FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG

RECHTS- UND WIRTSCHAFTS-
WISSENSCHAFTLICHE FAKULTÄT

Assessing Inflation Risk in Non-Life Insurance

Alexander Bohnert, Nadine Gatzert, Andreas Kolb

Working Paper

Department of Insurance Economics and Risk Management
Friedrich-Alexander University Erlangen-Nürnberg (FAU)

Version: October 2015

ASSESSING INFLATION RISK IN NON-LIFE INSURANCE

Alexander Bohnert, Nadine Gatzert, Andreas Kolb*

This version: October 24, 2015

ABSTRACT

Inflation risk is of high relevance in non-life insurers' long-tail business and can have a major impact on claims reserving. In this paper, we empirically study claims inflation with focus on automobile liability insurance based on a data set provided by a large German non-life insurance company. The aim is to obtain empirical insight regarding the drivers of claims inflation risk and its impact on reserving. Toward this end, we use stepwise multiple regression analysis to identify relevant drivers based on economic indices related to health costs and consumer prices, amongst others. We further study the impact of (implicitly and explicitly) predicting calendar year inflation effects on claims reserves using stochastic inflation models. Our results show that drivers for claims inflation can considerably vary for different lines of business and emphasize the importance of explicitly dealing with (stochastic) claims inflation when calculating reserves.

Keywords: Separation method, claims inflation, regression analysis, simulation, Vasicek
JEL Classification: C53; E31; G22; G32

1. INTRODUCTION

For non-life insurers, inflation associated with long-term liabilities represents one major risk source and can considerably impact the adequate estimation of technical provisions, thus directly influencing future earnings (see, e.g., Wüthrich, 2010; Ahlgrim and D'Arcy, 2012a; D'Arcy, Au, and Zhang, 2009). Furthermore, in the context of new risk-based capital requirements for insurers as imposed by Solvency II, all material risks have to be considered in the calculation of solvency capital requirements and the Own Risk and Solvency Assessment (ORSA), implying that inflation risk should at least be taken into consideration within an internal model of an insurance company. The aim of this paper is to empirically study claims inflation in non-life insurance based on automobile liability insurance, fully comprehensive car insurance, and third party liability insurance data provided by a large non-life insurance company in Germany. Toward this end, we first focus on claims inflation by determining the main driving factors for inflation risk based on economic indices for different

* Alexander Bohnert, Nadine Gatzert, and Andreas Kolb are at the Friedrich-Alexander University Erlangen-Nürnberg (FAU), Department of Insurance Economics and Risk Management, Lange Gasse 20, 90403 Nuremberg, Germany, alexander.bohnert@fau.de, nadine.gatzert@fau.de, andreas.kolb@fau.de.

lines of business of the considered non-life insurer. Second, we model claims inflation based on the calendar year effects and assess its impact on claims reserving for the case of automobile liability insurance, which is of special relevance in the presence of superimposed inflation.

In general, inflation is measured as the percentage change in the overall level of prices measured by a price index such as the consumer price index (CPI). However, insurers are likely to be exposed to specific components of the CPI such as medical inflation rather than the overall level of price changes (see, e.g., Cummins and Derrig, 1993; Ahlgrim and D'Arcy, 2012a). In this context, Masterson (1968), for instance, measures the impact of inflation on insurers by isolating components of the CPI that are related to specific lines of business. Morrow and Conrad (2010) identify economic indicators, which best measure the inflation inherent in claims costs. In addition, Ahlgrim and D'Arcy (2012a) investigate the effects of inflation or deflation on the insurance industry in general, thereby indicating that property liability insurers are impacted by inflation in several ways, e.g. by means of costs of future claims on current policies and calculation of loss reserves. Regarding loss reserves, D'Arcy and Au (2008) and D'Arcy, Au, and Zhang (2009) point out that loss reserves are commonly calculated based on the assumption that the inflation rate experienced in the recent past will continue until these claims are closed, which, however, can take decades. Thus, if inflation increases, costs will be more than expected, which in particular affects long-term liabilities. In this context, Verbeek (1972) and Taylor (1977) separate the impact of inflation from the run-off triangle, which allows incorporating a different inflation rate in the calculation of reserves. Moreover, inflation also affects asset returns (see, e.g., Fama and Schwert, 1977) and thus the asset side of an insurer. While this may offset or magnify reserving risks in the presence of inflation, in this paper we specifically focus on the liability side of the insurance company.

In this context, claims inflation can be defined as the general inflation plus all other relevant influencing factors, whereby these other factors are also referred to as "superimposed inflation". The average motor insurance claim, for instance, is not only affected by general inflation, but also by the wages of the people repairing vehicles, medical costs for those injured in vehicle accidents, and litigation costs (see Swiss Re, 2010). Moreover, as pointed out by Swiss Re (2010), for instance, the term "inflation" may be misleading as it refers to quality-adjusted price increases, which is why they suggest the term "change in claims severity" as an alternative, which refers to changes in the average value per claim. However, to be consistent with the academic literature, in what follows we use the term "claims inflation".

With respect to non-life insurance claim costs, Cummins and Powell (1980) compare two different approaches to forecast claim costs for automobile insurance. They show that econometric models (univariate and multivariate models), which take into account economic indices (e.g. price and wage indices) to forecast insurance claim costs, are more accurate than exponential trend models. They also point out that inflation plays an important role in this context. Cummins and Griepentrog (1985) further compare econometric models with ARIMA models, which do not require forecasts for the underlying economic indices, and find that econometric models do better in forecasting automobile insurance claim costs. In addition, Cummins and Derrig (1993) first review different approaches in the previous literature on forecasting insurance claim costs and then use fuzzy set theory in order to combine forecasts from alternative models in order to derive a good (improved) forecast of insurance claim costs.

In the academic literature on the modeling of calendar year effects (diagonal effects) and claims inflation, Clark (2006) and D'Arcy, Au, and Zhang (2009) model claims inflation using a mean-reverting time series model, while Barnett and Zehnwirth (2000) study calendar year effects within a probabilistic trend family, de Jong (2006) uses a calendar-correlation-model, and de Jong (2012) develops and implements a model for dependences between loss triangles using Gaussian copulas. In addition, Wüthrich (2010) studies a Bayesian chain ladder model that allows for calendar year effects and, using a gamma-gamma model, shows that calendar year effects substantially impact the uncertainty of prediction of the claims reserves. Moreover, Shi, Basu, and Meyers (2012), Salzmann and Wüthrich (2012), and Merz, Wüthrich, and Hashorva (2013), also study calendar year effects in a Bayesian inference approach using Markov chain Monte Carlo simulation methods, while Saluz and Gisler (2014) analyze the difference between the best estimate predictions of the ultimate claim in two successive calendar years. In addition, Jessen and Rietdorf (2011) present two different approaches in order to include diagonal effects in claims reserving, and Björkwall, Hössjer, and Ohlsson (2010) introduce a bootstrapping procedure for the separation method in claims reserving. Thus, while these papers analyze claims reserving, they do not specifically focus on the (stochastic) modeling of claims inflation in claims reserving or the identification of driving factors of claims inflation.

In this paper, we analyze claims inflation in non-life insurance on the basis of empirical data for automobile liability insurance, fully comprehensive car insurance, and third party liability insurance provided by a large German non-life insurance company. We thereby contribute to the literature in two main ways. First, we identify the main driving factors for claims inflation with focus on automobile liability insurance based on a real and representative data set for the non-life insurance market in Germany and thus provide unique empirical insights into the market. More specifically, we first empirically extract calendar year effects by means of the separation method, and then determine main driving factors (economic indices) that influence the observed inflation risk in automobile liability insurance, fully comprehensive car insurance, and third party liability insurance by using stepwise multiple linear regressions. This allows central insights in regard to main drivers of the respective claims inflation as, e.g., the progress in medical technology may considerably exceed the standard inflation as reflected by the consumer price index. Thus, an increase in prices for certain therapies may influence the costs for bodily injuries in, e.g., accident insurance, but may not affect the costs for other lines of business such as fully comprehensive car insurance. We show that inflation risk strongly depends on the line of business and that its major influencing factors may differ considerably.

Second, we introduce and present a modeling approach that comprises several steps of dealing with claims inflation in non-life insurance in regard to controlling and arriving at a final claims reserve. This approach is applied to the comprehensive data set of a large German non-life insurer consisting of the run-off triangle for the claims payments of the business line automobile liability insurance. Hence, we further contribute to the literature by studying the impact of the empirically observed superimposed inflation (addressed in the first step) on claims reserving for the considered business line. Toward this end, we use the bootstrapping procedure of the separation method presented in Björkwall, Hössjer, and Ohlsson (2010), where the incremental claims are assumed to be gamma distributed, to obtain the predictive distribution of the claims reserves, while we account for an extrapolation of future claims inflation based on key economic indices. In addition, to explicitly account for calendar year effects, we model and calibrate claims inflation using a multiple linear regression model and the Vasicek (1977) model and thus extend the model by Björkwall, Hössjer, and Ohlsson (2010). Our findings indicate that inflation risk can be substantial, thus being of high relevance in regard to the calculation of claims reserves.

The remainder of the paper is structured as follows. Section 2 illustrates the empirical extraction and analysis of the claims inflation using the separation method. Section 3 presents the modeling and calibration of the insurer's claims inflation using multiple linear regression and the Vasicek (1977) model, whereas the modeling of the claims reserves is presented in Section 4. The empirical analysis of claims inflation risk in the case of the automobile liability insurance of the German non-life insurer is presented in Section 5, and Section 6 concludes.

2. EMPIRICAL DERIVATION AND ANALYSIS OF CLAIMS INFLATION

2.1 Empirical derivation of the claims inflation

To empirically derive the historical claims inflation[1] from the available claims data by the non-life insurer, we apply the separation method, which was first introduced by Verbeek (1972), who applied the model in the reinsurance context to the projection of the number of reported claims. Taylor (1977) further generalized this method in order to apply it to claim amounts rather than claim numbers.

Let $i \in \{0,\ldots,n\}$ denote the rows corresponding to the accident year in the triangle, and $k \in \{0,\ldots,n\}$ denote the columns corresponding to the development year in the triangle. In addition, we assume that the claims are fully settled in development year n. The expected value of the incremental claims $Z_{i,k}$ ($i,k \in \nabla$, where $\nabla = \{i = 0,\ldots,n; k = 0,\ldots,n-i\}$ refers to the upper triangle), can then be stated as follows (see, e.g., Björkwall, Hössjer, and Ohlsson, 2010)[2]

$$E\left[Z_{i,k}\right] = v_i \lambda_t \vartheta_k \text{ with } \sum_{k=0}^{n} \vartheta_k = 1, \tag{1}$$

where v_i are volume measures of the accident years i that are assumed to be known (e.g. the expected number of claims for the corresponding accident year i) and ϑ_k denotes the unknown effect of the development year k. The also unknown effect λ_t of the calendar year $t = i+k$, represents the inflation parameter that has to be estimated. The idea behind the separation method is thus to distinguish the factors for the development year and the calendar (accounting) year effects. The development year effects impact the columns of the run-off triangle, whereas the calendar year effects operate on the diagonals of the table. The fundamental assumption of the separation method is that these two patterns are independent of each other. By means of the separation method, the data are analyzed to reveal the inflation inherent in the data, which can then be used to forecast the inflation rates for future years, e.g., for a specific line of business (see Section 3).

---

1 Here, claims inflation is defined as the sum of the general inflation and the superimposed inflation (see Swiss Re, 2010).

2 The notation in Björkwall, Hössjer, and Ohlsson (2010) is also consistent with the notation in Schmidt (2007), which is suggested by the German Insurance Association (see GDV, 2011).

The separation method consists of two steps: First, the incremental claims $Z_{i,k}$ are standardized by the known number of claims v_i in the accident year i:

$$X_{i,k} = \frac{Z_{i,k}}{v_i},$$

and, second, the unknown parameters of the calendar year effects $\hat{\lambda}_t$ and the development years $\hat{\vartheta}_k$ are estimated by

$$\hat{\lambda}_t = \frac{\sum_{i=0}^{t} X_{i,t-i}}{1-\sum_{k=t+1}^{n} \hat{\vartheta}_k} \text{ and } \hat{\vartheta}_k = \frac{\sum_{i=0}^{n-k} X_{i,k}}{\sum_{i=0}^{n-k} \hat{\lambda}_{n-i}}, \text{ respectively,} \tag{2}$$

where $k \in \{0,1,\ldots n\}$ denotes the development year and $t \in \{0,1,\ldots n\}$ denotes the diagonal of accident year i and development year k, i.e. $t = i+k$. The calculation of the parameters is done recursively with a starting point $t = n$. As a result of the separation method, one obtains the estimates of the calendar year effects $\hat{\lambda}_t$, which can be interpreted as the average claims of the different calendar years. The specific claims inflation rate r_t is then calculated as the rate of change between two sequent calendar year effects, i.e.,[3]

$$r_t = \frac{\hat{\lambda}_t}{\hat{\lambda}_{t-1}} - 1. \tag{3}$$

2.2 Analyzing claims inflation: Determination of main economic drivers

Given the historical claims inflation rates empirically extracted from claims data, one relevant question concerns the main economic drivers of claims inflation, which might deviate from the classical consumer price inflation index (i.e. general inflation) as laid out in the previous subsection. In particular, causes of superimposed inflation (i.e. inflation superimposed on top of the regular CPI) discussed in the academic literature especially comprise legal and legislative changes that increase the average claims payments (see Brickman, Forster, and Sheaf, 2005; Pearson and Beynon, 2007; Cutter, 2009; Lewin, 2009; Swiss Re, 2010). In addition, superimposed inflation arises from changing social conventions and medical cost

[3] See Taylor (1977, p. 228) for a numerical example of the separation method on automobile insurance illustrating the process from a reserve triangle to the corresponding vector of calendar year effects.

inflation (see Pearson and Beynon, 2007; Lewin, 2009; Swiss Re, 2010), where medical cost inflation also includes advances in medical technology, which create new treatment options, changing costs of medical treatment, and an increasing lifespan of seriously injured claimants. Cutter (2009) further points out that claims handling practices may also contribute to superimposed inflation. In addition, according to Brickman, Forster, and Sheaf (2005), wage inflation, changes in policy limits, and underwriting decisions can also play a relevant role.

In line with these observations, it has been shown that different individual economic indices are related to the specific claims inflation of different lines of business (see, e.g., Masterson, 1968; Cummins and Powell, 1980; Cummins and Griepentrog, 1985). Morrow and Conrad (2010), e.g., identified economic indicators that best explain claims inflation, e.g., the indices consumer price index (CPI), CPI–total medical care and CPI–medical services for fully comprehensive car insurance, as discussed later in more detail. Thus, the determination of explanatory economic indices can contribute to an improved understanding of the drivers of claims inflation and hence improve the calculation of claims reserves as well as asset-liability management decisions, for instance.

Following Colquitt and Hoyt (1997) and Manab and Ghazali (2013), we use stepwise regression to determine the relevant economic "driving factors" of claims inflation. The stepwise regression combines forward selection with backward elimination in order to select the best subset of predictor variables, i.e. at each stage, a variable may be added to the model or be removed from it. We fit the model based on the common Akaike information criterion (AIC), and choose the model that minimizes the AIC (see, e.g., Young, 2012, p. 161-188).[4] The selection of potential explanatory variables to be included in the stepwise multiple regressions is based on economic arguments by taking into account the academic literature and an analysis of the unique characteristics of the business line (see Verbeek, 2012, p. 63). The analysis focuses on the attributes that best characterize the costs of the respective line of business. The multiple regression model can be written as follows:

$$r_t = c + \sum_{j=1}^{m} \beta_j \cdot I_{t,j} + \varepsilon_t , \tag{4}$$

[4] A detailed description of the stepwise regression procedure can be found in Frees (2010), for instance. While stepwise regression ignores nonlinear alternatives and the effect of outliers, the procedure is still useful to search through several theoretically relevant models in order to select the explanatory variables (see Frees, 2010). See also Samson and Thomas (1987) and Brockett et al. (1994) for applications of stepwise multiple regressions.

where r_t denotes the claims inflation as the dependent variable at time $t \in \{0,1,\ldots n\}$, c the regression constant, $I_{t,j}$ the value of the explanatory variable j at time $t \in \{0,1,\ldots n\}$ (i.e., the economic index), β_j the corresponding regression coefficient and ε_t the error term.[5]

3. MODELING AND CALIBRATING CLAIMS INFLATION

Apart from identifying main drivers of inflation, a stochastic model for claims inflation is needed when forecasting future claims and for calculating claims reserves. In this context, we model claims inflation in two different ways: (1) a multiple linear regression model, and (2) the Vasicek (1977) model.

Multiple linear regression model

First, we use an empirical multiple linear regression model, where claims inflation is explained by different economic indices. Multiple regression is a widely used method to fit the observed data and to create models that can be used for prediction in different fields, such as biology, medicine, and economics. Multiple regression models have also been used to forecast indices, in particular stock indices (e.g., Cheng, Lo, and, Ma, 1990, and Sopipan, Kanjanavajee, and Sattayatham, 2012). In regard to forecasting insurance claim costs, Cummins and Powell (1980) and Cummins and Griepentrog (1985) also use econometric models (univariate and multivariate models) that are based on relevant economic indices, in particular price and wage indices, since insurance claims payments are closely related to economic indices. In addition, Masterson (1968) shows that different economic indices are related to the specific claims inflation of different lines of business and Morrow and Conrad (2010) identify economic indicators that best explain claims inflation. Thus, as claims inflation is driven by different economic indices, a multiple linear regression model allows combining these different economic indices in order to forecast claims inflation.

The multiple linear regression model can be compared to the stochastic investment model of Wilkie (1986), where the behavior of various economics factors is described by a stochastic time series. The Wilkie (1986) model comprises several separate variables, which are modeled in a cascade structure based on price inflation as the driving force. Thus, price inflation is described first, and the remaining variables are constructed next based on the modeling of the previous variable(s). In the present paper, focus is laid on the modeling of claims inflation based on the explanatory indices identified following the procedure laid out in

[5] Since moving averages can cause pseudo-correlations even if the data is independent, we do not analyze moving averages and time-shifted reactions (see Mittnik, 2011).

Section 2.2. In addition, before the multiple linear regression model can be used to forecast claims inflation, the explanatory variables have to be predicted into the future. In this paper, to obtain first insight, we use a simplified approach and do not model the explanatory indices $I_{t,j}$ in Equation (4) stochastically, but instead use the empirically estimated mean $\overline{I}_j$, which is constant for $t \in \{n+1,...,2n\}$ and implies less model volatility, thus reducing the model risk potentially arising due to the aggregation of multiple stochastic processes. Thus, the multiple linear regression model used for forecasting claims inflation is given by (see DAV, 2013)

$$r_t = c + \sum_{j=1}^{m} \beta_j \cdot \overline{I}_j + \varepsilon_t, \tag{5}$$

where r_t denotes the forecasted claims inflation at future time $t \in \{n+1,...,2n\}$, and ε_t the normally distributed error term with mean 0 and standard deviation σ. Furthermore, the constant c, and the coefficients β_i are derived with Equation (4).[6]

Vasicek (1977) model

Second, we use the Vasicek (1977) model to forecast claims inflation. The Vasicek (1977) model is often used for modeling inflation rates (see, e.g., de Melo, 2008; Falbo, Paris, and Pelizzari, 2010) due to its mean-reverting property and the feature of negative inflation rates. Chan (1998) and Ahlgrim and D'Arcy (2012b) also model the behavior of the inflation rate by means of a stochastic Ornstein-Uhlenbeck process and Clark (2006) and D'Arcy, Au, and Zhang (2009) model claims inflation using a mean-reverting time series model. In addition, the Vasicek (1977) model is often used to model inflation indices that describe the average rate of price increase for a specific basket. Thus, transferred to a non-life insurer, this means that we consider a portfolio of claims and that claims inflation denotes the change of the average rate of price increase for this specific basket of claims (see DAV, 2013).
The Vasicek (1977) model is described by

$$dr_t = \alpha(\theta - r_t)\,dt + \sigma dW_t, \tag{6}$$

where α, σ, and θ are strictly positive. Here, α controls the speed of the mean reversion to the long-term mean θ (see Cairns, 2004). The volatility of the inflation rate process is represented by σ. The resulting inflation rate r_t

6 An application of this model to claims inflation is also suggested by Towers Watson, who calculate the "Towers Watson Claim Cost Index", which is constructed from a variety of economic indices that reflect insurance costs (see Pecora and Thompson, 2012).

$$r_{t_i} = b/a \cdot \left(1 - e^{-a\cdot(t_i - t_{i-1})}\right) + e^{-a\cdot(t_i - t_{i-1})} \cdot r_{t_{i-1}} + \sigma \cdot e^{-a\cdot t_i} \int_{t_{i-1}}^{t_i} e^{a\cdot s} dW(s)$$

is normally distributed with mean $\left(r_s \cdot \exp\left(-\alpha \cdot (t-s)\right) + \theta \cdot \left(1 - \exp\left(\alpha \cdot (t-s)\right)\right)\right)$ and variance $\left(\sigma^2 / 2\cdot\alpha\right)\cdot\left(1 - \exp\left(-2\cdot\alpha\cdot(t-s)\right)\right)$. For $t \to \infty$ the mean converges to the long-term mean θ with long-term variance $\sigma^2 / 2\cdot\alpha$.

To calibrate the Vasicek (1977) model based on the empirical claims data provided by a non-life insurer, Equation (6) has to be rewritten by

$$dr_t = \alpha\left(\theta - r_t\right)dt + \sigma dW_{r_t} = (b - a\cdot r_t)dt + \sigma dW_{r_t}. \tag{7}$$

Next, Equation (7) has to be considered in discrete representation at time t_i (see Glasserman, 2010), such that

$$r_{t_i} = b/a \cdot \left(1 - e^{-a\cdot\Delta t}\right) + e^{-a\cdot\Delta t} \cdot r_{t_{i-1}} + \sigma\sqrt{\left(1 - e^{-2\cdot a\cdot\Delta t}\right)/2\cdot a} \cdot Z_{t_i},$$

where Z_{t_i} denotes a standard normally distributed random number (see Brigo and Mercurio, 2007). The time step is given by $\Delta t = t_i - t_{i-1}$ with a total of n observed data points. Setting the coefficient to

$$c = e^{-a\cdot\Delta t},\ d = b/a\cdot\left(1 - e^{-a\cdot\Delta t}\right) \text{ and } V = \sigma\sqrt{\left(1 - e^{-2\cdot a\cdot\Delta t}\right)/2\cdot a},^{7}$$

the unknown parameters can be derived by an OLS regression (see Brigo et al., 2009).[8]

4. THE IMPACT OF CLAIMS INFLATION ON RESERVING

As one main application and to identify the impact of stochastic claims inflation on claims reserving, we calculate the reserves by means of the separation method with the stochastic claims inflation for the calendar year effects. When extrapolating the calendar year effects to provide an estimator for future claims (and the reserve) by means of the separation method, we distinguish three cases. First, we assume the claims inflation rate r_t is constant over time, i.e. $r_t = r$ for $t \in \{n+1, ..., 2n\}$. Second, we stochastically model the future claims inflation

---

7 Applying the Euler discretization scheme, the parameter V simplifies to $V = \sigma\sqrt{\Delta t}$ (see Glasserman, 2010).

8 OLS (ordinary least squares) can be used to calibrate unknown parameters by a linear regression. When the distribution of the underlying process is Gaussian as in the case of the Vasicek (1977) model, this method is in accordance with the maximum likelihood estimates (see Brigo et al., 2009).

rates r_t according to Equation (5) using the multiple linear regression model and, third, we use the Vasicek (1977) model (Equation (6)). By applying the inflation estimators r_t with $t \in \{n+1,...,2n\}$, the unknown calendar year effects $\hat{\lambda}_t$ for $t \in \{n+1,...,2n\}$ can be calculated via

$$\hat{\lambda}_t = \hat{\lambda}_{t-1} \cdot (1+r_t) \tag{8}$$

with a given $\hat{\lambda}_n$ (see Equations (2) and (3)). The future incremental claims $\hat{Z}_{i,k}$ ($i,k \in \Delta$, where $\Delta = \{i=1,\ldots,n; k=n-i+1,\ldots,n\}$ denotes the unobserved future triangle) in the lower triangle can thus be predicted with the separation method by $\hat{Z}_{i,k} = v_i \hat{\lambda}_t \hat{\vartheta}_k$, where $\hat{\vartheta}_k$ is derived from Equation (2) and $\hat{\lambda}_t$ is given by Equation (8) with either a constant inflation rate $r_t = r$ or a stochastic inflation rate r_t for $t \in \{n+1,...,2n\}$, modeled by the multiple linear regression model or the Vasicek (1977) model. The accident year effect v_i is assumed to be known and represents the number of claims per accident year. This leads to a total reserve estimator $\hat{R}$ given by

$$\hat{R} = \sum_{\Delta} \hat{Z}_{i,k} \,. \tag{9}$$

The separation method of Taylor (1977) is a deterministic method similar to the classical chain ladder method. To provide a full predictive distribution, Mack (1993) analytically calculates the mean square error of prediction (MSEP)[9] for the chain ladder method and England and Verrall (1999) introduce bootstrapping using a generalized linear model (GLM) framework. In case of the separation method, GLM theory cannot be applied directly, since all incremental claims of the same accident year share the same number of claims and are thus dependent. Furthermore, the analytical calculation of the MSEP requires an explicit expression of the MSEP and further distributional assumptions in order to derive the predictive distribution of the claims reserves (see Björkwall, Hössjer, and Ohlsson, 2010, p. 866). Hence, we apply the parametric bootstrapping procedure of Björkwall, Hössjer, and Ohlsson (2010) to obtain the predictive distribution of the claims reserves for the separation method.

The starting point of the bootstrap procedure is the upper run-off triangle. Based on the claims data in the upper triangle, the aim of the bootstrap procedure described in Björkwall, Hössjer, and Ohlsson (2010) is to obtain a full predictive distribution of the claims reserves. Thus,

---

9 In Mack (1993) the MSEP $msep(\hat{R})$ of the estimator $\hat{R}$ of the total claims reserves R is defined by $msep(\hat{R}) = E\left(\left(\hat{R}-R\right)^2 \mid \nabla\right)$, where ∇ refers to the upper triangle.

instead of a deterministic point estimate, which can be derived by the separation method of Taylor (1977), the bootstrap procedure allows deriving a full distribution of claims reserves. The distribution of claims reserves is thereby derived based on the sum of the point estimates and the additional uncertainty of the prediction, which in turn is derived in two steps. First, we draw B pseudo upper triangles and predict the corresponding future incremental claims with the separation method, and second, we directly draw B times the pseudo future incremental claims in the lower triangle. The prediction uncertainty is then obtained by the standardized difference between these two pseudo claims reserves.

In particular, following Björkwall, Hössjer, and Ohlsson (2010), the relation between the claims reserves R and its estimator $\hat{R}$ in the real world, which is obtained by Equation (9), can be substituted by the true outstanding claims R^{**} in the bootstrap world and the estimated outstanding claims $\hat{R}^{*}$ in the bootstrap world. Thus, the process error and the estimation error are included in R^{**} and $\hat{R}^{*}$, respectively, which allows approximating the predictive distribution of the claims reserves. Hence, we use the notation * for random variables in the bootstrap world, which correspond to estimators in the real world. The notation ** is used for random variables in the bootstrap world, if the corresponding variable in the real world is not observed.

First, the number of claims v_i per accident year i is assumed to be known. In addition, we follow Björkwall, Hössjer, and Ohlsson (2010) and assume that the independent incremental claims $Z_{i,k}$ are gamma distributed,[10] i.e.

$$Z_{i,k} \sim \Gamma\left(\frac{v_i}{\hat{\phi}}, \hat{\vartheta}_k \hat{\lambda}_t \hat{\phi}\right), \tag{10}$$

with mean $v_i \hat{\lambda}_t \hat{\vartheta}_k$ and variance $v_i \left(\hat{\lambda}_t \hat{\vartheta}_k\right)^2 \hat{\phi}$, where $\hat{\phi}$ is given by

$$\hat{\phi} = \frac{1}{|\nabla| - q} \sum_{\nabla} v_i \frac{\left(Z_{i,k} - v_i \hat{\lambda}_t \hat{\vartheta}_k\right)^2}{\left(v_i \hat{\lambda}_t \hat{\vartheta}_k\right)^2},$$

where ∇ denotes the upper triangle, $|\nabla|$ is the number of observations in the upper triangle, q denotes the number of parameters that have to be estimated and $\hat{\vartheta}_k$ and $\hat{\lambda}_t$ are derived from Equation (2). Thus, the expected value of the incremental claims $Z_{i,k}$ is given by $v_i \hat{\lambda}_t \hat{\vartheta}_k$, which

10 See also Wüthrich (2010), where the cumulative claims also follow a gamma distribution.

is in line with Equation (1). In order to approximate the predictive distribution of the claims reserves, we next calculate the estimated outstanding claims in the bootstrap world and the true outstanding claims in the bootstrap world.

The estimated outstanding claims in the bootstrap world

To calculate the estimated outstanding claims $\hat{R}^*$ in the bootstrap world, first, each $Z_{i,k}^*$ ($i,k \in \nabla$, with $\nabla = \{i = 0,\ldots,n; k = 0,\ldots,n-i\}$) is drawn B times from Equation (10), to obtain B pseudo upper triangles. Second, for each pseudo upper triangle, the future incremental claims $\hat{Z}_{i,k}^*$ ($i,k \in \Delta$ with $\Delta = \{i = 1,\ldots,n; k = n-i+1,\ldots,n\}$) can be predicted with the separation method by $\hat{Z}_{i,k}^* = v_i \hat{\lambda}_t^* \hat{\vartheta}_k^*$ (where $\hat{\vartheta}_k^*$ is derived from Equation (2) and $\hat{\lambda}_t^*$ is given by Equation (8) with either a constant inflation rate $r_t = r$ for $t \in \{n+1,\ldots,2n\}$ or a stochastic inflation rate r_t for $t \in \{n+1,\ldots,2n\}$, modeled by the multiple linear regression model or the Vasicek (1977) model),[11] which leads to the estimated outstanding claims $\hat{R}^*$ in the bootstrap world

$$\hat{R}^* = \sum_{\Delta} \hat{Z}_{i,k}^* .$$

True outstanding claims in the bootstrap world

Next, to calculate the true outstanding claims R^{**} in the bootstrap world, $Z_{i,k}^{**}$ ($i,k \in \Delta$ with $\Delta = \{i = 1,\ldots,n; k = n-i+1,\ldots,n\}$) are sampled B times from Equation (10) to obtain B pseudo lower triangles and the true outstanding claims in the bootstrap world are given by

$$R^{**} = \sum_{\Delta} Z_{i,k}^{**} .$$

Calculation of the predictive distribution

Using $\hat{R}^*$ and R^{**}, the predictive distribution of the outstanding claims $\tilde{R}^{**}$ is obtained by the sum of the estimated claims reserve in the real world $\hat{R}$ (see Equation (9)) and the prediction error pe^{**} multiplied by the estimator of the variance of the claims reserves R, i.e.

$$\tilde{R}^{**} = \hat{R} + pe^{**}\sqrt{\widehat{Var}(R)} ,$$

where the estimator of the variance of the claims reserves R is given by

[11] Note that the parameters for modeling the stochastic inflation rate r_t using the Vasicek (1977) model and the multiple regression model are based on the empirical data for all simulations B.

$\widehat{Var}(R) = \sum_i v_i \hat{\phi} \sum_{\Delta} \left(\hat{\vartheta}_k \hat{\lambda}_t\right)^2$, with $i, k \in \Delta$ and $\Delta = \{i = 1, \ldots, n; k = n - i + 1, \ldots, n\}$.

The B prediction errors are in turn derived by the standardized difference between the true outstanding claims R^{**} and the estimated outstanding claims $\hat{R}^{*}$ in the bootstrap world, thus the prediction errors pe^{**} are given by

$$pe^{**} = \frac{R^{**} - \hat{R}^{*}}{\sqrt{\widehat{Var}\left(R^{**}\right)}},$$

where the estimator of the variance of R^{**} is given by
$\widehat{Var}\left(R^{**}\right) = \sum_i v_i \hat{\phi}^{*} \sum_{\Delta} \left(\hat{\vartheta}_k^{*} \hat{\lambda}_t^{*}\right)^2$, with $i, k \in \Delta$ and $\Delta = \{i = 1, \ldots, n; k = n - i + 1, \ldots, n\}$,

and the estimator $\hat{\phi}^{*}$ is derived by

$$\hat{\phi}^{*} = \frac{1}{|\nabla| - q} \sum_{\nabla} v_i \frac{\left(Z_{i,k}^{*} - v_i \hat{\lambda}_t^{*} \hat{\vartheta}_k^{*}\right)^2}{\left(v_i \hat{\lambda}_t^{*} \hat{\vartheta}_k^{*}\right)^2}.$$

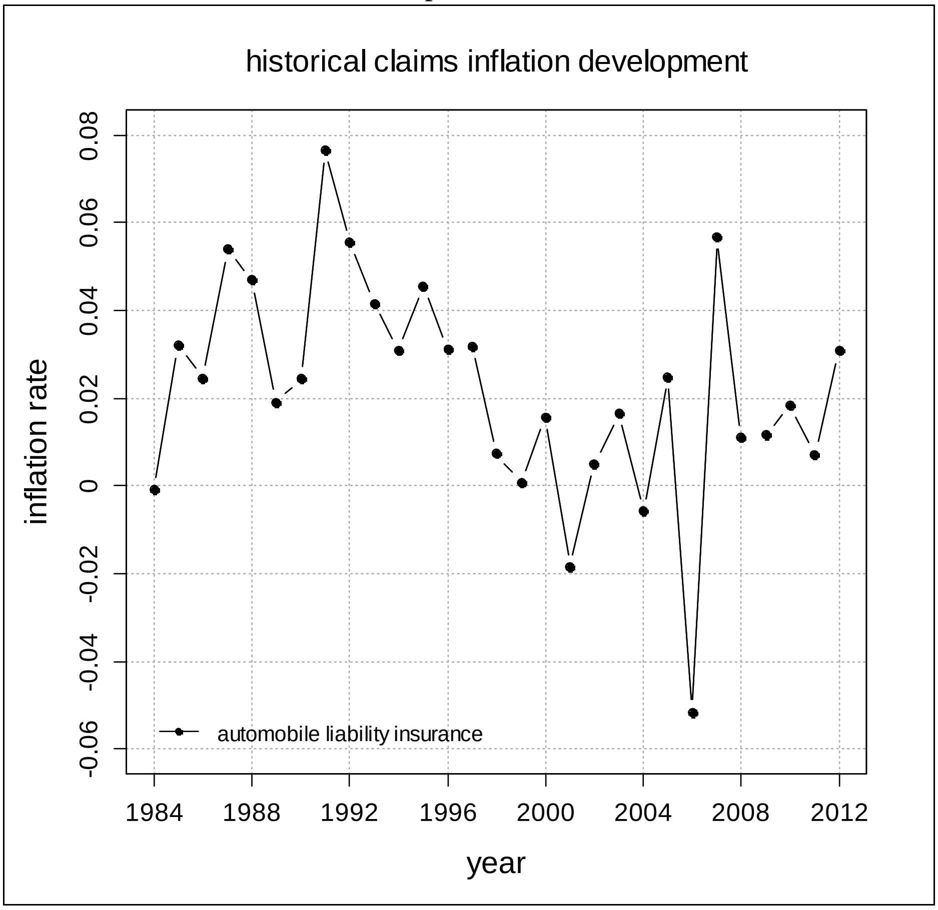
5. Empirical Analysis of Claims Inflation: The Case of a German Non-Life Insurer

This section presents an empirical and numerical analysis of claims inflation based on a data set provided by a German non-life insurer. In what follows we first describe the data provided by the insurer and the economic inflation indices used to analyze the empirically estimated claims inflation. Next, the process of deriving, analyzing, calibrating and simulating claims inflation is illustrated for the line of business "automobile liability insurance" along with the impact of inflation on claims reserves. Last, we additionally study further lines of business (third party liability insurance and fully comprehensive insurance) and identify relevant driving factors of claims inflation.

5.1 Data

We use a comprehensive data set of a large German non-life insurer consisting of the run-off triangle for the claims payments of the business line "automobile liability insurance". In automobile liability insurance, liabilities can arise from bodily injuries or physical damages. Since bodily injuries and physical damage are different, claims inflation may differ between these two types of damage and thus, splitting automobile liability insurance into separate portfolios or the use of policy-level data may improve the estimation and allow further analyses. However, due to the availability and structure of the data, we use a data set which contains both bodily injuries and physical damages on an aggregated level. The run-off triangle contains annual incremental payments for the dimensions accident year and development year for the years 1983 to 2012. As a result of the separation method, we obtain the calendar year effects λ from the year 1983 to 2012 and the specific claims inflation r_t for the years 1984 to 2012, which is calculated as the rate of change between two sequent calendar year effects (see Equation (3)). The average claims inflation in automobile liability insurance in the time interval 1984 to 2012 was 2.21% and the total claims inflation ranges between -5.17% and 7.65% (see Table 1) and Figure 1 illustrates the extracted historical claims inflation development over time. Note that the empirical data were scaled for anonymization.

Figure 1: Historical claims inflation development in the time interval 1984-2012



5.2 Analyzing claims inflation in automobile liability insurance

We next study the historically observed claims inflation in more detail by identifying the relevant economic driving factors based on the literature and stepwise regressions. As described before, the selection of relevant variables to be included in the stepwise multiple regressions is based on economic arguments and focuses on the attributes that best characterize the costs of the respective line of business, i.e. the business line automobile liability insurance of the German non-life insurer in our case.

Regarding automobile liability insurance, liabilities can arise from bodily injuries or property damage sustained by others in an automobile accident. In addition, automobile liability insurance protects the insured against being held liable for others' losses (see Cummins and Tennyson, 1992). Hence, claims can be divided into physical injuries, bodily injuries, and pure financial losses. In this context, Cummins and Powell (1980) consider several price and wage indices in their model to forecast automobile insurance claim costs. Their findings indicate that inter alia "the implicit price deflator for gross national product, the implicit price deflator for autos and parts, and wage indices for the service sector and for the private sector of the economy" (Cummins and Powell, 1980, p. 96) are important variables for the prediction. Moreover, Cummins and Griepentrog (1985) additionally find the implicit price deflator for personal consumption expenditures, the CPI, the CPI–medical care, and the service sector wage rate to be relevant indices for automobile insurance. In addition, Masterson (1968) identified the indices CPI–auto repairs and maintenance, average annual earnings and average annual income in the transport sector and a bodily injury loss index as relevant for automobile liability insurance.[12]

We thus hypothesize that the indices CPI, CPI–transportation, CPI–purchase of motor vehicles, turnover–motor vehicle maintenance and repair, gross earnings, and indices regarding health costs as stated in Table 1 have a significant impact on claims inflation in automobile liability insurance. Apart from providing descriptive statistics for our sample of explanatory variables, Table 1 also contains more information about the estimated claims inflation in automobile liability insurance.

---

[12] Masterson (1968) developed claim costs indices for various lines of business, using weighted averages of governmental price and wage indices. Cummins and Freifelder (1978) also refer to the list of available indices of Masterson (1968).

Table 1: Estimated claims inflation in automobile liability insurance and selection of explanatory variables for automobile liability insurance: Descriptive statistics[13]

Automobile liability insurance	*Interval*	*N*	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Estimated claims inflation r_t	1984-2012	29	2.21%	2.55%	-5.17%	7.65%
	1995-2012	18	1.32%	2.42%	-5.17%	5.68%
CPI	1992-2012	21	1.81%	0.92%	0.36%	4.30%
	1995-2012	18	1.55%	0.63%	0.36%	3.17%
CPI–transportation	1992-2012	21	2.70%	2.03%	-2.79%	6.15%
	1995-2012	18	2.54%	2.16%	-2.79%	6.15%
CPI–purchase of motor vehicles	1992-2012	21	1.08%	1.28%	-0.49%	3.96%
	1995-2012	18	0.85%	0.95%	-0.49%	3.32%
Turnover–motor vehicle maintenance and repair	1995-2012	18	-1.02%	11.00%	-20.03%	32.57%
Gross earnings	1992-2012	21	1.74%	1.93%	-0.13%	8.72%
	1995-2012	18	1.27%	1.05%	-0.13%	3.02%
OECD health–total current	1995-2012	18	3.41%	1.83%	-0.07%	7.52%
OECD health–nursing care	1995-2012	18	5.52%	4.30%	1.11%	18.47%
OECD health–medical goods	1995-2012	18	3.38%	3.83%	-5.81%	9.63%

In order to test these hypotheses and to identify the most relevant driving factors among the considered ones, we next conduct the stepwise regression procedure. Due to the limited availability of the economic indices (first line of each variable in Table 1), we base our analysis on the relevant variables given in Table 1 for the time interval from 1995 to 2012 (second line of each variable in Table 1, if available) using annual data.[14] Furthermore, we control for multicollinearity, which arises in case of highly correlated explanatory variables.[15]

[13] The economic indices stem from two sources: the database GENESIS-Online from the Federal Statistical Office of Germany and the Organization for Economic Co-operation and Development (OECD). The database GENESIS-Online contains a variety of publicly available indices that cover different public and economic fields (www.destatis.de). The OECD provides the index “Health Expenditure and Financing” that reflects prices of different aspects of medical care (www.oecd.org), which contains the sub-baskets “Total current expenditure” (here referred to as OECD health–total current), “Services of long-term nursing care” (here referred to as OECD health–nursing care) and “Medical goods” (here referred to as OECD health–medical goods). Note that the indices OECD health–total current, OECD health–nursing care, and OECD health–medical goods are German specific in our case.

[14] The time series of the indices “turnover–motor vehicle maintenance and repair” and “OECD health–total current” are only available after 1995.

[15] Results show that the index CPI–transportation is highly correlated to the CPI, as it represents a subcategory of the CPI.

Table 2 shows the result of the final multiple regression model. It can be seen that especially the indices OECD health–total current and turnover–motor vehicle maintenance and repair show a high statistically significant relationship with the claims inflation rate of the business line automobile liability insurance. The indices CPI and gross earnings also exhibit a positive relationship, which, however, is only statistically significant at the 10% level. Thus, the results emphasize that the general CPI is not sufficient to explain empirical claims inflation inherent in the considered automobile liability insurance claims data, which exceeds the standard inflation.[16] The analysis shows that it is particularly the OECD health–total current index that contributes most to the observed claims inflation according to the considered regression model, as the progress in medical technology strongly affects the costs for bodily injuries and thus strongly drives the claims inflation of the business line automobile liability insurance. As the risk of bodily injuries typically further depends on the respective portfolio (countryside versus cities), insurers should conduct further detailed analyses and distinguish between respective portfolios when studying claims inflation.

Table 2: Estimates of the multiple linear regression model for the business line automobile liability insurance (yearly observations from 1995 to 2012)

Business line automobile liability insurance	*Regression coefficient β_j*		*Standard error*	*Empirical mean*
Intercept	-0.045	***	0.014	-
CPI	1.256	*	0.682	0.018
Turnover–motor vehicle maintenance and repair	-0.131	***	0.042	-0.010
Gross earnings	0.908	*	0.447	0.017
OECD health–total current	0.757	***	0.236	0.034

Notes: '' statistical significance at the 10% level, '***' statistical significance at the 1% level; AIC = -142.43;* R^2*= 0.6214; p-value = 0.0091; VIF = 2.64.*

The present parameterization of the multiple regression model leads to an AIC of -142.43, an R-squared of 0.6214, a corresponding p-value for the F-test of 0.0091, and a variance inflation factor (*VIF*) of 2.64, which rejects multicollinearity.[17] Hence, the chosen indices contribute to the observed claims inflation and are thus able to explain a large part of the specific claims inflation of the business line. The analysis of claims inflation in regard to the various economic indices allows insight regarding the major economic drivers of claims inflation.

[16] Note that the same holds true for the indices CPI–transportation and CPI–purchase of motor vehicles according to further analyses.

[17] High values of *VIF* indicate multicollinearity, such as values greater than 10, which denotes a typical rule of thumb in the literature (see O'Brien, 2007).

This is also of relevance in regard to risk management and asset-liability management, for instance, in order to predict inflationary impacts on reserves (see also Morrow and Conrad, 2010).

5.3 The impact of stochastic claims inflation on reserving in automobile liability insurance

We next examine the impact of claims inflation on reserving by comparing the predictive distributions that are obtained with the separation method (Section 4) including stochastic and constant claims inflation rates. In addition, we compare our results with the classical chain ladder method. Based on the historical claims inflation data for automobile liability insurance, the Vasicek (1977) model and the multiple linear regression model can be calibrated. The resulting input parameters for the Vasicek (1977) model are given in Table 3, while the parameterization of the multiple linear regression model is given in Table 2.[18]

Table 3: Estimates of the Vasicek (1977) model for the business line automobile liability insurance

	Vasicek (1977)
α	2.101
θ	0.023
σ	0.052

To calculate the claims reserves of the insurer, we first simulate the claims inflation rate for the Vasicek (1977) model and the multiple linear regression model using Monte Carlo simulation with 50,000 sample paths.[19] In addition, we apply two constant claims inflation rates of 2.44% and 5.00%, where the first corresponds to the implicit inflation rate of the classical chain ladder method and the latter illustrates the case of a substantial increase in claims inflation. The bootstrapping procedure of Björkwall, Hössjer, and Ohlsson (2010) as described in Section 4 is then applied with B = 50,000 simulations for each prediction.[20]

[18] Note that the Kolmogorov-Smirnov test showed that the null hypotheses of normally distributed inflation rates cannot be rejected for the historical claims inflation rates (D = 0.1089, p-value = 0.8451), supporting the assumption of normal distribution as is the case for the Vasicek (1977) model.

[19] We chose a sufficiently high number of sample paths and ensured that the results remain stable for different sets of random numbers.

[20] Since we use 50,000 simulations for each prediction and the same number of stochastic inflation rates (in case of the Vasicek (1977) model and the multiple linear regression model), we generate one path of claims inflation rates for each simulation path.

Figure 2 displays the predictive distributions of the claims reserves of the automobile liability insurance calculated by means of the separation method, using two constant inflation rates, the Vasicek (1977) model, and the multiple linear regression model to forecast the claims inflation rates (calendar year effects). In the upper left graph of Figure 2, the predictive distribution of the claims reserves is displayed with a constant claims inflation rate of 2.44%. In this case, the expected value of the claims reserves coincides with the claims reserves calculated based on the deterministic chain ladder method, since the claims inflation rate is set to the intrinsic inflation rate of the chain ladder method. It can be seen that the mean of the distribution is about 248 million with a standard deviation of about 66 million, and that the distribution is skewed to the right due to the gamma distributed incremental claims. In the upper right graph, the predictive distribution of the claims reserves is displayed, now with a constant claims inflation rate of 5%, which illustrates an increase in claims inflation, e.g. an unforeseen increase in medical inflation. It can be seen that the predictive distribution is shifted to the right and the mean of the distribution of the claims reserves increases to about 368 million. Thus, the classical chain ladder method would underestimate the claims reserves, since it is not able to account for unforeseeable changes in the calendar year effects, which emphasizes the importance of explicitly dealing with claims inflation when calculating reserves.

In the lower left graph of Figure 2, the predictive distribution of the reserves is calculated with the stochastic claims inflation rates of the Vasicek (1977) model. It can be seen that the mean of the reserve distribution is about 273 million, which lies above the reserves predicted according to the chain ladder method, and the standard deviation is considerably larger with about 90 million. In comparison, the mean of the reserve distribution in the lower right graph of Figure 2, where inflation rates are forecasted with the multiple linear regression model, is about 234 million and thus, lies slightly below the reserves calculated by the classical chain ladder method, and the standard deviation is about 68 million, which at first glance appears similar to the deterministic model in the upper left graph. However, depending on a required risk-based solvency margin, e.g. a pre-defined high quantile of the reserve distribution, the claims reserves would be considerably higher, and thus, lie considerably above the one calculated by the chain ladder method. This can also be seen in Figure 3, which shows the cumulative distribution functions of the reserves depending on the respective approach (see Figure 2).

Figure 2: Distribution of the claims reserves calculated by the separation method using different claims inflation rates as a result of the Monte Carlo simulation

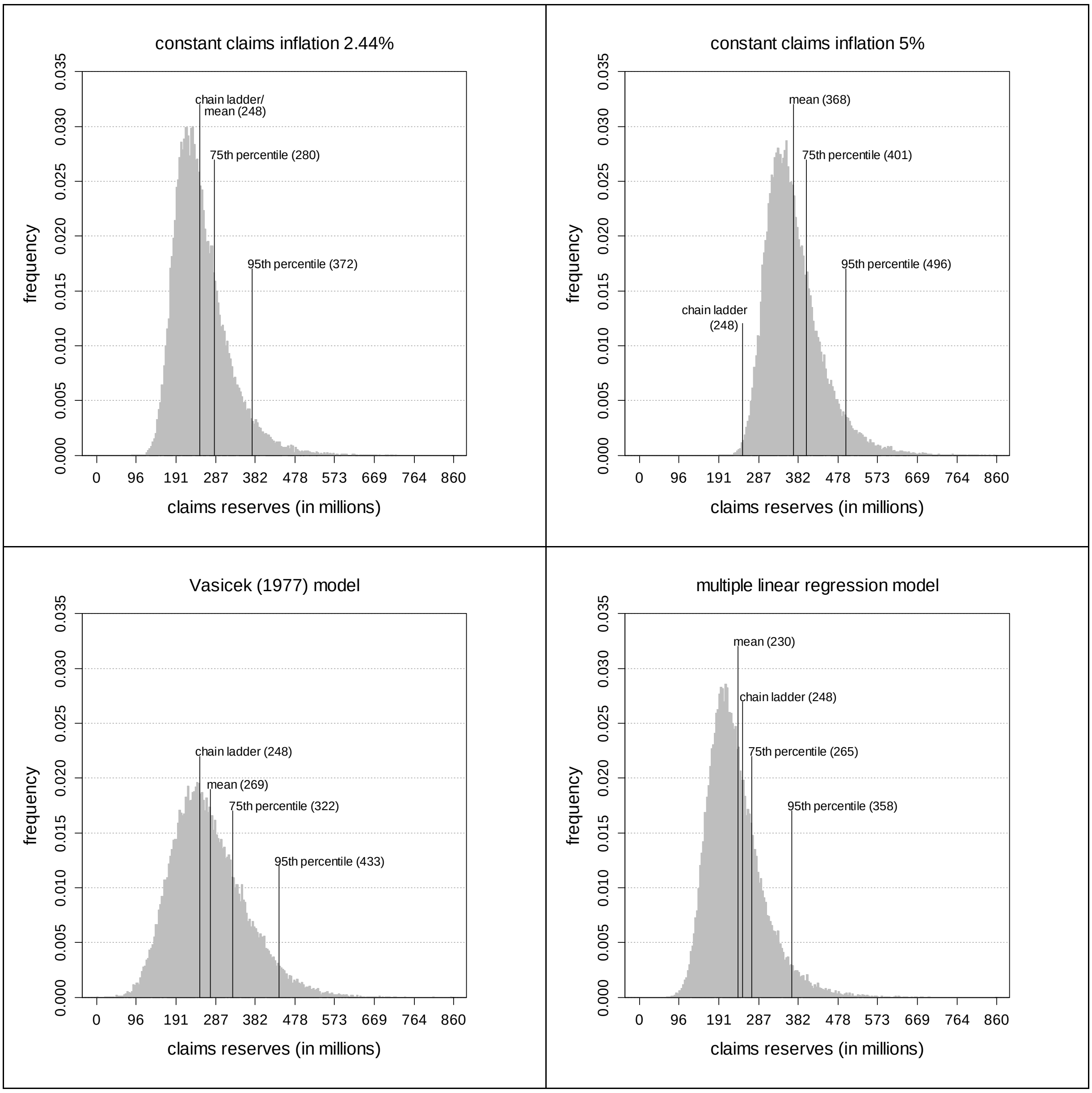
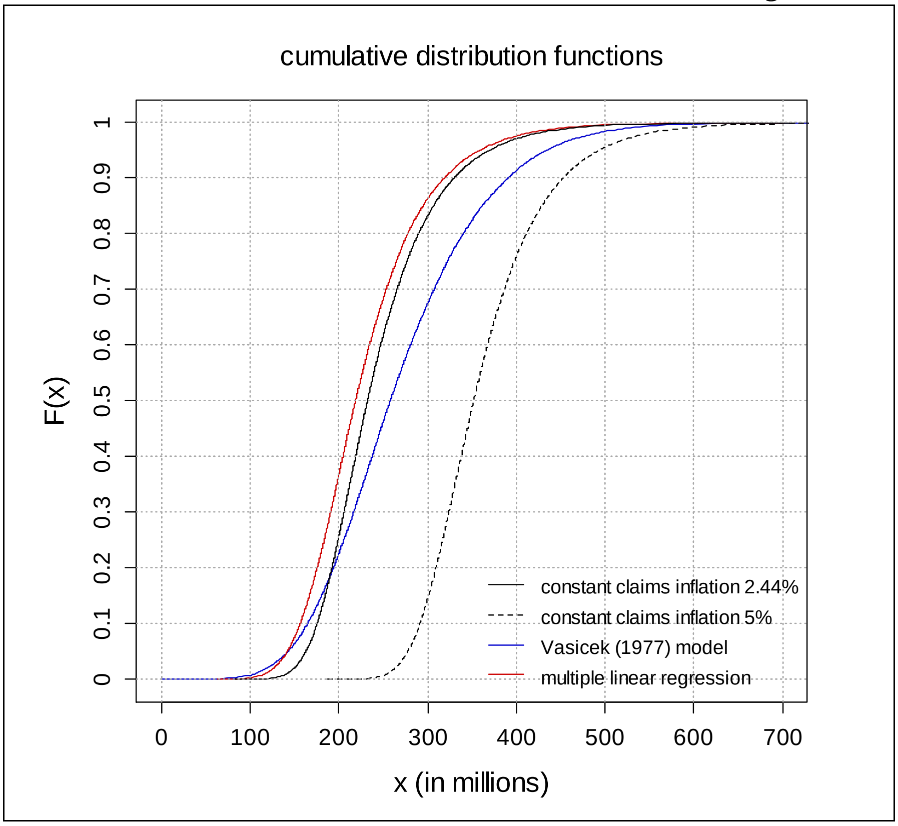


Figure 3: Cumulative distribution functions of the claims reserves in Figure 2



To further compare the claims reserves derived based on the different models, we tested for stochastic dominance using the algorithm presented in Porter, Wart, and Ferguson (1973) (see, e.g., Aboudi and Thon, 1994). The results show that the reserves calculated with a constant inflation rate of 5% (unforeseen increase in claims inflation) dominate the other three distribution functions of the claims reserves by second and third order (by first order in case of a constant inflation rate of 2.44% and the multiple linear regression model). In addition, the test shows that the distribution function calculated with a constant claims inflation of 2.44% dominates the distribution of the claims reserves based on the multiple regression model by first order. Thus, as also seen in Figure 2, the multiple regression model leads to slightly lower reserves in the present setting than the constant inflation model under the assumptions in Equation (5). However, this may change when one or more explanatory indices increase due to environmental changes, for instance, or if a stochastic representation of the explanatory variables is used for forecasting instead of the historical mean. In such a situation, the claims reserves calculated with the multiple linear regression model would increase, while the reserves calculated with the Vasicek (1977) model would not be impacted. Hence, in this way, multiple regression models allow incorporating future expectations in regard to the underlying economic indices driving claims inflation, which is of central importance in case of high unforeseen inflation (see also Cummins and Powell, 1980). Thus, the reserve calculation and the drivers of the reserves as related to inflation may be assessed on sounder basis.[21]

In summary, as the classical chain ladder method extrapolates the claims inflation using a constant factor based on the internal historical claims inflation rates, it is not able to account for unforeseen changes in the calendar year effects, which may be due to, e.g., external effects. In this case, the classical chain ladder method would underestimate the claims reserves, which emphasizes the importance of explicitly dealing with claims inflation when calculating reserves. In this study, we proposed two possibilities for the stochastic modeling of claims inflation. As the Vasicek (1977) model is calibrated based on historical data, external effects cannot be taken into account; however, economic indices are not needed as the calibration is directly based on historical data, which in turn eases the implementation. In comparison, the multiple regression model uses external economic indices, thus requiring a determination of explanatory variables, but it allows insight regarding the major economic drivers of claims inflation, which is of great relevance in regard to risk management and asset-liability management.

5.4 Comparing claims inflation in different lines of business in non-life insurance

In this subsection, we further study two additional lines of business of the German non-life insurer, namely fully comprehensive car insurance and third party liability insurance. We determine the relevant economic driving factors for the two lines of business using stepwise regressions and select potentially relevant variables based on economic arguments (see Sections 2.2 and 5.2). For fully comprehensive car insurance, we include the indices CPI, CPI–transportation, CPI–purchase of motor vehicles, turnover–motor vehicle maintenance and repair and gross earnings in the stepwise regressions. For third party liability insurance, we include the CPI, CPI–household equipment and furnishings, CPI–home maintenance and repair, gross earnings, and three indices regarding health costs in the stepwise regressions (see Masterson, 1968). Table 4 gives an overview of the results of the stepwise regressions for the three business lines fully comprehensive car insurance, third party liability insurance, and automobile liability insurance as studied in the previous subsection along with the relevant economic indices.

[21] See also Cummins and Griepentrog (1985) regarding the use of econometric models in this regard, and additionally Cummins and Derrig (1993) concerning a comparison and combination of different forecasting methods to derive good forecasts.

The results show that the business line fully comprehensive car insurance is influenced by the indices CPI–transportation, CPI–purchase of motor vehicles and turnover–motor vehicle maintenance and repair. For third party liability insurance, we find significant relations of the business line's claims inflation data with the indices CPI, CPI–home maintenance and repair and OECD health–total current.

These observations emphasize that the driving factors of claims inflation in different lines of business can differ considerably and that claims inflation should be analyzed and modeled separately for each line of business. In addition, claims inflation may even considerably differ between portfolios within the same business line depending on the respective risks (e.g., cities, countryside) as also discussed in Section 5.2. For instance, the negative signs in Table 4 may arise from such selection effects in the portfolio of an insurer (e.g. selling fully comprehensive insurance with focus on certain areas or clients). Therefore, the interpretation of the empirical results should take into account the aggregated structure of the dataset, which already provides relevant first insight, but where further research is necessary, e.g. on a policy-level data.

Table 4: Relevant explanatory indices for different lines of business (regression coefficients)

Economic indices	*Automobile liability insurance (VIF = 2.64)*	*Fully comprehensive car insurance (VIF = 2.06)*	*Third party liability insurance (VIF = 1.35)*
CPI	1.256 *	-	0.183 *
CPI–home maintenance and repair	-	-	0.094 *
CPI–transportation	-	-9.609 **	-
CPI–purchase of motor vehicles	-	-2.151 *	-
Turnover–motor vehicle maintenance and repair	-0.131 ***	0.179 *	-
Gross earnings	0.908 *	-	-
OECD health–total current	0.757 ***	-	0.091 *

Notes: '' Statistical significance at the 10% level, '**' Statistical significance at the 5% level , '***' Statistical significance at the 1% level.*

6. SUMMARY

This paper empirically and numerically analyzes claims inflation in non-life insurance with focus on automobile liability insurance based on a data set provided by a large German non-life insurance company. We empirically identify major economic drivers of claims inflation by means of a stepwise multiple linear regression. In addition, we assess the impact of an empirically calibrated (stochastic) claims inflation model on ultimate loss estimates and reserving and compare the results to the classical chain ladder method.

Our results show that claims inflation is particularly driven by factors and economic indices related to health costs and consumer prices, amongst others. The extent and the key drivers of claims inflation thereby strongly depend on the specific line of business, where we compare the lines of business automobile liability insurance, fully comprehensive car insurance and third party liability insurance. Our analysis revealed that influencing indices in regard to the automobile liability insurance are the CPI, turnover–motor vehicle maintenance and repair, gross earnings, and OECD health–total current. In regard to the line of business fully comprehensive car insurance, driving factors are the CPI–transportation, CPI–purchase of motor vehicles and turnover–motor vehicle maintenance and repair. For third party liability insurance, we found indices CPI, CPI–home maintenance and repair, and OECD health–total current to be driving factors of claims inflation. Overall, the basic findings are consistent (if available) with the very rare academic literature. However, more research is necessary, e.g. by using policy-level data and by distinguishing between claims data which results from bodily injuries or physical damages. Moreover, our findings emphasize that reserves calculated by the common chain ladder method may be misestimated as compared to stochastic reserving models that explicitly account for (stochastic) calendar year inflation effects and take into consideration econometric indices driving claims inflation, for instance.

In summary, our results emphasize the importance of adequately dealing with claims inflation risk when calculating reserves. Our findings further show that drivers for claims inflation can considerably vary depending on the respective line of business and that an inflation model thus should be calibrated separately for different lines of business and companies, respectively. Finally, an analysis of relevant influencing factors of claims inflation is of great relevance for risk management when considering different impact of inflation on assets and liabilities. In this regard, more research is necessary for a comprehensive asset-liability management.

REFERENCES

Aboudi, R., Thon, D. (1994): Efficient Algorithms for Stochastic Dominance Tests Based on Financial Market Data. *Management Science* 40(4), 508-515.

Ahlgrim, K., D'Arcy, S. (2012a): The Effect of Deflation or High Inflation on the Insurance Industry. Working Paper, Illinois State University, University of Illinois at Urbana-Champaign.

Ahlgrim, K., D'Arcy, S. (2012b): A User's Guide to the Inflation Generator. Working Paper, Illinois State University, University of Illinois at Urbana-Champaign.

Barnett, G., Zehnwirth, B. (2000): Best Estimates for Reserves. *Proceedings of the CAS* 87, 245-321.

Björkwall, S., Hössjer, O., Ohlsson, E. (2010): Bootstrapping the Separation Method in Claims Reserving. *ASTIN Bulletin* 40(2), 845-869.

Brickman, S., Forster, W., Sheaf, S. (2005): Claims Inflation – Uses and Abuses. GIRO Conference, http://www.actuaries.org.uk.

Brigo, D., Dalessandro, A., Neugebauer, M., Triki, F. (2009): A Stochastic Processes Toolkit for Risk Management: Mean Reverting Processes and Jumps, *Journal of Risk Management in Financial Institutions* 3(1), 65-83.

Brigo, D., Mercurio, F. (2007): Interest Rate Models - Theory and Practice, 2nd Edition, Springer, Berlin.

Brockett, P., Cooper, W., Golden, L., Piaktong, U. (1994): A Neural Network Method for Obtaining an Early Warning of Insurer Insolvency. *Journal of Risk and Insurance* 61(3), 402-424.

Cairns, A. (2004): Interest Rate Models - An Introduction, Princeton University Press, Princeton.

Chan, T. (1998): Some Applications of Levy Processes to Stochastic Investment Models for Actuarial Use. *ASTIN Bulletin* 28(1), 77-93.

Cheng, T., Lo, Y., Ma, K. (1990): Forecasting Stock Price Index by Multiple Regression. *Managerial Finance* 16(1), 27-31.

Clark, D. (2006): Variance and Covariance Due to Inflation. *CAS Forum* (fall), 61-95.

Colquitt, L., Hoyt, R. (1997): Determinants of Corporate Hedging Behavior: Evidence from the Life Insurance Industry. *Journal of Risk and Insurance* 64(4), 649-671.

Cummins, J. D., Derrig, R. A. (1993): Fuzzy Trends in Property-Liability Insurance Claim Costs. *Journal of Risk and Insurance* 60(3), 429-465.

Cummins, J. D., Freifelder, L. (1978): A Comparative Analysis of Alternative Maximum Probable Yearly Aggregate Loss Estimators. *Journal of Risk and Insurance* 45(1), 27-52.

Cummins, J. D., Griepentrog, G. (1985): Forecasting Automobile Insurance Paid Claim Costs Using Econometric and Arima Models. *International Journal of Forecasting* 1(3), 203-215.

Cummins, J. D., Powell, A. (1980): The Performance of Alternative Models for Forecasting Automobile Insurance Paid Claim Costs. *ASTIN Bulletin* 11(2), 91-106.

Cummins, J. D., Tennyson, S. (1992): Controlling Automobile Insurance Costs. *Journal of Economic Perspectives* 6(2), 95-115.

Cutter, K. (2009): Measuring and Understanding Superimposed Inflation in CTP Schemes. Institute of Actuaries of Australia, Australia.

D'Arcy, S., Au, A. (2008): A Two-Factor Approach to Loss Reserve Variability. Working Paper, University of Illinois.

D'Arcy, S., Au, A., Zhang, L. (2009): Property-Liability Insurance Loss Reserve Ranges Based on Economic Value. *Variance* 3(1), 42-61.

de Melo, E. (2008): Valuation of Participating Inflation Annuities with Stochastic Mortality, Interest and Inflation rates. Working Paper, Graduate School of Business, Federal University of Rio de Janeiro, Brazil.

de Jong, P. (2006): Forecasting Runoff Triangles. *North American Actuarial Journal* 10(2), 28-38.

de Jong, P. (2012): Modeling Dependence between Loss Triangles. *North American Actuarial Journal* 16(1), 74-86.

Deutsche Aktuarvereinigung e.V. (DAV) (2013): Zins und Inflation in der Schadenversicherung, Köln.

England, P, Verrall, R. (1999): Analytic and Bootstrap Estimates of Prediction Errors in Claims Reserving. *Insurance: Mathematics and Economics* 25, 281-293.

Falbo, P., Paris, F. M., Pelizzari, C. (2010): Pricing Inflation-Linked Bonds. *Quantitative Finance* 10(3), 279-293.

Fama, E., Schwert, G. (1977): Asset Returns and Inflation. *Journal of Financial Economics* 5(2), 115-146.

Frees, E. (2010): Regression Modeling with Actuarial and Financial Applications, Cambridge University Press, New York.

Gesamtverband der Deutschen Versicherungswirtschaft e. V. (GDV) (2011): Methoden zur Schätzung von Schaden- und Prämienrückstellungen in der Kompositversicherung, Berlin.

Glasserman, P. (2010): Monte Carlo Methods in Financial Engineering, Springer Press, New York.

Jessen, A., Rietdorf, N. (2011): Diagonal Effects in Claims Reserving. *Scandinavian Actuarial Journal* 2011(1), 21-37.

Lewin, D. (2009): Inflation: Implications for Long-Tail (Re)insurance. http://www.gccapitalideas.com.

Mack, T. (1993): Distribution-free Calculation of the Standard Error of Chain Ladder Reserve Estimates. *ASTIN Bulletin* 23(2), 213-225.

Manab, N., Ghazali, Z. (2013): Does Enterprise Risk Management Create Value. *Journal of Advanced Management Science* 1(4), 358-362.

Masterson, N. (1968): Economic Factors in Liability and Property Insurance Claims Costs, 1935-1967. *Proceedings of the CAS* 55, 61-89.

Merz, M., Wüthrich, M.V., Hashorva, E. (2013): Dependence Modelling in Multivariate Claims Run-Off Triangles. *Annals of Actuarial Science* 7(1), 3-25.

Mittnik, S. (2011): Solvency II Calibrations: Where Curiosity Meets Spuriosity. Working Paper, Center for Quantitative Risk Analysis, Department of Statistics, University of Munich.

Morrow, M., Conrad, T. (2010): Practical Considerations in Assessing the Impact of Inflation on Carried Reserves. *CAS E-Forum* (fall).

O'Brien, R. M. (2007): A Caution Regarding Rules of Thumb for Variance Inflation Factors, *Quality & Quantity* 41(5), 673-690.

Pearson, E., Beynon, C. (2007): Superimposed Inflation – Australian Accident Compensation Landscape in 2007. Institute of Actuaries of Australia, Australia.

Pecora, J., Thompson, E. (2012): Towers Watson Claim Cost Index: Severity Consistent with Inflation. *Emphasis* 2012(4), 18-19.

Porter, R. B., Wart, J. R., Ferguson, D. L. (1973): Efficient Algorithms for Conducting Stochastic Dominance Tests on Large Numbers of Portfolios. *Journal of Financial and Quantitative Analysis* 8(1), 71-81.

Saluz, A., Gisler, A. (2014): Best Estimate Reserves and the Claims Development Results in Consecutive Calendar Years. *Annals of Actuarial Science* 8(2), 351-373.

Salzmann, R., Wüthrich, M.V. (2012): Modeling Accounting Year Dependence in Runoff Triangles. *European Actuarial Journal* 2(2), 227-242.

Samson, D., Thomas, H. (1987): Linear Models as Aid in Insurance Decision Making: The Estimation of Automobile Insurance Claims. *Journal of Business Research* 15, 247-256.

Schmidt, K. D. (2007): A Note on the Separation Method. Dresdner Schriften zur Versicherungsmathematik 6/2007.

Shi, P., Basu, S., Meyers, G. (2012): A Bayesian Log-Normal Model for Multivariate Loss Reserving. *North American Actuarial Journal* 16(1), 29-51.

Sopipan, N., Kanjanavajee, W., Sattayatham, P. (2012): Forecasting SET50 Index with Multiple Regression based on Principal Component Analysis. *Journal of Applied Finance and Banking* 2(3), 271-294.

Swiss Re (2010): The Impact of Inflation on Insurers. *Sigma* 4/2010.

Taylor, G. (1977): Separation of Inflation and Other Effects from the Distribution of Non-Life Insurance Claim Delays. *ASTIN Bulletin* 9(1), 219-230.

Vasicek, O. (1977): An Equilibrium Characterization of the Term Structure. *Journal of Financial Economics* 5, 177-188.

Verbeek, H. (1972): An Approach to the Analysis of Claims Experience in Motor Liability Excess of Loss Reinsurance. *ASTIN Bulletin* 6(3), 195-202.

Verbeek, M. (2012): A Guide to Modern Econometrics, John Wiley & Sons Ltd, 4th edition, Chichester.

Wilkie, A. (1986): A Stochastic Investment Model for Actuarial Use. *Transactions of the Faculty of Actuaries* 39, 341-403.

Wüthrich, M.V. (2010): Accounting Year Effects Modeling in the Stochastic Chain Ladder Reserving Method. *North American Actuarial Journal* 14(2), 235-255.

Young, D. (2012): Model Building in Regression. In Weiss, N., ed., *Introductory Statistics* (Pearson Education, 9th edition, Essex).