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Bachelor Thesis

Nowcasting the Baltic States' GDP Using Common Indicators: A Cross-Country Analysis

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Abstract

The publication delay for quarterly real GDP growth may distort the decisions made by economic agents. To find a method of providing a timely estimate for GDP growth at the end of the respective quarter, we investigate the performance of bridge models (BMs), dynamic factor models (FMs), Mixed Data Sampling (MIDAS), and factor-MIDAS for the Baltic countries, using a wide variety of different indicators. We also investigate the controversial question of small versus large-scale FMs. We apply three automatic variable selection procedures for the BMs, two of which we introduce — the performance-based RMSFE-Individual and RMSFE-Group. We find that a small-scale FM estimated from a mix of Baltic and regional stock market returns nowcasts the best for Latvia, a BM with RMSFE-Group selection procedure estimated from production side variables nowcasts the best for Estonia, and that a BM with RMSFE-Individual selection procedure estimated from a mix of variables that prioritizes trade nowcasts the best for Lithuania. Tightly parametrized models outperform more inclusive models; small-scale FMs outperforms large-scale. We also find that M3 contains valuable information on the Latvian and Estonian GDP growth, even after joining the Eurozone; and that surveys, when properly selected, contain reliable information on GDP growth for all three countries.

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1. Introduction

It is of great importance for policy-makers and financial analysts to be aware of key economic indicators as quickly as possible. Information on Gross Domestic Product (GDP) is essential for anyone who wants to understand the overall state of the economy or to draw any comparisons with other countries. However, this much-needed data is published with a significant delay. For instance, the quarterly data on Latvia's GDP is available only 60 days after the end of the quarter, 57-58 days for Lithuania and 68-69 days for Estonia (Central Statistical Bureau of Latvia, 2015; Official Statistics Portal of Lithuania, 2015; and Statistics Estonia, 2015).

The publication lag of quarterly GDP might negatively influence the effectiveness of policy decisions. Since the official data is released only after two thirds of the next quarter has passed, a time inconsistency problem may arise. In other words, a decision maker might prefer a policy that was initiated using outdated information.

Fortunately, a list of other key economic indicators, such as industrial production, international trade, surveys, financials, prices, etc.[1], are available with a considerably lower publication lag. Thus, using relevant indicators and econometric techniques one might estimate the GDP growth before its official release. More information regarding indicators and selection criteria will be discussed in Section 5.

There are three different approaches to estimation: "backcasting," "nowcasting," and "forecasting". They differ in the relationship between the time of the estimation and the time of the realization of a variable. If we estimate something that is going to happen, we forecast. If we estimate something that is currently happening, we nowcast. If we estimate something that has already happened, we backcast. In this paper, we only nowcast by estimating the quarterly real GDP at the end of the reference period.

The attempt to nowcast the economy must be distinguished from the attempt to causally explain its growth. While the latter is based on fundamental economic theory and analyses causal relationships between various driving factors and growth, the former involves a sensitive mix of

[1] See Appendix A for the list of all indicators

relevance and availability. Publication lags may elevate some timely macroeconomic variables that are irrelevant in the grand scheme of things to usefulness for nowcasting. Causality is not implied at any point of this study. The importance of different variables is described in the Section 2, where it leads to hypotheses **H5** and **H6**. The variables used in this study are listed in Sections 3, 5.1 and Appendix A.

As there is no consensus on the best variables for nowcasting, there is none on the best tools. In this paper, we nowcast quarterly real GDP growth using a number of linear models: a bridge model, a dynamic factor model estimated with static principal components, Mixed Data Sampling (MIDAS) and its extension ─ factor-MIDAS. While bridge and factor models are common in the forecasting literature, MIDAS and factor-MIDAS are more recent approaches. The peculiarities, advantages and disadvantages of these models are described in the Sections 2 and 4.

There are several papers on short-term forecasting or nowcasting the quarterly GDP for individual Baltic States[2]. However, to our best knowledge, there is no study on nowcasting of quarterly GDP for all three Baltic States that compares models and methods based on databases that are built to be as similar as possible. Additionally, to the best of our knowledge, there is no study which applies MIDAS or factor-MIDAS to the Baltic States. Furthermore, we introduce two automatic indicator selection procedures for bridge models (see Section 5).

Applying the aforementioned econometric methods and constructing a similar database of indicators for all three Baltic countries, we will answer the following research question (RQ): **"Which model and indicators offer the most accurate nowcasts of quarterly real GDP growth for each of the Baltic States?"**

There are two main ways in which we try to answer the RQ. The first, which corresponds to the use of large-scale factor models, MIDAS and factor-MIDAS, strives to incorporate the greatest amount of available information into nowcasts. The second, which corresponds to the use of small-scale factor models and bridge models with and without automatic selection criteria, nowcasts using only a limited number of variables that are deemed important by reasoning or some automatic selection procedures. An intuitive assumption we make is that models that

[2] See Literature Review section (2.2 Baltic evidence) for a discussion of the main findings

incorporate more information are better than models than incorporate less. This is the driving principle behind hypotheses **H1-4** in Section 2.

The rest of the paper is organized as follows. Section 2 reviews the existing literature on models and indicators that have been used for nowcasting in the international and Baltic environment. Section 3 describes data collection and adjustment. Section 4 describes the models used in answering the **RQ** and the hypotheses. Section 5 discusses the construction of the databases, how their nowcasting performance is determined, and automatic selection schemes. Section 6 reports the results and answers **H1-4**. Section 7 discusses the results in detail, answers **H5-6**, and lists the limitations of this study. Section 8 concludes. Sections 9 and 10 contain the references and the appendices.

2. Literature Review

2.1 Background and International Evidence

We would like to stress that models for forecasting, nowcasting and backcasting are interchangeable. The difference lies in database construction, in which observations are assumed to be available at the time of the estimation. Thus, even if the articles reviewed refer to forecasting, their findings are relevant to a nowcasting exercise.

Bridge models (BMs) have proved to be useful in estimation when publication lags allow collecting a number of lesser indicators before main macroeconomic variables are available. In an early application, Ingenito and Trehan (1996) successfully forecast U.S. GDP with as few as two variables. Rünstler and Sédillot (2003) find that bridge models beat an Autoregressive Integrated Moving Average (ARIMA) benchmark in forecasting the euro area GDP, even if some data is still unpublished and has to be estimated by univariate or multivariate models. Baffigi et. al. (2004) establish that bridge models outperform univariate and multivariate benchmarks as long as some data is available for the period to be forecasted. Golinelli and Parigi (2014) manage to construct a system out of bridge models that forecasts about 70% of the world GDP better than the benchmark.

However, the number of variables supported by a BM is limited. The dynamic factor model (FM) is a method that bypasses the need to select just a few relevant variables by extracting information ("factors") from a large dataset. This approach dates back to the work of Sargent and Sims (1977). Factor models have established themselves as an efficient and popular tool in economics and finance.

In a number of seminal papers, Stock and Watson (1998, 2002b) establish the form and key characteristics of the dynamic factor model with static principal components. Empirically, Stock and Watson (2002a) forecast eight macroeconomic U.S. variables with a dynamic factor model based on principal component analysis and many monthly series. They find that successful forecasts can be conducted with as little as one factor. Dias et. al. (2015) find that a slight modification of the Stock and Watson (2002a) approach provides a reliable forecast for the Portuguese GDP even throughout the Great Recession. Bessec and Doz (2013) and Bessec (2013) demonstrate that factor models beat the benchmark for France. Similar improvements over benchmarks were found by Artis et. al (2001) for the UK, Rogleva (2011) for Bulgary, Godbout and Lombardi (2012) for Japan and Porshakov et. al. (2015) for Russia. However, writing for Germany, Schumacher and Breitung (2008) do not find that the dynamic factor model's (with static components) performance beats the benchmark. Schumacher and Breitung's conclusions in Germany reflect D'Agostino, Giannone and Surico's (2006) findings that the usefulness of different models, including factor models, in predicting U.S. macroeconomic variables has decayed since the 1980s.

Empirical comparisons between bridge and factor models' forecasting performance are inconclusive. Rünstler et. al. (2009) find that in forecasting the GDP of 9 European countries and the Euro region as a whole, factor models are superior to bridge models. Conversely, Antipa et. al. (2012) shows that a model based on dynamic principal components is inferior to bridge models in forecasting German GDP. This is reflected by Feldkircher et. al. (2015), who use bridge and factor models for seven countries in Central and Eastern Europe. Neither of the models consistently dominate the other, and the best performance is determined by country specifics.

An important question is the size of factor models. The number of series (N) and observations (T) are expected to be large for technical reasons. In empirical research, a large

number of variables is commonly used (e.g. see Stock and Watson (2002b), Schumacher (2007), Rünstler et. al. (2009). Furthermore, Stock and Watson (1998) establish that as long as N >> T, the model is robust to time variation in its coefficients. However, Boivin and Ng (2006) argue that a large number of variables may be detrimental to the model (see Section 5 for details). Bessec (2013) shows that a small, preselected database improves forecast accuracy for French quarterly GDP. This leads to the first two hypotheses:

H1: FMs result in a better performance than BMs

H2: Large-scale FMs result in a better performance than small-scale FMs

Both BMs and FMs require temporal aggregation to relate GDP to higher frequency variables; namely, daily and monthly conjunctural indicators are aggregated into quarterly frequency. Temporal aggregation has been recognized to distort relationships in the data (Christiano and Eichenbaum, 1987). Andreou, Ghysels and Kourtellos (2010) show that temporal aggregation can be expressed as an omitted variable bias when compared to an infeasible estimator that incorporates full information. A solution to this is the use of mixed-frequency models.

Mixed Data Sampling (MIDAS) was introduced by Ghysels et. al. (2004) as an alternative to Autoregressive Distributive Lag models (ADL) that does not require higher frequency variables to be aggregated into lower frequency for estimation. In theory, it provides an advantage over bridge models by incorporating more information. Although t is derived under the assumption of continuous sampling, which is more closely met in finance than in macroeconomics, there is some encouraging empirical evidence.

Clements and Galvão (2008) establish that an AR-MIDAS forecasts U.S. output growth better than an ADL benchmark. More convincingly, Foroni and Marcellino (2014) find that a factor-augmented AR-MIDAS often outperforms bridge model, a factor model with static estimation and mixed-frequency vector autoregression (MF-VAR) in forecasting the euro area GDP growth. Kuzin, Marcellino and Schumacher (2011) qualify this by noting that MIDAS is better than MF-VAR for forecasting over short time periods, making it appropriate for this study. This leads to the third and fourth hypotheses:

H3: MIDAS results in a better performance than BMs or small-scale FMs

H4: factor-MIDAS results in a better performance than the FM

H1, **H2**, **H3** and **H4** will be decided by the best-performing statistically significant specification. BM involves all types of BM, including the ones with automatic selection (described in Section 5). Any of these hypotheses will be accepted or rejected if they hold or fail to hold for at least two out of three countries. **H3** will be rejected if MIDAS is outperformed by either BMs or small-scale FMs.

2.2 Baltic evidence

Table 1 sums up the research done in Baltics. The current evidence is rather sparse, and there are no comparisons between different methods, with the exception of Bessonovs (2014).

Table 1. The empirical evidence from the Baltic region

Model	LATVIA	LITHUANIA	ESTONIA
Bridge model	Beņkovskis (2008), Bessonovs (2014)	-	-
Factor model	Ajevskis and Dāvidsons (2008), Bessonovs (2014)	Stakenas (2012)	Schulz (2007)
MIDAS	-	-	-
factor-MIDAS	-	-	-

Source: Created by the authors

Benkovskis (2008) investigates the relative performance of BMs and unobserved component model (state space model) against a benchmark model (ARIMA) for Latvia's real GDP. He finds that only specification where M3 is included perform better than the benchmark. The results might have been a product of its time since 2004-2007, the author's out-of-sample period, is associated with high levels of inflation. Additionally, the author asks for cautiousness when judging the importance of other indicators.

Ajevskis and Dāvidsons (2008) study the performance of a large-scale factor models in forecasting Latvia's GDP. The authors use static and dynamic estimation (see Section 4 for details). Both types of dynamic factor models offer better forecasts results than an autoregressive (AR) benchmark. However, the Diebold-Mariano (1995) test revealed the results to be insignificant.

Bessonovs (2014) forecasts Latvian GDP with univariate (random walk, AR, bridge models) and multivariate models (factor models, vector auto-regression, Bayesian vector auto-regression). The author assesses the performance of the disaggregated and aggregated approaches in short-term forecasting using several time periods (full sample, pre-crisis, and post-crisis). Factor models, aggregated or disaggregated, offer the best results. The author identifies that the disaggregated factor model (a small-scale factor model) performs well in the post crisis period (2010Q2 – 2013Q4).

Stakenas (2012) compares the forecasting ability of Lithuanian GDP obtained by several specifications of factor models. The author uses three estimation methods: principal components, generalized principal components and a state space model. All three beat the benchmark model (random walk). An additional analysis is conducted based only on five indicators (narrow money aggregate, retail sales, production in industry, and trade). The small-scale factor model reveals better results if compared with the initial extended dataset of 52 indicators. Lastly, the author tracks the weight assigned to different indicators in the extracted factors. Survey indicators, international trade and production in industry emerge as the overall most important.

Schulz (2007) estimates state space model and static principal components model to forecast Estonian GDP. Both models outperform the benchmark AR(1). Similarly to Benkovskis (2008), surveys do not provide a significant source of information, while financial variables and monetary aggregates do. The author notes that the forecasting performance of the model becomes weaker towards the end of the period, and cautiously infers that financial variables may be becoming less important in characterizing Estonia's growth.

2.3 On relevant variables

The a-theoretical nature of this paper makes identifying relevant variables difficult. Long-term determinants of economic growth, such as demographic or technological changes, may not be relevant when estimating output at very short terms. Bańbura and Rünstler (2011) find that variables reflecting real activity appear to be the most important predictors of short-term growth at first. However, when publication lags are accounted for, surveys and financial information, which has little or no publication lags, surpass real activity in supplying accurate forecasts. Hansson, Jansson and Löf (2005) investigate the information contained in surveys, concluding

that a properly filtered selection is useful, but surveys as a group include many superfluous variables.

The correlation between financial variables and output growth is more ambiguous. Bańbura et. al. (2013) review existing literature to conclude that low-frequency movement of stock prices contain some information about macroeconomic variables. Kuosmanen and Vataja (2014) find that a different mix of financial variables produces forecasts of different quality, depending on the state of the economy. During times of turbulence (by Finnish standards, we must note), stock returns increase in importance. A somewhat similar conclusion was reached by Florackis et. al. (2014) — the predictive power of stock markets increases during weak economic growth.

In the context of the Baltic States, Benkovskis (2008) and Schulz (2007) find the same patterns for Latvia and Estonia: weak performance from the surveys and good results using financial variables (monetary aggregates or stock exchanges). However, Stakenas (2012) ascribe surveys a higher weight in forecasting based on their strong correlation with GDP growth.

Based on the aforementioned results, we formulate the fifth hypothesis:

H5: For all countries**,** the best-performing database of variables for the best-performing model includes only variables with no publication lag

This accommodates both financial variables and surveys, and excludes all variables reflecting the real economy. If a factor model estimated from a database with only loose inclusion criteria (identified later as Large) delivers a superior performance, we will automatically reject **H5**.

H5 takes a very strong stance in the relevance-timeliness debate. For a more accommodating version, we introduce the sixth hypothesis:

H6: It is possible to create a successful nowcast for all Baltic States using only variables with no publication lag.

The condition for success is statistically significantly beating the benchmark, as it is defined in Section 5. **H6** does not require the variables to be the same for all Baltic States. This is a much weaker claim, but an affirmative answer would be unprecedented for the Baltics.

The next three sections describe how we prepared the models and datasets for nowcasting. Section 3 discusses the data sources and adjustments. Section 4 explains the models framing in this study. In Section 5, we review the exact setup for nowcasting- how we construct the sets of indicators to be compared, how the automatic selection criteria function, and how we gauge the performance of different models.

3. Data

We have compiled a database of common indicators for each of the Baltic States. In addition to quarterly real GDP growth, the database consists of 158 monthly indicators (see Appendix A). We have included both "hard" (e.g. industrial production, financials, prices etc.) and "soft" (surveys) indicators in the database. Due to data availability, the analyzed period was chosen to be 2000Q1 – 2015Q3, where 2000Q1 is reserved as data sample is used in quarterly growth rates. We use data from 2000Q2 to 2010Q3 (42 quarters) for in-sample estimation of parameters. The data from 2010Q4 to 2015Q3 (20 quarters) is used for out-of-sample nowcasting exercise. This corresponds to one third of our sample, following a rule of thumb (Rünstler and Sédillot, 2003). The database was compiled in January, 2016.

Eurostat served as the primary data source. Additionally, we consulted national bureaus of statistics to retrieve some more specific indicators. Thomson Reuters Databases was used for financial indicators (see Appendix A for the list of sources for each indicator).

We retrieved seasonally adjusted series whenever possible. In other cases, the series were seasonally adjusted using the default X12 option in Demetra+ software[3]. Lastly, we did not use real-time vintage data. In other words, any revisions the series may have undergone are not accounted for in this study.

We followed three criteria when selecting indicators. First, all indicators should be available before the official release of GDP for the nowcasted quarter. Second, since our main

[3] Source of the program: https://joinup.ec.europa.eu/software/demetraplus/description Out of 158 indicators, we adjusted 24 (Producer prices – 3 series; HICP – 12; car registrations – 6; monetary aggregates – 3)

task is to offer a cross-country analysis, the indicators should be available for all three countries. Finally, the selected indicators should cover the chosen time period, with some exceptions[4].

All of the selected indicators were available at monthly frequency, which was preferred to quarterly. First, it simplifies some coding issues. Second, monthly frequency is theoretically preferable to exploit the properties of MIDAS.

3.1 Transformations

First, we calculated growth rates for all "hard" indicators. Note, if indicators' original values is not changing signs in any successive periods (e.g. index type indicators) then logarithmic growth was calculated. Otherwise, we calculated percentage growth rates. For "soft" indicators, 48 in total, values at levels were used. This is because surveys contain a number of zeros[5] by design, which would result in missing observations upon calculating the growth rate. The same approach was used by Stakenas (2012).

Second, as the models require stationary data, we used the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, with the lag length selected by the Bayes Information Criterion (BIC) from an interval of [L-5,L+5], where L is a rule of thumb, the square root of the number of observations (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). If BIC failed to distinguish between the possible lags, the rule of thumb was used. This solution was introduced for computational efficiency when facing a large database. We took the first difference of any time series that were found to be non-stationary (see Appendix B for a list).

Third, we filled the missing values of any series that are used in the BM specifications (identified later in the section). We encountered only three problematic cases: Consumer Confidence Indicator (CCI) for Latvia and Lithuania; Turnover and volume of sales in wholesale and retail trade (non-food category) (hereinafter TSNF) for Estonia; and Unemployment monthly

[4] If the indicators was meant to be used only in the large scale factor model, then the admissible percent of missing value was chosen to be 15% (it corresponds to four years) because of the advantageously properties of EM.
[5] Out of total sample of survey values (48 indicators, 188 months) - 1.5% for Latvia; 1.2% for Lithuania; and 2.9% for Estonia are "0" values.

average rate for Estonia[6]. Since the sectoral confidence indicators are used in deriving the Economic Sentiment Indicator (ESI) (Eurostat, 2015), which has no missing values, we interpolated the absent values for CCI using OLS. We regressed the observed series of CCI on the corresponding series of ESI, and then interpolated the missing CCI values. Following the same logic, we filled the missing values of TSNF for Estonia using the Turnover and volume of sales in wholesale and retail trade (food category). This is justified because the two indicators are closely related to each other[7]. Finally, we replaced the one missing observation for Estonian monthly average unemployment rate with an autoregressive estimate of order 1 (AR(1)).

4. Models

In this section we provide a description of the models used in this thesis– bridge model, dynamic factor model estimated with static principal components, MIDAS and factor-MIDAS. All of the models and methods described henceforth are implemented using MATLAB 2015a with Spatial Econometrics and MIDAS toolboxes (Ghysels, 2015).

4.1 Bridge Model

A bridge model (BM) has the general form of

$$Y_t^Q = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i}^Q + \sum_{i=1}^{q} \sum_{j=1}^{k} \gamma_{j,i} X_{t+1-i}^Q + \varepsilon_t \qquad (1)$$

It relates the quarterly growth of GDP,Y_t^Q, to the quarterly growth in variables X_i, referred to as "indicators." α is a constant, k is the number of indicators, q is number of lags, and p is the order of AR terms. If indicators are published with a delay, they have to be replaced with estimates. For BM, we use AR(1) estimates. The model is estimated with Ordinary Least Squares (OLS).

[6] CCI for Latvia has missing values between 2000/04 and 2001/05; for Lithuania 2000/01 – 2001/04. TSNF for Estonia has missing values between 2000/01 and 2001/01. U for Estonia has missing value only for 2000/01.

[7] The t-statistic from the OLS regression is 4.1918, which means it is significant at 1%.

Monthly indicator growth rates x_t^M are transformed into quarterly x_t^Q with Mariano and Murasawa's (2003) method:

$$x_\tau^Q = \frac{1}{3}x_t^M + \frac{2}{3}x_{t-1}^M + x_{t-2}^M + \frac{2}{3}x_{t-3}^M + \frac{1}{3}x_{t-4}^M \qquad (2)$$

This assumes that quarterly value of an indicator is the arithmetic (or geometric, for log-transformation) mean of the respective monthly values.

It is very important to note that in all of our regressions, we change the lag length for all indicators at the same time. That is, we always have the same number of lags for all indicators (or factors, which are explained in the next section). This drawback derives from the breadth and ever-present automatization of our study, which left little room for customization.

4.2 Dynamic Factor Models

4.2.1 Theory

The number of indicators supported by the BM is limited. A way around this is to reduce the common variance of a large number of indicators to only few unobserved variables ("factors"). Stock and Watson (2002a, 2010) represent a dynamic factor model as

$$X_t = \lambda(L)f_t + e_t \qquad (3)$$

$$f_t = \psi(L)f_{t-1} + \eta_t \qquad (4)$$

where X_t is a Nx1 matrix of observed variables, $\lambda(L)$ is a Nxq matrix of lag polynomials, referred to as the loading matrix, f_t is a qx1 matrix of unobserved factors, e_t is a Nx1 matrix of unobserved idiosyncratic disturbances. $\psi(L)$ is a qxq matrix and η_t is a qx1 matrix of factor innovations. e_t and η_t are assumed to be uncorrelated in all lags. All variables are assumed to be stationary.

Then, the variable to be nowcasted can be expressed as

$$y_{t+1} = \beta(L)f_{t+1} + \gamma(L)y_t + \varepsilon_{t+1} \qquad (5)$$

where y_{t+1} is a scalar, $\beta(L)$ and $\gamma(L)$ are lag polynomials and ε_{t+1} is an exogenous error term.

Given that the order of lag polynomials is finite, equations (3) and (4) can be rewritten as

$$X_t = \lambda_0 f_t + \lambda_1 f_{t-1} + .. + \lambda_p f_{t-p} + e_t = \Lambda F_t + e_t \quad (6)$$

$$\Phi(\mathrm{L}) F_t = \mathrm{G}\eta_t \quad (7)$$

where $F_t = (f_t', \dots, f_{t-p}')'$ is a *r*x*1* matrix, r = (*q*x(*p+1*)), $\Lambda = (\lambda_0, \dots, \lambda_p)$ is a Nx*r* matrix, and $\Phi(\mathrm{L})$ is a matrix consisting of 1, 0 and elements of $\psi(L)$ to ensure that (4) and (7) are identical.

4.2.2 Estimation and Nowcasting

We use Principal Components (PC) or "static" estimation of dynamic factor models. This is a widely used and relatively simple method, popularized by Stock and Watson (2002b). For the Baltics, Ajevskis and Dāvidsons (2008), Bessonovs (2014) and Stakenas (2012) use this approach. It is static in the sense that lagged factors in the matrix F_t are treated as independent variables; temporal relationships are ignored. The goal is to find a weighting matrix W such that $\hat{F}_t = \frac{1}{N} W' X_t$ is consistent estimator of (6).

Static estimation selects $\widehat{\Lambda}$ as the matrix W, where $\widehat{\Lambda}$ minimizes the least squares expression of (6): $\frac{1}{NT}\sum_{t=1}^{T}(X_t - \Lambda F_t)'(X_t - \Lambda F_t)$. This is equivalent to maximizing the trace of $\Lambda' X' X \Lambda$. This is a PC problem that can be solved by equalling the columns of matrix $\widehat{\Lambda}$ to the r largest eigenvectors of the NxN covariance matrix XX′, multiplied by $\sqrt{N}$ (Stock and Watson, 2002b). The "stacked" matrix X includes both observations and a varying number of their lags. It is also possible to use a TxT covariance matrix. The only difference would be a decrease in computational efficiency, as in all of our databases N<T (Bai and Ng, 2002).

The time series have to be standardized to zero mean and unit variance before the estimation. This is a common approach to PC, a variance-maximization procedure, where having differently scaled variables could distort the results (Johnson and Wichern, 2007, p. 431).

We estimate factors from a database that contains monthly indicators up to and including the nowcasted quarter. To estimate the values missing at the time of the nowcast in the larger databases (described in greater detail in the next section), whether because of historical gaps or publication lags, we use the Expectation Maximization (EM) algorithm described by Stock and Watson (2002a). It exploits the co-movements of macroeconomic variables in a large dataset (thus making it inapplicable to smaller sets of variables). It works as follows

(1') Replace any missing observations in the matrix X with 0, obtaining matrix $\hat{X}$.

(2') Extract factors from the matrix $\hat{X}$. We always extract two factors in EM.

(3') Re-estimate the previously missing values by using factors extracted in step (2') as $X_{it} = \lambda_i(L)f_t$. Obtain a new version of the matrix $\hat{X}$.

(4') Return to step (2').

This continues until convergence, which we define as reached when the absolute value of difference between any two successive estimates does not exceed 10^{-7} (note that our datasets contain growth rates in decimals).

Then we aggregate monthly factors into quarterly with (2), and regress historical GDP growth on them. The last quarterly factor is then used to nowcast GDP growth of the given quarter, as in (5). There are two alternatives to this procedure. First, we could estimate factors from only quarterly (or aggregated monthly) variables. However, this would likely impair the convergence of PC, which is a consistent estimator. Second, we could disaggregate quarterly GDP growth into monthly by using an alternative version of EM, estimate growth for the three months of the nowcasted quarter, and aggregate it back into quarterly. We believe this would introduce an additional source of error in the estimates, and would only be appropriate if monthly GDP growth was our variable of interest (see Schumacher (2007) for an example).

An alternative to static is dynamic or generalized principal components estimation. It is commonly identified with the work of Forni et. al. (2005), although other approaches and extensions to their methods exist. This estimation allows modelling temporal relationships that the static approach ignores. See Boivin and Ng (2005) and Stock and Watson (2010) for a detailed description.

Boivin and Ng (2005) assert that neither static nor dynamic are necessarily superior to each other. The static approach may fail to exploit some underlying relationships, while the dynamic approach has a higher possibility of misspecification. Much is determined by the nature of the data. While Antipa et. al. (2012) found that the dynamic approach to be better, Schumacher (2007) and Marcellino and Schumacher (2007) could not reach a similar conclusion for Germany. Considering this, and Ajevkis and Dāvidsons' (2008) and Stakenas' (2012)

inability to reasonably differentiate between the performance of the two in pre-crisis Latvia and post-crisis Lithuania, we will work only with the static model, for the technical difficulties of dynamic estimation are likely to exceed the benefits.

4.3 MIDAS

Mixed Data Sampling, or MIDAS, due to Ghysels et. al. (2004) relates a low-frequency variable of interest to higher frequency explanatory variables Unlike BMs and FMs, it does not require using Mariano and Murasawa's (2003) aggregation method. Theoretically, this leads to estimates that incorporate more information. Following the notation of Foroni and Marcellino (2013), the model for a single indicator can be expressed as

$$y_{t_m+h_m} = \beta_0 + \beta_1 b(L_m, \theta) x_{t_m+w}^{(m)} + \varsigma_{t_m+h_m} \qquad (8)$$

where $y_{t_m+h_m}$ is the quarterly observed variable to be forecasted (nowcasted) over a horizon of h_m months (in our case, h_m is zero, and the indicator x has been extended to the end of the nowcasted quarter), $b(L_m, \theta) = \sum_{k=0}^{K} c(k;\theta)\, L_m^k$, L_m^k is a lag operator of order k, $x_{t_m+w}^{(m)}$ is the value of the monthly indicator that is available w times before the dependant variable is published, and $\varsigma_{t_m+h_m}$ is the error term.

$c(k;\theta)$ is a weighting scheme that parsimoniously parametrizes lagged coefficients. Multiple options are available, but the simplest and most popular is the Exponential Almond Lag:

$$c(k;\theta) = \frac{\exp(\theta_1 k + \cdots + \theta_Q k^Q)}{\sum_{k=1}^{K} \exp(\theta_1 k + \cdots + \theta_Q k^Q)} \qquad (9)$$

In practice, the number of coefficients θ is often restricted to two (Marcellino and Schumacher 2007, Foroni and Marcellino, 2014). We follow this example.

Once the weighting scheme has been decided on, the equation (8) can be estimated directly with Non-linear Least squares (NLS). It must be stressed that both $\hat{\theta}_1$ and $\hat{\theta}_2$ are among the estimated parameters. So, the weighting scheme changes with the data supplied to the model (Aastveit, Foroni, and Ravazzolo, 2014). However, MIDAS is still linear in the indicators.

Two straightforward extensions for the model include the factors estimated from (3), pioneered by Marcellino and Schumacher (2007), and AR components:

$$y_{t_m+h_m} = \beta_0 + \lambda y_{t_m} + \beta_1 b(L_m, \theta)\hat{f}^{(m)}_{t_m+w} + \varsigma_{t_m+h_m} \qquad (10)$$

Equation (10) identifies factor-MIDAS, the fourth model we estimate.

The use of MIDAS toolbox presents two minor technical difficulties. First, we can only regress GDP growth on one high-frequency indicator at a time. To work around this, we estimate as many regressions as required by the number of indicators and then combine the nowcasts under a flat weighting scheme. This is unlikely to impair the model, as estimation combination has been shown to increase their performance and stability (Bessonovs, 2014; Stock and Watson, 2004). However, this has to be considered when comparing the models. Second, we cannot run a model with only contemporaneous indicators. Thus, all of our MIDAS regressions have factor or indicator lags of 3, 6 and 9 months.

5. Methodology

This section finalizes the description of methods used for the nowcasting exercise. First, we describe how we arrange the data described in Section 3 into different sets, whose nowcasting performance will be tested in the study. Then, we review automatic selection procedures that will allow narrowing the selection even further during the exercise. Lastly, we discuss the specifics of the exercise — its setup and how the performance of the models and its significance are measured.

5.1 The grouping of variables

Once we had retrieved, adjusted and transformed every indicator, we formed two databases: "Small" and "Large." The differences in performance between the models based on the Small and the Large database will allow us to answer **H1**, **H2** and possibly **H4**[8]. The models based on the Small database will allow us to answer **H3**, possibly **H4**, **H5** and **H6**.

[8] H4 can be answered by using either the Large or the Small database, as it does not distinguish between small- or large- scale FMs

While the Large database consists of all 158 indicators retrieved, the Small database consists of twenty sets of indicators. The number of indicators in each varies from three to seven. These sets reflect the attempt to explain real GDP growth by using a small number of carefully selected indicators. This has roots in the attempts of Baffigi et. al. (2004), Foroni and Marcellino (2014) and many others to estimate GDP growth from variables that reflect the supply and demand side of the gross product. The next section explains the sets constituting the Small database in greater detail.

5.1.1 Sets for the Small database

We created twenty sets and grouped them into three categories. The Table 2 lists all indicators for each of the sets.

The "Specific" category includes the Production side set, Expenditure side set, and Business Confidence Indicators. Sets of this type are common in the literature. BCIs will be useful in answering **H5** and **H6**.

The "Balanced" category includes eight sets that mix together indicators that reflect different sides of the Baltic States' economies. In constructing the Balanced sets, we began with three vital indicators reflecting the real economy (imports, exports, production in industry). Then, we continued adding indicators; first, from the real economy, and then more exotic or external variables. For example, Balanced 3 consists of imports, exports, production in industry, unemployment and HICP, to which Balanced 5 adds Economic Sentiment Indicator and EuroCoin, a real-time estimate for Eurozone GDP growth.

The "External/Finance" category includes nine sets that consist of mostly external indicators. These series are identical for each country. We created this category to account for the openness of the Baltic economies, and for the potential of timely financial data to successively nowcast growth (thus addressing **H5** and **H6**).

Table 2. The composition of the databases

LARGE	All retrieved indicators - 158		
SMALL 20 sets (each set 3-7 indicators)	Specific set	Production side	**P**roduction in industry; **P**roduction expectations over next 3 m; **C**onstruction Confidence Indicator
		Expenditure side	**I**mports with EU27; **E**xports with EU27; **T**urnover in wholesale and retrail trade (food); Same as nr 3 (non-food)
		BCIs	**I**ndustrial C.I.; **C**onstruction C.I.; **R**etail trade C.I.; **E**conomic Sentiment Indicator (ESI)
	Balanced	Balanced 1	**I**mports with World; **E**xports with World; **P**roduction in industry
		Balanced 2	**I**mports with EU27; **E**xports with EU27; **P**roduction in industry
		Balanced 3	Balanced 2 + **U**nemployment rate; **H**ICP
		Balanced 4	Balanced 3 + **E**SI
		Balanced 5	Balanced 4 + **E**uroCoin
		Balanced 6	Balanced 2 + **E**uroCoin
		Balanced 7	Balanced 6 + **O**MX.Stockholm index returns
		Balanced 8	Balanced 2 + **M**3
	Externa/Finance	External 1	EUR/USD; RUB/USD; US Gov bond yields (10yr); Euro vs EURIBOR 6m swap 1y; 3-month interest rate avg (EA)
		External 2	OECD Composite Leading Indicator for EU; for Russia; BoP - GS (EA); BoP - CA (EA); Eurozone Business Climate
		Finance 1 - global	Returns of indices S&P500; CDAX; Shanghai SE A; Shenzhen SE B; STOXX600 Europe
		Finance 2 - regional	Returns of indices CDAX; OMX.Copenhangen; OMX.Stockholm; OMX.Helsinki
		Finance 3 - domestic	Returns of indices OMX.Riga; OMX.Vilnius; OMX.Tallinn
		Finance 4 - global+regional	Returns of indices S&P500; Shanghai SE A; STOX600 Europe; OMX.Copenhangen; OMX.Stockholm; OMX.Helsinki
		Finance 5 - regional+domestic	Returns of indices CDAX; OMX.Copenhangen; OMX.Stockholm; OMX.Helsinki; OMX.Riga; OMX.Vilnius; OMX.Tallinn
		Finance 6 - global+domestic	Returns of indices S&P500; Shanghai SE A; STOX600 Europe; OMX.Riga; OMX.Vilnius; OMX.Tallinn
		Finance 7 - other financials	Crude Oil-Brent; Lumber Random Length CME 1st Futures; Baltic indices: Dry, Panamax, Capesize, Dirty tanker

Note: C.I. stands for Confidence Indicator, HICP stands for Harmonised Indx of Consumer Prices, EA stands for Euro Area, BoP stands for Balance of Payments, GS stands for Goods & Services, CA stands for Curent Account

Source: Created by the authors

The Finance sets include three types of stock exchanges' index returns: Domestic (Baltic States), Regional (Scandinavia and Germany), and Global (US, Europe and China). There is a clear trade-off between the three. As we move from Domestic to Global, we increase the efficiency of the market, but lose country-specificity of the information. It is also possible that there is some optimal combination between different types of stock returns that mix the types. This is reflected in the first six Finance sets. Finance 1, Finance 2, and Finance 3 correspond to Global, Regional, and Domestic stock market returns. Finance 4, Finance 5, and Finance 6 mix Global with Regional, Regional with Domestic, and Global with Domestic. Finance 7 is a collection of other miscellaneous financial variables (oil price, shipping cost indices, etc.).

5.2 Indicators selection

5.2.1. Automatic Selection Procedures for the BM

There is a large number of macroeconomic indicators that may contain useful information on GDP growth. However, the number of variables accommodated by the BMs is limited. Moreover, we need to take into account Boivin and Ng's (2006) argument that a FM with carefully selected variables may outperform a larger version. Thus, appropriate selection procedures are essential for this study.

The initial requirements, which indicators had to satisfy to be included in the Small and Large databases, are described in Section 3. In this section, we describe automatic selection

procedures that are applied to the sets in the Small database. The sets include already pre-selected indicators, but we believe automatic selection to be a worthwhile exercise. Our limited intuitions allow identifying relevant sets of indicators only up to a certain degree. Thus, it is possible that some sets mix important and useless variables, which harms the overall performance.

We use three automatic selection procedures: LASSO, RMSFE-Group, and RMSFE-Individual. These allow using different indicators for each nowcast without manually changing the sets. While LASSO is a theoretical procedure, the latter two have no theoretical justification or known precedent in the literature. Both of them reflect the simple intuition that indicators that were the most useful a quarter ago should still be useful, which we consider a prudent approach in an environment as volatile and transient as the Baltics. We use them only in conjunction with the BM because they share a methodological basis in OLS, and developing corresponding versions for other models would have been computationally infeasible. Lastly, note that we keep track of the indicators that are automatically selected at each step (see Appendix K). A detailed description of the procedures follows.

<u>LASSO</u>

LASSO (Least Absolute Shrinkage and Selection Operator), introduced by Tibshirani (1996), allows identifying explanatory variables that are strongly correlated with the dependant variable, while controlling for other indicators. The operator is defined as

$$\left(\hat{\alpha}, \hat{\beta}\right) = \arg\min\left\{\sum_{i}^{N}(y_i - \alpha - X_i'\beta)^2 + \lambda \sum_{j=1}^{k} |\beta_j|\right\} \qquad (11)$$

where X_i' is a *1*x*k* vector of explanatory variables, β is a *k*x*1* vector of OLS coefficients, y_i is the dependent variable and λ is a constant. While the first term estimates OLS coefficients, the second penalizes their size. As λ increases, indicators that are weakly correlated with the dependent variable shrink to 0. MATLAB implements LASSO by varying λ from a small value to a value at which all regression coefficients become 0. For a nowcast at time *t*, we select *p* indicators that are the last to receive a zero coefficient in a regression of quarterly GDP growth on quarterly indicator growth at time *t-1*. If two coefficients become zero at the same step, the indicator with the largest coefficient in absolute terms is given priority.

In the Baltics, this is somewhat similar to Schulz (2007), who selects indicators for Estonia based on their cross-correlation with GDP. However, his method neglected to control for other variables in selection phase. Stakenas (2012) uses LARS-EN to select indicators for Lithuania, but he utilizes the entire database, which compromises the pseudo real-time exercise. Outside the Baltics, Antipa et. al. (2012) use general-to-specific (Gets) automatic selection procedure to nowcast German GDP, and Bessec (2013) preselects variables for a small-scale FM with a pseudo-real time LARS-EN.

RMSFE-Individual

For a nowcast at time *t*, series of *k* indicators (in quarterly growth rates) ending at time $t - 2$ are used to estimate OLS coefficients. Each individual series is then used to produce *k* forecasts at t – 1. The *p* indicators producing the smallest individual errors are then selected for the nowcast.

RMSFE-Group

RMSFE-Group reflects the same intuition as RMSFE-Individual — the indicators that performed the best a quarter ago are the most likely to perform well this quarter. It differs in that, instead of choosing a pre-defined number of indicators, we continue adding indicators as long as there is a reason to believe they add valuable information.

For a nowcast at time *t*, series of *k* indicators ending at time $t - 2$ are used to estimate coefficients from an OLS regression. Each individual series is then used to produce *k* forecast errors at $t - 1$. The best-performing indicator is selected, and its performance is recorded as RMSFE-best. Then all the remaining $k - 1$ indicators are combined on an individual basis with the best, and coefficients are estimated using a database ending in t – 2. Then, $k - 1$ forecasts are produced at $t - 1$. If the new combination of indicators that produces the best RMSFE vis-à-vis its alternatives has a smaller RMSFE then ϒ*RMSFE-best, where ϒ is a pre-defined coefficient, it is selected as the new best combination, and its RMSFE is recorded as RMSFE-best. The procedure is repeated by adding the remaining $k - 2$ indicators to the selected indicators. This continues until either a combination producing a forecast error smaller than ϒ*RMSFE-best cannot be found or all of the indicators are selected.

Notes on Automatic Selection

For LASSO and RMSFE-Individual, the number of indicators selected (p) varies from one to one fewer than the number of indicators in the considered set. For RMSFE-Group, the coefficient Υ, which modifies the historical forecast error that a new combination has to beat, takes the values of 0.6, 0.8 and 1 to permit a tighter or looser parameterization.

RMSFE-Individual was designed as a counterpart to RMSFE-Group. While the second seems more sophisticated in exploiting the relationships between indicators, it is also likely to be more fragile. A superior performance at $t\text{-}1$ could be caused by some momentary interplay between the indicators.

A problem with RMSFE-based procedures is the amount of historical information they incorporate in selection. All of them select indicators based on only one forecast error, but, to involve a stronger consideration of historical patterns, we introduce a varying number of lags (m_S) for indicators during the selection stage.

We do not include lags or AR terms in the LASSO selection stage, as one lag would double the number of parameters to be estimated, resulting in an unwanted proliferation. Furthermore, it would be hard to justify the procedure selecting only a particular lag of an indicator over the contemporaneous term. Lastly, we must note that these methods do not consider publication lags. All variables are assumed to be fully available (as they would have been at time t).

5.2.2. On Using a Smaller Number of Indicators in FM

In spite of the common practice, Boivin and Ng (2006) argue that a large number of variables may be detrimental to the FM. While weak cross-correlation is allowed in errors of (2) and (3), including additional "noisy" series may at some point negate the benefits of any additional information they contain.

Practically, Boivin and Ng (2006) recommend choosing the "best" series from a large category of variables. For example, a database having only CPI could perform better than a database with CPI breakdowns into different categories. Although they develop some rules, they are ad hoc illustrations that mostly revolve around dropping variables whose error terms are

excessively correlated in individual versions of (5). Stakenas (2012) uses an elastic net procedure (LARS-EN) to select a small-scale database, and finds it superior to a large-scale selection (the difference was of 5 v. 52 indicators). Bessec (2013) uses a similar approach and reaches a similar conclusion.

We estimate a large-scale FM using the Large database. We estimate a small-scale factor model from the sets in the Small database, described in detail in Section 4. The sets in the Small database do not have historical gaps, and any missing observations are replaced with AR(1) estimates.

Table 3 sums up the models, databases, and selection procedures we use in this study. The parameters and their range of values for different specifications is described in Appendix C.

Table 3. The list of all models, selection procedures and datasets use

Model	Selection Procedure	Dataset	Fitting missing values	Model	Selection Procedure	Dataset	Fitting missing values	Model	Selection Procedure	Dataset	Fitting missing values
BM	-	Small	AR(1)	FM	-	Small	AR(1)	MIDAS	-	Small	AR(1)
BM	LASSO	Small	AR(1)	FM	-	Large	EM	factor-MIDAS	-	Small	AR(1)
BM	RMSFE-group	Small	AR(1)					factor-MIDAS	-	Large	EM
BM	RMSFE-individual	Small	AR(1)								

Note: BM stands for Bridge model, FM stands for Factor mode, AR(1) stands for Autoregressive process of order 1, LASSO stands for Least Absolute Shrinkage and Selection Operator, RMSFE stands for Root Mean Squared Forecast Errors, MIDAS stands for Mixed Data Sampling, EM stands for Expectation Maximization algorithm.

Source: Created by the authors

5.3 Nowcasting and Performance Review

This study performs a pseudo real-time nowcasting exercise. A real GDP nowcast is made for twenty historical quarters using information that would have been available at the time. The real-time setup is violated only by adjustments described in Section 3.

We employ a recursive nowcasting scheme That is, as we move forward in time, we add observations to the estimation matrix, having $T - 1$ quarters of observations in the estimation matrix to use for the final nowcast, where T is the full sample size. An alternative is a rolling forecast, which drops the earliest observation upon adding a new one. It could possess the advantage of considering only the most relevant information. However, our preliminary results were strongly in favour of recursive nowcasting, and we use it throughout this study.

The nowcasting performance is tested against an AR model, a common a-theoretical benchmark in the literature. We divide the root mean squared forecast error (RMSFE) of the

model in question by the RMSFE of the benchmark to obtain the relative performance (RP). A RP below 1 indicates a well-performing model. BIC is commonly used for selecting the order of the AR benchmark (Antipa et. al., 2012; Foroni and Marcellino, 2014). We simply use AR(1), as we use the same specification to estimate missing indicators in any small-scale model, and we do not use BIC to select any indicator lags.

The RP alone does not imply a systematically better or worse performance of the model in question. The statistical significance of the performance is determined with a Diebold-Mariano (1995) test. The test statistic for *T* observations is

$$DM = \frac{\frac{1}{T}\sum_i^T (e_i^{Model})^2 - (e_i^{AR})^2}{\hat{\sigma}_{DM}} \qquad (12)$$

where $(e_i^{Model})^2$ and $(e_i^{AR})^2$ are the squared estimation errors of the tested model and the AR(1) benchmark, and $\hat{\sigma}_{DM}$ is an estimate for the asymptotic variance of the test statistic. When the estimation horizon is 1, $\hat{\sigma}_{DM}$ reduces to the sample variance. The test statistic follows the Standard Normal distribution, which we approximate as Student's distribution with T – 1 degrees of freedom, as in Ajevskis and Dāvidsons (2008). If the statistic is significantly larger than 0, the model in question is inferior to the benchmark. We perform the test right-handed and define the levels of statistically significant inferiority or superiority as starting at 15% and 85%, respectively. After this point, we refer to the test's p-value as "DM." Table 4 sums up the types of performance our models could generate.

Table 4. The performance assessment criteria

Relative Performance (RP)	DM	Model is … the AR(1) becnchmark
>1	≤ 15%	statistically significantly inferior to
>1	> 15%	statistically insignificantly inferior to
= 1	-	equivalent to
<1	<85%	statistically insignificantly superior to
<1	≥85%	statistically significantly superior to

Note: DM stands for Diebold-Mariano test p-value, AR(1) stands for Autoregressive process of order 1. Relative performance is the ratio of one model's root mean squared forecast residuals (RMSFE) to RMSFE of the benchmark model (AR(1))

Source: Created by the authors

6. Analysis of Results

In this section we reflect on the overall performance of our models. The hypotheses that revolve around performance (**H1-4**) of the models are answered in this section. As there is no consensus on the best tools for nowcasting, finding the best technical approach may be as important as finding the best indicators. With this in mind, we proceed.

Table 5. The hypotheses H1-H4 (related to models)

Related to models	**H1**	FMs result in a better performance than BMs
	H2	Large-scale FMs result in a better performance than small-scale FMs
	H3	MIDAS results in a better performance than BMs or small-scale FMs
	H4	factor-MIDAS results in a better performance than FM

Source: Created by the authors

Note that Tables 6-7 report only the best specifications (judged by relative performance - RP) from a given Model-Dataset dyad. Their exact parameters are given only in select cases. The full description is available online and upon request. The same holds for the entire, unreported range of our outputs. We recommend consulting Table 2 (the list of indicators for each set) while reading the next sections.

6.1 Automatic BMs

In this section, we compare the performance of the bridge models (BMs) that use all indicators in a given set to the performance of the BMs that utilize automatic selection criteria to narrow the list of indicators. These methods involve the most tightly parameterized models in this study. This discussion concerns only the Small database. This will not answer any hypotheses directly, but it will contribute to providing a more reliable answer to **H1**.

Automatic selection criteria dominate using the full set (that is, not applying any selection procedures) in almost all cases. Out of 60 best selection criteria-indicator set pairs (for 20 sets over 3 countries), only two deliver their best performance for a given country when the full set is used, and only one of them is significant (the Balanced 8 for Estonia, specifications given below). See Appendix E for details.

The absolutely best performance for all countries' BMs is generated by a RMSFE-based procedure (see Table 6). We want to stress that the best performance in this study for Lithuania (RP = 0.828, DM = 85%) and Estonia (RP = 0.627, DM = 98%) come from applying RMSFE-Individual and RMSFE-Group to Balanced 7 and Production side, respectively.

So, incorporating less information is preferable in BMs. However, they are not designed for handling a large number of indicators. To better asses the importance of using a large amount of information, we turn to factor models (FMs).

6.2 FMs

First, we look at the large scale-FM. It beats the benchmark for both Latvia and Estonia, but insignificantly. The Lithuanian model performs even worse, with a statistically insignificant inferior performance.

Applying the FM to the sets in the Small database immediately yields a number of encouraging results. Out of 20 indicator sets, there are no significant results for Lithuania, but six and three for Latvia and Estonia, respectively. As the large-scale FMs have no significant performance at all, **H2** is automatically rejected— using the small-scale FMs results in a better performance than using large-scale FMs.

In most cases when the small-scale FMs generate a significant performance, it is inferior to BM-RMSFE-based. This is universally true for Estonia and Lithuania. However, a notable exception is some of the Finance sets (Finance 3, 5, and 6). These sets in combination with the FM generate the three strongest performances for Latvia out of all models. Still, as it is negated for two countries out of three, we reject **H1**: BMs result in a better performance than FMs.

Answering **H1** amounted to differentiating between BMs with automatic selection procedures and small-scale FMs. In other words, it was a choice between the two most tightly parametrized models in this study, and the more selective prevailed. Introducing additional information in the form of more indicators has decisively failed to produce better results. To judge the usefulness of adding information in the form of more sensitive temporal aggregation, we look at the performance of MIDAS and factor-MIDAS.

Table 6. The performance of different BMs specifications

DATABASE	SET	Number of significant specifications	LATVIA								LITHUANIA								ESTONIA							
			Full Set		LASSO		RMSFE-Group		RMSFE-Individual		Full Set		LASSO		RMSFE-Group		RMSFE-Individual		Full Set		LASSO		RMSFE-Group		RMSFE-Individual	
			RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM
SMALL	Production side	6	**0.854**	82%	**0.812**	**87%**	**0.879**	80%	**0.808**	**92%**	**0.989**	55%	1.021	44%	**0.995**	53%	**0.992**	54%	**0.635**	**99%**	**0.675**	**99%**	**0.627**	**98%**	**0.716**	**97%**
	Expenditure side	7	**0.801**	**93%**	**0.796**	**93%**	**0.748**	**93%**	**0.763**	**95%**	1.059	29%	**0.959**	64%	**0.943**	73%	**0.902**	78%	**0.948**	66%	**0.760**	**95%**	**0.836**	**90%**	**0.747**	**95%**
	BCIs	1	1.123	8%	**0.935**	72%	1.102	22%	1.123	16%	**0.970**	68%	**0.903**	**91%**	1.148	10%	**0.945**	69%	**0.983**	56%	**0.983**	55%	1.000	50%	**0.959**	63%
	Balanced 1	4	**0.960**	58%	**0.928**	68%	**0.865**	78%	**0.791**	**97%**	1.010	47%	**0.947**	66%	**0.931**	72%	**0.877**	**90%**	**0.874**	75%	**0.868**	76%	**0.765**	**90%**	**0.778**	**89%**
	Balanced 2	6	**0.812**	**88%**	**0.744**	**95%**	**0.723**	**95%**	**0.714**	**95%**	**0.928**	74%	**0.914**	72%	**0.860**	**87%**	**0.868**	**89%**	**0.899**	75%	**0.870**	84%	**0.859**	84%	**0.872**	82%
	Balanced 3	5	1.225	17%	**0.800**	**90%**	**0.721**	**94%**	**0.714**	**95%**	1.024	43%	**0.946**	67%	**0.970**	61%	**0.952**	65%	**0.972**	60%	**0.822**	**92%**	**0.938**	62%	**0.807**	**89%**
	Balanced 4	5	1.352	3%	**0.924**	**86%**	**0.811**	**88%**	**0.796**	**90%**	1.099	21%	**0.936**	**90%**	1.074	14%	1.015	44%	1.145	14%	**0.822**	**92%**	**0.913**	71%	**0.890**	75%
	Balanced 5	4	1.240	12%	**0.935**	67%	**0.844**	84%	**0.822**	**87%**	1.060	31%	**0.921**	75%	1.140	11%	**0.990**	53%	1.000	50%	**0.822**	**92%**	**0.828**	**91%**	**0.809**	**98%**
	Balanced 6	5	**0.902**	72%	**0.789**	**93%**	**0.772**	**92%**	**0.730**	**95%**	1.068	35%	**0.964**	58%	**0.984**	55%	**0.925**	68%	1.030	43%	1.024	44%	**0.814**	**87%**	**0.817**	**91%**
	Balanced 7	5	**0.950**	61%	**0.789**	**93%**	**0.754**	**94%**	**0.712**	**96%**	1.097	29%	**0.926**	68%	**0.994**	52%	**0.828**	**85%**	1.122	27%	1.091	31%	**0.847**	82%	**0.807**	**92%**
	Balanced 8	9	**0.789**	**94%**	**0.743**	**98%**	**0.801**	**90%**	**0.705**	**96%**	1.185	16%	1.086	31%	**0.910**	79%	**0.884**	**86%**	**0.668**	**95%**	**0.683**	**95%**	**0.805**	**86%**	**0.806**	**89%**
	External 1	-	2.384	2%	2.015	4%	1.267	12%	1.134	25%	1.640	3%	1.293	11%	**0.958**	62%	**0.965**	60%	1.930	1%	1.393	4%	1.156	19%	**0.890**	69%
	External 2	6	**0.947**	67%	**0.810**	**89%**	**0.792**	**94%**	**0.753**	**96%**	**0.925**	67%	**0.899**	71%	1.067	34%	**0.900**	73%	**0.962**	62%	**0.764**	**99%**	**0.812**	**96%**	**0.701**	**99%**
	Finance 1	-	**0.944**	58%	**0.982**	53%	**0.871**	77%	**0.870**	75%	**0.967**	58%	**0.963**	59%	**0.974**	58%	**0.977**	56%	1.195	25%	**0.972**	57%	**0.876**	81%	**0.874**	81%
	Finance 2	-	1.213	23%	1.182	24%	**0.976**	55%	**0.945**	61%	1.033	43%	1.006	49%	1.013	47%	**0.996**	51%	**0.952**	59%	**0.959**	58%	**0.917**	66%	**0.914**	66%
	Finance 3	4	**0.822**	80%	**0.785**	**86%**	**0.833**	83%	**0.800**	**88%**	1.042	41%	1.005	49%	1.063	36%	1.006	48%	**0.962**	59%	**0.773**	**93%**	**0.849**	80%	**0.835**	**86%**
	Finance 4	-	1.222	13%	1.163	26%	**0.962**	59%	**0.876**	76%	1.159	16%	1.028	43%	1.087	32%	1.046	38%	1.244	19%	**0.890**	81%	**0.879**	75%	**0.858**	79%
	Finance 5	2	1.111	38%	**0.844**	83%	**0.847**	82%	**0.764**	**94%**	1.053	38%	1.001	50%	1.064	36%	**0.976**	56%	1.040	42%	**0.780**	**92%**	**0.829**	81%	**0.822**	84%
	Finance 6	3	**0.917**	67%	**0.844**	83%	**0.729**	**93%**	**0.754**	**94%**	1.110	30%	1.005	49%	1.049	36%	**0.988**	53%	1.324	12%	**0.765**	**94%**	**0.880**	74%	**0.861**	79%
	Finance 7	-	1.343	2%	1.118	28%	**0.872**	83%	**0.837**	84%	1.166	26%	1.012	47%	**0.860**	82%	**0.943**	64%	1.707	1%	1.023	46%	1.077	40%	1.003	49%
Number of significant specifications			3		10		9		14		0		2		1		4		2		10		7		10	
			36								**7**								**29**							
Best performers			Balanced 8		Balanced 8		Balanced 3		Balanced 8		External 2		External 2		Balanced 2		Balanced 7		Production side		Production side		Production side		External 2	
			0.789	94%	0.743	98%	0.721	94%	0.705	96%	0.925	67%	0.899	71%	0.860	87%	0.828	85%	0.635	99%	0.675	99%	0.627	98%	0.701	100%
	Indicator lags (Q)		0		3		0		0		0		0		1		3		2		2		3		3	
	AR lags		1		0		0		0		1		1		0		0		1		1		0		0	
	Indicators selected		-		2		-		2		-		4		-		2		-		2		-		1	
	ϒ		-		-		0.6		-		-		-		1		-		-		-		0.6		-	
	Lags in the selection matrix		-		-		0		0		-		-		2		0		-		-		0		1	

Note: BM stands for Bridge Model, LASSO stands for Least Absolute Shrinkage and Selection Operator, RMSFE stands for Root Mean Squared Forecasting Errors, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value, Q stands for quarters, AR lags stands for GDP lags, ϒ is a coefficient modifyng the inclusion criteria (used only for RMSFE-Group). Small database contains 20 sets of indicators, where each set has 3-7 indicators. Best performers are identified by looking at the lowest RP. The parameters at the bottom of this table are the details behind the best performers.The RP-DM dyads are colored when the performance is significantly superior to AR(1).

Source: Created by the authors

Table 7. The performance of all models without selection criteria

DATABASE	SET	LATVIA								LITHUANIA								ESTONIA							
		BM		FM		MIDAS		factor-MIDAS		BM		FM		MIDAS		factor-MIDAS		BM		FM		MIDAS		factor-MIDAS	
		RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM	RP	DM
LARGE	-	-	-	**0.946**	62%	-	-	**0.953**	76%	-	-	1.006	48%	-	-	**0.884**	**100%**	-	-	**0.970**	56%	-	-	**0.837**	**100%**
SMALL	Production side	**0.854**	82%	**0.974**	56%	**0.959**	72%	**0.818**	**90%**	**0.989**	55%	1.022	44%	1.000	50%	**0.971**	74%	**0.635**	**99%**	**0.965**	57%	**0.802**	**100%**	**0.778**	**100%**
	Expenditure side	**0.801**	**93%**	**0.984**	54%	**0.978**	63%	**0.888**	**88%**	1.059	29%	1.026	43%	**0.972**	75%	**0.938**	83%	**0.948**	66%	**0.876**	75%	1.004	34%	**0.822**	**100%**
	BCIs	1.123	8%	**0.978**	55%	1.061	22%	**0.823**	**91%**	**0.970**	68%	1.023	44%	**0.939**	82%	**0.921**	**90%**	**0.983**	56%	**0.977**	54%	**0.928**	**90%**	**0.796**	**100%**
	Balanced 1	**0.960**	58%	**0.896**	76%	**0.946**	76%	**0.799**	**95%**	1.010	47%	**0.957**	61%	**0.918**	**91%**	**0.898**	**98%**	**0.874**	75%	**0.885**	74%	**0.963**	**91%**	**0.738**	**100%**
	Balanced 2	**0.812**	**88%**	**0.839**	**86%**	**0.914**	**88%**	**0.824**	**92%**	**0.928**	74%	**0.941**	65%	**0.972**	74%	**0.919**	**88%**	**0.899**	75%	**0.910**	67%	**0.951**	**97%**	**0.774**	**100%**
	Balanced 3	1.225	17%	**0.752**	**96%**	1.012	43%	**0.812**	**96%**	1.024	43%	**0.896**	75%	**0.977**	71%	**0.921**	81%	**0.972**	60%	**0.979**	55%	**0.983**	68%	**0.786**	**100%**
	Balanced 4	1.352	3%	**0.840**	**90%**	1.015	40%	**0.964**	68%	1.099	21%	**0.973**	58%	**0.963**	84%	**0.941**	**88%**	1.145	14%	**0.959**	59%	**0.982**	69%	**0.725**	**100%**
	Balanced 5	1.240	12%	**0.901**	72%	**0.973**	69%	**0.901**	**87%**	1.060	31%	1.033	42%	**0.947**	**90%**	**0.934**	**87%**	1.000	50%	1.022	45%	**0.965**	83%	**0.774**	**100%**
	Balanced 6	**0.902**	72%	1.008	48%	**0.881**	**94%**	**0.786**	**95%**	1.068	35%	1.117	25%	**0.946**	84%	**0.890**	**86%**	1.030	43%	1.015	47%	**0.947**	**95%**	**0.901**	**96%**
	Balanced 7	**0.950**	61%	**0.996**	51%	**0.927**	85%	**0.832**	**94%**	1.097	29%	1.078	32%	**0.953**	81%	**0.857**	**89%**	1.122	27%	1.008	48%	**0.961**	81%	**0.947**	84%
	Balanced 8	**0.789**	**94%**	1.121	24%	**0.824**	**97%**	**0.765**	**97%**	1.185	16%	1.165	19%	**0.991**	56%	**0.926**	84%	**0.668**	**95%**	**0.931**	64%	**0.903**	**100%**	**0.702**	**100%**
	External 1	2.384	2%	2.102	1%	1.262	11%	1.037	40%	1.640	3%	1.274	11%	**0.945**	64%	**0.869**	**94%**	1.930	1%	1.437	5%	1.040	41%	**0.759**	**98%**
	External 2	**0.947**	67%	**0.863**	80%	**0.926**	78%	**0.830**	**93%**	**0.925**	67%	1.018	46%	**0.916**	**94%**	**0.907**	**88%**	**0.962**	62%	**0.898**	73%	1.003	48%	**0.916**	**99%**
	Finance 1	**0.944**	58%	**0.836**	82%	1.130	5%	**0.909**	**89%**	**0.967**	58%	1.033	41%	**0.973**	69%	**0.930**	**90%**	1.195	25%	**0.870**	77%	**0.983**	63%	**0.737**	**99%**
	Finance 2	1.213	23%	1.030	45%	1.196	2%	**0.880**	**90%**	1.033	43%	1.046	39%	**0.954**	79%	**0.922**	**91%**	**0.952**	59%	**0.911**	66%	1.016	42%	**0.799**	**99%**
	Finance 3	**0.822**	80%	**0.693**	**97%**	**0.955**	63%	**0.818**	**95%**	1.042	41%	**0.986**	53%	1.006	44%	**0.952**	83%	**0.962**	59%	**0.803**	**87%**	**0.999**	51%	**0.826**	**99%**
	Finance 4	1.222	13%	**0.973**	55%	1.168	3%	**0.911**	84%	1.159	16%	1.047	38%	**0.951**	83%	**0.933**	**90%**	1.244	19%	**0.895**	69%	1.021	34%	**0.784**	**99%**
	Finance 5	1.111	38%	**0.668**	**95%**	1.096	18%	**0.874**	**90%**	1.053	38%	**0.972**	58%	**0.973**	73%	**0.933**	79%	1.040	42%	**0.791**	**88%**	1.015	39%	**0.828**	**99%**
	Finance 6	**0.917**	67%	**0.695**	**97%**	1.043	32%	**0.832**	**98%**	1.110	30%	**0.991**	53%	**0.985**	64%	**0.941**	**91%**	1.324	12%	**0.795**	**88%**	**0.993**	57%	**0.740**	**98%**
	Finance 7	1.343	2%	1.060	38%	1.013	29%	**0.837**	**85%**	1.166	26%	**0.960**	61%	**0.965**	75%	**0.940**	85%	1.707	1%	**0.926**	64%	1.061	26%	**0.738**	**99%**
Best performers		Balanced 8		Finance 5		Balanced 8		Balanced 8		External 2		Balanced 3		External 2		Balanced 7		Prodution side		Finance 5		Production side		Balanced 8	
		0.789	94%	0.668	95%	0.824	97%	0.765	97%	0.925	67%	0.896	75%	0.916	94%	0.857	89%	0.635	99%	0.791	88%	0.802	100%	0.702	100%
	Indicator lags (Q)	0		-		-		-		0		-		-		-		2		-		-		-	
	Indicator lags (M)	-		-		9		-		-		-		6		-		-		-		9		-	
	Factors	-		3		-		3		-		2		-		1		-		2		-		1	
	Factor lags (Q)	-		3		-		-		-		2		-		-		-		3		-		-	
	Factor lags (M)	-		-		-		9		-		-		-		6		-		-		-		6	
	Indicator lags in the stacked matrix (M)	-		1		-		0		-		2		-		0		-		0		-		2	
	AR lags	1		1		0		0		1		0		0		0		1		1		0		1	

Note: BM stands for Bridge Model, FM stands for Factor Model, MIDAS stands for Mixed Data Sampling, RMSFE stands for Root Mean Squared Forecasting Errors, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value, Q stands for quarters, M stands for Months, AR lags stands for GDP lags. Large database contains all retrieved indicators, 159. Small database contains 20 sets of indicators, where each set has 3-7 indicators. Best performers are identified by looking at the lowest RP. The parameters at the bottom of this table are the details behind the best performers. The RP-DM dyads are colored when the performance is significantly superior to AR(1).

Source: Created by the authors

6.3 MIDAS and factor-MIDAS

The sets that perform the best for a simple BM also perform the best for MIDAS (Balanced 8 for Latvia, External 2 for Lithuania, and Production side for Estonia), stressing its role as an alternative to BMs. However, the statistically significant performance is worse for Latvia and Estonia. This is true both against a simple BM and a BM with automatic selection criteria. So, we reject **H3**: MIDAS is inferior to BMs.

The most striking aspect of factor-MIDAS is the increase in significance it provides for a wide range of sets. Out of 20 indicator set-model combinations that are simultaneously significant for all three countries, 16 involve factor-MIDAS (see Appendix D).

For factor-MIDAS, as for FMs, the best specifications involve small sets. For Latvia, the best FM (Finance 5) outperforms the best factor-MIDAS (Balanced 8). However, for Estonia and Lithuania, the best of factor-MIDAS (Balanced 7 and 8) prevails over the best of FMs (Finance 5 and Balanced 3). Thus, **H4** is confirmed: factor-MIDAS results in a better performance than FMs.

6.4 Overall

Table 8. The best performers by country

Country	Set	Model/Selection	Database	RP	DM	AR	Number of indicators selected	Indicators lags (Q)	Number of factors	Factor lags (Q)	Factor lags (M)	Lags in stacked matrix	Lags in selection matrix	Y
LATVIA	Finance 5	FM/-	Small	0.668	95%	1	-	-	3	3	-	1	-	-
	Finance 3	FM/-	Small	0.693	97%	1	-	-	2	3	-	1	-	-
	Finance 6	FM/-	Small	0.695	97%	1	-	-	2	3	-	0	-	-
	Balanced 8	BM/RMSFE-Individual	Small	0.705	96%	0	2	0	-	-	-	-	0	-
	Balanced 7	BM/RMSFE-Individual	Small	0.712	96%	0	1	0	-	-	-	-	0	-
LITHUANIA	Balanced 7	BM/RMSFE-Individual	Small	0.828	85%	0	2	3	-	-	-	-	0	-
	Balanced 7	factor-MIDAS	Small	0.857	89%	0	-	-	1	-	6	0	-	-
	Finance 7	BM/RMSFE-group	Small	0.860	82%	0	-	1	-	-	-	-	0	0.8
	Balanced 2	BM/RMSFE-group	Small	0.860	87%	0	-	1	-	-	-	-	2	1
	Balanced 2	BM/RMSFE-Individual	Small	0.868	89%	0	1	1	-	-	-	-	2	-
ESTONIA	Production side	BM/RMSFE-group	Small	0.627	98%	0	-	3	-	-	-	-	0	0.6
	Production side	BM/-	Small	0.635	99%	1	-	2	-	-	-	-	-	-
	Balanced 8	BM/-	Small	0.668	95%	1	-	1	-	-	-	-	-	-
	Production side	BM/LASSO	Small	0.675	99%	1	2	2	-	-	-	-	-	-
	Balanced 8	BM/LASSO	Small	0.683	95%	1	3	1	-	-	-	-	-	-

Note: BM stands for Bridge Model, FM stands for Factor Model, MIDAS stands for Mixed Data Sampling, LASSO stands for Least Absolute Shrinkage and Selection Operator, RMSFE stands for Root Mean Squared Forecasting Errors, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value, AR stands for GDP lags, Q stands for quarters, M stands for months, Y is a coefficient modifyng the inclusion criteria (used only for RMSFE-Group). Small database contains 20 sets of indicators, where each set has 3-7 indicators. Best performers are identified by looking at the lowest RP. The best performers for each country identified in this study are colored.

Source: Created by the authors

Table 8 presents the five best RPs for each of the Baltic countries. The list is dominated by BMs with RMSFE-based selection criteria, except for Latvia, where finance-related FMs outperform anything else.

All of the data comes from the Small database. The composition of sets is discussed in more detail in the next section. Appendix D presents the list of model and dataset combinations which are found to be significantly superior to the AR(1) benchmark model across all three countries.

Although we cannot test the statistical significance of rankings, they display a pattern that is unlikely to be due to chance. We have 20 sets of indicators featured in 7 models. If all of the 140 combinations are equally likely to succeed, the probability of drawing three and two specifications that share the same indicator set amongst themselves, as is the case for Estonia, is virtually 0[9]. The same holds for Lithuania and Latvia if for the latter we calculate the probability for models, instead of sets.

Lastly, we note that the best performance for Latvia comes from a set of indicators with no publication lag. The best performance for Lithuania and Estonia is produced by applying automatic selection to sets that mix indicators with and without publication lags. Therefore, we cannot answer **H6** at this point. To do this, we will analyse the structure of the best-performing sets in the next section.

7. Discussion of Results

This section analyses the performance of the previously described models, and answers the indicator-related hypotheses H5 and H6. We must stress once again that this is not an in-depth study of the determinants of the Baltic economy. The models chosen are not suitable for detecting economic causality and uncovering fundamental drivers of economic growth. Our primary interest is practical, and limited to detecting the set of variables and models that are useful for obtaining information on current economic conditions in almost real time.

[9] $140 * 6 * 133 * 5 * 6 * \frac{135!}{140!} \approx 0.00007\%$

Table 9. The hypotheses H5-H6 (related to indicators)

Related to indicators	**H5**	For all countries, the best-performing database of variables for the best-performing model includes only variables with no publication lag
	H6	It is possible to create a successful nowcast for all Baltic States using only variables with no publication lag.

Source: Created by the authors

The first three sub-sections are dedicated to discussing the types of economic indicators that are important for nowcasting (financial, real economy and timely variables), and conjecturing the reasons behind their significance. Table 10 reviews the indicators constituting the sets discussed in this section. The discussion is mostly concerned with the specifications listed in Table 8. For a few models we report the cumulative Relative Performance; that is, the value of the RP as it evolves throughout the out-of-sample period (see Appendix H). It reflects the stability of the performance, and its final value equals the RP reported in the output tables.

Before proceeding, we must note that the third best performer for Lithuania, Finance 7, is statistically insignificant (RP = 0.860, DM = 82%) and will not be considered. It is an economically counterintuitive set, featuring such indicators as Lumber Random Length CME 1st Futures and Baltic Exchange Dirty Tanker, so its loss is unlikely to damage the discussion.

Table 10. The sets relevant to the Discussion of Results

Balanced 2	Imports with EU27; Exports with EU27; Production in industry
Balanced 7	Imports with EU27; Exports with EU27; Production in industry; EuroCoin; OMX.Stockholm (returns)
Balanced 8	Imports with EU27; Exports with EU27; Production in industry; M3
Production side	Production in industry; Production expectations over next 3 m; Construction Confidence Indicator
Finance 3	Returns of stock indices: OMX.Riga; OMX.Vilnius; OMX.Tallinn
Finance 5	Returns of stock indices: CDAX; OMX.Copenhangen; OMX.Stockholm; OMX.Helsinki; OMX.Riga; OMX.Vilnius; OMX.Tallinn
Finince 6	Returns of stock indices S&P500; Shanghai SE A; STOX600 Europe; OMX.Riga; OMX.Vilnius; OMX.Tallinn
BCIs	Industrial C.I.; Construction C.I.; Retail trade C.I.; Economic Sentiment Indicator (ESI)

Source: Created by the authors

7.1 Financial Variables

A similar pattern can be observed for both Latvian and Estonian BMs — when M3 is added to the real-economy based Balanced 2, thus resulting in Balanced 8, the nowcasting

performance increases significantly. A BM with Balanced 8 delivers the fourth and fifth best overall RP for Latvia and Estonia, respectively. Using a post-crisis period, our findings support Benkovskis (2008) who found that M3 was an important indicator for short-term forecasting of the Latvian GDP before 2008. We can add that this holds after the crisis period and also for Estonia, a Eurozone member since 2011Q1. This is also in line with Schulz (2007), who found financial variables to be of great of importance for Estonia, and alleviates his doubts that they might be about to lose importance.

For Lithuania, when M3 is added to Balanced 2, it destroys the performance. This is the first indication that financial variables are a less useful variable for Lithuania. If we look at a simple proxy for the importance of monetary aggregates, private sector loans to GDP (Appendix I), the greater relative importance of M3 for Latvia and Estonia seems justified.

Another financial variable important for Latvia and Estonia, but less for Lithuania, is stock returns. When Finance 3, which includes only the returns of the Baltic stock exchanges, is plugged into a FM, it leads to the second best overall performance for Latvia (RP = 0.693). This is further improved by using Finance 5, which mixes the returns of the Baltic and regionally significant stock exchanges. The resulting performance is the best for Latvia (RP = 0.668). A somewhat similar, but less pronounced, pattern repeats for Estonia. Finance 5 delivers the best FM performance for Estonia (RP = 0.791, see Table 7), and improves over the significant Finance 3 and 6. However, these specifications are not among Estonia's best.

In both cases, the FMs with the returns of the three Baltic stock exchanges are improved upon by adding regional returns. The nowcasting performance of the regional exchanges alone is weak (the Finance 2 set), while Finance 3 (the returns of OMX Riga, Tallinn and Vilnius) is significant. So, the regional returns only provide marginal information to the already solid basis of the Baltic returns. Furthermore, if we look at cumulative RP of the Finance sets throughout the out-of-sample (see Appendix H), the RPs of the three stock return sets converge towards the end of the sample for both Latvia and Estonia. The superiority of Finance 5 over 3 can be mostly explained by errors in the first few quarters.

In terms of stock market capitalization to GDP (see Appendix I), Lithuania ranks higher than either Latvia or Estonia, which might lead us to expect different results. However, we must note that the FMs reflect the common movements of the returns, so they should be interpreted as

providing a timely reflection of the region's economic climate, not establishing a connection between a country and its stock market. An argument for this is afforded by inspecting Finance 5 BMs with well-performing automatic selection criteria. Both for Latvia (RMSFE-Individual, RP = 0.729) and Estonia (LASSO, RP = 0.780), external market returns are selected far more often than the nowcasted country's (see Table 11). In future applications, nowcasters and forecasters could use stock returns as scaled or selected by trade flows.

Further doubt is raised by the fact that Baltic stock markets are not known for their efficiency or liquidity. Yet, for our purposes, an efficient stock market is not required. As we nowcast at the end of the quarter, the market needs only to respond to whatever has happened during that quarter. These considerations invite a further study into the nowcasting reliability of the Baltic stock markets throughout the quarter, and their short-term forecasting performance.

Table 11. Indicator picks from BMs with automatic selection

Country	Set	RP	DM	Selection procedure	Tot. picks	Indicators selected
LATVIA	Balanced 8	0.705	96%	RMSFE-Individual	40	Exports with EU27 (13), Imports with EU27 (9), M3 (9), Production in Industry (9)
	Balanced 7	0.712	96%	RMSFE-Individual	20	Exports with EU27 (7), Imports with EU27 (4), OMX Stockholm returns (6), Production in Industry (2), EuroCoin (1)
	Production Side	0.812	87%	LASSO	20	Construction Confidence Indicator (17), Production Expectations Over Next 3m (3)
	Finance 5	0.729	94%	RMSFE-Individual	40	Returns of OMX.Riga (5), Tallinn (5), Vilniuns (6), Stockholm (9), Copenhagen (6), Helsinki (6), CDAX (3)
LITHUANIA	Balanced 7	0.828	85%	RMSFE-Individual	40	Exports with EU27 (8), Imports with EU27 (11), OMX Stockholm returns (5), Production in Industry (6), EuroCoin (10)
	Balanced 2	0.860	87%	RMSFE-Group	21	Exports with EU27 (8), Imports with EU27 (7), Production in Industry (6)
	Balanced 2	0.868	89%	RMSFE-Individual	20	Exports with EU27 (6), Imports with EU27 (7), Production in Industry (7)
	BCIs	0.903	91%	LASSO	60	Industrial Confidence (2), Construction Confidence (20), ESI (14), Retail trade Confidence (6)
ESTONIA	Production Side	0.627	98%	RMSFE-Group	25	Production in Industry (9), Production Expectations Over Next 3m (14), Construction Confidence Indicator (2)
	Production Side	0.675	99%	LASSO	40	Production Expectations Over Next 3m (20), Construction Confidence Indicator (20)
	Balanced 8	0.683	95%	LASSO	60	Imports with EU27 (20), M3 (20), Production in Industry (20)
	Balanced 8	0.806	89%	RMSFE-Individual	60	Exports with EU27 (18), Imports with EU27 (12), M3 (13), Production in Industry (17)
	Finance 5	0.780	92%	LASSO	20	OMX Vilnius returns (13), OMX Tallinn returns (2), CDAX returns (5)

Note: the number in parantheses indicates the how many times the respective indicats has been selected. RP stands for Relative Performance, DM stands for Diebold-Mariano test. Please consult Table 2 for an extended list of indicators for each set. For some sets we report more details in Appendix H.

Source: Created by the authors

7.2 Real Economy Variables

Unsurprisingly, trade with EU27 features prominently in nowcasting the output of the Baltic economies. This holds most strongly for Lithuania. Its first, fourth and fifth best indicator sets involve using automatic selection criteria, which pick imports and exports with EU27 more than any other variables (see Table 8 and 11). If we add Production in Industry, Lithuania is the only country whose best nowcasts involve more variables with a publication lag than without. Upon a quick inspection, it can be seen that the Lithuanian GDP growth is the most volatile during out-of-sample (see Appendix J). It also has more insignificant models and the significant

ones have a higher RP. As was noted in the Literature Review, economic volatility may change the best predictors of output. It is possible that this influences the relevance of readily available, forward-looking indicators that are so useful for Latvia and Estonia. However, we must note that OMX Stockholm returns and EuroCoin, a real-time estimate of the Eurozone growth rate, still provide some marginal information for the best Lithuanian specification (see Table 11 and Appendix K). At this point, we may reject **H5**: The best-performing databases for the best-performing models do not include only variables with no publication lag.

For Latvia, the fourth and fifth best performing specifications are BMs with automatic selection (RMSFE-Individual) from Balanced 8 and 7 sets. The list of selected variables are dominated by imports and exports with EU27 (see Table 11). This is similar for Estonia, where Balanced 8 shows the fifth and third best performance in BMs with LASSO and without any selection criteria.

However, a more ambiguous case presents itself in three Production side BM specifications, which are the best, second best and fourth best models for Estonia. While this set is based around Production in Industry, two out of three variables in it are surveys (Production Expectations over the Next 3 months and Construction Confidence Indicator). The overall RP between using RMSFE-Group, the best approach, and no selection criterion, the second best, is almost negligible (0.627 vs. 0.635). However, cumulative RP shows that using RMSFE-Group steadily outperforms the full set each quarter, even if just by a fraction (see Appendix H). Thus, the difference between the two seems too consistent to be ascribed to chance. Judging by the RMSFE-Group selections, surveys, especially Production Expectations, are overall more important than Production in Industry (see Table 11). Still, there are quarters towards the end of the out-of-sample when only Production in Industry is selected (see Appendix K).

The importance of Production side for Estonia cannot be justified with its economic structure, which is not much more industrialized than Latvia's or Lithuania's. The difference can be most feasibly explained by the surveys. As shown by Production side BM with LASSO selection, the fourth best model for Estonia, a successful nowcast can be created just with surveys about industrial production (see Table 11). However, if we try to use only Production in

Industry to nowcast the GDP, the results for Estonia are no better than for Latvia or Lithuania[10]. It seems possible that the importance of surveys for nowcasting depends on two relationships: how well a survey predicts the relevant variable, and how closely the variable is related to GDP growth. Even if industrial production is not more strongly related to GDP growth for Estonia than other Baltic countries, it is possible that the surveys predict production more efficiently, thus making Production side a superior set. To test this, future research could study the efficacy of surveys in predicting their underlying macroeconomic variables. Given the similar economic structures, if Estonian surveys are more informative, then their Latvian and Lithuanian counterparts may suffer from either methodological problems or the respondents' biases.

7.3 The Role of Timely Variables

Appendix F lists the indicators with no publication lag that significantly beat the benchmark. **H6** is accepted: It is possible to construct a successful nowcast only out of indicators with no publication lags. This can be done with both surveys and stock returns. The significance of stock returns has already been discussed at length. While it is notable that factor-MIDAS with stock returns delivers significant results for Lithuania, this model has significant, but rather weak, results for almost all specifications (see Appendix D), so this will not be discussed at length.

A more interesting point are the performance of surveys that can be achieved by either factor-MIDAS or a BM with automatic selection criterion, the latter being superior. For Latvia and Estonia, using LASSO with Production side yields a strong, survey-based performance. LASSO with BCIs results in the best-performing timely set for Lithuania, although it is not among the best five for this country.

This performance contradicts Benkovskis (2008) and Schulz (2007), who could not produce reliable forecasts with surveys. However, they used them as a full set, which we also found to lead to insignificant results. This was reversed by applying selection procedures to filter the data, somewhat similarly to Hansson, Jansson and Löf (2005). We are in partial agreement with Stakenas (2012), who ascribed surveys the greatest weight in forecasting based on their correlation with GDP.

[10] Results available upon request

To end the discussion, we explicitly answer the **RQ**: "Which model and indicators offer the most accurate nowcasts of quarterly real GDP growth for each of the Baltic States?"

For Latvia, the best nowcasts are made using the returns of OMX Riga, Vilnius, Tallinn, Stockholm, Helsinki, Copenhagen and CDAX in a dynamic factor model with static principal components.

For Lithuania, the best nowcasts are made using imports and exports with EU27, production in industry, EuroCoin and OMX Stockholm returns in a bridge model, in which two indicators are selected from the aforementioned group based on past forecasting performance.

For Estonia, the best nowcasts are made using production in industry, production expectations over the next 3 months and Construction Confidence Indicators in a bridge model, in which a varying number of indicators are selected from the aforementioned group based past forecasting performance

Appendices G-H illustrate the nowcasts of the best models and their cumulative RPs. As it can be seen, the RPs are mostly stable throughout the out-of-sample, even for the more volatile Lithuania.

7.4 Limitations

There are four major limitation to our paper. First, we have not considered the impact revisions of already published macroeconomic data might have on nowcast accuracy. Second, all of our models are linear in the parameters. It is possible that different conclusions regarding the use of many indicators could be achieved by using non-linear models. Third, we apply our selection procedures only to the BMs. This could be easily extended in further research. Fourth, we always have the same lag length for all variables in our model. This is a consequence of the extensive use of automatic selection in this study.

8. Conclusions

This study compared the performance of various models and indicators in nowcasting the real GDP growth of the three Baltic States. We nowcast the Baltic output growth over 20 quarters (2010 Q4 – 2015 Q3) using four models, three automatic selection procedures, two of which we introduce, and two databases, one of which consists of 20 subsets.

First, we found that the most important short-term predictors of Latvian output are a mix of Baltic and regional stock returns. For Estonia, a Production side specification, where two out of three indicators are surveys, dominates. These showcase the sensitive nature of nowcasting, where both timely availability and economic significance have to be balanced.

Lithuanian GDP is the hardest to nowcast. The most prominent predictor is trade with EU27, although OMX Stockholm stock returns and EuroCoin provide some valuable additional information. The differences and difficulties of the Lithuanian case provide a possible avenue for further research: how do the best short-term predictors of output change under economic volatility?

A somewhat surprising finding was the pervasive usefulness of surveys when automatic selection in BMs is applied. We have managed to produce significant nowcasts that use only surveys for all three countries. A similarly unexpected finding was that M3 has not lost its predictive power for Latvia and Estonia, although these countries were members of the Eurozone throughout some of the sample. This, in combination with the importance of stock returns for nowcasting the Latvian and Estonian GDP, invites a further study on the information domestic and regional stock exchanges contain about Baltic macroeconomic fundamentals.

Using smaller, carefully selected databases has universally outperformed larger databases. This is striking in the case of factor models, where the consistent inferiority of large to small scale confirms the conjecture of Boivin and Ng (2006). This provides a valuable guide for empirical researchers in creating more reliable forecasts. Further research is necessary, and if our results are confirmed for a wider set of countries, the mathematical groundings of factor models have to be reworked. In addition, developing rigorous criteria for indicator inclusion in factor models could prove to be useful.

Bridge models with RMSFE-based selection procedures dominate the list of best models. This method represents the most selective way of choosing indicators. The only instance of information-preserving method succeeding is factor-MIDAS generally outperforming factor models. However, it never produces the best performance, and it was applied to an already pre-selected database. MIDAS has failed to produce strong results. It should be noted for tending to increase the significance of performance, albeit it could be because of nowcast weighting, and it is decisively defeated in this by factor-MIDAS, which faces a similar performance problem.

The weak performance of MIDAS, and the superior performance of BMs with automatic selection and small-scale FMs show two things. First, a more sophisticated model that works around some theoretical problems may fail to beat the raw performance of much simpler approaches. Second, even if we settle on the two classical models, there is still room for further improvement in their application.

An immediate improvement over this paper would be to generalize our performance-based selection procedures to weighting procedures, where the indicators that have shown the best historical performance are given higher weights. Our current approach is a special version of this, where the weights are either zero or one. A more nuanced model could lead to an increase in accuracy and reliability, a thing for which economic forecasters must always strive.

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10. Appendices

Appendix A. The list of all indicators

Category	N	Indicator name	Type	Source	Publication lag (in days)	Trans.
Production	1	Production in industry - Total (2010 = 100)	Specific	Eurostat	40	ln Δ
	2	Production in industry - MIG - intermediary goods (2010 = 100)	Specific	Eurostat	40	ln Δ
	3	Production in industry - MIG -capital goods (2010 = 100)	Specific	Eurostat	40	ln Δ
	4	Production in industry - MIG - consumption goods (2010 = 100)	Specific	Eurostat	40	ln Δ
	5	Production in industry - mining and quarrying (2010 = 100)	Specific	Eurostat	40	ln Δ
	6	Production in industry - manufacturing (2010 = 100)	Specific	Eurostat	40	ln Δ
	7	Production in industry - electricity (2010 = 100)	Specific	Eurostat	40	ln Δ
	8	Turnover in retail trade - nominal, retail of food, beverages, and tobacco	Specific	Eurostat	30	ln Δ
	9	Turnover in retail trade - nominal, retail of non-food products (include fuel)	Specific	Eurostat	30	ln Δ
	10	Turnover in retail trade - deflated, retail of food, beverages, and tobacco	Specific	Eurostat	30	ln Δ
	11	Turnover in retail trade - deflated retail of non-food products (include fuel)	Specific	Eurostat	30	ln Δ
Employment	12	Unemployment rate by sex and age, monthly avg - Total	Specific	Eurostat	30	ln Δ
	13	Unemployment rate by sex and age, monthly avg - Males, total	Specific	Eurostat	30	ln Δ
	14	Unemployment rate by sex and age, monthly avg - Females, total	Specific	Eurostat	30	ln Δ
	15	Unemployment rate by sex and age, monthly avg - Total, <25y	Specific	Eurostat	30	ln Δ
	16	Unemployment rate by sex and age, monthly avg - Males, <25y	Specific	Eurostat	30	ln Δ
	17	Unemployment rate by sex and age, monthly avg - Females, <25y	Specific	Eurostat	30	ln Δ
	18	Unemployment rate by sex and age, monthly avg - Total, >26 <74y	Specific	Eurostat	30	ln Δ
	19	Unemployment rate by sex and age, monthly avg - Males, >26 <74y	Specific	Eurostat	30	ln Δ
	20	Unemployment rate by sex and age, monthly avg - Females, >26 <74y	Specific	Eurostat	30	ln Δ
Trade	21	Imports with EU27 - Total	Specific	Eurostat	40	ln Δ
	22	Imports with EU27 - Intermediary goods	Specific	Eurostat	40	ln Δ
	23	Imports with EU27 - Capital goods	Specific	Eurostat	40	ln Δ
	24	Imports with EU27 - Consumption goods	Specific	Eurostat	40	ln Δ
	25	Imports with EU27 - Consumption, and motor goods	Specific	Eurostat	40	ln Δ
	26	Exports with EU27 - Total	Specific	Eurostat	40	ln Δ
	27	Exports with EU27 - Intermediary goods	Specific	Eurostat	40	ln Δ
	28	Exports with EU27 - Capital goods	Specific	Eurostat	40	ln Δ
	29	Exports with EU27 - Consumption goods	Specific	Eurostat	40	ln Δ
	30	Exports with EU27 - Consumption, and motor goods	Specific	Eurostat	40	ln Δ
	31	Imports with World - Total	Specific	Eurostat	40	ln Δ
	32	Imports with World - Intermediary goods	Specific	Eurostat	40	ln Δ
	33	Imports with World - Capital goods	Specific	Eurostat	40	ln Δ
	34	Imports with World - Consumption goods	Specific	Eurostat	40	ln Δ
	35	Imports with World - Consumption, and motor goods	Specific	Eurostat	40	ln Δ
	36	Exports with World - Total	Specific	Eurostat	40	ln Δ
	37	Exports with World - Intermediary goods	Specific	Eurostat	40	ln Δ
	38	Exports with World - Capital goods	Specific	Eurostat	40	ln Δ
	39	Exports with World - Consumption goods	Specific	Eurostat	40	ln Δ
	40	Exports with World - Consumption, and motor goods	Specific	Eurostat	40	ln Δ
	41	EU27 Trade with extra EU27 - Balance	External	Eurostat	40	Δ
	42	EU27 Trade with extra EU27 - Imports	External	Eurostat	40	ln Δ
	43	EU27 Trade with extra EU27 - Exports	External	Eurostat	40	ln Δ
	44	Exports (FOB) - Total	Specific	TR	40	ln Δ
	45	Imports (CIF) - Total	Specific	TR	40	ln Δ
Inflation and other prices	46	Producer prices in industry - Total (2010 = 100)	Specific	Eurostat	35	ln Δ
	47	Producer prices in industry - Domestic Market (2010 = 100)	Specific	Eurostat	35	ln Δ
	48	Producer prices in industry - Non-domestic market (2010 = 100)	Specific	Eurostat	35	ln Δ
	49	HICP - Total (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	50	HICP - Food and non-alcoholic products (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	51	HICP - Alcoholic beverages (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	52	HICP - Clothing and footwear (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	53	HICP - Housing (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	54	HICP - Furnishing (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	55	HICP - Health (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	56	HICP - Transport (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	57	HICP - Communications (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	58	HICP - Recreation and culture (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	59	HICP - Education (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	60	HICP - Restaurants and hotels (2005 = 100)	Specific	Eurostat	9-12	ln Δ
	61	HICP - Miscellaneous goods and other (2005 = 100)	Specific	Eurostat	9-12	ln Δ

Category	N	Indicator name	Type	Source	Publication lag (in days)	Trans.
Survey	62	Financial situation over the last 12 months	Specific	Eurostat	0	-
	63	Financial situation over the next 12 months	Specific	Eurostat	0	-
	64	General economic situation over the last 12 months	Specific	Eurostat	0	-
	65	General economic situation over the next 12 months	Specific	Eurostat	0	-
	66	Price trends over the last 12 months	Specific	Eurostat	0	-
	67	Price trends over the next 12 months	Specific	Eurostat	0	-
	68	Unemployment expectations over the next 12 months	Specific	Eurostat	0	-
	69	The current economic situation is adequate to make major purchases	Specific	Eurostat	0	-
	70	Major purchases over the next 12 months	Specific	Eurostat	0	-
	71	The current economic situation is adequate for savings	Specific	Eurostat	0	-
	72	Savings over the next 12 months	Specific	Eurostat	0	-
	73	Statement on financial situation of household	Specific	Eurostat	0	-
	74	Consumer confidence indicator	Specific	Eurostat	0	-
	75	Building activity development over the past 3 months	Specific	Eurostat	0	-
	76	Evolution of the current overall order books	Specific	Eurostat	0	-
	77	Employment expectations over the next 3 months	Specific	Eurostat	0	-
	78	Price expectations over the next 3 months	Specific	Eurostat	0	-
	79	Construction confidence indicator	Specific	Eurostat	0	-
	80	Factors limiting building activity - None	Specific	Eurostat	0	-
	81	Factors limiting building activity - Insufficient demand	Specific	Eurostat	0	-
	82	Factors limiting building activity - Weather conditions	Specific	Eurostat	0	-
	83	Factors limiting building activity - Shortage of labour	Specific	Eurostat	0	-
	84	Factors limiting building activity - Shortage of material and/or equipment	Specific	Eurostat	0	-
	85	Factors limiting building activity - Other	Specific	Eurostat	0	-
	86	Factors limiting building activity - Financial constraints	Specific	Eurostat	0	-
	87	Production development observed over the past 3 months	Specific	Eurostat	0	-
	88	Employment expectations over the next 3 months	Specific	Eurostat	0	-
	89	Assessment of order-book levels	Specific	Eurostat	0	-
	90	Assessment of export order-book levels	Specific	Eurostat	0	-
	91	Assessment of the current level of stocks of finished products	Specific	Eurostat	0	-
	92	Production expectations over the next 3 months	Specific	Eurostat	0	-
	93	Selling price expectations over the next 3 months	Specific	Eurostat	0	-
	94	Industrial confidence indicator	Specific	Eurostat	0	-
	95	Business activity (sales) development over the past 3 months	Specific	Eurostat	0	-
	96	Volume of stocks currently hold	Specific	Eurostat	0	-
	97	Expectations of the nr of orders placed with suppliers over the next 3m	Specific	Eurostat	0	-
	98	Business activity expectations over the next 3 months	Specific	Eurostat	0	-
	99	Employment expectations over the next 3 months	Specific	Eurostat	0	-
	100	Retail confidence indicator	Specific	Eurostat	0	-
	101	Economic Sentiment Indicator	Specific	Eurostat	0	-
	102	Business situation development over the past 3 months	Specific	Eurostat	0	-
	103	Evolution of demand over the past 3 months	Specific	Eurostat	0	-
	104	Expectation of the demand over the next 3 months	Specific	Eurostat	0	-
	105	Evolution of employment over the past 3 months	Specific	Eurostat	0	-
	106	Expectation of the employment over the next 3 months	Specific	Eurostat	0	-
	107	Services Confidence Indicator	Specific	Eurostat	0	-
	108	Expectations of the prices over the next 3 months	Specific	Eurostat	0	-
	109	Euro-zone Business Climate Indicator	External	Eurostat	0	-
Finance	110	M1	Specific	Eurostat	0	ln Δ
	111	M2	Specific	Eurostat	0	ln Δ
	112	M3*	Specific	Eurostat	0	ln Δ
	113	US Government bond yields, 10 years' maturity	External	Eurostat	0	Δ
	114	Money market interest rates - Euro Area	External	Eurostat	0	Δ
	115	Day-to-day money market interest rates - Euro Area	External	Eurostat	0	Δ
	116	3-month interest rates (average) - Euro Area	External	Eurostat	0	Δ
	117	EUR/USD	External	TR	0	ln Δ
	118	RUB/USD	External	TR	0	ln Δ
	119	Euro vs EURIBOR 6m swap 1y	External	TR	0	Δ
	120	Euro vs EURIBOR 6m swap 5y	External	TR	0	Δ
	121	Crude Oil-Brent Cur. Month FOB U$/BBL	External	TR	0	ln Δ
	122	Baltic Dry Index	External	TR	0	ln Δ
	123	S&P 500	External	TR	0	ln Δ
	124	NASDAQ	External	TR	0	ln Δ
	125	Dow Jones	External	TR	0	ln Δ
	126	Shanghai SE A share	External	TR	0	ln Δ
	127	Shenzhen SE B share	External	TR	0	ln Δ
	128	CDAX	External	TR	0	ln Δ
	129	STOXX EUROPE 600 E	External	TR	0	ln Δ
	130	EURONEXT 100	External	TR	0	ln Δ
	131	OMX COPENHAGEN (OMXC)	External	TR	0	ln Δ
	132	OMX COPENHAGEN (OMXC20)	External	TR	0	ln Δ
	133	OMX HELSINKI (OMXH)	External	TR	0	ln Δ
	134	OMX STOCKHOLM (OMXS)	External	TR	0	ln Δ
	135	OMX STOCKHOLM 30 (OMXS30)	External	TR	0	ln Δ
	136	OMX TALLINN (OMXT)	External	TR	0	ln Δ
	137	OMX RIGA (OMXR)	External	TR	0	ln Δ
	138	OMX VILNIUS (OMXV)	External	TR	0	ln Δ
	139	Lumber Random Length CME 1st Futures	External	TR	0	ln Δ
	140	Baltic Exchange Capesize	External	TR	0	ln Δ
	141	Baltic Exchange Clean Tanker	External	TR	0	ln Δ
	142	Baltic Exchange Dirty Tanker	External	TR	0	ln Δ
	143	Baltic Exchange Panamax	External	TR	0	ln Δ
	144	EuroCoin**	External	TR	0	-

Category	N	Indicator name	Type	Source	Publication lag (in days)	Trans.
Other	145	BoP - Current Account - EuroArea - Balance	External	Eurostat	45	Δ
	146	BoP - Current Account - EuroArea - Credit	External	Eurostat	45	Δ
	147	BoP - Goods - EuroArea - Balance	External	Eurostat	45	Δ
	148	BoP - Goods - EuroArea - Credit	External	Eurostat	45	Δ
	149	BoP - Primary Income - EuroArea	External	Eurostat	45	Δ
	150	BoP - Secondary Income - EuroArea	External	Eurostat	45	Δ
	151	BoP - Goods & Services - EuroArea	External	Eurostat	45	Δ
	152	OECD Composite Leading Indicator - OECD Europe	External	Eurostat	45	ln Δ
	153	OECD Composite Leading Indicator - Russia	External	Eurostat	30	ln Δ
	154	Car registrations - new heavy commercial vehicles over 16t	Specific	TR	25	ln Δ
	155	Car registrations - new light commercial vehicles up to 3.5t	Specific	TR	25	ln Δ
	156	Car registrations - new medium & heavy cml.vehicles over 3.5t	Specific	TR	25	ln Δ
	157	Car registration - new passenger voln	Specific	TR	25	Δ
	158	Car registrations - new commercial vehicles including buses & coach	Specific	TR	25	Δ

Note: The column "Type" indicates if a series is country specific or it's external indicator for all Baltic States. TR stands for Thomsom Reuters Database.
**The missing values for M3 (LV) during 2000-2004 was calculating using available data on overnight deposits, time deposits, and currency outside MFI.*
***EuroCoin indicator was not transformed, since it is a proxy of GDP growth.*

Source: Created by the authors

Appendix B. The list of growth rates found to be non-stationary

ESTONIA	**LITHUANIA**
Producer prices in industry - Total (2010 = 100)	Producer prices in industry - Domestic Market (2010 = 100)
Producer prices in industry - Non-domestic market (2010 = 100)	HICP - Total (2005 = 100)
Turnover in retail trade - deflated, retail of food, beverages, and tobacco	Expectations of the nr of orders placed with suppliers over the next 3m
Expectation of the employment over the next 3 months	HICP - Food and non-alcoholic products (2005 = 100)
HICP - Education (2005 = 100)	HICP - Alcoholic beverages (2005 = 100)
LATVIA	HICP - Clothing and footwear (2005 = 100)
Producer prices in industry - Total (2010 = 100)	HICP - Housing (2005 = 100)
HICP - Total (2005 = 100)	HICP - Health (2005 = 100)
Production expectations over the next 3 months	HICP - Transport (2005 = 100)
HICP - Food and non-alcoholic products (2005 = 100)	HICP - Communications (2005 = 100)
HICP - Alcoholic beverages (2005 = 100)	HICP - Miscellaneous goods and other (2005 = 100)
HICP - Housing (2005 = 100)	
HICP - Transport (2005 = 100)	
HICP - Education (2005 = 100)	
HICP - Miscellaneous goods and other (2005 = 100)	

Note: The list of indicators which were found non-stationary using Kwiatkowski–Phillips–Schmidt–Shin (KPPS) test. The optimal lag length was selected using Bayesian Information Criterion (BIC). The above indicators for respective country were adjusted. Specifically, (t) - (t-1) adjustment was done.

Source: Created by the authors

Appendix C. The descriptions and range of inputs used in each model

Model	Selection Procedure	Inputs	Description	Range
BM	-	m	Quarterly lags of all indicators	0-3
		a	Order of AR terms	0-1
	LASSO	a	Order of AR terms	0-1
		m	Lags of all indicators	0-3
		p	Number of indicators selected for the regression	1-(N-1)
	RMSFE-Group	m	Quarterly lags of all indicators	0-3
		a	Order of AR terms	0-1
		m_s	Lags of all indicators in the selection matrix	0-2
		Ϋ	A coefficient modifyng the inclusion criteria	0.6, 0.8, 1
	RMSFE-Individual	m	Quarterly lags of all indicators	0-3
		a	Order of AR terms	0-1
		m_s	Lags of all indicators in the selection matrix	0-2
		p	Number of indicators selected for the regression	1-(N-1)
FM	-	m	Monthly lags of all indicators in the stacked estimation matrix	0-3
		r	The number of factors extracted	1-4 for Large, 1-(N-1) for Small
		f	Quarterly factor lags in the regression and estimation	0-3
		a	Order of AR terms	0-1
	LASSO	m	Monthly lags of all indicators in the stacked estimation matrix	0-3
		r	The number of factors extracted	2-(N-1) for Small
		f	Quarterly factor lags in the regression and estimation	0-3
		p	Number of indicators selected for PC estimation	1-9, 1-(N-1) for Small
		a	Order of AR terms	0-1
MIDAS	-	m	Monthly lags of all indicators	3-9
		a	Order of AR terms	0-1
factor-MIDAS	-	m	Monthly lags of all indicators in the stacked estimation matrix	0-3
		q	The number of factors extracted	1-4 for Large, 1-(N-1) for Small
		f	Monthly factor lags in the regression and estimation	3-9
		a	Order of AR terms	0-1

Note: BM stands for Bridge model, FM stands for Factor model, LASSO stands for Least Absolute Shrinkage and Selection Operator, RMSFE stands for Root Mean Squared Forecast Errors, MIDAS stands for Mixed Data Sampling. Large and Small are the databases. Large contains all retrieved indicators, 158. Small contains 20 sets of pre-selected indicators (3-7).

Source: Created by the authors

Appendix D. The specifications found significant across all countries

	Model	Selection procedure	Database	Set	LATVIA		LITHUANIA		ESTONIA	
					RP	DM	RP	DM	RP	DM
1	BM	LASSO	Small	Balanced 4	0.924	86%	0.936	90%	0.822	92%
2	BM	RMSFE-Individual	Small	Balanced 1	0.791	97%	0.877	90%	0.778	89%
3	BM	RMSFE-Individual	Small	Balanced 7	0.712	96%	0.828	85%	0.807	92%
4	BM	RMSFE-Individual	Small	Balanced 8	0.705	96%	0.884	86%	0.806	89%
5	factor-MIDAS	-	Small	Balanced 1	0.799	95%	0.898	98%	0.738	100%
6	factor-MIDAS	-	Small	Balanced 2	0.824	92%	0.919	88%	0.774	100%
7	factor-MIDAS	-	Small	Balanced 3	0.812	96%	0.935	88%	0.786	100%
8	factor-MIDAS	-	Small	Balanced 5	0.901	87%	0.934	87%	0.774	100%
9	factor-MIDAS	-	Small	Balanced 6	0.786	95%	0.890	86%	0.901	96%
10	factor-MIDAS	-	Small	Balanced 8	0.765	97%	0.929	86%	0.702	100%
11	factor-MIDAS	-	Small	Expenditure side	0.888	88%	0.975	88%	0.822	100%
12	factor-MIDAS	-	Small	BCIs	0.823	91%	0.921	90%	0.796	100%
13	factor-MIDAS	-	Small	External 2	0.830	93%	0.907	88%	0.916	99%
14	factor-MIDAS	-	Small	Finance 1	0.909	89%	0.930	90%	0.737	99%
15	factor-MIDAS	-	Small	Finance 2	0.880	90%	0.922	91%	0.799	99%
16	factor-MIDAS	-	Small	Finance 3	0.818	95%	0.964	90%	0.826	99%
17	factor-MIDAS	-	Small	Finance 4	0.917	86%	0.933	90%	0.784	99%
18	factor-MIDAS	-	Small	Finance 5	0.874	90%	0.972	93%	0.828	99%
19	factor-MIDAS	-	Small	Finance 6	0.832	98%	0.941	91%	0.740	98%
20	factor-MIDAS	-	Small	Finance 7	0.837	85%	0.940	85%	0.738	99%

Note: BM stands for Bridge Model, MIDAS stands for Mixed Data Sampling, LASSO stands for Least Absolute Shrinkage and Selection Operator, RMSFE stands for Root Mean Squared Forecasting Errors, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value. Small database contains 20 sets of indicators, where each set has 3-7 indicators. The colored RP-DM dyads identify the best performance for each country from this specific list.

Source: Created by the authors

Appendix E. The best performing bridge model specifications

DATABASE	SET	LATVIA			LITHUANIA			ESTONIA		
		RP	DM	Method	RP	DM	Method	RP	DM	Method
SMALL	Production side	**0.808**	**92%**	RMSFE-Individual	**0.989**	55%	Full Set	**0.627**	**98%**	RMSFE-Group
	Expenditure side	**0.748**	**93%**	RMSFE-Group	**0.902**	78%	RMSFE-Individual	**0.747**	**95%**	RMSFE-Individual
	BCIs	**0.935**	72%	LASSO	**0.903**	**91%**	LASSO	**0.959**	63%	RMSFE-Individual
	Balanced 1	**0.791**	**97%**	RMSFE-Individual	**0.877**	**90%**	RMSFE-Individual	**0.765**	**90%**	RMSFE-Group
	Balanced 2	**0.714**	**95%**	RMSFE-Individual	**0.860**	**87%**	RMSFE-Group	**0.859**	84%	RMSFE-Group
	Balanced 3	**0.714**	**95%**	RMSFE-Individual	**0.946**	67%	LASSO	**0.807**	**89%**	RMSFE-Individual
	Balanced 4	**0.796**	**90%**	RMSFE-Individual	**0.936**	**90%**	LASSO	**0.822**	**92%**	LASSO
	Balanced 5	**0.822**	**87%**	RMSFE-Individual	**0.921**	75%	LASSO	**0.809**	**98%**	RMSFE-Individual
	Balanced 6	**0.730**	**95%**	RMSFE-Individual	**0.925**	68%	RMSFE-Individual	**0.814**	**87%**	RMSFE-Group
	Balanced 7	**0.712**	**96%**	RMSFE-Individual	**0.828**	**85%**	RMSFE-Individual	**0.807**	**92%**	RMSFE-Individual
	Balanced 8	**0.705**	**96%**	RMSFE-Individual	**0.884**	**86%**	RMSFE-Individual	**0.668**	**95%**	Full Set
	External 1	1.134	25%	RMSFE-Individual	**0.958**	62%	RMSFE-Group	**0.890**	69%	RMSFE-Individual
	External 2	**0.753**	**96%**	RMSFE-Individual	**0.899**	71%	LASSO	**0.701**	**99%**	RMSFE-Individual
	Finance 1	**0.870**	75%	RMSFE-Individual	**0.963**	59%	LASSO	**0.874**	81%	RMSFE-Individual
	Finance 2	**0.945**	61%	RMSFE-Individual	**0.996**	51%	RMSFE-Individual	**0.914**	66%	RMSFE-Individual
	Finance 3	**0.785**	**86%**	LASSO	1.005	49%	LASSO	**0.773**	**93%**	LASSO
	Finance 4	**0.876**	76%	RMSFE-Individual	1.028	43%	LASSO	**0.858**	79%	RMSFE-Individual
	Finance 5	**0.764**	**94%**	RMSFE-Individual	**0.976**	56%	RMSFE-Individual	**0.780**	**92%**	LASSO
	Finance 6	**0.729**	**93%**	RMSFE-Group	**0.988**	53%	RMSFE-Individual	**0.765**	**94%**	LASSO
	Finance 7	**0.837**	84%	RMSFE-Individual	**0.860**	82%	RMSFE-Group	1.003	49%	RMSFE-Individual
Best performers		Balanced 8			Balanced 7			Production side		
		0.705	96%		0.828	85%		0.627	98%	
Indicator lags (Q)		0		RMSFE-Individual	3		RMSFE-Individual	3		RMSFE-Group
AR lags		0			0			0		
Indicators selected		2			2			-		
Y		-			-			0.6		
Lags in the selection matrix		0			0			0		

Note: BM stands for Bridge Model, LASSO stands for Least Absolute Shrinkage and Selection Operator, RMSFE stands for Root Mean Squared Forecasting Errors, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value, Q stands for quarters, AR lags stands for GDP lags, Y is a coefficient modifyng the inclusion criteria (used only for RMSFE-Group). Small database contains 20 sets of indicators, where each set has 3-7 indicators. Best performers are identified by looking at the lowest RP. The parameters at the bottom of this table are the details behind the best performers.The RP-DM dyads are colored when the performance is significantly superior to AR(1).

Source: Created by the authors

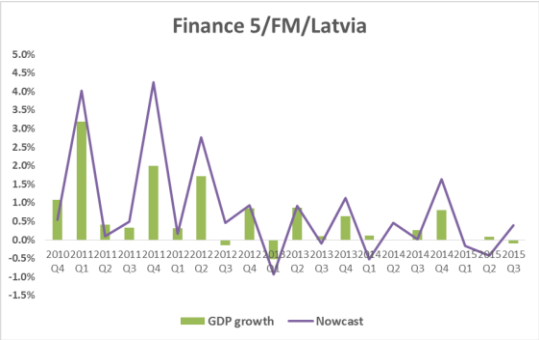
Appendix F. Sets of timely indicators that significantly beat the benchmark

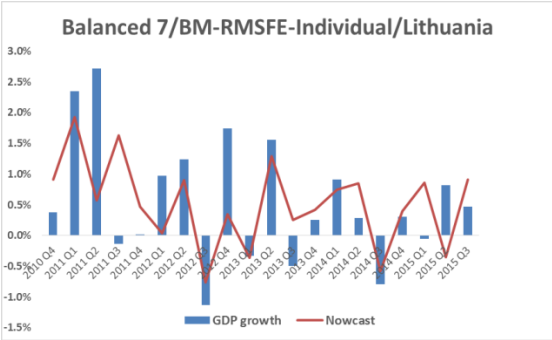
Country	Set	Model/Selection	RP	DM	AR	Number of indicators selected	Indicators lags (Q)	Indicators lags (M)	Number of factors	Factor lags (Q)	Factor lags (M)	Lags in stacked matrix	Lags in selection matrix	ϒ
LATVIA	Finance 5	FM/-	0.668	95%	1	-	-	-	3	3	-	1	-	-
	Finance 3	FM/-	0.693	97%	1	-	-	-	2	3	-	1	-	-
	Finance 6	FM/-	0.695	97%	1	-	-	-	2	3	-	0	-	-
	Finance 3	BM/LASSO	0.785	86%	1	2	3	-	-	-	-	-	-	-
	Finance 6	RMSFE-Group	0.729	93%	0	-	3	-	-	-	-	-	0	0.6
	Finance 5	BM/RMSFE-Individual	0.764	94%	1	2	3	-	-	-	-	0	-	-
	Finance 3	BM/RMSFE-Individual	0.800	88%	1	2	3	-	-	-	-	1	-	-
	Finance 6	BM/RMSFE-Individual	0.754	94%	0	2	3	-	-	-	-	0	-	-
	Finance 1	factor-MIDAS	0.909	89%	1	-	-		1	-	6	0	-	-
	Finance 2	factor-MIDAS	0.880	90%	1	-	-	-	1	-	6	0	-	-
	Finance 3	factor-MIDAS	0.818	95%	1	-	-	-	1	-	6	1	-	-
	Finance 5	factor-MIDAS	0.874	90%	1	-	-	-	2	-	6	0	-	-
	Finance 6	factor-MIDAS	0.832	98%	1	-	-	-	2	-	6	0	-	-
	Finance 7	factor-MIDAS	0.837	85%	1	-	-	-	2	-	3	1	-	-
	Production side	BM/LASSO	0.812	87%	0	1	3	-	-	-	-	-	-	-
	BCIs	factor-MIDAS	0.823	91%	1	-	-	-	1	-	9	1	-	-
LITHUANIA	BCIs	BM/LASSO	0.903	91%	1	3	0	-	-	-	-	-	-	-
	BCIs	factor-MIDAS	0.921	90%	1	-	-	-	1	-	3	0	-	-
	Finance 1	factor-MIDAS	0.930	90%	0	-	-	-	2	-	3	2	-	-
	Finance 2	factor-MIDAS	0.922	91%	0	-	-	-	2	-	3	2	-	-
	Finance 4	factor-MIDAS	0.933	90%	0	-	-	-	1	-	6	1	-	-
	Finance 6	factor-MIDAS	0.941	91%	0	-	-	-	1	-	6	2	-	-
ESTONIA	Finance 5	BM/LASSO	0.780	92%	1	1	3	-	-	-	-	-	-	-
	Finance 3	BM/LASSO	0.773	93%	1	1	3	-	-	-	-	-	-	-
	Finance 6	BM/LASSO	0.765	94%	1	1	3	-	-	-	-	-	-	-
	Finance 3	BM/RMSFE-Individual	0.835	88%	1	2	2	-	-	-	-	-	1	-
	Production side	BM/LASSO	0.675	99%	1	2	2	-	-	-	-	-	-	-
	Finance 5	FM/-	0.791	88%	1	-	-	-	2	3	-	0	-	-
	Finance 3	FM/-	0.803	87%	1	-	-	-	1	2	-	0	-	-
	Finance 6	FM/-	0.795	88%	1	-	-	-	3	3	-	0	-	-
	BCIs	factor-MIDAS	0.796	100%	1	-	-	-	1	-	3	0	-	-
	Finance 1	factor-MIDAS	0.737	99%	1	-	-	-	1	-	9	2	-	-
	Finance 2	factor-MIDAS	0.828	99%	1	-	-	-	1	-	9	2	-	-
	Finance 3	factor-MIDAS	0.826	99%	1	-	-	-	1	-	9	2	-	-
	Finance 5	factor-MIDAS	0.828	99%	1	-	-	-	1	-	9	2	-	-
	Finance 6	factor-MIDAS	0.740	98%	1	-	-	-	1	-	9	2	-	-
	Finance 7	factor-MIDAS	0.738	99%	1	-	-	-	1	-	9	2	-	-

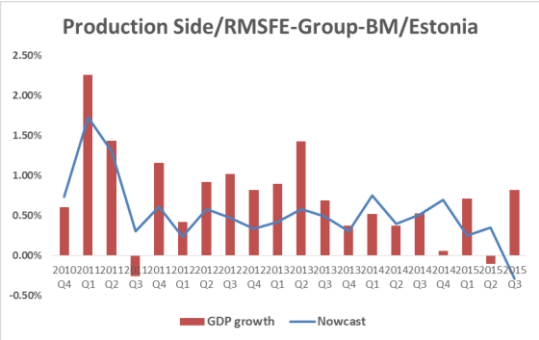
Note: BM stands for Bridge Model, FM stands for Factor Model, MIDAS stands for Mixed Data Sampling, LASSO stands for Least Absolute Shrinkage and Selection Operator, RMSFE stands for Root Mean Squared Forecasting Errors, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value, AR stands for GDP lags, Q stands for quarters, M stands for months, ϒ is a coefficient modifyng the inclusion criteria (used only for RMSFE-Group). Small database contains 20 sets of indicators, where each set has 3-7 indicators.

Source: Created by the authors

Appendix G. The actual GDP growth and best nowcasts from this study

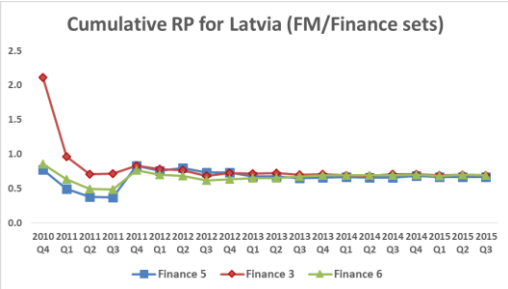


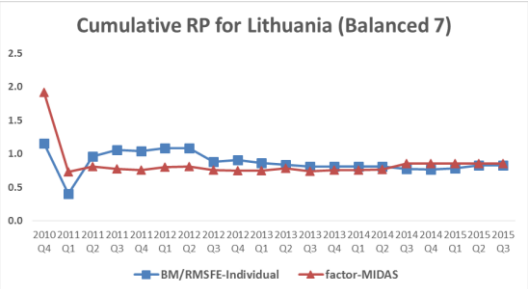


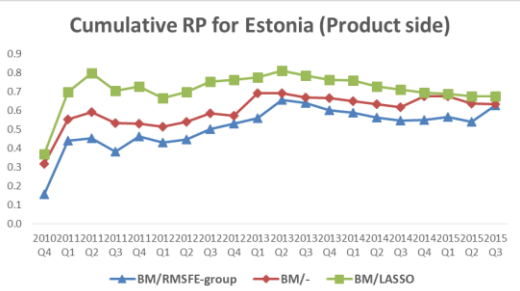


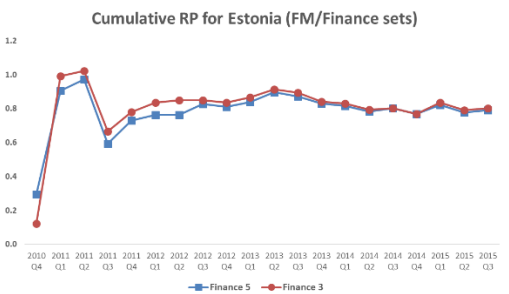
Source: Created by the authors

Appendix H. Cumulative relative performance for some cases



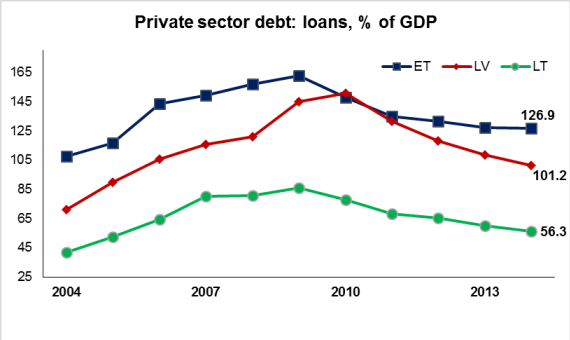


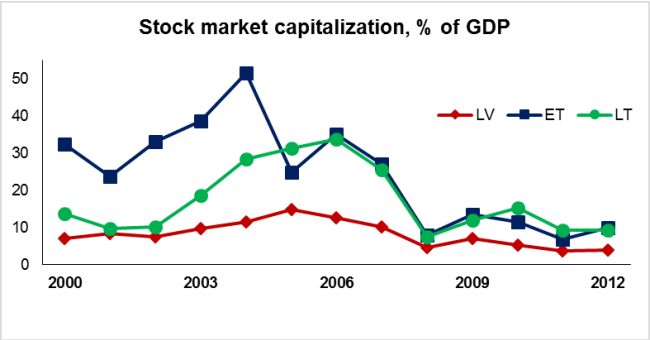




Source: Created by the authors

Appendix I. Private Sector loans and stock market capitalization, as % of GDP





Source: Created by the authors using data from World Bank and Eurostat.

Appendix J. The sample standard deviation of GDP growth

	LATVIA	LITHUANIA	ESTONIA
Standard deviation of GDP growth	0.87%	1.00%	0.57%

Source: Created by the authors

Appendix K. The list of selected indicators from automatic BMs

RMSFE-Group

BM / RMSFE-GROUP / SMALL

SET: Production side

(Production in industry, Production expectations over the next 3months, Construction confidence)

ESTONIA

Y	Indicator lag	AR lags	M_S lags	RP	DM
0.6	3	0	0	0.627	98%

Quarter	Indicators		
1	Production exp. over the next 3m		
2	Production in Industry		
3	Production exp. over the next 3m		
4	Production exp. over the next 3m	Production in Industry	Construction confidence
5	Production in Industry		
6	Production exp. over the next 3m	Production in Industry	
7	Production exp. over the next 3m		
8	Production exp. over the next 3m		
9	Production exp. over the next 3m		
10	Production exp. over the next 3m		
11	Production exp. over the next 3m		
12	Production exp. over the next 3m		
13	Production exp. over the next 3m	Construction confidence	Production in Industry
14	Production exp. over the next 3m		
15	Production exp. over the next 3m		
16	Production in Industry		
17	Production in Industry		
18	Production in Industry		
19	Production exp. over the next 3m		
20	Production in Industry		

BM / RMSFE-GROUP / SMALL

SET: Balanced 2

(Imports with EU27, Exports with EU27, Production in Industry)

LITHUANIA

Y	Indicator lag	AR lags	M_S lags	RP	DM
1	1	0	2	0.860	87%

Quarter	Indicators	
1	Exports with EU27	Imports with EU27
2	Production in Industry	
3	Imports with EU27	
4	Exports with EU27	
5	Production in Industry	
6	Imports with EU27	
7	Exports with EU27	Production in Industry
8	Imports with EU27	Production in Industry
9	Production in Industry	
10	Production in Industry	
11	Imports with EU27	Production in Industry
12	Imports with EU27	Production in Industry
13	Production in Industry	
14	Production in Industry	
15	Imports with EU27	Exports with EU27
16	Imports with EU27	
17	Exports with EU27	
18	Production in Industry	
19	Exports with EU27	Production in Industry
20	Exports with EU27	

Note: RMSFE stands for Root Mean Squared Forecast Errors, AR lags are the GDP lags, M_S lags are lags of all indicators in the selection matrix, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value. Y a coefficient modifyng the inclusion criteria (the parameter is specific to RMSFE-Group).

LASSO

BM / LASSO / SMALL

SET: Business Confidence Indicators (BCIs)

(Industrial, Retail trade, Construction, ESI)

LITHUANIA

Nr of indicators	Indicator lag	AR lags	RP	DM
3	0	1	0.903	91%

Quarter	Indicators
1	Industrial C. I., Construction C.I., ESI
2	Industrial C. I., Construction C.I., ESI
3	Industrial C. I., Construction C.I., ESI
4	Industrial C. I., Construction C.I., ESI
5	Industrial C. I., Construction C.I., ESI
6	Industrial C. I., Construction C.I., ESI
7	Industrial C. I., Construction C.I., ESI
8	Industrial C. I., Construction C.I., ESI
9	Industrial C. I., Construction C.I., ESI
10	Industrial C. I., Construction C.I., ESI
11	Industrial C. I., Construction C.I., ESI
12	Industrial C. I., Construction C.I., ESI
13	Industrial C. I., Construction C.I., ESI
14	Industrial C. I., Construction C.I., ESI
15	Industrial C. I., Construction C.I., Retail trade C.I.
16	Industrial C. I., Construction C.I., Retail trade C.I.
17	Industrial C. I., Construction C.I., Retail trade C.I.
18	Industrial C. I., Construction C.I., Retail trade C.I.
19	Industrial C. I., Construction C.I., Retail trade C.I.
20	Industrial C. I., Construction C.I., Retail trade C.I.

BM / LASSO / SMALL

SET: Balanced 8

(Trade with EU27, Production in industry, M3)

ESTONIA

Nr of indicators	Indicator lag	AR lags	RP	DM
3	1	1	0.683	95%

Quarter	Indicators
1	Imports with EU27, Production in industry, M3
2	Imports with EU27, Production in industry, M3
3	Imports with EU27, Production in industry, M3
4	Imports with EU27, Production in industry, M3
5	Imports with EU27, Production in industry, M3
6	Imports with EU27, Production in industry, M3
7	Imports with EU27, Production in industry, M3
8	Imports with EU27, Production in industry, M3
9	Imports with EU27, Production in industry, M3
10	Imports with EU27, Production in industry, M3
11	Imports with EU27, Production in industry, M3
12	Imports with EU27, Production in industry, M3
13	Imports with EU27, Production in industry, M3
14	Imports with EU27, Production in industry, M3
15	Imports with EU27, Production in industry, M3
16	Imports with EU27, Production in industry, M3
17	Imports with EU27, Production in industry, M3
18	Imports with EU27, Production in industry, M3
19	Imports with EU27, Production in industry, M3
20	Imports with EU27, Production in industry, M3

Note: RMSFE stands for Root Mean Squared Forecast Errors, AR stands for the GDP lags, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value. LASSO is an automatic selection procedure, it stands for Least Absolute Shrinkage and Selection Operator

BM / LASSO / SMALL

SET: Production side

(Production in industry, Production expectations over the next 3months, Construction confidence)

LATVIA

Nr of indicators	Indicator lag	AR lags	RP	DM
1	3	0	0.812	87%

Quarter	Indicators
1	Construction Confidence Indicator
2	Construction Confidence Indicator
3	Construction Confidence Indicator
4	Construction Confidence Indicator
5	Construction Confidence Indicator
6	Construction Confidence Indicator
7	Construction Confidence Indicator
8	Construction Confidence Indicator
9	Construction Confidence Indicator
10	Construction Confidence Indicator
11	Construction Confidence Indicator
12	Construction Confidence Indicator
13	Construction Confidence Indicator
14	Construction Confidence Indicator
15	Construction Confidence Indicator
16	Construction Confidence Indicator
17	Construction Confidence Indicator
18	Production expectations over the next 3months
19	Production expectations over the next 3months
20	Production expectations over the next 3months

ESTONIA

Nr of indicators	Indicator lag	AR lags	RP	DM
2	2	1	0.675	99%

Quarter	Indicators
1	Production exp. over next 3m, Construction C.I.
2	Production exp. over next 3m, Construction C.I.
3	Production exp. over next 3m, Construction C.I.
4	Production exp. over next 3m, Construction C.I.
5	Production exp. over next 3m, Construction C.I.
6	Production exp. over next 3m, Construction C.I.
7	Production exp. over next 3m, Construction C.I.
8	Production exp. over next 3m, Construction C.I.
9	Production exp. over next 3m, Construction C.I.
10	Production exp. over next 3m, Construction C.I.
11	Production exp. over next 3m, Construction C.I.
12	Production exp. over next 3m, Construction C.I.
13	Production exp. over next 3m, Construction C.I.
14	Production exp. over next 3m, Construction C.I.
15	Production exp. over next 3m, Construction C.I.
16	Production exp. over next 3m, Construction C.I.
17	Production exp. over next 3m, Construction C.I.
18	Production exp. over next 3m, Construction C.I.
19	Production exp. over next 3m, Construction C.I.
20	Production exp. over next 3m, Construction C.I.

Note: RMSFE stands for Root Mean Squared Forecast Errors, AR stands for the GDP lags, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value. LASSO is an automatic selection procedure, it stands for Least Absolute Shrinkage and Selection Operator

BM / LASSO / SMALL

SET: Finance 5 (regional + domestic)

Returns of indices OMX.Riga, Vilnius, Tallinn, Copenhagen, Helsinki, Stockholm, CDAX

ESTONIA

Nr of indicators	Indicator lag	AR lags	RP	DM
1	3	1	0.780	92%

Quarter	Indicators
1	OMX Vilnius returns
2	OMX Vilnius returns
3	OMX Vilnius returns
4	OMX Vilnius returns
5	OMX Tallinn returns
6	OMX Tallinn returns
7	OMX Vilnius returns
8	OMX Vilnius returns
9	OMX Vilnius returns
10	OMX Vilnius returns
11	OMX Vilnius returns
12	OMX Vilnius returns
13	OMX Vilnius returns
14	OMX Vilnius returns
15	OMX Vilnius returns
16	CDAX returns
17	CDAX returns
18	CDAX returns
19	CDAX returns
20	CDAX returns

RMSFE-Individual

BM / RMSFE-INDIVIDUAL / SMALL

SET: Balanced 7

(Trade with EU27, Production in industry, EuroCoin, OMX.Stockholm)

LATVIA

Nr of indicators	Indicator lag	AR	M_S lags	RP	DM
1	0	0	0	0.712	96%

Quarter	Indicators
1	Exports with EU27
2	Exports with EU27
3	Exports with EU27
4	OMX.Stockholm
5	Production in industry
6	Imports with EU27
7	Exports with EU27
8	Imports with EU27
9	OMX.Stockholm
10	Exports with EU27
11	Production in industry
12	OMX.Stockholm
13	OMX.Stockholm
14	EuroCoin
15	OMX.Stockholm
16	OMX.Stockholm
17	Exports with EU27
18	Imports with EU27
19	Exports with EU27
20	Imports with EU27

LITHUANIA

Nr of indicators	Indicator lag	AR	M_S lags	RP	DM
2	3	0	0	0.828	85%

Quarter	Indicators	
1	Exports with EU27	EuroCoin
2	Imports with EU27	Production in industry
3	Imports with EU27	EuroCoin
4	Exports with EU27	EuroCoin
5	Imports with EU27	Production in industry
6	Imports with EU27	OMX.Stockholm
7	Imports with EU27	Exports with EU27
8	Imports with EU27	OMX.Stockholm
9	EuroCoin	OMX.Stockholm
10	Imports with EU27	Production in industry
11	Exports with EU27	EuroCoin
12	Imports with EU27	OMX.Stockholm
13	EuroCoin	OMX.Stockholm
14	Imports with EU27	EuroCoin
15	Imports with EU27	EuroCoin
16	Exports with EU27	Production in industry
17	Exports with EU27	Production in industry
18	Exports with EU27	EuroCoin
19	Imports with EU27	Production in industry
20	Exports with EU27	EuroCoin

BM / RMSFE-INDIVIDUAL / SMALL

SET: Balanced 2

(Imports/Exports with EU27, Production in industry)

LATVIA

Nr of indicators	Indicator lag	AR	M_S lags	RP	DM
1	1	0	2	0.868	89%

Quarter	Indicators
1	Exports with EU27
2	Production in Industry
3	Imports with EU27
4	Exports with EU27
5	Production in Industry
6	Imports with EU27
7	Exports with EU27
8	Imports with EU27
9	Production in Industry
10	Production in Industry
11	Imports with EU27
12	Imports with EU27
13	Production in Industry
14	Production in Industry
15	Imports with EU27
16	Imports with EU27
17	Exports with EU27
18	Production in Industry
19	Exports with EU27
20	Exports with EU27

Note: RMSFE stands for Root Mean Squared Forecast Errors, AR stands for the GDP lags, M_S lags are lags of all indicators in the selection matrix, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value

BM / RMSFE-INDIVIDUAL / SMALL

SET: Balanced 8

(Trade with EU27, Production in industry, M3)

LATVIA						ESTONIA					
Nr of indicators	Indicator lag	AR	M_S lags	RP	DM	Nr of indicators	Indicator lag	AR	M_S lags	RP	DM
2	0	0	0	0.705	96%	3	1	0	0	0.806	89%

Quarter	Indicators	Quarter	Indicators
1	Imports with EU27, Exports with EU27	1	Imports, Exports, Production in Industry
2	Exports with EU27, Production in Industry	2	Imports, Exports, Production in Industry
3	Imports with EU27, Exports with EU27	3	Imports, Exports, Production in Industry
4	Production in Industry, M3	4	Imports, Exports, Production in Industry
5	Production in Industry, M3	5	Imports, Exports, Production in Industry
6	Imports with EU27, Exports with EU27	6	Exports, Production in Industry, M3
7	Imports with EU27, Exports with EU27	7	Exports, Production in Industry, M3
8	Imports with EU27, Exports with EU27	8	Exports, Production in Industry, M3
9	Imports with EU27, Production in Industry	9	Imports, Exports, M3
10	Exports with EU27, M3	10	Imports, Production in Industry, M3
11	Exports with EU27, Production in Industry	11	Exports, Production in Industry, M3
12	Production in Industry, M3	12	Imports, Production in Industry, M3
13	Imports with EU27, Production in Industry	13	Exports, Production in Industry, M3
14	Exports with EU27, M3	14	Imports, Exports, M3
15	Exports with EU27, M3	15	Imports, Exports, M3
16	Exports with EU27, M3	16	Exports, Production in Industry, M3
17	Exports with EU27, Production in Industry	17	Exports, Production in Industry, M3
18	Imports with EU27, M3	18	Imports, Exports, Production in Industry
19	Exports with EU27, Production in Industry	19	Exports, Production in Industry, M3
20	Imports with EU27, M3	20	Imports, Exports, Production in Industry

Note: RMSFE stands for Root Mean Squared Forecast Errors, AR stands for the GDP lags, M_S lags are lags of all indicators in the selection matrix, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value

BM / RMSFE-INDIVIDUAL / SMALL

SET: Finance 5 (regional + domestic)

Returns of indices OMX Riga, Vilnius, Tallinn, Copenhagen, Helsinki, Stockholm, CDAX

LATVIA					
Nr of indicators	Indicator lag	AR	M_S lags	RP	DM
2	3	1	0	0.764	94%

Quarter	Indicators	
1	OMX Copenhagen returns	OMX Riga returns
2	OMX Vilnius returns	OMX Tallinn returns
3	OMX Copenhagen returns	OMX Vilnius returns
4	CDAX returns	OMX Helsinki returns
5	OMX Riga returns	OMX Tallinn returns
6	OMX Stockholm returns	OMX Helsinki returns
7	OMX Stockholm returns	OMX Vilnius returns
8	OMX Copenhagen returns	OMX Vilnius returns
9	OMX Stockholm returns	OMX Riga returns
10	CDAX returns	OMX Copenhagen returns
11	OMX Stockholm returns	OMX Tallinn returns
12	OMX Vilnius returns	OMX Tallinn returns
13	OMX Stockholm returns	OMX Helsinki returns
14	CDAX returns	OMX Stockholm returns
15	OMX Stockholm returns	OMX Helsinki returns
16	OMX Stockholm returns	OMX Vilnius returns
17	OMX Copenhagen returns	OMX Riga returns
18	OMX Copenhagen returns	OMX Helsinki returns
19	OMX Riga returns	OMX Tallinn returns
20	OMX Stockholm returns	OMX Helsinki returns

Note: RMSFE stands for Root Mean Squared Forecast Errors, AR stands for the GDP lags, M_S lags are lags of all indicators in the selection matrix, RP stands for relative performance (ratio between RMSFE of a model and RMSFE of the benchmark model), DM stands for Diebold-Mariano p-value

Source: Created by the authors