FORECASTING INSURANCE PREMIUMS AND CLAIMS IN NORTH MACEDONIA: AN EXPONENTIAL SMOOTHING PROCEDURE

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ABSTRACT
This paper deals with the concept of predictive analytics in time series analysis by utilizing the forecasting methods. Statistical and econometric advances have predominantly focused on classical modeling and estimation techniques in economics and finance, but however, such a great attention has not been paid to forecasting. By using the exponential smoothing methods to forecast the gross written premiums (GWP) and gross claims, this study focuses on the insurance sector in the Republic of North Macedonia for the period between 2012Q1-2021Q4. The results imply that univariate forecasting through the exponential smoothing methods can be a sufficient approach in predicting future premiums and claims on the national insurance market. Most importantly, the approach is flexible and can account for clear trend and seasonal components in the observed data. The research demonstrates how econometric techniques may be applied to corporate predictions to develop plans and set expectations, giving businesses an advantage in Macedonian insurance market.

Keywords: Insurance, predictive analytics, forecasting, exponential smoothing, North Macedonia.
JEL classification: C53, G22.

1. INTRODUCTION

Insurance may be regarded as an ancient concept, with the earliest primitive forms of insurance agreements dating before Christ. However, it was not until the late 14th century in Genoa, Italy when autonomous insurance contracts emerged. At first, the concept is quite simple. For a small financial contribution, the insurer agrees to underwrite the underlying risks which the client is exposed to. By pooling a vast amount of so-called premiums i.e., the price of a respective insurance policy, the insurer is now able to financially support those that experience adverse events. However, the idea is rather complex and not restricted to such simple business. Through the employment of complex actuary models based on the probability of a specific risk occurrence and the expected losses, insurance companies are able to adequately set the premium – sufficient to cover the filed claims, finance the insurance operations and on top of all remain profitable.

In global context, developing economies struggle to pivot the insurance market into the financial system. For example, the Macedonian insurance market can still be regarded as underdeveloped, with the dominant non-life insurance class being the compulsory and government-regulated motor third party liability (MTPL) insurance. A total of 11 non-life insurance companies operate on the Macedonian insurance market, each experiencing structural changes throughout the last decade. Market strategies differ depending on the corporate goals and the developed distribution channels. Paying specific attention to such emerging market is of key importance, since global insurance literature remains scarce for the Western Balkan region.

The paper deals with a rather intriguing problem lying at the core of corporate governance in insurance companies. Business planning for companies, formulating expectations for future market development and the consequent policy positioning by the national Insurance Supervision Agency (ISA) is necessary. By employing time series methods for predictive analysis, the study contributes to the global insurance and forecasting literature while being the pioneer of such format for the Macedonian insurance market. The study can be regarded as a microfundamental and quantitative, combining inductive-deductive methods, qualitative analysis and econometric approach to the problem set.

Through the use of ETS exponential smoothing methods, this research aims at forecasting future gross written premiums and gross claims in the Macedonian insurance sector. Secondary data obtained from the national supervisor is used, ranging at a decade long period between 2012 and 2022. Since the study deals with problematizing the optimal forecasting method and its systematic approach, a generalized model is used – total market premiums and claims instead of company-specific datasets are incorporated. A comprehensive guide to incorporating the respective methods is given, which proves that econometric methods can be utilized in corporate projections to form strategies and create expectations, thus obtaining advantage on market competition in North Macedonia. The obtained results indicate that econometric forecasting in predictive analytics are suitable and robust for usage in the Macedonian insurance market.

The research is structured as follows. After the introduction, a theoretical background to the topic is visited. Section 3 discusses the methodological approach to data acquiring and analysis prior to the proposed time series forecasting methods. Next, we present the obtained results from the modeling and compare different techniques. Finally, the paper end with a concise conclusion of the research.

2. LITERATURE REVIEW

Predictive analytics has been widely used in finance, especially banks and insurance companies to predict/forecast future prices, costs and market trends or relevant importance. As noted by Daub (1984), 'forecasting is a fundamental component of public and private policy-making', and thus special attention should be paid. As a rather complex approach in modelling, forecasting wages between technicalities and art. The iterative nature of the process emerges up front, with various stages such as defining a system, collecting and refining data, specification of the functional form, as well as *ex post* and *ex ante* comparations with a naïve forecasting model are necessary in the entire process (Fildes, 1985).

Numerous studies exist which employ various techniques to predict and forecast certain parameters. ARIMA models were popularized by Box and Jenkins (1976) and since then, several new and upgraded methods emerged. For example, Harvey and Fernandes (1989) give an overview on employing Poisson and Gaussian-based time series models for insurance claims. However, when modelling the contextual influence for insurance premiums, the dynamics are mostly regarded to real output and policy uncertainty (Gupta, 2016). Premiums and claims have been previously analyzed and forecasted through an ARIMA setting by Raeva and Nikolaev (2022). A rather different approach is also used in the literature are the ergodic Markov model forecasts used in predicting the annual insurance premium, which prove to be a good approach (Fan and Feng, 2018). On the contrary, forecasting future claims has been studied by Berridge (1998) and Dal Pozzolo (2011).

Recently, Big Data analytics have appeared as a frontrunner in technologically advanced companies. In an instance, Fang *et al.* (2016) forecast customer profitability in insurance and propose that for example, the random forest (RF) method outperforms linear regression, decision trees, SVM and generalized boosted models. According to empirical research, the geography, age, insurance status, sex, and customer source of the customer are the most crucial variables that determine insurance customer profitability. Customer relationship in the Swiss insurance sector has been studied through a random forest classification model to predict costumer's tendency to adjust or extend the insurance coverage in the near future, noting that adding online quotes to existing client data results in a useful method for forecasting. A state-of-the-art analysis on the available literature related to Big Data in forecasting research is provided by Tang *et al.* (2022).

Exponential smoothing methods are also an alternative to consider when dealing with forecasts. Pires et al. (2022) note that Holt-Winter methods are a practical substitute to traditional Box-Jenkins autoregressive methods, when considering a home insurance case. Their robustness comes from the ability to account for errors, trends and seasonality in data, and a multi-modelling approach is plausible which minimizes the information criteria (Ravinder, 2013). Our study builds upon these findings, emerging as the first national study that deals with insurance forecasting for the Macedonian insurance sector and incorporation of the ETS exponential smoothing methods.

3. METHODOLOGICAL APPROACH

This section discusses the data acquiring approach, the chosen source of information, reasons behind the variables of interest, and types of data. Data visualization, descriptive statistics and transformation methods are also considered throughout this chapter. At last, the modeling techniques are concisely explained, reasoning behind the exponential smoothing forecasting.

3.1. Data acquiring and visualization

For this study, we use quarterly data for the 2012Q1-2021Q4 period published in the insurance industry reports by the national Insurance Supervision Agency (ISA) in the Republic of North Macedonia. We consolidate the data for the non-life insurance sector consisted of 11 insurance companies as we are interested in a sectoral study. Since monthly data are publicly unavailable, we employ frequency transformation to monthly intervals based on a quadratic transformation embedded in the EViews software. This is done to extend the number of observations available and for better understanding of the overall dynamics. The main variables of interest are the gross written premiums (GWP) and the gross claims paid (liquidated). Figure 1 portrays the total GWP in the Macedonian insurance sector after employing the mentioned transformation. The data seem to exhibit both trend and seasonality, with obvious distortion in the series with the beginning of the COVID-19 pandemic. During the 2016-2018 period, the insurance industry experienced stable rates of growth.

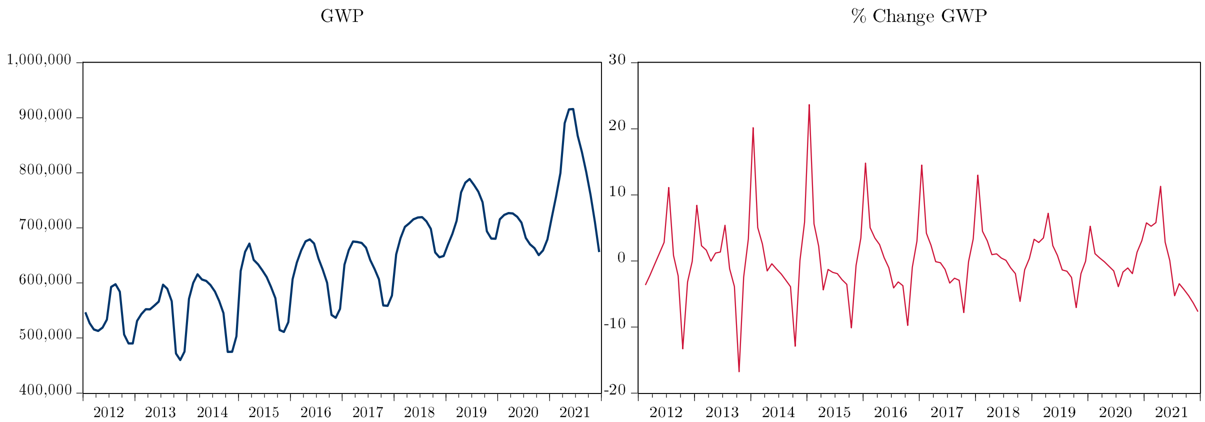


Figure 1a and 1b. Total gross written premiums (GWP) in 000 of MKD (left) and relative change (right), monthly data.

The following Figure 2 shows the dynamics of gross paid claims in the Macedonian insurance sector for the last decade. The trend and seasonal components are easily noticeable, but with a differing seasonality compared to the GWP. During the last quarters of 2021, an inverse movement is observed between premiums and clams, narrowing the gap between them. Each of the visualized series portray a rising trends with a probable damping component, which is left to be further proven under the ETS parametrization.

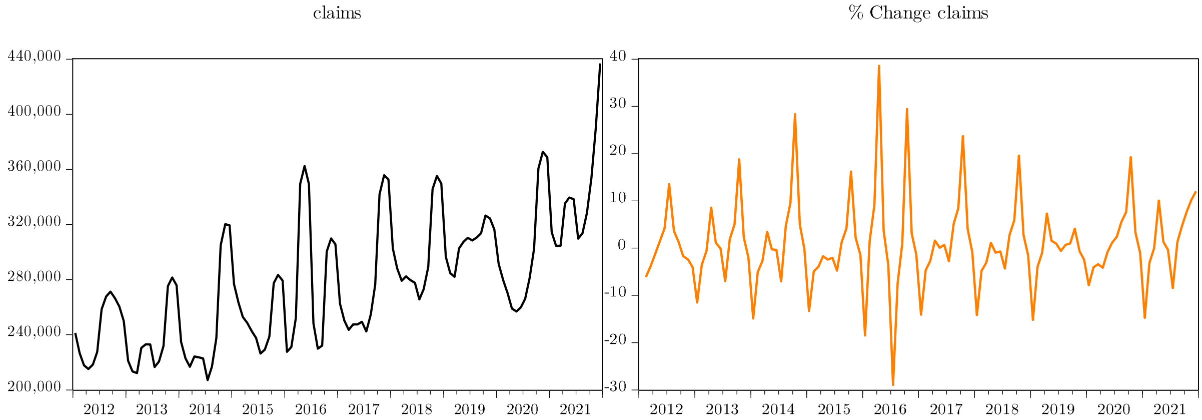


Figure 2a and 2b. Gross claims paid (liquidated) in 000 of MKD (left) and relative change (right), monthly data.

Clearly, the annual rates of change portray a similar dynamic but a larger interval of variation for the claims. This can be accounted to the uncertainty nature of risks, as predicting the outcome and its moment of occurrence is relatively impossible. On contrary, GWP is easier to predict as it largely depends on the business activity of insurance companies. The correlation between the gross written premiums and claims is estimated at 0.4096, signalling a moderate and direct relationship.

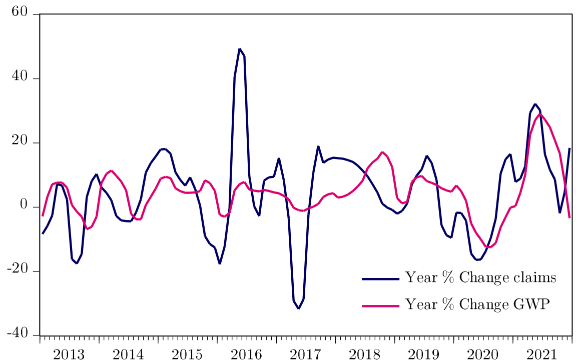


Figure 3. Annual rates of change of GWP and claims.

The corresponding descriptive statistics for the transformed (monthly) series are provided in Table 1. Measured by the coefficient of variation, the claims series has a 1.7% larger variability than the gross written premiums, corresponding with the risk component earlier mentioned.

Table 1. Descriptive statistics of gross written premiums and claims, monthly data.

Descriptive Statistic	GWP	Claims
Mean	639,503.9	278,390.2
Median	643,151.6	275,554.5
Max	915,946.5	436,863.7
Min	460,100.9	207,100.2
Std. Deviation	96,407.6	46,709.8
CV	0.1508	0.1678
Skewness	0.4665	0.6305
Kurtosis	3.1848	2.9377
Observations	120	120

3.2. Exponential smoothing methods

There are various approaches to exponential smoothing, and one is the ETS (error, trend, seasonal) employed in this study. It focuses on the trend and seasonal components in time series with various model combinations that can be employed based off data properties. If we distance from the error component (none, additive or multiplicative), the modelling approaches are depicted in Table 1.

Table 2. Approaches in ETS exponential smoothing

Trend component	Seasonal component		
	N (None)	A (Additive)	M (Multiplicative)
N (None)	NN	NA	NM
A (Additive)	AN	AA	AM
AD (Additive Damped)	ADN	ADA	ADM
M (Multiplicative)	MN	MA	MM
MD (Multiplicative Damped)	MDN	MDA	MDM

The incorporated econometric model is based on the well-known exponential smoothing, but however, the decision to go with the triple exponential smoothing has a few reasons. First off, insurance gross written premiums (GWP) and claims tend to depict a trending component throughout time. Second, a seasonality is particularly observed in the case of the GWP, so incorporating it into the forecasting model may raise its predicting capabilities. We start off with the mathematical approach to the state space models for exponential smoothing, where each model is made up of a measurement equation that represents the observed data and a number of state equations that explain how the unseen components or states (level, trend, and seasonality) vary over time. We ought to start with the basic model where we abstract from having an error term (which is in fact included in our calculations later on) due to simplicity, where the simple exponential smoothing model can be depicted as

Forecast equation	$\hat{y}_{t+h\|t} = l_t$	(1)
Level equation	$l_t = \alpha y_t + (1-\alpha) l_{t-1}$	(2)

such that y is the measured observation for the targeted variable in period $t = 0, 1, 2, \ldots, T$, $\hat{y}_{t+h|t}$ is the forecasted value for the next h sequence of periods (predominantly one) conditional on the forecasted value in period t, while α plays the role of a smoothing parameter so that $\alpha \in [0,1]$. The smoothing parameter depends on the informational components contained in historical observations, playing a weighting role. In an instance, when $\alpha \to 0$ more weight is given for distant observations, contrary to the opposing case when $\alpha \to 1$. This level smoothing parameter can be optimally determined by minimizing the sum of squared errors

$$\min SSE = \sum_{t=1}^{T} (Y_t - F_t)^2 \tag{3}$$

or alternatively, by arbitrarily setting its value prior to theoretical knowledge, modeling preferences or literature suggestions. Commonly and when arbitrarily set, α takes values between 0.2 and 0.3 giving higher weights to historical rather than present observations. Upon the level form of exponential smoothing models, we introduce the Holt's method i.e., the double exponential smoothing (DES) which takes the trend component into consideration when making forecasts. Additionally, to the level equation we include a trend equation so that

Forecast equation	$\hat{y}_{t+h\|t} = l_t + h b_t$	(4)
Level equation	$l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1})$	(5)
Trend equation	$b_t = \dot{\beta}(l_t - l_{t-1}) + \left(1-\dot{\beta}\right) b_{t-1}$	(6)

with b_t being the trend estimate at time t, α is the level smoothing parameter $0 \le \alpha \le 1$ and $\dot{\beta}$ being the trend smoothing parameter so that $0 \le \dot{\beta} \le 1$. At last, the triple exponential smoothing i.e., Holt-Winters' method in its additive seasonality form can be represented as

Forecast equation	$\hat{y}_{t+h\|t} = l_t + h b_t + s_{t+h-m(k+1)}$	(7)
Level equation	$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1})$	(8)
Trend equation	$b_t = \dot{\beta}(l_t - l_{t-1}) + \left(1-\dot{\beta}\right) b_{t-1}$	(9)
Seasonality equation	$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma) s_{t-m}$	(10)

where s_t is the seasonal estimate at time t, m is the frequency of the seasonality ($m = 12$ in our case) based on the data used. The seasonality smoothing γ parameter is often restricted to be in the interval $0 \leq \gamma \leq 1 - \alpha$.

A large number of mathematical representations are available, which due to objective reasons we can not represent them entirely. We formulate only a basic additive exponential smoothing model, abstracting from the addition of errors into the state space. For complete representation of the models used we can refer to the brilliant work of Hyndman *et al.* (2008).

For this study, we utilize the capabilities in the EViews software which based on optimizing techniques, minimizes the MAPE criteria and chooses the most proper model based on data provided. The minimization procedure yields the optimal α, β and γ parameters. The disposable timeframe for the data can be segregated into evaluating and forecasting period, with the line being drawn at 2019M12. By doing so, we provide an 8-year timeframe for estimating the fitted model and generating 2-year monthly forecasts, not taking into account the influence of the COVID-19 pandemic on the insurance market. Next, to compare the obtained results and optimal models, we extend the estimation period up to the end of 2020. Finally, an out-of-sample prediction is obtained.

4. EMPIRICAL RESULTS AND DISCUSSION

Problematizing future values depends on the model adequacy and inputs. Consequently, this research does not conform to a single and particular ETS model, but rather through a series of computation and subsequent iterations, the optimal model is chosen based on the training sample. A total of 30 model combinations are probable when we include error variations, and logically each defines a certain model that may suit the best for the purpose of the study as well as the intuitive and expected future developments.

While introducing the methodological approach, premiums and claims are modelled as discrete research topics. Even though an arbitrary model can be set based on our preferences, knowledge of the problem, and observed patterns in the historical data, several iterations are conducted in order to estimate the best fit model to the control data. At first, we study the dynamic and the forecast for a training sample ending in 2019M12 in order to emphasize the following deterrence of expected forecast values from the realized data in the pandemic and post-pandemic period. Then, we continue with the same process, however this time expanding the training sample to the end of 2020. This way, the research incorporates the structural impact of the COVID-19 pandemic on the insurance market. Each of the estimated models are presented alongside the baseline realized data, to observe the overall fit. As this research tends to simultaneously test various models, figures are given so that all model outputs are compared.

Finally, the core of the study lies in the actual out-of-sample forecast for the following 21 months. To do this, the training sample is expanded with the latest publicly available data by the national ISA (2022) thus working with a 2012M01-2022M03 timeline. The predicted values are portrayed until the end of 2023 alongside confidence bounds with α being 0.05 and 0.15, respectively. Reader's caution is advised, since later predictions face higher uncertainty even though confidence bounds remain constant in the analysis. All data are represented in thousands of denars.

4.1. Forecasting gross written premiums (GWP)

The forecast GWP depicts some interesting information. The trained model data ended before the outbreak of the pandemic, with the forecast being relatively stable levels of GWP with usual cycles for the following two years. However, the economic inactivity resulted in significant decrease in GWP throughout 2020 followed by a peak in 2021 mostly due to extensive economic rebound. The following Figure 4 portrays the optimal ETS exponential smoothing model which minimizes the AIC information criterion i.e., a model with additive error, additive-damped trend and additive seasonality. Forecasting and training periods are separated with the vertical dotted line. The estimated smoothing parameters of the model are $\alpha = 1$, $\beta = 1$, $\gamma = 0$, and $\phi = 0.46375$. The model, however, does not seem to properly explain the dynamics of the 2020-2021 period. This may be due to the evident structural break in insurance activity during the second, third and fourth quarter of 2020 as a result to the ongoing pandemic. Even though the seasonality component is retained, the damped trend restricts the forecast of such exponential growth, especially during 2021.

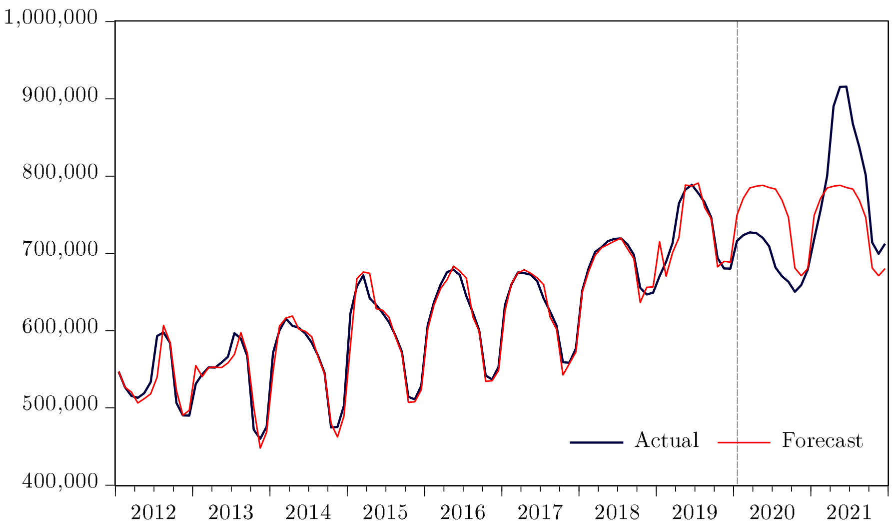


Figure 4. Best fit model (training data 2012Q1-2019Q4) – A,AD,A.

Various models have been tested and the Akaike Information Criterion (AIC) has been used for minimization i.e., estimating the best model. Out of the 30 modelling combinations, the best fitted models minimizing the information criterion besides the elaborated one are the A,MD,M (additive error-multiplicative-damped trend-multiplicative seasonality) and the M,N,M (multiplicative error, no trend, multiplicative seasonality) models.

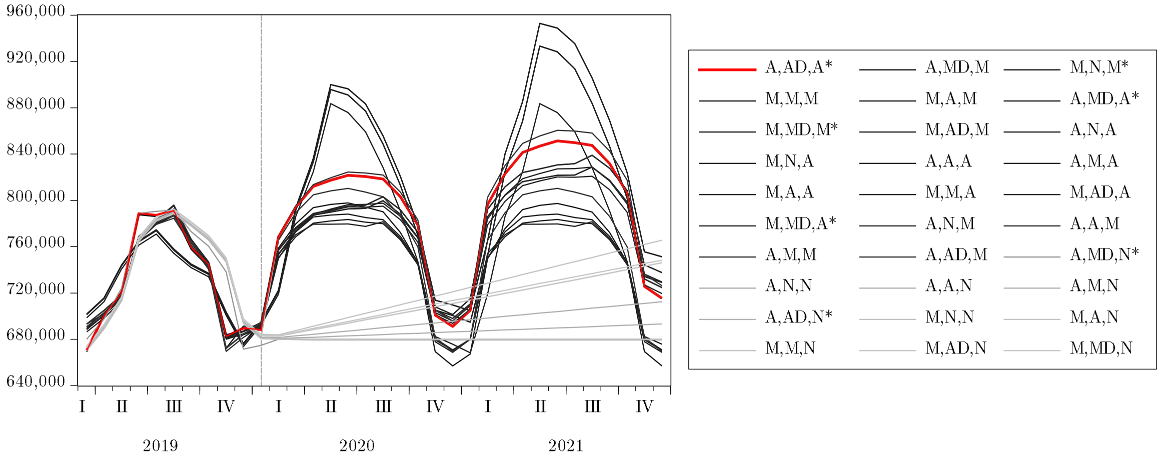


Figure 5. Trained model performances (training data 2012Q1-2019Q4).

In the next step, the training period is expanded to account for the shock of the COVID-19 pandemic. Consequently, the resulting forecast should be much more realistic and should not extremely differ from the realized data. The computation is being re-run once more, ending up with a slightly different setting this time. Now, an additive error-multiplicative-damped trend-multiplicative seasonality model (A,MD,M) is estimated as the most appropriate, and Figure 6 shows that the difference between fitted and realized data in 2021 is significantly smaller this time. Moreover, the proposed model fairly well explains the dynamic in the entire training and testing periods. As expected, the smoothing parameters differ from the previously estimated model with values of $\alpha = 1$, $\beta = 0.900795$, $\gamma = 0.989007$, and $\phi = 0.269172$. For example, the peak of the GWP reached in 2021M05 differs by approximately 71 million MKD in the newly estimated forecast, compared to the previous one (approximately 127 million MKD). With this, we can confirm the hypothesis that the ETS exponential smoothing methods are robust enough to sufficiently forecast insurance premiums in North Macedonia.

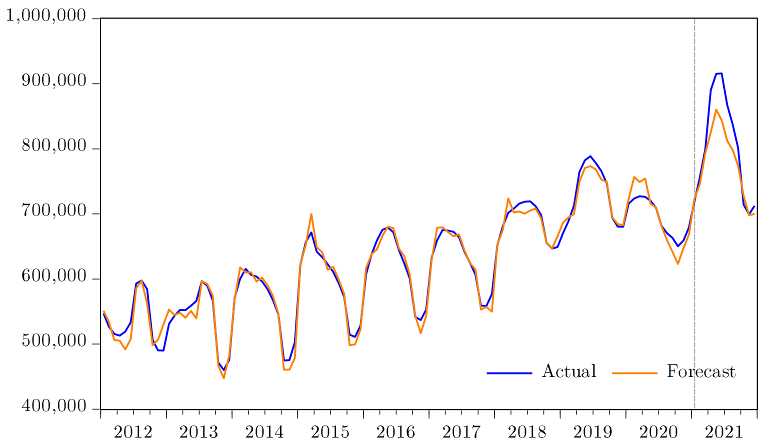


Figure 6. Best fit model (training data 2012Q1-2020Q4)– A,MD,M.

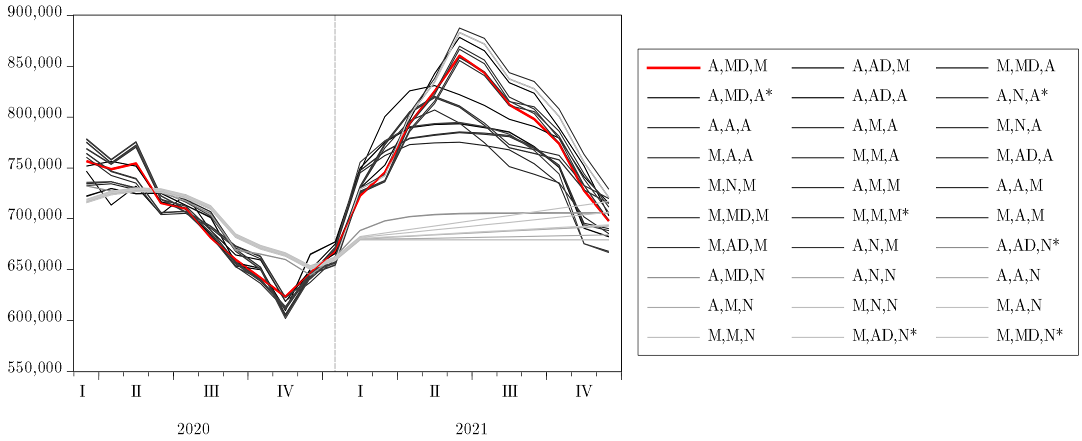


Figure 7. Trained model performances.

The following Figure 8 observes and incorporates the latest publicly available data ending in 2022Q1. As previously done, we apply quadratic transformation to the data to raise its frequency to monthly observations. First, we train the GWP model and forecast for the following 21 periods i.e., up to the end of 2023. The best fit model that minimizes the AIC is estimated to be the A-MD-M model which incorporates additive errors, multiplicative-damped trend, and multiplicative seasonality in the data. Confidence intervals are presented on Figure 8b with the significance level α being 0.05 and 0.15, respectively. The forecasted values portray a retention in the growth component, reaching the peak of approximately 1.1 billion MKD of GWP in May 2022, or the second quarter as the seasonality suggests. However, we believe that a moderate growth scenario is more realistic, found in the 95% confidence bound.

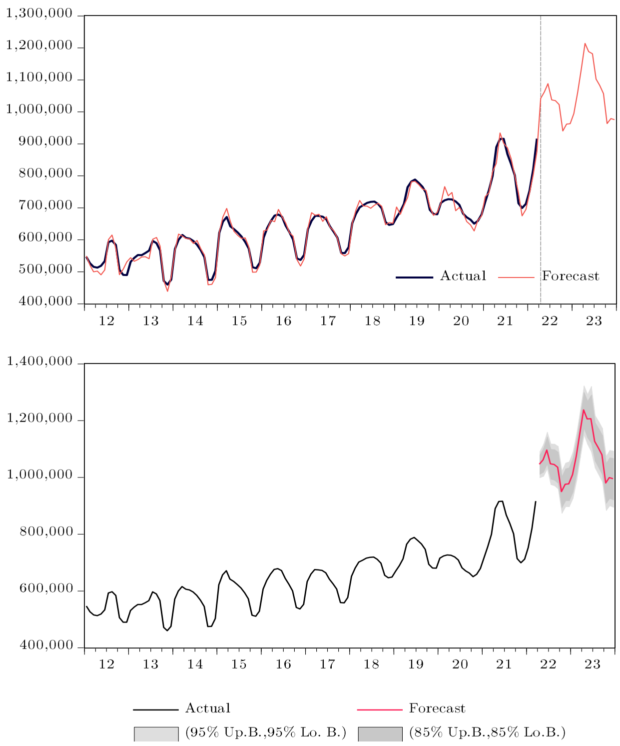


Figure 8a and 8b. GWP forecast model (A,MD,M).

At last, a rather different approach is considered. Instead of minimizing the Akaike Information Criterion (AIC) this time we set the model to be optimized based on the Mean Squared Error (MSE), which uses the average squared differences between the observed and predicted values. As a much-used adequacy measure in predictive analytics, we can expect greater levels of accuracy for the fitted values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{11}$$

The confidence intervals and the predicted values of the gross written premiums for the 2022M04-2023M12 period are depicted in Figure 9. We also include the previously estimated values (subject to minimization of the AIC), providing a head-to-head comparation between the two models. Subsequently, the latest model takes the M,AD,M form (multiplicative error-additive-damped trend-multiplicative seasonality) and yields a much more realistic view of the expected GWP dynamics in the following period. The MSE penalizes predicted values and thus yields a moderate estimate, compared to our previous model. The peak GWP in 2022 is estimated around 1.03 billion MKD in April, rising to 1.08 billion MKD in the same period in 2023.

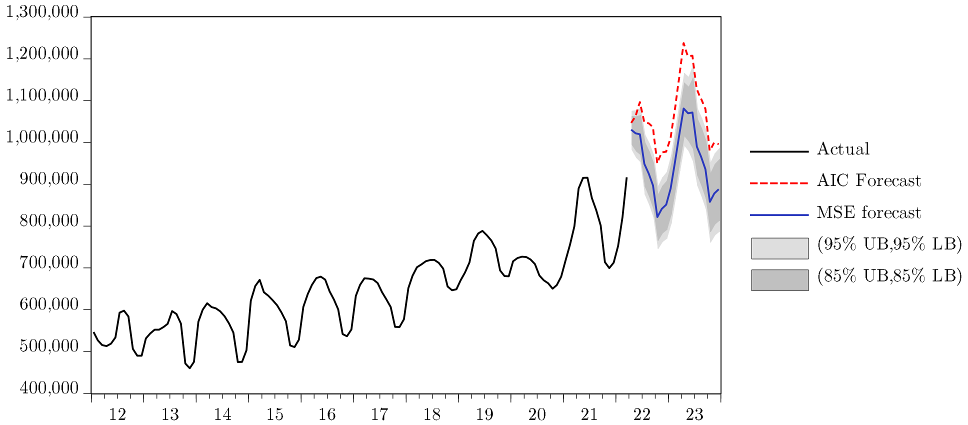


Figure 9. Comparing forecasting results, A,MD,M (minimizing AIC) vs. M,AD,M (minimizing MSE).

4.2. Forecasting gross claims liquidated

Compared to gross written premiums, claims can be quite problematic to predict. Submitting a claim depends on risk occurrence, which is entirely stochastic and uncertain. It may be debatable whether claims should be subject to time series modelling techniques, but nevertheless, this paper emphasizes the role of historical i.e., prior information in the data as a determinant for the future. The research conducted on gross claims paid follows the same steps as in the previous section.

The data deterrence as a result of the pandemic is observed on Figure 10. Even though a M,N,M model minimizes the Akaike criterion, fitted values are high-off the observed values in 2020 and 2021. The proposed model lacks a trend component and incorporates multiplicative errors and seasonality in the data. In the first months of the pandemic, with the reduced insurance activity and demand, claims decreased significantly prior to picking up as the pandemic progressed. According to the ISA (2021), significant growth is noted in casco claims (30.36% in respect to 2019), and other non-life insurance classes (18.24% growth) apart from MTPL, property, accident, and travel insurance.

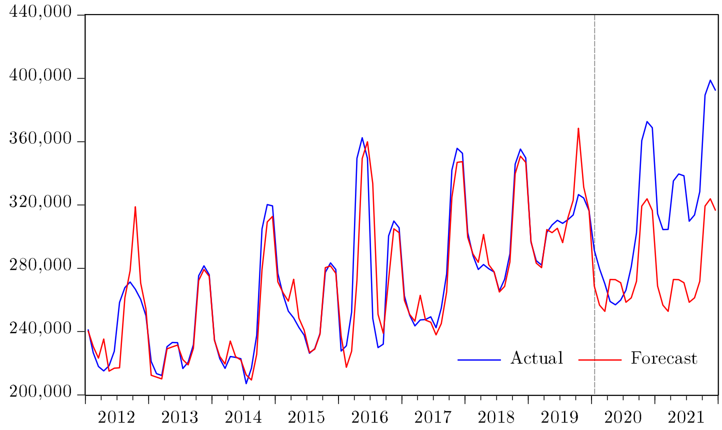


Figure 10. Best fit model (training data 2012Q1-2019Q4) – M,N,M.

Similar forecasts are obtained with other model combinations, with M,N,A and A,AD,A being the second and third best models (minimizing the Akaike criterion).

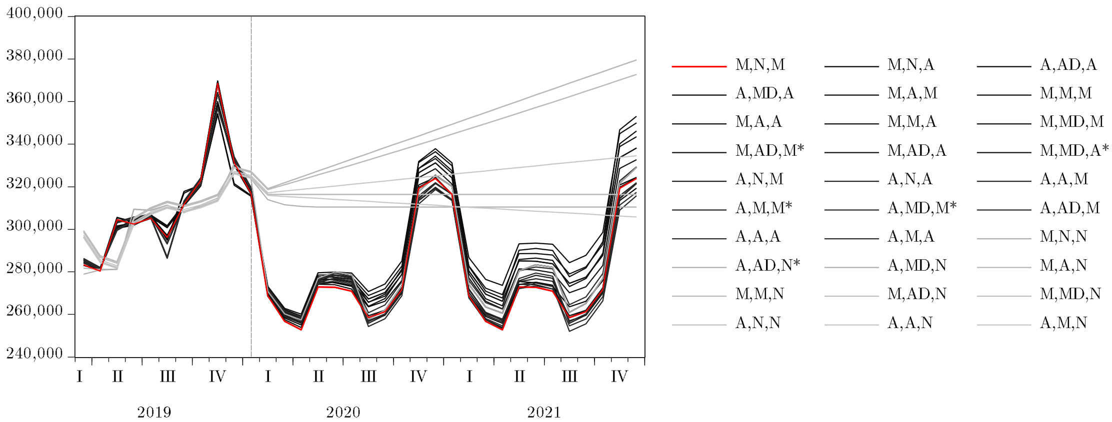


Figure 11. Trained model performances (training data 2012Q1-2019Q4).

To incorporate the impact of the COVID-19 pandemic od claims dynamics, we extend the training dataset until the end of 2020. As in the case when forecasting GWP, including the structural impacts of significant events produces better overall outcomes with higher predictability even though the optimal model remained the same – M,N,M (multiplicative error, no trend, multiplicative seasonality).

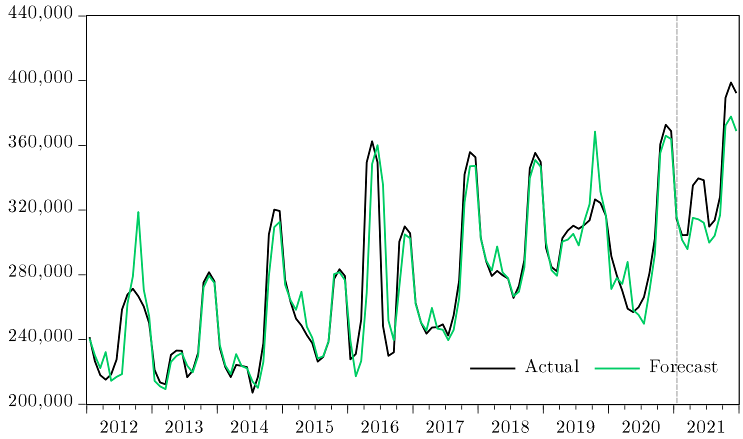


Figure 12. Best fit model (training data 2012Q1-2020Q4) – M,N,M.

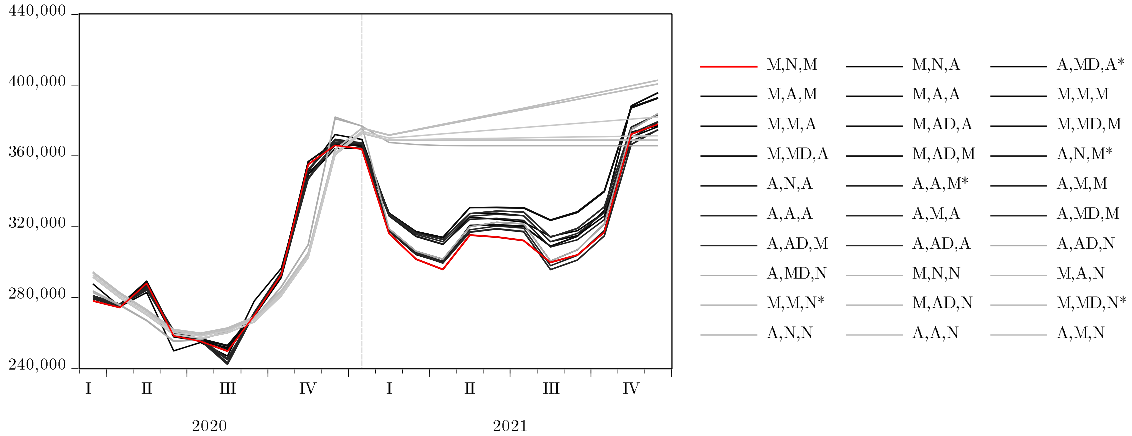
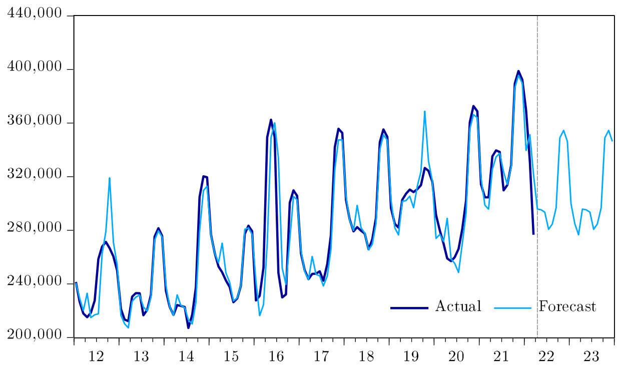
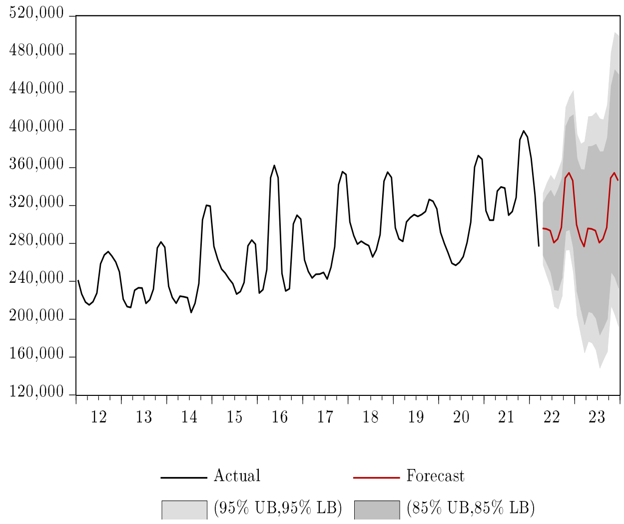


Figure 13. Trained model performances (training data 2012Q1-2020Q4).

At last, we end with the out-of-sample forecasting of gross written premiums for the 2022M04-2023M12 period. The AIC minimizing model is again estimated to be the M,N,M model with smoothing parameters $\alpha = 1$ and $\beta = 0$. Figure 14b portrays both the 85% and 95% confidence intervals of the predicted values. According to the estimated model it seems that a certain stabilization of gross claims liquidated can be expected in the following period, with an approximate peak of 355 million MKD in November 2022.





Graph 14a and 14b. Gross claims forecast model (M,N,M) in reference to actual data (left) and predicted values with confidence intervals (right).

Consistently with the previous sub-section dealing with GWP, we ought to check model performance subject to minimizing the average mean squared error (MSE). Automatic model selection is considered, yielding an A,A,M model (additive error-additive trend-multiplicative seasonality) with $\alpha = 1$, $\beta = 0$ and $\gamma = 0$. Once more a stabilizing tendency is observed, which may be accounted to the data properties in the control sample. Since claims exhibit a seasonal pattern of decreasing in the first quarter, the claims models underperform in estimating potential exponential growths. Having this in mind, fitted values should be especially considered under the 95% confidence bound in the following period. As can be noted, there is no significant difference between predicted values estimated by both variants of the models, unlike the case with the gross written premiums.

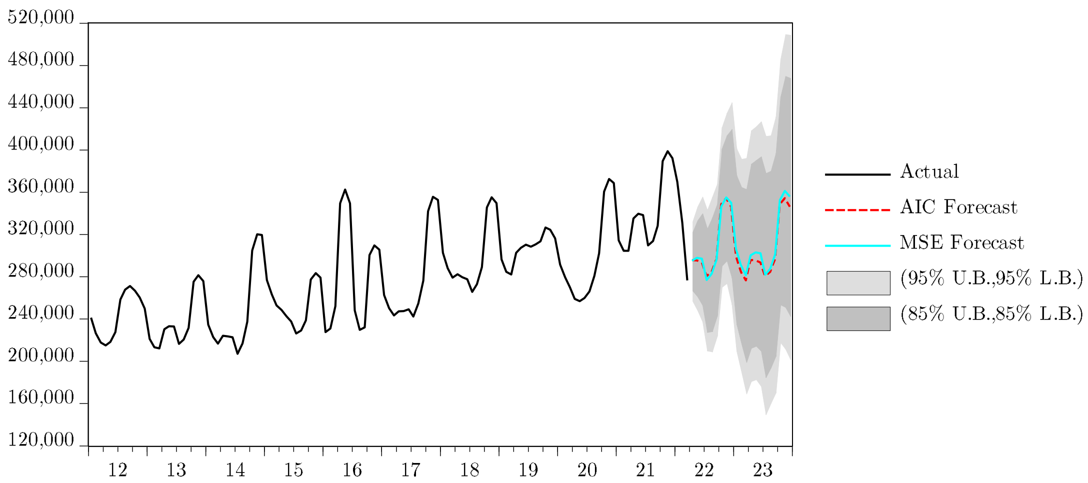


Figure 9. Comparing forecasting results, M,N,M (minimizing AIC) vs. A,A,M (minimizing MSE).

CONCLUSION

The insurance industry needs new methodologies for predictive analytics to optimize its business strategy, especially if we take into consideration the level of industry development in North Macedonia. With the introduction of econometric forecasting via time series methods, the paper aims at providing a comprehensive guideline in predicting two of the most studied insurance components – gross premiums and claims. Subject to prior problematization, the usage of Error-Trend-Seasonality exponential smoothing methods i.e., Holt-Winter's approach shows to be a robust tool in forecasting since both premiums and claims on the Macedonian insurance market exhibit the aforementioned components.

Results show that the COVID-19 pandemic created evident structural break in the insurance business, deterring prior trends for both total premiums and claims. However, including such shocks contributes towards higher accuracy models and realistic expectations for the near future. The ETS exponential smoothing methods allow for automatic selection of the best-fit model based on minimizing certain information criteria i.e., the Akaike Information Criterion and the Average Mean Squared Error. The optimal out-of-sample predictions for the following 21 periods (2022M04-2023M12) in the case of gross written premiums yielded A,MD,M (minimizing AIC) and M,AD,M (minimizing MSE) models. The latter, seems to be a more realistic estimate than the prior. For the case of gross claims liquidated on the Macedonian insurance market, there is no significant difference when minimizing each of the two information criteria (M,N,M - minimizing AIC and A,A,M - minimizing MSE), but since claims are rather highly uncertain and stochastic, the confidence intervals tend to allow continuation of the growing trend in claims.

After successful integration of time series methods in business analytics, insurance companies should consider orienting towards new technologies and using Big Data and machine learning in the following period. Such an approach would undoubtedly yield better performance, greater optimization, competitive advantage, and more precise expectations for the future – resulting in data-driven and resilient insurance companies, from which all stakeholders achieve mutual benefit.

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