std. Dev.	0.08	0.09	0.02	0.07	0.10	0.02
Skewness	0.36	1.05	1.86	1.02	0.01	-0.25
Kurtosis	2.83	3.93	8.87	4.45	2.64	5.54
Jarque-Bera	30	287	2607	336	7	363
Obs.	1296	1296	1296	1296	1296	1296
PROPERTY INDUSTRY						
	β_1	β_2	β_3	β_4	β_5	β_6
Mean	0.08	0.13	0.19	0.05	0.27	0.29
Median	0.06	0.10	0.16	0.03	0.28	0.29
Std. Dev.	0.07	0.12	0.13	0.05	0.09	0.17
Skewness	2.01	1.40	0.84	2.29	-0.14	0.11
Kurtosis	9.49	4.96	3.46	10.50	3.25	2.11
Jarque-Bera	1567	313	82	2077	4	23
Obs.	645	645	645	645	645	645
LIABILITY INDUSTRY						
	β_1	β_2	β_3	β_4	β_5	β_6
Mean	0.50	0.12	0.08	0.07	0.19	0.05
Median	0.52	0.09	0.06	0.05	0.19	0.04
Std. Dev.	0.12	0.09	0.07	0.08	0.09	0.05
Skewness	-0.94	1.35	1.84	2.36	0.26	1.71
Kurtosis	4.31	5.41	8.37	12.70	2.91	7.38
Jarque-Bera	730	1838	5923	16257	40	4308
Obs.	3353	3353	3353	3353	3353	3353
PECUNIARY INDUSTRY						
	β_1	β_2	β_3	β_4	β_5	β_6
Mean	0.12	0.57	0.12	0.08	0.08	0.03
Median	0.11	0.61	0.10	0.06	0.07	0.02
Std. Dev.	0.08	0.17	0.09	0.08	0.05	0.03
Skewness	1.12	-0.99	1.42	1.89	1.41	2.31
Kurtosis	5.04	3.74	6.19	7.74	6.74	10.71
Jarque-Bera	1406	688	2783	5625	3360	12375
Obs.	3674	3674	3674	3674	3674	3674
ACCIDENT INDUSTRY						
	β_1	β_2	β_3	β_4	β_5	β_6
Mean	0.75	0.09	0.06	0.05	0.03	0.03
Median	0.75	0.08	0.05	0.05	0.02	0.02
Std. Dev.	0.03	0.05	0.04	0.03	0.02	0.02
Skewness	-1.44	0.40	0.77	0.55	1.57	1.38
Kurtosis	15.94	2.64	3.36	3.03	6.70	6.69
Jarque-Bera	62823	269	899	440	8423	7624
Obs.	8584	8584	8584	8584	8584	8584

Note: the coefficients β_1 - β_6 represent weights of realized claims (C), realized expenses (E), market power (MP), conditionally expected expenses (E^c), conditionally expected claims (C^c) and conditionally expected volatility of claims (V_c) respectively.

Figure 1: Posterior Distributions of β_s for Motor Industry

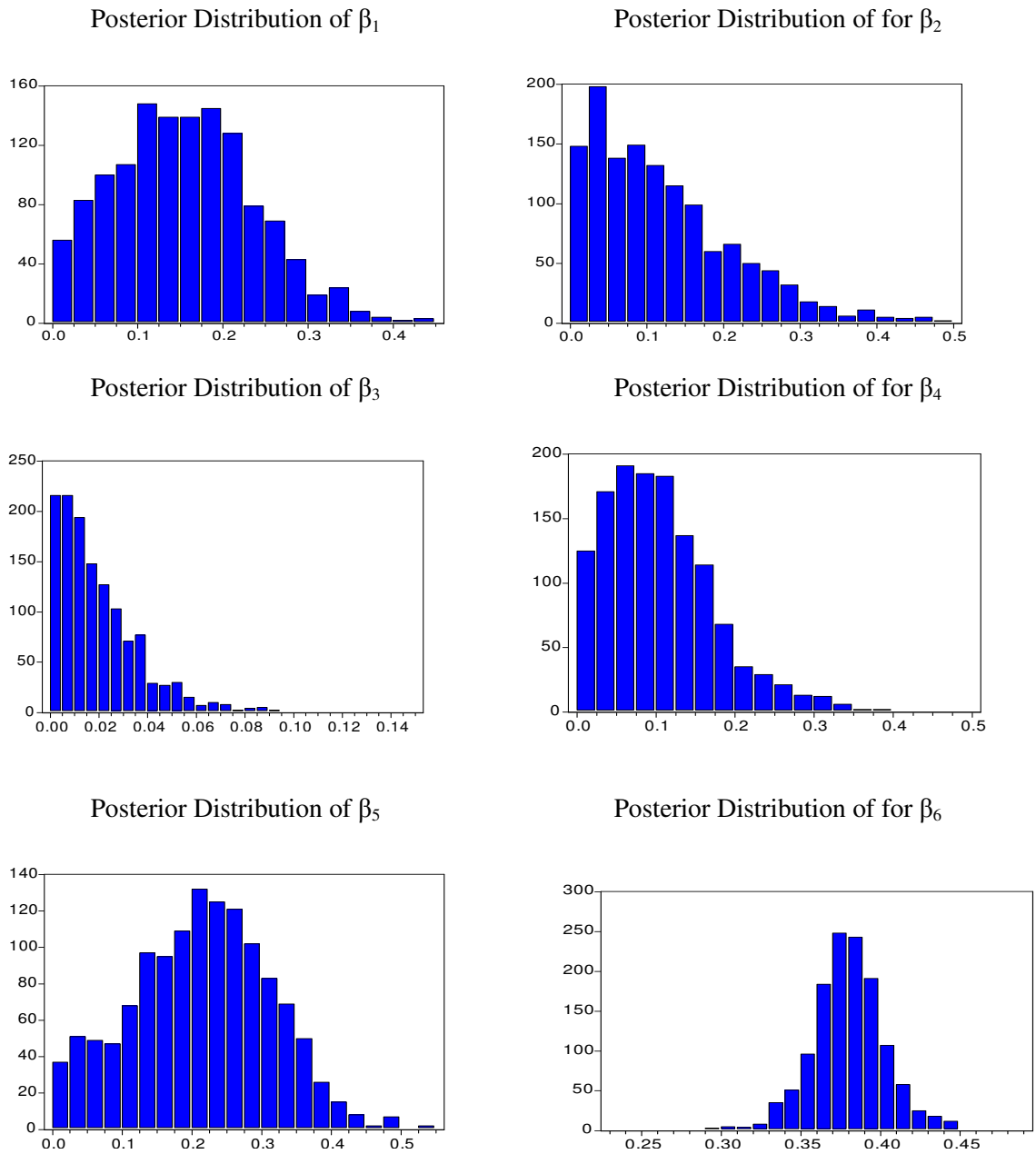
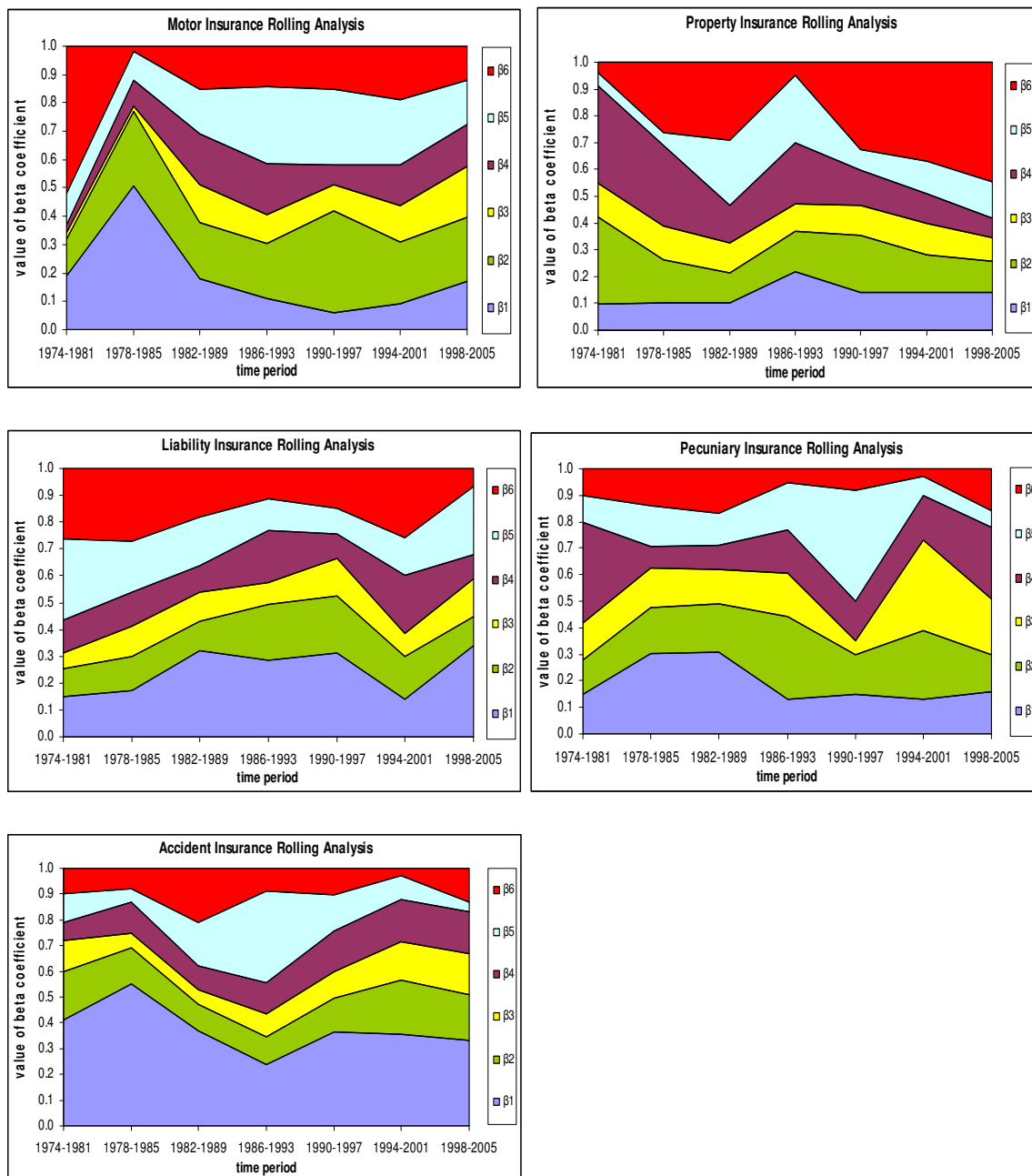


Figure 2: Rolling Analysis per Sector



Note: the coefficients β_1 - β_6 represent weights of realized losses and expenses, market power, conditionally expected expenses and losses and conditional volatility of losses, respectively.