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Nowcasting the Czech Trade Balance

Oxana Babecká Kucharčuková and Jan Brůha*

Abstract

In this paper we are interested in nowcasting and short-run forecasting of the main external trade variables. We consider four empirical methods: principal component regression, elastic net regression, the dynamic factor model and partial least squares. We discuss the adaptation of those methods to asynchronous data releases and to the mixed-frequency set-up. We contrast them with a set of univariate benchmarks. We find that for variables in value terms (both nominal and real), elastic net regression typically yields the most accurate predictions, followed by the dynamic factor model and then by principal components. For export and import prices, univariate techniques seem to have the higher precision for backcasting and nowcasting, but for short-run forecasting the more sophisticated methods tend to produce more accurate forecasts. Here again, elastic net regression dominates the other methods.

Abstrakt

V tomto článku se zabýváme „teďpovědí“ (nowcasting) a krátkodobou předpovědí hlavních veličin zahraničního obchodu. Uvažujeme čtyři empirické metody: regresi založenou na hlavních komponentách, elastickou síť, dynamický faktorový model a metodu částečných nejmenších čtverců. Diskutujeme, jak lze tyto metody adaptovat na situaci řad s různou frekvencí a nesynchronní publikací. Srovnáváme tyto metody s jednorozměrnými metodami. Ukazujeme, že pro nominální a reálné dovozy i vývozy dává nejpřesnější predikce metoda elastické sítě následovaná dynamickým faktorovým modelem a metodou hlavních komponent. Pro dovozní a vývozní ceny dávají nejlepší predikce pro „zpětpověď“ (backcasting) a teďpověď jednorozměrné metody, pro krátkodobou předpověď však přesnější výsledky poskytují sofistikovanější metody. I zde dominuje nad ostatními metodami elastická síť.

JEL Codes: C53, C55, F17.

Keywords: Dynamic factor models, elastic net regression, mixed-frequency data, nowcasting, principal component analysis, state space models, trade balance.

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Non-Technical Summary

In recent years, nowcast models have become a popular econometric tool for current-quarter nowcasting and short-term forecasting of GDP. A nowcast model is an empirical model based on a broad range of time series with different lengths and publication frequencies and lags. By construction, the model is able to account for the most recent information, which is not always straightforward due to broad dispersion of publication lags across series. For instance, the lag can be zero or slightly positive in the case of leading indicators, but for Czech national accounts subcomponents it exceeds two months.

In contrast to previous studies focused on GDP, this paper presents nowcast models for external trade, Czech external trade in our case. To the best of our knowledge, no nowcast model for trade has been described in the literature so far. Exports and imports are exposed to foreign shocks, which increases the importance of foreign variables for nowcast models. Furthermore, in contrast to GDP growth, which is mainly meaningful in real terms, for trade both real and nominal developments (BoP statistics) are important.

Once the model is set up, regular updates can be produced as new data become available. Fast incorporation of the latest information is one of the reasons why nowcast modelling is of great interest not only to researchers, but also to central bankers. Indeed, the model described in this paper is also intended to be used for regular forecasting at the CNB as an alternative or complement to existing econometric models as well as to the core CNB model.

Nowcasts and short-term forecasts are prepared for nine variables. Four of them have quarterly frequency: exports and imports from the national accounts statistics at both constant and current prices. Monthly nowcasts are produced for nominal trade (exports and imports separately) and the relevant price indexes. In addition, given the high importance of the foreign PPI for the Czech economy, the result for the foreign effective PPI is also shown here. All variables are transformed into growth rates relative to the corresponding period of the previous year. As for explanatory variables, five groups of economic and financial indicators are used for this purpose. Roughly half of them describe domestic developments. The remaining half describe the foreign sector – mainly the euro area, but also Germany and the United States. The sample span starts in January 2006 or 2006q1 and ends in September 2016, or 2016q2 in the case of quarterly data.

The quality of the nowcasts is evaluated using a pseudo-real time framework, which mimics the actual publication lag structure and is compared across four empirical models: principal component regression, elastic net regression, the dynamic factor model and partial least squares. For exports and imports in both nominal and real terms, as well as for trade price indexes, the winner is elastic net regression. The forecasting performance of the elastic net is better even than that of the dynamic factor model, which is widely believed to produce the most accurate nowcasts, at least for GDP. The other methods could be used as alternative checks. In addition, the dynamic factor model could be used to create alternative scenarios using conditional forecasts.

1. Introduction

Interest in nowcasting has increased dramatically over the last decade. This forecasting technique is now widely applied by many central banks and research institutions across the globe. Nowcasting usually refers to forecasting of the recent past and present values of an economic indicator not yet available due to low frequency and publication delay, and to short-term forecasting of that indicator. Missing and future values are projected on a set of relevant variables having the same or higher frequency but shorter or zero time lags. Because new data releases appear in an asynchronised manner (creating a ragged edge problem), nowcast models are designed to be able to produce updated forecasts immediately as new information becomes available. This type of forecast is often prepared as a judgment-free forecast that tries to reap data from a large set of indicators that may contain useful, but scattered, pieces of information. Although data-driven estimation can be considered a model weakness, fast incorporation of the latest information, good forecasting performance at shorter horizons and the use of rich dataset are certainly big advantages of this technique.

At the central bank, nowcast models are useful as a complementary tool to other forecasting techniques such as large structural models (i.e. DSGE models). Their ability to incorporate newly released data immediately into the forecast is beneficial for timely assessment of changes in economic developments. Furthermore, current-period forecasts from nowcast models can serve as inputs to DSGE models, where a more precise forecast at the beginning of the forecasting horizon by construction increases the accuracy of forecast at its end (del Negro and Schorfheide, 2013). Although the main CNB forecasting tool is a DSGE model called g3 (Andrle et al., 2009), nowcasts and near-term forecasts are discussed in depth at the beginning of each prediction round (Brůha et al., 2013). Camacho, Perez-Quiros and Poncela (2013) give an overview of empirical techniques that can be used for nowcasting and short-run forecasting.

GDP growth is the most frequently nowcasted indicator. This key measure of economic activity is published with a considerable delay, and the Czech Republic is no exception. The time lag is particularly striking in the case of GDP subcomponents – investment, consumption and external trade, where new data become available with a lag of more than two months. In addition, frequent revisions of national accounts introduce higher uncertainty about the precision of the latest data and make the forecasting exercise more challenging.[1] Nowadays, GDP growth nowcasts are produced for all the most important economies, for example the USA, the euro area, Germany and even China.

For the Czech Republic, an aggregated GDP growth nowcast is prepared at the CNB and regularly used as an alternative forecast during the quarterly forecasting exercise. Several models have been developed for this purpose. Arnoštová et al. (2011) build nowcast models using monthly indicators. The authors compare results based on a simple autoregression model and bridge equations with those obtained from principal components and dynamic factor models. They find that the principal components model has the best predictive power up to three quarters ahead. Beyond this horizon, the most precise forecast is the near-term forecast of the CNB model. Rusnák (2013) evaluates the forecasting performance of dynamic factor models using vintage data

[1] As an illustration see, for instance, Appendix A in Brůha et al. (2013).

and accounting for publication lag. The author also stresses the importance of foreign variables for Czech GDP nowcasting. His results suggest that the nowcasting performance of the medium-scale dynamic factor model is comparable with the CNB's judgmental nowcasts. Finally, Franta et al. (2014) extend the two above-mentioned analyses and focus on several types of mixed-frequency data models: mixed-frequency VAR, a mixed-data sampling model and a dynamic factor model. The authors find that in the short term the dynamic factor model is comparable with the CNB's forecasts. At longer horizons, the mixed-frequency VAR and BVAR models slightly outperform the CNB's forecasts.

In contrast to previous studies, the purpose of the present analysis is to construct and estimate a set of nowcast models for the Czech trade balance. To the best of our knowledge, there is no nowcast model focused on Czech external trade and there is no description of a nowcast trade model in the literature. Although net exports are a part of GDP, a nowcast model designed for GDP is not directly applicable to external trade for a number of reasons. First, external shocks are more important in the case of trade than in the case of GDP on aggregate. The use of a "universal model" with hundreds of time series for both GDP and trade may not be an appropriate solution. As previous research shows, a nowcast model based on a very large dataset containing hundreds of economic and financial indicators does not produce a better forecast than a model with fewer, but carefully selected, inputs (Boivin and Ng, 2006). Second, recent research shows that the elasticity between trade growth and GDP growth has changed since the crisis (ECB, 2016). As the relation between trade and GDP is time-varying, the good fit of GDP models may not hold for trade over the whole sample period. Third, GDP growth models are by construction focused on forecasting of real variables. In the case of external trade, forecasts at both current and constant prices are important. Constant prices allow the results to be compared with the core DSGE model and used as DSGE inputs. Nominal prices give us an idea about the evolution of an important part of the balance of payments (BoP). However, national accounts, cross-border and BoP statistics are not fully identical. BoP statistics are available at current prices only and released and revised independently of the national accounts statistics. Thus, our intention is to construct a nowcast model of Czech exports and imports in both nominal and real terms. The main reason for doing so is the planned regular use of this model for making alternative estimates during the quarterly forecasting exercise at the CNB. The results will be compared with the CNB's econometric models – forecasts of trade at constant prices and price indexes. Furthermore, a direct nowcast at current prices allows for straightforward comparison with the trade balance forecast based on BoP statistics, which is available at current prices only. In addition to unconditional forecasting, one of our estimation techniques will allow for conditional forecasting and, by consequence, scenario analysis based, for example, on different assumptions about foreign GDP or foreign PPI growth, which could also be used at the CNB.

The structure of the paper is the following. The next two sections describe the data we use. Section 4 explains the methodology applied for nowcasting and short-term forecasting of the Czech trade balance and shows the results for the Czech economy. Section 5 compares the forecasting performance of the methods, and the final section 6 concludes. Appendices contain additional materials.

2. Data

In this paper, we present nowcasts and short-term forecasts of the main external trade variables: exports and imports and their prices. All the variables are transformed into yearly growth rates.[2] We are primarily interested in nominal and real exports and imports published as part of the national accounts statistics. These data are released at quarterly frequency and can be used directly as near-term forecasts for the main g3 model. In addition, we consider monthly nominal exports and imports published by the Czech Statistical Office for nowcasting of the trade balance at monthly frequency. We are also interested in import and export prices at monthly frequency. Furthermore, we apply the chosen methods to the effective foreign producer price index (PPI), also taken at a yearly growth rate. This variable is important for the CNB's macroeconomic forecast for at least two reasons. First, the foreign PPI is a proxy for foreign inflation pressures on the Czech economy in the CNB's main forecasting model. Second, the relative price of Czech exports in the g3 model is the ratio of the foreign PPI to Czech export prices.

To sum up, we are interested in nowcasts of nine variables. Four of them are of quarterly frequency, namely the nominal and real growth rates of exports and imports from the national accounts. The remaining five are of monthly frequency: the growth rates of nominal exports and imports, their price indexes and the foreign PPI.

As for predictors for the nowcast and short-term forecast, we collected a large dataset of variables that can be used for predicting the variables of interest. These variables are listed in Appendix A along with their sources and publication lags.

Our dataset runs from January 2006 to September 2016 (monthly time series) and from 2006Q1 to 2016Q2 (quarterly series). All data are in yearly growth rates, which are the percentage change relative to the same period (month or quarter) of the previous year. We do not work with data prior to 2005 so as to avoid the structural break in the Czech trade data time series related to EU entry in May 2004.

3. Descriptive Statistics

The components of Czech trade have been steadily increasing in both nominal and real terms since the start of the economic transition. The entry of the Czech Republic to the European Union in May 2004 caused an upward shift in both the level and the trend growth rate of exports and imports. The only significant drop in the volumes and values of exports and imports occurred during the 2008/2009 recession, but this was quickly reversed and by 2011 the figures were back at their pre-crisis levels.

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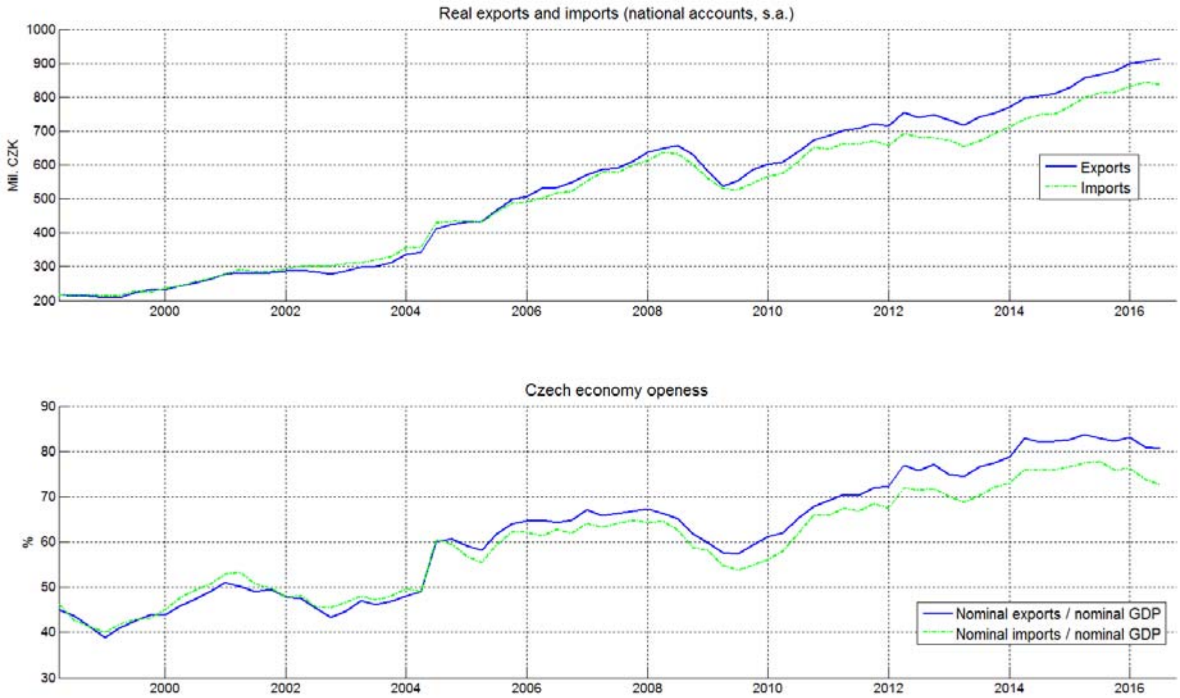
[2] While for monthly data these are, by construction, moving averages of the monthly growth rates, transformation into one-period change introduces additional noise and extracting seasonality may reduce the precision of the estimates. Furthermore, yearly growth rates make the results more comparable with those of other CNB models during the regular forecasting exercise. As we intend to use the model at the CNB for regular forecasting, we selected this method of transformation. Last but not least, we run the nowcast model on one-period transformed data. The results obtained are broadly comparable with the yearly growth rates and lead to the same conclusion as in the case of nowcasts based on yearly growth rates.

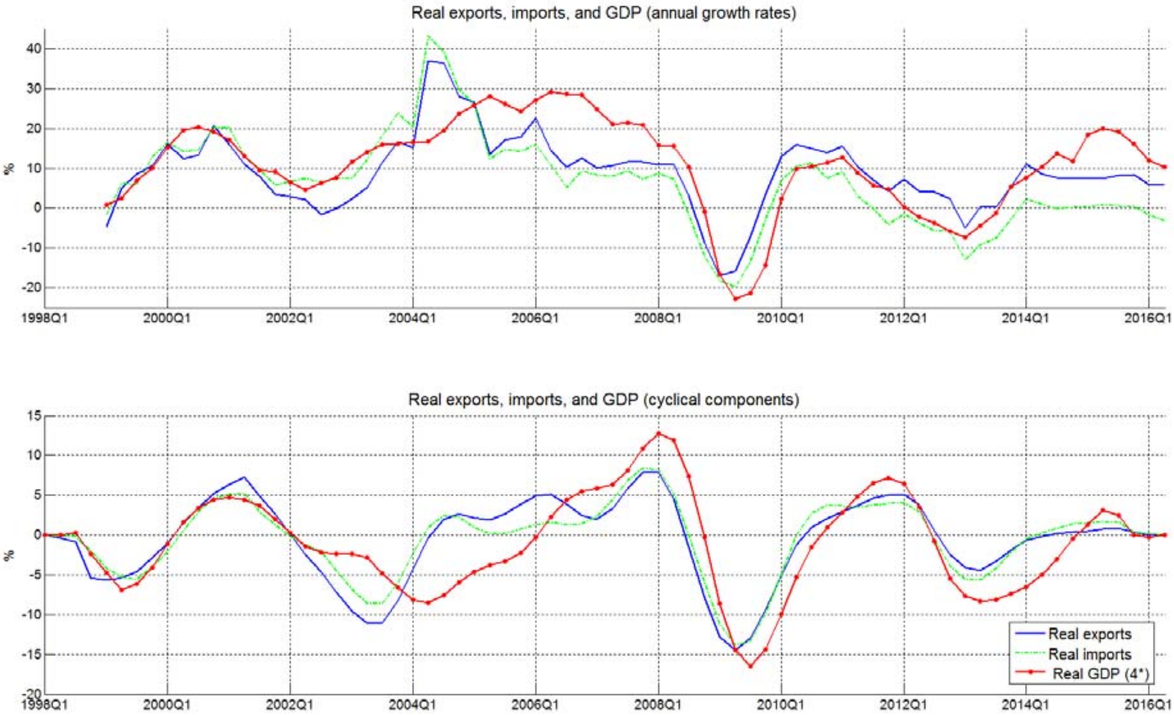
The evolution of real exports and imports is displayed in the upper subfigure of Figure 1, where both EU entry and the 2008–2009 recession are clearly visible. The lower subfigure shows that the openness of the Czech economy has been increasing as well: the ratios of both nominal exports and nominal imports to nominal GDP have increased from about 45% in the pre-EU entry period to about 80% now. This means that the trend growth rates of the two trade balance components have been significantly higher (by about 4% annually) than the trend growth rate of GDP. EU entry almost immediately increased the openness share by about 10 p.p.

Figure 1: Czech Exports and Imports Through Time



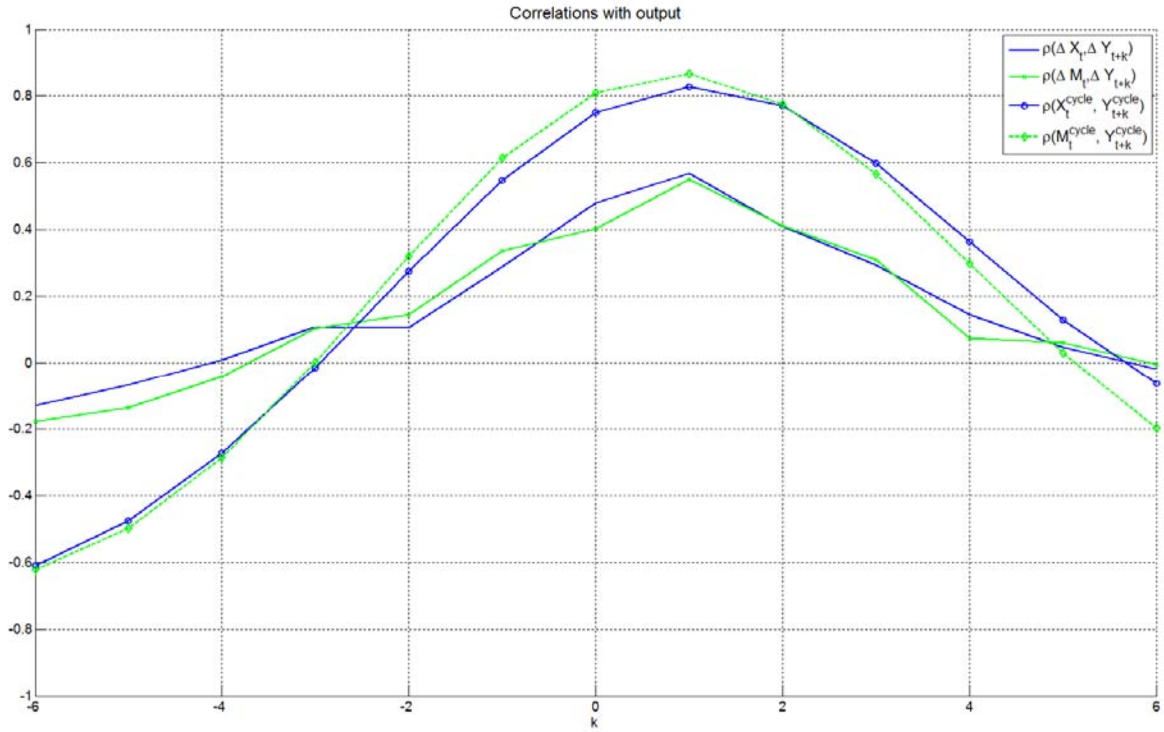
It is not only the level of exports and imports that is important for the Czech economy. Both series are also strongly cyclical. This is illustrated in Figure 2. The upper subfigure shows the annual growth rates of exports, imports and GDP (which is multiplied by a factor of 4). The comovements in the growth rates are clearly visible. The comovements are even greater for the cyclical components shown in the lower subfigure: here, the cyclical components were isolated using the univariate Christiano-Fitzgerald filter and correspond to frequencies of 6 to 32 quarters.

Figure 2: Cyclical Characteristics of Czech Exports and Imports



Apparently, real exports and imports lead real GDP by one quarter. This can be seen from the following Figure 3, which displays the sample correlation of the quarterly growth rates and the cyclical components of these variables for various lags and leads (these are in quarters).

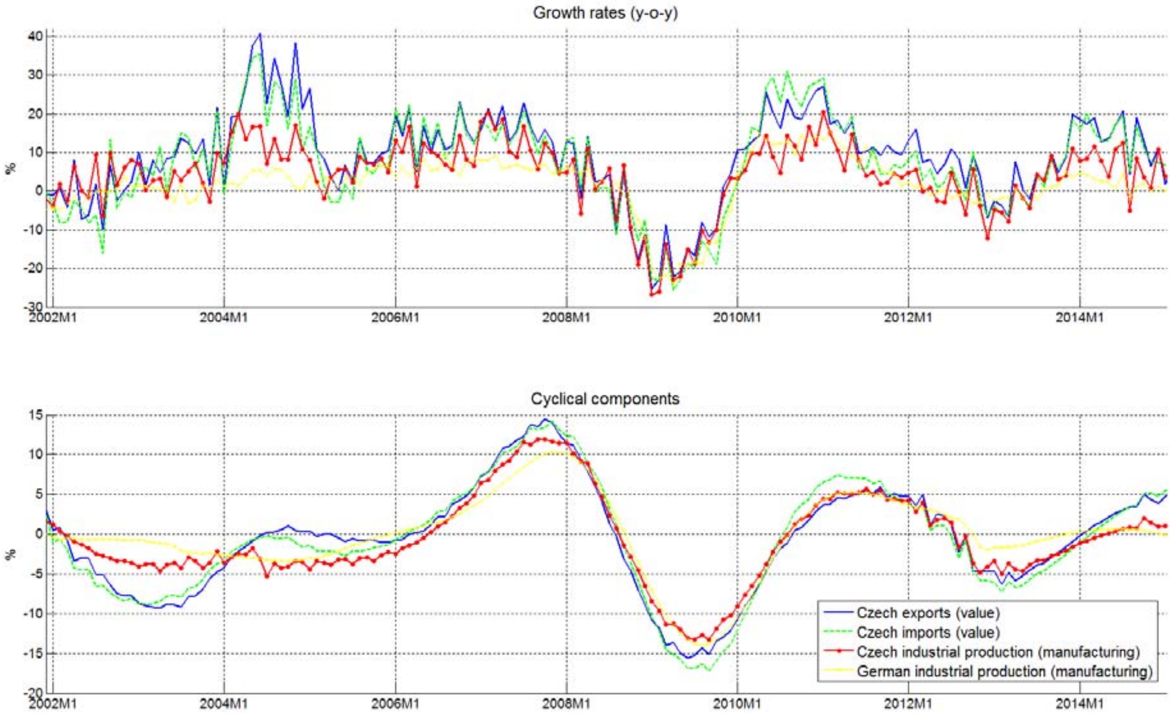
Figure 3: Correlations Between Real Exports and Imports and GDP



The correlation is especially strong for the cyclical components and peaks at the first quarter lead, i.e., the real export and import cycles lead the GDP cycle by one quarter. The correlations between quarterly growth rates are rather lower, but the pattern of a one-quarter lag still holds.

Looking at monthly data, the values of Czech exports and imports are significantly correlated with both Czech and German industrial production in manufacturing. This is illustrated in Figure 4, which shows both the yearly growth rates and the cyclical components of these variables. The correlation between Czech exports and imports and both industrial productions peaks at the zero lag and attains a value of 0.8 for growth rates and 0.95 for the cyclical components in the case of Czech industrial production. The correlation with German industrial production is rather lower, but still impressive: 0.7 for growth rates and 0.85 for the cyclical components. These four series comove contemporaneously. Czech exports and imports are also correlated with various measures of business confidence. To sum up, exports and imports are strongly cyclical variables in the case of the Czech Republic.

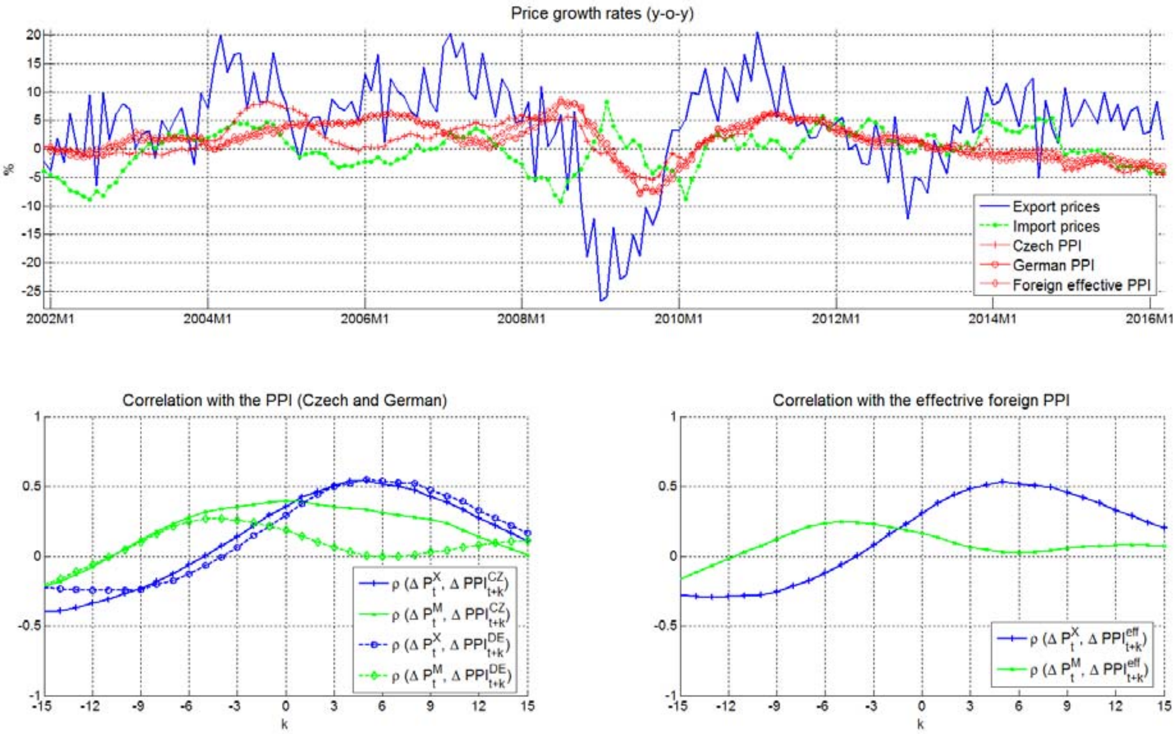
Figure 4: Exports, Imports and Industrial Production



Finally, Figure 5 displays the yearly growth rates of export and import prices and the Czech, German and foreign effective PPI.[3] The figure also shows the correlations of export and import prices with the three PPI series. Czech export price growth is weakly correlated with the Czech PPI. Export price growth leads domestic PPI growth by three or four months, i.e. knowing today's export prices can help in predicting the Czech PPI. However, the correlation is not strong. The series is almost uncorrelated with the foreign and German PPI. The low correlation is due to the 2009 episode of a sudden and temporary depreciation of the Czech koruna. On the other hand, import price growth is well aligned with both German and foreign effective PPI growth (both expressed in Czech currency). The effect of the exchange rate floor on the Czech koruna introduced in November 2013 is clearly visible in the import price series.

[3] The effective PPI is a weighted PPI of 14 euro area members, which enter the index according to the importance of Czech exports to those countries. The euro area is the Czech Republic's main trade partner. Roughly half of total Czech exports to the euro area go to Germany. The export share to Slovakia is 14% and those to Austria, France and Italy are between 6% and 8% of total Czech exports to the euro area (nominal prices).

Figure 5: Export and Import Prices and Their Correlation with the PPI



4. Methods and Results

The nowcast and short-term forecast methods can be characterised as an attempt to distil the information content from indicators, in particular from those which are available sooner than the data of interest. The methods selected for our analysis are adapted to mixed-frequency frameworks and to asynchronous data releases. Leaving aside the potential complexities arising from mixed frequency, all the methods considered here can be classed as data shrinkage procedures. The forecast of the variable $y_{t+k|t}$ at horizon $t+k$ given the data available at time t D_t can be written as follows:

$$y_{t+k|t} = \Lambda_K D_t. \qquad (1)$$

In infinite samples, such a prediction can be estimated just by OLS. With a large number of possibly highly correlated predictors in D_t, the OLS approach would obviously yield a very poor prediction due to the unreliability of the estimation of matrix Λ_k. Nowcast estimation methods differ in the way the projection matrix Λ_k is generated so as to avoid the curse of dimensionality caused by a large number of possible predictors in D_t. Carrasco and Rossi (2016) provide a nice discussion of a unifying framework behind the estimation of predictive equations when dataset D_t is large.

The comparison of forecast methods is based on a pseudo-real time forecast,[4] where we respect the lag structure of the published data. We use two main statistics: the root mean square error (RMSE) and the mean absolute error (MAE). For most cases, the two statistics give the same ranking of relative forecast performance. Only in a very few cases where the two methods show similar forecast performance do the rankings of the two statistics differ. In such cases, however, the differences between the two methods are immaterial. Readers interested in whether there is a systematic correlation between the forecast errors for our variables of interest are referred to Appendix C.

We compare all our models against six univariate benchmark models: (i) usual random-walk predictions, (ii) predictions based on the unconditional past mean of the series, (iii) predictions based on various forms of exponential smoothing (see Hyndman et al., 2008, for an overview), (iv) autoregressive (AR) models of various lags, (v) Bayesian AR models that shrink the coefficients towards zero, and (vi) time-varying AR models.

Turning to the lag structure, for the monthly time series of nominal exports and imports, the best univariate prediction models were obtained from large AR models with four to six lags. The differences between the lags at these horizons are small and insignificant. Also, Bayesian AR models and AR models with time-varying parameters provide only a marginal improvement compared to plain-vanilla OLS estimation.[5] Again, the differences between these two more sophisticated variants and the standard AR models – for a given lag – are both statistically and economically insignificant.

For the monthly series of the price indexes, the best univariate models are either low-lag AR models or the exponential smoothing model. Again, the differences between the usual AR models and their more sophisticated counterparts are not significant. For these series, the unconditional mean forecast (i.e. the forecast that sets the forecasted values at their past unconditional means) tends to be as good as these forecasts for longer forecast horizons. Detailed results for the univariate models can be found in Appendix B.

4.1 Principal Component Regressions

This method is based on the estimation of principal components (PC), i.e. a low-dimensional object that spans the data. Instead of regressing the forecasted variables on the set D_t as in (1), the PC prediction starts with estimation of a low number of mutually orthogonal series – principal components – that span sufficiently well the space of data available D_t. Since the dimension of the principal components is low and because they are orthogonal, regression of future values on them is much more efficient than regression on the original variables.

[4] Given that the historical time series of GDP and its subcomponents were recently subject to special major revision, estimation of model performance and forecast evaluation on true vintages will, in our opinion, be less reliable for the planned future regular practical application of the model compared to the pseudo-real time forecast applied here.

[5] In fact, although we allowed a significant degree of time variation of the AR coefficients, the estimated time-varying AR coefficients drift very little.

The principal components can be easily derived from the eigenvalue decomposition of the covariance matrix (Bai and Ng, 2002). To impute any missing data,[6] the EM algorithm is used; see Stock and Watson (2002) or Foroni and Marcellino (2013).

As the highest frequency of our data is monthly, the dataset used to span the principal components operates at monthly frequency and hence the principal components also have monthly frequency. Given the estimate of the principal components, the forecast of variables operating at monthly frequency is straightforward:

$$y^{m}_{t+k|t} = \Lambda_k \hat{f}_t + \varrho y_{l(t)}, \qquad (2)$$

where $\hat{f}_t$ is the vector of estimated principal components at time t. As it is common, we include the last available value of the forecasted variable $y_{l(t)}$ as an additional predictor.[7] The symbol $l(t)$ denotes the last observation of the forecasted variable available at time t, which for our application is typically $t-1$. Given the estimated principal components, the estimation of the matrix Λ_k and of the autoregressive term ϱ is quite straightforward and can be done using OLS.

The forecast for the quarterly variables is generated as follows:

$$y^{Q}_{t_Q+k|t_Q} = \Lambda_k c(L) \hat{f}_t + \varrho y_{l(t_Q)}, \qquad (3)$$

where $c(L)$ is the polynomial in the lag operator L that aggregates the monthly series to quarterly frequency.

We estimate the predictive equations for a number of principal components ranging from one to six. The number of components was based on the forecasting accuracy. It turns out that the best forecasting performance for all nine time series considered is achieved with four principal components.

We also experimented with time variation in Equations (2) and (3) by making the projection matrices Λ_k time varying. We did this in a relatively unsophisticated but robust way by means of weighted least squares where, in estimating Λ_k at time *t*, more distant observations receive lower weights according to exponential decay. We find that the use of such time variation did not improve the forecasting properties of the model and the cross-validated choice of forgetting factor was very close to 1, meaning no preference for time variation. Therefore, we do not report these results below.

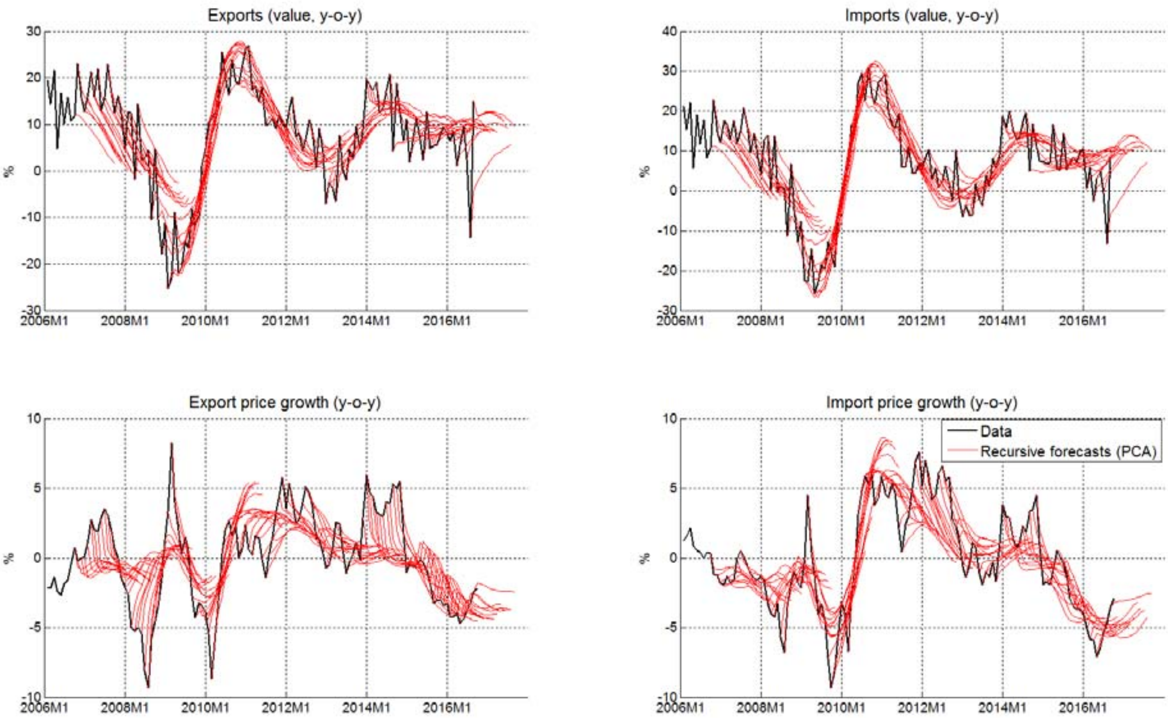
The resulting recursive forecasts are displayed in Figure 6. For export and imports, the model seems to capture the turning points around the Great Recession, although it was not able to fully foresee the significant trade increase that occurred in 2014.

[6] For our data, this occurs typically at the end of the sample, but more general patterns of missing data can be considered.

[7] To our surprise, this autoregressive term is important for backcasting and nowcasting only. For near-term forecasting it is not necessary and its inclusion even makes the forecast slightly less accurate.

We use our own Matlab codes to estimate the principal components, to impute missing values by the EM algorithm and to estimate predictive equations (2) and (3) or their time-varying counterparts.

Figure 6: Recursive Predictions Using Principal Components



4.2 Elastic Net Regression

While the principal component approach attempts to solve the curse of dimensionality by constructing a low number of mutually orthogonal principal components, there are regularisation techniques that control the number and/or the magnitude of the regression coefficients of (1) directly.

Elastic net regression (Zou and Trevor, 2005) is a linear regularised regression method that combines both so-called L1 and L2 penalties; hence it covers as a special case both Lasso (L1 penalty only) and ridge (L2 penalty only) regressions. This method estimates the regression coefficients of a variable Y on X as a solution to the following problem:

$$\beta = argmin\{\sum_i (Y_i - \sum_l X_{il}\beta_l)^2 - \lambda_1 \sum_l |\beta_l| - \lambda_2 \sum_l \beta_l^2\}, \qquad (4)$$

where λ_1 and λ_2 are two positive constants. We use the elastic net to estimate the reduced-form forecasting relationship between the variables of interest $y_{t+k|t}$ and the data D_t.

The presence of the L1 penalty in the objective function implies that only some of the coefficients β_l will be non-zero (as in the Lasso case). The presence of the L2 penalty term also shrinks the coefficients towards zero (as in the case of ridge regression), but also ensures that not too many coefficients will be set to zero.[8] Obviously, the performance of elastic net regression depends crucially on the choice of the two coefficients λ_1 and λ_2.

For each variable of interest and each forecast horizon *k*, we obtain an estimation of the regression coefficients, which can be used to predict the variable of interest:

$$y_{t+k|t} = \beta(\lambda_1, \lambda_2) D_t,$$

where the dependence of the forecast on λ_1 and λ_2 is explicitly shown. In our exercises, these penalty terms λ_1 and λ_2 were set by means of cross-validation.

Our choice of data D_t is the following. We use the data that we used for the principal component analysis from zero to two lags, subject to availability. Hence, if we denote by $X_{\tau(t)}$ the data at time τ that are available at time *t*:

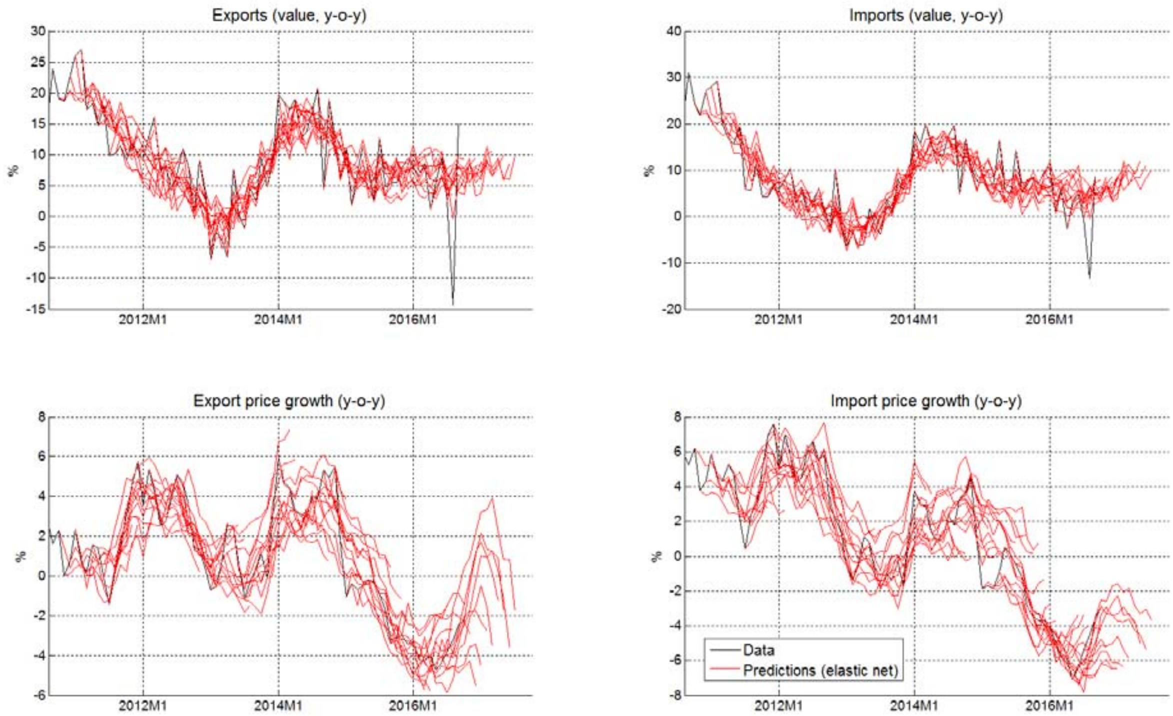
$$D_t = X_{t(t)} \cup X_{t-1(t)} \cup X_{t-2(t)}.$$

Elastic net regression can be used for any variable of any publication lag and any frequency without further complications. To numerically solve for the coefficients in (4), we use the `lasso` function from the Statistical and Machine Learning Toolbox of Matlab.

The recursive forecasts using elastic net regression are displayed in Figure 7. Apart from some outliers the elastic net model captures the dynamics of exports and imports and their prices relatively well.

[8] Hence, elastic net regression combines the virtues of the two approaches. In the case of highly correlated predictors, the L1 penalty would typically choose just one of them. The presence of the L2 penalty weakens this effect and more predictors can appear in the model. On the other hand, without the L1 penalty, all variables – possibly even irrelevant ones – would have non-zero weight, as is the case with ridge regression.

Figure 7: Recursive Forecasts Using Elastic Net Regression



4.3 Dynamic Factor Model

In the time domain, the dynamic factor model (DFM) is represented using the state space form as follows. The state equation governs the dynamics of unobserved factors using a low-dimensional VAR model:

$$f_t = A_1 f_{t-1} + \cdots + A_K f_{t-K} + \varepsilon_t. \tag{5}$$

These factors are specified at monthly frequency. The observation equation links these unobserved factors to the observed variables, which also operate at monthly frequency:

$$y_t^m = D + C_0 f_t + \cdots + C_L f_{t-L} + \upsilon_t^m. \tag{6}$$

Knowing the coefficients $\{A_i\}_{i=1}^K, D, \{C_j\}_{j=0}^L$ and the variances of the error terms $\varepsilon_t, \upsilon_t^m$, it is easy to apply the Kalman smoother[9] to filter the unobserved states and to predict the variables of interest $y_{t+k|t}^m$. The virtue of the Kalman smoother is that it automatically adapts to missing data and asynchronous data releases.

[9] See Harvey (1989) for an introduction to Kalman filtering.

Maximum likelihood estimation of this model would be difficult due to the large amount of parameters, but fortunately, Doz et al. (2011) proposed a simple but efficient two-stage method for estimating the system (5)–(6). The first step of the method involves estimating the principal components f_t. VAR is used to estimate the parameters of the state equation (5), while the regression of y_t^m on f_t and its lags can yield estimates of the parameters of the observation equation (6). We use own our Matlab codes to estimate this model.

Moreover, the model can be extended to the mixed-frequency setting. One can set up an equation linking unobserved factors to observations at quarterly frequency:

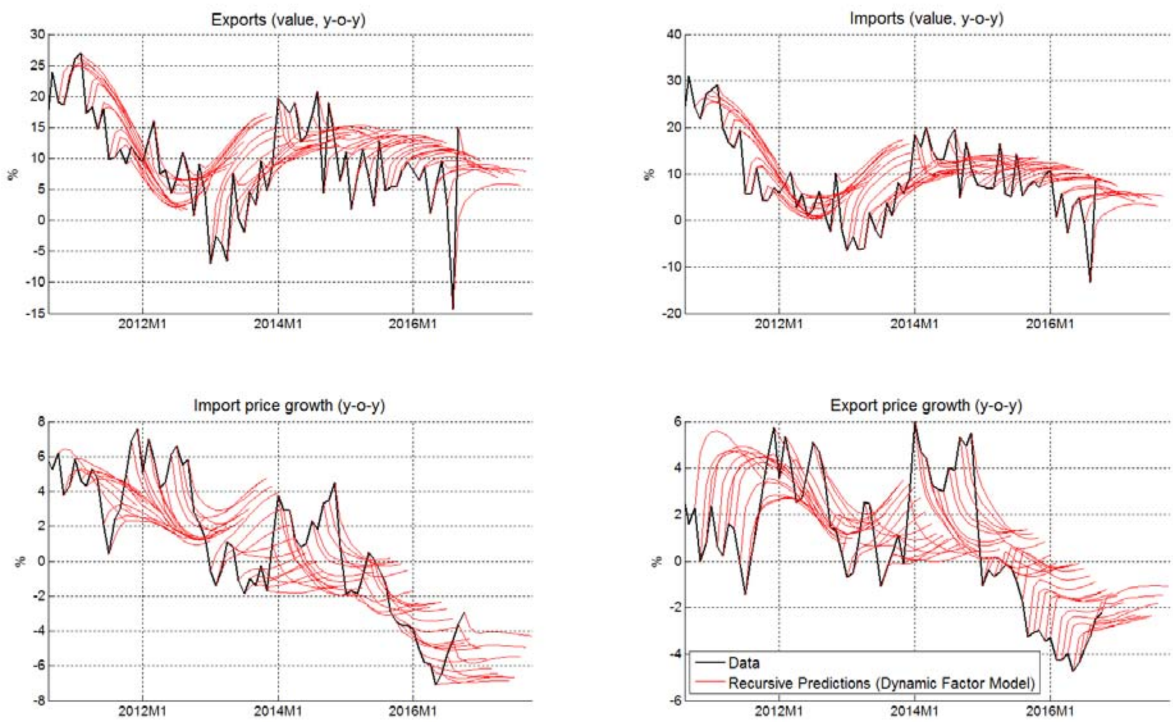
$$y_{t_Q}^Q = D^Q + C_0^Q f_t + \cdots + C_L^Q f_{t-L} + v_t^Q. \qquad (7)$$

Either equation (7) can be a part of the system and hence the Kalman filter will take into account the information in $y_{t_Q}^Q$, or the Kalman filter can be run just on the monthly system (5)–(6) and the variables $y_{t_Q}^Q$ will be predicted out of the state space models. In order not to increase the number of parameters of the state space model (5)–(6), we chose the second approach.

As the Kalman filter is extremely convenient for working with missing data and jittered ends of the sample, the dynamic factor model can be used for imposing judgments and scenarios.

In our application, we set the lag length of the VAR in the state equation (5) $K = 4$. The number of dynamic factors is three. This is lower than the number of static principal components that we use in (4). This reflects the benefit of the dynamic nature of the model: the lead-lag relationship between factors can substitute out one static factor in the data. The lag of the loadings in the observation equations (6) and (7) is set to $L = 3$. This choice was based on the observation that if lower lags were chosen, the model fit was worse. The choice of more lags than three or four results in overfit, which makes the forecasting properties of the model worse, especially for longer forecasting horizons. The recursive forecasts for the dynamic factor model are displayed in Figure 8.

Figure 8: Recursive Forecasts Using the Dynamic Factor Model



4.4 Partial Least Squares

The last method we consider here is partial least squares. The motivation to apply this method is the same as in the case of principal components. Namely, it helps us to obtain a well-behaved low-dimensional object that avoids the curse of dimensionality in (1). The principal components method constructs orthogonal components of the predictors to maximise the variance explained. This approach, however, has one potential drawback. Some of the principal components that contribute significantly to the explanation of the predictors may be only weakly related to the forecasted variables and hence the principal component regression (2) may be inefficient.

The method of partial least squares (PLS) tries to overcome this possible difficulty. The PLS method also constructs a low-dimensional object of mutually orthogonal series, but instead of maximising the explained variance of the predictors, it maximises the explained covariance between the predictors and the predicted variables. See Vinzi et al. (2010) for more details on the motivation, techniques and applications of this approach.

For comparison, we use the same matrix of predictors as in the principal component analysis. The missing values among the predictors (at the end of the sample) were imputed using the same EM algorithm as we use for the PC regression.

To solve the problem of partial least squares numerically, we use the plsregress function from the Statistical and Machine Learning Toolbox of Matlab

5. Comparison across Methods

First, we present our results for the monthly indicators. For principal components and partial least squares, the numbers in parenthesis show the number of components that give the best prediction. For the sake of comparison, we also report three univariate models: an unconditional mean forecast, a random walk forecast and the best of the univariate methods.

Given that the model evaluation using the pseudo-real time set-up (which mimics the actual publication lag) was done on the sample starting in 2006, we evaluate only forecasts based on the datasets ending in 2010 or later.[10] Tables 1 and 2 report the RMSE and MAE for the four prediction methods.

Our forecast horizon for monthly data runs from -1 to 9 months. Due to the fact that the monthly external trade data are available with a two-month lag, while some predictors have a one-month lag only, our forecasting horizon starts at -1. To give an example: in mid-October, the last available data for trade end in August, while some time series are already available for September. Hence, the horizon -1 means the prediction of the September trade data is based on the data available in October (i.e. the backcast), while horizon 0 means the nowcast of the October trade data is based on the data available in October.

For **nominal export growth rates** at monthly frequency, the RMSE strongly favours the prediction based on the elastic net, which is followed by the AR model with six lags and then by the PC prediction based on the first four principal components. The MAE criterion also favours the elastic net prediction for horizons greater than 1, while the backcast and nowcast are most accurate for the AR model, but now with four lags.[11] For this time series, we thus prefer elastic net regression as the main forecasting method. AR models and PC prediction may be used as alternative checks.

For **nominal import growth rates** at monthly frequency, both the RMSE and the MAE favour the PC prediction based on the four first principal components for horizons up to 1 month, while elastic net regression is preferred for longer horizons.

For the yearly **growth rate of export prices**, the accuracy of the backcast and the nowcast is dominated by univariate models: random walk prediction and the AR(1) model, with the latter being slightly more accurate. At these horizons, all the sophisticated methods are worse than these two univariate benchmarks. At longer horizons, elastic net prediction outperforms all the other methods, followed by principal components and the dynamic factor model.

For the yearly **growth rate of import prices**, the backcast (i.e. horizon -1) is dominated by univariate models (either the AR(1) model or the local-level model of exponential smoothing, followed by random walk prediction), but for the nowcast (i.e. horizon 0), all the sophisticated

[10] As all the methods (with the exception of the random walk) require estimation of unknown parameters, the forecast exercise cannot start at the beginning of the sample. The first four years ensures that for any dataset considered there are some data that can be used for the pseudo-real time estimation of the required parameters.

[11] The differences between the forecasting performances of AR models (with four to six lags for both criteria) are marginal.

methods start performing better, with PC prediction being the best. For forecast horizons longer than 1, the elastic net dominates all the other methods.

Finally, for horizons -1 to 1 the prediction of the growth rates of the **foreign effective PPI** is dominated by univariate models (be it exponential smoothing or the AR(1) model), while at longer horizons, elastic net regression again dominates. Note that we do not put the foreign effective PPI into our DFM model, as this worsens its forecasting properties. Therefore, for the foreign effective PPI, we do not report DFM statistics.

To summarise, for nominal quantities, elastic net regression (at all horizons) and principal component regression (for horizons up to 0 or 1) are clearly the preferable methods. For growth rates of price indexes, the univariate methods are the winners for backcasting and in some cases also for nowcasting, while for longer horizons the elastic net is typically the most accurate method. This difference may be caused by the large volatility of the time series of price changes. All in all, the elastic net approach ends up as a robust and reliable method. This is consistent with recent findings (e.g., Smeekes and Wijler, 2016) that demonstrate excellent nowcasting and near-term forecasting properties of penalised regressions comparing to other regularisation techniques.

Tables 3 and 4 show the results for the RMSE and MAE for the **quarterly national accounts** for time horizons ranging from -1 (backcast) to 0 (nowcast) to 2 quarters. As for the monthly data, we report the RMSE and MAE statistics for three benchmark univariate models (random walk prediction, unconditional mean prediction and the best AR model[12]) and three mixed-frequency data: principal component analysis for the best number of principal components, elastic net regression and the dynamic factor model. We did not consider partial least squares for the quarterly data, as to the best of our knowledge there is no established model for partial least squares in the mixed-frequency setting.

For these data, in both nominal and real quantities, the sophisticated models outperform the univariate benchmarks. As in the case of monthly data, the elastic net prediction is typically the winner of the forecasting contest, while the principal component prediction and the dynamic factor models also sometimes have excellent forecasting properties.

[12] Again for these quarterly data, time-varying or Bayesian AR models have slightly better forecasting performance than the plain-vanilla AR model. We therefore consider the simple variant as a benchmark.

Table1: Root Mean Square Error for Monthly Data

(evaluated using pseudo-real time data 2010M1 to 2016M8)

	Prediction horizon										
	-1	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Exports (nominal, yearly growth rates), monthly data											
Unconditional mean	8.58	8.69	8.78	8.86	8.67	8.61	8.63	8.45	8.39	8.33	8.14
Random walk	6.90	6.90	6.36	7.61	8.06	8.17	9.26	9.38	9.66	10.64	10.93
AR model (6)	5.79	5.94	6.07	6.77	7.16	7.24	7.44	7.38	7.56	7.93	7.93
PCA (4)	5.84	6.07	6.09	6.86	7.02	7.37	7.83	7.87	8.04	8.11	8.03
Elastic Net	**5.74**	**5.63**	**5.84**	**5.72**	**5.98**	**6.11**	**6.05**	**5.97**	**6.46**	**6.50**	**6.25**
DFM	5.48	5.93	6.37	7.29	7.65	8.29	8.79	8.97	9.37	9.70	9.82
PLS (3)	9.44	9.59	10.16	11.01	11.47	12.32	12.78	12.92	13.09	14.16	14.19
Imports (nominal, yearly growth rates), monthly data											
Unconditional mean	10.08	10.26	10.34	10.44	10.25	9.97	9.87	9.47	9.27	9.14	8.78
Random walk	6.56	6.91	6.85	8.46	8.99	9.21	10.72	10.66	11.14	12.40	12.42
AR model (6)	5.51	5.78	6.04	6.94	7.24	7.37	7.82	7.44	7.72	8.33	8.20
PCA (4)	5.45	**5.56**	**5.56**	**6.45**	6.66	7.02	7.57	7.62	7.93	8.06	8.06
Elastic Net	5.77	5.80	6.03	5.74	**6.09**	**6.31**	**6.30**	**6.10**	**6.25**	**6.23**	**6.49**
DFM	**5.38**	5.75	6.25	7.25	7.72	8.45	9.01	9.23	9.78	10.10	10.25
PLS (3)	8.59	8.89	9.72	10.70	11.58	12.63	13.45	14.09	14.71	15.58	15.74
Export prices (yearly change)											
Unconditional mean	3.31	3.26	3.27	3.31	3.35	3.37	3.39	3.42	3.44	3.48	3.51
Random walk	1.43	2.16	2.69	3.06	3.25	3.29	3.29	3.30	3.44	3.79	4.12
AR model (1)	**1.41**	2.05	2.50	2.79	2.95	2.99	3.00	3.03	3.14	3.34	3.48
PCA (4)	2.05	2.41	2.61	2.72	2.78	2.78	2.74	2.72	2.69	2.63	2.59
Elastic Net	2.04	2.11	**2.15**	**2.16**	**2.34**	**2.25**	**2.19**	**2.10**	**2.09**	**2.14**	**2.06**
DFM	1.75	**2.02**	2.23	2.32	2.41	2.48	2.54	2.60	2.66	2.77	2.89
PLS (3)	2.04	2.43	2.61	2.85	3.14	3.55	3.59	3.79	4.13	4.48	4.52
Import prices (yearly change), monthly data											
Unconditional mean	4.23	4.28	4.35	4.42	4.45	4.45	4.43	4.42	4.39	4.40	4.40
Random walk	1.52	2.30	2.91	3.36	3.60	3.63	3.63	3.69	3.81	4.15	4.49
AR model (1)	**1.51**	2.31	2.94	3.40	3.67	3.70	3.69	3.73	3.83	4.16	4.52
PCA (4)	1.59	**1.97**	2.15	2.24	2.34	2.41	2.47	2.54	2.58	2.59	2.61
Elastic Net	2.03	2.07	**2.14**	**2.20**	**2.17**	**2.20**	**2.12**	**2.01**	**2.05**	**2.02**	**2.09**
DFM	1.74	2.22	2.59	2.77	2.90	3.02	3.11	3.15	3.18	3.22	3.27
PLS (3)	1.90	2.20	2.52	3.00	3.02	3.21	3.42	3.68	4.09	4.49	4.57
Effective foreign PPI (yearly change)											
Unconditional mean	3.27	3.28	3.31	3.35	3.40	3.46	3.51	3.56	3.60	3.65	3.70
Random walk	0.51	0.88	1.17	1.40	1.58	1.75	1.88	2.04	2.20	2.36	2.54
Local trend model	**0.49**	**0.83**	**1.10**	1.36	1.52	1.64	1.77	1.85	1.95	2.07	2.25
PCA (4)	0.88	1.01	1.21	1.47	1.73	2.02	2.30	2.52	2.72	2.88	3.01
Elastic Net	1.23	1.14	1.23	**1.21**	**1.29**	**1.32**	**1.33**	**1.38**	**1.37**	**1.39**	**1.39**
PLS (3)	1.34	1.68	2.04	2.40	2.85	3.14	3.41	3.77	4.13	4.42	4.65

Table 2: Mean Absolute Error for Monthly Data

(evaluated using pseudo-real time data 2010M1 to 2016M8)

	Prediction horizon										
	-1	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Exports (nominal, yearly growth rates), monthly data											
Unconditional mean	6.58	6.65	6.69	6.72	6.59	6.53	6.51	6.38	6.32	6.26	6.11
Random walk	5.09	5.41	4.92	6.25	6.44	6.40	7.64	7.53	7.91	8.86	8.89
AR model (4)	**4.20**	**4.51**	4.69	5.27	5.57	5.57	6.15	6.16	6.46	6.93	6.96
PCA (4)	4.60	4.81	4.86	5.49	5.51	5.87	6.04	6.04	6.14	6.15	6.03
Elastic Net	4.57	4.54	**4.63**	**4.48**	**4.88**	**4.88**	**5.05**	**4.91**	**5.19**	**5.17**	**4.83**
DFM	4.31	4.63	4.94	5.67	6.03	6.52	7.04	7.24	7.54	7.78	7.80
PLS (3)	8.06	8.19	8.54	8.87	8.92	9.34	9.31	9.42	9.40	10.02	10.06
Imports (nominal, yearly growth rates), monthly data											
Unconditional mean	7.59	7.71	7.71	7.74	7.59	7.39	7.27	7.02	6.85	6.72	6.50
Random walk	5.05	5.51	5.34	6.93	7.18	7.13	8.77	8.67	9.00	10.33	10.20
AR model (6)	4.39	4.68	4.76	5.70	5.80	5.88	6.27	5.84	6.31	6.87	6.51
PCA (4)	**4.33**	**4.39**	**4.44**	5.04	5.19	5.47	5.78	5.79	6.01	6.05	5.98
Elastic Net	4.62	4.67	4.73	**4.48**	**4.82**	**5.03**	**5.12**	**4.80**	**4.89**	**4.94**	**5.20**
DFM	4.38	4.72	5.09	5.80	6.25	6.89	7.43	7.57	8.08	8.46	8.50
PLS (3)	7.23	7.31	7.60	8.02	8.41	9.06	9.33	9.67	10.13	10.70	10.84
Export prices (yearly change)											
Unconditional mean	2.85	2.82	2.83	2.86	2.90	2.91	2.92	2.93	2.94	2.98	3.01
Random walk	1.12	1.64	2.00	2.31	2.45	2.51	2.59	2.69	2.92	3.27	3.58
AR model (1)	**1.09**	**1.59**	1.92	2.20	2.34	2.41	2.52	2.61	2.72	2.89	3.05
PCA (4)	1.70	1.95	2.09	2.17	2.15	2.11	2.07	2.05	2.07	2.03	2.00
Elastic Net	1.62	1.65	**1.67**	**1.66**	**1.85**	**1.80**	**1.72**	**1.64**	**1.66**	**1.65**	**1.61**
DFM	1.32	1.73	2.08	2.23	2.34	2.45	2.54	2.58	2.62	2.66	2.68
PLS (3)	1.59	1.87	1.97	2.17	2.35	2.68	2.76	3.07	3.32	3.64	3.68
Import prices (yearly change), monthly data											
Unconditional mean	3.58	3.60	3.68	3.75	3.77	3.76	3.74	3.72	3.69	3.68	3.67
Random walk	1.22	1.81	2.30	2.64	2.76	2.82	2.84	2.96	3.18	3.46	3.83
Local level model	**1.20**	1.81	2.32	2.68	2.81	2.88	2.88	2.98	3.16	3.41	3.82
PCA (4)	1.70	1.95	2.09	2.17	2.15	2.11	2.07	2.05	2.07	2.03	2.00
Elastic Net	1.56	**1.61**	**1.64**	**1.69**	**1.77**	**1.79**	**1.73**	**1.65**	**1.60**	**1.61**	**1.64**
DFM	1.32	1.73	2.08	2.23	2.34	2.45	2.54	2.58	2.62	2.66	2.68
PLS (3)	1.59	1.87	1.97	2.17	2.35	2.68	2.76	3.07	3.32	3.64	3.68
Effective foreign PPI (yearly change)											
Unconditional mean	2.88	2.89	2.91	2.96	3.02	3.08	3.13	3.19	3.23	3.28	3.33
Random walk	**0.38**	**0.66**	0.89	1.08	1.22	1.34	1.46	1.58	1.73	1.88	2.04
AR (1)	0.39	0.66	**0.89**	1.07	1.21	1.33	1.43	1.55	1.69	1.83	1.96
PCA (4)	0.68	0.80	0.96	1.17	1.36	1.59	1.78	1.96	2.10	2.22	2.32
Elastic Net	0.87	0.78	0.90	**0.94**	**1.01**	**1.04**	**1.02**	**1.07**	**1.05**	**1.09**	**1.09**
PLS (5)	1.11	1.33	1.54	1.82	2.12	2.48	2.69	2.89	3.08	3.15	3.21

Table 3: Root Mean Square Error for Quarterly National Account Data

(evaluated using pseudo-real time data 2010Q1 to 2016Q2)

	Prediction horizon			
	-1	**0**	**1**	**2**
Exports (nominal, yearly growth rates)				
Unconditional mean	6.19	6.08	5.77	5.60
Random walk	4.14	5.93	7.35	8.60
AR model (1)	4.13	5.58	6.47	7.14
PCA (5)	3.55	5.18	6.13	6.71
Elastic Net	**2.06**	**2.19**	3.38	**3.21**
DFM	4.29	3.59	**3.26**	3.38
Exports (real, yearly growth rates)				
Unconditional mean	5.03	4.87	4.73	4.61
Random walk	3.06	4.27	5.36	6.42
AR model (1)	3.00	3.86	4.48	4.93
PCA (5)	3.67	5.56	6.45	6.69
Elastic Net	**2.69**	**2.84**	**2.31**	**2.60**
DFM	4.57	4.32	3.62	3.45
Imports (nominal, yearly growth rates)				
Unconditional mean	7.67	7.62	6.84	6.34
Random walk	4.83	7.48	9.00	10.18
AR model (2)	4.11	5.99	6.68	7.42
PCA (4)	3.98	6.16	7.32	7.69
Elastic Net	**2.21**	**2.16**	**2.80**	**3.52**
DFM	4.51	4.17	4.02	3.74
Imports (real, yearly growth rates)				
Unconditional mean	5.98	5.88	5.32	5.12
Random walk	3.74	5.57	6.73	7.96
AR model (3)	3.40	4.55	4.70	5.07
PCA (4)	3.80	5.81	6.76	6.94
Elastic Net	**2.07**	**2.42**	**2.70**	**2.54**
DFM	4.08	4.32	3.32	4.05

Table 4: Mean Absolute Error for Quarterly National Account Data

(evaluated using pseudo-real time data 2010Q1 to 2016Q2)

	Prediction horizon			
	-1	**0**	**1**	**2**
Exports (nominal, yearly growth rates)				
Unconditional mean	5.02	4.93	4.75	4.62
Random walk	3.15	4.80	6.20	7.34
AR model (1)	3.02	4.14	5.29	5.42
PCA (4)	2.79	4.06	4.81	5.11
Elastic Net	**2.62**	**2.75**	2.91	3.56
DFM	3.54	2.76	**2.61**	**2.75**
Exports (real, yearly growth rates)				
Unconditional mean	3.80	3.67	3.52	3.38
Random walk	2.27	3.13	4.02	5.05
AR model (1)	2.27	2.95	3.39	3.68
PCA (4)	2.74	4.01	4.71	5.08
Elastic Net	**1.71**	**2.80**	**2.64**	2.84
DFM	3.32	3.11	2.65	**2.49**
Imports (nominal, yearly growth rates)				
Unconditional mean	5.92	5.80	5.31	4.92
Random walk	3.77	6.21	7.53	8.67
AR model (2)	3.26	5.20	5.64	6.04
PCA (4)	3.12	4.73	5.80	6.13
Elastic Net	**1.71**	**1.80**	**2.64**	**2.84**
DFM	3.91	3.45	3.02	3.13
Imports (real, yearly growth rates)				
Unconditional mean	4.85	4.76	4.45	4.30
Random walk	2.89	4.43	4.99	6.20
AR model (2)	2.55	3.79	3.89	3.77
PCA (4)	3.06	4.51	5.19	5.32
Elastic Net	**1.71**	**2.15**	**2.25**	**2.18**
DFM	3.39	3.39	2.54	3.18

6. Conclusion

In this paper, we compare various methods that can be used for nowcasting and short-run forecasting of the main external trade variables – both values and price indexes. First, we evaluate a set of univariate benchmark models, such as random walk prediction, exponential smoothing and AR models. Among these simple models, AR models with four to six lags are the best predictors for trade values (both real and nominal), while low-lag AR models and exponential smoothing tend to be better for trade price indexes and the PPI.

We then consider four empirical methods: principal component regression, elastic net regression, the dynamic factor model and partial least squares. We discuss the adaptation of these methods to asynchronous data releases and to the mixed-frequency set-up. We find that for trade values (both nominal and real), elastic net regression typically yields the most accurate predictions, followed by principal components and the dynamic factor model. These sophisticated methods dominate the univariate models in terms of accuracy for all horizons.

For export and import prices, univariate techniques seem to have higher precision for backcasting and nowcasting, but for short-run forecasting the more sophisticated methods tend to produce more accurate forecasts. Here again, elastic net regression dominates the other methods.

For some cases, we examined a time-varying approach. However, we did not find any evidence that time-varying models outperform models with time-constant parameters.

We conclude that elastic net regression seems to be a promising tool for nowcasting and short-term forecasting for the Czech trade balance. Other methods, such as principal component regression and the dynamic factor model, may serve as a useful check. Moreover, in contrast to the elastic net approach, the dynamic factor model can easily be used to create alternative scenarios or impose judgments.

We plan to regularly update our models and present the results during the quarterly forecasting exercise at the CNB.

References

ANDRLE, M., T. HLÉDIK, O. KAMENÍK, AND J. VLČEK (2009): "Implementing the New Structural Model of the Czech National Bank." Czech National Bank Working Paper No. 2/2009.

ARNOŠTOVÁ, K., D. HAVRLANT, L. RŮŽIČKA, AND P. TÓTH (2011): "Short-Term Forecasting of Czech Quarterly GDP Using Monthly Indicators." *Finance a Úvěr – Czech Journal of Economics and Finance 6*, pp. 566–583.

BAI, J. AND S. NG (2002): "Determining the Number of Factors in Approximate Factor Models." *Econometrica 70(1)*, pp. 191–221.

BAI, J. AND P. WANG (2015): "Identification and Bayesian Estimation of the Dynamic Factor Model." *Journal of Business and Economic Statistics 33(2)*, pp. 221–239.

BOIVIN, J. AND S. NG (2006): "Are More Data Always Better for Factor Analysis?" *Journal of Econometrics 132(1)*, pp. 169–194.

BRŮHA, J., T. HLÉDIK, T. HOLUB, J. POLANSKÝ, AND J. TONNER (2013): "Incorporating Judgments and Dealing with Data Uncertainty in Forecasting at the Czech National Bank." Czech National Bank Research and Policy Note No. 2/2013.

CAMACHO, M., G. PEREZ-QUIROS, AND P. PONCELA (2013): "Short-Term Forecasting for Empirical Economists. A Survey of the Recently Proposed Algorithms." Banco de España Working Paper 1318.

CARRASCO, M., AND B. ROSSI (2016): "In-Sample Inference and Forecasting in Misspecified Factor Models." *Journal of Business & Economic Statistics 34(3)*, pp. 313–338.

DEL NEGRO, M. AND F. SCHORFHEIDE (2013): "DSGE Model-Based Forecasting." *Handbook of Economic Forecasting*, Elsevier.

DOZ, C., D. GIANNONE, AND L. REICHLIN, (2011): "A Two-Step Estimator for Large Approximate Factor Models Based on the Kalman Filter." *Journal of Econometrics 164(1)*, pp. 188–205.

ECB (2016): "Understanding the Weakness in Global Trade: What is the New Normal." IRC Trade Task Force, ECB Occasional Paper Series 178, September 2016.

FORONI, C. AND M. MARCELLINO (2013). "A Survey of Econometric Methods for Mixed-Frequency Data." Norges Bank Research Working Paper 2013/6.

FRANTA, M., D. HAVRLANT, AND M. RUSNÁK (2013): "Near-Term Forecasting of Czech GDP Using New Mixed Frequency Data Models." Czech National Bank Working Paper No. 8/2014.

HARVEY, A. C. (1989): *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge University Press.

HYNDMAN, R. J., A. B. KOEHLER, J. K. ORD, AND R. D. SNYDER (2008): *Forecasting with Exponential Smoothing*, Springer Series in Statistics.

RUSNÁK, M. (2013): "Nowcasting Czech GDP in Real Time." Czech National Bank Working Paper No. 6/2013.

SMEEKES, S. AND E. WIJLER (2016): "Macroeconomic Forecasting Using Penalized Regression Methods." Research Memorandum 039, Maastricht University, Graduate School of Business and Economics (GSBE).

STOCK, J. H. AND M. W. WATSON (2002): "Forecasting Using Principal Components from a Large Number of Predictors." *Journal of the American Statistical Association 97*, pp. 1167–1179.

STOCK, J. H. AND M. W. WATSON (2012): "Generalized Shrinkage Methods for Forecasting Using Many Predictors." *Journal of Business & Economic Statistics 30(4)*, pp. 481–493.

VINZI, V. E., W. CHIN, J. HENSELER, AND H. WANG (eds.) (2010): *Handbook of Partial Least Squares: Concepts, Methods and Applications*, Springer.

ZOU, H. AND H. TREVOR (2005): "Regularization and Variable Selection via the Elastic Net." *Journal of the Royal Statistical Society, Series B 67,* pp. 301–320.

Appendix A

Table A1: Czech Republic, Quarterly Indicators (17 indicators + trade)

Description	Source	data release	for …	lag, days
Exports of goods & services, current prices	Czech Statistical Office	30.9.2016	June	-92
Exports of goods & services, constant prices	Czech Statistical Office	30.9.2016	June	-92
Imports of goods & services, current prices	Czech Statistical Office	30.9.2016	June	-92
Imports of goods & services, constant prices	Czech Statistical Office	30.9.2016	June	-92
GDP, current	Czech Statistical Office	30.9.2016	June	-92
GDP, constant	Czech Statistical Office	30.9.2016	June	-92
GDP deflator	Czech Statistical Office	30.9.2016	June	-92
Implicit price deflator of GDP	Thomson Reuters	30.9.2016	June	-92
Gross fixed capital formation, constant	Czech Statistical Office	30.9.2016	June	-92
Gross fixed capital formation, current	Czech Statistical Office	30.9.2016	June	-92
Final consumption - government, constant	Czech Statistical Office	30.9.2016	June	-92
Final consumption - government, current	Czech Statistical Office	30.9.2016	June	-92
Final consumption - households, constant	Czech Statistical Office	30.9.2016	June	-92
Final consumption - households, current	Czech Statistical Office	30.9.2016	June	-92
Change in inventories, current	Czech Statistical Office	30.9.2016	June	-92
Employees	Czech Statistical Office	29.9.2016	June	-91
Gross external debt, current	Czech Statistical Office	20.9.2016	June	-82
Average monthly wages - manufacturing, current	Czech Statistical Office	5.9.2016	June	-67
Average monthly wages, current	Czech Statistical Office	5.9.2016	June	-67
Housing started, volume	Czech Statistical Office	8.8.2016	June	-39
Employed persons	Czech Statistical Office	5.8.2016	June	-36

Table A2: Czech Republic, Monthly Indicators (26 indicators)

Description	Source	data release	for …	lag, days
Total import prices	Czech Statistical Office	17.10.2016	August	-47
Import prices - food and live animals,	Czech Statistical Office	17.10.2016	August	-47
Import prices - raw materials, except fuels	Czech Statistical Office	17.10.2016	August	-47
Import prices - fuel	Czech Statistical Office	17.10.2016	August	-47
Import prices - chemicals and related products	Czech Statistical Office	17.10.2016	August	-47
Import prices - manuf. goods classif. by material	Czech Statistical Office	17.10.2016	August	-47
Import prices - machinery and transport equip.	Czech Statistical Office	17.10.2016	August	-47
Import prices - miscellaneous manuf. articles	Czech Statistical Office	17.10.2016	August	-47
Export prices, total	Czech Statistical Office	17.10.2016	August	-47
Industrial production	Czech Statistical Office	7.10.2016	August	-37
Industrial new orders	Czech Statistical Office	7.10.2016	August	-37
Industrial orders from abroad	Czech Statistical Office	7.10.2016	August	-37
Domestic industrial orders	Czech Statistical Office	7.10.2016	August	-37
Industrial sales	Czech Statistical Office	7.10.2016	August	-37
Industrial revenues from direct exports	Czech Statistical Office	7.10.2016	August	-37
Retail (including retail sales of fuels)	Czech Statistical Office	6.10.2016	August	-36
Sale of motor vehicles; trade, maintenance and repair of motorcycles	Czech Statistical Office	6.10.2016	August	-36
The number of unemployed	Czech Statistical Office	30.9.2016	August	-30
The number of vacancies	Czech Statistical Office	30.9.2016	August	-30
General unemployment rate	Czech Statistical Office	30.9.2016	August	-30
New job applicants	Czech Statistical Office	30.9.2016	August	-30
Discontinuation, % of the number of unemployed	Czech Statistical Office	30.9.2016	August	-30
Producer price index (PPI)	Czech Statistical Office	17.10.2016	September	-17
PPI - base metals and fabricated metal products	Czech Statistical Office	17.10.2016	September	-17
PPI - coke and refined petroleum, petrol.products	Czech Statistical Office	17.10.2016	September	-17
PPI - manufacturing	Czech Statistical Office	17.10.2016	September	-17

Table A3: External Sector, Monthly Data (18 indicators)

Description	Source	data release	for …	lag, days
Germany. New orders	Deutsche Bundesbank	23.9.2016	July	-54
Germany. Productivity in industry	Deutsche Bundesbank	17.10.2016	August	-47
Euro area. Extra-EMU imports, current	Eurostat	14.10.2016	August	-44
Euro area. Extra-EMU exports, current	Eurostat	14.10.2016	August	-44
Germany. Total imports of goods, curn	Deutsche Bundesbank	12.10.2016	August	-42
EA19. Industrial production excluding construction	Eurostat	12.10.2016	August	-42
Germany. Total exports of goods, current	Deutsche Bundesbank	12.10.2016	August	-42
Germany. Ind. production: ind. incl construction	Federal Statistical Office, Germany	7.10.2016	August	-37
Germany. Industrial production: manufacturing	Federal Statistical Office, Germany	7.10.2016	August	-37
Germany. Manufacturing orders	Deutsche Bundesbank	6.10.2016	August	-36
EA19 Import price idex -total ind.excluding constr.	Eurostat	6.10.2016	August	-36
Euro area. Effective PPI	CNB staff estimation	17.10.2016	August + est.	-30
Germany. Import price index	Federal Statistical Office, Germany	27.9.2016	August	-27
Germany. PPI - total industry	Destatis	20.10.2016	September	-20
USA. CPI - excluding energy and food	Bureau of Labor Statistics	18.10.2016	September	-18
Germany. CPI, total	Federal Statistical Office, Germany	5.10.2016	September	-5
Germany. CPI - excluding energy and food	Federal Statistical Office, Germany	5.10.2016	September	-5
Germany. New passenger car registrations	KBA - Federal Motor Transport Authority, Germany	5.10.2016	September	-5

Table A4: Leading, Survey and Financial Indicators (22 indicators)

Description	Source	data release	for …	lag, days
A. External sector				
Germany. Industrial confidence indicator	OECD	11.10.2016	September	-11
Euro area. Eff. exch.rate: (38 partners) - real CPI	ECB	5.10.2016	September	-5
Germany. Business expectations (pan Germany)	Ifo	29.9.2016	September	1
Germany. Consumer confidence indicator	EC, DG ECFIN	29.9.2016	September	1
Euro area. Industrial confidence indicator	EC, DG ECFIN	29.9.2016	September	1
Germany. Ifo business climate index (pan Germany)	Ifo	26.9.2016	September	4
Germany. Business expectations (pan Germany)	Thomson Reuters	26.9.2016	September	4
Germany. OECD Composite leading indicator	OECD	10.10.2016	October	21
B. Exchange rate and commodity prices				
US dollar exchange rate to the euro	Datastream	1.10.2016	October	0
CZK contribution to the YoY% chg. in the koruna pri	CNB staff estimation	1.10.2016	October	0
Brent price in USD per barrel	Datastream	1.10.2016	October	0
The price of oil WTI (futures for the nearest month)	Bloomberg	1.10.2016	October	0
Price index of industrial metals	Bloomberg, CNB staff estimation	1.10.2016	October	0
Price index of food commodities	Bloomberg, CNB staff estimation	1.10.2016	October	0
Price index of energy commodities	Bloomberg, CNB staff estimation	1.10.2016	October	0
Price index of non-energy commodities, total	Bloomberg, CNB staff estimation	1.10.2016	October	0
Price of natural gas in USD / 1000 cubic meters	IMF via Bloomberg, CNB staff est.	1.10.2016	October	0
C. Czech Republic				
Confidence indicator, base index	CZSO, Business cycle survey	29.9.2016	September	1
Consumer confidence indicator, base index	CZSO, Business cycle survey	29.9.2016	September	1
Business confidence indicator, base index	CZSO, Business cycle survey	29.9.2016	September	1
Confidence indicator in trade	CZSO, Business cycle survey	29.9.2016	September	1
Confidence indicator in services. Base index	CZSO, Business cycle survey	29.9.2016	September	1

Appendix B: An Overview of Univariate Models

This part of the paper provides an overview of the univariate models that we considered as the benchmark for the comparison. We selected the unconditional mean forecast, the random walk forecast, AR models estimated using OLS for lags 1 to 6, time-varying AR models with the same lag structure and two exponential smoothing models: the local level model and the damped trend model (see Hyndman et al., 2008, for an overview). Both exponential smoothing models were estimated using prediction error minimisation. Tables B1 and B2 display the RMSE statistics of the pseudo-real time forecasts for the variables of interest.

Table B1: Root Mean Square Error of Univariate Models for National Accounts Data

(evaluated using pseudo-real time data 2010Q1 to 2016Q2)

	Prediction horizon				Prediction horizon			
	-1	**0**	**1**	**2**	**-1**	**0**	**1**	**2**
	Exports (nominal, yearly growth rates)				**Imports (nominal, yearly growth rates)**			
Unconditional mean	6.19	6.08	**5.77**	**5.60**	7.67	7.62	6.84	**6.34**
Random walk	4.14	5.93	7.35	8.60	4.83	7.48	9.00	10.18
Local linear model	4.14	5.93	7.35	8.60	4.84	7.48	9.00	10.18
Damped trend model	4.41	6.88	9.29	12.12	4.73	8.55	12.62	16.88
AR model (lag = 1)	4.13	5.58	6.47	7.14	4.86	7.11	7.97	8.43
AR model (lag = 2)	4.15	5.57	6.11	7.11	4.11	5.99	6.68	7.42
AR model (lag = 4)	4.34	6.26	7.67	9.13	4.42	7.58	10.71	12.77
AR model (lag = 6)	4.63	6.64	9.46	13.26	5.25	9.58	14.25	19.02
Time-varying AR model (lag = 1)	**4.12**	5.57	6.45	7.11	4.86	7.11	7.97	8.43
Time-varying AR model (lag = 2)	4.14	**5.56**	6.08	7.06	**4.10**	**5.98**	**6.65**	7.39
Time-varying AR model (lag = 4)	4.32	6.27	7.70	9.12	4.44	7.74	11.15	13.46
Time-varying AR model (lag = 6)	4.71	6.84	9.47	13.21	5.30	9.80	14.57	19.46
	Exports (real, yearly growth rates)				**Imports (real, yearly growth rates)**			
Unconditional mean	5.03	4.87	4.73	4.61	5.98	5.88	5.32	5.12
Random walk	3.06	4.27	5.36	6.42	3.74	5.57	6.73	7.96
Local linear model	3.06	4.27	5.36	6.42	3.74	5.57	6.73	7.96
Damped trend model	3.71	5.64	7.31	9.12	3.76	5.92	7.67	9.71
AR model (lag = 1)	**3.00**	3.86	4.48	4.93	3.69	5.13	5.68	6.31
AR model (lag = 2)	3.45	4.43	4.58	**4.59**	3.46	**4.58**	**4.59**	**4.96**
AR model (lag = 4)	3.72	5.32	6.72	7.45	**3.41**	4.78	5.39	5.86
AR model (lag = 6)	4.34	7.33	11.02	13.42	3.83	6.12	7.90	10.00
Time-varying AR model (lag = 1)	**3.00**	**3.85**	**4.47**	4.89	3.69	5.13	5.68	6.31
Time-varying AR model (lag = 2)	3.46	4.46	4.61	4.62	3.46	**4.58**	4.60	4.97
Time-varying AR model (lag = 4)	3.71	5.23	6.48	7.04	3.39	4.75	5.39	5.74
Time-varying AR model (lag = 6)	4.31	7.27	11.04	13.56	3.85	6.31	8.08	10.23

Table B2: Root Mean Square Error of Univariate Models for Monthly Data

(evaluated using pseudo-real time data 2010M1 to 2016M8)

	Prediction horizon										
	-1	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Exports (nominal, yearly growth rates), monthly data											
Unconditional mean	8.58	8.69	8.78	8.86	8.67	8.61	8.63	8.45	8.39	8.33	8.14
Random walk	6.90	6.90	6.36	7.61	8.06	8.17	9.26	9.38	9.66	10.64	10.93
Local linear model	6.01	6.22	6.45	7.50	7.83	8.23	9.05	9.26	9.75	10.48	10.76
Damped trend model	5.82	6.09	6.42	7.67	8.43	9.09	10.15	10.83	11.83	13.16	14.06
AR model (lag = 1)	6.47	6.53	6.42	7.35	7.54	7.69	8.17	8.10	8.17	8.39	8.27
AR model (lag = 2)	6.11	6.18	6.20	7.12	7.28	7.58	8.18	8.15	8.45	8.93	8.95
AR model (lag = 4)	**5.78**	5.97	**6.05**	6.85	**7.15**	7.43	7.89	7.93	8.25	8.78	8.99
AR model (lag = 6)	5.79	**5.94**	6.07	6.77	7.16	**7.24**	7.44	**7.38**	**7.56**	7.93	7.93
TV-AR model (lag = 1)	6.47	6.53	6.43	7.35	7.53	7.73	8.22	8.15	8.24	8.44	8.32
TV-AR model (lag = 2)	6.10	6.17	6.19	7.12	7.27	7.57	8.17	8.14	8.44	8.92	8.94
TV-AR model (lag = 4)	**5.78**	5.97	**6.05**	**6.84**	**7.15**	7.42	7.89	7.93	8.25	8.77	8.98
TV-AR model (lag = 6)	5.79	**5.94**	6.07	6.77	7.17	**7.24**	**7.43**	**7.38**	**7.56**	**7.92**	**7.91**
Imports (nominal, yearly growth rates), monthly data											
Unconditional mean	10.08	10.26	10.34	10.44	10.25	9.97	9.87	9.47	9.27	9.14	8.78
Random walk	6.56	6.91	6.85	8.46	8.99	9.21	10.72	10.66	11.14	12.40	12.42
Local linear model	6.10	6.77	7.35	8.76	9.31	9.77	10.84	10.94	11.56	12.46	12.60
Damped trend model	5.76	6.38	7.21	9.06	10.37	11.91	14.03	15.53	17.63	20.05	21.96
AR model (lag = 1)	6.30	6.78	7.00	8.23	8.54	8.61	9.24	8.95	8.99	9.30	8.95
AR model (lag = 2)	6.03	6.44	6.96	8.16	8.52	8.88	9.68	9.54	9.97	10.54	10.38
AR model (lag = 4)	5.66	6.08	6.42	7.44	7.81	8.13	8.78	8.65	9.05	9.64	9.63
AR model (lag = 6)	**5.51**	5.78	**6.04**	**6.94**	7.24	**7.37**	7.82	7.44	7.72	8.33	**8.20**
TV-AR model (lag = 1)	6.29	6.78	7.00	8.25	8.59	8.65	9.27	9.06	9.08	9.43	9.15
TV-AR model (lag = 2)	6.01	6.44	6.95	8.16	8.52	8.87	9.67	9.53	9.96	10.54	10.38
TV-AR model (lag = 4)	5.65	6.08	6.41	7.43	7.81	8.13	8.78	8.65	9.06	9.64	9.65
TV-AR model (lag = 6)	**5.51**	**5.77**	**6.04**	**6.94**	**7.23**	**7.37**	**7.81**	**7.43**	**7.71**	**8.31**	**8.20**
Export price (nominal, yearly growth rates), monthly data											
Unconditional mean	3.31	3.26	3.27	3.31	3.35	3.37	3.39	3.42	3.44	3.48	3.51
Random walk	1.43	2.16	2.69	3.06	3.25	3.29	3.29	3.30	3.44	3.79	4.12
Local linear model	1.43	2.16	2.69	3.06	3.25	3.29	3.29	3.30	3.44	3.79	4.12
Damped trend model	1.41	2.18	2.75	3.15	3.37	3.42	3.42	3.39	3.48	3.83	4.17
AR model (lag = 1)	1.41	2.05	**2.50**	**2.79**	**2.95**	**2.99**	**3.00**	**3.03**	**3.14**	**3.34**	3.48
AR model (lag = 2)	**1.38**	**2.04**	2.51	2.83	3.02	3.11	3.17	3.22	3.28	3.39	**3.46**
AR model (lag = 4)	1.40	2.08	2.57	2.90	3.12	3.22	3.28	3.32	3.37	3.44	3.49
AR model (lag = 6)	1.52	2.34	2.93	3.30	3.52	3.63	3.74	3.83	3.88	3.90	3.85
TV-AR model (lag = 1)	1.41	2.05	2.51	2.80	**2.95**	**2.99**	3.01	**3.03**	**3.14**	**3.34**	3.48
TV-AR model (lag = 2)	**1.38**	**2.04**	2.52	2.84	3.03	3.12	3.18	3.22	3.28	3.39	3.47
TV-AR model (lag = 4)	1.40	2.08	2.58	2.91	3.12	3.21	3.27	3.31	3.36	3.43	3.48
TV-AR model (lag = 6)	1.52	2.33	2.92	3.29	3.51	3.62	3.73	3.81	3.87	3.88	3.85
Import price (nominal, yearly growth rates), monthly data											
Unconditional mean	4.23	4.28	4.35	4.42	4.45	4.45	4.43	4.42	4.39	4.40	4.40
Random walk	1.52	2.30	2.91	3.36	3.60	3.63	3.63	3.69	3.81	4.15	4.49
Local linear model	1.52	2.30	2.91	3.36	3.59	3.63	3.63	3.69	3.81	4.15	4.49
Damped trend model	**1.51**	2.31	2.94	3.40	3.67	3.70	3.69	3.73	3.83	4.16	4.52
AR model (lag = 1)	1.55	2.30	**2.86**	**3.26**	3.49	3.56	3.59	3.68	3.76	3.97	4.15
AR model (lag = 2)	1.54	2.37	3.01	3.48	3.77	3.90	3.96	4.04	4.09	4.22	4.33
AR model (lag = 4)	1.59	2.47	3.09	3.49	3.73	3.84	3.89	3.97	4.03	4.19	4.34
AR model (lag = 6)	1.71	2.62	3.31	3.78	4.19	4.55	4.89	5.19	5.35	5.48	5.57
TV-AR model (lag = 1)	1.54	**2.29**	**2.86**	**3.26**	**3.47**	**3.54**	**3.57**	**3.66**	**3.74**	**3.95**	**4.13**
TV-AR model (lag = 2)	1.54	2.36	3.01	3.47	3.75	3.88	3.94	4.02	4.07	4.19	4.31
TV-AR model (lag = 4)	1.59	2.46	3.07	3.47	3.71	3.81	3.86	3.95	4.01	4.17	4.32
TV-AR model (lag = 6)	1.70	2.62	3.30	3.77	4.18	4.53	4.86	5.17	5.33	5.47	5.56

	Prediction horizon										
	-1	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Foreign effective PPI (nominal, yearly growth rates), monthly data											
Unconditional mean	3.27	3.28	3.31	3.35	3.40	3.46	3.51	3.56	3.60	3.65	3.70
Random walk	0.51	0.88	1.17	1.40	1.58	1.75	1.88	2.04	2.20	2.36	2.54
Local linear model	0.51	0.88	1.17	1.40	1.58	1.75	1.88	2.04	2.20	2.36	2.54
Damped trend model	0.49	0.83	1.10	1.36	1.52	**1.64**	**1.77**	**1.85**	**1.95**	**2.07**	**2.25**
AR model (lag = 1)	0.53	0.91	1.22	1.46	1.65	1.83	1.96	2.12	2.27	2.43	2.60
AR model (lag = 2)	**0.47**	**0.81**	**1.06**	**1.31**	**1.50**	1.67	1.85	2.03	2.19	2.35	2.51
AR model (lag = 4)	0.52	0.88	1.20	1.56	1.90	2.22	2.61	2.92	3.19	3.44	3.65
AR model (lag = 6)	0.52	0.89	1.21	1.58	1.91	2.21	2.57	2.87	3.13	3.37	3.59
TV-AR model (lag = 1)	0.52	0.90	1.21	1.45	1.64	1.82	1.95	2.11	2.26	2.43	2.60
TV-AR model (lag = 2)	**0.47**	**0.81**	**1.06**	**1.31**	1.51	1.69	1.88	2.07	2.24	2.40	2.57
TV-AR model (lag = 4)	0.53	0.89	1.23	1.61	1.97	2.32	2.73	3.06	3.35	3.60	3.82
TV-AR model (lag = 6)	0.52	0.90	1.23	1.63	1.98	2.31	2.71	3.03	3.32	3.57	3.78

Note: TV-AR model is Time-varying AR model

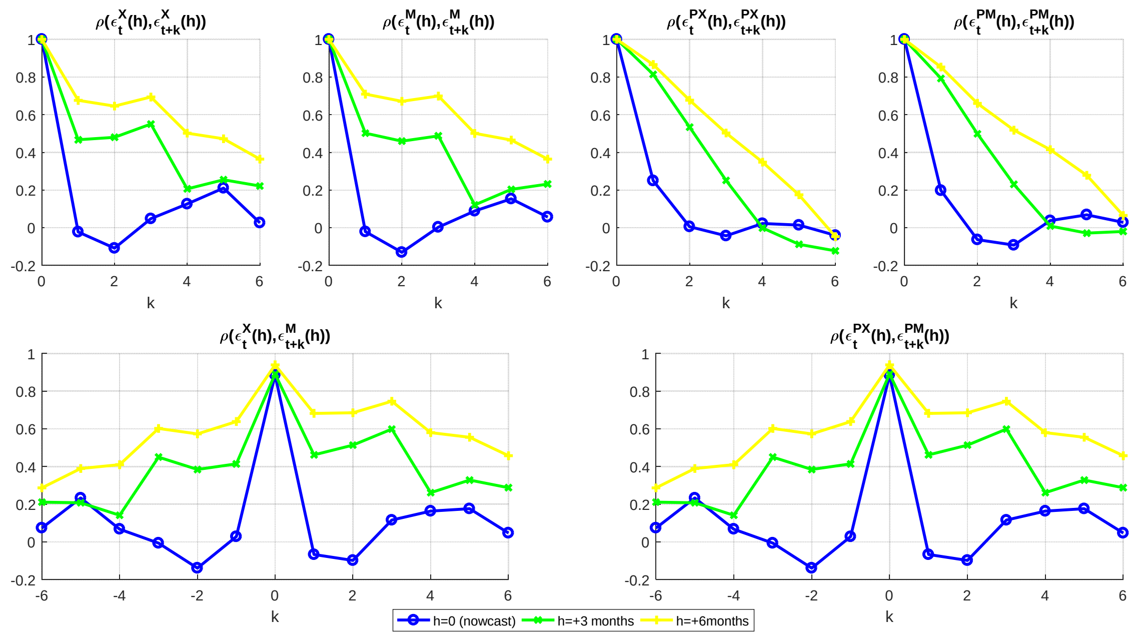
Appendix C: Correlation Among Forecasting Errors

In this appendix, we evaluate the second-order characteristics of forecasting errors. For each method considered in this paper, we compute the autocorrelation function (ACRF) of the forecast errors for the yearly growth rates of the volume of exports and imports and for export and import prices. We also look at the cross-correlation for various leads and lags between the forecast errors of export and import volume growth and the cross-correlation of the forecast errors of export and import price growth.

We did this exercise for various forecast horizons and the figures below show the results for three selected forecast horizons: h = 0 (i.e. the nowcast), h = 3 and h = 6.

Figure C1 displays the second-order characteristics of the forecast errors for the univariate model that yielded the best prediction for each variable, i.e. the AR(6) process for import and export growth and the AR(1) process for import and export prices. For the nowcast and the short-term forecasts, the ACRF quickly returns to insignificant numbers, while for longer horizons the persistence of the forecast errors is growing, which is quite an intuitive result. The forecast errors between exports and imports are contemporaneously highly correlated for any forecast horizon, and the same applies for the correlation between the forecast errors of import and export prices. The correlation between these errors for various lags and leads follows a similar pattern as the individual ACRFs, i.e. for the nowcast these correlations quickly go to zero and for larger forecast horizons they are more persistent.

Figure C1: Correlation of Forecast Errors: Univariate Benchmarks



Curiously, this general pattern also holds for the sophisticated techniques: principal component analysis and the dynamic factor models (see Figures C2, C3, and C4).

Figure C2: Correlation of Forecast Errors: PCA

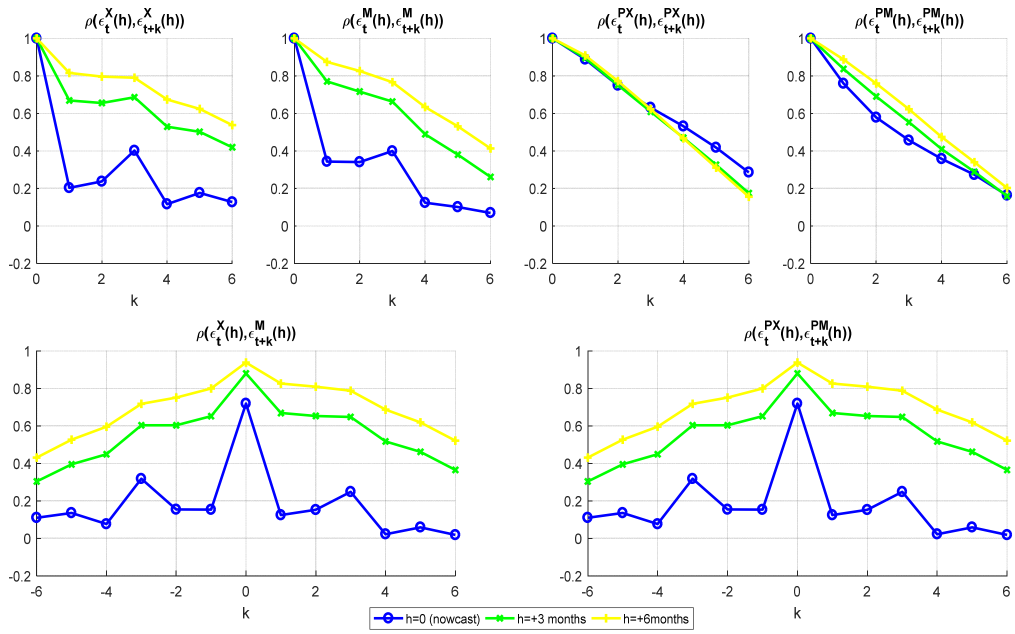


Figure C3: Correlation of Forecast Errors: Dynamic Factor Model

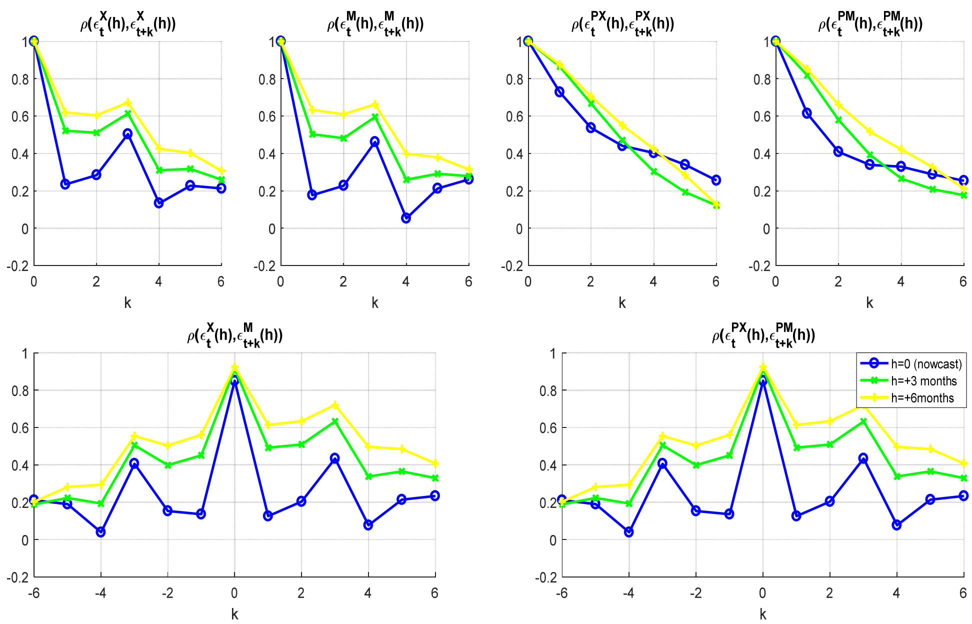
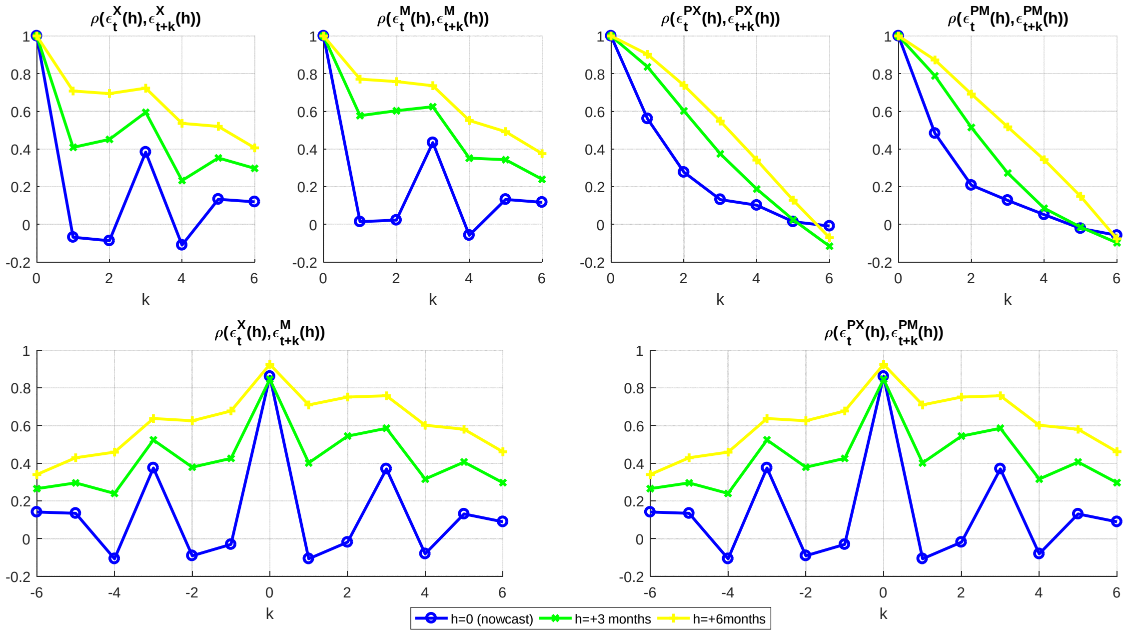


Figure C4: Correlation of Forecast Errors: Elastic Net Regression



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