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FORECASTING ECONOMIC ACTIVITY IN THE BALTICS: LET US GOOGLE IT

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FORECASTING ECONOMIC ACTIVITY IN THE BALTICS: LET US GOOGLE IT

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Abstract

In this research we incorporate Google Trends into forecasting methodology to assess if there is any valuable information contained in search queries that can be useful in the Baltics. Using the search queries data we verify if the searches for terms related to unemployment, inflation, car sales and apartment sales represent real economic activities. Building on Box-Jenkins and Diebold-Mariano methodologies we check the improvements Google Trends might provide for forecasting accuracy. We further investigate Google Trends' ability to act as a leading indicator and via Hodrick-Prescott filter predict turning points in trends. The analysis reveals that Google Trends data represents the real economic activities, helps to improve in-sample prediction accuracy, but provides no strong evidence that Google Trends might be useful in predicting turning points in trends at the moment.

Keywords: Google Trends, Google, search queries, forecasting, economic variables, turning point, the Baltics, ARIMA, Diebold-Mariano, Hodrick-Prescott

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1. Introduction

Timely and accurate statistical information is important for the informational efficiency of the market economy in which agents make economic decisions based on the data they have. In tranquil times forecasting models do well in predicting near future developments. It is not the case though with unstable or turning-trend environments, as the recent financial crisis has demonstrated all too well. The flaws of forecasting models have become a headache for many international organisations, not least for central banks, upon forecasts of which economic monetary policies rely. David Stockton, in 2012's review of the Monetary Policy Committee's Forecasting Capability at Bank of England evaluated the forecasting performance of the Committee and concluded that the errors deteriorated in the last 5 years and UK was no exception from the collective errors by central banks around the world (Stockton, 2012). When even the most regarded institutions fail at accurate forecasting there is little doubt forecasting errors and the actions induced by them penetrate deep into operations of the underlying economies.

Better forecasts can serve to the benefit of many agents and there are parties involved in constant development of forecasting models. Businesses equipped with accurate information can allocate their capital more efficiently. Policy makers can initiate programs which do not overachieve or under achieve their targets. For these and other reasons central banks, hedge funds, national statistics departments have constantly turned to academia to carry out research to improve their predictive capability. Not long ago Google Trends search querieswere found as a useful source of faster and more dynamic information. The internet has been rapidly penetrating into the daily lives of modern society. With the growing use of the internet in search for news, information and research purposes, it is tempting to consider online activity as a reflection of the collective concerns, interests and intentions of the population. From this point of view, it is logical to consider that what people look for today is predictive of their actions in the near future.

Although Google Trends analysis may be performed on many topics, in the aftermath of economic crisis, however, the most relevant topic to us is that of economic activity forecasting. From this perspective, people that have lost their jobs may be looking for new placements online; consumers who intend to purchase a new house or an automobile might research about different options and characteristics; and, less intuitively, economists, worried about the potential rise in inflation might look for inflation-related material online – all of which can be captured by internet search engine and systemised for statistical analysis to forecast unemployment, sales and even inflation.

Google Trends is a service that drew most of the attention in search of this new data. Since its inception in 2009, it has been providing weekly scaled and normalised data on different search terms. It is the Google Trends that sparked a new wave of research called Google econometrics, the followers of which try to apply the service to many uses in search of better forecasting accuracy in a variety of fields. Being a new wave of research there is a huge gap in literature around the world. From its application in predicting influenza outbreaks (Ginsberg et al., 2009) to forecasting US unemployment, housing and automotive sales or foreign visitors' number in Hong Kong (Varian & Choi, 2009) it has proved a significant tool for improving short sample forecasting accuracy.

In the Baltics, Google is the leading search engine, therefore it is the best available tool to be used in capturing real internet users' interests. Google search engine accounts for 97.7% in Lithuania, 97.4% in Latvia and 73.7% in Estonia of the total search engine market (Query Click, 2012). This provides us with a firm grounding that the results will reflect the search activity of the majority of internet users. On back of these supportive facts, we set up a research question and hypotheses to guide our study.

Research question: *Does Google Trends search data contain valuable information in forecasting economic activities, their trends and turning points in the Baltics?*

Hypothesis I: There is a positive correlation between Google Trends search data and corresponding statistics on unemployment, automotive and housing sales and inflation in the Baltics.

Hypothesis II: Inclusion of Google Trends search data into forecasting models of unemployment, automotive, housing sales and inflation statistics reduces the prediction error in the Baltics.

Hypothesis III: Google Trends-adjusted models are better at spotting the turning points in the trends than the baseline models.

Our study is structured as follows. In Section 2 we overview the literature on Google Trends studies around the world, placing particular focus on the economic variables we analyse. We further detail our methodology in Section 3, where we describe our research design, explain Google Trends search data, procedures which prepare our data for analyses, ARIMA model and its application and finally Hodrick-Prescott filter. In section 4 we provide the empirical results on correlations, forecasts and turning points, which refer to the three hypotheses, respectively. We finally summarise and conclude our study in Section 5 and provide suggestions on further research.

2. Literature review

Since the two pioneering papers by Ginsberg, Mohebbi, Patel, Brammer, Smalinski and Brilliant (2009) and Varian and Choi (2009), a multitude of research was conducted in attempts to build better forecasts and obtain more accurate and timely information on many statistics. At the most generic level, all of the research can be broken down into epidemiology, business and economics related studies and other studies that are considerably fewer in volume. We divide our literature review into 5 areas. The first four are directly linked to the economic statistics that we analyse: unemployment rate, inflation rate, car sales and apartment sales. The fifth area groups some studies from other fields than economics or business. It includes medicine, tourism, stock markets and other.

The current spate of Google Trends research was sparked by two break-through studies. The first was a study by Ginsberg et al. (2009) when they pioneered the Google Trends application in the medicine by creating a faster and more precise influenza-like illness epidemics' outbreak detection model in US. In April of the same year, the first paper applying Google Trends for economic forecasting was written by Hal Varian, chief economist at Google, and Hyunyoung Choi who proved it useful to include Google Trends search query data into forecasting models of unemployment, auto sales, housing sales and even visitors' number to Hong Kong (Varian & Choi, 2009). These studies are the corner stone of the research field called Google Econometrics. Several years into the future, today we have numerous papers focusing on no fewer than 10 different topics in which Google Trends has been found beneficial. However, the very first attempt to harness internet search data in analysing economic variables goes back to 2005, when Michael Ettredge, John Gerdes and Gilbert Karuga (2005) in their study covering a period of only 77 weeks showed that internet search query data was a significant explanatory variable in a short lead-lag relation between job-related searches and US monthly unemployment rate. Besides, they found internet-based information was more informative of unemployment developments than traditionally used leading data such as unemployment insurance claims. Given limited data at that time, though, authors did not draw any stronger conclusions about the predictive power of internet search data in making longer period forecasts. At about the same time, a study on cancer-related topics came out (Cooper, Mallon, Leadbetter, Pollack, & Peipins, 2005). Nevertheless, a rapid proliferation of research did not immediately follow these studies. In short, the key findings in the area can be summarised:

Table 1 Summary of the key studies on Google Econometrics.

Key contributory studies			
Unemployment	**Inflation**	**Automotive sales**	**Home sales**
Askitas & Zimmerman (2009) D'Amuri & Marcuci (2010) Ettredge et al. (2009) Suhoy (2009) Varian & Choi (2009)	Guzman (2011)	Carrière-Swallow & Labbé (2010) Varian & Choi (2009)	Kulkarni et al. (2009) Varian & Choi (2009) Wu & Brynjolfsson (2009)

Source: Compiled by the authors.

2.1. Unemployment rate

In the most parsimonious ways Varian & Choi (2009) uncovered the forecasting potential of Google Trends and encouraged future research in Google application. Ever since The Economist posted an article *"Economic indicators: Googling the future"* discussing the paper, it has become the basis on which all other researchers build (The Economist, 2009). Following this study, a bulk of research turned focus on predicting very important statistics, such as unemployment using Google Trends.

Nikolaos Askitas and Klaus F. Zimmermann of German Institute for Economic Research in May 2009 published a study called *"Google econometrics and unemployment forecasting"* (Askitas & Zimmermann, 2009). The authors apply Google Trends by creating word sets, the query data of which is tested on its predictability for the German Unemployment Rate as reported by the Federal Employment Agency on the monthly basis. Four groups of words that potentially represent correlation with employment: "unemployment office or agency", "unemployment rate", "personal consultant", "most popular job search engines in Germany". The logic for these is the following. First of all, people who have lost their jobs are expected to contact an unemployment office or agency, as such the rise in search for these agencies must mark the flow into unemployment. Secondly, searches for personal consultant are expected to reflect the fear of losing the job or an attempt to change the workplace, reflecting the fear of unemployment. The last term – the search engines – should reflect attempts of trying to get employment, therefore predicting the flow into employment. As an underlying model for the analysis the simple autoregressive method, the same as in Choi and Varian (2009), is used. This model is well-known as the error-correction model specification (Engle & Granger, 1987). Identically, the lag values of one and 12 months are supplemented by Google search queries variables and additionally their different lagged values are included in search of the best fit. The best model is selected using R-squared, log-likelihood values and BIC model selection techniques. It is shown that using this simple technique significant result can be achieved, but the modelling must be taken with caution because various policies can distort its significance.

Tanya Suhoy of Bank of Israel in 2009 published a study *"Query indices and a 2008 downturn: Israeli Data"* (Suhoy, 2009). In this work she tests if Google search queries can help monitor economic cycle in Israel. She argues that if there is a shift from a long-term trend of Google variables, the probability of recession increases. Six leading Google Insights for Search categories are found to contain cyclical information: human resources (recruiting and staffing), home appliances, travel, real estate, food and drink, and beauty and personal care. Her proposition is that the first index can be used to predict the unemployment (the rise in the search index corresponds to rising unemployment) and the latter five might be used for analysing consumer confidence (positive relation). The most predictive category of economic recession is found to be human resources. This reiterates the conclusions by other studies that Google Search may be useful in predicting unemployment, which is the reflection of economic cycle. For the purposes of our thesis, this is an important point since we expect this reflection to be extrapolated in the Baltics.

A second study by Choi and Varian follows the methodologies built by Askitas and Zimmermann (2009) and Suhoy (2009) and is released under the name *"Predicting initial claims for unemployment benefits"*(Varian & Choi, 2009). The authors run tests to show that Google Trends can be useful in forecasting the initial claims for unemployment benefits which are released by US Department of Labor on a weekly basis. Initial claims for unemployment benefits statistic are considered the leading indicator of the health of the labor market in US. The authors using standard ARIMA model selection procedures picked AR(1) model as a baseline. First of all, they run the baseline model where the dependant variable is regressed on a one period lagged value of itself. Then they added Google Trends series to see if this improves the forecasting power. The procedure follows the logic of *"Predicting the present with Google Trends"* (Varian& Choi, 2009). Because National Bureau of Economic Research declared that the crisis in US had begun in December 2007, the authors decided to evaluate the model both in the long term encompassing pre- and post-crisis periods and in the short, representing only after-crisis period. Google Trends series on search queries "Jobs" and "Welfare & Unemployment" categories are used, which are bundled by Google Trends according to the search words. The model which includes Google Trends data is significantly better than the baseline and its out-of-sample mean-absolute-error estimated with the rolling window of 24 weeks is decreased by 15.7% for the long term model and by 12.9% for the short term model. Results indicate that in US unemployment-related statistics can also be forecast using Google Trends and after Askitas and Zimmermann (2009) in Germany and Suhoy (2009) in Israel, encourage continuing to research with US unemployment forecasting.

It was not long until another study on US unemployment rate forecasting came out. Francesco D'Amuri and Juri Marcucci of Bank of Italy, in 2010 released the study in which they compare traditional unemployment rate forecasting models with Google-adjusted forecasting models and test the best model accuracy against the forecasts released by the Survey of Professional Forecasters (D'Amuri & Marcuci, 2010). ARMA standard model is chosen as the baseline and is augmented by Initial Claims for unemployment, Google Index (GI) on job-search-related queries and combinations of both with differing lags and time series. They find that the model augmented by GI significantly outperform traditional forecasting models: the mean squared error (MSE) of their best model including GI is 29% smaller in one-period ahead forecasting and 40% lower in three-periods ahead forecasting. As a check, they forecast unemployment rate separately in 51 US states and find that in 70% of cases, the model outperforms its traditional counterparts. Moreover, the model is adjusted to forecast quarterly unemployment rate and is compared to Survey of Professional Forecasters, conducted by Federal Reserve Bank of Philadelphia and again prove that their GI-augmented model is better even in this case. Having run several hundred of different tests and robustness checks they conclude that GI is the best leading indicator for US Unemployment Rate.

In 2011 several other papers on unemployment forecasting expanded the geographical coverage of the research field. Fondeur and Karame (2011) introduce some advanced methodological features to deal with Google data and forecast French Unemployment rate. Dr. Jacques Bughin (2011), a director at McKinsey & Company, finds that in general Google search queries data explains between 16 and 46 percent of fluctuation in Belgian unemployment and retail sales. Nick McLaren and Rachana Shanbogue of Bank of England's Structural Economic Analysis division provide some account of benefits and problems related to Google Search data used in forecasts and overview how it helps analysing UK's labour and housing markets (McLaren & Shanbouge, 2011). Among the benefits they mention that such data is very timely and cover potentially a vast part of the population; it is collected as a by-product of activity and avoids problems related to data collected via surveys (low or inaccurate responses); finally, the data is collected on many different subjects and not on predefined questions, which can help analyse issues that occur unexpectedly. However, there are demerits, too. Google Trends has data available only since 2004, therefore the sample period is rather short at the moment; internet usage is highly correlated with factors such as age and income, therefore the sample may not be fully representative; finally, the way the search queries data is collected poses some problems, because different people may enter same queries for different reasons, which creates noise; in addition, there are still many economic issues which do not directly involve internet search activity, such as firms' investment decisions etc. With all the shortcomings present, however, even the current form of the data is useful in predicting unemployment and housing sales in UK. They use the same methodology as in studies covering Germany, Italy and Israel and find that Google indicators are at least as useful as existing leading indicators in UK and the Bank of England is to continue researching further on the topic.

As regards unemployment forecasting studies in countries where unemployment rate is available on monthly basis, the latest work was done by Chadwick and Sengul of Central Bank of the Republic of Turkey (Chadwick & Sengul, 2012). In their study they show that Google augmented model is better at forecasting non-agricultural unemployment rate in Turkey both in-sample and out-of-sample. When compared to their baseline model, which uses only the lag values of unemployment rate, the Google model is 47.8% more accurate in-sample and 38.8% more accurate in one month ahead forecasts on grounds of relative root mean square error (RMSE). A unique feature of the paper, in relation to other studies, is that they also use Harvey, Leybourne, and Newbold (1998) modification of the Diebold-Mariano test which shows Google search data indeed performs statistically significantly better than the baseline specification.

In Italy, Francesco D'Amuri conducted a study called *"Predicting unemployment in short samples with internet job search query data"* (D'Amuri, 2009). The quarterly data presents more hurdles, as the sample size is notoriously smaller, nevertheless, they prove the results significant and beneficial for better prediction. The dependable variable is the quarterly unemployment number released by Italian Labour Force Survey. Since Google provides weekly search results, these are converted into quarterly frequency simply by taking the average of the queries in that period. The important notice is made by the author regarding the nature of the employees' job search and the unemployment data. He notes that a person is considered unemployed if he has no job and has been actively seeking for it at least once in the last 4 weeks. This said, it is not appropriate to compare the current Google Index search data to the current unemployment rate. Instead he uses a 2-week shift forward for the Google Index data. This is not absolutely true, but it reduces noise in data, even though you cannot exactly tell which period is appropriate because all people have their own intervals of job search. By this he marks that a two-weeks-ago search data is more representative and comparable to today's unemployment than the current search results which will show up in the next unemployment measure. In addition to the Google Index, they include Industrial Production Index (released by Italian authorities) and Employment Expectation Index. Having tested many models with different lag specifications using BIC and AIC, the simple ARIMA(1,1,0) model augmented by GI and EEM lagged value and quarterly seasonal dummies is chosen. ARIMA (1,1,0) model is one of the most cited articles on the unemployment forecasting (Montgomery, Zarnowitz, Tsay, & Tiao, 1998). They conclude that Google Index outperforms other leading indicators in forecasting short term unemployment rate in Italy.

Another study in a country with the quarterly unemployment data is a Master's Thesis by Anvik and Gjelstad from Norwegian School of Management (Anvik & Gjelstad, 2010). They also find that Google search query data contains information useful in short sample forecasting of unemployment rate. Best performing ARIMA Google augmented model has an 18.3% lower MSE than the baseline model. It is also more accurate than the leading indicator of "published job advertisements". These two studies, in spite of noise in data and short sample period, encourage us to apply the methodology to the Baltic countries in expanding geographical coverage of the study.

2.2. Inflation

A very distinct study was written by Guzman on forecasting inflation expectations in the US (Guzman, 2011). In a study he examines 38 different inflation expectation measures – 36 of which are survey based, one market-implied, and one metadata measure. In the examination are included accuracy, predictive power, rationality and out-of-sample forecasting evaluations. Google Trends is incorporated through keyword "inflation". The author argues that Google searches reveal expectations, and if a household is worried about the rising level of prices, it may look for information related to inflation. Since deflation is not a big worry for individuals in a sticky wages economy, the increase in searches for "inflation" should mean the growing anxiety over rising prices and therefore reflect the inflation expectations. In the results he shows that high frequency forecasting models tend to outperform lower frequency models, most popular of which are – the quarterly Michigan Survey, the quarterly Survey of Professional Forecasters and the semi-annual Livingston Survey. He also notes that the best measures are those that are not commonly referred to in the literature. Most interestingly, he finds that the most impressive performance was given by

Google Inflation Search Index. It not only had the lowest out-of-sample forecasting error but also passed weak-form and strong-form efficiency tests when examined separately. And even though, it fails unbiasedness tests and the efficiency test under joint specification, the benefit of near-real time statistic may outweigh these drawbacks.

2.3. Automotive and home sales

The study by Varian and Choi (2009) encompasses not only unemployment or tourism, but also housing and car sales topics. First of all, the authors pick automotive sales for analysis which are reported by US Census Bureau in Advanced Monthly Retail Sales survey (Varian & Choi, 2009). The Google Trends explanatory variables are the data on search categories “auto insurance”, “motorcycles”, “trucks & SUVs” as provided by Google Insights for Search. They find that the model which is adjusted by inclusion of “trucks & SUVs” search data, the R-square increases from 0.6206 to 0.7852 and the mean absolute error (MAE) of the Google-adjusted model is 18% lower compared to the baseline model. Secondly, the automotive sales for brand categories are tested. The results are not consistent among various brands, however. In part, this can be explained by different marketing policies which the simple autoregressive model fails to observe. For instance, in case of forecasts of Ford sales, there was one significant outlier. Having checked company specific reasons, the authors find that a policy called ‘employee pricing promotion’ was the reason behind this outlier. A dummy variable was added to control for that effect and they found that 32.4% of the increase in sales was explained by that dummy variable with the signs on other coefficients unchanged. Thirdly, in forecasting home sales, the data by US Department of Housing and Urban Development is used for housing forecasting and Google search query index on ‘Real Estate Agencies’ is found to be mostly correlated with the housing sales. As a result of its inclusion to the seasonally-adjusted autoregressive model, they find that MAE is reduced by 12%.

Carrière-Swallow and Labbé (2010) conduct, to our knowledge, the first study on car sales forecasting applying Google search queries in an emerging market. The study is important, because it is conducted in a country where Google Trends does not categorise keyword searches into different sections on which the majority of the research has relied. Instead, the authors build their own index of Google index automotive-related searches in Chile and find that the augmented model does better at forecasting in both in-sample and out-of-sample specifications. Their results demonstrated that models that incorporated Google search results performed significantly better than competing benchmark specifications in out-of-sample and in-sample nowcasting exercises. What is more important, the authors found that the accuracy of the models for automobile sales in Chile can be improved using current search queries patterns, which suggests that Google data is a promising source of information when predicting short-term demand for the automobiles.

There are at least two other papers that focus directly on housing sales and prices forecasting using Google Trends. The first was written by Kulkarni, Haynes, Stough and Paelinck (2009) of George Mason University and Erasmus Rotterdam University. In the paper called "*Forecasting housing prices with Google Econometrics*" the authors develop the leading indicator for S&P Case-Shiller index for 20 cities in US. Through several sets of word combinations the authors build Google search variable and perform Granger Causality tests. They find that at the city level Google search Granger causes housing prices, while the opposite causality does not occur. In addition, they find on a national level that Google search can Granger cause national Housing Price Index, therefore creating more timely housing information. The second study and very similar study was conducted by Wu and Brynjolfson (2009) where they predicted not only the price indices, but also the sales volume of houses in 50 US states. It used HPI and Case-Shiller for price and volume forecasting to which Google search queries on predefined 'Real estate' category were added. They estimate that a percentage point increase in the housing search index is associated with additional sales of 67,220 houses in the next quarter. Moreover, the use of search data in out-of-sample forecasts bears MAE of 0.102, which is significantly lower compared to baseline model's 0.441. Finally, they demonstrate that housing sales data can be used for other market movements' predictions, such as sales of house appliances that are directly linked to the sales of new houses.

2.4. Other research areas

Consumer sentiment and private consumption studies fall into another quite broadly researched area. Schmidt and Vosen (2009) build a Google search based consumer sentiment index which they compare to University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index. Their Google based index in almost all in-samples and out-of-sample forecasts outperforms the two indices. Another study, almost identical is written by Huang and Penna (2009) who construct consumer sentiment index using Google search. The final index consists of four components and is highly correlated to University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index. The Google index leads in time among these three indices and provides more accurate forecasts that are tested to be robust and provide additional information than that contained in the other two indices.

Financial markets are yet another topic of interest when it comes to new source of information applications. Firstly, Preis, Reith and Stanley (2010) find that increased search for S&P 500 company names leads to a significant increase in trading volume. Secondly, Da, Engleberg and Gao (2011) in the study called *"In search of attention"* construct a new direct measure of investor attention using Google search frequency. They find that, in a sample of Russell 3000 stocks from 2004 to 2008: 1) Google indicator is correlated and different from existing investor attention measure; 2) Google indicator captures investor attention faster; 3) the indicator is likely measuring retail investor attention. Higher Google indicator results in higher stock price in two weeks and a reversal in a year and higher indicator values also benefit IPO price rise and long-term underperformance. Finally, Ding and Hou (2011) relate higher stock searches to retail investor attention and higher stock liquidity as a result. The results are valid not only in S&P 500, but are also tested in FTSE 100, Euro Stoxx 50, Shanghai 180 markets.

Some studies were initiated in tourism sector. Pan, Wu, & Song (2009) build econometric model to forecast hotel demand based on Google searches, whereas Artola and Galan (2012) forecasted British tourist numbers in Spain. Other studies that were difficult to group into one specific category and they wrote about the predictability of news headlines (Radinsky & Markovitch, 2008); the predictability of the Google search data itself (Matias, Efron, & Shimshoni, 2009); job seeker's reaction to unemployment benefits (Baker & Fradkin, 2011); measuring public attentiveness (Ripberger, 2010) and other.

We next turn to the methodology part of our study where we develop the procedures to apply Google Trends specifically in the Baltics countries.

3. Methodology

3.1. Research design

In our study we try to indentify if Google Trends data has valuable information in forecasting economic variables in the Baltics, therefore we rely on forecasting methodology. The backbone of our study is structured on the Box-Jenkins framework. This method is appealing to our analysis since the Box-Jenkins approach allows identifying the usefulness of introducing any sentiment-based indicator to some baseline model, compare the forecasting ability and identify the best model specification. ARIMA model, as this method is widely known, is a straightforward autoregressive model that is used to make forecasts and introduce other explanatory variable to analyse their contribution to the model.

We, first of all, prepare the data for analysis, which we describe in data description, search queries, seasonal adjustment, Google Trends search queries index and search queries applied sections. Then we choose relevant search queries based on the quality of data and extract relevant statistics and adjust these for seasonality. The first hypothesis is addressed by computing correlation coefficients between real statistics and Google search indices. After that, we use principal component analysis to combine Google searches into best Google components to be used in ARIMA model.

In the second part of our methodology, we describe our ARIMA model procedures. The Box-Jenkins approach in our paper consists of the following steps: data preparation and model selection and forecasting. The first phase starts with examining the collected data statistically for stationarity, for which we apply Augmented Dickey-Fuller tests. We then build autoregressive models of order one and add the Google Indicators to compare if there is any difference in the baseline specification and that augmented by the Google variable. ARIMA model, in essence, makes predictions of time series based on past values of the same series. Aiming to spot the best model specification we try different ARIMA(p,d,q) specifications by varying the p, d and q parameters. We compare all of these models using AIC/BIC information criteria and select the best ARIMA models for baseline and Google-adjusted specifications. Then we are able to compute RMSFE of the best specifications and compare the accuracy of the models, which answers our second hypothesis, mainly if Google augmented models are more accurate than their baseline counterparts.

Finally, we describe the Hodrick-Prescott filter and methodology for analysing the turning points in forecast trends, which is our last hypothesis. It consists of forecasting 6-months ahead and smoothing the obtained trend, and comparing the trend with the actual outcome in order to evaluate whether there are any particular patterns that indicate a turning point.

3.2. Data description

We can describe our data selection process in several steps: choosing key words related to the economic factors of interest, retrieving the Google Search results for these words and converting the data into monthly series, adjusting for seasonality and building the component of the search queries for each of the economic variables we analyse. The components of keywords are used as Google explanatory variables. The dependent variables in our ARIMA models are real statistics on unemployment, inflation, housing sales and automotive sales provided by Lithuanian Statistics Department, Central Statistical Bureau of Latvia, Statistics Estonia, Oberhaus and Datacenter.

The search data is publicly available from Google through their Insights/Trends interface, and is available at a weekly frequency. The interface returns one series per keyword for a given geographical area. It does not return the direct number of searches entered in a given week, but rather provides a normalised statistic which is reported as a fraction of the maximum series value, 100 being the maximum and 0 the minimum. After differencing the data, the available sample period used in our analysis is weekly-level data since January 2004, which amounts to 468 series. When we convert it into monthly statistics, which is needed to comply with the monthly availability of the official statistics of our dependent variable, we have a series of 108 months, however for majority of the variables the sample is much shorter and ranges from 36 to 108 months (observations).

Table 2 Real and search data sources.

	Lithuania	**Latvia**	**Estonia**
Unemployment	*Lithuanian Statistics Department*	*Central Statistical Bureau of Latvia*	*Statistics Estonia*
Inflation	*Lithuanian Statistics Department*	*Central Statistical Bureau of Latvia*	*Statistics Estonia*
Auto sales	*UAB DataCenter*	*UAB DataCenter*	*UAB DataCenter*
Apartment sales	*UAB Oberhaus*	*UAB Oberhaus*	*UAB Oberhaus*
Google queries	*Google Trends*	*Google Trends*	*Google Trends*

Source: Compiled by the authors.

3.2.1. Google Trends search index

In this section, we briefly describe how Google Trends index/value is computed inside the Google search engine. Google Trends provides data on intensity of search queries starting from 1 January 2004. In other words, Google Trends' main purpose is to provide a time series index of the volume of search queries. The value of the index is based only on a share of search query volume. The total aggregated volume for the particular search query is obtained from a specific geographic region. Mathematically speaking the formula is as follows:

$$Google\ Trends\ Index\ value = \frac{Search\ queries\ volume\ at\ period\ t\ (relative\ value)}{Total\ search\ volume\ (highest\ relative\ value)} * 100 \tag{1}$$

The scale is presented in the range of 0-100, where 100 represent the search peak or the highest frequency and intensity of searching activity for the specific query. Firstly, the ratio of new search queries and total volume i.e. relative value is computed. Then Google

Trends Index values for every period are calculated by dividing the relative value by the highest relative value. The peak gets assigned 100, while the rest of them are divided proportionally. If the number of search queries is insufficient the index value is equal to 0 (see Table 3).

Table 3 A numerical example of Google Trends computation.

	1	**2**	**3**	**4**	**5**	**6**	**7**
A number of new search queries (A)	100	200	300	400	500	600	1200
Total volume of search queries (B)	500	700	1000	1400	1900	2500	3700
Relative value (= A/B)	0.20	0.29	0.30	0.29	0.23	0.24	0.32
Google Trends Index value [1]	62	88	93	88	81	74	100

Source: Compiled by the authors.

3.2.2. Search queries applied

We have consulted native speakers of the three languages to find out which searches are used in that country to look for specific information. A list of many keywords then was gathered and each of the words was tested in Google Trends engine. In assessing the useful words we viewed if the time series of the keyword were long enough and if there was any variability or extreme distortions in the series (see Appendix J). The following list of words has been picked as the most qualitative data set.

Table 4 Search queries applied in the computation of Google Trends components.

Category/Country	**Lithuania**	**Latvia**	**Estonia**
Unemployment	*(i) ieskau darbo* *(ii) darbo pasiulymai* *(iii) darbo skelbimai* *(iv) cv online*	*(i) meklē darbu* *(ii)piedāvā darbu* *(iii) reklama lv* *(iv) darba sludinājumi* *(v) cv online*	*(i) cv online* *(ii) otsin tööd* *(iii) cv keskus*
Automotive sales	*(i) autoplius* *(ii) naudoti auto* *(iii) auto skelbimai* *(iv) autogidas*	*(i) automašīnas* *(ii) reklama lv*	*(i) kasutatud autod* *(ii) autoaed*
Housing sales	*(i) butai* *(ii) aruodas* *(iii) nekilnojamas turtas*	*(i) dzīvokļi* *(ii) nekustamais īpašums*	*(i) kinnisvara* *(ii) kv* *(iii) city24* *(iv) korterid*
Inflation	*(i) infliacija*	*(i) inflācija*	*(i) inflatsioon*

Source: Created by the authors.

[1] This is an actual value obtained from Google engine. Calculated by relative/normalized value divided by peak value e.g. Period 6 = (0.2400/0.3243)*100 = 74

3.2.3. Seasonal adjustment

Google search time series data might be affected by seasonal trends, because there are underlying seasonal trends in the real statistics we intend to forecast. For instance, unemployment rate has a certain seasonal trend and this trend is potentially also present in the searches related to unemployment. Before running our tests, we therefore adjust our data for seasonality.

To have an equivalent seasonal adjustment for both real and Google data we use the same method of adjustment. We first extract real statistics which are not adjusted for seasonality and apply Census X-12 seasonal adjustment in eViews software. Then we do the same procedure for each of the Google Trends time series that we have, 32 in total. As a result, we can run tests that will not be predicting seasonal trends themselves, but rather the other effects which we are interested in.

3.2.4. Principal Components Analysis

Google Trends, as a service, is relatively young and its full operations are available only for the largest countries. Among the services that are not available in countries such as Lithuania, Latvia or Estonia is the “Search Categories” function. This service allows selecting a specific search category, for example Auto & Vehicles, and Google Trends presents the single time series for the most related searches with the automotive industry. Because of its convenience, many researchers have utilised this function and used the time series as the Google Indicator in their tests. In the absence of this tool, however, we turn to statistical methods to combine our own Google Indicators from a wide variety of search queries into components.

For this matter a few methods can be used. The most basic method is taking the simple average of the several time series to arrive at a single series, which is arguably inaccurate, because different search queries have different explanatory power. The second way to combine a variety of time series into fewer series, therefore, is to take the weighted average that will account for differences in the explanatory power. With this method, though, there is a question of which series deserve higher or lower weights assigned. Consequently, author’s educated guesses might strongly affect the outcome. The third method, which we use in our study, alleviates the above problems and is based on statistical tests underpinning Principal Components Analysis.

Principal Components Analysis (PCA) is a set of statistical tools with which a few best components are built out of many time series (Smith, 2002). There are two general characteristics of the principal components. First, the components are combined in such a way that they explain the most of the variance. Second, whenever there is more than one component created, they will be uncorrelated among each other and will explain different variances.

The analysis consists of three main steps that we complete in STATA (STATA, 2013). Firstly, a set of similar indicators has to be selected. In our case, the search queries that relate to the same real statistics measure are chosen. For instance, to build the best components to be used in analysing and predicting unemployment in Lithuania, we use time series of these phrases: “CV Online”, “darbo pasiulymai” (job offerings), “darbo skelbimai” (job advertisements), “ieskau darbo” (looking for job). Secondly, we compute eigenvalues and eigenvectors according to which the decision is made on the number of components to be kept. The rule of thumb is to retain the components with eigenvalue greater than unity (Shepherd, 2009). Finally, based upon this rule the number of components is chosen and the time series of these components are created. The variables are now ready to be used in prediction, regressions and other analyses as reliable and high explanatory power possessing components.

3.3. ARIMA framework

The identification process primarily seeks to determine the degree of *p*, *d* and *q* in the ARIMA model. In the ARIMA, we have an intersection of 3 models parameters: *Autoregressive (p), Integrated (d)* and *Moving Average (q)* processes, where the first two deals with incorporation of historical stationary data and the latter one with the moving average of forecasting errors or disturbances i.e. the longer historical data we have the more accurate forecasts we will have, as it learns and smoothens the errors (Alonso & Martos, 2012). Moving average of random disturbances assists on the better overall model fit as it smoothens the errors. Integrated process helps to cope with the non-stationarity or data that contains a unit root, which is important to take into account. Otherwise, the analysis might result in spurious regressions or other econometric shortfalls. We briefly depict the theory and working principle behind each of the 3 components.

Autoregressive model of the pth order:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \beta_1 G_t + \beta_2 G_{t-1} + \ldots + \beta_p G_{t+1-p} + \epsilon_t \qquad (2)$$

Y_t– the dependent variable for real data (unemployment rate, inflation rate, cars and housing sales statistics)

$Y_{t-1}, Y_{t-2},\ldots,Y_{t-p}$ – independent variables at time t-1, t-2…. t-p (all real data)

$\phi_0,\phi_1,\phi_2,\ldots, \phi_p$ – coefficients

$G_{t,}G_{t-1,}G_{t-2,\ldots,}G_{t-p,}$ –independent variables at time t, t-1, t-2…. t+1-p (Google components)

$\beta_1,\beta_2,\ldots, \beta_p$ – coefficients

ϵ_t – error term or disturbances

As a second process in the ARIMA model we have **Moving Average** model of the qth order:

$$Y_t = \mu + \epsilon_t - \theta_1\epsilon_{t-1} - \theta_2\epsilon_{t-2} - \ldots - \theta_q\epsilon_{t-q} \quad (3)$$

Y_t - dependent variable for real data (unemployment rate, inflation rate, cars and housing sales)

μ – constant mean of the series we applied in the models.

$\theta_1,\theta_2,\ldots, \theta_q$ – coefficients

$\epsilon_t, \epsilon_{t-1},\epsilon_{t-2},\ldots,\epsilon_{t-q}$ – error terms or disturbances at times t, t-1, t-2…. t – q

A combination of these two processes results in having ARMA model or ARIMA model with d = 0. In other words, if the data does not contain a unit root (d = 0), we end up having an ARMA model.

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \beta_1 G_t + \beta_2 G_{t-1} + \ldots + \beta_p G_{t+1-p} + \epsilon_t - \theta_1\epsilon_{t-1} - \theta_2\epsilon_{t-2} - \ldots - \theta_q\epsilon_{t-q} \quad (4)$$

To be able to apply our chosen methodology, we must have a time series that is stationary or a series that is stationary at least after data transformation. When the estimated model is to be used for forecasting we must make an assumption that the features of this model are constant through time. Likewise, the importance of stationary data will be investigated and analyzed as it provides valid basis for forecasting. A stationary series is defined by a constant mean, variance as well as auto-covariance. On the other hand, in a non-stationary time series it is seen that the series behaviour is specific only for the time period under consideration, which might result in spurious regressions. Hence, non-stationary time series may be of little practical value unless it is differentiated for the purpose of forecasting. In our methodology this is done by performing Augmented Dickey-Fuller test for stationarity. Furthermore, whenever a time series is stationary it should decay rapidly from the initial value at lag zero. The Dickey-Fuller test could be applied to investigate whether a unit root is present in the time series and hence identifying d in the general ARIMA (*p, d, q*).

$$Y_t = \phi_0 + \rho Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \epsilon_{t-1} \tag{5}$$

We test the null hypothesis that$\rho = 1$ against the alternative hypothesis that$\rho < 1$. Under the null hypothesis, the time series follows a random walk. Subsequently, the test is conducted by substracting Y_{t-1} on both sides of the equation if the data is stationary (Cortez & Rocha, 2004). Using OLS, we run the regression:

$$Y_t - Y_{t-1} = \phi_0 + (1-\rho)Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \epsilon_{t-1} \tag{6}$$

Another important aspect of the model is a number of lags that is usually found out by experimentation. Generally, a rule of thumb is to choose as low degree of lags as possible in order not to lose the degrees of freedom while at the same time large enough that would result in removing any possible autocorrelation in the residuals. Needless to mention, a common pitfall when selecting ARIMA models is to over-specify or over-fit the model, which, on one hand, would improve the explanatory power when using in-sample selection criteria such as the root mean squared error (RMSE), but, on the other, could lead to poor out-of-sample forecasting. Therefore there is a clear need to use selection criteria that will penalise the in-sample variance of residual by taking into account the degrees of freedom in our model. For this purpose we rely on Akaike`s Information Criterion (AIC) and Schwartz Criterion/Bayesian Information Criteria (SC/BIC).

3.4. *Forecasting accuracy measurement*

To assess the applicability and usefulness of our models we use a holdout set when evaluating the predictability and comparing the selected models with and without Google Indicators. Furthermore, the end of the time series is omitted in order to see how well the ARIMA models perform when estimating the variables. As long as we compare the models on their predictive ability we have to compute the RMSFE of the different models on our holdout set. The formula of RMSFE over T periods is as follows:

$$RMSFE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_t^2} \tag{7}$$

$$e_t = \widehat{y_T} - y_t \tag{8}$$

In order to see if Google improves prediction over time we estimate a series of predictions and compute the RMSFE through the period from the best model obtained through Box-Jenkins methodology (Ederington & Guan, 2004). We compare how Google-adjusted models' RMSFE differs from the baseline ARIMA specification.

In addition, we apply a statistical method for evaluating if the difference in RMSFE between Google-adjusted and baseline models is statistically significant. For this matter we use Diebold-Mariano test. In this test model y_t denotes the series that are forecasted; $y^1_{t+k|t}$ and $y^2_{t+k|t}$ denote two competing forecasts of y_{t+k} coming from 2 different models (Mariano, 2000). For instance, $y^1_{t+k|t}$ is computed from our chosen ARIMA models with and without Google components and $y^2_{t+k|t}$is computed from the model without taking into account Google search queries. We call y_{t+k} - Baseline (a baseline model), $y^1_{t+k|t}$ - Forecast (as a pure forecast without a Google component) and $y^2_{t+k|t}$ – Google Forecast (as a forecast that contains search queries from Google). Hence, the forecast errors from the two models would be:

$$\varepsilon^1_{t+k|t} = Baseline - Forecast \tag{9}$$

$$\varepsilon^2_{t+k|t} = Baseline - Google\ Forecast \tag{10}$$

Here, the k-step forecasts are calculated for periods of $t = t_0,\ldots,T$.

$$\{\varepsilon^1_{t+k|t}\}^T_{t_0}, \{\varepsilon^2_{t+k|t}\}^T_{t_0} \tag{11}$$

We should note that data is overlapping, as we use models with real data and the models with real data + search queries from Google search engine. Hence, the errors that come from both forecast models in $\{\varepsilon^1_{t+k|t}\}^T_{t_0}$ and $\{\varepsilon^2_{t+k|t}\}^T_{t_0}$would certainly contain serial correlations. Thus, the accuracy of each forecast can be estimated by a particular loss function:

$$N(y_{t+k,}y^i_{t+k|t}) = N\left(\varepsilon^i_{t+k|t}\right), \ \ i = 1,2 \tag{12}$$

Further, we use the absolute error loss function as we are aiming to evaluate predictive accuracy or difference between two competing forecasts:

$$N(\varepsilon^i_{t+k|t}) = \ |\varepsilon^i_{t+k|t}| \tag{13}$$

The next step in comparing forecasting accuracies is to determine which model gives more accurate forecasting. Hence, consider the following null hypothesis that says the both models contain equal predictive power:

$$H_0\!: E[N(\varepsilon^1_{t+k|t})] = E[N(\varepsilon^2_{t+k|t})] \tag{14}$$

In the end, we see that the Diebold-Mariano test is based on the loss differential:

$$D_t = N(\varepsilon^1_{t+k|t}) - N(\varepsilon^2_{t+k|t}) \tag{15}$$

where, the null hypothesis that forecast accuracy of both types of models are equal or the difference is not statistically significant:

$$H_0: E[D_t] = 0 \tag{16}$$

Therefore, the Diebold-Mariano test statistic is summarized as follows:

$$\overline{D} = \frac{1}{T_0}\sum_{t=t_0}^{T} D_t \tag{17}$$

$$Long\ Term\ Variance(\widehat{LTV}_{\overline{D}}) = \gamma_0 + 2\sum_{n=1}^{\propto} \gamma_{n,}\gamma_n = Cov(D_t, D_{t-n}) \tag{18}$$

$$S = \frac{\overline{D}}{\sqrt{(\widehat{LTV}_{\overline{D}}/T)}} \tag{19}$$

In theory and common research practice the long-run variance is used, because the sample of loss differentials $\{D_t\}_{t_0}^{T}$contains a serial correlations long as k > 1(Costantini & Kunst, 2007).Finally, we consider that the forecasting power is not equal or the differences is not statistically significant if the actual value is higher than 10% critical value S = 1.645, as Mariano (2000) suggested that the errors follows a normal distribution with the classical features of N (1,0).

3.5. Hodrick-Prescott Filter

In this section, we go through the main points of our methodology for testing 3rd hypothesis whether search queries from Google Trends engine contain any valuable information in forecasting trend’s turning points. The working principle might be subdivided in key 3 stages: 1) Making 6-steps (months) ahead forecasting that are mainly based on ARIMA model augmented by Google Trends data and creating the trend from the forecasts; 2) Carrying out the trend smoothing with Hodrick-Prescott filter (HP)=14400in statistical software eViews; 3) Comparing this forecasted trend with the actual outcome graphically and evaluating whether the trend turned earlier and, thus, indicated the turn in the real data. In other words, we evaluate Google Trends ability to perform as a new leading indicator in economic activities.

To begin with, HP filter is a favourable empirical technique and is used in many areas among researchers. The filter is a specialised filter for cyclical trend that works as a smoother (Maravall & Rio, 2001). This technique is particularly useful in coping with short-term fluctuations that are very common in the business cycle. What is more important, it helps to reveal true long-term trends of any macroeconomic variable or economic activity (Pedregal & Young, 2000). For successful implementation of this filter, we have decided to employ the statistical software eViews. The main working principle is the following:

$$x = t + c \tag{20}$$

Where $x \epsilon R^T$ is a time series, which consists of a trend $t \epsilon R^T$ as well as a cycle $c \epsilon R^T$. We make a definition for the trend disturbance $v \epsilon R^{T\text{-}2}$and suppose that

$$v_t = ((t_t - t_{t-1}) - (t_{t-1} - t_{t-2})) \qquad t = 3,4, \dots, T \tag{21}$$

$$v = Kt \tag{22}$$

$$K = \begin{bmatrix} 1 & -2 & 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & -2 & 1 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \dots & 1 & -2 & 1 \end{bmatrix}^{(T-2)xT} \tag{23}$$

The second step of HP filter procedure consists of resolving the original time series $x \epsilon R^T$, which we have defined previously, into trend $t \epsilon R^T$ and irregular component or cycle c ϵR^T. This is obtained by the minimization approach of the sum of squares, which is also weighted:

$$c'c + \lambda v'v = (x - t)'(x - t) + \lambda t'K'Kt \tag{24}$$

We make a first order derivative with respect to *t* and rearrange the equation.

$$t = (I_T + \lambda K'K)^{-1}x \tag{25}$$

Lastly, the outcome from the equation (25) is our smoothed line in turning points analysis as this equation is the HP filter that connects the trend $t \epsilon R^T$ to the time series $x \epsilon R^T$, depending on the smoothing parameter λ, which in our case is equal to 14,400 and has been proven to be an optimal value for monthly statistics (Doorn, 2001).

In the next section we turn to the empirical findings of our study. First of all, we test our first hypothesis and provide the correlation analysis which helps to answer if Google search data is related in any way to real statistics. Secondly, we present the choice of ARIMA models and assess if Google-adjusted models have lower RMSFE and are more accurate than their baseline counterparts, which answers our second hypothesis. Finally, we present the results of the analysis intended to show if Google-adjusted models help more accurately predict the turning points in trends.

4. Empirical findings

4.1. Correlation analysis

In answering the research question of whether Google Trends has valuable information in forecasting macroeconomic variables in the Baltic countries, we start out by testing our first hypothesis. We postulate that the popularity of the search queries people are entering into search engine Google must be positively correlated with the real activity in the economy, which is represented by real data statistics. The real data statistics are the monthly statistics on unemployment rate, inflation rate, car sales and apartment sales, all of which are in bold in the tables below. Below them we state the related search queries that we analyse and the corresponding correlation coefficients and significance level.

4.1.1. Lithuania

The unemployment rate and Google search queries for the related terms have very strong correlations in Lithuania (with an exception for one term) and virtually all of the coefficients are statistically significant event at 1% level of significance. Most closely related to the actual unemployment rate is the search “CV Online” with the correlation coefficient of 0.886. This result compares positively with 0.821 correlation coefficient achieved in the study of forecasting Italian unemployment (D’Amuri, 2009). CV Online is the largest employment agency in Lithuania and the result is therefore completely intuitive. When people are jobless or are about to become unemployed, they turn to job advertisements and employment agencies, which increases the searching activity for the term and reflects the real economic movement to unemployment. Furthermore, two other terms “darbo pasiūlymai” (job offers) and “darbo skelbimai” (job advertisements”) have strong positive and statistically significant correlations as can be seen from the Appendix O. However, there are one time series that have a counterintuitive correlation coefficient. “Ieškau darbo” (look for a job) seems to be negatively correlated to the unemployment rate. Besides the coefficients does not have the same level of statistical significance as other search queries and the correlation rapidly converges to zero. We argue that this might occur, because the search term itself is not so popular and too broad, that it fails to represent the unemployment rate and hence an illogical correlation. Overall, the unemployment search queries have mostly intuitive correlations and therefore are ready to be tested further.

Inflation and its testing using Google Trends is quite difficult as people rarely look for inflation rate and capturing the inflation effect in the Google search engine is almost impossible. Nevertheless, we postulate that when there is a broad concern for rising prices in a country, there will appear students, researchers and other citizens who follow the state of the economy and look up inflation rate on the internet. We find that in Lithuania there is actually quite a strong and positive correlation of 0.427 between the inflation rate and the search query "infliacija" (inflation) with the first 3 lags being statistically significant at 1-5% levels of significance. This positive relationship allows using inflation searches in testing further hypotheses.

Automotive sales statistics are analysed against 5 different search queries. Only two out of these have positive correlation coefficients. Positive coefficient in this case is interpreted as an indicator that whenever there is an increase in search activity for "nauji automobiliai" (new cars) and "Autoplius" (the largest auto advertisements platform) there is a corresponding rise in actual car sales. Because the car sales statistics provided by DataCentre refer mainly to new car sales statistics, we notice the largest coefficient of 0.695 with the new cars search query. A surprising result is that Autogidas, the second largest online auto advertisements portal in Lithuania, has a negative correlation with the car sales statistics. In this case it is also plausible that the overall interest in Autogidas webpage is not as great as that of its leading competitor Autoplius, which is the reason behind this unexpected result and the fact that the majority of cars sold through Autogidas are second-hand cars which do not represent our real statistics of new cars. We should also note that the correlations were not statistically significant where we did not obtain an expected sign for a search query e.g. "auto skelbimai", "naudoti automobiliai".

Finally, we look into our findings in apartments and related searches' correlations. Two out of four search queries turn out to be useful. Firstly, Aruodas, the largest real estate advertisements portal in Lithuania, has a correlation coefficient of 0.481, which is statistically significant at 1%. Secondly, "parduodami butai" (apartments for sale) have the correlation coefficient of 0.338, which is statistically significant at 5%. The other two terms "butai" (flats) and "nekilnojamas turtas" (real estate) prove not to be the best searches for analysing apartment sales. The first query may refer not only to sales, but perhaps more often than not to the apartments for rent. In the latter case, real estate is too broad a term which may be used for looking for other forms of assets than apartments alone.

Overall, Google search queries are mostly positively correlated with the actual underlying economic statistics in Lithuania and most importantly, all of the correlations are statistically significant at 1-5%, which provides valid basis for our further investigation and testing all of our hypotheses. Note, however, that in (see Appendix O) there are time series whose *t-12* correlations are stronger than current *t* correlations, which may give rise to spurious regressions. To avoid these problems in performing further tests we transform the data set using first differences and obtain stationary time series, which is supported by the Augmented Dickey-Fuller test.

4.1.2. Latvia

Unemployment correlations in Latvia prove slightly worse than in Lithuania. Only one time series acquire intuitive positive correlation and three other Google search queries turn out negatively correlated (see Appendix P). CV Online, the most popular online employment portal in the Baltics, is the single most statistically significant correlated variable, with the coefficient of 0.820. This is almost identical to the result achieved by D'Amuri in Italy (D'Amuri, 2009). While "darba sludinajumi" (job advertisements), "mekle darbu" (look for a job) fail to comply with our expectations and are negatively correlated with the actual Latvian monthly unemployment rate.On the other hand, the negative correlation of "piedava darbu" (offer a job) and the unemployment rate is correct, as the increase in the number of job offers decreases the unemployment rate. Furthermore, the coefficients for "darba sludinajumi" and "mekle darbu" are virtually statistically insignificant at all 12 lags.

The correlation between inflation and relevant search term is slightly stronger in Latvia than in Lithuania and statistically significant at 1% for all 12 lags that we are investigating. Period **t** correlation coefficient reaches 0.460 and offers a medium sign of relationship. Although the coefficient is not too strong, it is interesting to see the resemblance of the pattern to Lithuania and Estonia. As long as it is positive we apply the queries in further hypotheses' tests.

Automotive sales and the related terms have positive correlation coefficients. "Automasinas" (cars) and "reklama.lv" (a local advertisements portal) correlation coefficients are 0.552 and 0.381, respectively. "reklama.lv" is not a pure auto advertisements agency, which creates unnecessary volatility in the data and results in a weaker correlation as well as smaller level of significance. For auto sales in Latvia we have considered other search terms, too, such as "Autoplius", but the search activity is too small or the resulting time series are too short and too noisy to be included.

Finally, Google search queries fail to obtain positive correlation coefficients on the apartment sales statistics in Latvia, and there are reasons for that. The primary reason is that when it comes to looking for a flat online in Latvia the first website to visit is SS.LV rather than searching “dzivokli” (apartments) or “nekustamais ipasums” (real estate). However, we could not use this search term as the webpage consists of many more categories people visit to explore, for example, job advertisements, auto advertisements, leisure etc.

4.1.3. Estonia

Estonia compared to Lithuania or Latvia has shown much better results (see Appendices O-Q). Out of 10 different search queries that we apply in Estonia, only one series obtain negative sign of correlation, which is also statistically insignificant. In analysing unemployment rate we use “otsin tood” (look for a job), CV Online and CV Keskus (another online employment agency) and they all have positive and statistically significant at 1-5% first order correlation coefficients of 0.272, 0.604 and 0.680, respectively. CV Keskus in this case is the most accurate measure and is slightly more correlated than the unemployment search query CV Online which is the best indicator in the other countries.

Using the logic and practice established by Guzman (2011), we use the keyword “inflatsioon” (inflation) to capture a potential concern of rising inflation. Inflation testing returns very similar coefficients among the three countries. In Estonia it is a positive 0.340, and they are 0.427 and 0.460 in Lithuania and Latvia, respectively. Besides, the coefficient exhibits statistical significance that provides a valid basis for our model.

Auto sales statistics and the terms “autoaed” (cars) and “kasutatud autod” (used cars) are positively correlated. The former has the coefficient of 0.647 and the latter obtains the coefficient of 0.595, which both are relatively strong results. No other terms related to cars were significant in volume, volatility across time or were statistically significant event at 10%.

Finally, Estonian statistics on apartment sales have 3 positively correlated Google search terms. Similar to the results in Latvia and Lithuania, the search terms relating to some online agency or portal do best in reflecting the search activity and changes in interest level. City24, a real estate agency, is chosen as a search term for the apartment sales and it obtains the correlation coefficient of 0.708. “korterid” (apartments) comes in second with the coefficient equal to 0.423. “kinnisvara” and “kv”, which both relate to the real estate, have performed slightly worse and were not statistically significant.

To sum up, we have shown that the vast majority of the search queries we postulated that the search queries that are correlated with the real statistics possessed strong and statistically significant correlation in the Baltic countries. The positive and significant correlations allow us to build principal components out of these series and use them in our further tests. These results support our first hypothesis and we proceed in the following sections with further analysis to answer our research question.

4.2. ARIMA models selection and forecasting

We continue our review of the empirical findings by moving to the second hypothesis testing, which postulates that the inclusion of Google search data into forecasting model improves the prediction accuracy vis-à-vis the baseline model. We start out by making necessary data transformation and choosing the right number of *MA(q)* and *AR(p)* terms. Furthermore, the obtained data is examined using statistical tests. A sample that consists of over 50 variables and 36-108 observations for each variable allows us conducting univariate time series predicting. In applying the Box-Jenkins methodology it is required that the time series be stationary or, in other words, should not contain a unit-root. Otherwise, as we discussed previously the data must be transformed by taking the differences. Needless to mention, the main objective of Box-Jenkins methodology is to find out and estimate a chosen model before even applying ARIMA model forecasting and evaluation of the outcome. Hence, for the purpose of credible forecasting, stationary time series data that contains a unit root will be worthless unless it is differentiated. The differentiated series indicate that the autocorrelation function rapidly converges to 0 as the number of lags increases (much faster than before differencing), and in our correlation analysis we spotted some time series that do not converge to 0.The Dickey-Fuller has been applied with the aim to investigate if time series data is non-stationary and contains a unit root (*ARIMA(p,d,q)).* In the example below (see Table 5) we clearly see that non-transformed data for unemployment rate in Lithuania contains a unit root (non-stationary). For instance, non-transformed data of unemployment rate in Lithuania does contain unit root, since actual value in Interpolated Dickey-Fuller test is equal to -0.7980 and it lies within acceptance range. Having done first differencing (d = 1), the value becomes equal to -5.2600, meaning that we strongly reject the hypothesis that data is non-stationary. In all of the cases, except for inflation, the data was non-stationary in the first place and required taking the difference that fixed this problem and Dickey-Fuller test strongly rejected the hypothesis that time series data contained a unit root after the differencing had been completed (see Appendices L-M).

Table 5 First difference data transformation for unemployment rate in Lithuania.

Interpolated Dickey-Fuller critical value				
	Actual value	1%	5%	10%
ue_lt	-0.7980	-3.4840	-2.8850	-2.5750
D.ue_lt	**-5.2600**	**-3.4840**	**-2.8850**	**-2.5750**

Source: Computed by the authors.

Selecting pure *AR(p)* and *MA(q)* models as stated previously is very important in Box-Jenkins methodology. Undoubtedly, there usually will be more than one model that might seem suitable to the research and further analysis. However, it is also worth noting, that a very common trap when selecting ARIMA models is to over-specify the model through data mining. On one hand, it would improve RMSFE in our in-sample forecasting. On the other hand, it might clearly result in poor predicting power in the out-of-sample forecasts. Therefore, we understand that there is a necessity to use selection criteria that would penalise the variance of in-sample residual. We apply Akaike`s Information Criterion (AIC) and Bayesian Information (BIC) criteria, that aims to minimise the residuals sum of squares and add a penalty term which takes into the account the number of estimated parameters. In addition, the advantage of applying a penalty model is that it is objective and allows a comparison of different ARIMA models. We run the models with up to 3 autoregressive and moving average lags, which is a common practice among researchers. Below there is an example of our selection method for *AR(p)* and *MA(q)*:

Table 6 AR(p) and MA(q) identification for unemployment rate in Lithuania.

		AIC	**BIC**
ue_lt	(1,1,1)	91.1694	103.8965
	(1,1,2)	87.1971	103.1061
	(1,1,3)	85.5953	104.6860
	(3,1,1)	89.2127	108.3034
	(2,1,1)	89.2995	105.2085
	(3,1,3)	**65.3232**	**90.7775**
	(3,1,2)	87.2934	109.5659
	(2,1,3)	90.8252	113.0976
	(2,1,2)	87.2605	106.3512

Source: Computed by the authors.

In general, AIC is more favourable compared to the BIC as it will usually result in a lower number of *AR(p)* or *MA(q)* terms. However, the differences between AIC and BIC criteria are not that remarkable in most of the cases and result in very similar suggested models. We have run 9 different combinations of ARIMA models containing *p* and *q* legs from 1-3 and, hence, choosing the models that contain the lowest AIC or BIC and progress with them to the next steps in the Box-Jenkins methodology. In total, there were 26 different baseline ARIMA models (with and without search queries from Google) and this selection resulted in 234 (9 x 26) combinations of possible models for our further research. In Appendix R we list baseline and Google-augmented models that we selected.

4.3. Prediction error comparison

Having selected the baseline ARIMA models and the Google-adjusted ARIMA models we compare the predictive accuracies and answer our second hypothesis which argues that Google-adjusted models are more accurate than their baseline counterparts. In the Table 7below we state the RMSFE for the twelve best baseline models and 14 Google-adjusted models which we selected in the previous section (see Appendix R).We then calculate the difference between the RMSFE of baseline and Google-enhanced models to check if it changes. Finally, we run Diebold-Mariano significance test to assess if the improvement in forecasting accuracy is significant. This procedure is carried out on two data sets, the first is the whole data set and the resulting forecasts are in-sample; the other case is when we divide the data set into two parts and use the model developed with one part of the data set to predict the other part's data, and hence it is out-of-sample forecasting.

In 11 out of 14 cases we find that Google-adjusted ARIMA models are more accurate than the baseline model specifications, which supports our second hypothesis (see Table 7).

Table 7 In-sample forecasting, accuracy and significance test.

	RMSFE (before)	**RMSFE (component1)**	**Change**	**Diebold-Mariano test (P-value)**	**RMSFE (component2)**	**Change**	**Diebold-Mariano test (P-value)**
ue_lt	0.2817	0.2579	-8.47%	0.1007	0.2650	-5.93%	0.0949
ue_lv	0.6028	0.5710	-5.28%	0.0833	-	-	-
ue_ee	0.4864	0.4940	1.55%	0.2098	-	-	-
inf_lt	0.4493	0.3586	-20.19%	0.0025	-	-	-
inf_lv	0.3295	0.3366	2.18%	0.3369	-	-	-
inf_ee	0.3725	0.3596	-3.48%	0.0961	-	-	-
cars_lt	146.2053	139.1834	-4.80%	0.0890	135.7119	-7.18%	0.0866
cars_lv	129.3272	142.6068	10.27%	0.2315	-	-	-
cars_ee	133.0732	80.4510	-39.54%	0.0353	-	-	-
housing_lt	48.7325	46.1874	-5.22%	0.4217	-	-	-
housing_lv	49.7215	46.5963	-6.29%	0.0872	-	-	-
housing_ee	47.5956	46.1401	-3.06%	0.0917	-	-	-

Source: Created by the authors.

Firstly, let us analyse the improvements achieved in forecasting unemployment. By adding Google search component into the baseline ARIMA model specification we obtain lower RMSFE for Lithuania and Latvia, however, a higher one for Estonia. The RMSFE declines by 8.5% and 5.3% in Lithuania and Latvia, respectively, but rises 1.6% in Estonia. Diebold-Mariano significance test yields that the results are significant for the first two countries and insignificant for Estonia at a 10% significance level. There were two components related to unemployment searches in Lithuania, and if we use component 2 the RMSFE decreases by 5.9% and is also statistically significant. If compared to the previous research, our result is slightly weaker than Varian and Choi (2009) where their short-time forecasting model for US unemployment enhanced by Google searches returned a 12.9% lower prediction error than the baseline specification. D'Amuri and Marcuci (2010), on the other hand, in their study on US unemployment forecasting go way further and augment simple ARMA standard model by Initial Claims for unemployment, Google Index (GI) on job-search-related queries and combinations of both with differing lags. They achieve a 29% decrease in the mean squared error (MSE).

Secondly, we look at the inflation forecasting using Google. The RMSFE is reduced by 20.19% in Lithuania and 3.48% in Estonia, whereas it increases in Latvia when we augment the baseline models. We argue that searching for inflation is least intuitive representation of a possible rise in inflation rate, which is reflected in rather weak 0.3-0.4 first order correlations between searches and inflation statistics in the Baltics.

Thirdly, we compare the predictive accuracy of Google-adjusted models in forecasting car sales. We find that Google searches for cars in Lithuania, as bundled to component 1 and component 2, reduce the RMSFE by 4.8% and 7.2%, respectively. A huge error reduction is achieved in Estonia, where the RMSFE lowers by 39.5% compared to the baseline model. No improvement is achieved in Latvia, however, where the accuracy decreases by 10.3%. Our results resemble these of several other studies. Varian and Choi (2009) find that Google index improves forecast accuracy by 18% measured by decrease in MSE. Carrière-Swallow and Labbé (2010) in Chile find that their built Google Trends Automotive Index reduces RMSE by around 10% across several specifications.

Moreover, Google searches turn out useful in predicting apartment sales across the three Baltic countries. We find that RMSFE in Lithuania, Latvia and Estonia are reduced by 5.2%, 6.3% and 3.1%, respectively. Unlike previous search categories, apartment sales show better results for all of the countries. However, the improvements are not that significant as in US studies and Diebold-Mariano test fails to reject the hypothesis that forecasting accuracies of the baseline and Google models are different in Lithuania. The main reason for lower improvement is that apartment sales data quality in the Baltics is worse than in US. In

Lithuania, for instance, National Registry is the body which provides real estate data for companies, however, this information is inaccurate and the largest real estate companies have their own data sourcing techniques and therefore have very different data sets. The Register data is not correct, because it depends on the date when the property is officially registered which might take place at a different time than the actual purchase date, hence distorting the statistics. In US, on the other hand, there is the famous S&P Case-Shiller Home Price Index for home prices and US Census Bureau which provides the volumes of home sales statistics, which are reliable and have been successfully used in Google studies by Kulkarni (2009) and Wu and Brynjolfsson (2009).

Besides, we performed computations and RMSFE changes as well as predictive accuracy with equal ARIMA models. In other words, we employed ARIMA models with the same number of *p* and *q* for AR and MA processes correspondingly. The tests for stationarity have been performed in both case regardless the choice of the model. The results indicate that search queries from Google contain some valuable information as the forecasting errors have decreased (see Table 8). However, we have a smaller number of macroeconomic variables where forecasting errors decreased. For instance, forecasting error for unemployment rate in Latvia has actually increased as much as 14.7% though the hypothesis that the models with and without Google components had the same predictive accuracy has been rejected i.e. p-value = 0.3194. In a similar manner, the predictive accuracy decreased for inflation rate in Estonia, however not statistically significant, too. Generally speaking, the results obtained were not as good as in the case of the best models (with and without Google component) selection. On the other hand, the majority of forecasting errors decreased and was statistically significant at 5-10% level while the results were statistically insignificant in the cases of absence of RMSFE improvement.

Table 8 In-sample forecasting accuracy and significance test (Models with the same p and q in ARIMA).

	RMSFE (before)	RMSFE (component1)	Change	Diebold-Mariano test (p-value)	RMSFE (component2)	Change	Diebold-Mariano test (p-value)
ue_lt	0.2817	0.2579	-8.47%	0.1007	0.2656	-5.71%	0.1052
ue_lv	0.6028	0.6914	14.69%	0.3194	-	-	-
ue_ee	0.4864	0.4940	1.55%	0.2098	-	-	-
inflation_lt	0.4493	0.3899	-13.24%	0.0006	-	-	-
inflation_lv	0.3295	0.3489	5.90%	0.5064	-	-	-
inflation_ee	0.3725	0.3781	1.50%	0.9656	-	-	-
cars_lt	146.2053	139.1834	-4.80%	0.0890	137.7734	-5.77%	0.0460
cars_lv	129.3272	147.8174	14.30%	0.4105	-	-	-

cars_ee	133.0732	80.4510	-39.54%	0.0353	-	-	-
housing_lt	48.7325	46.1999	-5.20%	0.0722	-	-	-
housing_lv	49.7215	48.8358	-1.78%	0.0946	-	-	-
housing_ee	47.5956	46.1401	-3.06%	0.0917	-	-	-

Source: Created by the authors.

Finally, we carry out the same tests out-of-sample. The Google-adjusted models fail at out-of-sample forecasting and in the majority of cases the RMSFE of the adjusted model increases quite significantly. This might be caused by very short samples that Google Trends now offers and therefore models become over specified for the given sample. It is very convenient to compare the graphical representation of the model performance in-sample and out-of-sample by looking at the Appendices A, B, C for in-sample and Appendices D, E, F for out-of-sample performance. Notice how the latter models are less aligned with the real data.

In closing, the second hypothesis is not rejected if we analyse in-sample, whereas it can be rejected in an out-of-sample analysis. We argue that currently the data set has its flaws, because it is too short and contains two business cycles that cannot be fixed for in this set.

4.4. Turning points

In this section we describe and analyse graphically Google Trends' ability to predict turning points of trends earlier than the benchmarks. On one hand, the incorporation of search queries from Google in forecasting turning points makes this study novel, on the other, the small sample size (2007-2012) obtained from the Google interface and the fact that this short sample was used for 6-months prediction, makes the interpretation and robust conclusions extremely challenging. As we have discussed in the methodological part, the forecasting accuracy is compared against the real data at time t and forecasts that are based on all information except search queries from Google (Benchmark). In general, the smoothed line has to be: 1) Remarkably closer to the baseline; 2) Make a turn earlier than the baseline or at least benchmark.

4.4.1. Lithuania

Given the size of the sample, the most significant and interpretable results were obtained for unemployment rate and car sales (see Appendix G). Car sales significance is consistent with the fact that more and more shoppers gather information carefully and intensively when considering a large acquisition that demands huge financial commitment (Wesley, LeHew, & Woodside, 2006). Although there is a sufficient amount of data for a real inflation rate the stationary nature of data and a very small sample for search queries resulted in the fact that the line is quite straight. This issue brings some interesting, but not insuperable challenges in making the interpretations of the data. If we look at the car sales we see that the line turns a little bit earlier than the baseline (see Appendix G). For instance, Google component 1 (dotted line) began demonstrating a possible drop in cars' sales already in 2007 while the sales peaked in the beginning of 2008 and started decreasing sharply as a result of the global crisis in 2008. This suggests that smoothed series of search queries can be a particularly useful sentiment indicator. The possible success can also be explained by a sufficient amount of search queries, which comes from an increased activity in searching for autos on mobile phones, as well as the fact that people tend to consider a large acquisition more carefully before making the decision that requires a large financial commitment (Wesley, LeHew, & Woodside, 2006). For instance, the independent survey agency indicated that as much as 11% of all consumers tend to make large acquisitions on the internet (RinkodaraLT, 2012). However, we to be cautious as the Hodrick-Prescott filter does possess high accuracy at the ends of the sample and we will not venture to draw robust conclusions as the predicted turning points were in the beginning of the sample.

On the other hand, housing sales have not demonstrated as good a performance with the primary reason of relatively small sample of the search queries related to housing activities i.e. it is often the case, that there is simply not enough search queries (Google Trends = 0). Nevertheless, we still can see increasing Google components line together with very volatile, but rising level of housing sales virtually at the same time. In this scenario, it did not perform well as a leading indicator. Apart from that, Google component is a better predictor than just a straight benchmark line (see Appendix G). Unfortunately, the performance of forecasted trend in inflation rate suggests that there is no value in anticipating a major change well in advance. Moreover, the correlation between search queries and the real data is remarkably lower than among other macroeconomic variables and corresponding search keywords. Hence, one should not be surprised by the absence of relationship between people's sentiment or activity in searching information about inflation and real data. As a result, we have very straight lines and very little to zero value in predicting turning points in Lithuanian inflation rate.

As it is clearly seen from the graph (see Appendix G), the search queries for job-related activities started to climb in the period of June 2007- June 2008when the unemployment rate was at historical lows. Moreover, the pattern of search queries suggested possible sharp jump in number of unemployed people several months in advance. As it proved to be the case, unemployment rate just skyrocketed afterwards. On the other hand, we would not venture to strictly conclude that job-related search queries anticipate major changes in unemployment rate in advance, as our sample contains only one type of business cycle – economic downturn.

4.4.2. Latvia

The Google components did perform equally well to benchmark lines and did not indicate a major change in real data in advance. For instance, the unemployment rate peaks around January2010, so do Google search queries (see Appendix H). Certainly, a number of search queries are partly related to and dependent on emigration scale, as whenever the unemployment rate goes up there is a higher temptation to look for career opportunities abroad and Latvia still remains as one of top countries in emigration across Europe (Elta, 2011). Latvia is also among top 3 as a frequent shopper online with as much as 70% population shopped at least once online (Gemius, 2010). As a result, we can see that housing and cars' sales are moving in step, suggesting that people do not search for exploring or consideration purposes, which could indicate their willingness or plans to make a large acquisition, but rather to make a predetermined action to buy a car or home.

The results for inflation rate again proved to be very insignificant and of little value, suggesting that there is no value of Google components in trying to anticipate particular patterns or, more importantly, breakouts in the inflation rate. All in all, the results are less significant and contain less valuable information compared to Lithuania.

4.4.3. Estonia

Interestingly enough, the results reveal the fact that usage or penetration of internet does not necessarily result in a stronger Google Trends' power of being a leading indicator. Estonia has had the highest internet penetration in the Baltics in the period (Eurostat, 2013), however Google Trends data does not perform better in spotting turning trends than in other countries. In Estonia we see that there is a direct relationship between search queries and the number of new cars sold at time **t**, meaning that the timeframe between search query and an acquisition is very small – no valuable information in forecasting a turning point in advance (see Appendix I). Hence, we can conclude that the search queries from Google do not have a superior ability to predict a turning point in advance. Also, the turning points were not predicted for inflation rate in advance either, which is in line with the findings for Latvia and Lithuania. All in all, the smoothed 6-months ahead forecast did not show outstanding performance in anticipating major changes or breakouts in real data of key economic activities and resulted in the strong rejection of 3rd hypothesis for Estonia, in particular.

Taking into account the fact that the search queries contain valuable information for forecasting short-term activities we aimed to raise the question whether adding search queries would result in ability to predict turning points in advance. Hence, we were seeking for further comparison of the forecasting performance of the models that contains and does not contain Google Trends (Benchmark and Google components). In a similar manner to the previous computations and econometric analysis, we have used the existing database of the variables for our model estimation. Our analysis suggests that search queries might contain some valuable information in forecasting turning points. This is particularly the case in forecasting unemployment rate and cars sales in Lithuania, where the turning points changed its direction earlier (several steps in advance) than a turn in real data occurred. Unfortunately, it is not the case with the remaining countries, as the absolute numbers of search queries are remarkably lower. Our findings from this section conclude that there is a potential for the method used, however limited availability of data makes practical implementation extremely challenging and nearly impossible. Hence, we reject the 3rd hypothesis as majority of the results did not demonstrate Google components superior ability of anticipating a turning point in key economic activities in advance.

4.5. Baltic comparison

Given the results of our three hypotheses' testing, we compare the results across the three countries. If we firstly look at the correlation analysis we find that Lithuania and Latvia obtained 6 and 5 unexpected correlations, respectively, while in Estonia only 1 such case occurred. What is more, that case ("kinnisvara") itself can be explained by the fact, that the search query does not entirely render the intended meaning. The evidence of such a remarkable difference in correlations of Estonia, as compared to the other two countries, raises a question of whether there are any structural or other reasons underlying this case.

Our main reckoning is that there must be something with the overall internet usage in Estonia that makes Google search results more accurate and significant. Google data is available from 2004 onwards; therefore we analyse the internet penetration statistics of the three Baltic countries for the same period. We find that at the start of the period, in 2004, Estonia's internet penetration was 45%, which was almost double the size of penetration in

Lithuania and Latvia at that time (Eurostat, 2013). The gap between internet usage in Estonia and the other two countries has almost disappeared by today, however, Estonia has persistently had higher level of internet usage.

There are underlying reasons for that. Ever since Estonia became a democratic state after the collapse of the Soviet Union, it started investing into the Information and Communication Technologies (ICT) and has become one of the most advanced e-societies in the world (Estonia, 2012). Today it offers e-Government, e-Vote, e-Healthcare, e-ID and many other electronic services that other countries are far away from introducing. With a strong focus on becoming technologically advanced, through constant investment in ICT and educational programs, such as the famous Tiger Leap program (Kangur, 2009), Estonian citizens are more sophisticated when it comes to computers and therefore internet usage and this provides a potential explanation for more significant correlations.

As a second step, we look at the prediction error reductions across the Baltics. On this occasion Lithuania sees all 4 ARIMA models' prediction accuracy improve when the Google components are added. In Estonia, on the on the other hand, there are 3 out of 4 cases when the Google inclusion helps to reduce RMSFE and there are 2 such cases in Latvia (see Table 7).That said, the expectation that the higher internet penetration in Estonia will help to better improve ARIMA benchmark models has not been fulfilled. Higher penetration did help with more logical correlations, but was not in any way exceptionally helpful in predicting more accurately. Some people might be more inclined to gather a vast variety of information before turning to real actions, whereas others might be quick with that, which makes internet penetration alone not an all-encompassing factor deciding the usefulness of search queries in forecasting.

Finally, we investigate Google Trend's potential of anticipating turning points and breakouts in economic activity well in advance. The smoothed lines of 6-months forecast show that there is very little value in predicting a turning point in real data in all 3 Baltic countries in all 12 cases, except for unemployment rate and cars sales in Lithuania (see Appendix G). The improved turning point forecasts in Lithuania, however, have to be viewed with caution, as Hodrick-Prescott filter is usually not precise at the ends of the sample. The prediction for the turning points in 2008 was based on the data in the beginning of our sample, which is a potentially inaccurate case.

In conclusion, the viability of Google Trends as a new source of leading data is very similar across the Baltics. Initially, it might seem that Estonia's better alignment between search queries and real statistics data has to be more useful in forecasting exercises; however it does not turn out to be the case. Google Trends being a very young application it is now too soon to judge which underlying factors might be behind more accurate Google-adjusted models in some countries as compared to the others. This can be caused by cultural decision making differences and other reasons, which would require a separate study to find out.

5. Conclusions

The study aims to introduce Google Trends to the Baltic countries, develop methodology and assess if there is valuable information contained in search queries that can be useful in forecasting economic activity in the Baltics. By focusing on three hypotheses we conduct a study that comprehensively assesses Google Trend's potential in the Baltic countries. We use ARIMA model as our forecasting tool, which is a common practice among researchers in this new field. In addition, we are first to use principal component analysis to incorporate Google Trends data into the models, which is a useful innovation for the studies in emerging markets. Besides, we apply Diebold-Mariano in testing Google Trends' forecasting accuracy and include a unique analysis of trend's turning points which we develop via Hodrick-Prescott filter.

Firstly, we find that across the Baltic countries the majority of our selected search queries are positively correlated with the real economic statistics, which suggests that the searching activity on Google search engine represents the society's real concerns and intentions. The positive correlations between Google searches and corresponding real statistics vary from 0.338 to 0.886 in Lithuania, 0.381 to 0.820 in Latvia and 0.179 to 0.708 in Estonia. In addition, we spot underlying structural reasons for Estonia's superior correlation results as compared to Lithuania and Latvia. The country has had a greater internet penetration and better IT-educated people throughout the study period.

Secondly, we generate 12 best baseline and 14 best Google Trends-adjusted ARIMA forecasting models that are built in accordance with AIC and BIC information criteria. We find that in 11 out of 14 cases the inclusion of Google Trends data makes in-sample forecasting more accurate. The results are quite remarkable that we achieve 8.5% more accurate Lithuanian unemployment rate forecasts, 20.2% better prediction for Lithuanian inflation rate and 39.5% better forecasts for Estonian car sales, when Google Trends data is used. As a robustness check, we find that Google Trends benefits forecasts even if not the optimal specification is chosen (the one identical in its *AR(p), I(d), MA(q)* to the best baseline model). The Google Trends-adjusted models, though, do not perform well in out-of-sample exercise.

Thirdly, we use Hodrick-Prescott filter to create long term trends and evaluate whether Google data, being more dynamic and sentiment based, can help in predicting the turning points in trends quicker. We find that at the moment, Google data is not ready to be used in trend movement analysis for two reasons. One is that the data set contains two major business cycles and the other one is that with that short sample it is impossible to avoid this issue. From the graphical analysis that we conduct there is little to gain, as the trend lines do not differ significantly if we adjust our baseline models by Google Trends data. Although Google Trends smoothed line provides leading information in some cases, we do not conclude its superiority for now.

In closing, Google Trends search queries closely resemble the real economic activities in the Baltic countries. It proves to be beneficial in short-term forecasting of unemployment, inflation, car sales and apartment sales and can serve as an additional indicator of economic activity. There is no strong evidence of Google Trends' ability to predict turning points in trends. Although being so young Google Trends does not offer large data set and poses many challenges, we prove that it deserves more attention from academic and business community in the Baltics.

Our paper is first in this field in the Central and Eastern Europe region and therefore there are a number of suggestions that further researchers could follow. First of all, Google Trends' predictability could be compared with other leading indicators, such as the Consumer Confidence Index and other measures used by a professional forecaster. Secondly, through interactions with other leading indicators and leading forecasting methods Google Trends can be used in looking for the best possible method of forecasting in the Baltics. We have run short-term forecasts using Google Trends-adjusted ARIMA models and show that they move in accordance with the forecasts of Bank of Latvia, Lithuanian Bank and Estonian Bank (see Appendix N). This suggests that more complex models than ARIMA might bear very interesting results. Finally, Google Trends as an application can be applied in such areas as epidemiology, tourism, financial markets, which can also be analysed in the Baltics and Central and Eastern Europe region at large.

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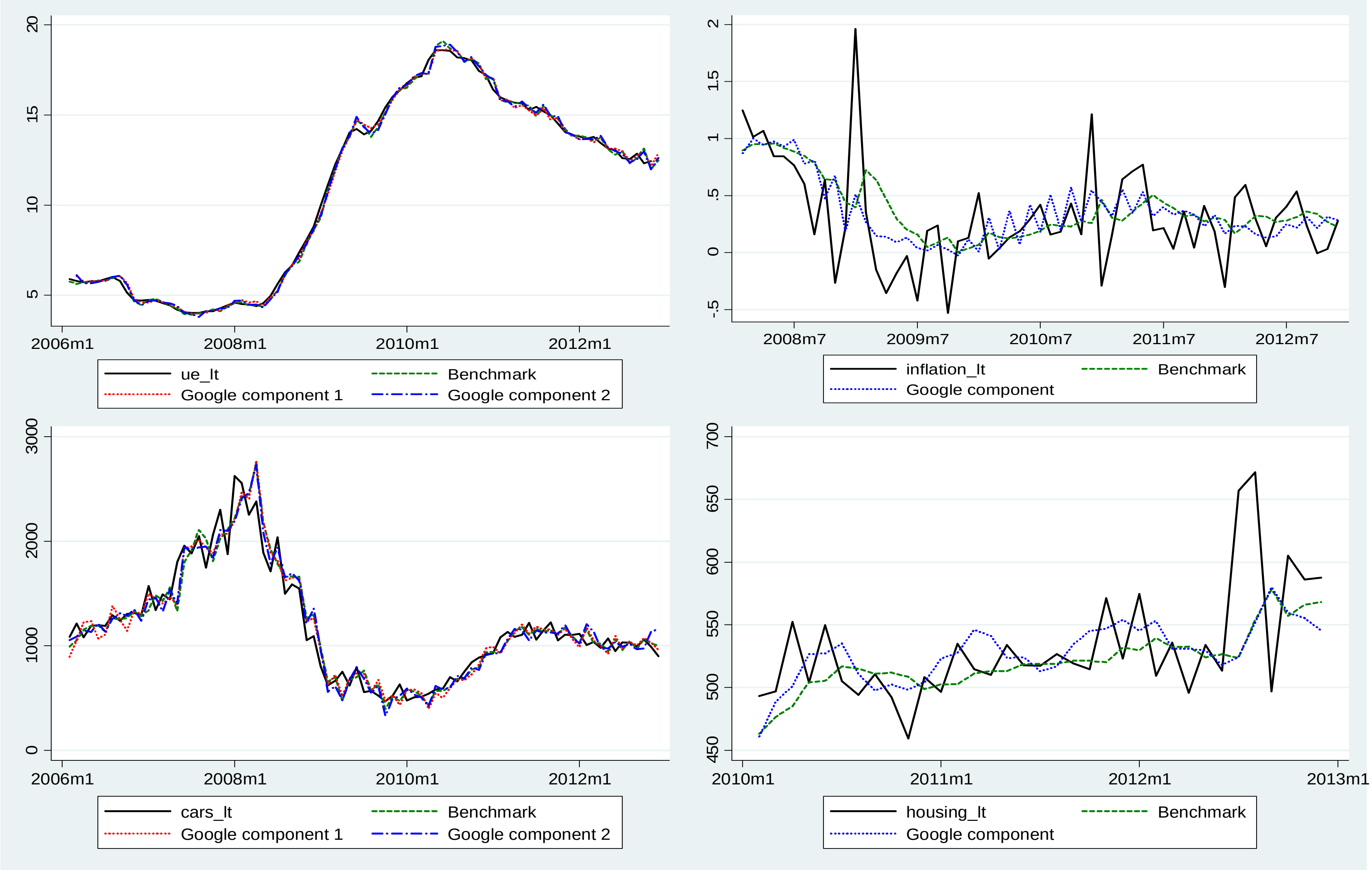
Appendix 1

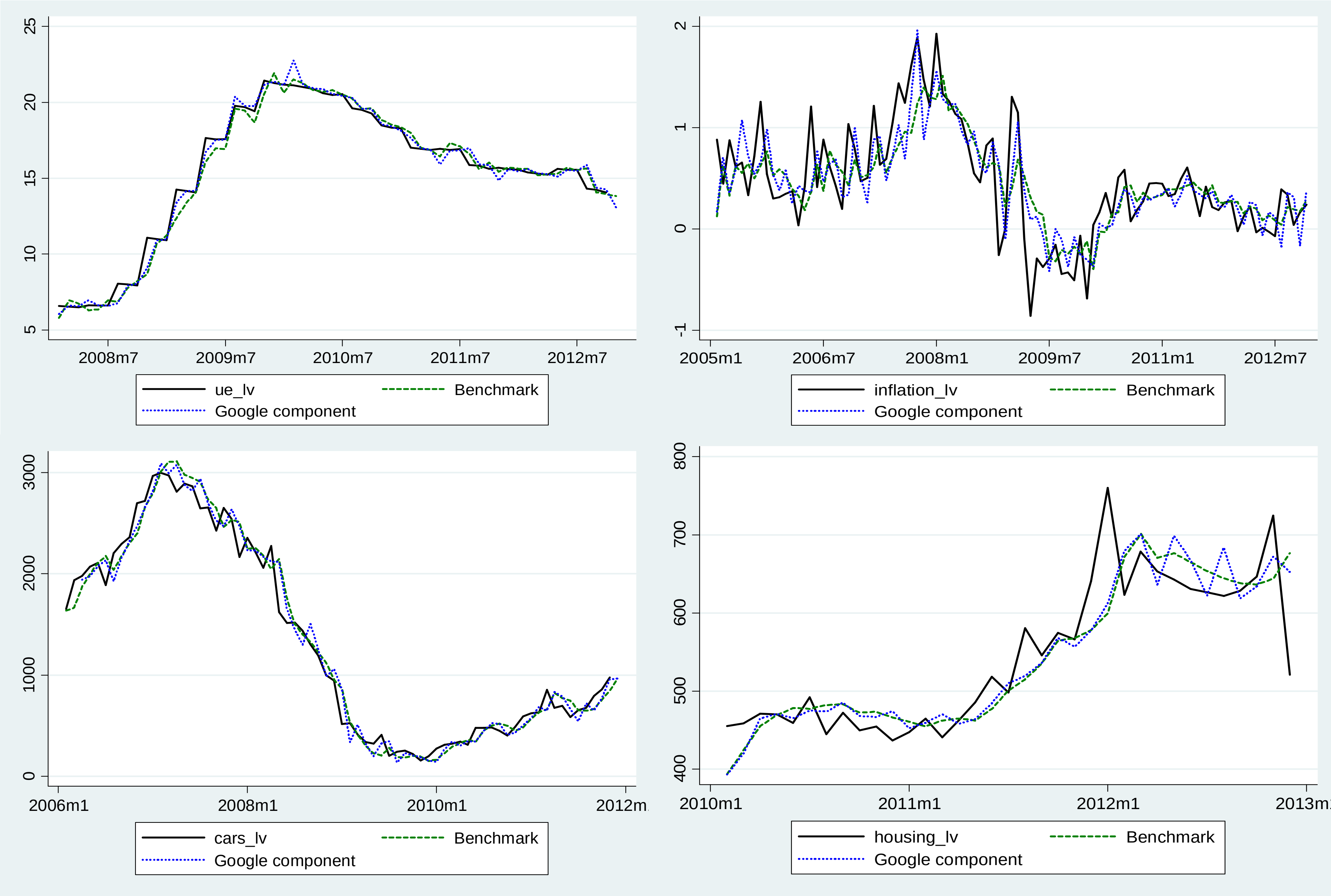
Figure 1: One-step ahead forecasting with and without Google components for Lithuania (In-sample).



Source: Created by the authors.

Appendix 2

Figure 2: One-step ahead forecasting with and without Google components for Latvia (In-sample).



Source: Created by the authors.

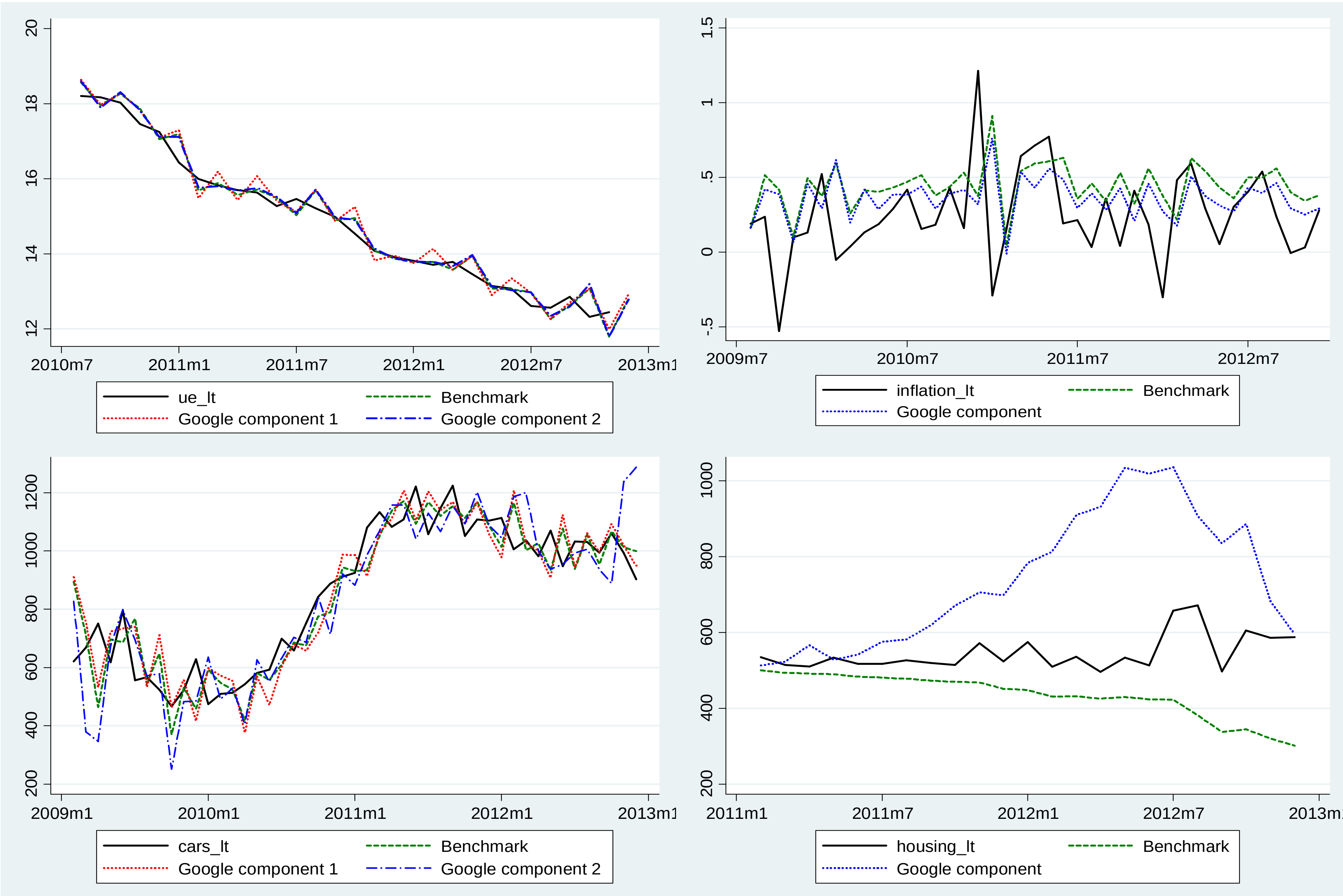
Appendix 3

Figure 3: One-step ahead forecasting with and without Google components for Estonia (In-sample).

Source: Created by the authors.

Appendix 4

Figure 4: Out-of-sample forecasting for Lithuania.



Source: Created by the authors.

Appendix 5

Figure 5: Out-of-sample forecasting for Latvia

Source: Created by the authors.

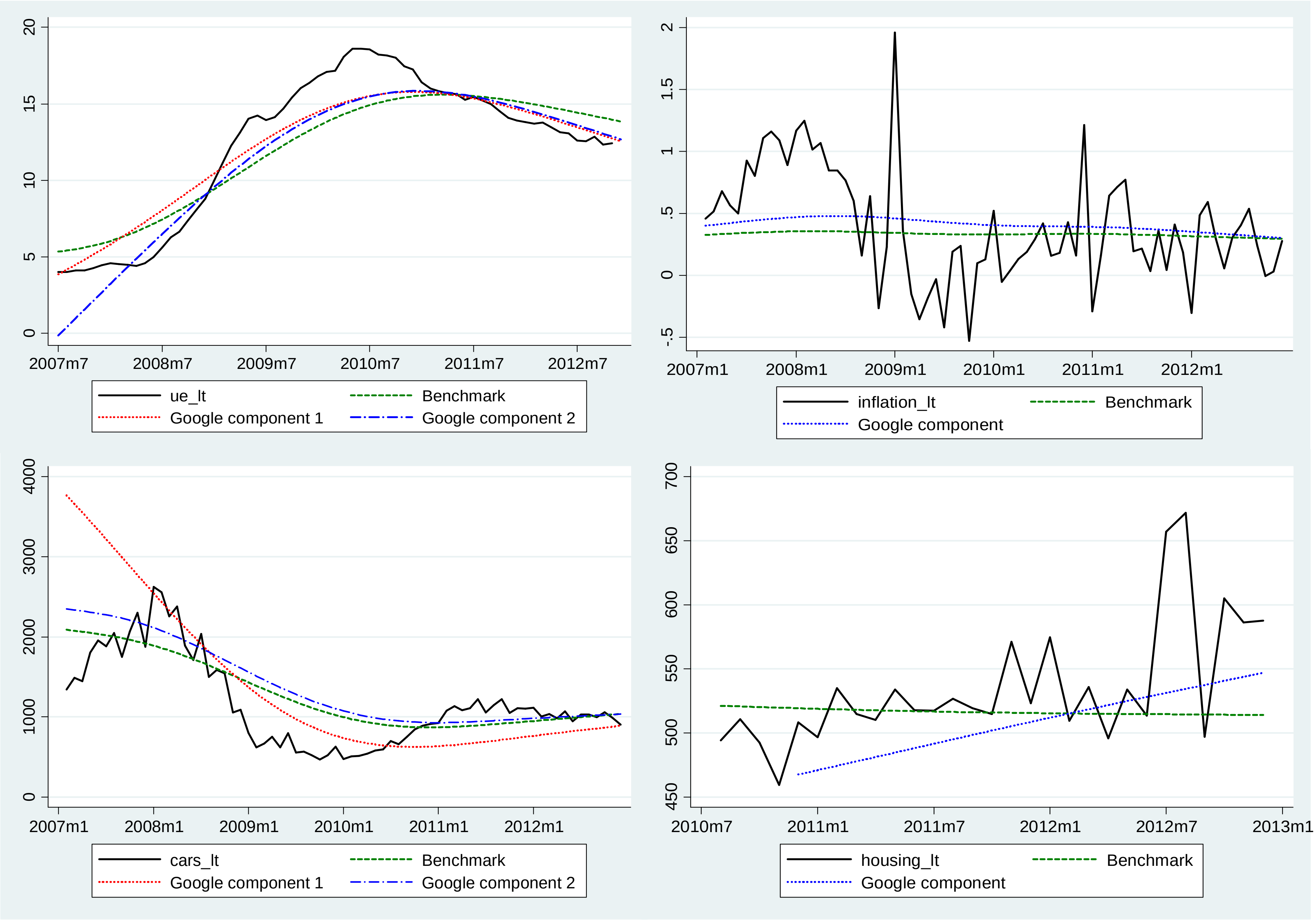
Appendix 6

Figure 6: Out-of-sample forecasting for Estonia.

Source: Created by the authors.

Appendix 7

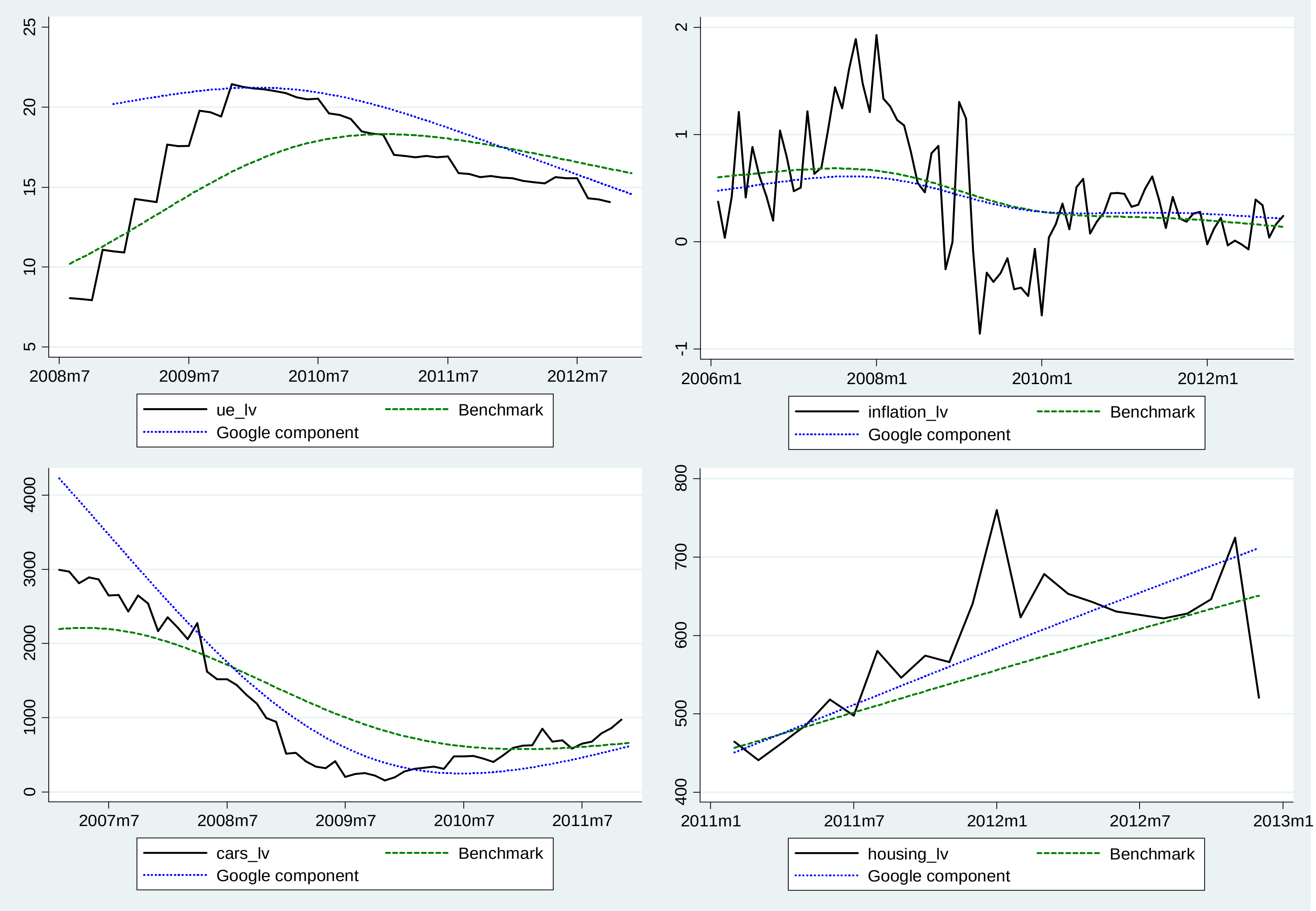
Figure 7: Six-steps ahead forecasting for Lithuania (Hodrick-Prescott filter λ=14400).



Source: Created by the authors.

Appendix 8

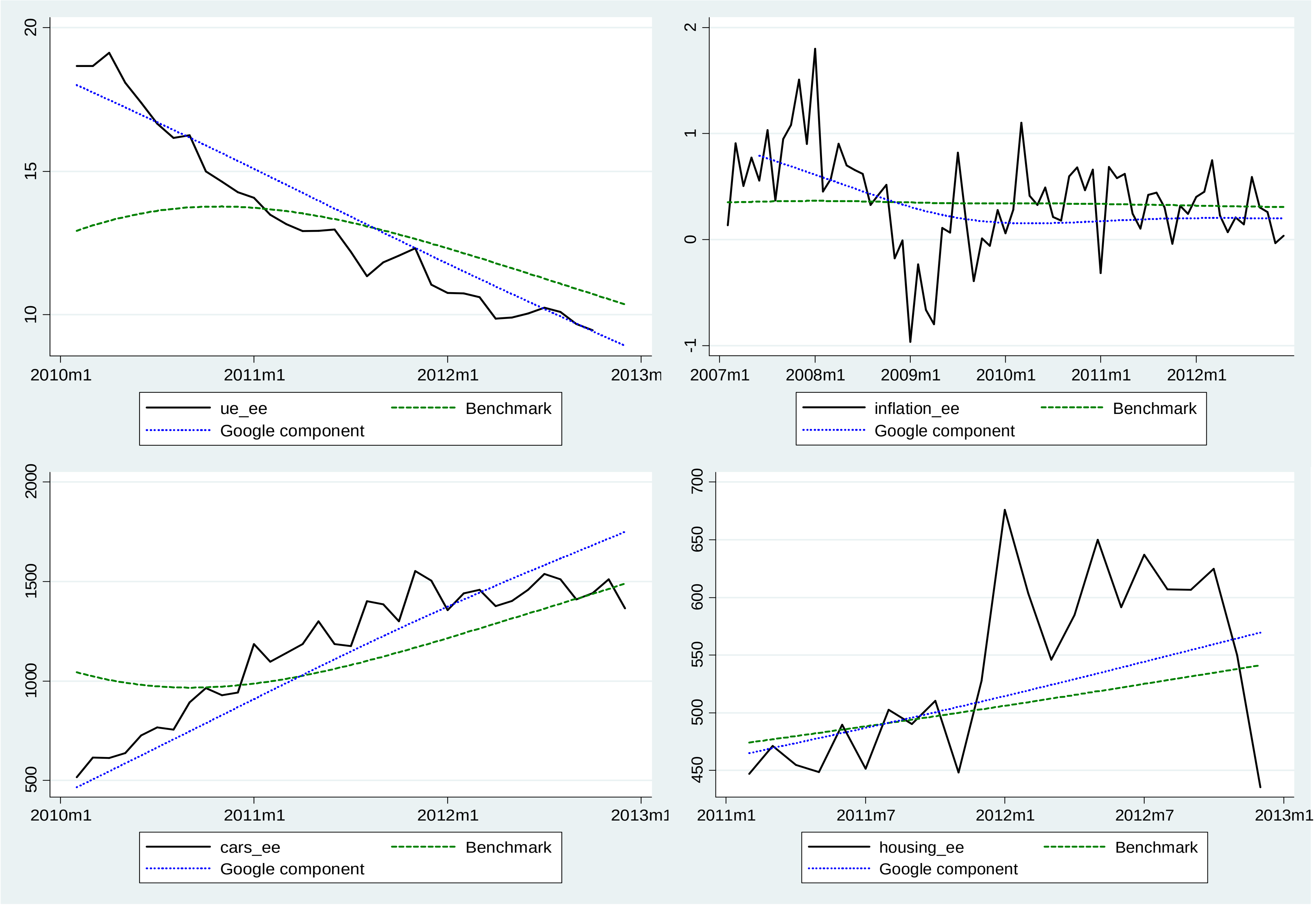
Figure 8: Six-steps ahead forecasting for Latvia (Hodrick-Prescott filter λ=14400).



Source: Created by the authors.

Appendix 9

Figure 9: Six-steps ahead forecasting for Estonia (Hodrick-Prescott filter λ=14400).



Source: Created by the authors.

Appendix 10

Table 9 Out-of-sample forecasting models, accuracy and significance tests.

	RMSFE (before)	RMSFE (component1)	Change	Diebold-Mariano test (P-value)	RMSFE (component2)	Change	Diebold-Mariano test (P-value)
ue_lt	0.3488	0.4015	15.09%	0.0655	0.3474	-0.43%	0.9066
ue_lv	0.8801	0.6110	-30.58%	0.0001		-	-
ue_ee	0.6101	0.7509	23.07%	0.0492	-	-	-
inf_lt	0.4162	0.3749	-9.92%	0.0000	-	-	-
inf_lv	0.3795	0.4395	15.81%	0.0000	-	-	-
inf_ee	0.3238	0.3378	4.32%	0.4821	-	-	-
cars_lt	111.8944	117.8960	5.36%	0.3511	140.1325	25.24%	0.0996
cars_lv	112.0812	101.4130	-9.52%	0.0002	-	-	-
cars_ee	123.9251	162.5358	31.16%	0.1122	-	-	-
housing_lt	143.1234	252.6676	76.54%	0.0411	-	-	-
housing_lv	69.3454	83.9615	21.08%	0.0000	-	-	-
housing_ee	94.5541	94.9702	0.44%	0.0056	-	-	-

Source: Computed by the authors.

Appendix 11

Table 10 I(d) identification and test of stationarity for all variables.

Interpolated Dickey-Fuller critical value				
	Actual value	1%	5%	10%
ue_lt	-1.0410	-3.4840	-2.8850	-2.5750
D.ue_lt	-5.1990	-3.4840	-2.8850	-2.5750
ue_lv	-0.6980	-3.5090	-2.8900	-2.5800
D.ue_lv	-10.0600	-3.5090	-2.8900	-2.5800
ue_ee	-1.3500	-3.4930	-2.8870	-2.5770
D.ue_ee	-9.0120	-3.4930	-2.8870	-2.5770
inf_lt	-10.4000	-3.4760	-2.8830	-2.5730
inf_lv	-6.4710	-3.5080	-2.8900	-2.5800
inf_ee	-7.4620	-3.5080	-2.8900	-2.5800
cars_lt	-1.8110	-3.5480	-2.9120	-2.5910
D.cars_lt	-11.5050	-3.5480	-2.9120	-2.5910
cars_lv	-1.2190	-3.5180	-2.8950	-2.5820
D.cars_lv	-9.4760	-3.5180	-2.8950	-2.5820
cars_ee	-2.8150	-3.4920	-2.8860	-2.5760
D.cars_ee	-16.0000	-3.4920	-2.8860	-2.5760
housing_lt	-5.1440	-3.6820	-2.9720	-2.6180
housing_lv	-3.8650	-3.6820	-2.9720	-2.6180
housing_ee	-3.3630	-3.6820	-2.9720	-2.6180
D.housing_ee	-6.8270	-3.6890	-2.9750	-2.6190
ue_lt_factor1	-2.2370	-3.5350	-2.9040	-2.5870
D.ue_lt_factor1	-12.0860	-3.5350	-2.9040	-2.5870
ue_lt_factor2	-1.6740	-3.5350	-2.9040	-2.5870
D.ue_lt_factor2	-11.1880	-3.5350	-2.9040	-2.5870
cars_lt_factor1	-2.0930	-3.5270	-2.9000	-2.5850
D.cars_lt_factor1	-11.6090	-3.5270	-2.9000	-2.5850
cars_lt_factor2	-1.5330	-3.5270	-2.9000	-2.5850
D.cars_lt_factor2	-9.5690	-3.5280	-2.9000	-2.5850

Source: Created by the authors.

Appendix 12

Table 11 I(d) identification and test of stationarity for all variables (Continued).

Interpolated Dickey-Fuller critical value (continued)	Actual value	1%	5%	10%
housing_lt_factor1	-3.0240	-3.5370	-2.9050	-2.5880
D.housing_lt_factor1	-8.8400	-3.5370	-2.9050	-2.5880
ue_lv_factor1	-2.6040	-3.5590	-2.9180	-2.5940
D.ue_lv_factor1	-9.4380	-3.5590	-2.9180	-2.5940
ue_lv_factor2	-3.4950	-3.5590	-2.9180	-2.5940
D.ue_lv_factor2	-10.9450	-3.5590	-2.9180	-2.5940
housing_lv_factor1	-3.0240	-3.5370	-2.9050	-2.5880
D.housing_lv_factor1	-8.8400	-3.5370	-2.9050	-2.5880
ue_ee_factor1	-2.6240	-3.5730	-2.9260	-2.5980
D.ue_ee_factor1	-9.9170	-3.5730	-2.9260	-2.5980
cars_ee_factor1	-3.4670	-3.6280	-2.9500	-2.6080
D.cars_ee_factor1	-8.2120	-3.6280	-2.9500	-2.6080
housing_ee_factor1	-2.2400	-3.5720	-2.9250	-2.5980
D.housing_ee_factor1	-7.7650	-3.5720	-2.9250	-2.5980
infliacija	-2.9570	-3.5370	-2.9050	-2.5880
D.infliacija	-10.2060	-3.5370	-2.9050	-2.5880
inflacija	-3.5040	-3.5140	-2.8920	-2.5810
D.inflacija	-12.3550	-3.5140	-2.8920	-2.5810
inflatsioon	-3.3240	-3.5460	-2.9110	-2.5900
D.inflatsioon	-12.9610	-3.5460	-2.9110	-2.5900
automasinas	-2.7600	-3.5380	-2.9060	-2.5880
D.automasinas	-14.7990	-3.5380	-2.9060	-2.5880

Source: Created by the authors.

Appendix 13

Table 12 Monthly forecast values from Google models for unemployment and inflation rates in the Baltics

2013	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Lithuania												
Unemployment rate (%)	11.38	11.43	11.56	10.51	10.50	10.88	9.75	9.69	10.27	9.13	9.03	9.76
Inflation rate (%)	0.2422	0.2393	0.3079	0.3126	0.3095	0.3398	0.344	0.3423	0.3572	0.3594	0.3586	0.3661
Latvia												
Unemployment rate (%)	13.85	13.71	13.82	13.60	13.92	13.67	14.11	13.84	14.34	14.07	14.59	14.34
Inflation rate (%)	0.1169	0.1864	0.2322	0.172	0.2163	0.2458	0.2138	0.2449	0.2655	0.2465	0.2695	0.2849
Estonia												
Unemployment rate (%)	9.70	9.94	9.98	10.07	10.39	10.23	10.46	10.78	10.55	10.82	11.11	10.86
Inflation rate (%)	0.1797	0.1109	0.2594	0.1577	0.2883	0.1904	0.2981	0.2144	0.3009	0.2326	0.3012	0.2467

Source: Created by the authors using data from Central Bank of the Republic of Lithuania (2013), Bank of Latvia (2013), Bank of Estonia (2013).

Table 13 Monthly forecast values from Google models for unemployment and inflation rates in the Baltics

2014	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Lithuania												
Unemployment rate (%)	8.65	8.51	9.36	8.33	8.16	9.07	8.16	7.98	8.9	8.13	7.94	8.84
Inflation rate (%)	0.3672	0.3668	0.3706	0.3711	0.3709	0.3728	0.3731	0.3730	0.3740	0.3741	0.3740	0.3745
Latvia												
Unemployment rate (%)	14.84	14.6	15.08	14.86	15.31	15.11	15.51	15.34	15.69	15.54	15.86	15.72
Inflation rate (%)	0.2722	0.2899	0.3018	0.2926	0.3065	0.3158	0.3089	0.3199	0.3272	0.3219	0.3306	0.3365
Estonia												
Unemployment rate (%)	11.13	11.38	11.14	11.38	11.58	11.38	11.58	11.73	11.57	11.72	11.84	11.71
Inflation rate (%)	0.3007	0.2576	0.3000	0.2661	0.2994	0.2728	0.2989	0.278	0.2985	0.2821	0.2981	0.2853

Source: Created by the authors using data from Central Bank of the Republic of Lithuania(2013), Bank of Latvia (2013), Bank of Estonia(2013).

Table 14 Average forecast values for unemployment and inflation rates (2013-2014) from LT, LV and EE central banks and Google models

	2013	2014		2013	2014		2013	2014
Lithuanian Bank			**Bank of Latvia**			**Eesti Pank**		
Unemployment rate (%)	11.6	10	*Unemployment rate (%)*	N/A	N/A	*Unemployment rate (%)*	9.4	8.9
Inflation rate (%)	2.4	3	*Inflation rate (%)*	2	N/A	*Inflation rate (%)*	3.6	2.4
Google forecast			**Google forecast**			**Google forecast**		
Unemployment rate (%)	**10.3**	**8.5**	*Unemployment rate (%)*	**14.0**	**15.3**	*Unemployment rate (%)*	**10.4**	**11.5**
Inflation rate (%)	**3.9**	**4.6**	*Inflation rate (%)*	**2.7**	**3.8**	*Inflation rate (%)*	**2.8**	**3.5**

Source: Compiled by the authors.

Appendix 14

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Table 15 Search queries and real data statistics correlation in Lithuania

Search queries and real statistics data correlation in Lithuania													
Unemployment	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
CV online	0.886 ***	0.907 ***	0.921 ***	0.933 ***	0.940 ***	0.941 ***	0.939 ***	0.935 ***	0.926 ***	0.917 ***	0.906 ***	0.892 ***	0.870 ***
darbo pasiūlymai	0.455 ***	0.533 ***	0.602 ***	0.664 ***	0.718 ***	0.765 ***	0.804 ***	0.840 ***	0.872 ***	0.898 ***	0.917 ***	0.928 ***	0.932 ***
darbo skelbimai	0.369 ***	0.428 ***	0.483 ***	0.533 ***	0.581 ***	0.625 ***	0.663 ***	0.698 ***	0.731 ***	0.763 ***	0.791 ***	0.814 ***	0.832 ***
ieškau darbo	-0.587 ***	-0.537 ***	-0.487 ***	-0.431 ***	-0.373 ***	-0.316 ***	-0.256 ***	-0.196 **	-0.136	-0.074	-0.009	0.057	0.118
Inflation	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
infliacija	0.427 ***	0.329 ***	0.322 ***	0.240 **	0.156	0.091	0.224 *	0.141	-0.083	-0.057	-0.082	-0.111	-0.098
Car sales	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
auto skelbimai	-0.160	-0.120	-0.082	-0.047	-0.003	0.043	0.087	0.126	0.176	0.224 **	0.264 **	0.288 *	0.331 *
autogidas	-0.562 ***	-0.552 ***	-0.542 ***	-0.532 ***	-0.522 ***	-0.515 ***	-0.505 ***	-0.497 ***	-0.489 ***	-0.480 ***	-0.473 ***	-0.464 ***	-0.458 ***
autoplius	0.482 ***	0.510 ***	0.509 ***	0.462 ***	0.450 ***	0.415 ***	0.381 ***	0.347 ***	0.294 ***	0.242 **	0.204 *	0.135	0.067
naudoti automobiliai	-0.109	-0.072	-0.020	0.041	0.069	0.118	0.152	0.179	0.202 *	0.236 **	0.258 **	0.277 **	0.301 ***
nauji automobiliai	0.695 ***	0.683 ***	0.687 ***	0.687 ***	0.712 ***	0.686 ***	0.680 ***	0.673 ***	0.628 ***	0.618 ***	0.550 ***	0.480 ***	0.465 ***
Apartment sales	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
butai	-0.295 *	-0.338 **	-0.348 **	-0.399 **	-0.262	-0.329 **	-0.256	-0.333 **	-0.348 **	-0.381 **	-0.420 **	-0.451 ***	-0.407 **
aruodas	0.481 ***	0.418 **	0.210	0.098	0.113	-0.080	-0.183	-0.523 ***	-0.474 ***	-0.566 ***	-0.622 ***	-0.732 ***	-0.631 ***
parduodami butai	0.338 **	0.347 **	0.490 **	0.490 ***	0.486 ***	0.482 ***	0.560 ***	0.523 ***	0.583 ***	0.558 ***	0.499 ***	0.352 **	0.293 *
nekilnojamas turtas	-0.404 **	-0.450 ***	-0.502 ***	-0.484 ***	-0.327 **	-0.396 **	-0.372 **	-0.390 **	-0.386 **	-0.478 ***	-0.483 ***	-0.481 ***	-0.521 ***

Source: Calculated by the authors using data from Datacentre (2013), Oberhaus (2013), Lithuanian Statistics Department (2013), Google Trends (2013).

Note: *, **, *** indicate that the results are significant at 10% ($P \leq 0.1$), 5% ($P \leq 0.05$) and 1% ($P \leq 0.01$) significance levels, respectively.

Appendix 15

Table 16 Search queries and real data statistics correlation in Latvia.

Search queries and real statistics data correlation in Latvia													
Unemployment	t	t-1	t-2	t-3	t-4	t-5	t-6	t-7	t-8	t-9	t-10	t-11	t-12
CV Online	0.820 ***	0.827 ***	0.813 ***	0.809 ***	0.792 ***	0.744 ***	0.706 ***	0.635 ***	0.538 ***	0.435 ***	0.325 **	0.189	0.042
darba sludinajumi	-0.137	-0.120	-0.095	-0.080	-0.043	-0.004	0.004	0.025	0.060	0.089	0.106	0.136	0.153
mekle darbu	-0.212 *	-0.186	-0.183	-0.199	-0.170	-0.173	-0.188	-0.162	-0.151	-0.151	-0.111	-0.112	-0.127
piedava darbu	-0.293 ***	-0.272 ***	-0.258 **	-0.241 **	-0.215 **	-0.197 *	-0.178	-0.154	-0.141	-0.131	-0.114	-0.105	-0.107
Inflation	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
inflacija	0.460 ***	0.429 ***	0.427 ***	0.452 ***	0.403 ***	0.386 ***	0.385 ***	0.323 ***	0.339 ***	0.351 ***	0.328 ***	0.323 ***	0.371 ***
Car sales	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
automasinas	0.552 ***	0.573 ***	0.585 ***	0.604 ***	0.637 ***	0.651 ***	0.675 ***	0.696 ***	0.707 ***	0.716 ***	0.728 ***	0.739 ***	0.733 ***
reklama lv	0.381 ***	0.330 ***	0.289 **	0.237 *	0.183	0.145	0.114	0.077	0.041	0.003	-0.036	-0.067	-0.067
Apartment sales	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
dzivokli	-0.501 ***	-0.478 ***	-0.552 ***	-0.561 ***	-0.497 ***	-0.420 **	-0.442 ***	-0.478 ***	-0.439 ***	-0.440 ***	-0.441 ***	-0.383 **	-0.424 ***
nekustamais ipasums	-0.461 ***	-0.469 ***	-0.503 ***	-0.525 ***	-0.560 ***	-0.507 ***	-0.569 ***	-0.620 ***	-0.627 ***	-0.695 ***	-0.693 ***	-0.729 ***	-0.719 ***

Source: Calculated by the authors using data from Datacentre (2013), Oberhaus (2013), Google Trends (2013), Central Statistical Bureau of Latvia (2013).
Note: *, **, *** indicate that the results are significant at 10% ($P \leq 0.1$), 5% ($P \leq 0.05$) and 1% ($P \leq 0.01$) significance levels, respectively.

Appendix 16

Table 17 Search queries and real data statistics correlation in Estonia.

Search queries and real statistics data correlation in Estonia													
Unemployment	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
otsin tood	0.272**	0.132	0.071	0.029	-0.056	-0.138	-0.207	-0.311*	-0.354**	-0.385***	-0.390***	-0.381**	-0.451***
CV Online	0.604***	0.575***	0.545***	0.509***	0.473***	0.436***	0.402***	0.363***	0.330**	0.297*	0.264	0.207	0.148
CV keskus	0.680***	0.669***	0.660***	0.646***	0.630***	0.611***	0.588***	0.562***	0.541***	0.516***	0.487***	0.455***	0.408***
Inflation	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
inflatsioon	0.340***	0.411***	0.409***	0.534***	0.464***	0.490***	0.477***	0.496***	0.480***	0.477***	0.432***	0.393***	0.349***
Car sales	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
autoaed	0.647***	0.663***	0.675***	0.701***	0.685***	0.662***	0.650***	0.619***	0.578***	0.575***	0.542***	0.546***	0.538***
kasutatud autod	0.595***	0.636***	0.618***	0.594***	0.608***	0.646***	0.665***	0.628***	0.619***	0.643***	0.559***	0.521***	0.514***
Apartment sales	**t**	**t-1**	**t-2**	**t-3**	**t-4**	**t-5**	**t-6**	**t-7**	**t-8**	**t-9**	**t-10**	**t-11**	**t-12**
kinnisvara	-0.019	-0.055	0.007	0.016	0.002	0.154	0.164	0.145	0.117	0.086	0.110	0.273	0.196
korterid	0.423**	0.401**	0.397**	0.185	0.287*	0.360**	0.445***	0.189	0.130	0.159	0.249	0.154	0.206
kv	0.179	0.212	0.149	0.067	0.011	0.298*	0.460***	0.372**	0.230	0.456***	0.482***	0.436***	0.330**
City24	0.708***	0.699***	0.645***	0.644***	0.633***	0.532***	0.450***	0.370**	0.350**	0.265	0.247	0.156	0.059

Source: Calculated by the authors using data from Datacentre (2013), Oberhaus (2013), Google Trends (2013), Statistics Estonia (2013).

Note: *, **, *** indicate that the results are significant at 10% ($P \leq 0.1$), 5% ($P \leq 0.05$) and 1% ($P \leq 0.01$) significance levels, respectively.

Appendix 17

Table 18 AR(p) and MA(q), best model identification.

		Chosen model	AIC	BIC
Baseline models	ue_lt	(3,1,3)	65.3232	90.7775
	ue_lv	(2,1,3)	245.2951	265.3138
	ue_ee	(3,1,3)	80.4549	95.0840
	inflation_lt	(1,0,1)	250.8305	264.0833
	inflation_lv	(3,0,2)	124.9669	147.3176
	inflation_ee	(2,0,3)	167.5806	189.8923
	cars_lt	(3,1,1)	1074.6540	1089.1670
	cars_lv	(1,1,2)	1792.8830	1807.6620
	cars_ee	(2,1,3)	1968.8480	1990.1520
	housing_lt	(1,0,1)	386.5317	392.8658
	housing_lv	(1,1,1)	379.6525	385.8739
	housing_ee	(2,1,3)	381.8850	391.2171
Google-adjusted models	ue_lt + ue_lt_component1	(3,1,3)	28.0728	47.2284
	ue_lt + ue_lt_component2	(3,1,1)	28.0740	44.8351
	ue_lv + ue_lv_component1	(3,1,1)	113.1450	127.4464
	ue_ee + ue_ee_component1	(3,1,3)	78.8748	88.0180
	inflation_lt + infliacija	(3,0,3)	77.3398	94.1868
	inflation_lv + inflacija	(3,0,3)	77.9967	98.6765
	inflation_ee + inflatsioon	(3,0,3)	74.6155	95.4729
	cars_lt + cars_lt_component1	(3,1,1)	1067.6150	1084.5470
	cars_lt + cars_lt_component2	(3,1,2)	1066.9520	1086.3030
	cars_lv + cars_lv_component	(3,1,3)	882.0781	899.8341
	cars_ee + cars_ee_component1	(2,1,3)	510.9890	525.0786
	housing_lt + housing_lt_component1	(3,0,2)	390.7529	401.8376
	housing_lv + housing_lv_component1	(2,1,3)	381.9509	392.8383
	housing_ee + housing_ee_component1	(2,1,3)	381.8850	391.2171

Source: Computed by the authors.