International Bachelor Thesis Econometrics and Operations Research

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The Predictive Power of Financial Stability Reports

Abstract

This research concentrates on the relationship between real GDP and the attitude of central banks towards various economic sectors. The dataset consists of 13 countries, which are analysed quarterly over a time period stretching from 2005 to 2019. In order to characterize sentiment related to different topics in Financial Stability Reports (FSRs), I recreate the so-called Financial Stability Sentiment (FSS) index, as introduced by Correa et al. (2017). The underlying relationship between traditional measures and the FSS indices is analysed through panel-regression models. This is followed by forecasting future values of GDP through Support Vector Regression (SVR). The models indicate that several of the FSS indices explain a significant amount of time variability in GDP. However, the forecasting performance of the SVR model is not improved by implementing the indices into the training process.

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1 Introduction

Understanding what the future holds is an important responsibility of policy makers. It contributes to the decision making process, such that a country is able to maintain positive economic growth, reach the inflation target or decrease unemployment. By means of fiscal policies, a government adjusts tax rates and spending levels in order to oversee and influence the economy. Furthermore, monetary policies are set by the central bank with the intention to advocate sustainable growth. All these decisions need to be made far in advance, since it can take multiple years for a policy change to have full effect. Therefore, forecasts play a very critical role in the management of financial stability. This paper aims to provide new insights on the value that sentiment, communicated by central banks, could add to strategic decision making.

The Gross Domestic Product (GDP) is an indicator of a country's economic health and possibly one of the most carefully followed financial measures. It allows policy makers to determine if the economy is either expanding or contracting and it is also used to foresee periods of uncontrollable inflation and economic recession. The swift anticipation of such events is needed to protect not only the economic state of a country, but the livelihood of its citizens as well. Increasing the current forecasting capability of GDP supports this primary goal.

After the Global Financial Crisis (GFC) of 2008, many central banks started to annually publish so-called Financial Stability Reports (FSRs). In these reports, central banks discuss the current state of the financial system and express their concerns towards various economic sectors. Their main intention is to raise awareness among policy makers and financial institutions for possible shocks to the economy. Correa et al. (2017) created an index that portrays the sentiment that is conveyed in FSRs. Part of their research shows that this index holds predictive power for a multitude of financial indicators, including GDP-related measures. Whilst the number of FSR publications is relatively small, this study concentrates on the relationship between a country's GDP and the attitude of central banks towards various economic sectors. In particular, are sentiment related indices able to capture a significant amount of the time variability in GDP? In order to formulate an appropriate answer, the following sub-questions are defined:

1. Sentiment of which economic sectors explain most of the time variability in GDP, as communicated by central banks?

2. How accurate are GDP forecasts when using small datasets?

3. Are sentiment based indicators able to consistently improve the forecast accuracy?

The dataset consists of the real GDP series for 13 countries, which are analysed quarterly over a time period stretching from 2005 to 2019. In addition, various economic indicators are used that relate to the different financial sectors. To depict the attitude of central banks with respect to financial stability, I reconstruct the sentiment indices that are described in Correa et al. (2017). Recent studies show promising results for forecasting monetary values using Support Vector Regression (SVR) with small training sets. In this paper, I evaluate the SVR model for different rolling-windows and included lags. The impact of the sentiment indices is tested on the model specification that exhibits the best forecasting performance. Machine learning algorithms, such as SVR, do not allow for comprehensive analysis between the variables in question. Therefore, two panel-regression models are constructed to help explain the cross-sectional relationship between GDP and the sentiment indices.

The findings of this research indicate that sentiment related to the external and sovereign sector capture most of the time variability in GDP, compared to other financial topics that are discussed in FSRs. It also shows that the attitude of central banks towards different financial topics is associated with several traditional economic measures. This underlying relationship seems to vary over time. After evaluating the performance of SVR under different circumstances, the final model consists of two lagged observations per data point and a rolling-window of two quarters. For most countries a 1-step ahead forecast has an average absolute error of around 0.9%, which typically grows to an error of 4% when predicting two years ahead. Nevertheless, the analysis shows that there is still a significant part of the time variability in GDP that the SVR model is not able to predict. In addition, implementing the sentiment based indicators into the training process did not lead to a consistent decrease of this forecast bias.

The paper proceeds with a literature review which explains the position of the research amongst the existing literature. This is followed by a description of both the dataset and the procedure that is executed to construct the sentiment related indices. Subsequently, the theoretical framework of the methods are described, together with the metrics that are used to evaluate the forecasting performance. Finally, the results are discussed and the research questions are answered within the final conclusion of the research.

2 Literature review

This research is primarily motivated by the findings of Correa et al. (2017), regarding the relationship between the financial cycle and the sentiment expressed in FSRs. They perform sentiment analysis by means of a dictionary-based approach, in order to gain more knowledge about the value of information that is communicated by central banks. To realise this, they construct a so-called Financial Stability Sentiment (FSS) index. While there exist various text analysis dictionaries, this approach is tailored for capturing sentiment about financial stability. Part of their research shows that the FSS index has predictive power for a multitude of financial indicators, including GDP-related measures. This paper tries to extend their research by further analysing the sector specific indices and evaluating the added value that sentiment brings to forecasting models of real GDP.

One of the instruments used by policy makers to measure the economic state of a country is real GDP. While it should not be interpreted as an indicator of citizens' general well-being, Callen (2008) explains that it still holds important information regarding the size and performance of the economy. In particular, an increase in real GDP signals that the economy is doing well. Fatas and Mihov (2001) analyse the effect of fiscal policies on economic activity. Their findings suggest that larger governments are associated with less volatile business cycles, due to the stabilizing effects of fiscal policies. Predictions are necessary to sustain growth and evade periods of recession, since fiscal and monetary policies need to be implemented years in advance. Traditional forecasting models are often based on economic theory or linear time series. The studies by Dritsaki (2015) and Barnett et al. (2012), both show that such linear approaches can be very effective for explaining economic activity. In this study I focus on improving the accuracy of long-term predictions, as this is beneficial for policy makers in practice. Consequently I resort to a less traditional forecasting approach, taking advantage of the promising developments in the field of machine learning.

The current literature on including sentiment analysis in financial research is mostly focussed on the stock market. Stock prices change on a daily basis and therefore the sentiment analysis is performed on frequently observed text data. Often studies resort to unofficial sources such as social media posts and online articles. Nguyen et al. (2015) and Deng et al. (2011) are among many that show promising results in this field. Both are able to improve their stock predictions by including sentiment-based variables in their models. While these outcomes justify the interest of using sentiment in forecasting models, the scientific validation of their text data remains questionable.

Official communications such as FSRs are authored by professionals and consist of views that are scientifically supported. Social media platforms, however, are not exclusive and therefore topics are discussed by a variety of different people. This results in a large amount of irrelevant information that should not be taken into account. One might argue that only extracting information from users that are verified professionals would solve this issue. As stated by Glänzel et al. (2019), while it is assumed that every piece of information conveyed in scientific publications is relevant, the same cannot be said about social media posts of professionals. Here, their comments are often filled with both scholarly content and personal remarks.

The strength of official sources can be seen in the study by Hájek et al. (2013), which used the sentiment hidden in corporate annual reports to successfully predict short-run stock price returns. Furthermore, they show that Neural Networks and SVR outperform linear regression models especially when using sentiment-based variables. Regarding SVR, Ülker and Ülker (2019) experience similar outcomes in a monetary setting. In their research they predict the unemployment rate and GDP using existing historical data. It was concluded that SVR is a very powerful model for predicting the GDP of a country. Nonetheless, both studies primarily based their findings on the forecasting errors that they observe and lack statistical tests. This is a general tendency in current research concerning machine learning. The models are often viewed as a black-box and additional analysis is disregarded. Therefore this paper implements the SVR model in a small training set environment and further evaluates the reliability of the forecasting results.

3 Data description

In this section, both the economic and sentiment related data of the research are described. The first part concentrates on the specific GDP series that is used to characterize the economic health of countries. This is followed by a short explanation of different economic topics that drive financial sentiment. Finally, I explain the procedure that is applied to extract the sentiment related indices from the FSRs of central banks.

3.1 Economic data

In order to study the relationship between sentiment and financial stability, I will analyse real GDP from 2005 until 2019 for 13 countries that are part of the Organization for Economic Cooperation and Development (OECD). The quarterly observations are obtained from the Federal Reserve Bank of St. Louis (FRED) and measured in millions of the respective national currency[1]. Furthermore, observations are adjusted by the FRED to exclude misleading seasonal components. The level of GDP varies considerably among the

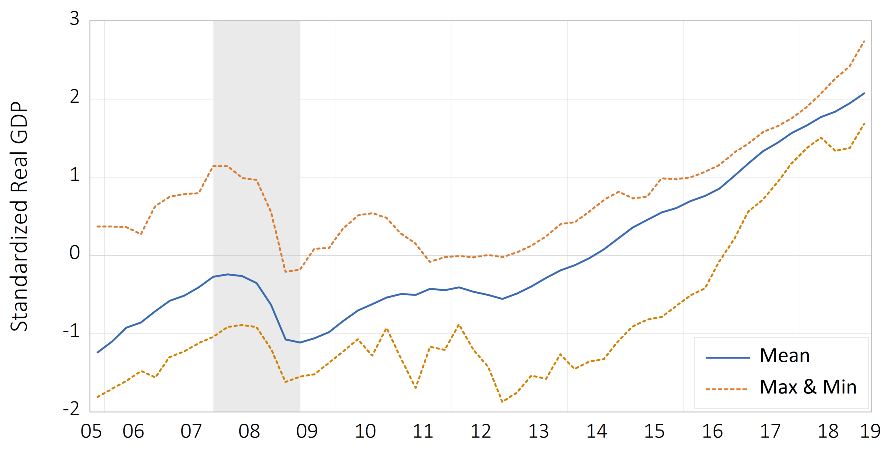

Figure 1: Cross-sectional mean of standardized real GDP (shaded areas are NBER-defined recessions).

different countries. Therefore, I standardize the time series of each individual country to visualise the general behaviour within a similar range. This implies subtracting the mean from every observation and dividing by

[1]Exception for Japan: measured in billions of Yen.

the corresponding standard deviation. Figure 1 displays the cross-sectional mean of this rescaled GDP series. Apart from the periods surrounding the Lehman bankruptcy during the 2008 GFC and the ratification of Greece's second bailout package in 2012, the figure suggests the presence of an upward sloping deterministic trend. The analysis in Appendix A confirms the existence of this pronounced trend.

The study by Correa et al. (2017) divides sentiment related to financial stability into 7 separate economic topics. Firstly, sentiment towards the banking sector. This consists of statements regarding services provided by financial and depository institutions, such as loans or interbank transactions. The second topic concerns asset valuations for financial markets, which involves stocks and bonds. Sentiment associated with real estate is analysed separately from the rest of the household sector. This results in an individual topic related to the property market and another topic that concentrates on the private consumption and credit of households. Views towards non-financial corporations are indicated by the corporate sector. This is followed by the external sector, which relates to the parts of a country's economy that interact with other countries. The final topic is the so-called sovereign sector. This identifies all sentiment towards the debt and fiscal balance of a government. Each of the individual topics is assigned a set of regressors that relate to both the topic and the financial cycle. For more detailed information on these financial indicators, see Appendix B.

3.2 Sentiment data

Central banks publish FSRs on their official website in the form of PDFs. To evaluate the reports, I first obtain all textual information that is contained in the files using the *pdfminer.six* package for python 3.8. Thereafter I convert the text to *HTML*, which allows for instantly extracting the main paragraphs by means of unique *XPaths*. This data query language utilizes the element tags and thereby is able to exclude irrelevant text such as titles, footnotes and boxes. In order to measure the sentiment expressed by central banks, I reconstruct the FSS index as described by Correa et al. (2017). Using their sentiment-based dictionary, words get assigned a connotation in the context of financial stability. However, not everything discussed in an FSR should be included in the sentiment analysis. Some specific topics are either not related to the prospect of financial stability or have a more theoretical point of view. These topics are generally discussed at the end of a report. For that reason, each individual document is only analysed for a limited number of pages. Together with the corresponding *XPaths*, the page limit is stored in the dataset for the purpose of replication. Finally, all the words that remain after removing punctuation and stop words[2] are considered in the FSS index.

This procedure is a generalized version of the approach from Correa et al. (2017) and supports a more automated pre-processing structure for all countries. While it considerably reduces the needed amount of manual labour, it still takes some irrelevant paragraphs into account that are not necessarily near the end of the report. To compensate for this, a slightly altered version of the FSS index is adopted, such that the

[2]Frequently used words, such as: "the", "for" and "is" (see Stone et al. (2010)).

values still closely mirror the original index. For each country i, the FSS index at time t is determined as follows:

$$FSS_{i,t} = \frac{\#Negative\ words - \#Positive\ words}{\#Total\ words - \#Neutral\ words}, \tag{1}$$

where I subtract the number of neutral words from the total amount, instead of simply dividing by the total number of words. Removing them compensates for the excess of words in the analyses and due to their neutral connotation, the ratio between positive and negative sentiment is not distorted. Hence, an increase of the index still translates to a downturn in sentiment regarding the stability of the economy. As in Correa et al. (2017), I count words with positive connotation that have a negation indicator within the range of 3 words as negative. The descriptive statistics of the FSS index for each of the OECD countries are given in Table 1. See Appendix C, for comparison with the original time period of 2005 to 2015.

Table 1: Descriptive Statistics of the FSS index over a period from 2005 to 2019.

Country	**N**	**Mean***	**Std. Dev.***	**Kurtosis**	**Skewness**	**Min.**	**Max.**
Belgium	15	0.98	0.50	2.21	0.08	2005-2	2009-2
Canada	28	2.31	1.17	2.38	-0.57	2019-2	2011-2
Czech Republic	14	1.18	0.48	2.03	0.31	2005-4	2009-2
Denmark	22	1.07	1.16	5.81	1.73	2019-2	2009-2
Germany	14	1.44	0.33	2.96	0.14	2018-4	2014-4
Hungary	27	1.34	0.83	2.17	0.31	2006-2	2009-2
Japan	26	0.89	0.84	3.39	0.58	2005-3	2009-1
Netherlands	28	2.11	0.86	2.60	0.14	2010-4	2009-2
Norway	23	1.76	0.80	2.30	-0.63	2005-2	2009-2
Poland	27	0.78	0.47	1.95	0.27	2006-2	2009-2
Portugal	23	0.63	0.68	4.92	1.16	2015-2	2008-4
Sweden	29	1.44	0.64	3.50	0.99	2018-2	2008-4
United Kingdom	28	2.11	0.78	2.44	0.46	2017-2	2008-4

Note: *Actual values are times 10^{-2}; maximum and minimum values given by quarter.

On average all countries attain a positive index, which signals that the sample exhibits relatively negative sentiment towards stability. In addition, the standard deviation is on average close to 59% of the mean value. This indicates that the sentiment of central banks varies substantially across publications. The majority of the countries reach their maximum value around the 2008 GFC. Canada is one of the exceptions, which attains its highest index closer to Greece's second bailout package in 2012. As noted in the previous section, most countries exhibit a decreasing slope in real GDP around both these time periods.

To further analyse the issues that drive the FSS index, I also replicate the specific sentiment indicators of Correa et al. (2017) for the before mentioned 7 financial topics. The procedure is similar to that of the total FSS index, however, now a subset of the text is analysed. Given a set of words that indicate a certain topic[3], only the sentences that contain such indicators are considered for the index of that specific topic.

4 Methodology

In this section, the methods of the research are defined. The first part concentrates on panel-regression models that help explain the relationship between GDP and the topic specific FSS indices. This is followed by the theoretical framework of the implemented ϵ-SVR model. Finally, I discuss the metrics and statistical tests that are needed to analyse the forecasting performance.

4.1 Topics in financial sentiment

Analysing the relationship between GDP and the various FSS indices is important for the remaining parts of this study. Machine learning algorithms, such as SVR, do not allow for comprehensive analysis between the variables in question. Having a better understanding of this relationship beforehand helps further explain the logic behind the predictive capability of the index. Therefore the first research question regards the different topics that drive financial sentiment. To evaluate this I construct two separate models in Eviews 10 using a similar approach as Correa et al. (2017), however modified in the sense that they now concentrate on the relationship with GDP.

Firstly, I want to investigate which specific topics have a bigger role in explaining GDP. Hence, the following panel-data regression is estimated for GDP over countries as a function of the different indices:

$$GDP_{i,t} = c_i + \sum_{j=1}^{S} \beta_{1,j} FSS_{i,t}^{j} + \sum_{j=1}^{S} \beta_{2,j} Freq_{i,t}^{j} + \delta_t + e_{i,t}, \tag{2}$$

where $GDP_{i,t}$ is the GDP of a certain country i at time t and $FSS_{i,t}^{j}$ are the corresponding FSS indices for the different topics j. Furthermore, δ_t represents the specific cross-sectional effects which are handled as illustrated in Baltagi (2005) through orthogonal projections. Both GDP and the topic indices are standardized by subtracting the mean and dividing by the standard deviation of the corresponding series. Due to this transformation I can compare the magnitude of the resulting estimates. The total amount of words for a topic could have an impact. For this reason, there is a control variable $Freq_{i,t}^{j}$, which considers the frequency of words for a specific topic. The coefficients are estimated using panel ordinary least squares. To account for cross-sectional heteroskedasticity the standard errors are corrected by Huber-White standard deviations, as covered in Wooldridge (2001).

[3]Topic indicators are given in the research of Correa et al. (2017); see appendix C for mean values of the topic indices.

Secondly, I want to investigate how information from historic data is incorporated into the different indices. To that end I perform another panel-data regression, however now the sentiment indices take the role of the dependent variable:

$$FSS^j_{i,t} = c_i + \beta H^j_{i,t-h} + e_{i,t}, \tag{3}$$

here the historic variables that were assigned to topic j are depicted as $H^j_{i,t-h}$. Financial Policy Committees (FPCs) first have to observe what is happening, before stating their views in FSRs. Therefore I regress the indices on a lagged version of the historic data. Different lag sizes h are considered to explore the time dependency of the indices.

Note that a country's GDP and the corresponding historic data is observed quarterly in the dataset, while the FSRs are only published biannually or even annually. To solve this issue, I apply linear interpolation as covered by Davis (1974). Given two observed quarters ($FSS_{i,t}$ and $FSS_{i,t+n}$), values in the intermediate quarters can be assigned as follows:

$$FSS_{i,t+x} = FSS_{i,t} + \frac{x}{n}[FSS_{i,t+n} - FSS_{i,t}] \quad \text{with} \quad 0 < x < n, \tag{4}$$

here n represents the number of quarters between two consecutively published FSRs and x indicates the intermediate quarter in question. This results in a set of quarterly indices, which is also used in the prediction model. The same formula applies for the topic specific indices, $FSS^j_{i,t}$.

4.2 Forecasting GDP

The next step of the research is to try and make accurate predictions for future values of real GDP. As previously discussed in the literature review, the use of SVR shows promising results for forecasting financial measures. In this study I construct an ε-SVR model, where the formulation below combines the multivariate representation of Awad and Khanna (2015) with the detailed one-dimensional explanation of Smola and Schölkopf (2004).

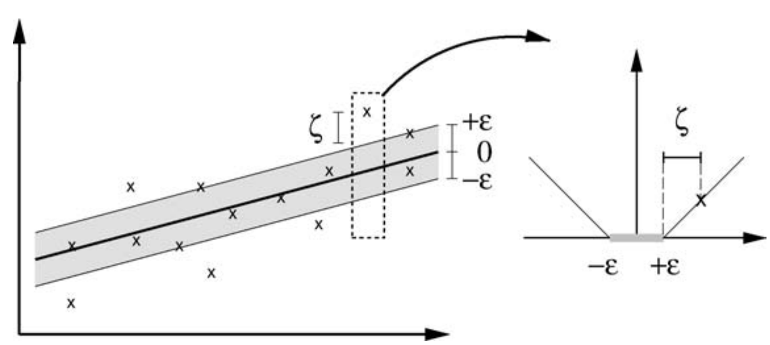

Figure 2: Illustration of the soft margin loss setting for a linear SVM (Smola and Schölkopf (2004))

Supervised learning algorithms only predict single values and are not directly capable of forecasting multiple quarters into the future. In order to preserve the practical relevance of the model, I implement the Direct

Multi-Step (DMS) forecasting strategy of Chevillon and Hendry (2005). This results in developing separate models for each of the different forecasting horizons. In addition, training observations are assigned the same horizon as the DMS forecast to scale down the increasing prediction error for larger steps ahead. Given a rolling-window of m quarters, the training set for an h-step forecast then contains the following elements at time t:

$$(x^{(j)}(\iota),\ GDP_j) \quad \text{with} \quad x^{(j)}(\iota) = \{GDP_{j-1}\ ,\ \dots\ ,\ GDP_{j-\iota}\} \quad \text{for} \quad t-m\ <\ j\ \leq\ t, \tag{5}$$

where $x^j(\iota) \in \mathbb{R}^M$ is the vector of lagged GDP values, $GDP_j \in \mathbb{R}^1$ the target value and ι denotes the number of lags that are given to each of the individual training observations. Figure 2 illustrates the main objective of ε-SVs, that is to find the flattest function with at most ε deviation from all of the observed GDP values. Provided with the training set in (5) for a certain country i, a linear version of this function can be formulated as:

$$GDP_{t+h|t}(x(\iota)) = \begin{bmatrix} w \\ b \end{bmatrix}^T \begin{bmatrix} x(\iota) \\ 1 \end{bmatrix} = w^T x(\iota) + b, \tag{6}$$

where b is a scalar, $x(\iota)$ is a vector of data points $x^{(j)}(\iota)$, and w a weight vector such that $\|w\|$ is the magnitude of the normal vector towards the approximated surface. The task of flattening the function and thus narrowing the shaded area in Figure 2, is tackled as the following optimization problem:

$$\begin{aligned} min_w \quad & \frac{1}{2}\|w\|^2 + C \sum_{j=t-m+1}^{t} (\xi_j + \xi_j^*) \\ s.t \quad & GDP_j - w^T x^{(j)}(\iota) \leq \varepsilon + \xi_j \qquad \forall\ \ t-m\ <\ j\ \leq\ t \\ & w^T x^{(j)}(\iota) - GDP_j \geq \varepsilon + \xi_j^* \qquad \forall\ \ t-m\ <\ j\ \leq\ t \\ & \xi_j, \xi_j^* \geq 0 \end{aligned} \tag{7}$$

here the slack variables ξ and ξ^* are included to handle infeasible situations of the constraints. In addition, the constant C dictates the trade-off between narrowing the shaded area and the amount of tolerated deviations above epsilon. This optimization problem is solved by minimizing the corresponding Lagrangian function, based of the *Karush-Kuhn-Tucker* (KKT) conditions. After substituting the resulting partial derivatives into the Lagrangian, one can obtain the dual form of the optimization problem[4].

The support vector can be mapped to a higher dimensional space, in order to create a non-linear version of the function in (6). This is done by replacing all instances of $x(\iota)$ with a so-called kernel function $K(x(\iota), x(\iota)^T)$. The studies by Ülker and Ülker (2019) & Hájek et al. (2013), compared the performance of different kinds of kernels in a similar monetary setting. Both concluded that the Radial Basis Function (RBF) had by far the best regression results. For that reason, I employ the following version of the RBF kernel inside the ϵ-SVR model:

$$K(x(\iota), x(\iota)^T) = exp(-\frac{\left\|x(\iota) - x(\iota)^T\right\|^2}{n\sigma^2}), \tag{8}$$

[4]See Appendix D for more detailed derivations related to the discussed optimization problem.

where one divides by the number of features n multiplied by the variance of $x(\iota)$. Finally, the impact of sentiment is analysed by adding the seven topic specific FSS indices to the training set (5) for each of the included lags. To assess the reliability of the forecasts for small training sets, the ϵ-SVR model is evaluated under various circumstances. In the remainder of this paper I denote an ϵ-SVR with a rolling-window of length m and ι included lags as ϵ-SVR(m,ι).

4.3 Forecast analysis

The prediction quality of the various SVR models is evaluated with respect to unbiasedness, accuracy and efficiency. In practice, models are not able to capture all the variability of a series with the forecast error indicating the part that could not be predicted. Forecast bias implies that the model has a common tendency to produce forecasts that are consistently different from the actual outcomes. In order to assess how the length of the rolling-window affects the bias, I calculate the Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{j=t+1}^{n} e_j^2}{n}}, \tag{9}$$

here e_{t+h} is the forecasting error $(GDP_{t+h} - \widehat{GDP}_{t+h|t})$ of quarter $t+h$ and n is the total number of predictions that are made. The unit scale of the RMSE is equal to that of the GDP series, which helps to comprehend the actual size of the average forecasting error. However, since it is a scale-dependent measure it can only be used to compare different window lengths for a specific country.

The Akaike information criterion (AIC) and the Bayes information criterion (BIC) are constructed, as covered by Montgomery et al. (2011), to decide the optimal number of lags for the model:

$$AIC = n\ln(\frac{\sum_{j=t+1}^{n} e_j^2}{n}) + 2p \qquad \& \qquad BIC = n\ln(\frac{\sum_{j=t+1}^{n} e_j^2}{n}) + p\ln(n), \tag{10}$$

where p indicates the total number of regressors and $n\ln(\frac{\sum_{j=t+1}^{n} e_j^2}{n})$ the uncertainty in the model. Both criteria obtain lower values for models that fit the data better. Their difference lies within the distinct penalties, where for $n > 8$ the BIC tends to prefer models with fewer regressors compared to the AIC. After finding both the optimal length of the rolling-window and the number of included lags, I calculate the Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100\sum_{j=t+1}^{n} \frac{|GDP_j - \widehat{GDP}_j|}{GDP_j}}{n}, \tag{11}$$

here the percentage errors are unit-free and therefore allow for analysing the general forecasting accuracy across the various countries.

Forecasting models are efficient if it is not possible to predict the actual error from the available information at time t. This requires that the forecast error is indeed unpredictable. To assess the efficiency of the forecasts and determine if the bias represented by the RMSE and MAPE is insignificant, I adopt the Mincer-Zarnowitz (MZ) regression as described by Elliott and Timmermann (2013):

$$GDP_{t+h} = \beta_0 + \beta_1 \widehat{GDP}_{t+h|t} + \eta_{t+h} \tag{12}$$

where the coefficients are estimated using the Newey-West standard errors with h lags, to consider serial correlation of overlapping forecasts. In case the bias is insignificant, the intercept should be equal to zero and the slope equal to one. This joint null hypothesis is tested by means of an F-test. Here, the intercept indicates if the forecasts are consistently different from the actual outcomes and the slope checks if the deviations differ significantly from the mean.

Finally, I employ the Diebold-Mariano (DM) test to see if including the sentiment indices results in significantly different predictions:

$$DM = \frac{\overline{d}}{\sqrt{V(\hat{d}_{t+h})/n}} \overset{a}{\sim} N(0,1), \tag{13}$$

here $d_{t+h} = e^2_{i,t+h} - e^2_{j,t+h}$ is the so-called loss differential between the two models and $\overline{d}$ is the corresponding mean. The variance of the loss differential can be computed as follows:

$$V(\hat{d}_{t+h}) = \frac{1}{n-1} \sum_{j=t+1}^{n} (d_{t+h} - \overline{d})^2, \tag{14}$$

where n still indicates the total number of predictions that are made by the rolling-window. The DM-test has the tendency to reject the null hypothesis of equal forecast errors too often when the sample is relatively small. Therefore, I correct the DM statistic for evaluating small-sample properties, as proposed by Harvey et al. (1997):

$$HLN = DM\sqrt{(n+1-2h+h(h-1))/n} \overset{a}{\sim} T(n-1), \tag{15}$$

where instead of a standard normal distribution, the Harvey, Leybourne and Newbold (HLN) test statistic is compared with a Student-t distribution.

5 Results

In this section, the results of the research are presented and discussed. The first part concentrates on the relationship between the financial cycle and sentiment, which is represented by the topic specific FSS indices. This is followed by optimizing the ϵ-SVR model for small training sets and evaluating the corresponding forecasting performance. Finally, the practical impact of the indices is tested after implementing them in the optimized forecasting model. Note that in the forecast analysis only out-of-sample errors are considered.

5.1 The financial cycle and sentiment

As previously mentioned, the data is scaled differently across countries which makes it difficult to interpret one direct relationship between GDP and sentiment. Therefore, I compare the relative importance of the various FSS topic indices with respect to GDP. The indices in model (2) are standardized before the actual panel-regression. Hence, the absolute values of these coefficients depict how strong the underlying effect of the sentiment is to real GDP. The corresponding coefficient estimates are displayed in Table 2 and sorted by their relevance.

Table 2: Panel-regression results of GDP with respect to sentiment in different topics.

Topic	**Coef.**	**Std. Error.**
External	-0.214***	0.054
Sovereign	0.186***	0.055
Household	-0.145***	0.035
Real Estate	-0.132*	0.050
Bank	-0.085*	0.047
Valuation	0.016	0.029
Corporate	-0.008	0.033

Note: ***, **, and * represent the 1%, 5% and 10% significance levels.

Apart from the corporate sector and asset valuation, all topic indices explain a significant amount of the time variation in GDP, at least at a 10 percent confidence level. Higher significance levels coincide with lower absolute values, which shows that a bigger impact relates to stronger statistical evidence found for the relationship within the dataset. Sentiment of central banks concerning the external (-0.214) and sovereign (0.186) sector explain most of the variability. As GDP includes all finished goods and services at a certain time, it is understandable that their attitude towards import and export can convey a lot of information on the variation in GDP. The same holds for the sovereign sector, since it is directly related to the fiscal balance of a government. In particular, a change of one standard deviation in the external index results in a standard deviation decrease in GDP of around 0.214 (given that everything else is kept constant). This implies that observations of GDP tend be less spread out, when the magnitude of sentiment towards the external sector differs considerably from its average level. For the sovereign sector, observations tend to be more spread out. Sentiment towards households (-0.145), real estate (-0.132) and the banking sector (-0.085) also account for a significant amount of time variation in GDP.

In order to get a better understanding of the FSS indices, I analyse which economic indicators drive the sentiment related to the four most important topics. Lagged values of the indicators are considered for different time-horizons, where for instance a time-horizon of 4 quarters implies that the index is regressed on values from the previous year. Recognizing that it could take 2 years for new policies to actually have an effect, I compare up to a 8 quarter time-horizon to find out if the impact changes over time. Only the most important findings from model (3) are discussed, while Appendix E contains a more detailed outline of the results for all topics. In addition, the indices below are multiplied by 100 to simplify the discussion.

Table 3: Panel-regression results of topic indices with respect to historic economic indicators.

Topic	Variable	h = 0	h = 1	h = 4	h = 8
External ($\mu = 0.65$)	*Balance of payments*	-0.031***	-0.038***	-0.059***	-0.047***
		(0.010)	(0.010)	(0.011)	(0.014)
	Trade in goods, import	-0.013**	0.012**	-0.001	-0.009*
		(0.006)	(0.005)	(0.005)	(0.005)
Sovereign ($\mu = 1.46$)	*Credit to government sector*	-0.009**	-0.012**	-0.019***	-0.022***
		(0.005)	(0.005)	(0.004)	(0.003)
Household ($\mu = 0.51$)	*Credit to households*	0.041***	0.039***	0.023	-0.011
		(0.012)	(0.012)	(0.017)	(0.027)
	Long term interest rate	0.438***	0.503***	0.505***	0.285***
		(0.096)	(0.098)	(0.074)	(0.056)
Real Estate ($\mu = 1.44$)	*Nominal property price*	-0.170**	-0.160**	-0.089***	0.108***
		(0.068)	(0.065)	(0.034)	(0.038)
	Long term interest rate	0.194***	0.245***	0.378***	0.097*
		(0.066)	(0.682)	(0.076)	(0.052)

Note: ***, **, and * represent the 1%, 5% and 10% significance levels; all values are times 10^{-2}.

Two of the financial indicators related to the external sector seem to have a significant impact on the corresponding FSS index. Table 3 shows that most of the sentiment is driven by the balance of payments (BoP), which is measured as a percentage of GDP. In contemporaneous terms, a one percent point increase in the BoP results on average in a decrease of around 0.031 in the external index. The cross-sectional mean of the external index is 0.65, therefore the decrease corresponds to the index being 4.7% lower than usual. At first the impact increases for higher time-horizons, with the index being around 9% lower for a lag of one year. Nevertheless, the effect gradually decreases again for even higher horizons. Remember that a decrease of the FSS index translates to a less pessimistic stance of the central bank. The observed change could be explained by the following long term scenario. As described by Eun (2009), a higher surplus on the BoP account might improve the economic growth in the short term. However, it is also possible that a country becomes too reliant on its export-driven growth in the long run. The import of goods (GMP) only has a significant effect in the short run, at a confidence level of 5%. It is important to note that the impact is completely mirrored after one quarter. If the indicators are not lagged, a one-unit increase of GMP results in a 2% lower external index compared to the cross-sectional mean. Yet, for a one quarter time-horizon the index is 2% higher after the same one-unit increase in GMP.

The attitude of central banks towards the sovereign sector exhibits a positive correlation with the total credit that is extended to the government. Furthermore, this impact slowly grows over time. Measured as a percentage of GDP, a one percent point increase in total credit corresponds to the attitude being 0.6% (-0.009) lower than normally for concurrent indicators. This expands to a decrease of around 1.5% (-0.022) for indicators from two years prior. The institution that extends credit to the central government is actually the central bank itself, which explains their slightly positive stance towards their own credit adjustments. For the household topic, long-term interest rates have the most consistent significant effect on sentiment. On average the coefficient lies around 0.5 for indicators lagged up to one year. This implies, given that everything else is kept constant, the central bank is 10% more negative than usual towards the household sector for an 0.1 percent point increase in the long-term interest rate. Similarly, central banks' sentiment takes a downturn in the short run for an increase in credit to households. Here, it is the domestic banks that extend the credit.

The long-term interest rate is also the most important indicator for sentiment related to real estate, however the impact does not last as long as for the other indices. While the household index shows a relatively constant positive effect for the first five time-horizons, real estate exhibits a more monotonic increase. For lags related to the prior year, a 0.1 percent point increase in the long-term interest rate results in an average increase of around 0.038 of the real estate index. The cross-sectional mean of this FSS index is around 1.44, therefore the increase corresponds to the index being 2.6% higher than usual. Mowell and Pekowitz (2015) state that the investment demand and availability of capital are affected by interest rates. In particular, it influences the supply and demand of property and consequently affects the underlying price. They believe that, as a result, real estate investors often put pressure on property prices when they anticipate variability in interest rates. This could explain the diminishing impact of the long-term interest rate, since it coincides with an increasing effect of the nominal property price (NPP). At first the NPP is negatively correlated with the real estate index, however, when the interest rate becomes less relevant it starts to have a significant positive effect. This may suggest that central banks are more concerned about the long run fluctuations in property prices than the initial increase in the long-term interest rate that might have triggered the change.

5.2 Evaluation of Support Vector Regression

5.2.1 Tolerance and regularization

Due to the limited amount of training variables, there is the possibility that the model is not capable of explaining a significant amount of the variability in GDP. As previously discussed, the key factors of an ϵ-SVR model are the margin of tolerance ϵ and regularization parameter C. Both parameters can be interpreted as a trade-off between possible under-fitting and over-fitting of the model. Decreasing ϵ results in more support vectors to be selected. Consequently, more observations are penalized and the complexity of the training estimates increases. Higher values of C translate to increased penalties on these points that are not in the margin, which also leads to more support vectors and thus possible over-fitting. To find their optimal combination within the GDP framework, I perform a so-called grid search on a variety of possible options. The results overlap for different lag sizes and rolling-window horizons. For the sake of simplicity, I therefore only discuss the grid search of the ϵ-SVR(2,2) model in this paper.

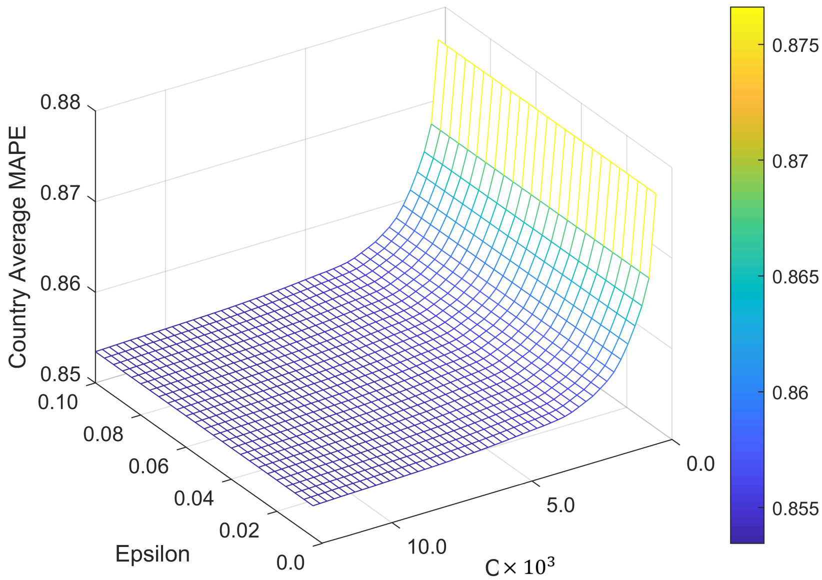

Figure 3: Country average of the MAPE for the ϵ-SVR(2,2) 1-step forecasts from 2011Q2 to 2019Q1

Figure 3 displays the corresponding average MAPE over all countries for a one-quarter forecasting horizon. It is clear that, on average, decreasing the value of ϵ has a negligible effect on the MAPE of a country. This suggests the presence of possible forecasting bias, since the predictions of the model exhibit errors of a consistent magnitude for different margins of tolerance. Nonetheless, placing higher penalties on points that are outside the margin does have a decreasing effect on the MAPE. For a margin of $\epsilon = 0.1$, the grid search finds the lowest MAPE for a regularization factor of around 4268. As can be seen in Figure 3, the average MAPE shows signs of exponential decay and converges to roughly 0.85 for higher values of C. Increasing the penalties even further only raises the computational time of the model. The final decrease in MAPE is around 0.025 percent points and since GDP is measured in millions of the national currency this should not be undervalued. It is important to mention that the observed behaviour of ϵ merely suggests forecast bias and does not serve as substantial proof. However, it does indicate a lack of ability to improve for ϵ-SVR in the GDP framework. After obtaining the final composition of the model, I therefore test the presence of forecast bias for each individual country.

5.2.2 Rolling-window and lagged observations

The next step is to evaluate the performance of the model under different training sets. In this research the length of the rolling-window m and the number of included lags ι are the only factors that alter the training process. Table 4 displays the RMSE of Belgium and Portugal for an increasing number of observations in the training window. Besides the magnitude of the errors, the overall relationship between the two factors and RMSE remains the same across all countries. To simplify the discussion, I do not discuss each individual case. For a more comprehensive outline of the results, see appendix F.

Table 4: RMSE of the ϵ-SVR(m,2) and ϵ-SVR(m,8) models for Belgium and Portugal from 2013Q2 to 2019Q1

Window length	**2 lags**				**8 lags**			
Belgium	**h = 2**	**h = 4**	**h = 6**	**h = 8**	**h = 2**	**h = 4**	**h = 6**	**h = 8**
2	638.8	1111.7	1578.0	2041.5	538.9	1105.5	1570.1	2032.6
5	889.7	1418.2	1924.6	2332.5	754.5	1420.9	1879.7	2249.7
8	989.5	1735.6	2295.3	2628.8	900.5	1681.6	2077.7	2356.6
Portugal	**h = 2**	**h = 4**	**h = 6**	**h = 8**	**h = 2**	**h = 4**	**h = 6**	**h = 8**
2	1000.3	1736.6	2441.7	3112.4	841.1	1702.2	2430.8	3107.3
5	1412.1	2219.8	2893.5	3551.0	1188.2	2138.8	2839.5	3506.2
8	1460.3	2509.2	3164.6	3790.6	1343.7	2451.2	3202.3	3892.2

The length seems to have a continuous negative effect on the forecasting performance of further predicted quarters. Additionally, including more lags per data point results in a similar negative interaction. This shows that increasing the number of observations in the training set is actually intensifying the forecasting errors, which can be explained by the structure of the ϵ-SVR. The growth of GDP varies across periods and Figure 1 indicates that the average country in the dataset starts growing faster over time. Given that the model is trained on the most recent available data points, increasing the length of the rolling-window requires adding older observations to the training set. These points relate to a lower magnitude of growth and therefore characterize a slope of the GDP series that is not steep enough. As a result it only creates additional noise for the training process. It is more relevant for the model to have extra information on the increasing rate of growth and this is also suggested by the RMSE. For a fixed length of the rolling-window, a lower out-of-sample RMSE is observed when including more lags. Therefore providing the model with more information on each individual data point reduces the average size of the forecasting errors.

In order to select the optimal amount of lags for a window of 2-quarters I calculate the AIC and BIC. The results for several of the OECD countries are displayed in Table 5. Note that to reduce complexity this table is restricted to a maximum of 5 lags[5]. For a 1-step ahead forecast there is no universal agreement to what the optimal amount of lags is. While 9 of the 13 countries attain their lowest value at 2 lags for at least one of the information criteria, it is still suggested for multiple countries to include more lagged observations.

[5] Belgium, Portugal and the United Kingdom attain their lowest AIC and BIC for more than 5 lagged observations. See appendix F for a more comprehensive overview of these results.

Table 5: AIC and BIC of OECD countries for a ϵ-SVR(2,ι) model from 2011Q4 to 2019Q1.

	1-step forecast									
Lags	**1**		**2**		**3**		**4**		**5**	
Criterion	*AIC*	*BIC*	*AIC*	*BIC*	*AIC*	*BIC*	*AIC*	*BIC*	*AIC*	*BIC*
Belgium	383.6	387.0	383.0	385.8	381.7	385.9	378.0	383.6	374.9	381.9
Germany	516.6	520.0	514.6	517.4	515.1	519.3	514.7	520.3	514.0	521.0
Japan	517.7	521.1	515.1	517.9	515.1	519.3	517.6	523.2	518.6	525.6
Portugal	373.2	377.6	372.3	375.1	370.9	375.1	367.8	373.4	365.1	372.1
United Kingdom	490.3	494.8	488.7	491.5	486.6	490.8	482.7	488.3	479.3	486.3
	8-step forecast									
Belgium	487.8	488.2	484.9	487.7	486.9	491.1	489.1	494.7	491.2	498.2
Germany	623.5	623.9	620.2	623.0	622.3	626.5	624.2	629.9	626.2	633.2
Japan	595.7	596.1	592.9	595.7	594.7	598.9	596.6	602.3	598.4	605.4
Portugal	467.2	467.6	464.2	467.0	466.2	470.4	468.1	473.7	470.0	477.0
United Kingdom	595.3	595.7	592.3	595.1	594.3	598.5	596.3	601.9	598.3	605.3

Note: The lowest AIC and BIC are underlined for each country with respect to a 5 lag maximum.

For larger forecasting steps the information criterion of these specific countries also starts to favour a lower number of lags. At a certain point the forecast is too far ahead and the growth rates in training period differ considerably from the prediction period. Similar to increasing the rolling-window, adding more information will only make it harder to find a vector with a small margin. As previously mentioned, it is more valuable for policy makers to have accurate predictions of periods further into the future. Hence, two lagged observations are implemented into the final forecasting model.

5.2.3 Predictive performance and influence of sentiment

After evaluating the performance of ϵ-SVR under different circumstances, the final model is specified as an ϵ-SVR(2,2) with a margin of tolerance equal to 0.1 and a regularization factor of 4268. The box-plot in Figure 4 shows for each of the 13 OECD countries the MAPE for different forecast horizons, ranging from 1 to 8 quarter steps ahead[6]. As indicated by the RMSE, the average forecasting error of the rolling-window increases when making predictions further into the future. This means that the box-plot displays the growth in MAPE that comes along with larger forecasting steps, where each quantile consist of two consecutive h-step ahead predictions. Apart from Hungary, Japan and Poland, each country clearly shows a bigger increase in errors for the first quantile than for the last quantile. For most countries a 1-step ahead forecast has an average absolute error of around 0.9%, which typically grows to an error of 4% when predicting two years ahead. Poland is by far the country for which the forecasting errors increase the most, with an 8-step ahead

[6]Appendix H contains a table with the actual values that are illustrated in Figure 4

MAPE of almost 7. In general, the model is able to predict some of the time variation of GDP. However, a 1% error should not be neglected, since the GDP series is measured in millions of the national currency.

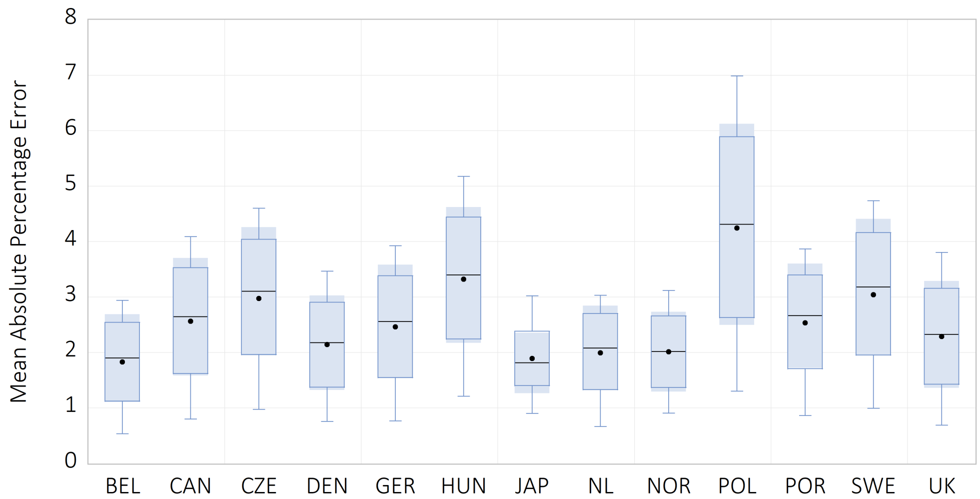

Figure 4: MAPE for h-step ahead forecasts ranging from 1 to 8 during 2010Q2 to 2019Q1.

To evaluate if the size of the errors is significant, I perform a Mincer-Zarnowitz regression for each of the forecasting models. For a detailed overview of the regression coefficients, see Appendix H. This also includes the p-values that correspond to the F-test with a joint null hypothesis of no forecast bias. Table 6 concentrates on all the countries that have cases in which the null hypothesis cannot be rejected at a 1% confidence level.

Table 6: P-values of F-test corresponding to the Mincer-Zarnowitz regressions.

Country	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**
Czech Republic	<u>0.014</u>	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Japan	<u>0.149</u>	<u>0.011</u>	0.000	0.000	0.000	0.000	0.000	<u>0.032</u>
Netherlands	<u>0.013</u>	0.002	0.000	0.000	0.000	0.000	0.010	0.000
Portugal	<u>0.643</u>	<u>0.862</u>	<u>0.725</u>	<u>0.655</u>	<u>0.087</u>	<u>0.013</u>	0.000	0.000

Note: the underlined values indicate that the joint null hypothesis is not rejected for the 1% confidence level.

In the dataset, four countries experience situations in which there is not enough statistical evidence to reject the null. Nevertheless, only Portugal shows this consistently up to a 6-step ahead forecast. This indicates that on a consistent basis, the optimized ϵ-SVR(2,2) model is not able to capture a significant amount of the time variation in GDP. Note that in most instances it is the intercept that is significantly different from zero, while the slope often lies close to one. Therefore, deviations still lie relatively close to the mean. The final step is to investigate if implementing sentiment indices into the training process is able to steadily capture some of the remaining time variation that is conveyed in the forecast bias.

Table 7: Difference in MAPE after including sentiment indices in the training process.

Country	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**
Belgium	0.030***	0.002**	0.000	-0.001	-0.002*	-0.008	-0.004	-0.007***
Canada	0.032***	0.011	0.001	0.005	0.000	-0.008	-0.006	-0.012**
Czech Republic	0.034***	0.007***	0.010	0.006	0.002	0.002***	0.004	0.002
Hungary	0.005***	-0.001	-0.001	0.001	0.002	-0.004**	0.002	-0.002
Netherlands	0.019***	0.016*	0.003	0.001	0.003	0.002	0.003	0.002
Portugal	0.036***	0.006	0.001	-0.002*	0.006	-0.009	0.000	-0.004
Sweden	0.031***	0.004	-0.002	0.014**	-0.004	-0.010	-0.017**	0.007
United Kingdom	0.031	0.008	0.005***	0.004***	0.004***	0.000	0.002***	-0.003***

Note: ***, **, and * represent the 1%, 5% and 10% significance levels.

To test if introducing the sentiment indices changes the MAPE, each model is compared by means of the HLN test. Appendix I serves as a comprehensive overview of both the DM and HLN statistics. For 27% of the different forecasting windows there is a significant difference in errors, at a minimum confidence level of 10%. However, more than 60% of these cases actually experiences an increase in the average forecasting error. Several countries reject the null hypothesis of the HLN test multiple times across the different forecasting steps. In Table 7 the difference in MAPE of these countries is shown. Here, the significance level corresponds to the outcome of the HLN test. It is clear that for smaller forecasting steps, the models experience a consistent increase in their prediction errors. Note that all countries that experience a significant difference for the 8-steap ahead forecast, actually encounter a reduction in errors. While there are various cases in which the FSS indices seem to reduce the forecasting errors more over time, there is often not enough statistical evidence to reject the null hypothesis of equal predictions. The performance analysis does not confirm a consistent significant impact from the sentiment indices across the different countries in the dataset, when incorporated into the forecasting model. In addition, the indices seem to increase the existing forecast bias more often than they decrease it.

6 Conclusion

This study focused on the relationship between a country's economic health and the attitude of central banks towards various economic sectors. The financial stability of countries is characterised by their real GDP, while the view of the central bank, regarding specific topics, is defined by the FSS indices as introduced by Correa et al. (2017). To investigate which specific topics have a bigger role in explaining the time variability in GDP and how the corresponding sentiment is related to traditional economic measures, I construct several panel-regression models. The results indicate that sentiment of the central bank that is related to the external, sovereign, household, real estate and banking sectors, all explain a significant amount of the time variability in GDP. In addition, the biggest driver of the position taken on the external sector is the balance of payments. While the credit that is extended to the government sector has a significant effect on the attitude towards the sovereign sector. Both for households and real estate, the negative attitude in the FSRs can be partly explained by increases in the long-term interest rate.

The indices are also implemented into an ϵ-SVR model, to evaluate their practical value. However, the forecasting performance of the SVR model was not improved by adding the indices into the training process. In most cases, the indices seemed to increase the average error and therefore brought more noise to the model. Before the introduction of sentiment, the model was optimized within the GDP framework of this paper. The final model specification is an ϵ-SVR(2,2) with a margin of tolerance equal to 0.1 and a regularization factor of 4268. Decreasing the margin of tolerance had a negligible effect on the MAPE across all countries, which suggested possible forecast bias. This is verified through multiple MZ-regressions, which indicate that there still is a significant amount of time variation in GDP that cannot be explained by the forecasting model. For most countries a 1-step ahead forecast had an average absolute error of around 0.9%, which typically grew to an error of 4% when predicting two years ahead.

In general, this research finds that the topic specific sentiment indices do hold some predictive power towards the time variation in GDP. Nevertheless, their impact is not strong enough to make a significant difference to the forecasting performance of the SVR model. In spite of this, the relationship between sentiment and financial measurements is promising. The main limitation of this research, however, is the existing bias in the SVR model. This is most likely due to the small sample size and the model could be improved by implementing additional measures of financial stability. Furthermore, it might be valuable to focus on a different forecasting approach that is more suitable to the frequency in which central banks publish FSRs.

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A Trend analysis

The estimates given below are associated with the following panel-data regression regarding the GDP trend analysis:

$$GDP_{i,t} = c_i + \beta_i t + \epsilon_t \qquad t = 1, ..., T$$

where $GDP_{i,t}$ is the standardized value of real GDP for country i at time t. To account for potential heteroskedasticity in the cross-sectional data, Huber-White standard deviations are used to correct the standard errors (see Wooldridge (2001)). The coefficients are significant at the 1% level which confirms the overall presence of a trend in the GDP series.

Table 8: Panel-regression regarding the trend analysis of real GDP.

Variable	**Coeff.**	**Std. Error**
Constant	-1.414*	0.122
Trend	0.051*	0.004

Note: *Attains 1% significance level.

B Explanatory topic variables

Table 9: Economic variables, indicator and corresponding topic.

Variable	**Indicator**	**Topic**
Unemployment Rate	UNEMP	Household
Real Property Price	RPP	Real Estate
Nominal Property Price	NPP	Real Estate
Price to Rent	PR	Real Estate
Share Price Index	SPI	Valuation
Credit to GDP Gap	CTGG	Bank
DSR, private non-financial	DSR	Bank, Corporate
Credit to Households	CTH	Household
Balance of Payments	BOP	External
Consumer Price Index	CPI	Household
Short Term Interest Rate	STINT	Bank, Valuation
Long Term Interest Rate	LTINT	Bank, Household, Real Estate
Credit to Non-Financial Corporations	CTN	Corporate
Trades in Goods, Export	GXP	External
Trades in Goods, Import	GMP	External
Trades in Services, Export	SXP	External
Trades in Services, Import	SMP	External
Credit to Government Sector	CTGS	Sovereign

Table 10: Description and data sources of economic variables.

Variable	**Description**	**Source**	**Units**
Real Gross Domestic Product	Gross Domestic Product adjusted for inflation and seasons.	FRED	Domestic Currency
Unemployment Rate	Number of unemployed people as a percentage of the labour force.	OECD	Percent
Real Property Price	Year-on-year change in the BIS real property price index.	BIS	Percent
Nominal Property Price	Year-on-year change in the BIS nominal property price index.	BIS	Percent
Price to Rent	Indicator of residential rent price.	OECD	Index (2010 = 100)
Share Price Index	Share price index for the traded common shares of companies.	OECD	Index (2010 = 100)
Credit to GDP Gap	Deviations of the credit to GDP ratio from its long-run trend.	BIS	Percent
DSR, private non-financial	Debt Service Ratio, reflects the share of income used to service debt.	BIS	Percent
Credit to Households	Captures the borrowing activity of households as a percentage of GDP.	BIS	Percent
Balance of Payments	The current account balance of payments as a percentage of GDP.	OECD	Percent
Consumer Price Index	Annual growth rate of inflation measured by the CPI.	OECD	Percent
Short Term Interest Rate	Interest rates referring to short-term borrowing.	OECD	Percent
Long Term Interest Rate	Interest rates referring to goverment bonds maturing in ten years.	OECD	Percent
Credit to Non-Financial Institutions	Captures the borrowing activity of the private non-financial sector.	BIS	Percent
Trades in Goods, Export	All goods that leave the economic territory in terms of million USD.	OECD	US Dollars
Trades in Goods, Import	All goods that enter the economic territory in terms of million USD.	OECD	US Dollars
Trades in Services, Export	All services exchanged within economic territory in terms of million USD.	OECD	US Dollars
Trades in Services, Import	All services exhanged with foreign affiliates in terms of million USD.	OECD	US Dollars
Credit to Government Sector	Core debt at market value as a percentage of GDP.	BIS	Percent

Note: *All currency units are in millions (except for Japan).

C Descriptive statistics of the FSS indices

Table 11: Descriptive statistics of the total FSS index over a period from 2005 to 2015.

Country	N	Mean*	Std. Dev.*	Kurtosis	Skewness	Min.	Max.
Belgium	11	0.97	0.57	1.84	0.13	2005-2	2009-2
Canada	22	2.54	0.95	2.25	-0.46	2006-2	2008-4
Czech Republic	10	1.27	0.53	1.79	-0.08	2005-4	2009-2
Denmark	15	1.33	1.28	4.37	1.43	2013-2	2009-2
Germany	10	1.37	0.27	2.27	-0.84	2014-4	2013-4
Hungary	20	1.57	0.83	2.35	-0.09	2006-2	2009-2
Japan	19	0.82	0.96	3.02	0.72	2005-3	2009-1
Netherlands	21	2.07	0.91	2.64	0.32	2010-4	2009-2
Norway	19	1.65	0.81	1.99	-0.50	2005-2	2009-2
Poland	20	0.81	0.50	1.85	0.22	2006-2	2009-2
Portugal	16	0.69	0.78	3.67	0.90	2015-2	2008-4
Sweden	22	1.47	0.61	3.81	1.00	2005-2	2008-4
United Kingdom	21	2.30	0.79	2.22	0.14	2014-2	2008-4

Note: *Actual values are times 10^{-2}; maximum and minimum values given by publication.

Table 12: Mean values of the topic specific indices for all countries from 2005 to 2019.

Country	Bank	Valuation	Household	Real estate	Corporate	External	Sovereign
Belgium	0.88	0.74	0.00	1.20	0.30	0.47	1.23
Canada	1.87	1.12	0.98	2.21	1.69	1.55	2.38
Czech Republic	1.24	1.32	0.34	0.96	0.74	0.78	1.38
Denmark	1.22	1.58	0.67	1.16	1.87	0.83	1.25
Germany	1.11	0.76	0.54	1.43	0.97	0.70	1.46
Hungary	1.62	0.97	0.52	1.86	2.08	0.84	1.24
Japan	0.56	0.00	-0.62	1.26	0.70	-0.01	0.78
Netherlands	1.79	0.54	0.30	1.75	0.23	0.93	2.14
Norway	2.18	2.67	0.07	1.23	1.90	0.86	1.66
Poland	0.76	1.66	0.46	0.75	-0.15	0.15	0.70
Portugal	0.39	1.23	1.11	1.09	2.48	-0.16	0.81
Sweden	1.29	1.48	0.82	0.95	0.70	0.28	1.92
United Kingdom	1.76	1.27	1.48	2.84	1.26	1.18	2.02

Note: All values are times 10^{-2}.

D Derivations of SVR model

The following formulation combines the multivariate representation of Awad and Khanna (2015) with the detailed one-dimensional explanation of Smola and Schölkopf (2004). In addition, the form is altered in order to represent the problem setting of this research. For the sake of simplicity: $t - m + 1$ is denoted by z.

Optimization problem:

$$\begin{aligned} & min_w \quad \frac{1}{2}\|w\|^2 + C\sum_{j=z}^{t}(\xi_j + \xi_j^*) \\ & s.t \quad GDP_j - w^T x^{(j)}(\iota) \leq \varepsilon + \xi_j \qquad \forall \;\; z \;\leq\; j \;\leq\; t \\ & \qquad w^T x^{(j)}(\iota) - GDP_j \geq \varepsilon + \xi_j^* \qquad \forall \;\; z \;\leq\; j \;\leq\; t \\ & \qquad \xi_j, \xi_j^* \geq 0 \end{aligned} \tag{16}$$

Corresponding Lagrangian function:

$$\begin{aligned} \mathcal{L} \;\; = \;\; & \frac{1}{2}\|w\|^2 + \; C\sum_{j=z}^{t}(\xi_j + \xi_j^*) \; - \sum_{j=z}^{t}(\eta_j\xi_j + \eta_j^*\xi_j^*) \\ & - \sum_{j=z}^{t}\alpha_j(\epsilon + \xi_j - GDP_j - w^T x^{(j)}(\iota)) \\ & - \sum_{j=z}^{t}\alpha_j^*(\epsilon + \xi_j^* - GDP_j - w^T x^{(j)}(\iota)) \end{aligned} \tag{17}$$

Partial derivatives:

$$\begin{aligned} & \frac{\partial \mathcal{L}}{\partial w} = w - \sum_{j=z}^{t}(\alpha_j^* - \alpha_j)x^{(j)}(\iota) = 0 \;\; ; \;\; \frac{\partial \mathcal{L}}{\partial \xi_j} = C - \eta_j - \alpha_j = 0 \;\; ; \\ & \frac{\partial \mathcal{L}}{\partial \xi_j^*} = C - \eta_j^* - \alpha_j^* = 0 \;\; ; \;\; \frac{\partial \mathcal{L}}{\partial \eta_j} = \sum_{j=z}^{t}\xi_j \leq 0 \;\; ; \;\; \frac{\partial \mathcal{L}}{\partial \eta_j^*} = \sum_{j=z}^{t}\xi_j^* \leq 0 \;\; ; \\ & \frac{\partial \mathcal{L}}{\partial \alpha_j} = -GDP_j + w^T x^{(j)}(\iota) - \epsilon - \xi_j \leq 0 \;\; ; \;\; \frac{\partial \mathcal{L}}{\partial \alpha_j^*} = GDP_j - w^T x^{(j)}(\iota) - \epsilon - \xi_j^* \leq 0. \end{aligned} \tag{18}$$

Dual optimization problem:

$$\begin{aligned} & max_{\alpha,\alpha^*} \quad -\epsilon\sum_{j=z}^{t}(\alpha_j + \alpha_j^*) + \sum_{j=z}^{t}(\alpha_j^* - \alpha_j)GDP_j - \frac{1}{2}\sum_{j=z}^{t}\sum_{i=z}^{t}(\alpha_j^* + \alpha_i)(\alpha_i^* - \alpha_i)(x^{(j)}(\iota))^T x^{(i)}(\iota) \\ & s.t. \qquad \sum_{j=z}^{t}(\alpha_j^* - \alpha_j) = 0 \quad \text{for} \quad \alpha_j, \; \alpha_j^* \in \; [0, C] \end{aligned} \tag{19}$$

E Economic information conveyed in topic indices

Table 13: Panel-regression results of topic indices with respect to historic economic variables.

Topic	Variable	h = 0	h = 1	h = 4	h = 8
External	*Balance of payments*	-0.031***	-0.038***	-0.059***	-0.047***
		(0.010)	(0.010)	(0.011)	(0.014)
	Trade in goods, import	-0.013**	0.012**	-0.001	-0.009*
		(0.006)	(0.005)	(0.005)	(0.005)
	Trade in goods, export	0.007	0.005	0.005	0.007
		(0.005)	(0.005)	(0.006)	(0.005)
	Trade in services, import	0.000	0.000	0.000*	0.000*
		(0.000)	(0.000)	(0.000)	(0.000)
	Trade in services, export	0.000*	0.000***	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Sovereign	*Credit to government sector*	-0.009**	-0.012**	-0.019***	-0.022***
		(0.005)	(0.005)	(0.004)	(0.003)
Household	*Unemployment rate*	-0.070	-0.123*	-0.181***	-0.134
		(0.064)	(0.066)	(0.057)	(0.093)
	Credit to households	0.041***	0.039***	0.023	-0.011
		(0.012)	(0.012)	(0.017)	(0.027)
	Consumer price index	0.100	0.061	-0.033	-0.081*
		(0.088)	(0.087)	(0.057)	(0.042)
	Long-term interest rate	0.438***	0.503***	0.505***	0.285***
		(0.096)	(0.098)	(0.074)	(0.056)
Real Estate	*Real property price*	0.093	0.095	-0.652	-0.125***
		(0.070)	(0.068)	(1.748)	(0.041)
	Nominal property price	-0.170**	-0.160**	-0.089***	0.108***
		(0.068)	(0.065)	(0.034)	(0.038)
	Price to rent	0.005	0.000	0.014	-0.044***
		(0.014)	(0.013)	(0.017)	(0.097)
	Long-term interest rate	0.194***	0.245***	0.378***	0.097*
		(0.066)	(0.682)	(0.076)	(0.052)

Note: ***, **, and * represent the 1%, 5% and 10% significance levels; all values are times 10^{-2}.

Table 13: Panel-regression results of topic indices with respect to historic economic variables, continued.

Topic	Variable	h = 0	h = 1	h = 4	h = 8
Bank	*Credit to GDP gap*	0.010***	0.009***	0.005**	0.006*
		(0.003)	(0.003)	(0.002)	(0.003)
	DSR, private non-financial	0.025	0.005	-0.103***	-0.104***
		(0.036)	(0.036)	(0.026)	(0.018)
	Short-term interest rate	-0.050	0.000	0.059*	0.024
		(0.033)	(0.031)	(0.035)	(0.041)
	Long-term interest rate	0.077**	0.054	0.078**	0.085**
		(0.039)	(0.041)	(0.043)	(0.038)
Valuation	*Share price index*	-0.013***	0.008**	0.000	0.002
		(0.004)	(0.004)	(0.032)	(0.005)
	Short-term interest rate	0.076	0.119**	0.152***	0.063
		(0.057)	(0.058)	(0.057)	(0.064)
Corporate	*DSR, private non-financial*	0.320***	0.369***	0.478***	0.461***
		(0.063)	(0.773)	(0.069)	(0.073)
	Credit to non-financial institutions	-0.012	-0.022**	-0.050***	-0.075***
		(0.010)	(0.011)	(0.013)	(0.015)

Note: ***, **, and * represent the 1%, 5% and 10% significance levels; all values are times 10^{-2}.

F Lag and rolling-window comparison

Table 14: RMSE of the 1-step ahead forecasts for the ϵ-SVR(w,2) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	606.6	708.1	727.0	733.5	725.3	705.0	721.1
Canada	4345.8	5110.9	5745.1	6471.3	7031.5	7612.5	8018.9
Czech Republic	15108.1	19199.3	22998.0	26606.5	29871.5	33214.5	36174.2
Denmark	4886.2	5544.0	6374.0	7135.0	7940.8	8629.7	9162.4
Germany	5428.4	6465.6	7455.4	8383.4	9210.7	10073.7	10887.7
Hungary	123744.3	160475.7	195417.0	230804.9	264138.2	297588.1	328731.6
Japan	5015.3	5841.7	6720.2	7627.2	8162.9	8536.5	8973.2
Netherlands	1404.4	1665.7	1762.9	1797.4	1859.3	1940.5	1964.1
Norway	6510.3	7406.3	8427.1	8597.3	9294.2	9989.5	10673.9
Poland	6700.3	8074.5	9470.6	10678.2	11846.2	13057.2	14075.1
Portugal	391.6	454.7	483.0	498.9	498.2	481.2	490.7
Sweden	10648.8	13355.5	15900.3	18379.1	20579.0	22656.9	24698.1
United Kingdom	3342.5	3948.0	4150.0	4638.6	5079.4	5444.1	5803.8

Table 15: RMSE of the 1-step ahead forecasts for the ϵ-SVR(w,8) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	418.7	499.7	549.5	584.2	596.0	612.0	619.7
Canada	3710.2	4521.1	5135.4	5787.0	6500.6	7087.3	7668.7
Czech Republic	14216.4	18323.1	21527.2	25363.4	28709.3	32281.4	35375.8
Denmark	4222.4	4951.3	5488.7	6162.9	6813.0	7575.9	8267.1
Germany	4910.0	5796.6	6475.9	7470.9	8308.5	9218.8	10068.5
Hungary	123044.7	159376.3	193895.2	229540.2	262892.9	296785.2	328118.7
Japan	4611.7	5545.9	6166.6	6744.3	7311.0	7979.7	8482.6
Netherlands	923.5	1089.9	1255.1	1375.5	1506.8	1650.1	1766.2
Norway	6338.6	6943.4	7745.3	8189.1	8915.1	9511.6	10280.4
Poland	5806.2	7005.4	7913.4	9246.9	10431.3	11751.1	13047.3
Portugal	265.4	327.5	346.1	354.5	374.0	383.0	393.6
Sweden	9910.0	12596.2	14662.1	17233.5	19495.7	21788.7	23999.8
United Kingdom	2362.3	2595.3	3028.4	3657.4	4226.3	4598.5	5240.4

Table 16: RMSE of the 2-step ahead forecasts for the ϵ-SVR(w,2) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	1000.3	1168.9	1311.2	1412.1	1468.7	1472.8	1460.3
Canada	7111.5	8157.4	8926.0	9680.1	10458.7	11130.1	11804.8
Czech Republic	24673.4	28815.9	32684.4	36322.6	39704.7	42972.5	46172.3
Denmark	7578.6	8740.8	9660.1	10487.3	11470.9	12302.3	13036.1
Germany	8848.0	10415.6	11681.7	12847.3	13879.9	14873.3	15864.1
Hungary	197838.5	233892.4	268264.5	302401.4	333947.9	365655.0	394642.3
Japan	7499.8	8826.6	9703.0	10523.0	11295.9	11958.4	12346.2
Netherlands	2338.2	2745.5	3048.1	3334.3	3566.3	3692.0	3784.7
Norway	9587.8	10979.7	11747.8	12290.4	13200.0	14034.2	14787.5
Poland	11100.9	13024.0	14847.8	16411.6	17890.7	19173.6	20471.4
Portugal	638.8	739.0	821.3	889.7	931.4	954.0	989.5
Sweden	17410.2	20496.4	23431.6	26090.8	28465.4	30779.4	33038.7
United Kingdom	5727.6	6812.9	7644.0	8369.2	9004.1	9561.0	10047.9

Table 17: RMSE of the 2-step ahead forecasts for the ϵ-SVR(w,8) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	841.1	1016.2	1124.3	1188.2	1242.4	1300.6	1343.7
Canada	6631.7	7586.0	8467.4	9283.5	10129.1	10886.1	11575.2
Czech Republic	24126.3	28239.9	31825.9	35671.5	39072.2	42518.3	45686.9
Denmark	7195.7	8107.3	9008.1	9865.7	10729.6	11642.8	12393.5
Germany	8371.4	9637.9	10754.8	11946.4	13090.7	14172.5	15083.7
Hungary	197173.6	233103.9	267112.7	301334.0	332874.4	364740.7	393789.8
Japan	7230.6	8227.2	8893.8	9770.2	10583.3	11443.0	12175.0
Netherlands	1943.1	2318.0	2594.0	2774.1	2981.7	3211.8	3410.7
Norway	9418.4	10394.0	11066.3	11832.3	12757.7	13578.6	14489.4
Poland	10380.1	12046.0	13526.9	15092.7	16528.9	17909.4	19253.6
Portugal	538.9	650.1	699.7	754.5	813.4	860.0	900.5
Sweden	16863.9	19873.4	22454.1	25212.1	27687.5	30082.2	32449.7
United Kingdom	4759.8	5450.7	6166.6	6980.4	7747.1	8277.2	8932.4

Table 18: RMSE of the 3-step ahead forecasts for the ϵ-SVR(w,2) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	1368.9	1548.3	1707.0	1832.7	1922.6	1970.1	1990.3
Canada	9656.4	10686.9	11611.6	12520.2	13559.7	14474.2	15390.3
Czech Republic	33476.3	37429.9	41307.0	45121.8	48438.3	51798.0	54934.8
Denmark	10144.7	11373.4	12310.1	13204.9	14135.4	14967.3	15814.2
Germany	12177.0	13573.2	14932.8	16292.9	17644.0	18830.2	19894.9
Hungary	269436.6	303729.4	335975.6	368310.0	397383.5	426738.3	453440.2
Japan	9915.8	11163.4	11955.9	12656.6	13419.1	14057.6	14721.0
Netherlands	3232.5	3618.1	3966.0	4292.6	4612.5	4868.5	5078.9
Norway	12485.6	13507.8	14643.3	15940.9	17176.1	18092.1	18843.8
Poland	15274.7	17141.3	18914.1	20525.1	21995.9	23324.4	24721.2
Portugal	878.7	979.8	1077.3	1171.2	1260.8	1341.0	1429.3
Sweden	23911.7	26894.8	29639.7	32414.4	34920.7	37371.2	39747.4
United Kingdom	7981.6	9054.5	10123.6	11141.0	12057.4	12886.1	13649.8

Table 19: RMSE of the 3-step ahead forecasts for the ϵ-SVR(w,8) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	1286.2	1476.6	1615.2	1705.6	1799.5	1886.5	1950.3
Canada	9415.8	10394.3	11365.9	12206.3	13070.6	13941.0	14684.1
Czech Republic	33246.9	37272.0	40920.8	44587.9	48035.7	51457.9	54664.4
Denmark	9994.1	11064.6	12069.5	13028.2	13957.0	14967.6	15870.4
Germany	11872.5	13197.8	14563.1	15949.6	17244.6	18492.0	19559.4
Hungary	269283.2	303496.5	335558.0	367676.0	396914.4	426349.9	452787.0
Japan	9669.0	10605.2	11560.7	12513.9	13423.6	14292.1	15138.8
Netherlands	3096.8	3495.5	3843.4	4107.6	4403.4	4688.5	4941.2
Norway	12265.2	12999.9	13892.0	15052.6	16128.7	17123.6	18198.6
Poland	14993.2	16825.3	18447.7	20048.8	21521.6	22923.4	24267.0
Portugal	848.7	962.1	1048.1	1136.4	1228.5	1309.1	1382.6
Sweden	23671.4	26722.4	29396.4	32072.3	34625.9	37060.0	39551.8
United Kingdom	7555.9	8456.2	9390.2	10297.5	11173.4	11895.1	12678.3

Table 20: RMSE of the 4-step ahead forecasts for the ϵ-SVR(w,2) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	1736.6	1912.3	2070.2	2219.8	2345.9	2432.9	2509.2
Canada	12010.5	13004.2	14100.0	15212.3	16280.0	17293.7	18099.9
Czech Republic	41830.2	45833.1	49756.8	53508.6	57009.1	60346.1	63369.4
Denmark	12646.0	13697.6	14635.9	15614.9	16608.5	17536.7	18575.7
Germany	15369.6	16819.8	18217.4	19616.8	20904.6	22025.4	23245.5
Hungary	337174.3	369229.4	399135.8	428668.1	455164.1	482235.2	507935.4
Japan	11736.5	12541.1	13469.4	14356.1	15432.3	16313.6	17359.9
Netherlands	4079.3	4506.5	4891.7	5250.9	5578.0	5874.3	6105.6
Norway	14844.2	15870.7	17000.9	18547.6	19833.7	21146.8	22409.5
Poland	19171.9	20918.8	22655.7	24183.9	25792.6	27236.6	28692.8
Portugal	1111.7	1217.8	1318.0	1418.2	1529.2	1649.2	1735.6
Sweden	30170.1	33089.9	35962.6	38689.0	41374.9	43916.1	46146.3
United Kingdom	10209.1	11333.3	12422.9	13479.2	14494.5	15479.1	16358.1

Table 21: RMSE of the 4-step ahead forecasts for the ϵ-SVR(w,8) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	1702.2	1873.8	2008.8	2138.8	2260.5	2358.1	2451.2
Canada	11877.3	12883.8	13835.3	14771.3	15722.9	16677.4	17545.0
Czech Republic	41749.5	45670.9	49266.4	52898.6	56332.4	59777.4	63006.6
Denmark	12607.5	13629.4	14600.7	15653.9	16626.1	17616.8	18614.4
Germany	15253.1	16625.4	18017.2	19433.7	20800.8	22080.5	23278.3
Hungary	337114.3	369108.0	398714.3	428386.3	454884.7	481419.7	506773.4
Japan	11806.7	12780.1	13637.5	14515.3	15450.0	16368.5	17332.1
Netherlands	4048.9	4442.4	4769.8	5089.3	5402.2	5699.7	5985.5
Norway	14873.6	15713.4	16850.1	18145.5	19337.2	20371.0	21540.0
Poland	19067.9	20871.4	22502.3	24073.8	25560.1	26978.3	28317.9
Portugal	1105.5	1220.9	1315.1	1420.9	1521.4	1605.1	1681.6
Sweden	30118.9	33015.5	35684.8	38396.7	40991.3	43446.6	45876.4
United Kingdom	10081.6	11112.2	12136.4	13122.5	14117.8	14986.7	15856.0

Table 22: RMSE of the 5-step ahead forecasts for the ϵ-SVR(w,2) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	2097.0	2262.5	2423.5	2569.5	2688.9	2795.6	2865.0
Canada	14355.0	15391.9	16502.7	17703.0	18811.8	19873.4	20709.8
Czech Republic	49814.1	53859.3	57606.0	61271.6	64535.8	67407.1	69738.3
Denmark	14930.5	15973.0	17035.8	18083.9	19158.8	20226.4	21208.7
Germany	18500.7	20066.6	21439.9	22687.8	23867.3	25098.5	26234.4
Hungary	399923.9	429701.2	456583.0	483363.8	508743.0	534705.8	558499.9
Japan	13679.9	14621.4	15576.4	16540.0	17498.6	18664.8	19775.6
Netherlands	4884.0	5263.3	5642.2	5941.0	6245.1	6545.7	6807.1
Norway	17109.1	18170.1	19550.2	21355.8	22551.0	23877.9	24981.5
Poland	22888.7	24619.6	26250.7	27727.4	29276.8	30665.8	32019.6
Portugal	1339.6	1443.0	1548.3	1648.7	1750.3	1856.5	1963.2
Sweden	36263.3	39108.7	42016.3	44661.3	47069.1	49233.9	51296.8
United Kingdom	12427.2	13531.8	14624.8	15684.4	16721.4	17738.5	18748.6

Table 23: RMSE of the 5-step ahead forecasts for the ϵ-SVR(w,8) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	2079.5	2233.1	2387.3	2519.7	2638.6	2757.7	2875.0
Canada	14249.1	15263.6	16224.3	17190.6	18079.5	19008.9	19896.0
Czech Republic	49794.3	53535.2	57078.7	60624.7	64069.5	67559.3	70344.4
Denmark	14910.3	15835.8	16937.2	17995.5	19090.3	20067.7	21103.7
Germany	18358.9	19785.8	21120.1	22465.3	23806.4	25135.2	26313.4
Hungary	399873.3	429373.8	456245.3	483064.3	508119.1	533054.6	556670.0
Japan	13745.0	14638.8	15488.1	16349.5	17305.7	18287.4	19187.4
Netherlands	4877.9	5246.5	5594.9	5886.6	6203.2	6514.5	6801.3
Norway	17221.4	18459.9	19663.9	21013.0	22163.6	23239.8	24433.0
Poland	22835.3	24581.5	26126.9	27608.8	29047.5	30425.9	31805.1
Portugal	1336.5	1455.0	1558.6	1664.0	1758.7	1837.7	1903.6
Sweden	36121.5	38877.3	41573.1	44312.0	46802.3	49197.2	51526.0
United Kingdom	12394.4	13446.4	14519.8	15566.5	16650.3	17603.4	18596.5

Table 24: RMSE of the 6-step ahead forecasts for the ϵ-SVR(w,2) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	2441.7	2607.6	2765.9	2893.5	3000.3	3089.1	3164.6
Canada	16631.7	17833.0	19015.5	20095.3	21178.3	22316.7	23280.8
Czech Republic	57467.5	61229.7	64728.6	68027.8	70502.1	72828.0	75315.1
Denmark	17071.4	18259.9	19295.2	20335.1	21323.0	22394.8	23381.1
Germany	21553.7	22988.1	24372.3	25583.7	26760.9	27975.4	29405.7
Hungary	457540.1	484162.3	509635.3	535170.1	558703.5	582165.1	603212.2
Japan	15781.5	16804.7	17866.0	18893.5	19766.9	20809.1	21621.7
Netherlands	5661.5	6003.1	6306.9	6620.4	6882.3	7117.2	7354.9
Norway	20361.8	21479.7	22727.9	24007.9	25285.2	26462.0	27505.4
Poland	26351.0	27873.0	29464.8	30877.8	32276.8	33666.2	34912.6
Portugal	1578.0	1695.4	1807.2	1924.6	2051.3	2180.1	2295.3
Sweden	42080.6	44868.1	47417.7	49751.1	52054.2	54181.2	56196.1
United Kingdom	14665.0	15749.6	16834.6	17847.8	18906.6	20005.3	21141.4

Table 25: RMSE of the 6-step ahead forecasts for the ϵ-SVR(w,8) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	2430.8	2586.5	2725.6	2839.5	2958.4	3082.8	3202.3
Canada	16541.1	17568.8	18546.7	19504.9	20410.3	21377.8	22321.9
Czech Republic	57480.6	61165.2	64609.8	68085.5	70968.9	73787.5	76279.8
Denmark	17014.3	18093.4	19244.8	20289.9	21391.9	22349.5	23350.7
Germany	21437.5	22781.2	24025.8	25244.0	26531.6	27884.7	29247.8
Hungary	457200.3	483984.5	509475.4	534841.0	558135.1	581452.4	602267.0
Japan	15580.4	16523.8	17458.1	18468.5	19433.8	20428.9	21465.2
Netherlands	5657.2	5996.3	6291.9	6581.5	6869.7	7134.8	7375.2
Norway	20222.9	21393.8	22651.9	23972.6	25169.5	26244.5	27346.9
Poland	26313.9	27906.5	29406.4	30845.5	32321.1	33710.0	35135.4
Portugal	1570.1	1683.3	1783.5	1879.7	1958.8	2020.9	2077.7
Sweden	41920.5	44651.2	47148.2	49750.6	52012.6	54299.2	56602.0
United Kingdom	14653.8	15694.8	16815.6	17883.8	18987.8	20020.7	21109.2

Table 26: RMSE of the 7-step ahead forecasts for the ϵ-SVR(w,2) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	2776.6	2939.4	3080.9	3207.7	3321.2	3423.3	3514.8
Canada	18779.5	19818.8	20927.9	22106.9	23159.6	24132.6	25037.1
Czech Republic	64981.4	68493.2	71410.8	73880.9	76261.6	78747.5	81388.4
Denmark	19268.7	20218.9	21380.1	22328.1	23377.9	24336.5	25247.1
Germany	24439.4	25887.4	27302.8	28780.9	30197.5	31595.2	33008.3
Hungary	509783.1	535702.0	559208.8	583017.8	603627.8	624235.4	644375.5
Japan	17775.2	18941.8	20009.2	21007.3	22160.7	23311.1	24264.2
Netherlands	6390.1	6683.1	6948.8	7242.9	7547.0	7794.3	8003.2
Norway	23160.7	24461.5	25688.6	27122.1	28180.1	29265.9	30496.6
Poland	29614.8	31034.6	32546.0	33981.1	35406.2	36593.9	37878.0
Portugal	1807.8	1917.2	2014.1	2107.1	2196.2	2283.4	2355.5
Sweden	47816.4	50455.5	52824.2	55222.7	57483.6	59731.1	61904.9
United Kingdom	16880.7	17964.2	19053.6	20101.7	21185.2	22289.3	23403.0

Table 27: RMSE of the 7-step ahead forecasts for the ϵ-SVR(w,8) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	2776.6	2939.4	3080.9	3207.7	3321.2	3423.3	3514.8
Canada	18779.5	19818.8	20927.9	22106.9	23159.6	24132.6	25037.1
Czech Republic	64981.4	68493.2	71410.8	73880.9	76261.6	78747.5	81388.4
Denmark	19268.7	20218.9	21380.1	22328.1	23377.9	24336.5	25247.1
Germany	24439.4	25887.4	27302.8	28780.9	30197.5	31595.2	33008.3
Hungary	509783.1	535702.0	559208.8	583017.8	603627.8	624235.4	644375.5
Japan	17775.2	18941.8	20009.2	21007.3	22160.7	23311.1	24264.2
Netherlands	6390.1	6683.1	6948.8	7242.9	7547.0	7794.3	8003.2
Norway	23160.7	24461.5	25688.6	27122.1	28180.1	29265.9	30496.6
Poland	29614.8	31034.6	32546.0	33981.1	35406.2	36593.9	37878.0
Portugal	1807.8	1917.2	2014.1	2107.1	2196.2	2283.4	2355.5
Sweden	47816.4	50455.5	52824.2	55222.7	57483.6	59731.1	61904.9
United Kingdom	16880.7	17964.2	19053.6	20101.7	21185.2	22289.3	23403.0

Table 28: RMSE of the 8-step ahead forecasts for the ϵ-SVR(w,2) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	3112.4	3266.9	3413.6	3551.0	3640.0	3711.0	3790.6
Canada	21008.0	22061.1	23059.3	23933.9	24843.6	25764.5	26723.3
Czech Republic	71948.5	74769.2	77277.8	79874.1	82593.5	85149.6	87659.0
Denmark	21673.2	22717.9	23755.4	24633.0	25602.2	26668.4	27615.4
Germany	27186.7	28638.7	30046.2	31544.6	33036.0	34430.5	35717.2
Hungary	559585.5	583277.5	603989.0	624984.2	644105.6	663244.1	683290.6
Japan	20120.6	21026.0	21868.1	23230.8	24427.8	25392.1	26297.6
Netherlands	7057.2	7302.8	7552.2	7819.0	8104.2	8290.8	8456.4
Norway	26005.1	26976.4	28208.8	29601.9	30629.6	31825.3	33163.9
Poland	32776.5	34337.9	35793.7	37044.9	38366.9	39761.0	41093.5
Portugal	2041.5	2136.9	2229.7	2332.5	2429.1	2531.2	2628.8
Sweden	52768.4	55235.4	57583.6	59947.4	62230.3	64449.3	66720.3
United Kingdom	19075.2	20214.6	21284.8	22345.0	23428.3	24546.5	25750.2

Table 29: RMSE of the 8-step ahead forecasts for the ϵ-SVR(w,8) during 2013Q2 to 2019Q1.

	Rolling-window length						
Country	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Belgium	3107.3	3236.2	3379.4	3506.2	3627.8	3758.8	3892.2
Canada	20987.0	21950.9	22920.7	23864.8	24831.0	25864.1	26821.0
Czech Republic	71932.2	74866.8	77387.5	79885.9	82168.1	84578.9	87010.5
Denmark	21643.9	22700.8	23788.2	24821.7	25917.4	26955.8	27935.5
Germany	27164.9	28458.8	29690.0	31064.0	32631.3	34410.0	36124.7
Hungary	559402.8	583182.1	604006.8	624882.5	644130.9	663334.7	683490.1
Japan	20079.5	21115.4	22190.3	23245.4	24285.5	25259.1	26131.2
Netherlands	7061.8	7360.2	7634.4	7863.3	8088.2	8267.5	8455.1
Norway	26041.8	27120.7	28321.0	29715.2	30929.6	32136.3	33370.8
Poland	32756.2	34290.9	35831.4	37312.1	38776.2	40206.1	41661.0
Portugal	2032.6	2123.1	2194.3	2249.7	2294.1	2326.8	2356.6
Sweden	52762.6	55123.2	57296.2	59749.6	62012.6	64503.4	66945.8
United Kingdom	19070.2	20167.5	21282.5	22327.0	23469.1	24662.3	26030.8

Table 30: AIC and BIC for 1-step ahead forecasts of ϵ-SVR(2,ι) for lags 1 up to 4 during 2011Q4 to 2019Q3.

Lags	**1**		**2**		**3**		**4**	
Criterion	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
Belgium	383.6	387.0	383.0	385.8	381.7	385.9	378.0	383.6
Canada	506.0	507.4	504.3	507.1	503.3	507.5	502.2	507.8
Czech Republic	576.4	578.8	575.6	578.4	576.3	580.5	576.8	582.4
Denmark	508.2	512.6	507.7	510.5	507.5	511.7	508.2	513.8
Germany	516.6	520.0	514.6	517.4	515.1	519.3	514.7	520.3
Hungary	703.0	704.4	702.8	705.6	704.7	708.9	706.5	712.1
Japan	517.7	521.1	515.1	517.9	515.1	519.3	517.6	523.2
Netherlands	435.2	438.6	434.8	437.6	433.3	437.5	430.5	436.1
Norway	535.5	538.9	534.5	537.3	536.3	540.6	537.4	543.0
Poland	527.9	531.3	526.8	529.6	525.0	529.2	523.3	528.9
Portugal	372.2	376.6	372.3	375.1	370.9	375.1	367.8	373.4
Sweden	556.2	559.6	555.4	558.2	556.0	560.2	556.7	562.3
United Kingdom	490.3	493.8	488.7	491.5	486.6	490.8	482.7	488.3

Table 31: AIC and BIC for 1-step ahead forecasts of ϵ-SVR(2,ι) for lags 5 up to 8 during 2011Q4 to 2019Q3..

Lags	**5**		**6**		**7**		**8**	
Criterion	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
Belgium	374.9	381.9	373.5	381.9	372.8	382.6	372.7	383.9
Canada	501.9	508.9	501.8	510.2	504.1	513.9	506.3	517.5
Czech Republic	577.8	584.8	579.4	587.8	581.4	591.3	583.7	594.9
Denmark	508.2	515.2	507.4	515.8	508.6	518.4	510.8	522.0
Germany	514.0	521.0	515.7	524.1	517.7	527.6	520.6	531.8
Hungary	708.5	715.5	710.5	718.9	712.5	722.3	714.6	725.8
Japan	518.6	525.6	519.7	528.1	520.9	530.7	522.5	533.7
Netherlands	427.3	434.3	425.2	433.6	423.3	433.1	423.1	434.3
Norway	538.3	545.3	540.8	549.2	542.8	552.6	545.0	556.2
Poland	523.5	530.5	525.3	533.7	527.7	537.5	530.4	541.6
Portugal	365.1	372.1	363.6	372.1	363.3	373.1	363.6	374.8
Sweden	557.4	564.4	559.1	567.5	560.9	570.7	563.5	574.7
United Kingdom	479.3	486.3	477.7	486.1	479.6	489.4	483.0	494.2

Table 32: AIC and BIC for 8-step ahead forecasts of ϵ-SVR(2,ι) for lags 1 up to 4 during 2011Q4 to 2019Q3.

Lags	**1**		**2**		**3**		**4**	
Criterion	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
Belgium	487.8	488.2	484.9	487.7	486.9	491.1	489.1	494.7
Canada	606.6	607.0	603.5	606.3	605.5	609.7	607.4	613.1
Czech Republic	672.2	672.6	669.1	671.9	671.1	675.3	673.1	678.7
Denmark	601.1	601.5	598.1	600.9	600.1	604.3	602.1	607.7
Germany	623.5	623.9	620.2	623.0	622.3	626.5	624.2	629.9
Hungary	794.6	795.1	791.7	794.5	793.7	797.9	795.6	801.2
Japan	595.7	596.1	592.9	595.7	594.7	598.9	596.6	602.3
Netherlands	532.5	532.9	529.7	532.5	531.8	536.0	533.8	539.4
Norway	615.7	616.1	612.8	615.6	614.8	619.0	616.9	622.5
Poland	628.7	629.1	625.7	628.5	627.7	631.9	629.7	635.3
Portugal	467.2	467.6	464.2	467.0	466.2	470.4	468.1	473.7
Sweden	657.7	658.1	654.5	657.3	656.6	660.9	658.6	664.2
United Kingdom	595.3	595.7	592.3	595.1	594.3	598.5	596.3	601.9

Table 33: AIC and BIC for 8-step ahead forecasts of ϵ-SVR(2,ι) for lags 5 up to 8 during 2011Q4 to 2019Q3.

Lags	**5**		**6**		**7**		**8**	
Criterion	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
Belgium	491.2	498.2	493.2	501.6	495.0	504.8	496.7	507.9
Canada	609.3	616.4	611.3	619.7	613.3	623.1	615.3	626.6
Czech Republic	675.1	682.1	677.1	685.5	679.0	688.8	681.0	692.3
Denmark	604.1	611.1	606.1	614.5	608.0	617.8	610.0	621.3
Germany	626.2	633.2	628.2	636.6	630.2	640.0	632.2	643.4
Hungary	797.6	804.6	799.6	808.0	801.6	811.5	803.6	814.9
Japan	598.4	605.4	600.5	608.9	602.6	612.4	604.7	615.9
Netherlands	535.8	542.8	537.8	546.2	539.8	549.6	541.8	553.0
Norway	618.8	625.8	620.7	629.1	622.8	632.6	624.8	636.0
Poland	631.7	638.7	633.7	642.1	635.7	645.5	637.6	648.9
Portugal	470.0	477.0	472.0	480.4	474.0	483.8	476.0	487.2
Sweden	660.5	667.6	662.6	671.0	664.5	674.3	666.5	677.7
United Kingdom	598.3	605.3	600.3	608.7	602.3	612.1	604.3	615.5

G Forecasting performance

Table 34: MAPE for h-step ahead forecasts ranging from 1 to 8 during 2010Q2 to 2019Q1 (without sentiment).

Country	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**
Belgium	0.54	0.94	1.32	1.72	2.09	2.42	2.68	2.95
Canada	0.81	1.36	1.90	2.42	2.89	3.34	3.73	4.10
Czech Republic	0.98	1.66	2.28	2.87	3.34	3.83	4.26	4.60
Denmark	0.76	1.15	1.61	1.99	2.37	2.73	3.09	3.47
Germany	0.77	1.30	1.81	2.33	2.80	3.20	3.58	3.93
Hungary	1.22	1.92	2.58	3.15	3.66	4.20	4.70	5.18
Japan	0.91	1.25	1.57	1.75	1.89	2.23	2.55	3.03
Netherlands	0.67	1.12	1.56	1.93	2.24	2.57	2.85	3.04
Norway	0.91	1.23	1.52	1.88	2.16	2.51	2.82	3.12
Poland	1.31	2.19	3.08	3.91	4.72	5.52	6.27	6.99
Portugal	0.87	1.45	1.98	2.48	2.85	3.24	3.57	3.87
Sweden	1.00	1.64	2.27	2.89	3.48	3.96	4.38	4.74
United Kingdom	0.69	1.20	1.67	2.13	2.54	2.96	3.37	3.81

Table 35: MAPE for h-step ahead forecasts ranging from 1 to 8 during 2010Q2 to 2019Q1 (with sentiment).

Country	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**
Belgium	0.57	0.94	1.32	1.72	2.09	2.41	2.68	2.94
Canada	0.84	1.37	1.90	2.42	2.89	3.33	3.73	4.08
Czech Republic	1.02	1.66	2.29	2.88	3.35	3.83	4.26	4.61
Denmark	0.77	1.17	1.61	2.00	2.38	2.74	3.09	3.48
Germany	0.81	1.31	1.82	2.33	2.79	3.19	3.57	3.93
Hungary	1.22	1.92	2.58	3.15	3.66	4.19	4.70	5.18
Japan	0.90	1.27	1.58	1.76	1.88	2.21	2.55	3.00
Netherlands	0.69	1.13	1.56	1.93	2.25	2.57	2.85	3.04
Norway	0.92	1.23	1.53	1.86	2.16	2.51	2.83	3.12
Poland	1.35	2.20	3.08	3.91	4.72	5.52	6.27	6.99
Portugal	0.91	1.46	1.98	2.48	2.86	3.23	3.56	3.87
Sweden	1.03	1.65	2.27	2.91	3.47	3.95	4.36	4.75
United Kingdom	0.72	1.20	1.68	2.13	2.54	2.96	3.37	3.80

H Test results of forecast bias

Table 36: P-values of the F-test corresponding to the Mincer-Zarnowitz regressions.

Country	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**
Belgium	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Canada	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Czech Republic	<u>0.014</u>	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Denmark	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Germany	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hungary	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Japan	<u>0.149</u>	<u>0.011</u>	0.000	0.000	0.000	0.000	0.000	<u>0.032</u>
Netherlands	<u>0.013</u>	0.002	0.000	0.000	0.000	0.000	0.010	0.000
Norway	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Poland	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Portugal	<u>0.643</u>	<u>0.862</u>	<u>0.725</u>	<u>0.655</u>	<u>0.087</u>	<u>0.013</u>	0.000	0.000
Sweden	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
United Kingdom	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: the underlined values indicate that the joint null hypothesis is not rejected for the 1% confidence level.

Table 37: Regression coefficients of the Mincer-Zarnowitz regressions for several h-steps ahead.

Country		**h=2**	**h=4**	**h=6**	**h=8**
Belgium	β_0	-242.99	2808.13	1595.25	-4200.32
		(2259.22)	(2302.40)	(3340.21)	(4041.60)
	β_1	1.01	0.99	1.01	1.08
		(0.02)	(0.02)	(0.04)	(0.04)
Canada	β_0	21912.45	40227.36	36309.99	22969.18
		(11395.13)	(13290.89)	(7418.58)	(9549.75)
	β_1	0.97	0.94	0.96	0.99
		(0.02)	(0.03)	(0.02)	(0.02)
Czech Republic	β_0	-71160.86	-132472.30	-256846.90	-426197.00
		(51822.80)	(40171.71)	(38547.08)	(16676.31)
	β_1	1.08	1.15	1.29	1.46
		(0.05)	(0.03)	(0.03)	(0.01)
Denmark	β_0	-22259.80	-44743.21	-85314.17	-125166.10
		(13849.49)	(13123.79)	(11212.45)	(12616.53)
	β_1	1.06	1.12	1.21	1.30
		(0.03)	(0.03)	(0.02)	(0.03)
Germany	β_0	51321.83	88446.69	79791.07	58615.45
		(29371.37)	(22628.75)	(25713.67)	(41924.25)
	β_1	0.94	0.89	0.91	0.95
		(0.04)	(0.03)	(0.04)	(0.06)
Hungary	β_0	-924998.00	-1805281.00	-2830112.00	-3267786.00
		(235697.70)	(263906.40)	(699471.20)	(1068123.00)
	β_1	1.14	1.28	1.43	1.50
		(0.03)	(0.03)	(0.09)	(0.14)
Japan	β_0	14822.46	12021.15	-19811.58	30027.24
		(20007.77)	(35636.31)	(18433.72)	(17586.53)
	β_1	0.98	0.99	1.06	0.96
		(0.04)	(0.07)	(0.03)	(0.04)

Note: standard errors are given in brackets.

Table 37: Regression coefficients of the Mincer-Zarnowitz regressions for several h-steps ahead (continued).

Country		**h=2**	**h=4**	**h=6**	**h=8**
Netherlands	β_0	-18854.04	-35692.07	-61795.45	-87291.52
		(7223.03)	(4632.01)	(8606.02)	(14388.55)
	β_1	1.12	1.23	1.40	1.56
		(0.04)	(0.03)	(0.06)	(0.09)
Norway	β_0	-2428.30	-15665.43	-50941.88	-104843.00
		(21033.43)	(17831.25)	(22247.02)	(2741.04)
	β_1	1.01	1.04	1.10	1.19
		(0.03)	(0.03)	(0.03)	(0.04)
Poland	β_0	-19288.17	-31027.83	-38017.83	-45754.70
		(9944.73)	(7421.30)	(4700.59)	(16056.08)
	β_1	1.07	1.12	1.16	1.19
		(0.02)	(0.02)	(0.02)	(0.06)
Portugal	β_0	-2807.47	3036.00	18415.16	37452.76
		(5220.39)	(7572.13)	(13189.09)	(3501.50)
	β_1	1.07	0.94	0.59	0.15
		(0.13)	(0.18)	(0.31)	(0.08)
Sweden	β_0	48279.08	85981.89	80515.65	30946.33
		(42143.22)	(27582.35)	(28701.91)	(24615.43)
	β_1	0.97	0.94	0.95	1.02
		(0.04)	(0.03)	(0.03)	(0.03)
United Kingdom	β_0	5087.22	6003.86	-8116.24	-25177.31
		(9712.27)	(8785.65)	(11350.06)	(30775.79)
	β_1	1.00	1.01	1.05	1.10
		(0.02)	(0.02)	(0.03)	(0.06)

Note: standard errors are given in brackets.

I Test results of sentiment analysis

Table 38: Diebold-Mariano test statistic regarding the implementation of sentiment indices (continued).

Country	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 7	h = 8
Belgium	-4.119	-2.265	-0.400	0.569	1.746	1.132	0.925	1.907
Canada	-3.791	-1.706	-0.006	-0.658	0.040	1.428	0.311	1.542
Czech Republic	-6.156	-2.986	-1.550	-1.446	-0.443	-2.771	-1.038	-0.198
Denmark	-0.235	-1.523	-1.044	-1.888	-0.374	0.409	0.487	-0.880
Germany	-2.475	-1.335	-1.359	-1.004	1.474	1.340	0.810	-0.182
Hungary	-3.777	-0.218	-0.270	-0.942	-0.655	1.870	-1.239	0.816
Japan	-0.239	-1.834	0.575	-0.417	-0.346	1.011	0.080	1.240
Netherlands	-3.408	-2.007	-0.213	-0.240	-0.863	-0.385	-0.796	0.280
Norway	-0.092	-0.239	-0.634	0.451	-0.353	0.131	-0.757	-0.325
Poland	-1.583	-0.691	0.396	-0.121	-0.227	-0.153	1.337	1.196
Portugal	-4.481	-1.533	-0.318	1.678	-0.383	1.043	0.492	0.916
Sweden	-2.888	-1.384	-0.890	-1.666	0.756	1.342	1.835	-0.999
United Kingdom	-1.186	-0.684	-5.189	-4.628	-4.318	0.006	-2.068	5.874

Note: null hypothesis relates to no significance difference in forecast errors after including sentiment.

Table 39: HLN test statistic regarding the implementation of sentiment indices.

Country	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 7	h = 8
Belgium	-4.061	-2.233	-0.405	0.607	1.995	1.399	1.243	2.789
Canada	-3.738	-1.683	-0.006	-0.702	0.046	1.765	0.418	2.255
Czech Republic	-6.070	-2.944	-1.572	-1.544	-0.506	-3.425	-1.395	-0.289
Denmark	-0.231	-1.502	-1.058	-2.015	-0.428	0.505	0.654	-1.287
Germany	-2.441	-1.316	-1.378	-1.071	1.684	1.656	1.089	-0.266
Hungary	-3.724	-0.215	-0.274	-1.006	-0.748	2.312	-1.664	1.194
Japan	-0.236	-1.808	0.583	-0.445	-0.395	1.250	0.107	1.814
Netherlands	-3.360	-1.979	-0.216	-0.256	-0.986	-0.476	-1.070	0.409
Norway	-0.091	-0.235	-0.643	0.482	-0.404	0.161	-1.017	-0.475
Poland	-1.561	-0.681	0.402	-0.129	-0.259	-0.189	1.797	1.748
Portugal	-4.419	-1.512	-0.322	1.791	-0.438	1.289	0.661	1.340
Sweden	-2.847	-1.365	-0.902	-1.778	0.863	1.658	2.466	-1.461
United Kingdom	-1.169	-0.674	-5.261	-4.939	-4.934	0.008	-2.779	8.591

Note: null hypothesis relates to no significance difference in forecast errors after including sentiment.

Table 40: P-values of the HLN-test for a t-distribution with 35 degrees of freedom.

Country	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**
Belgium	0.000	0.032	0.688	0.548	0.054	0.171	0.222	0.008
Canada	0.001	0.101	0.995	0.487	0.964	0.086	0.679	0.030
Czech Republic	0.000	0.006	0.125	0.132	0.616	0.002	0.172	0.774
Denmark	0.818	0.142	0.297	0.052	0.671	0.617	0.517	0.206
Germany	0.020	0.197	0.177	0.291	0.101	0.107	0.284	0.792
Hungary	0.001	0.831	0.786	0.321	0.459	0.027	0.105	0.241
Japan	0.815	0.079	0.564	0.659	0.695	0.220	0.915	0.078
Netherlands	0.002	0.056	0.830	0.800	0.331	0.637	0.292	0.685
Norway	0.928	0.815	0.525	0.633	0.689	0.873	0.316	0.637
Poland	0.128	0.500	0.690	0.898	0.797	0.851	0.081	0.089
Portugal	0.000	0.140	0.749	0.082	0.664	0.206	0.513	0.189
Sweden	0.007	0.181	0.373	0.084	0.394	0.106	0.019	0.153
United Kingdom	0.250	0.504	0.000	0.000	0.000	0.994	0.009	0.000

Note: null hypothesis relates to no significance difference in forecast errors after including sentiment.

Table 41: Difference in MAPE after including sentiment indices in the training process.

Country	**h = 1**	**h = 2**	**h = 3**	**h = 4**	**h = 5**	**h = 6**	**h = 7**	**h = 8**
Belgium	0.030***	0.002**	0.000	-0.001	-0.002*	-0.008	-0.004	-0.007***
Canada	0.032***	0.011	0.001	0.005	0.000	-0.008	-0.006	-0.012**
Czech Republic	0.034***	0.007***	0.010	0.006	0.002	0.002***	0.004	0.002
Denmark	0.012	0.014	-0.001	0.008*	0.003	0.004	-0.005	0.007
Germany	0.033**	0.012	0.007	0.002	-0.007	-0.011	-0.008	-0.004
Hungary	0.005***	-0.001	-0.001	0.001	0.002	-0.004**	0.002	-0.002
Japan	-0.003	0.021*	0.006	0.016	-0.002	-0.015	0.003	-0.027*
Netherlands	0.019***	0.016*	0.003	0.001	0.003	0.002	0.003	0.002
Norway	0.006	-0.001	0.004	-0.016	-0.006	0.005	0.007	-0.002
Poland	0.044	0.012	-0.002	0.001	0.001	0.001	-0.001*	-0.001*
Portugal	0.036***	0.006	0.001	-0.002*	0.006	-0.009	0.000	-0.004
Sweden	0.031***	0.004	-0.002	0.014**	-0.004	-0.010	-0.017**	0.007
United Kingdom	0.031	0.008	0.005***	0.004***	0.004***	0.000	0.002***	-0.003***

Note: ***, **, and * represent the 1%, 5% and 10% significance levels.

J Summary of python scripts

FSRreader.py - This python script extracts textual information from FSRs and calculates the corresponding FSS indices. The script consists of the following functions:

1. *pdf_to_html*: extracts all information of a given PDF and transforms it to HTML format.
2. *html_to_text*: extracts all individual sentences from HTML, using a given XPath for the paragraphs of interest.
3. *text_to_index*: calculates the various FSS indices corresponding to a given set of sentences.
4. *specific*: checks if sentence is related to one of the specific topics.
5. *negation*: checks for negative negation words within three words of a found positive word.

Interpolation.py - This python script applies linear interpolation on the set of FSS indices that are calculated using *FSRreader.py*. In particular, it assigns values, that represent the FSS indices, to intermediate quarters between two consecutive FSR publications of a country. The script consists of the following functions:

1. *get_value*: applies linear interpolation given two consecutively observed quarters.
2. *get_date*: retrieves year and quarter from strings that indicate observation and incorporates them into the dataset.
3. *create_date*: creates the observation indicators for the unobserved quarters.
4. *inter_values*: assigns linear interpolated values to the unobserved intermediate quarters.

GDPpredicter.py - This python scripts creates the ϵ-SVR model for a set rolling-window. In addition, it allows for the implementation of the FSS indices. The script consists of the following functions:

1. *predict*: Constructs h-step predictions with a SVR for a rolling-window given a set sample and number of lags to be included.
2. *current_window*: Generates training and test set of a specific country for the current iteration of the rolling-window.