IS THE CLAIMS RATIO DYNAMIC PREDICTABLE? A STUDY OF THE MACEDONIAN NON-LIFE INSURANCE SECTOR

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ABSTRACT
Insurance, simplified to a risk management concept, offers protection against unexpected losses arising from adverse events. As a financial service of structural importance in modern economies, it requires specific attention due to its risk protection component. Consequently, insurance companies devote sufficient resources towards stable, resilient, and profitable operations. However, a scarce amount of research treats the topic of financial stability maintenance and claims management with even fewer studies dealing with its prediction. This study deals with claims ratio (CR) dynamics in the Macedonian non-life insurance sector and its prediction. Utilizing a data set of 138 monthly observations between January 2012 and June 2023, this paper models the CR indicator through multiple approaches i.e., naïve, ARIMA, ETS exponential smoothing, and random forest (RF) thus making suitability and accuracy comparisons. Results suggest that the SARIMA(4,0,2)(2,1,2,12) model is superior in predicting the claims ratio in both the training and test samples. Moreover, the random forest algorithm shows good performances in the test set but is only superior to the ETS(A,N,A) model.

Keywords: *Insurance, Predictive modeling, ARIMA, Exponential smoothing, Random forest.*

JEL classification: *C22, G22.*

1. INTRODUCTION

Insurance can be considered an ancient concept, with the earliest primitive iterations of insurance agreements predating the Common Era. Nonetheless, it was not until the late 14th century in Genoa, Italy, that autonomous insurance contracts first surfaced. Initially, the premise was relatively straightforward. In exchange for a nominal financial contribution, the insurer undertook the responsibility of mitigating the inherent risks to which the client was exposed. By amassing a substantial pool of premiums, signifying the cost associated with the respective insurance policy, the insurer could provide financial assistance to those encountering adverse events. However, the conceptual framework transcends this simplicity and extends beyond rudimentary business dealings. Through the application of intricate actuarial models predicated upon the probability of specific risk occurrences and the anticipated losses, insurance enterprises possess the capacity to sensibly establish premiums that are adequate to cover filed claims, sustain their insurance operations, and, notably, yield profitability. In a global context, emerging economies often encounter challenges when integrating the insurance sector into their financial systems. To illustrate, the Macedonian insurance market may still be characterized as emerging, with compulsory and government-regulated motor third-party liability (MTPL) insurance dominating the non-life insurance sector. Notably, 11 non-life insurance companies currently operate within the Macedonian

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insurance market, each undergoing structural transformations over the past decade. Market strategies exhibit variability contingent upon corporate objectives and the maturation of distribution channels. Given the scarcity of global insurance literature devoted to the Western Balkan region, focusing particular attention on such growing markets assumes key significance.

This paper studies the problem of choosing an adequate approach toward claims ratio prediction in the Macedonian non-life insurance market. Companies must engage in strategic business planning, encompassing the formulation of anticipations regarding the forthcoming evolution of the market. Subsequently, the National Insurance Supervision Agency (ISA) must adopt a corresponding policy stance in response to these expectations. Through the utilization of predictive models, the study contributes to the global literature by observing the Macedonian case, which is a previously unexplored topic.

Secondary data is obtained from the national Insurance Supervision Agency (ISA) reports on the performance of the insurance undertakings by the 11 non-life insurance companies currently operating. Univariate time series data on gross written premiums (GWP) and gross liquidated claims (GLC) were obtained for the 2012Q1 to 2023Q2 period. Since the data at hand is initially supplied on a quarterly cumulative basis, while we are interested in a higher frequency i.e., monthly data, necessary transformations were conducted. Additionally, the study can be regarded as sectoral as we are not interested in studying individual company cases. Since the claims ratio (CR) is not readily available, we calculate it additionally. By employing several models for predicting the future dynamics of CR, we ought to find the best model and compare the accuracy performances of each, thus making a predictive power distinction. A naïve, ARIMA, and ETS exponential smoothing models are estimated, and their performance is observed. Finally, through time series embedding for the application of supervised learning, we run a random forest (RF) algorithm as a distinct solution for univariate forecasting concerning the previous. Accuracy measures are evaluated for the training and test period, with each of the models utilized for obtaining out-of-sample predictions. Results indicate that the seasonal ARIMA model outperforms the ETS state-space and random forest approach for a univariate set of data. In the test sample, the seasonal naïve model outperforms the exponential smoothing approach by 6.785 p.p. which rejects the previously set hypothesis. Overall, the random forest algorithm provides a novel and efficient approach to univariate forecasting but lacks predictive power based on the limited input and time series embedding.

The paper is structured in the following manner. After the introduction, Section 2 summarizes the global literature regarding insurance, risk management, and applications of predictive analytics in insurance. Next, we provide a detailed exploratory data analysis followed by a theoretical framework behind the models employed. In Section 4, we discuss and summarize the results and research limitations of our study. In the last section, we conclude the study adequately.

2. LITERATURE REVIEW

The claims ratio within the insurance industry constitutes a pivotal performance indicator aiding insurance enterprises in evaluating their fiscal well-being and the efficiency of their underwriting and claims administration procedures. It is a ratio that compares the total value of claims paid out by an insurance company to the total premiums collected from policyholders (Mahlow and Wagner, 2016) over a specific period, typically spanning a year. A heightened claims ratio signifies that the insurance firm is disbursing a substantial proportion of the premiums it accumulates in the form of claims, potentially affecting its profitability. Conversely, a diminished claims ratio implies that the firm is retaining a greater proportion of the premiums as revenue. Insurance entities strive to maintain an equilibrium in their claims ratio. If the claims ratio is excessively elevated, it may signal that the company is either pricing its policies too conservatively or encountering a substantial influx of claims, which can engender financial instability. Conversely, a markedly low claims ratio may suggest that the company is inadequately fulfilling its obligations to policyholders or engaging in an overly assertive underwriting approach. According to Korir (2020), insurers should have a claim ratio between 60% and 90% to maintain financial soundness and profitability. However, one shoe does not fit all since the optimal level may be determined by a palette of micro and macro factors with claim ratios differing between various insurance classes. For example, property insurance companies may look for a lower ratio in order to generate profits and buffer possible natcat (natural catastrophe) events. Reinsurers on the other hand usually target a claims ratio near 100% as their primary function is to take on risks from primary insurance providers. Insurance companies employ claims ratios as a mechanism for risk appraisal and financial strategizing, and they may modify their pricing strategies, underwriting criteria, or claims handling procedures to attain a sustainable claims ratio that simultaneously facilitates profitability as one of its main micro-determinants in non-life insurance (Camino-Mogro and Bermúdez-Barrezueta, 2019). Empirically, the negative relationship between profitability and the claims ratio is studied by Ortyński (2016). The claims ratio, alongside other factors explored by Tsvetkova et al. (2021), accounts for approximately 45.1% of the total variability in the performance of insurance companies in Russia. However, some authors such as Tarsono et al. (2019) do not find a significant relationship between financial performance and claims ratio in the case of life insurance companies. Subsequently, if the claims ratio is one of the determinants of overall insurance performance, then the question of its predictability arises.

Since the claims ratio (CR) itself has been rarely studied, we observe research advances for its counterparts – the gross written premiums and claims. Traditional time series forecasting of premiums and claims is often found in the literature, with the ARIMA models being the frontrunner. Kumar et al. (2020) found that an ARIMA(1,0,1) acceptably predicts motor insurance claim data. A similar approach to ours is done by Olszowy (2013), which advocated that gross written premiums in the Polish insurance market follow a seasonal pattern and thus can be modeled by a SARIMA(0,1,2)(1,0,0,4) model. Contrary to classic time series methods, Goundar et al. (2020) study the predictability of medical claims through artificial neural networks (ANN), confirming their effectiveness in forecasting. Contrary to our approach, Quan and Valdez (2018) find that multivariate tree models marginally outperform univariate tree models for insurance claims. On the other hand, Fauzan and Murfi (2018) conclude that the XGBoost algorithm gives better accuracy compared to other supervised learning methods i.e., AdaBoost, Stochastic GB, Random Forest, and Neural Networks. For additional and expanded usage of machine learning in predicting insurance claims we suggest the work of Poufinas et al. (2023).

We extend the existing body of research by adopting a distinct approach. Our investigation centers on a multimodal framework, wherein we assess the precision metrics associated with each of the suggested methodologies. Additionally, the limited body of literature about the prediction of claims ratios has established a novel space for research, wherein predictive techniques can be leveraged to monitor the operational performance of insurance firms over an extended temporal horizon.

3. RESEARCH APPROACH

The study can be considered quantitative, employing predictive models for time series which are purely econometric or machine learning through supervised learning. A qualitative assessment of the problem at hand is also given, supporting the empirical findings of the research. This paper focuses on two research aspects which we aim to solve i.e., unravel: a) finding the best possible univariate model of claims ratio (CR) based on model diagnostics and b) determining the financial health of the Macedonian non-life insurance sector and its future developments. Next, we set two interconnected hypotheses that we test: a) the ETS exponential smoothing models offer a more adequate approach when predicting the CR, and b) the employed random forest algorithm offers a powerful prediction but is a subordinated approach to classical time series methods. Both will be tested through a comparison of the accuracy measures of the training and test samples at hand. Model accuracy in the prediction of the claims ratio is evaluated based on time series splitting into two subsets. The first, also called a training set is used for model estimation and usually consists of the larger portion of the data. The test set is used to observe and evaluate model adequacy. Traditionally, the split is done on a 70:30 or 80:20 ratio. For our research, we split the disposable series such that 90% of data points are used for model estimation, while the remaining 10% for testing the models' accuracy. This is done largely due to the higher volatility observed in the premiums and claims in recent months since a smaller proportion for training would give predominantly inaccurate results.

3.1. Data analysis

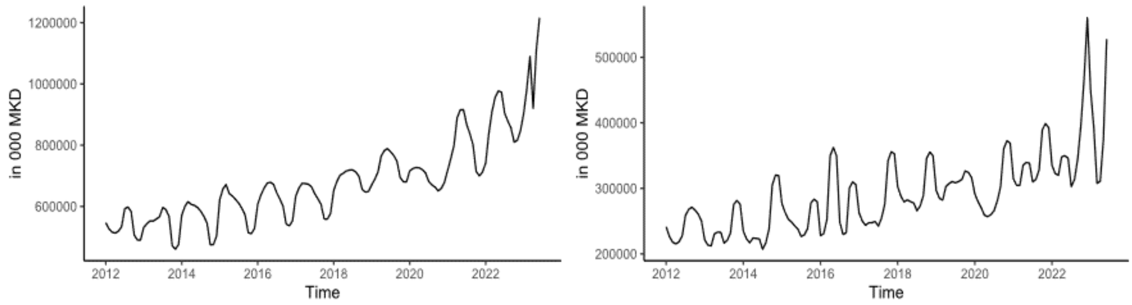
For this research, we have utilized quarterly datasets for over a decade-long period, between 2012Q1 and 2023Q2. These data sources were procured from the insurance industry publications issued by the national regulatory body i.e., the Insurance Supervision Agency (ISA). Our analysis is particularly focused on the non-life insurance sector in the Republic of North Macedonia, which is comprised of eleven distinct insurance enterprises. The selection of this sector is underpinned by our specific interest in conducting a sectoral examination and the relative importance of non-life over life insurance in the country. Given the unavailability of publicly accessible monthly data, we have undertaken a transformation process to convert the quarterly data to monthly periodicity. This transformation was executed through the utilization of a quadratic transformation technique, which is an integral feature of the EViews software package. Consequently, this conversion has allowed us to establish a temporal framework spanning from January 2012 to June 2023. The rationale behind this conversion is twofold: firstly, it serves the purpose of enhancing the number of observations at our disposal, thereby bolstering the robustness of our modeling efforts; secondly, it facilitates a more nuanced comprehension of the main dynamics in the sectoral CR.

Since the claims ratio is not directly available, we calculate it based on the data at hand i.e., the gross written premiums (GWP) and the gross claims liquidated (GCL). The calculation of the claims ratio (CR) involves the division of the aggregate claim amounts settled during a specific fiscal year by the total premiums received during the same period. Thus, we can calculate it as

$$CR_t = \frac{GCL_t}{GWP_t} \tag{1}$$

where t denotes the observed period, with $t = 1,2,3, \dots T$. Figure 1 depicts the consolidated sectoral series of premiums and claims for the Macedonian non-life insurance market. Both series portray a rising trend, with evident seasonal components, which are emphasized for the GWPs. The COVID-19 pandemic notably created a structural break in the series for the 2020 period, after which the insurance activity experienced a sharp growth. It is worth mentioning that the last 12 or 18 months show a deterioration from the historical performance, especially evident for the claims series. While such a dynamic may be an indicator of claims liquidation for large adverse events, that seems not to be the case. We believe that it is due to a balance sheet maneuver by specific entities, liquidating a larger buildup of multi-period claims.

Figure 1: Time series of gross written premiums (GWP) and gross liquidated claims (GLC), monthly sectoral data.

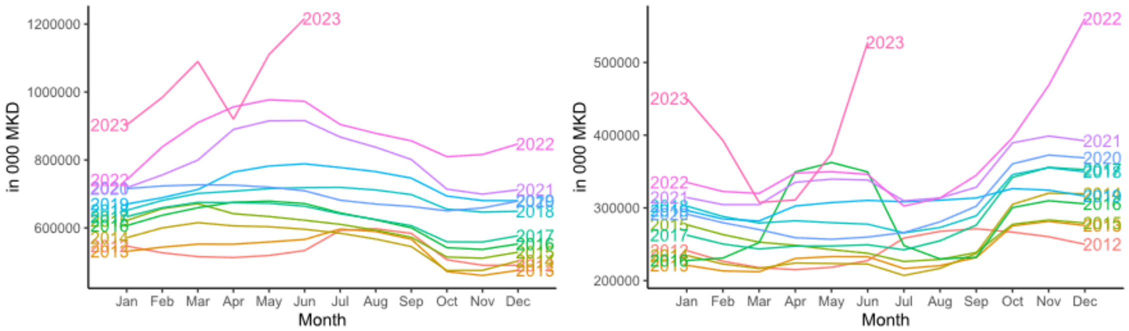


a) Gross written premiums *b) Gross liquidated claims*

(Source: ISA reports on the performance of the insurance undertakings (2012-2023); Authors' depiction.)

The seasonal performance can be observed in Figure 2 which portrays the seasonal plots for each of the input variables. For the gross written premiums, it seems that they reach their peak during the second quarter of the year notably in June. On the contrary, claims usually peak during the last months of the year, mostly in December i.e., the fourth quarter. A certain degree of seasonality is thus also expected when calculating the claims ratio.

Figure 2: Seasonal plots of gross written premiums (GWP) and gross liquidated claims (GLC), monthly sectoral data.

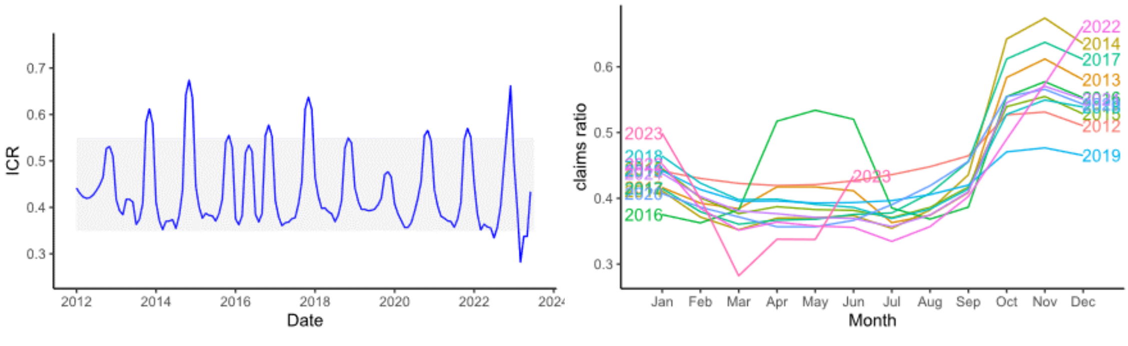


a) Gross written premiums *b) Gross liquidated claims*

(Source: ISA reports on the performance of the insurance undertakings (2012-2023); Authors' depiction.)

The non-life insurance claims ratio can be observed in Figure 3 alongside their seasonality for each of the years under analysis. The shaded grey area portrays the 'assumed' level of the claims ratio to retain the financial stability of the insurance companies and it ranges between 35%-55%, based on median data of the European insurance markets which predominantly fall in this range (EIOPA, 2022). Predominantly, the claims ratio rarely breaches the lower bound of 35%. Even though such information may indicate lost profitability, the levels at which non-life insurance premiums are set in North Macedonia seem to be adequate in the coverage of the potential claims filed. Isolated cases of such dynamics may be observed only in 2022 and 2023, while peaks above the upper bound of the 0.55 ratio are notable during 2013, 2014, 2017, 2018, 2020, 2021, and 2022.

Figure 3: Time series and seasonal plots of Macedonian non-life insurance claims ratio.

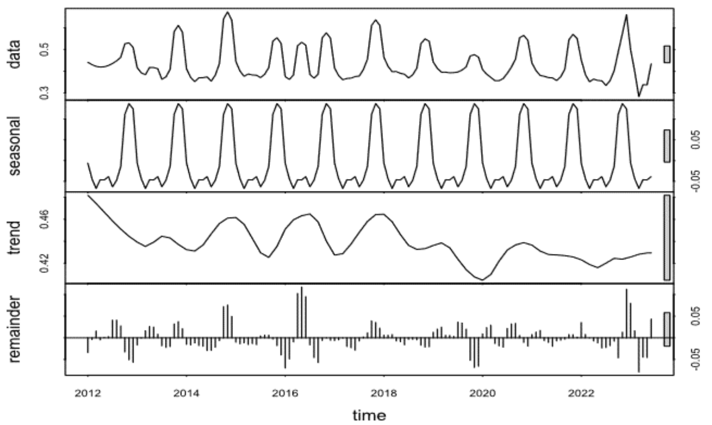


a) Claims ratio *b) Seasonal plot of the claims ratio.*

(Source: Authors' calculations.)

According to the descriptive statistic, the claims ratio ranges between 0.6739 and 0.2823 with a mean value of 0.4367. Additionally, the median value of the CR is 0.4083, 25% of the data is found up to the level of 0.3766, and 75% of the data is up to 0.4752. Thus, half of the time analyzed, the claim ratio ranges between the first and the third quartile or in the highlighted grey area. The standard deviation of the data is 0.0824 while the coefficient of variation (CV) of 18.85% shows a relatively low variation present in the data. Based on the skewness and kurtosis values of the dispersion of the dataset (1.0381 and 3.143, respectively), we conclude that the CR series is positively skewed and with fatter tails compared to the normal distribution. After decomposing the CR series to check for its components, we found a strong seasonality present in the data peaking during Q4 each year as well as the absence of a clear trend, especially between 2014 and 2020.

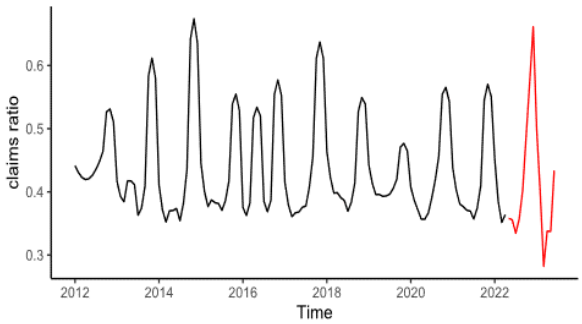
Figure 4: STL decomposition of the non-life claims ratio.



(Source: Authors' calculations.)

We split the claims ratio time series into two segments for our study. We employed a 90:10 split for the training and test sets, mostly due to the significant change in dynamics in the last 14 months for the gross written premiums and liquidated claims. Symbolically, the red line shows the test set upon which we check for model accuracy in the later stages.

Figure 5: Training and test split of non-life insurance claims ratio.



(Source: Authors' depiction.)

3.2. Methodology

Utilizing a variety of models in time series forecasting is essential due to the inherent complexity and variability present in real-world data. Employing multiple models allows for a more comprehensive exploration of the data's characteristics and patterns. Furthermore, model diversity helps in detecting anomalies, validating results, and accounting for uncertainties, which are crucial considerations in decision-making processes. Consequently, we aim to compare multiple approaches in forecasting the non-life insurance claims ratio (CR) in the Republic of North Macedonia in order to highlight the most suitable one.

Naïve models within the area of time series forecasting represent an elementary approach employed for predictive purposes, primarily reliant upon historical data. These models hypothesize that forthcoming values within a time series are either identical to or predominantly influenced by the most recently observed data points while disregarding underlying trends, patterns, or seasonality. Despite their lack of sophistication and susceptibility to underperform in scenarios involving intricate and dynamic time series data, naive models serve as helpful benchmarks for comparative assessments against more advanced forecasting methodologies. Even though they particularly find utility in instances where the data lacks a discernible pattern, we employ such an approach primarily to assess other models' performance in relation to the naïve approach. For instance, the seasonal naïve model, for example, can take the following form

$$\hat{Y}_{t+1} = Y_{t-k} \tag{2}$$

where k is the seasonal lag, which in the case of monthly data would be 12.

On the other hand, ARIMA (AutoRegressive Integrated Moving Average) models constitute a foundational and extensively utilized framework within the domain of time series analysis (Box and Jenkins, 1976). These models offer a robust methodology for capturing and modeling intricate temporal patterns embedded within time-dependent data. ARIMA models comprise three fundamental components: the autoregressive (AR) terms, which elucidate the temporal association between a data point and its historical values; the integrated (I) element, which states the number of differencing operations required to make the time series stationary; and moving average (MA) terms, which account for the impact of previous forecast errors on the current data point. Through thorough determination of the order of these components (typically represented as p, d, and q, respectively), ARIMA models can adeptly accommodate a diverse spectrum of time series data characteristics, encompassing trends, seasonality, and the presence of autocorrelation. Other extended models are also popular, with the seasonal ARIMA and the ARIMAX being the most common. For example, a SARIMA(p,d,q)(P,D,Q,m) model, assuming it is stationary, can be expressed as

$$y_t = \mu + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_i \varepsilon_{t-j} + \sum_{i=1}^{P} \mathrm{A}_i y_{t-mi} + \sum_{j=1}^{Q} \mathrm{B}_i \varepsilon_{t-mj} + \varepsilon_t \qquad (3)$$

such that, A_i are the seasonal autoregressive parameters of order P and B_i are seasonal moving average parameters of order Q. With d and D we denote the differencing and seasonal differencing orders, while for indicating the seasonality we choose m. Additionally, for the ARIMAX form, we can include an additional exogenous regressor which should be significant in explaining the series dynamics.

The ETS (Error, Trend, Seasonality) exponential smoothing models represent a prominent category of methodologies extensively employed in the realm of time series analysis and forecasting. They present a versatile framework for the comprehensive modeling of diverse temporal patterns inherent in sequential data. ETS models encompass three fundamental constituents: error term (E), signifying the quantification of the residual variance or stochasticity within the time series, trend (T), which captures any systematic ascending or descending tendencies manifested over time, and seasonality (S), explaining the recurring patterns or cyclical components embedded within the data. Through manipulation of the smoothing parameters associated with these components, ETS models demonstrate proficiency in accommodating time series data characterized by varying combinations of error structures, trend dynamics, and seasonal influences (Holt, 2004). ETS models find particular utility in circumstances where data adherence to specific functional forms is not guaranteed or where the underlying temporal patterns evolve dynamically. Since there are a large number of plausible model combinations, hereby we present the multiplicative Holt-Winters form

Level equation: $$l_t = \alpha\left(\frac{y_t}{s_{t-L}}\right) + (1-\alpha)(l_{t-1} + b_{t-1}) \qquad (4)$$

Trend equation: $$b_t = \gamma(l_t - l_{t-1}) + (1-\gamma)b_{t-1} \qquad (5)$$

Seasonal equation: $$s_t = \delta\left(\frac{y_t}{l_t}\right) + (1-\delta)s_{t-L} \qquad (6)$$

Forecast equation: $$\hat{y}_{t+h|t} = (l_t + hb_t)s_{t+h-L(k+1)} \qquad (7)$$

where the α, γ, and δ are the smoothing constants that require optimization, and L denotes the seasonal period. Unlike the ARIMA models, the exponential smoothing models are less rigorous in terms of achieving stationarity prior to model estimation. Moreover, they are less oriented towards posterior residual diagnostics and fit well on most of the data at hand.

The Random Forest (RF) algorithms, originally devised for classification and regression purposes, have been adapted for utilization in the domain of time series analysis. These supervised learning algorithms harness the principles of ensemble learning by constructing a multitude of decision trees and subsequently aggregating their predictive outputs. When applied to time series data, Random Forest models are modified to incorporate lagged observations and temporal features as input variables, thereby enabling the exploitation of temporal dependencies and underlying trends within the time series. While Random Forest algorithms may not possess the specialized focus on time series exhibited by dedicated models like ARIMA or ETS, they offer a versatile and robust approach that we aim to put side to side with the aforementioned time series models.

4. RESULTS AND DISCUSSION

The seasonal naïve forecast replicates the previous season of values for the claims ratio as an intuitive way of portraying test period dynamics. It is interesting that even though this approach ranks among the simplest, still provides sufficient accuracy for our test period with a MAPE value of 8.552% (compared to 9.0629% during the training sample) which is regarded as a high accuracy. The MASE measure in the training period indicates that the model is exactly as good as just picking the last observation – which is logical to its nature, while for the test period, it is slightly better than that.

Upon estimation of the ARIMA model for the claims ratio, we imposed several restrictions on the *auto.arima()* function in R. To stabilize the variance, we use the $\lambda = 0$ parameter which is the same as taking the natural logarithm of the series. We also checked for the number of seasonal differences necessary in order to make the CR series stationary. The test indicated only one seasonal difference of lag 12 and no first-order differences necessary. The subsequent ACF and PACF plots resulted in ambiguous results, so we let the *auto.arima()* function chooses the optimal model based on minimizing the AICc. The maximum number of AR and MA terms was preset to 6, while the seasonal terms were set at a maximum of 2, with the maximum order of the model $(p + q + P + Q) = 16$. After estimating 882 different model combinations, the algorithm chose the $SARIMA(4,0,2)(2,1,2,12)$ model with drift as the one with the lowest AICc of -418.69. The mean absolute percentage error for the test period indicates a good model accuracy with a value of 1.8829%. By checking for residual autocorrelation through the Ljung-Box test, with a p-value of 0.7142 we could not reject the null hypothesis of no residual autocorrelation, which indicates a suitable prediction model. Even though the subsequent test model accuracy measures indicate improvement in predictability, we ought to emphasize that this model is unstable resulting in an infinite AICc. This is predominantly accounted for the especially short test period (14 months) to estimate a model with 13 parameters, thus yielding an irrelevant accuracy result.

Unlike the ARIMA model, the exponential smoothing does not require stationarity in the series prior to model estimation. However, we retain the logarithmic transformation in this model. Resembling the *auto.arima()* function, the *ets()* function under the forecast package also estimates a series of models and optimizes the smoothing parameters to reach the minimum information criteria. The model of choice is the additive $ETS(A, N, A)$ with no trend – as recalled earlier with the series decomposition. The optimized smoothing parameters $\alpha = 0.7975$ and $\gamma = 0.0395$ indicate a more responsive reaction to recent changes in the level of the series and slow adaptation to the seasonality changes, thus focusing more on historical seasonality dynamics. Subordinated to the SARIMA model, the ETS model has a slightly worse accuracy in the training period with MAPE of 4.7025%. If we check the model accuracy in the test period, due to the short time frame, the seasonal component is not estimated yielding just a simple exponential smoothing with additive errors or $ETS(A, N, N)$.

Finally, we observe how supervised learning deals with time series. The claims ratio as a vector of values needs to go through a procedure called time series embedding in order for the random forest algorithm to work. To feed the model with enough information upon building the regression trees, the features are the 12 lags of the original series. Then, they are embedded into a matrix structure suitable for applying our method. Consequently, we end up with a log-differenced series. By subsequently removing the blank values, we run the random forest algorithm on the training set and observe its behavior on the test sample. The forecasting horizon h is set to the length of the test sample i.e., 14 observations. Even though the *auto.arima()* and the *ets()* functions revert the series to their original form, here we have to do it manually. We revert the process, i.e., we first reverse the differencing and then the natural log transform through an exponent function. The resulting model shows good forecasting accuracy with a MAPE of 10.629% for the test sample, making it a better approach than the exponential smoothing procedure.

Table 1: Model performances.

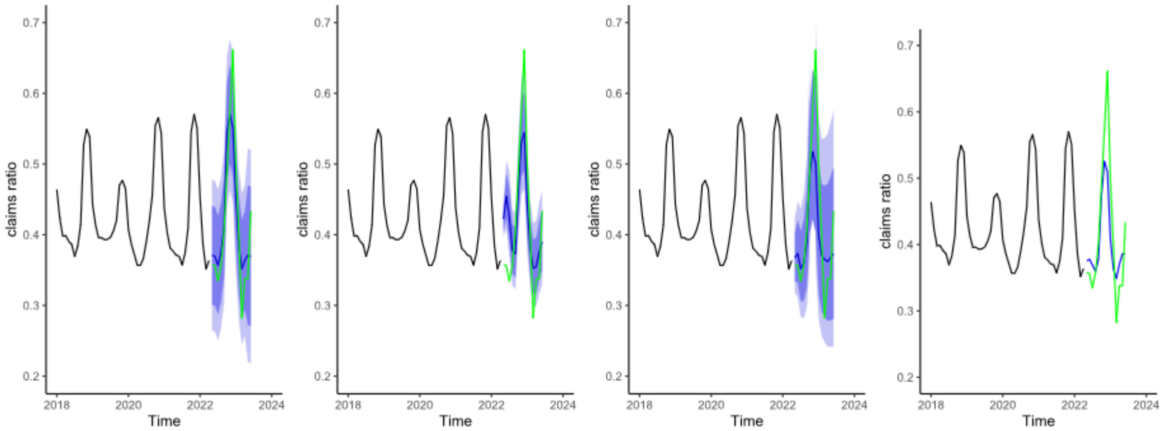
Training sample model	**AICc**	**RMSE**	**MAPE**	**MASE**
Seasonal Naïve	n.a.	0.054	9.063%	1
SARIMA(4,0,2)(2,1,2,12) with drift	-418.69	0.012	1.883%	0.204
ETS(A,N,A)	-33.43	0.031	4.703%	0.514
Random Forest Regression	n.a.	n.a.	n.a.	n.a.
Test sample model	**AICc**	**RMSE**	**MAPE**	**MASE**
Seasonal Naïve	n.a.	0.046	8.552%	0.877
SARIMA(4,0,2)(2,1,2,12) with drift	Inf.	0.009	0.718%	0.061
ETS	n.a.	0.085	15.848%	1.369
Random Forest Regression	n.a.	0.059	10.629%	n.a.

(Source: Authors' calculations.)

As can be observed, model accuracy increased for the testing period only for the seasonal naïve approach. By using the mean absolute percentage error as a relative measure of accuracy, fit for comparison between various models, we reject the hypothesis that the ETS exponential smoothing model provides better predictions. Moreover, it seems to be the worst-performing model for the testing period of May 2022 to June 2023 with a MAPE of 15.848% even though it's still regarded as a good prediction. On the other hand, the random forest algorithm can be applied to time series and offers a good prediction but is subordinated to the seasonal naïve and the SARIMA approach in the test period, confirming the initially set hypothesis. However, we can conclude that all models adequately predict the claims ratio which is expected to remain stable in the 35%-55% interval. The following Figure 6 shows how well each of the models predicts the test period dynamics alongside the confidence intervals (which are objectively omitted only for the random forest case). As can be observed, the SARIMA model offers smaller prediction intervals compared to the seasonal naïve and ETS models. Most of the data fits in the 80% intervals, especially for the naïve and exponential smoothing cases.

It is worth noting that there are some limitations to the research. At first, we only discuss univariate modeling while in reality, the case can be much more complex thus emphasizing the importance of exogenous predictors. The SARIMAX models are a possible fit but one should carefully choose the most significant exogenous variables. Second, the random forest regression employed is a novel approach to dealing with univariate data. The algorithm itself is built for multivariate data frames which by default provide a higher explanation for the cumulative variability. Finally, due to a lack of high-frequency data, we imposed a series of transformations to the original data so that we could work with stationary series. A small degree of important properties in the series were inevitably eliminated as a result.

Figure 6: Test period forecasts of claims ratio.



(Source: Authors' depiction.)

5. CONCLUSION

This research study addresses a pivotal concern about the prediction of claims ratios (CR) within the non-life insurance sector of Macedonia. The primary objective of this investigation was to make a substantive contribution to the extant scholarly literature by exploring a hitherto unexplored subject matter, specifically, the prediction of CR dynamics. Various predictive models were deployed, encompassing a simplistic naïve approach, ARIMA models, ETS exponential smoothing, and the random forest algorithm. These modeling choices were made to evaluate their appropriateness and precision in forecasting CR dynamics, thereby offering valuable insights to both insurance enterprises and regulatory bodies, with particular emphasis on the Insurance Supervision Agency (ISA) concerning the profitability and financial stability of the insurance sector. The research findings unveiled that the seasonal ARIMA model, specifically the SARIMA(4,0,2)(2,1,2,12) configuration, demonstrated superior predictive accuracy for CR, both within the training and test datasets. This model, characterized by its adeptness in capturing seasonal patterns and underlying trends, exhibited a mean absolute percentage error (MAPE) of 1.8829% during the test period, thereby underscoring its efficacy in CR prediction. Although the random forest algorithm exhibited promise, it was discerned to be comparatively less effective than the SARIMA model, albeit still outperforming the ETS model in the test dataset. Additionally, the seasonal naïve model, despite its inherent simplicity, demonstrated a commendable degree of accuracy in predicting CR during the test period, registering a MAPE of 8.552%, thus underscoring its potential as an uncomplicated yet potent forecasting tool. In summary, this research effort contributes significantly to the comprehension of CR dynamics within the Macedonian non-life insurance sector and underscores the paramount significance of judicious model selection for predictive purposes. The research findings offer valuable insights for stakeholders within the industry and regulatory authorities, thereby facilitating informed decision-making and enabling assessments of financial stability. Future research initiatives in this domain should contemplate the augmentation of the dataset and the exploration of advanced modeling methodologies to further enhance predictive precision. In the broader context, this study serves as a valuable point of reference for academicians, practitioners, and policymakers with a vested interest in the financial robustness and performance of insurance entities operating within an evolving market milieu. The outcomes suggest that the incorporation of predictive models could greatly augment the anticipations of profitability and financial stability for both the ISA and insurance companies.

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