**Chapter 7.**

# ECONOMIC UNCERTAINTY IN SERBIA: SOME ECONOMETRIC EVIDENCE

Over the past two decades, several major events, including the global financial crisis, Brexit, the US-China trade war, the COVID-19 pandemic and the Russian invasion of Ukraine, have significantly increased global uncertainty and impacted economies around the world. Increased uncertainty can strongly influence the decisions and behaviour of market participants and policy makers. High levels of uncertainty about future economic conditions may cause compa-nies to postpone investment and hiring, while consumers concerned about their future income and job security may respond by saving more and spending less. As uncertainty increases, investors expect higher returns for greater risk, which ultimately drives up financing costs.[163] In addition, some studies suggest that as uncertainty increases, economic agents tend to react less quickly to business changes, reducing the effectiveness of monetary and fiscal policy.[164]

Since uncertainty influences economic development, every economy has an interest in developing an indicator that monitors changes in uncertainty. A central question in empirical research is how to measure uncertainty, and in recent years, this topic has been widely studied by researchers. Various approaches to measuring uncertainty have been developed. The result is indicators that capture uncertainty in economic factors such as macroeconomic uncertainty, monetary policy uncertainty, inflation uncertainty, economic policy uncertainty and more.

One approach is based on the use of directly observable proxies for uncertainty. A commonly used indicator is the Chicago Board Options Exchange Volatility Index (VIX), which measures the implied volatility of the S&P 500 Index.[165] The second approach is based on observing the frequency of keywords related to

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[163] Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, *28*, pp. 153-176.

[164] Aastveit, K. A., Natvik, G. J., & Sola, S. (2017). Economic uncertainty and the influence of monetary policy. *Journal of International Money and Finance*, *76*, pp. 50-67; Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, *86*, pp. 1031-1065.

[165] Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, *77*, pp. 623-685; Basu, S., & Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica*, *85*, pp. 937-958.

uncertainty in newspaper articles.[166] These uncertainty indicators are based on the idea that when important events, such as political or economic shocks, occur, the number of articles covering these topics increases. The third approach uses surveys of companies, households and other market participants to create uncertainty indicators. The survey-based measures of uncertainty depend on the type of survey. Some indicators are based on the dispersion of professional forecasters' subjective forecasts[167], while others reflect firms' and households' views on uncertainty regarding various economic aspects such as production, purchases, prices, unemployment, etc.[168] The fourth approach uses an econometric framework to construct an uncertainty indicator. The prominent measure in this approach is the macroeconomic uncertainty indicator.[169] This indicator is created by aggregating the uncertainty of individual macroeconomic variables, defined as the volatility of the forecast error of the series.

In this chapter, we consider the index of economic uncertainty in Serbia based on the data defined by Thomson Reuters MarketPsych Indices in order to econometrically analyse its main dynamic properties.[170] We are primarily interested in identifying the extreme observations that indicate the increase in economic uncertainty. The modelling of extremes is a topic of extreme value theory, which provides a mathematical framework for considering the tails of the probability distribution of random variables.[171] However, our intention is to extract extreme observations by looking at the entire data set and treating them

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[166] Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics, 131*, pp. 1593-1636; Husted, L., Rogers, J. H., & Sun, B. (2020). Monetary policy uncertainty. *Journal of Monetary Economics*, *115*, pp. 20-36.

[167] Ozturk, E. O., & Sheng, X. S. (2018). Measuring global and country-specific uncertainty. *Journal of International Money and Finance*, *88,* pp. 276-295. Grishchenko, O., Mouabbi, S., & Renne, J. P. (2019). Measuring inflation anchoring and uncertainty: A US and euro area comparison. *Journal of Money, Credit and Banking*, *51,* pp. 1053-1096.

[168] Bachmann, R., Elstner, S., & Sims, E. R. (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics*, *5*, pp. 217-249; Leduc, S., & Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, *82*, pp. 20-35.

[169] Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105,* pp. 1177-1216.

[170] https://www.lseg.com/data-analytics

[171] Embrechts, P., Kluppelberg, C., & Mikosch, T. (2008). *Modelling Extremal Events*. Berlin: Springer; Mladenović, P. (2024). *Extreme Values In Random Sequences*. Cham: Springer.

as additive outliers.[172] Several techniques are used, originating from different statistical approaches. Applying different statistical methods can improve the robustness of the results.

The appropriate consideration of additive outliers is relevant from an econometric and economic point of view. If these outliers are neglected, standard econometric tools can lead to incorrect specifications of univariate and multivariate time series models, which in turn can lead to poor performance in the forecasting.[173] Furthermore, misleading economic conclusions can be drawn. Therefore, the presence of outliers must be treated with caution.

The above is also important for technical, i.e. mathematical statistical organization of insurance that represents the key specificity of insurance. Insurance has a large number of functions: the function of protection, i.e. asset protection, social function, financial accumulator function, promotes exchange and trade, contributes to more efficient allocation of capital, etc. The basic function of insurance is to provide economic protection to insurance users against the risks they are exposed to. In order to fulfill the aforementioned function, insurance companies carry out the timely transformation of smaller amounts of accumulated insurance premiums into larger amounts of assets (reserves). The aforementioned funds can be invested in the financial market until the maturity of contractually defined obligations towards insurance beneficiaries. Non-life insurance contracts are usually concluded for a period of one year, and life insurance contracts are concluded for several years (10, 20, 30, etc.). Depending on the type of insurance, it is necessary to harmonize the maturity of obligations and sources of funds. The goal of investing is to obtain an adequate return and capital gain with as little risk as possible.

Optimizing the portfolio of insurance companies is highly dependent on the relationship between economic uncertainty and financial markets. The situation is similar with voluntary pension funds, since the amounts of pension compensation depend to a large degree on the return on invested contribution funds in the financial markets. Depending on the relationship between economic uncertainty and financial markets, voluntary pension funds will opt for an active or passive portfolio management strategy. An active portfolio management strategy implies more frequent portfolio changes with the aim of adapting to new situations. A passive strategy involves buying and holding a security for a long time with minor and infrequent changes. Both insurance companies and pension

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[172] Wei, W. W. S. (2006). *Time Series Analysis: Univariate and Multivariate Methods*, 2nd ed., Boston: Pearson-Addison Wesley.

[173] Castle, J. L., Clements, M. P., & Hendry, D. F. (2016). An overview of forecasting facing breaks. *Journal of Business Cycle Research, 12*, pp. 3-23.

funds are cautious investors where the key investment principles are liquidity and safety, and only then profitability.

In addition, the pattern of time-varying conditional variability of the data is analyzed in the context of GARCH (generalized autoregressive conditional heteroskedastic) models. Finally, the relationship between the economic uncertainty index and the BELEX sentiment index is examined to determine the nature of the dynamic correlation between these two variables. This may serve as an indication of the co-movement between economic and financial uncertainty in Serbia.

The rest of the chapter is structured as follows. Section 1 explains the concept of Thomson Reuters economic uncertainty index in general and then discusses the data for Serbia. Section 2 provides econometric results based on weekly and monthly aggregations of this economic uncertainty index. The analysis of the dynamic interdependence between the monthly data of the economic uncer-tainty index and the BELEX sentiment index in Serbia is presented in Section 3.

## 1. DESCRIPTION OF THOMSON REUTERS ECONOMIC UNCERTAINTY

Thomson Reuters MarketPsych Indices (TRMI) are based on sentiment analysis. The primary idea behind these indicators is to provide relevant and real-time information through the analysis of text content. The availability of such information is crucial for market participants, as it helps them to make more informed decisions.

The estimation of index values is based on three sets of content. The first group of indices is formed using only news data, the second group relies on social media data, while the third group combines both sources. This approach focuses on extracting meanings and relevant information from the sentences of the texts. For each sentence, the MarketPsych software identifies words from the MarketPsych lexicon, analyzes whether it has a positive or negative context, and determines whether it refers to the future, present, or past.[174] The MarketPsych lexicon is a large collection of both simple and complex English-language words and phrases.

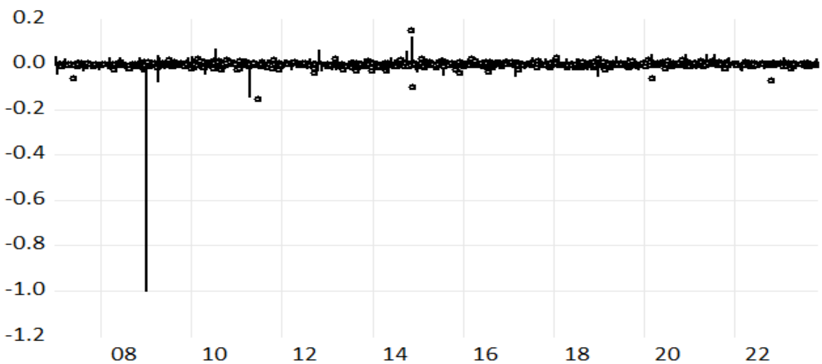
Our analysis is based on using Thomson Reuters economic uncertainty index for Serbia. The index values are derived from news references to uncertainty about business climate, net of references to confidence and certainty. Daily data are employed covering the period: 1/1/2007-10/31/2023. The index values range

[174] Peterson, R. L. (2016). *Trading on Sentiment: The Power of Minds Over Markets*. Hoboken: John Wiley & Sons.

between -1 and 1. Negative values suggest periods of uncertainty. If no relevant text is found, the index value is "NA", while a zero value means that the relevant text's sentiment cancel each other out.

The daily data on the Thomson Reuters economic uncertainty index are shown in Figure 1. On January 1, 2009, the index reached its minimum value which is -1. The result implies that the most significant episode of uncertainty coincides with the global financial crisis. The maximum index value was recorded on November 9, 2014, and it was 0.15. In November 2014, a three-year precautionary loan deal was reached with the International Monetary Fund, resolving months of uncertainty for the dinar currency.

*Figure 1. The Thomson Reuters daily economic uncertainty index for Serbia*




*Source: LSEG Data & Analytics*

Analysis of the index is challenging due to the absence of relevant text on certain days, causing the index values for those days to be treated as missing observations. Consequently, econometric analysis presented in sections 2 and 3 is based on weekly and monthly data that are created from daily data.

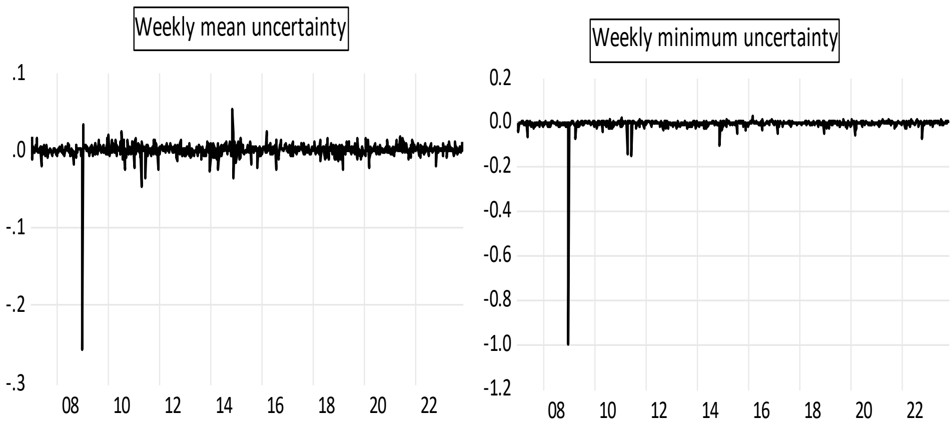
## 2. ECONOMETRIC TIME-SERIES ANALYSIS OF THOMSON REUTERS ECONOMIC UNCERTAINTY

Our econometric study has two objectives. The first objective is to identify extreme observations – additive outliers in the dynamic behaviour of the index of economic uncertainty. The second objective is to find the econometric specification that satisfactorily captures the main statistical properties of the economic uncertainty index. The econometric analysis is performed separately for weekly and monthly frequencies.

## 2.1. Weekly aggregation

Daily data are aggregated into weekly data using two approaches. The first approach defines the observation for a given week as the minimum value of the corresponding seven daily observations. The second approach is based on the sample mean of seven daily observations. In both cases, missing observations are interpolated by linear trend functions. The number of observations is 878. The two weekly series are shown in Figure 2.

*Figure 2. The Thomson Reuters weekly economic uncertainty index for Serbia*




*Source: LSEG Data & Analytics and author's calculation*

Weekly minimum data put weight on the negative daily values and therefore provide valuable information for tracking negative extreme events that have caused an increase in uncertainty.

The outliers are identified by applying various statistical techniques. Two of them recognise outliers by constructing intervals, and all data points that lie outside these intervals are marked as outliers. The Tukey method[175] uses the quartiles of the data to construct an interval, while the second method uses the mean and standard deviation of the data. In both methods, the width of the interval is influenced by a constant set by the researcher, which affects the sensitivity to outliers. A higher value leads to a wider interval and makes the methods less sensitive to outliers, while a lower value increases the sensitivity.

[175] Tukey, J. W. (1977). *Exploratory Data Analysis*. Massachusetts: Addison-Wesley.

The third method is based on wavelet analysis.[176] In this approach, a discrete wavelet transform is applied to the observed series, filtering the data and calculating the wavelet coefficients. High-pass and low-pass filters for the Haar wavelet are used to separate high-frequency and low-frequency content. The focus is on the wavelet coefficient with high-frequency content, as it is very sensitive to outliers. If the value of the wavelet coefficient exceeds the critical value, this method indicates the existence of an outlier. The last method is based on the detection of outliers in ARMA models.[177] Four different types of outliers are defined by their impact on the time series. The procedure for identifying outliers follows these steps: First, an ARMA model is estimated and the residuals are determined. Second, the impact of each type of outlier on the residuals is evaluated and standardized test statistics are calculated. If the highest test statistic exceeds the critical value, the corresponding outlier type is detected. By choosing the false discovery rate and the critical values, the researcher influences how sensitive the last two methods are to outliers.

The identification of outliers is based on a low sensitivity given the data frequency. Of the 20 outliers found, 19 indicate an increase in uncertainty due to their negative values. The most extreme negative values are extracted for the weeks that were associated with the following dates: 12/27/2008, 4/16/2011, 6/18/2011, 11/22/2014, 11/28/2015, 2/25/2017, 12/22/2018, 3/7/2020, and 10/22/2022.

The weekly average data is subjected to econometric modelling. We have opted for the time-changing conditional variability of GARCH form.[178] More precisely, power GARCH-in-mean[179], PGARCH(1,1)-M, is used under the assumption that an error term has a t-distribution. The power parameter is set to 1, so that conditional standard deviation is considered. The estimated model is presented in

[176] Bilen, C., & Huzurbazar, S. (2002). Wavelet-based detection of outliers in time series. *Journal of Computational and Graphical Statistics, 11,* pp. 311-327.

[177] Chen, C., & Liu, L. M. (1993). Joint estimation of model parameters and outlier effects in time series. *Journal of the American Statistical Association*, *88,* pp. 284-297.

[178] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31,* pp. 307-328.

[179] Ding, Z., Granger, C. W. J., & Engle, R. F. (1993). Long memory property of stock market returns and a new model. *Journal of Empirical Finance, 1,* pp. 83-106; Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk in the term structure: the ARCH-M model. *Econometrica, 55,* pp. 391-407.

Table 1. The BHHH algorithm[180] with Bollerslev-Wooldridge standard errors[181] is employed.

*Table 1. Estimated model for weekly mean economic uncertainty*

| **Mean equation** | | |
|---|---|---|
| Variable | Estimate | z-statistic |
| Constant | 0.002 | 68.87 |
| GARCH | -0.258 | -77.36 |
| **Volatility equation for standard deviation** | | |
| Variable | Estimate | z-statistic |
| Constant | 0.003 | 41.25 |
| ARCH(1) | 0.216 | 22.75 |
| GARCH(1) | 0.383 | 56.42 |
| t-distribution degrees of freedom | 3.03 | 19.60 |
| Diagnostic statistics: SC=-7.4386, Q(7)=1.57(0.98), Q(14)=4.59(0.99), $Q^2(7)$=1.60(0.98), $Q^2(14)$=19.60(0.14), ARCH1-14=18.96(0.17), Joint Statistic of the Nyblom test of stability:1.17. | | |

Note: The mean equation contains impulse dummy variable for the week that starts on December 27, 2008. Data were prewhitened prior to modelling.
*Source: Author's calculation*

The model performs well statistically. It shows significant temporal changes in the conditional standard deviation, represented by the absolute lagged shock (0.216) and the lagged own conditional standard deviation (0.383). The estimated standard deviation enters the mean equation with a negative estimate (-0.258), indicating that an increase in volatility causes a decrease in the level of the economic uncertainty index. This means that there is a tendency towards more bad news.

The estimated degree of freedom of the t-distribution is 3, which suggests the presence of heavy tails in the empirical distribution of the data. Such a shape of an empirical distribution is due to outliers that were previously discussed.

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[180] Berndt, E., Hall, B., Hall, R., & Hausman, J. (1974). Estimation and inference in nonlinear structural models. *Annals of Economic and Social Measurement, 3,* pp. 653-666.

[181] Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews, 11,* pp. 143-172.

## 2.2. Monthly aggregation

Using the similar approach of aggregation we have created two monthly series of uncertainties (202 observations). Upon correcting for the extreme dropdown at the beginning of 2009, we have searched for the outliers. Given that data are now of lower frequency, we opted for the medium criterion for outlier detections. The months for which extreme negative values were found are summarized in Table 2 below. They largely correspond to the weeks previously extracted.

*Table 2. Negative outliers for monthly minimum uncertainty data*

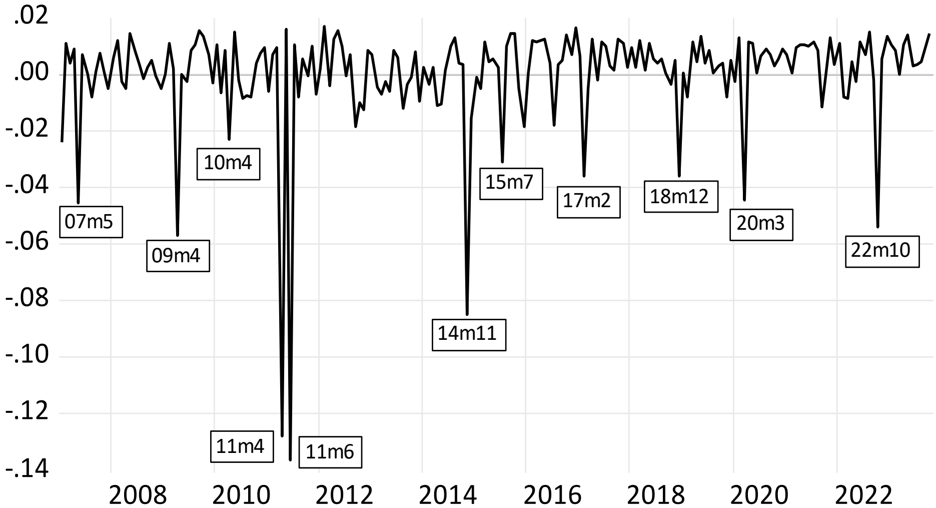
| Month | Tukey | Mean/Std | Wavelet | Influence |
|---|---|---|---|---|
| **2007m5** | Y | | | |
| **2009m1** | | | | Y |
| **2009m4** | Y | Y | Y | Y |
| **2010m4** | Y | | | |
| **2011m4** | Y | Y | Y | Y |
| **2011m6** | Y | Y | Y | Y |
| **2014m11** | Y | Y | Y | Y |
| **2015m7** | Y | | | |
| **2017m2** | Y | | | |
| **2018m12** | Y | | | |
| **2020m3** | Y | | | |
| **2022m10** | Y | Y | | Y |

*Source: Author's calculation*

All four methods indicate the presence of outliers in the following periods: April 2009, April and June 2011, and November 2014. The first outlier corresponds to the global financial crisis period. In the second quarter of 2011 there was a significant spike in global oil prices and a rise in food prices in Serbia that contributed to increased economic uncertainty. At the end of 2014, there was a significant drop in industrial output, driven mainly by a sharp fall in power production and mining. This result was due to severe floods in Serbia in May 2014. Only the Tukey method indicates an increase in uncertainty in March 2020, which coincides with the first wave of the COVID-19 pandemic. Three out of four methods detect an outlier in October 2022, which coincides with a surge in global energy prices and a sharp rise in inflation, triggered by the Russian invasion of Ukraine in early 2022.

Negative outliers found in the monthly minimum economic uncertainty index are noted in Figure 3.

*Figure 3. Negative outliers detected in monthly minimum uncertainty index*




Note: This graph represents a series corrected for the lowest value observed in January 2009. If the original data were used, other outliers would hardly be visible due to the extreme negative value of observation in January 2009.
*Source: LSEG Data & Analytics and author's calculation*

In an attempt to uncover the correlation structure of the data for the monthly mean index of economic uncertainty that we use in the econometric modelling, we calculated the sample ordinary and partial autocorrelation functions for the level values and the squared values. The results for the sample ordinary autocorrelation function presented in Table 3 show that the data do not exhibit a statistically significant pattern of dynamic correlation. However, the presence of outliers can produce a particular component that often overshadows the actual correlation pattern of the data. For this reason, we corrected the data for the presence of dominant outliers in the mean uncertainty index and recalculated the sample ordinary and partial autocorrelation functions. The new results are now substantially different (Table 4) and they indicate a significant individual autocorrelation for the first lag and a significant joint autocorrelation for the first four lags. The new results provided a clue to the structure of the moving average form in the mean equation. A further examination of the conditional variability showed the appropriateness of the ARCH(1) specification. The estimated model is presented in Table 5.

*Table 3. Sample ordinary autocorrelation function for monthly mean uncertainty index*

| **lag** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| estimate | 0.036 | 0.049 | 0.033 | 0.037 | 0.043 | 0.016 |
| p-value of Q statistic | 0.61 | 0.68 | 0.80 | 0.86 | 0.89 | 0.94 |
| **lag** | **7** | **8** | **9** | **10** | **11** | **12** |
| estimate | -0.052 | -0.021 | 0.005 | -0.004 | -0.040 | -0.041 |
| p-value of Q statistic | 0.94 | 0.97 | 0.98 | 0.99 | 0.99 | 0.99 |

Note to Tables 3 and 4: The 95% confidence interval is [-0.138; 0.138].
*Source: Author's calculation*

*Table 4. Sample ordinary autocorrelation function for monthly mean uncertainty index corrected for outliers*

| **lag** | **1** | **2** | **3** | **4** | **5** | **6** |
|---|---|---|---|---|---|---|
| estimate | 0.171 | 0.113 | -0.009 | 0.014 | -0.036 | 0.004 |
| p-value of Q statistic | 0.02 | 0.01 | 0.04 | 0.07 | 0.11 | 0.18 |
| **lag** | **7** | **8** | **9** | **10** | **11** | **12** |
| estimate | 0.055 | 0.068 | 0.091 | -0.042 | -0.053 | 0.013 |
| p-value of Q statistic | 0.22 | 0.23 | 0.20 | 0.24 | 0.27 | 0.35 |

*Source: Author's calculation*

*Table 5. Estimated model for monthly mean economic uncertainty*

| **Mean equation** | | |
|---|---|---|
| Variable | Estimate | z-statistic |
| Constant | -0.0008 | -3.35 |
| MA(1) | 0.262 | 3.36 |
| MA(2) | 0.149 | 2.25 |
| **Volatility equation** | | |
| Variable | Estimate | z-statistic |
| Constant | 4.08E-06 | 6.42 |
| ARCH(1) | 0.171 | 2.08 |
| Diagnostic statistics: SC=-8.825, Q(6)=1.63(0.80), Q(12)=5.19(0.88), $Q^2(6)$=3.41(0.76), $Q^2(12)$=11.69(0.47), ARCH1-6=2.99 (0.81), Joint Statistic of the Nyblom test of stability: 2.13. | | |

Note: The mean equation contains impulse dummy variables for the following months: 2009m1, 2011m4, 2011m6, 2014m4, 2014m11, 2015m3, 2021m7, 2021m11. BHHH algorithm with Bollerslev-Wooldridge standard errors is used.
*Source: Author's calculation*

The monthly mean uncertainty index is also characterized by a changing volatility, which is now well captured by only one variable, the lagged squared shock (0.171). The mean equation contains moving average components of order one and two and thus shows a dynamic structure with short memory. Such a structure could not be found if we neglected the additive outliers.

## 3. CO-MOVEMENT WITH THE BELEX SENTIMENT INDEX

Numerous studies have examined the link between economic uncertainty and financial markets, yet the empirical evidence remains inconclusive. On the one hand, rising uncertainty about economic conditions can make investors worry about future profits or potential changes in interest rates, which can cause stock prices to fall.[182] On the other hand, a decline in stock prices may indicate that investors are losing faith in both the stock market and the economy. This can lead to reduced business investment and production, increasing economic uncertainty.[183] One of the objectives of the chapter is to examine the relationship between economic uncertainty and the financial market in Serbia. BELEX sentiment index is used as financial market indicator.

### 3.1. Explanation of the BELEX sentiment index

BELEX sentiment index is formed to capture the predictions of market participants about financial market trends in Serbia. Tracking index movement is crucial for making informed investment decisions, as it helps investors to anticipate market changes and adjust their strategies. This monthly indicator is constructed by Belgrade Stock Exchange.[184]

BELEX sentiment index is based on the votes of the following three groups of voters: Stock Exchange members, portfolio managers of investment and voluntary pension funds, and users of the Belgrade Stock Exchange official site. Participants can select one of seven categories that best represents their forecast

[182] Li, X. L., Balcilar, M., Gupta, R., & Chang, T. (2016). The causal relationship between economic policy uncertainty and stock returns in China and India: Evidence from a bootstrap rolling window approach. *Emerging Markets Finance and Trade*, *52*, pp. 674-689.

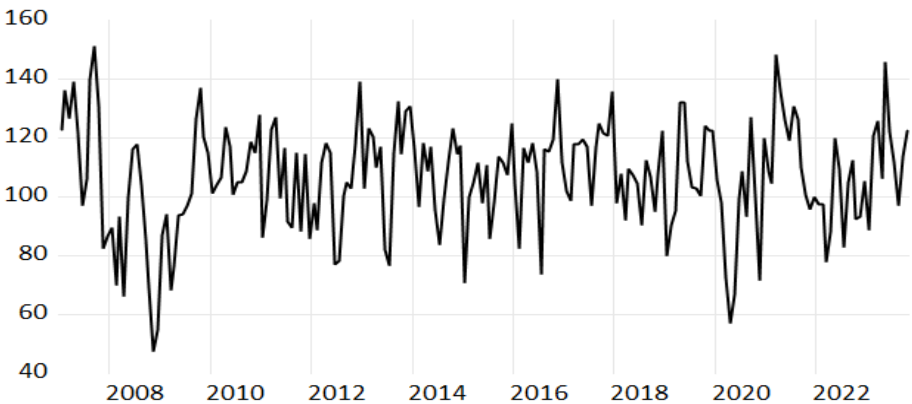
[183] Chang, T., Chen, W. Y., Gupta, R., & Nguyen, D. K. (2015). Are stock prices related to the political uncertainty index in OECD countries? Evidence from the bootstrap panel causality test. *Economic Systems*, *39*, pp. 288-300.

[184] https://www.belex.rs

for the market trends in the next month, including strong fall, moderate fall, slight fall, stagnation, slight rise, moderate rise, and strong rise.[185]

The base value of the index is 100 points, and its value can vary from 0 to 200 points. If the index value is less than 100, it suggests negative market expectations, whereas a value greater than 100 reflects positive market sentiment. The monthly data on BELEX sentiment index from January 2007 to Octobar 2023 are shown in Figure 4. The lowest index values were recorded during the global financial crisis (the end of 2008) and the first wave of the COVID-19 pandemic (the beginning of 2020).

*Figure 4. BELEX sentiment index*




*Source: Belgrade Stock Exchange*

## 3.2. Dynamic relation between the BELEX sentiment index and economic uncertainty index

Economic uncertainty can be linked to the risk associated with unpredictable future economic policy and regulatory environments. We want to find out how this uncertainty is related to the BELEX sentiment index, which serves as an indicator of market participants' perceptions of future movements in the financial markets.

The characteristics of the dynamic relationship between economic uncertainty and the BELEX sentiment index are assessed on a monthly basis by applying standard and time-varying Granger causality tests. The values of the BELEX sentiment index are standardized prior to modelling.

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185 https://www.belex.rs/files/e_trgovanje/BELEXsentiment-site-english.pdf

The conventional Granger test shows that there is no causality in either direction. To get a better insight into the interdependencies, we used the recently introduced time-varying Granger causality test.[186]

Three versions of the test were developed based on recursive estimation, and their limiting distributions are derived.[187] These are: forward expanding, rolling and recursive evolving windows. All tests are calculated as Wald tests, but with differently generated subsamples. An algorithm to control heteroscedastic-consistent sequences is also developed. The simulation results show that the performance of the recursive evolving window tests is better than that of the other two tests in small samples.

The significant causality is only found in one direction, namely from the BELEX sentiment index to the index of economic uncertainty (see Figure 5). This causality is confirmed by two tests that show significance for the most part of the sample - from the end of 2016. Causality in the opposite direction, running from the economic uncertainty index, is not found (Figure 6). The figures presented are from the VAR model based on the window of size 72. The results are robust to a change in the window size.

One could argue that the standard VAR model does not provide an adequate framework for capturing the specific characteristics of the time series under consideration, given the way they are computed, the presence of numerous additive outliers and the changing variability. For this reason, we estimated the Markov-Switching VAR model (MS-VAR)[188] under the assumption that the error covariance matrix and the effects of the lagged explanatory variables vary between the two regimes. The BHHH algorithm is applied. It is estimated that the average constant duration of regime 1 is about 3 months and about 2 months in regime 2. The probability of remaining in regime 1 while in this regime is estimated to be 0.70. The probability of remaining in regime 2 when already in this regime is estimated at 0.55.

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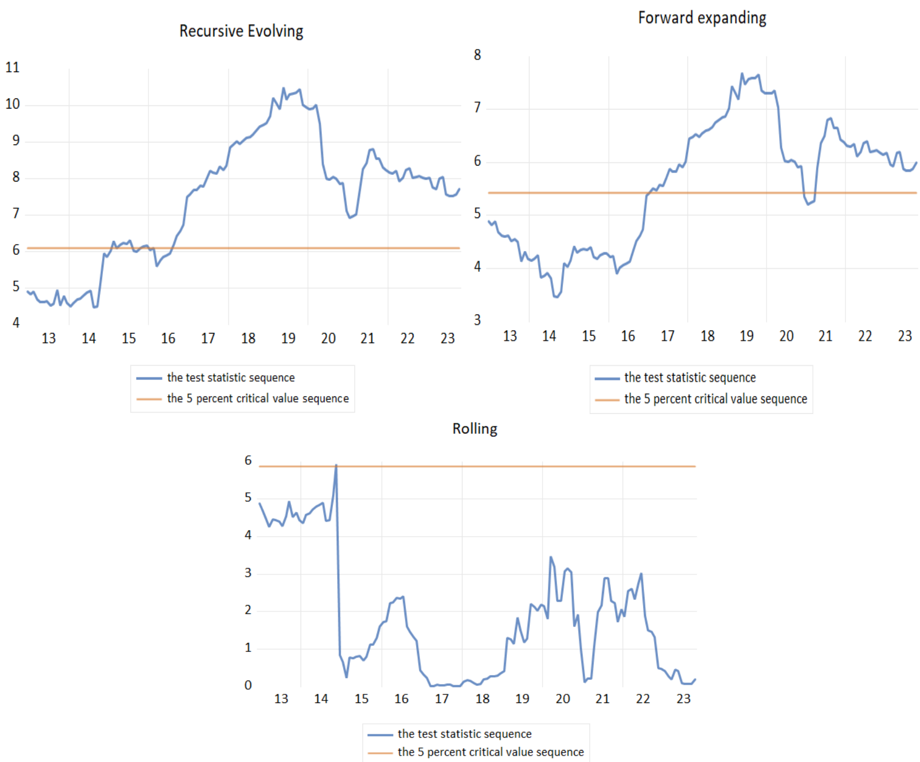
[186] Shi, S., Hurn, S., & Phillips, P. C. B. (2020). Causal Change Detection in Possibly Integrated Systems: Revisiting the Money-Income Relationship? *Journal of Financial Econometrics, 18*, pp. 158-180.

[187] Ibid.

[188] Krolzig, H. M. (1997). *The Markov-Switching Vector Autoregressions.* New York: Springer.

The calculated variance decomposition of the forecast error from the estimated MS-VAR model after 12 months, based on the order: BELEX Sentiment - economic uncertainty, shows that in regime 1, each variable is predominantly explained by its own unexpected shocks and that the same is true for the BELEX sentiment index in regime 2. However, about 46% of the variability of the economic uncertainty index can be attributed to the unexpected shocks of the BELEX sentiment index in regime 2. The results are relatively robust to a reversed ordering of the variables.

*Figure 5. Time-varying Granger causality from BELEX sentiment to economic uncertainty*




*Source: Author's calculation*

*Figure 6. Time-varying Granger causality from economic uncertainty to BELEX sentiment*


*Source: Author's calculation*

In addition to insurance risks associated with the types of insurance that insurers deal with, as well as certain extreme factors (risk of insurance premiums, risk of reserves, risk of insured behaviuor, etc.), credit and operational risks, market risks are also important for insurers. These risks (interest rate risk, foreign exchange risk, etc.) are easier to measure than insurance risks thanks to the availability of high frequency data from the financial markets and the application of financial and econometric models that can be employed to model these risks. In this context, our econometric results based on the analysis of the time series properties of Thomson Reuters economic uncertainty index in Serbia can provide valuable information and insights.