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Do global output gaps help forecast inflation in Russia?

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Abstract

I assess the usefulness of the global output gap in forecasting CPI inflation in Russia through pairwise comparison of domestic and global Hybrid New Keynesian Phillips curve specifications in terms of their Root Mean Square Error and absolute error at each date of out-of-sample forecasts. I estimate a huge number of models formed by all possible combinations of predictors, thereby ensuring the results are robust to the choice of specification. Moreover, I consider various proxies for the global output gap and domestic slack including those from other authors, statistical agencies and those of my own. Additionally, I single out the contribution of each predictor to a model's forecast accuracy both on the whole period and at each date of out-of-sample forecasts. I find that the models with the global gap perform worse than those without for each measure considered when compared in terms of RMSE. However, in the cross-sections of models' absolute errors at different dates of out-of-sample forecasts, there are periods when global models outperform the domestic ones. Yet both types of output gaps, domestic and global, worsen forecast accuracy. Instead, such predictors as inflation expectations, real effective exchange rate gap, and capacity utilisation improve it, even in the times of crises, when the errors of all models increase dramatically.

1 Introduction

1.1 Overview

In this paper, I assess the role of the global output gap in forecasting CPI inflation in Russia. Having estimated a huge number of Philips curve specifications, I augment each of them with the global output gap component for subsequent pairwise comparison in terms of their RMSE and absolute error in time. My analysis involves different measures of the global output gap and of domestic slack - those from other authors, statistical agencies and the proxies of my own. Additionally, I use different measures of the domestic and open-economy variables, such as inflationary expectations, imported inflation, commodity prices, etc.

Importantly, I also look at the distributions of the models' errors at all points of estimation, which reveals subtler intricacies than looking at the models' RMSEs only. Moreover, I try to find the reasons for why a given predictor may prove useful - to this end, I look at the interactions of the predictor with other variables and assess whether the presence or the absence of those drives the change in forecast accuracy associated with the predictor in question.

My paper tests the predictive power of quite a few global output gap measures. First, I deal with the proxies that are common in the literature, such as statistical indices from OECD and IMF. Second, I use the proxies constructed by other authors such as the world gap from Kilian 2009. Since most papers conduct panel data analysis, their measure of the global gap must be common for all the countries in the sample. However, a more nuanced approach lies in constructing a separate global output gap for each country - the one that would reflect the relative importance of the country's trading partners and hence capture the exact ways in which it interacts with the global economy. Thus, third, I construct the measures of the global output gap that account for the importance of the Russian trading partners using the methodology by Borio and Filardo 2007. Finally, I come up with my own proxies, such as the Baltic Dry Exchange Index, total world imports, re-weighted OECD gap and global output gap based on the slack measures from Hong et al. 2018 and Forbes 2019 (I elaborate on the methodologies in Section 3.2)

In testing the predictive power of these global output gap measures, I pay close attention to the robustness of the results to the choice of specification and domestic variables. Thus I estimate 325125 models in an expanding window and three rolling windows of different length, varying the measures of domestic variables, for the comparisons between global and domestic specifications to be based on a large set of pairs. In a sense, this work provides an analytical framework for answering dichotomous questions on whether or not some predictor is of use for forecast accuracy.

1.2 Literature review

This paper relies on the following groups of literature: (i) the papers describing and estimating the very connection between the global output gap and domestic inflation; (ii) the papers that use the global output gap in forecasting inflation; (iii) the papers that provide a framework for single-country analysis of the global output gap's effect on forecast accuracy; (iv) the papers exploring the determinants of the connection between the global output gap and inflation. I also review the ways the global output gap is measured in the literature, and the Philips curve specifications frequently used.

1.2.1 Globalisation and domestic inflation: the intuition and key channels

One of the earliest observations regarding the effect of globalisation on domestic price level was heard from Rogoff 2003: "globalization - interacting with deregulation and privatization - has played a strong supporting role in the past decade's disinflation."

The idea that globalisation may have caused domestic Philips curves around the world to fall apart came to be seen as a new research agenda thanks to the speeches of monetary policy-makers (Bean 2006 White et al. 2006; Kohn et al. 2006). The suggestion they aired was to mend domestic Philips curves by including the global output gap in the equations. They proposed a number of theoretical ways in which the global output gap may interfere with domestic price formation. According to Bean (2006), globalisation could cause greater inflation through increased spending on domestic goods and services as an income effect of cheapening overseas imports. Alternatively, globalisation could lower inflation because of decreased wage bills due to higher competition and easier outsourcing in world labour market. These potential channels of influence were taken on by empirical researchers as a blueprint for the search of proxies to measure the intangible global output gap.

1.2.2 Empirical evidence

A famous work supporting the impact of globalisation on inflation is Borio and Filardo 2007 where the authors demonstrate that the conventional ways to capture foreign influence in an open-economy Philips curve (such as import prices and exchange rates) lack the information contained in the global output gap that reflects the aforementioned consequences of increased competition and trade. By augmenting the Philips curve with the global gap component they find it to possess significant explanatory power for a lot of countries. Similar results were obtained by Manopimoke et al. 2015, Forbes 2019, R. A. Auer, Levchenko, and Sauré 2019.

The criticisms towards the findings of Borio and Filardo 2007 raised the questions of the results' robustness to alternative Philips curve specifications and different metrics of the global output gap. Namely, Ihrig et al. 2010 stress the excessive reliance on the long term inflationary expectations, on the choice of annualised inflation instead of period-to-period rates, and on the very metrics of the global gaps. Similar criticism was voiced by Calza 2009. Ball 2006 is resolute to report no effect of globalisation on domestic price formation processes at all, backing this conclusion with theoretical arguments. Most recent and most comprehensive critique of Borio and Filardo 2007 comes from Mikolajun and Lodge 2016 who found no effect of the global slack on domestic inflation. Yet they find the effect of the global inflation component, which, however, merely serves as a proxy for long term inflationary expectations that are able to catch the slow-moving trends in inflation rates (which, according to Faust and Wright 2013, is crucial for successful forecasting). Moreover, Mikolajun and Lodge 2016 find that the global inflation used to be valuable in forecasting inflation back in the 1970s and 80s marked by the presence of significant variation in inflation trends, thus confirming the result of Ciccarelli and Mojon 2010 (and the strand of literature focusing on the effect of the global inflation rather than that of the global slack, e.g. Neely and Rapach 2011,) and putting it into common framework.

1.2.3 Single-country studies

Most papers exploring the effect of the global output gap on domestic inflation are multi-country studies based on panel data analysis as described above. The papers that are focused on the US or EU hinge on the VAR framework as these large economic regions are assumed to be capable of influencing the global output (for instance, Milani 2009, Bobeica and Jarociński 2019.) Among the few papers focused on single-country analysis which assume the global output gap to be an exogenous factor is the study Łyziak 2019 examining the effect of globalisation on the inflation in Poland.

1.2.4 Measuring the global output gap

The literature concerning the ways to quantify the global production capacity overlaps with the papers searching for the ways to measure domestic slack since the global output gap is but a weighted sum of the individual countries' gaps. The estimates suggested by OECD (or CBO in case of the US) have been widely criticised for obscure methodology and excessive reliance on expert judgment Coibion, Gorodnichenko, and Ulate 2018). They are based on a mix of production functions estimation, filtering of GDP and unemployment series and expert judgment regarding the development perspectives of the countries in question. They were shown to disagree with alternative measures (Guisinger, Owyang, and Shell 2018, such as HP filtered output series, which, in turn, was also questioned (Hamilton 2018).

Hong et al. 2018 came up with a new way to measure domestic slack - they collected an extensive dataset comprising different types of unemployment across a range of countries and produced a global unemployment gap as a weighted sum of the first principal components extracted from all those unemployment series for each country. The key deficiencies of this approach are the reliance on interpolation of all series from annual to quarterly values and the scarcity or even complete lack of data for many countries. Moreover, they perform the principal component analysis for the entire series, thereby neglecting the real-time implications.

A different measure of the global output gap that is available on monthly basis is the index suggested by Kilian 2009. It is described as the *"business-cycle index expressed in percent deviations from trend. It is derived from a panel of dollar-denominated global bulk dry cargo shipping rates* *and may be viewed as a proxy for the volume of shipping in global industrial commodity market"*[1]. The index is regularly updated as a part of the Federal Reserve Bank of Dallas statistical database.

Another way to measure the global slack that is very popular in academic literature is one of the methods proposed by Borio and Filardo 2007. According to it, the global output gap is specific to each country, as it is a weighted average of the output gaps of the country's main trading partners. Individual weights for each partner are computed as that partner's share of trade in the total volume of trade between the country of interest and the set of its most important trade partners, whereas each individual gap is computed as a percentage deviation from the HP filter trend of the country's GDP.

1.2.5 The global output gap in forecasting

Few papers performed forecasting in real time. Moreover, the papers that aimed at analysing forecast improvements were actually relying heavily on interpolation of annual OECD data (linear interpolation in Forbes 2019, cubic splines in Mikolajun and Lodge 2016), full-sample HP-filtering, to say nothing of the neglect of the data publication lags. Hence the use of their results for practitioners in forecasting domestic inflation is beyond precarious.

1.2.6 Specifications of a domestic Philips Curve

As Faust and Wright 2013 write, subjective forecasts often do best. Practitioners from the Central Banks around the world rarely if ever commit to using a benchmark model for forecasting inflation. Instead, they lean on expert judgement, nowcasting, and "old school" equations. Thus, in terms of absolute error, it becomes particularly challenging to beat the performance of a non-existent model. Bearing these considerations in mind, I estimate thousands of models in search of a plausible benchmark and, more importantly, without sticking to any particular equation, but rather focusing on the entire distribution of the models' results.

Banbura and Bobeica 2020 stress the difficulty in selecting a benchmark model for inflation forecasting. Although there are popular univariate benchmarks by Atkeson, Ohanian, et al. 2001 and Stock and Watson 2007, there is evidence in favour of using long-term inflation expectations (Banbura and Bobeica 2020, Borio and Filardo 2007, Albuquerque and Baumann 2017, Mikolajun and Lodge 2016) and of non-linearities (Albuquerque and Baumann 2017). The famous finding of Borio and Filardo 2007 concerning the effect of the global output gap on domestic inflation was criticized by Ihrig et al. 2010 for not being robust to the specifications without the assumption of anchored long-term inflation expectations. Thus my paper searches over a huge grid of specifications (similar to the approach of Łyziak 2019, except for their set of models is narrower), all of

[1] https://www.dallasfed.org/research/igrea

them being in the spirit of New Keynesian Philips curves, yet comprising different variables, their respective proxies and lags. In this sense my work is most similar to Mikolajun and Lodge 2016 who estimate backward-looking, forward-looking, and hybrid New Keynesian Philips curves with various combinations of other regressors.

The inclusion of external factors in domestic Philips curves is by no means new and by no means specific to the globalisation literature. Instead, it is asserted, the global output gap can bring additional information not contained in those (Forbes 2019). Moreover, accounting for the exchange rate, commodity prices (especially for commodity-exporters), and trade openness is crucial to single out the effect of the global output gap (Tanaka and Young 2008, Mikolajun and Lodge 2016). From a practitioner's perspective, when examining the effect of the global output gap on forecast accuracy, not only am I trying to beat some benchmark, but also am attempting to construct the one to beat.

The importance of this research for a policy maker is twofold. First, it is the practical use of the global output gap proxies for quarterly inflation forecasts. As already described above, this paper is different from all the existent empirical research on the topic in its narrow focus on forecasting using a number of predictors that are rather quickly available and are almost free of the benefit of hindsight.

Secondly, the impact of globalisation on domestic inflation has policy implications on a theoretical level. Gali and Monacelli 2005 assume world output to be inversely related to current and anticipated world real interest rates, so that the global output gap influences an open economy's equilibrium. In turn, this factor is one of the determinants of the optimal monetary policy which, in their model, turns out to be a hybrid regime between domestic inflation targeting and an exchange rate peg, depending on the economy's degree of openness. This line of research gave rise to models with richer dynamics such as Soffritti and Zanetti 2008. Thus, the knowledge of the global output gap's impact is of use in structural models.

1.2.7 Behind the global gap coefficient

Although the link between global output gap and domestic inflation is often found, the exact channels of influence are unclear. It is crucial to place the effect of globalisation in the context of more conventional external factors, such as commodity prices and exchange rates, to see if those already contain globalisation or, alternatively, there are some intricately interconnected spillovers Tanaka and Young 2008. Importantly, emerging economies demonstrate the dependence of CPI on exchange rate movements Jašová, Moessner, and Takáts 2020.

To study these interconnections, Manopimoke et al. 2015 not only quantifies the effect of globalisation on the domestic inflation, but also searches for the exact channels of global influence by running regressions of the global gap coefficient on the variables that may reflect the particular channels.

R. Auer, Borio, and Filardo 2017 use new proxies to GVCs to explain the difference between the global gap coefficients and the domestic gap coefficients from the panel regression of Bianchi and Civelli 2015.

In my work, I find that there often clear-cut clusters of models - the ones for which the addition of the global output gap improves forecast accuracy and those for which it worsens the error. I run dummy regressions on all domestic predictors, looking for the determinants of the forecast improvement for each pair of models.

2 Methodology and Data

2.0.1 Estimation

In my work, I focus solely on the forecasting performance of different model specifications. The estimation is carried out using OLS on the dataset comprising the time period 2002 Q2 - 2020 Q2.

I estimate a model's coefficients on a given sample and then make a one-step-ahead forecast, computing the error at the time of the forecast. As a next step, I re-estimate the model on the new resulting sample and compute the corresponding error and so on. The forecasting procedures that I try are the following:

- Expanding window one-step-ahead forecast from 2009 Q4 (starting with 30 observations width and ending up with 73 points);
- Rolling window one-step-ahead forecast:
  - ☐ from 2007 Q2 (20 observations width)
  - ☐ from 2009 Q4 (30 observations width)
  - ☐ from 2013 Q3 (45 observations width)

2.1 Specifications

This paper examines the influence of global output gap on forecast accuracy over a large family of specifications, rather than a single forecasting equation. That is, there are many specifications of a "domestic" Philips Curve, and each of them is nested into several specifications that include one of the measures of the global output gap.

2.1.1 Baseline domestic specifications

The general form of the prediction equation that engenders the family of subsequent specifications is a form of a Philips Curve similar to Mikolajun and Lodge 2016 and Łyziak 2019:

$$\begin{aligned}\pi_{t+h} = \alpha + \sum_{i=1}^{l+h} \beta_i^{inf} \pi_{t+h-i} + \sum_{i=1}^{l+h} \beta_i^{e} \pi_{t+h-i}^{e} + \sum_{i=1}^{l+h} \beta_i^{\pi\ imp}\ \pi_{t+h-i}^{imp} + \sum_{i=1}^{l+h} \gamma_i^{dom} gap_{t+h-i}^{dom} + \\ + \sum_{i=1}^{l+h} \delta_i comm_{t+h-i} + \epsilon_t\end{aligned} \tag{1}$$

The variables and the multiple ways they are measured are the following:

- π_t - **inflation** - measured as seasonally adjusted quarter-on-quarter CPI (seasonal adjustment performed by the author). [2].

[2] https://rosstat.gov.ru/price

- π_t^e - **inflationary expectations** - come from the survey of entrepreneurs conducted by the Bank of Russia [3].

- π_t^{imp} - **imported inflation**

  is the HP filter gap of real broad effective exchange rate (initial series taken from Federal Reserve Bank of St. Louis and then seasonally adjusted) [4]. I borrow this measure of imported inflation from Łyziak 2019. Moreover, Jašová, Moessner, and Takáts 2020 demonstrate increased dependence of inflation in emerging economies on exchange rate movements, which is especially important for the Russian oil-exporting economy.

- gap_t^{dom} - **domestic output gap** - is calculated as

  - ratio of cyclical component to the HP trend of a series of seasonally adjusted quarter-on-quarter real GDP (author's calculations) [5].
  - Cargo index, showing the volume of railway freight turnover, taken from the Federal State Statistics Service
  - Workforce load, based on the survey of firms by the Federal State Statistics Service
  - PMI for Russia

- $comm_t$ - **commodity prices** - measured as

  - Urals oil price
  - Bloomberg Commodity Index (BCOM)

One can see that not all the "domestic" variables are purely domestic: there are the real broad effective exchange rate and commodity prices. Their inclusion is important to decouple their effect from that of the global output gap (Tanaka and Young 2008). The globalisation hypothesis implies that the channels of influence are different from conventional trade variables - instead, they lie within the global value chains and the integration of labour market.

h stands for forecast horizon, which, in our case is $h = 1$. l means the maximum possible lag and is $l = 4$. Each variable is present in a specification in the form of an $AR(i)$ process, where $i = 1, 2, 3, 4$ as the maximum lag order is $l = 4$.

Whereas Łyziak 2019 estimates the grid of only those specifications that include every variable from the initial equation taken in different combinations of their lags, I extend the grid to include *every combination of the variables' lag polynomials (up to the fourth lag).*

[3] http://old.cbr.ru/dkp/surveys/inflation
[4] https://fred.stlouisfed.org/series/RBRUBIS
[5] https://rosstat.gov.ru/accounts

There are 5 variables in domestic specifications each of which is either absent from the equation or present in the form of either $AR(1), AR(2), AR(3)$ or $AR(4)$. Thus there are 5 options for each variable. Coupled with the fact that there are several ways to measure some variables (4 for domestic gap and 2 for commodity prices), the **total number of domestic models** is

$$\begin{aligned}&\Pi_i{}^v(l \times number\ of\ measures_i + 1) = \\&= (1+4)^3 \times (4 \times 4 + 1) \times (4 \times 2 + 1) = 19125\end{aligned} \tag{2}$$

where v is the number of variables.

2.1.2 Addition of the global output gap

The thing that turns a domestic Philips Curve into a "global" one is the addition of the global output gap to the equation:

$$\begin{aligned}\pi_{t+h} = \alpha + \sum_{i=1}^{l+h} \beta_i^{inf} \pi_{t+h-i} + \sum_{i=1}^{l+h} \beta_i^{e} \pi_{t+h-i}^{e} + \sum_{i=1}^{l+h} \beta_i^{\pi\ imp}\ \pi_{t+h-i}^{imp} + \sum_{i=1}^{l+h} \gamma_i^{dom} gap_{t+h-i}^{dom} + \\ + \sum_{i=1}^{l+h} \delta_i comm_{t+h-i} + \sum_{i=1}^{l+h} \gamma_i^{glob} gap_{t+h-i}^{glob} + \epsilon_t\end{aligned} \tag{3}$$

I use quite a few measures of the global output gap - let us denote their number by w.

2.1.3 Measures of the global output gap

Global output gap is a notion of intangible nature, so the methodology of its measurement causes great dissent. Thus this paper tests the effect of multiple measures of global output gap used in the literature. Moreover, I include a number of my own measures in the analysis.

- **OECD gap**. It is the most common measure used in the literature, computed according to the OECD methodology (combining expert judgement, production possibilities frontiers and the use of filters; for the complete methodology see Chalaux and Guillemette 2019). It is available on the annual basis. Similar to all the authors who use this metric (even in forecasting), I interpolate the annual values to quarterly using cubic splines.

- **Weighted sum of trading partners' output gaps** in the spirit of Borio and Filardo 2007.

  The output gap of each country is computed using Hodrick-Prescott filter:

$$trade\ gap_t = \sum_{i=1}^{countries} w_{it} gap_{it}^{GDP\ HP\ filter} \tag{4}$$

The "global" output gap is specific to the country in question (in our case, Russia), as it is a weighted average of the output gaps of the country's trading partners. Individual weights are computed as a partner's share of trade in the total volume of trade between Russia and the set of most important trade partners:

$$w_t^{country} = \frac{imports_t^{country} + exports_t^{country}}{imports_t^{rus} + exports_t^{rus}} \tag{5}$$

The data on imports and exports is provided by the federal Customs Service of Russia on annual basis. Thus I compute the weights for each year and set the quarterly values to be the same as the corresponding annual figure. The trade shares of the countries included in the set of trade partners are shown in the chart below (for the complete table of partners' trade shares for all years see the Appendix).

One can see that the group of the key partners stays stable and the changes in the shares occur within the group of the key partners.

- **Kilian global output gap - Index of Global Economic Activity** It is described as the "business-cycle index expressed in percent deviations from trend. It is derived from a panel of dollar-denominated global bulk dry cargo shipping rates and may be viewed as a proxy for the volume of shipping in global industrial commodity markets".[6]
- **Baltic Exchange Dry Index (BDI)**[7] which is a proxy for dry bulk shipping stocks and a general shipping market bellwether

The **total number of all the models** estimated in this paper is given by

$$\begin{aligned} &number\ of\ domestic\ models\ \times (l \times\ number\ of\ global\ gap\ measures\ + 1) = \\ &= 19125 \times (4 \times 4 + 1) = 325125 \end{aligned} \tag{6}$$

Thus each domestic model has 16 global counterparts.

2.1.4 Overall RMSE analysis

Graphical analysis

To start with, I investigate the Root Mean Square Error of the two families of models - domestic and global ones.

[6] https://www.dallasfed.org/research/igrea
[7] https://www.bloomberg.com/quote/BDIY:IND

$$RMSE = \sqrt{\frac{\Sigma_{t=k}^{n}(CPI_t - \widehat{CPI}_t)^2}{n-k}}$$

Graphically, I compare the two distributions of the RMSE using their density plots. Namely, I look at the tails and the relative positions of the density curves on the horizontal axis of RMSE values - the more is it situated to the left, the better. This way of comparison is able to show the absolute performance of the models and a rough understanding of the use of the global output gap on the level of the population of models.

I also use boxplots to compare domestic specifications' distribution of RMSE with those of the different measures of the global gap, thereby inferring the relative performance of each gap.

Regressional analysis

A refinement to the above comparison is to single out the contribution of each predictor to the RMSE of a model. To this end, I put forward the following method of mine: I run a regression of RMSE on a set of dummy variables each corresponding to the presence of the absence of the respective regressor. Namely,

$$\begin{aligned} RMSE = \alpha + &\sum_{i=1}^{l+h} dummy_i^{inf}\gamma_i^{inf} + \sum_{i=1}^{l+h} dummy_i^{expect}\gamma_i^{expect} + \sum_{i=1}^{l+h} dummy_i^{\pi\, imp}\gamma_i^{\pi\, imp} + \\ &+ \sum_{i=1}^{l+h} dummy_i^{dom}\gamma_i^{dom} + \sum_{i=1}^{l+h} dummy_i^{glob}\gamma_i^{glob} + \epsilon_t \end{aligned} \tag{7}$$

For instance, $dummy_1^{expect}$ is 1 when the variable π_{t-1}^e is present in a given model and 0 otherwise. Note that $dummy_2^{expect}$ is equal to 1 when *both* π_{t-1}^e *and* π_{t-2}^e are included in a specification. The number of observations used for this regression equals the total number of models, which is 325125.

2.1.5 Controlling for specification: pairwise comparison

As a nest step of the analysis,I compare the models pairwise instead of looking at the populations of the models in their entirety. Each domestic Philips curve equation is now paired with all its global counterparts. That is, for each domestic specification, there are four different counterparts coming from each global output gap measure - this leaves us with four times four global specifications per each domestic specification. Thus we deal with 306000 pairs.

Then, for each pair, the difference in squared errors is computed at each forecast date. I conduct this pairwise analysis for the case of one-step-ahead forecasts in an expanding window starting from 2009 Q4 which initially comprises 30 observations and extends to 73, so that there are 43 forecast errors. Each pair of specifications yields a time series of 43 differences between the squared errors of the two.

$$(e_t^{domestic})^2 \; - \; (e_t^{global})^2, \; t = 31, ...73$$

Based on these series, I conduct the Romer and Romer test described below.

Romer and Romer test

Similar to Łyziak 2019, I use the Romer and Romer test (C. D. Romer and D. H. Romer 2000) to compare forecast accuracy of domestic versus global specifications. Faust and Wright 2013 suggest using the Romers' test as a way to assess the difference of forecast accuracy between two models. The advantage of this test is its simplicity and applicability to nested models. The test procedure is

$$\begin{aligned} (e_t^{domestic})^2 - (e_t^{global})^2 &= \alpha + \epsilon_t \\ H_0 : \alpha &= 0 \end{aligned} \tag{8}$$

That is, I run 306000 linear regressions of the difference in squared errors on a constant, each regression comprising a sample of 43 observations.

2.1.6 Controlling for specification and time: pairwise comparison at each forecast date

The Romers' test does not take into consideration the time variation of the specifications' performance relative to each other. Moreover, it does not account for the direction of a model's error as the errors are squared.

Now I conduct the Romers' test on a cross-section of all models at a given date. That is, I compute the difference in squared errors of all global models paired with their domestic counterparts and run a regression comprising 306000 observations. I run a separate regression for each date, meaning that I end up with 43 regressions, each based on 306000 points.

Finally, I run the dummy regression described above (in the context of overall RMSE) on the sample of all global models paired with the corresponding domestic ones - 306000 distinct pairs - for a given date.

$$
\begin{aligned}
(e_m^{domestic})^2 - (e_m^{global})^2 = \alpha + &\sum_{i=1}^{l+h} dummy_{i,m}^{inf}\gamma_{i,t,m}^{inf} + \sum_{i=1}^{l+h} dummy_{i,m}^{exp}\gamma_{i,m}^{exp} + \\
&\sum_{i=1}^{l+h} dummy_{i,m}^{\pi\ imp}\gamma_{i,m}^{\pi\ imp} + \sum_{i=1}^{l+h} dummy_{i,m}^{dom}\gamma_{i,m}^{dom} + \epsilon_t
\end{aligned}
\tag{9}
$$

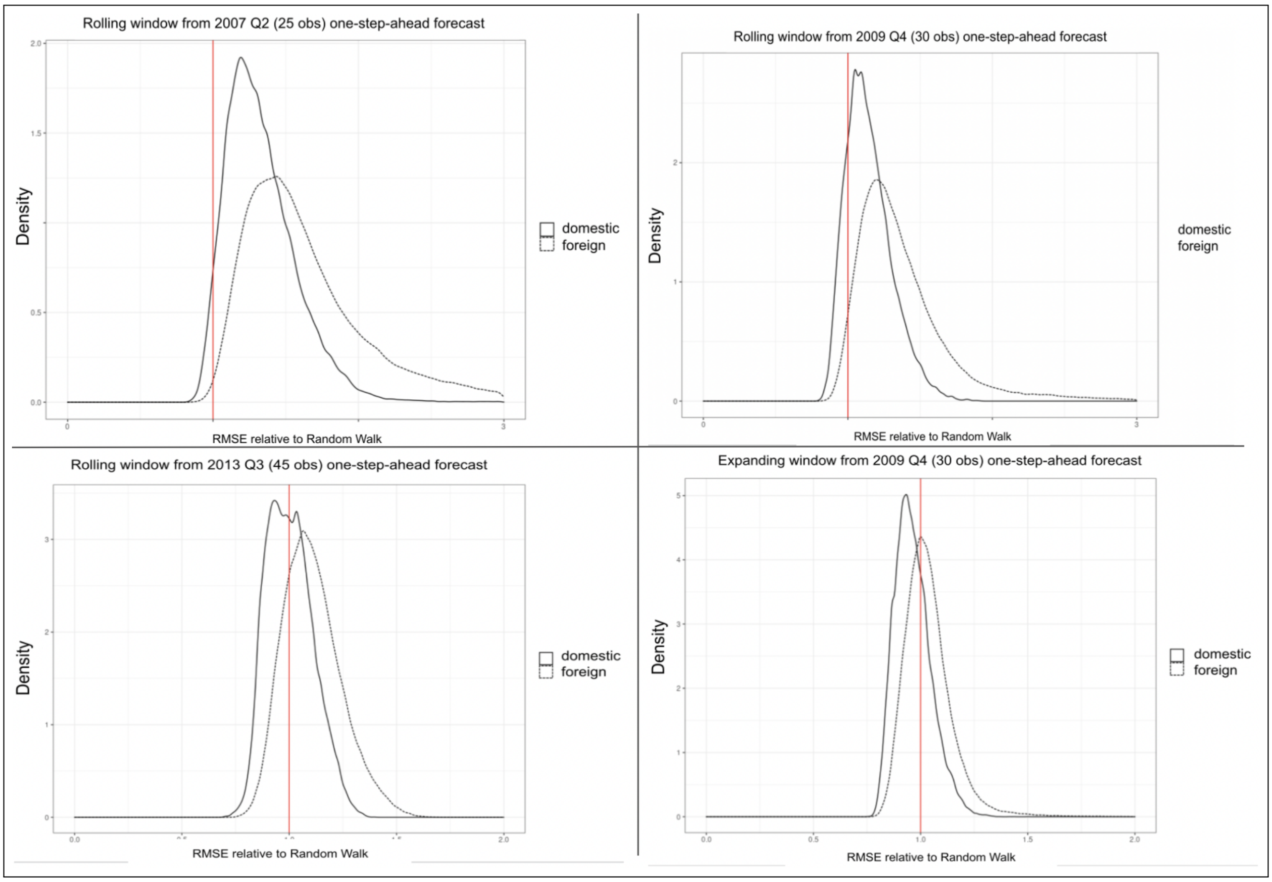
Then I repeat the regression for each date, running 43 regressions in total. As the final step, I find the coefficients that are persistently significant and track the changes in their signs. By doing so, I control for specification, as I track the *changes* in forecast accuracy resulting from the addition of the global output gap. Moreover, I conduct the analysis in dynamic perspective and detect the *interactions of the global gap's forecasting performance with domestic variables.*

3 Results

3.1 Overall RMSE

I compare the overall RMSE (relative to random walk) of global and domestic models. The histogram shows the two *density plots* of the RMSE for the forecasts from three rolling windows and one expanding window.

Figure 1: Density plots of RMSE for rolling and expanding window forecasts

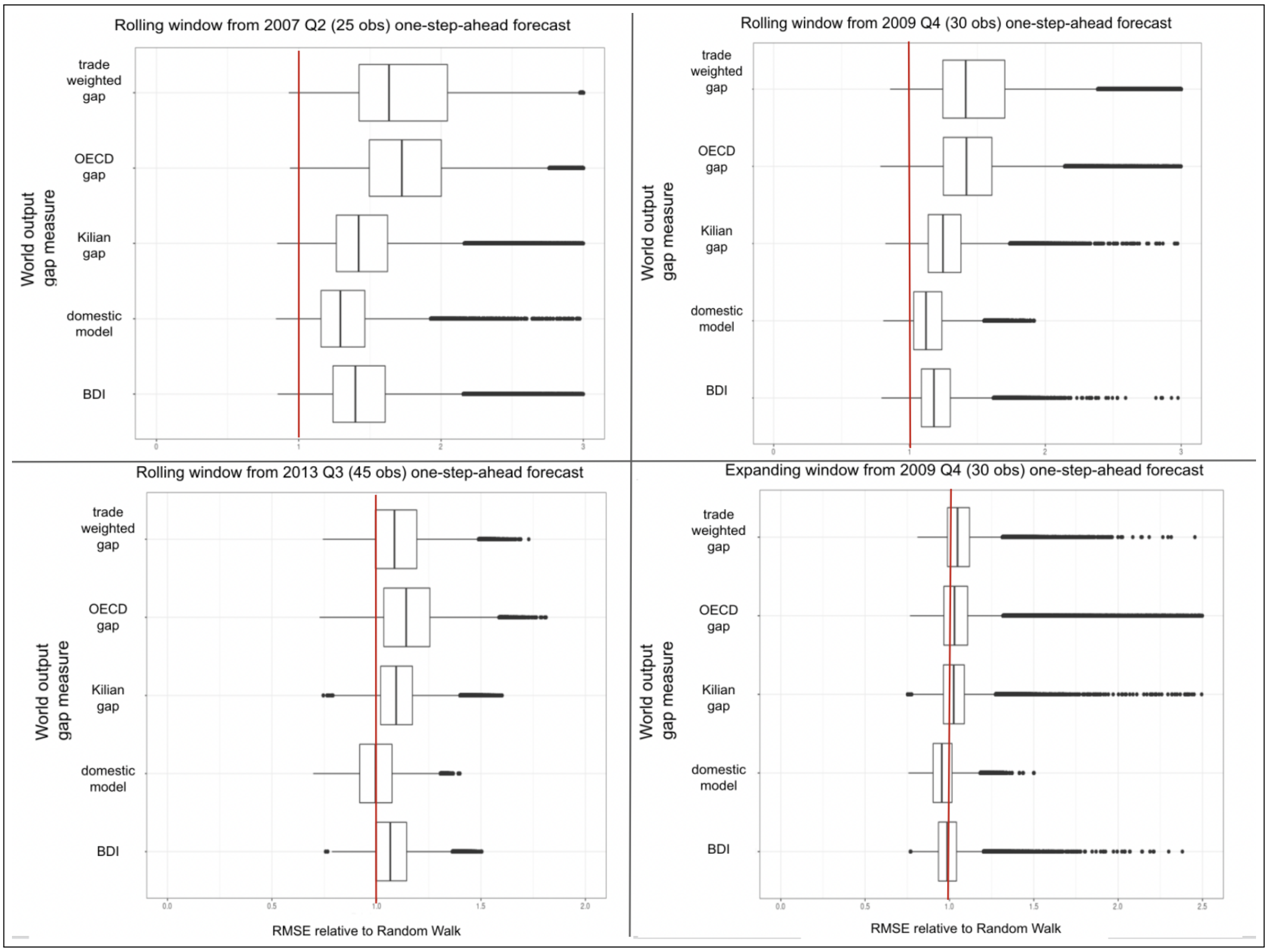


The red lines in the above diagrams correspond to 1 on the horizontal axis, denoting the equality of a model's RMSE to that of the Random Walk model. In all four cases the density curves of the global models' RMSE (the dotted lines) lie to the right of the corresponding curve for the domestic specifications, with their mean RMSE being larger than that of the Random Walk in all rolling windows, the exception being the expanding window where the mean is equal to the RMSE of Random Walk. In all cases, global models perform worse than the domestic ones.

Overall, the expanding window produces best results for the population of models in terms of both precision and accuracy, followed by the forecasts from the rolling window of width 45.

Bearing in mind the fact that there might be considerable variation in the performance of the proxies for the global output gap, I carry out the comparison of the distributions of total RMSEs between domestic and global models for each particular measure of the world output gap separately using the box plots below.

Figure 2: Box plots of RMSEs for rolling and expanding window forecasts by type of global gap



Again, the red line corresponds to the equality of a model's RMSE to that of the Random Walk model. Now we see that the best results are demonstrated by the Baltic Dry Exchange Index, yet only in that it worsens forecast accuracy less than all the other global gap measures do.

In the subsequent analysis, I will use the results from the expanding window only. In order to single out the contribution of each regressor to the RMSE of the model, I run the following regression (described in the Methodology section above):

$$RMSE_i = \sum_{i=1}^{l+h} dummy_i^{inf}\gamma_i^{inf} + \sum_{i=1}^{l+h} dummy_i^{expect}\gamma_i^{expect} + \sum_{i=1}^{l+h} dummy_i^{\pi\ imp}\gamma_i^{\pi\ imp} + \\ + \sum_{i=1}^{l+h} dummy_i^{dom}\gamma_i^{dom} + \sum_{i=1}^{l+h} dummy_i^{glob}\gamma_i^{glob} + \epsilon_t$$

The coefficients denote the mean RMSE among all the models that contain a given variable, respectively. Thus, 1.176 is the mean RMSE among all those models that *contain* domestic gap. The results of this regression are not simply a numerical restatement of the diagrams above. The

Table 1: Simple dummy regression for model type

	Dependent variable:
	RMSE
BDI	1.214***
	(0.001)
Domestic	1.176***
	(0.001)
Kilian	1.263***
	(0.001)
OECD gap	1.298***
	(0.001)
Trade gap	1.297***
	(0.001)
Observations	500,000
R^2	0.981
Adjusted R^2	0.981
Residual Std. Error	0.173 (df = 499995)
F Statistic	5,204,200.000*** (df = 5; 499995)
Note:	*p<0.1; **p<0.05; ***p<0.01

dummy for the group "domestic" comprises both domestic-only and domestic-and-global specifications, so that this group intersects all the other, which was not the case for the diagrams above. This is different for the case of global gaps, as none of the groups intersects because each global model is build to contain only one of the proxies for the global gap.

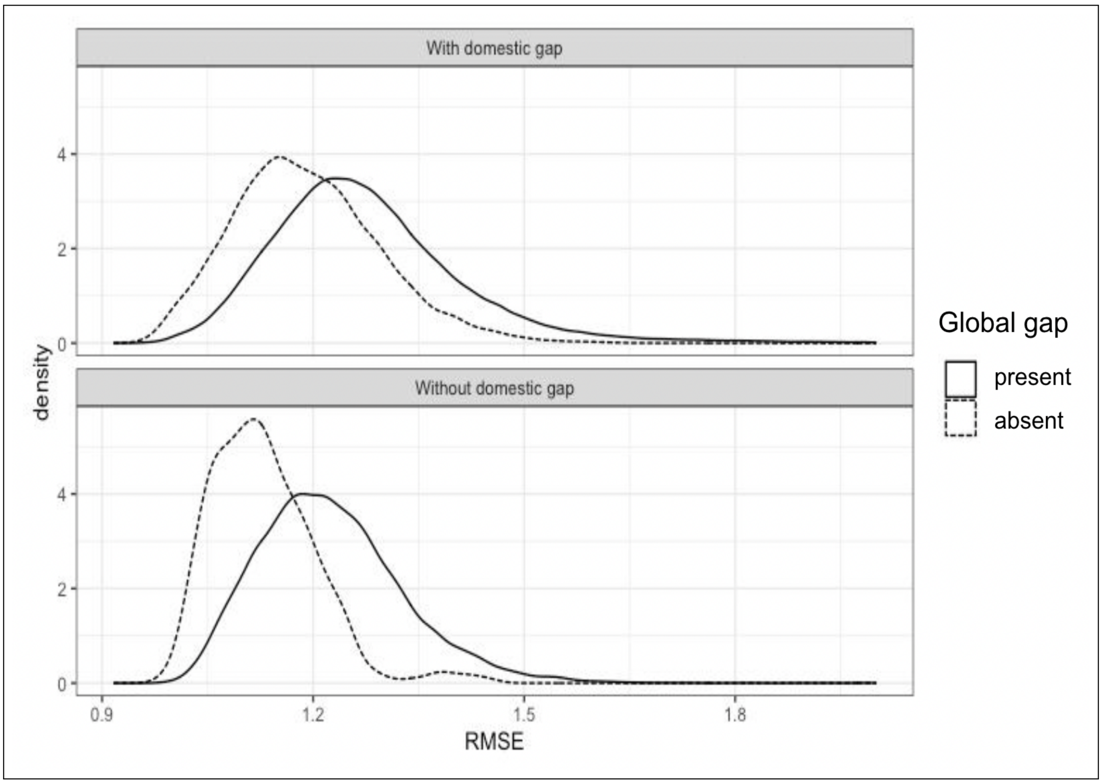
The fact that the lowest mean RMSE is found among the models with domestic gap including those with both domestic and global means that there might be a possibility that the global gap might still be useful in bolstering the predictive performance of a small group of domestic one, which is explored in subsequent analysis.

An aspect in which this work differs from the literature is that I also consider the models that do not fall in the strict pairwise comparison framework. This means that there are lots of models which contain neither the global gap nor the domestic one, as well as the models with a global gap, but no domestic gap. Figure 3 shows the distributions of RMSEs for the four possible combinations of gaps. The upper part: domestic only, domestic and global. The lower part: global only, no gaps at all. One can see that the presence of domestic gap renders the average performance of the models poorer. Thus both global and domestic output gaps worsen the models' forecast accuracy.

However, these graphs do not provide the full picture, as they only describe forecast performance over the whole out-of-sample range. A more nuanced view is given by Figure 4 which shows the density curves of forecast errors of all domestic and global models at each forecast date. Forecast error is defined as

$$e_t = CPI_t - \widehat{CPI}_t$$

Figure 3: Density plots of RMSE by presence of gaps



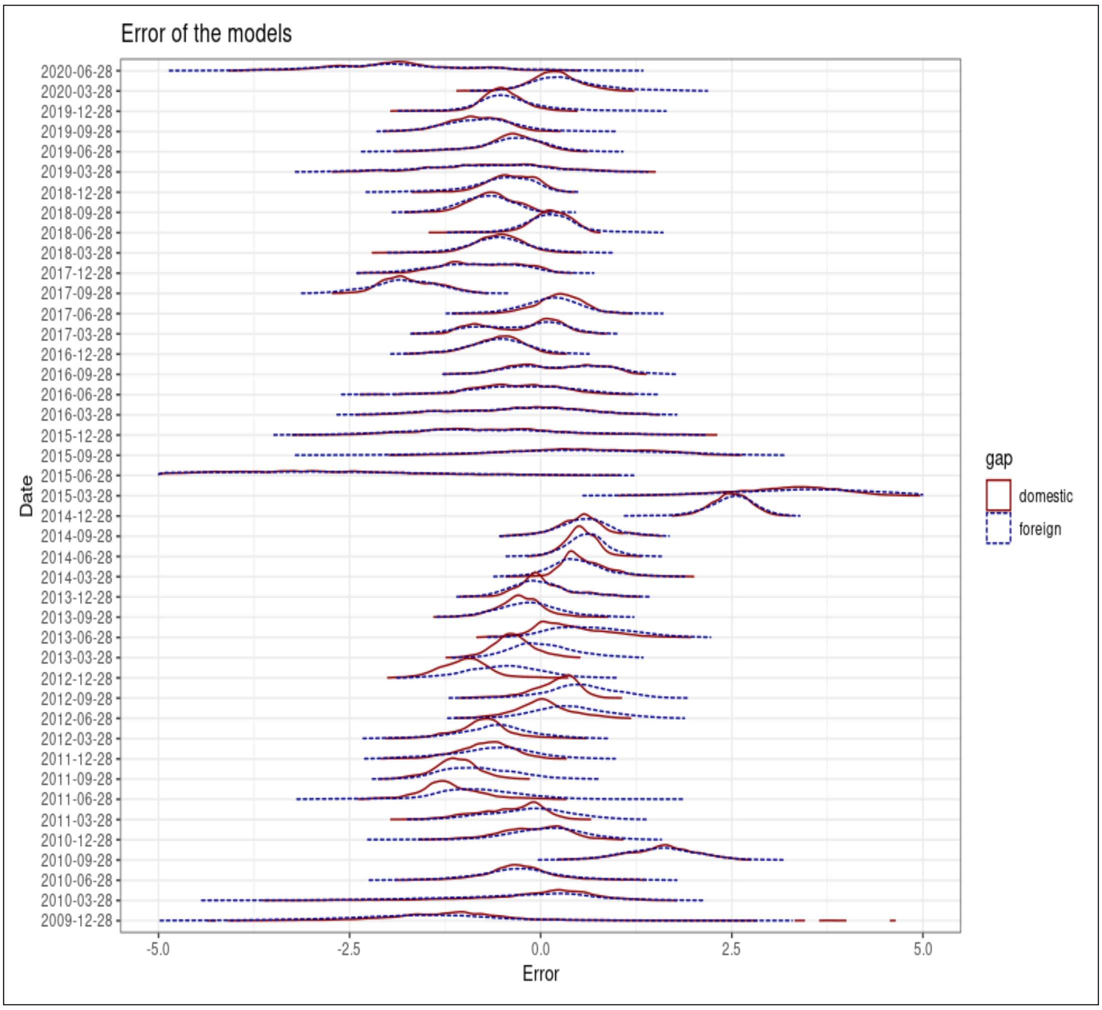
There are 43 sections in the graph, each section corresponding to a given out-of-sample date (quarterly). This part of analysis is conducted in the expanding window framework, the window's width increasing from 30 to 72, as there are 73 observations in the sample.

Clearly, there are dates when the global models outperformed the domestic ones as the absolute errors of the former were closer to zero. Yet the distributions of errors from the global models have greater variance than those from the domestic ones, which can be the reason for the poor overall performance of the population of global models relative to the domestic specifications. Thus it becomes important to single out those global models whose performance managed to beat the purely domestic ones, since we are dealing with a huge multitude of models. As an additional exercise, I also disentangle the models' performance with respect to both time and regressors present.

3.2 Romer and Romer test

It becomes important to track the models down to particular specifications in order to disentangle the determinants of their forecasting performance. Tables 2 and 3 below contain the results of the Romer and Romer test aimed to establish if there is forecast improvement when an additional regressor (in our case, the global output gap) is added to a model.

Figure 4: Forecast errors distributions for each date



$$(e_t^{domestic})^2 - (e_t^{global})^2 = \alpha + \epsilon_t$$
$$H_0 : \alpha = 0 \tag{10}$$

Tables 2 and 3 below summarise the results from running 306 000 unique regressions. They show the proportion of those pairs where the global model turned out to have significantly outperformed the domestic counterpart. Tables 4 and 5 provide the ratios of the average RMSE of the global models that outperformed their domestic counterparts to the average RMSE of the domestic models that outperformed or equalled their global partners in the test (i.e. with significant negative alphas or no significant difference). That is, these tables compare the "global winners" to "domestic winners" and those that are not significantly different in forecast performance - "draw".

In presenting the results of the test, I did the blocking on the proxy of the domestic output gap and the type of commodity variable. Each line in the table corresponds to the models with particular measures of the global output gap, commodity prices, and domestic gap. The columns

$AR(1), AR(2), AR(3)$ and $AR(4)$ represent the number of lags of the global output gap variable present in the models with the given types of commodity prices and domestic gap. The regressors that are not blocked on are inflation π, inflationary expectations π^e, and imported inflation π^{imp} (measured as effective real exchange rate HP-filter gap), so that there 5 ways in which each of them can enter the equation (absent, $AR(1), AR(2), AR(3)$ or $AR(4)$). There are also 4 options for a given domestic proxy and commodity type ($AR(1), AR(2), AR(3)$ or $AR(4)$). This leaves us with $5^3 \times 4^2 = 2000$ pairs of models in each cell in the cases where both domestic gap and commodities are present. As regards the lines with "none" in place of either domestic gap or commodities, there are only $5^3 \times 4$ models, and only 5^3 when neither is present.

The highest proportion of the global models that significantly outperform the domestic ones was 4.8 % (attained by the models containing the BDI taken in the form of AR(3) as the world gap proxy, Urals oil price as a commodities measure, and PMI Russia as a measure of the domestic output gap). Overall, the highest proportions are achieved by the world gap measured as the BDI when combined with Urals oil price and capacity utilisation or cargo index as proxies for the domestic gap. However small the proportion of 5 % may sound, one needs to bear in mind that 5 % of 2000 makes up 100 models.

It is worth noting that whenever the effect of commodities is proxied by the Bloomberg Commodities Index (BCOM), the global models cease to outperform the domestic counterparts *for all* the global gap measures. One may try to interpret this by the fact that Russia is a commodity exporting economy for which the effect of globalisation may be fully encapsulated into information contained in the commodities data.

Table 2: Proportion of models with significant constant in the Romer and Romer test by type of proxy for the global gap, domestic gap, and commodities measures, controlled for the number of lags of the global gap

global gap	commodities	domestic gap	global gap as AR(1)	AR(2)	AR(3)	AR(4)
BDI	BCOM	capacity	0	0	0	0
BDI	BCOM	cargo	0	0	0	0
BDI	BCOM	none	0	0	0	0
BDI	BCOM	PMI_Rus	0	0	0	0
BDI	BCOM	HP_gdp_Rus	0	0	0	0
BDI	none	capacity	0.008	0.008	0.004	0
BDI	none	cargo	0.034	0.030	0.018	0.012
BDI	none	none	0.040	0.040	0.032	0.008
BDI	none	PMI_Rus	0.020	0.020	0.012	0.012
BDI	none	HP_gdp_Rus	0.010	0.008	0.004	0.002
BDI	urals	capacity	0.030	0.026	0.016	0.012
BDI	urals	cargo	0.040	0.040	0.038	0.032
BDI	urals	none	0.040	0.040	0.034	0.030
BDI	urals	PMI_Rus	0.031	0.029	0.048	0.033
BDI	urals	HP_gdp_Rus	0.017	0.017	0.009	0.014
Kilian	BCOM	capacity	0	0	0	0
Kilian	BCOM	cargo	0	0	0	0
Kilian	BCOM	none	0	0	0	0
Kilian	BCOM	PMI_Rus	0	0	0	0
Kilian	BCOM	HP_gdp_Rus	0	0	0	0
Kilian	none	capacity	0.004	0	0	0
Kilian	none	cargo	0.008	0.006	0	0.004
Kilian	none	none	0.008	0.016	0.008	0.008
Kilian	none	PMI_Rus	0.008	0.008	0.006	0.002
Kilian	none	HP_gdp_Rus	0.002	0	0	0.002
Kilian	urals	capacity	0.011	0.008	0.006	0.004
Kilian	urals	cargo	0.020	0.018	0.008	0.008
Kilian	urals	none	0.024	0.012	0.008	0.008
Kilian	urals	PMI_Rus	0.013	0.012	0.006	0.004
Kilian	urals	HP_gdp_Rus	0.009	0.008	0.008	0.008

Note on Variables (refer to Section 2)
Global gaps: *BDI* - Baltic Exchange Dry Index, *Kilian* - Index of Global Real Economic Activity by Lutz Kilian.
Commodities measures: *BCOM* - Bloomberg commodities index, *urals* - Urals oil price.
Domestic gap types: *capacity* - workforce load, *cargo* - volume of railway freight turnover, *PMI_Rus* - Purchasing Managers' Index for Russia, *HP_gdp_Rus* - Hodrick-Prescott filter gap of Russia's GDP.

Table 3: Proportion of models with significant constant in the Romer and Romer test by type of proxy for the global gap, domestic gap, and commodities measures, controlled for the number of lags of the global gap

global gap	commodities	domestic gap	global gap as AR(1)	AR(2)	AR(3)	AR(4)
OECD_gap	BCOM	capacity	0	0	0	0
OECD_gap	BCOM	cargo	0	0	0	0
OECD_gap	BCOM	none	0	0	0	0
OECD_gap	BCOM	PMI_Rus	0.004	0	0	0
OECD_gap	BCOM	HP_gdp_Rus	0	0	0	0
OECD_gap	none	capacity	0.006	0	0	0
OECD_gap	none	cargo	0.018	0	0	0
OECD_gap	none	none	0.016	0	0	0
OECD_gap	none	PMI_Rus	0.020	0	0	0
OECD_gap	none	HP_gdp_Rus	0.010	0	0	0
OECD_gap	urals	capacity	0.028	0	0	0
OECD_gap	urals	cargo	0.018	0	0	0
OECD_gap	urals	none	0.014	0	0	0
OECD_gap	urals	PMI_Rus	0.016	0	0	0
OECD_gap	urals	HP_gdp_Rus	0.021	0.004	0	0
trade_gap	BCOM	capacity	0	0	0	0
trade_gap	BCOM	cargo	0	0	0	0
trade_gap	BCOM	none	0	0	0	0
trade_gap	BCOM	PMI_Rus	0	0	0	0
trade_gap	BCOM	HP_gdp_Rus	0	0	0	0.0005
trade_gap	none	capacity	0	0	0	0
trade_gap	none	cargo	0	0	0	0
trade_gap	none	none	0	0	0	0
trade_gap	none	PMI_Rus	0	0	0	0
trade_gap	none	HP_gdp_Rus	0	0.004	0.002	0.004
trade_gap	urals	capacity	0	0	0	0
trade_gap	urals	cargo	0	0	0	0
trade_gap	urals	none	0	0	0	0
trade_gap	urals	PMI_Rus	0	0	0	0
trade_gap	urals	HP_gdp_Rus	0	0.013	0.006	0.002

Note on Variables (refer to Section 2)
Global gaps: *OECD* - global gap according to OECD, *trade* - weighted sum of trade partners' gaps.
Commodities measures: *BCOM* - Bloomberg commodities index, *urals* - Urals oil price.
Domestic gap types: *capacity* - workforce load, *cargo* - volume of railway freight turnover, *PMI_Rus* - Purchasing Managers' Index for Russia, *HP_gdp_Rus* - Hodrick-Prescott filter gap of Russia's GDP.

However, one needs to be cautious in interpreting the results of the test, as it is important to note which models were rendered better by the inclusion of the global output gap. Namely, it can be the case that bad models got a bit better, but still remained bad or, alternatively, that the bad models became the best ones after the inclusion of the global gap. To this end, I compute the ratios of mean RMSE of the global models which won to the mean RMSE of the domestic models which outperformed other global models in that group. That is, I am comparing winners to winners. One needs to remember that the Romers' test is one-sided, so that the group of the domestic "winners" is in fact composed by both those domestic models who were significantly better at forecasting than the global ones and those whose dominance was insignificant or uncertain.

As the tables show, almost all winning global models were a only better than the bad domestic models as the ratio is almost everywhere exceeding 1. Yet the models with the BDI, Urals and HP-filtered gap of domestic GDP have this ratio close to 0.98, meaning that they brought some improvement. Additionally, the combination of OECD gap and PMI Russia with urals or no commodity proxy provided the lowest ratios of 0.92. When coupled with the fact that the proportions of the winners in the latter cases were 1.6 % and 2 % respectively, this may be leading us to the best models.

Table 4: Relative mean RMSE: computed as the ratio of the mean RMSE of the global models from the pairs where the global version yields significantly higher accuracy to the mean RMSE among the domestic models from the pairs in which the domestic version yields significantly better or same accuracy as their global counterparts, i.e. "global winners" to "domestic winners and draw game guys"

global gap	commodities	domestic gap	global gap as AR(1)	AR(2)	AR(3)	AR(4)
BDI	BCOM	capacity				
BDI	BCOM	cargo				
BDI	BCOM	none				
BDI	BCOM	PMI_Rus				
BDI	BCOM	HP_gdp_Rus				
BDI	none	capacity	1.075	1.082	1.082	
BDI	none	cargo	1.095	1.093	1.064	1.044
BDI	none	none	1.120	1.111	1.088	1.062
BDI	none	PMI_Rus	1.047	1.040	1.026	1.011
BDI	none	HP_gdp_Rus	1.030	1.034	1.000	1.005
BDI	urals	capacity	1.077	1.080	1.073	1.075
BDI	urals	cargo	1.058	1.063	1.055	1.044
BDI	urals	none	1.069	1.075	1.062	1.058
BDI	urals	PMI_Rus	1.003	1.020	0.976	0.994
BDI	urals	HP_gdp_Rus	0.983	0.986	0.966	0.985
Kilian	BCOM	capacity				
Kilian	BCOM	cargo				
Kilian	BCOM	none				
Kilian	BCOM	PMI_Rus				
Kilian	BCOM	HP_gdp_Rus				
Kilian	none	capacity	1.098			
Kilian	none	cargo	1.094	1.093		1.063
Kilian	none	none	1.158	1.118	1.113	1.084
Kilian	none	PMI_Rus	1.050	1.052	1.050	1.029
Kilian	none	HP_gdp_Rus	1.028			1.009
Kilian	urals	capacity	1.060	1.080	1.074	1.091
Kilian	urals	cargo	1.069	1.079	1.062	1.040
Kilian	urals	none	1.094	1.093	1.071	1.047
Kilian	urals	PMI_Rus	1.039	1.038	1.017	1.021
Kilian	urals	HP_gdp_Rus	1.004	1.006	1.005	0.991

Note on Variables (refer to Section 2)
Global gaps: *BDI* - Baltic Exchange Dry Index, *Kilian* - Index of Global Real Economic Activity by Lutz Kilian.
Commodities measures: *BCOM* - Bloomberg commodities index, *urals* - Urals oil price.
Domestic gap types: *capacity* - workforce load, *cargo* - volume of railway freight turnover, *PMI_Rus* - Purchasing Managers' Index for Russia, *HP_gdp_Rus* - Hodrick-Prescott filter gap of Russia's GDP.

Table 5: Relative mean RMSE: computed as the ratio of the mean RMSE of the global models from the pairs where the global version yields significantly higher accuracy to the mean RMSE among the domestic models from the pairs in which the domestic version yields significantly better or same accuracy as their global counterparts, i.e. "global winners" to "domestic winners and draw game guys"

global gap	commodities	domestic gap	global gap as AR(1)	AR(2)	AR(3)	AR(4)
OECD_gap	BCOM	capacity				
OECD_gap	BCOM	cargo				
OECD_gap	BCOM	none				
OECD_gap	BCOM	PMI_Rus	0.927			
OECD_gap	BCOM	HP_gdp_Rus				
OECD_gap	none	capacity	1.135			
OECD_gap	none	cargo	1.150			
OECD_gap	none	none	1.170			
OECD_gap	none	PMI_Rus	0.921			
OECD_gap	none	HP_gdp_Rus	1.030			
OECD_gap	urals	capacity	1.149			
OECD_gap	urals	cargo	1.144			
OECD_gap	urals	none	1.125			
OECD_gap	urals	PMI_Rus	0.922			
OECD_gap	urals	HP_gdp_Rus	1.041	1.029		
trade_gap	BCOM	capacity				
trade_gap	BCOM	cargo				
trade_gap	BCOM	none				
trade_gap	BCOM	PMI_Rus				
trade_gap	BCOM	HP_gdp_Rus				0.935
trade_gap	none	capacity				
trade_gap	none	cargo				
trade_gap	none	none				
trade_gap	none	PMI_Rus				
trade_gap	none	HP_gdp_Rus		0.974	0.995	0.998
trade_gap	urals	capacity				
trade_gap	urals	cargo				
trade_gap	urals	none				
trade_gap	urals	PMI_Rus				
trade_gap	urals	HP_gdp_Rus		0.980	1.005	0.992

Note on Variables (refer to Section 2)
Global gaps: *OECD* - global gap according to OECD, *trade* - weighted sum of trade partners' gaps.
Commodities measures: *BCOM* - Bloomberg commodities index, *urals* - Urals oil price.
Domestic gap types: *capacity* - workforce load, *cargo* - volume of railway freight turnover, *PMI_ Rus* - Purchasing Managers' Index for Russia, *HP_ gdp_ Rus* - Hodrick-Prescott filter gap of Russia's GDP.

3.3 Regressional analysis of RMSE

A deeper analysis of the impact of all regressors on the models' predictive ability shows that, in fact, the models containing the variables identified in the Romers' test table are not the top performing ones.

Instead, such predictors as capacity utilisation, real effective exchange rate gap and inflationary expectations significantly lower models' RMSE.

On the contrary, remembering the Romers' test, the winning global models contained such variables as Urals, domestic HP-filtered GDP gap and PMI Russia, which all turned out to be among the worst as they increase models' RMSE according to the regressional analysis presented in tables 6 and 7 below.

Extending this type of analysis, I run a dummy regression where there is a dummy for every predictor, the number of predictors in the equation, and also for every date of prediction (the model is briefly described in the Appendix along with the estimation results). Again, capacity utilisation, real effective exchange rate gap and inflationary expectations significantly lower models' RMSE when the date of prediction is controlled for. This is important because such episodes as sharp devaluation of 2015 or the 2020 pandemic aggravated the inaccuracies of all models, rendering it difficult to trace the quality of certain predictors for these dates.

Table 6: Coefficients of the dummy variables corresponding to each predictor on RMSE.
Part 1/2: global gaps.

	Dependent variable:		
	RMSE	Percentile of RMSE	Log(RMSE)
	(1)	(2)	(3)
Kilian_AR(1)	1.045*** (0.002)	0.074*** (0.002)	0.068*** (0.001)
Kilian_AR(2)	1.071*** (0.002)	0.140*** (0.002)	0.090*** (0.001)
Kilian_AR(3)	1.120*** (0.002)	0.260*** (0.002)	0.129*** (0.001)
Kilian_AR(4)	1.181*** (0.002)	0.352*** (0.002)	0.171*** (0.001)
BDI_AR(1)	0.005*** (0.002)	0.009*** (0.002)	0.005*** (0.001)
BDI_AR(2)	0.028*** (0.002)	0.062*** (0.002)	0.023*** (0.001)
BDI_AR(3)	0.044*** (0.002)	0.101*** (0.002)	0.037*** (0.001)
BDI_AR(4)	0.077*** (0.002)	0.179*** (0.002)	0.062*** (0.001)
trade_gap_AR(1)	0.085*** (0.002)	0.209*** (0.002)	0.069*** (0.001)
trade_gap_AR(2)	0.084*** (0.002)	0.192*** (0.002)	0.067*** (0.001)
trade_gap_AR(3)	0.134*** (0.002)	0.302*** (0.002)	0.105*** (0.001)
trade_gap_AR(4)	0.175*** (0.002)	0.371*** (0.002)	0.133*** (0.001)
OECD_gap_AR(1)	0.037*** (0.002)	0.051*** (0.002)	0.025*** (0.001)
OECD_gap_AR(2)	0.098*** (0.002)	0.184*** (0.002)	0.074*** (0.001)
OECD_gap_AR(3)	0.156*** (0.002)	0.286*** (0.002)	0.115*** (0.001)
OECD_gap_AR(4)	0.222*** (0.002)	0.384*** (0.002)	0.159*** (0.001)
Note:			*p<0.1; **p<0.05; ***p<0.01

Note on Variables (refer to Section 2)
Global gaps: *OECD* - global gap according to OECD, *trade* - weighted sum of trade partners' gaps, *BDI* - Baltic Exchange Dry Index, *Kilian* - Index of Global Real Economic Activity by Lutz Kilian.

Table 7: Coefficients of the dummy variables corresponding to each predictor on RMSE.
Part 2/2: domestic variables.

	Dependent variable:		
	RMSE	Percentile of RMSE	Log(RMSE)
	(1)	(2)	(3)
Constant	1.017*** (0.002)	0.006*** (0.002)	0.045*** (0.001)
BCOM_AR(1)	0.026*** (0.001)	0.057*** (0.001)	0.020*** (0.001)
BCOM_AR(2)	0.045*** (0.001)	0.092*** (0.001)	0.034*** (0.001)
BCOM_AR(3)	0.066*** (0.001)	0.129*** (0.001)	0.049*** (0.001)
BCOM_AR(4)	0.093*** (0.001)	0.168*** (0.001)	0.067*** (0.001)
PMI_Rus_AR(1)	0.039*** (0.002)	0.100*** (0.002)	0.031*** (0.001)
PMI_Rus_AR(2)	0.078*** (0.002)	0.190*** (0.002)	0.062*** (0.001)
PMI_Rus_AR(3)	0.091*** (0.002)	0.211*** (0.002)	0.071*** (0.001)
PMI_Rus_AR(4)	0.114*** (0.002)	0.233*** (0.002)	0.085*** (0.001)
capacity_AR(1)	0.045*** (0.002)	0.110*** (0.002)	0.036*** (0.001)
capacity_AR(2)	−0.023*** (0.002)	−0.062*** (0.002)	−0.018*** (0.001)
capacity_AR(3)	−0.046*** (0.002)	−0.109*** (0.002)	−0.039*** (0.001)
capacity_AR(4)	−0.023*** (0.002)	−0.088*** (0.002)	−0.025*** (0.001)
cargo_AR(1)	0.017*** (0.002)	0.045*** (0.002)	0.015*** (0.001)
cargo_AR(2)	0.047*** (0.002)	0.113*** (0.002)	0.037*** (0.001)
cargo_AR(3)	0.048*** (0.002)	0.050*** (0.002)	0.030*** (0.001)
cargo_AR(4)	0.182*** (0.002)	0.197*** (0.002)	0.113*** (0.001)
urals_AR(1)	0.001 (0.001)	−0.010*** (0.001)	0.0002 (0.001)
urals_AR(2)	0.026*** (0.001)	0.047*** (0.001)	0.019*** (0.001)
urals_AR(3)	0.054*** (0.001)	0.113*** (0.001)	0.041*** (0.001)
urals_AR(4)	0.089*** (0.001)	0.171*** (0.001)	0.065*** (0.001)
effrate_HP_gap_AR(1)	0.094*** (0.001)	0.223*** (0.001)	0.074*** (0.0004)
effrate_HP_gap_AR(2)	−0.008*** (0.001)	−0.033*** (0.001)	−0.007*** (0.0004)
effrate_HP_gap_AR(3)	0.038*** (0.001)	0.071*** (0.001)	0.028*** (0.0004)
effrate_HP_gap_AR(4)	0.094*** (0.001)	0.177*** (0.001)	0.069*** (0.0004)
HP_gdp_Rus_gap_AR(1)	0.038*** (0.002)	0.100*** (0.002)	0.031*** (0.001)
HP_gdp_Rus_gap_AR(2)	0.063*** (0.002)	0.161*** (0.002)	0.051*** (0.001)
HP_gdp_Rus_gap_AR(3)	0.109*** (0.002)	0.268*** (0.002)	0.085*** (0.001)
HP_gdp_Rus_gap_AR(4)	0.171*** (0.002)	0.339*** (0.002)	0.128*** (0.001)
expect_AR(1)	−0.040*** (0.001)	−0.103*** (0.001)	−0.032*** (0.0004)
expect_AR(2)	−0.034*** (0.001)	−0.091*** (0.001)	−0.028*** (0.0004)
expect_AR(3)	0.016*** (0.001)	0.008*** (0.001)	0.009*** (0.0004)
expect_AR(4)	0.075*** (0.001)	0.085*** (0.001)	0.048*** (0.0004)
CPI_AR(1)	0.005*** (0.001)	0.018*** (0.001)	0.005*** (0.0004)
CPI_AR(2)	0.023*** (0.001)	0.055*** (0.001)	0.017*** (0.0004)
CPI_AR(3)	0.042*** (0.001)	0.088*** (0.001)	0.031*** (0.0004)
CPI_AR(4)	0.045*** (0.001)	0.077*** (0.001)	0.031*** (0.0004)
Observations	325,125	325,125	325,125
R^2	0.983	0.899	0.905
Adjusted R^2	0.983	0.899	0.905
Residual Std. Error (df = 325072)	0.169	0.184	0.081
F Statistic (df = 53; 325072)	352,747.600***	54,334.690***	58,275.900***
Note:			*p<0.1; **p<0.05; ***p<0.01

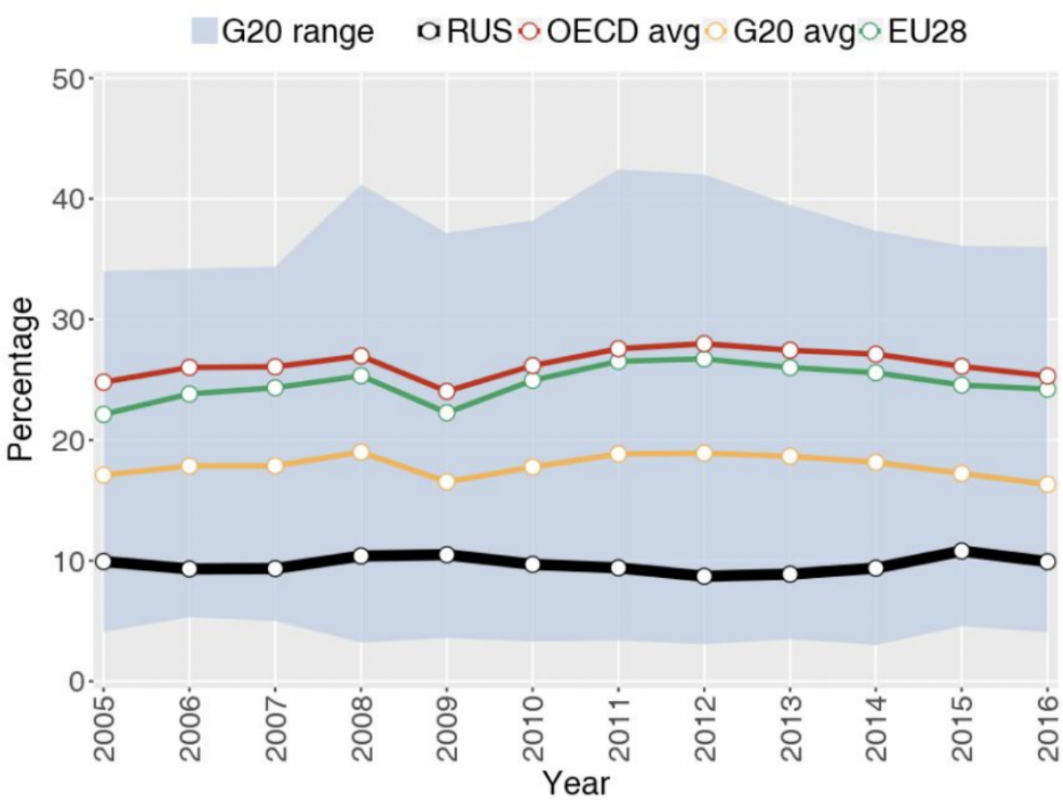
Note on Variables (refer to Section 2)
Commodities measures: *BCOM* - Bloomberg commodities index, *urals* - Urals oil price.
Domestic gap types: *capacity* - workforce load, *cargo* - volume of railway freight turnover, *PMI_Rus* - Purchasing Managers' Index for Russia, *HP_gdp_Rus* - Hodrick-Prescott filter gap of Russia's GDP.
Imported inflation: *effrate_HP_gap* - HP-filter gap of real effective exchange rate.
Inflation expectations: *expect*.

4 Discussion and conclusion

Global output gaps do not improve forecast performance of the models that have RMSE lower than simple benchmarks such as AR(1) of CPI or Random Walk. Instead, they bring some improvement to the models that perform poorly.

The reason behind this is likely to lie within the fact that the Russian economy is driven by commodity exports. Yet it was shown that effective real exchange rate is a better predictor of inflation than Bloomberg commodity index or Urals oil price.

Figure 5: Share of foreign value added in gross exports



The findings can be explained by the country's persistently low level of participation in global value chains. Moreover, the share of value added coming from foreign consumer demand fell from the 2005 level of 28.6% to 25.3% in 2015[8]. The share of intermediate goods imports for the use in exports fell from the 2005 level of 31.1% to 27% in 2015[9]

However, the global output gap when measured as a trade-weighed sum of the HP-filter gaps of Russia's trading partners is strongly correlated with the Russian domestic output gap measure as an HP-filter gap of domestic GDP. In a sense, one may say that the global output gap does not influence Russia's inflation because the very inflation is not influenced by the domestic output gap.

[8]OECD, TiVA 2018 country notes
[9]ibid.

To sum up, the models with the global gap perform worse than those without for each measure considered when compared in terms of RMSE. However, in the cross-sections of models' absolute errors at different dates of out-of-sample forecasts, there are periods when global models outperform the domestic ones. Yet both types of output gaps, domestic and global, worsen forecast accuracy. Instead, such predictors as inflation expectations, real effective exchange rate gap, and capacity utilisation improve it, even in the times of crises, when the errors of all models increase dramatically.

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5 Appendix

5.1 Data pre-processing

Variable	Different measures	Initial data format	Author's transformations	Data source
expectations	firms' survey	monthly values	quarterly average	CB of Russia
imported inflation	real broad effective exchange rate	monthly levels	➢ end of quarter values: ➢ then, HP gap	FRED St. Louis Fed
commodities				
	BCOM	quarterly levels		Bloomberg
	Urals price	M1/M2	Q1/Q2	Bloomberg
domestic gap				
	Russian real GDP	quarterly values	HP gap	Federal State Statistics Service
	cargo	M1/M2	Q1/Q2	Federal State Statistics Service
	capacity	monthly levels	quarterly average	Federal State Statistics Service
	PMI Russia	monthly levels	quarterly average	Bloomberg
global gap				
	OECD gap	annual levels	interpolation to quarterly using cubic splines	OECD
	BDI	end of quarter levels	leave it as it	Bloomberg
	Kilian index of global economic activity	monthly values	➢ end of quarter values	Dallas Fed
	Trade gap	• quarterly GDPs • (all SA, ex. Bel) • annual shares up to 2019	➢ SA Bel ➢ HP all GDPs ➢ Weight each quarter by the year's share	CEIC, WB Global Economic Monitor, CB of Belarus, Federal Customs Service of Russia

5.2 Descriptive statistics

Table 8: Descriptive statistics

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
BCOM	73	126.304	36.407	61.858	88.167	152.885	233.035
urals	73	1.030	0.205	0.367	0.939	1.128	1.834
PMI_Rus	73	53.610	4.970	33.533	52.067	57.233	61.067
capacity	73	75.999	4.082	63.001	73.898	79.115	81.101
cargo	73	1.003	0.041	0.722	0.996	1.013	1.128
HP_gdp_Rus_gap	73	−0.061	3.583	−10.507	−2.218	1.806	9.740
OECD_gap	73	−1.108	2.170	−7.340	−2.219	0.346	2.614
Kilian	73	16.119	75.466	−136.600	−50.200	64.410	184.830
BDI	73	2,391.192	2,084.825	429	1,004	2,993	9,589
expect	73	17.363	6.754	6.860	11.927	23.387	32.003
effrate_HP_gap	73	0.236	8.879	−27.071	−3.197	5.666	15.474
CPI	73	102.062	1.169	100.000	101.200	102.900	107.000
trade_gap	73	−0.050	2.965	−11.035	−1.288	1.526	5.878

Figure 6: Simultaneous correlation of the data series: Pearson and Spearman

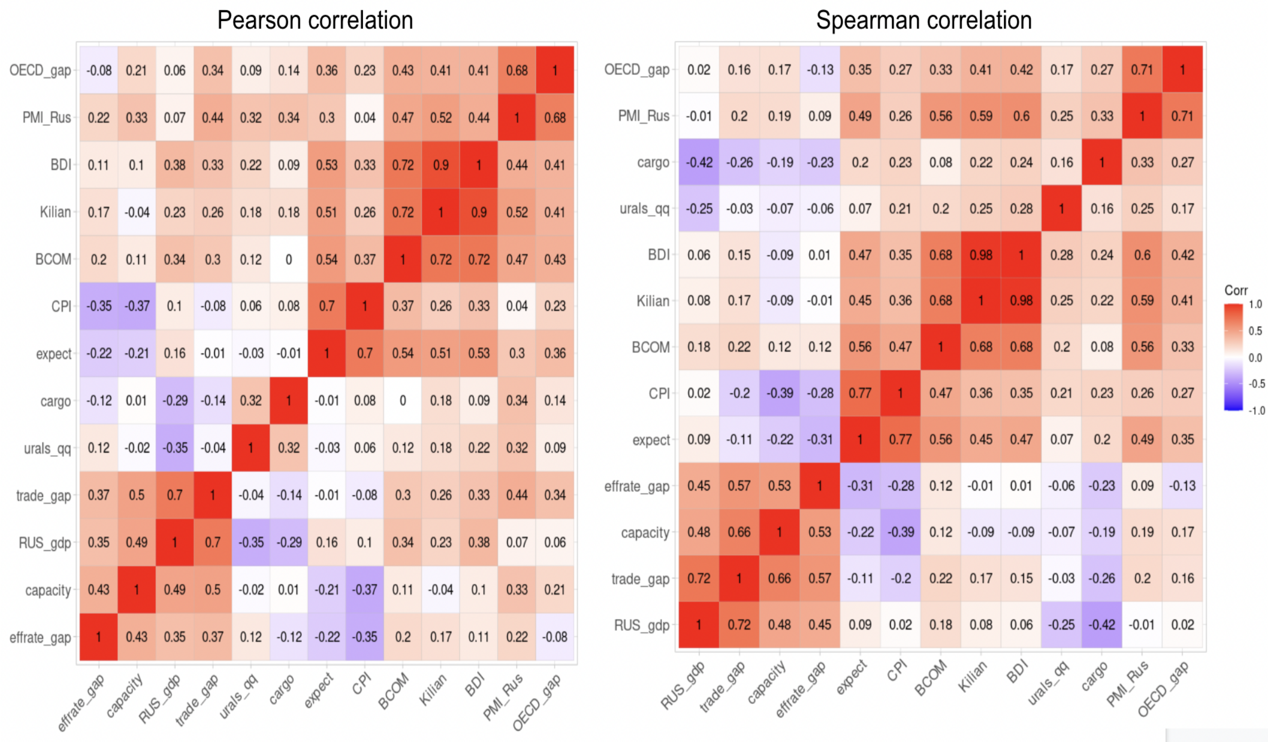

Figure 7: Time series of the data

Table 9: Total trade shares of the main trading partners as percentage of all trade including the minor partners not included in the paper. Part 1: 2002 - 2010.

	2002	2003	2004	2005	2006	2007	2008	2009	2010
Germany	9,59%	9,70%	9,27%	9,70%	9,79%	9,59%	9,16%	8,52%	8,28%
Netherlands	5,62%	5,19%	6,47%	7,81%	8,78%	8,47%	8,41%	8,53%	9,33%
China	6,04%	6,05%	5,77%	5,97%	6,53%	7,31%	7,61%	8,42%	9,49%
Italy	6,32%	5,72%	5,94%	6,90%	7,02%	6,54%	7,21%	7,03%	5,99%
Ukraine	5,96%	6,30%	6,56%	5,94%	5,52%	5,39%	5,42%	4,90%	5,94%
Belarus	6,47%	6,54%	6,88%	4,65%	4,54%	4,73%	4,64%	5,00%	4,45%
Turkey	2,67%	3,00%	3,37%	3,70%	3,88%	4,12%	4,60%	4,18%	4,03%
Japan	1,82%	2,25%	2,86%	2,81%	2,79%	3,69%	3,94%	3,09%	3,70%
Poland	3,28%	3,32%	3,11%	3,34%	3,39%	3,25%	3,71%	3,56%	3,32%
US	4,56%	3,76%	3,82%	3,20%	3,43%	3,23%	3,70%	3,90%	3,76%
UK	3,22%	3,28%	3,00%	3,25%	3,20%	3,02%	3,06%	2,69%	2,54%
Kazakhstan	2,84%	3,01%	3,15%	2,87%	2,92%	3,00%	2,68%	2,74%	2,44%
France	2,98%	3,06%	2,91%	2,88%	3,08%	2,98%	3,02%	3,66%	3,60%
Finland	2,91%	3,23%	3,17%	3,16%	3,01%	2,86%	3,05%	2,80%	2,68%
South Korea	1,44%	1,39%	1,55%	1,87%	2,17%	2,72%	2,50%	2,25%	2,83%
Belgium	1,02%	1,06%	1,16%	1,16%	1,11%	1,09%	1,18%	1,40%	1,31%

Note that the weights used for the computation of the trade-weighted global gap are taken as percentages relative to the total trade within this group of the selected largest partners, not the total amount of trade.

Table 10: Part 2: 2011 - 2019

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Germany	8,73%	8,80%	8,88%	8,94%	8,70%	8,70%	8,54%	8,68%	7,96%
Netherlands	8,34%	9,86%	9,00%	9,35%	8,35%	6,89%	6,75%	6,85%	7,30%
China	10,12%	10,43%	10,52%	11,25%	12,07%	14,11%	14,86%	15,73%	16,69%
Italy	5,60%	5,46%	6,38%	6,11%	5,82%	4,23%	4,09%	3,92%	3,78%
Ukraine	6,15%	5,38%	4,69%	3,55%	2,84%	2,22%	2,20%	2,18%	2,18%
Belarus	4,80%	4,34%	3,98%	4,17%	4,64%	5,15%	5,23%	5,00%	4,99%
Turkey	3,86%	4,08%	3,88%	4,03%	4,43%	3,35%	3,77%	3,71%	3,91%
Japan	3,61%	3,72%	3,93%	3,92%	4,05%	3,42%	3,11%	3,09%	3,04%
Poland	3,41%	3,26%	3,31%	2,93%	2,61%	2,80%	2,83%	3,16%	2,67%
US	3,77%	3,37%	3,29%	3,71%	3,97%	4,25%	3,96%	3,64%	3,93%
UK	2,58%	2,77%	2,91%	2,46%	2,13%	2,22%	2,18%	2,00%	2,59%
Kazakhstan	2,51%	2,82%	3,14%	2,77%	2,96%	2,83%	2,98%	2,67%	2,94%
France	3,42%	2,89%	2,63%	2,32%	2,21%	2,84%	2,64%	2,50%	2,24%
Finland	2,29%	2,03%	2,22%	2,03%	1,85%	1,93%	2,11%	2,14%	2,03%
South Korea	3,03%	2,96%	2,98%	3,48%	3,43%	3,23%	3,29%	3,61%	3,65%
Belgium	1,41%	1,34%	1,39%	1,63%	1,61%	1,71%	1,66%	1,70%	1,37%

5.3 The dummy regression of predictors' presence in an equation on RMSE, controlling for the date of prediction and the number of coefficients present in the model.

Model:

$$e_{t,i}^2 = d^T F_i + \lambda_t + \gamma^T g_i + \epsilon_{t,i}$$

d_i - vector of dummy variables

$$F_i = \begin{bmatrix} f_i^1 \\ f_i^2 \\ \cdots \\ f_i^2 0 \end{bmatrix} \text{ where } f_i^j = \begin{cases} 1, & \textit{if regressor } j \textit{ is in the model } i \\ 0, & \textit{if regressor } j \textit{ is not in the model } i \end{cases} \quad \text{- dummy (time invariant)}$$

$$G_i = \begin{bmatrix} g_i^1 \\ g_i^2 \\ \cdots \\ g_i^{21} \end{bmatrix} \text{ where } g_i^j = \begin{cases} 1, & \textit{if number of regressors in model } i \textit{ equals to } j \\ 0, & \textit{if number of regressors in model } i \textit{ is not equal to } j \end{cases} \quad \text{- dummy}$$

(time invariant)

λ_t - vector of coefficients corresponding to quarter

d_i - shows impact on RMSE independent of date

λ_t - shows impact on RMSE relative to a given forecast date

Table 11: The dummy regression of predictors' presence in an equation on RMSE, controlling for the date of prediction and the number of coefficients present in the model.
Part 1/3: coefficients of the date dummies.

	Dependent variable:
	RMSE
2009-12-28	2.203^{***} (0.092)
2010-03-28	1.246^{***} (0.092)
2010-06-28	0.807^{***} (0.092)
2010-09-28	1.849^{***} (0.092)
2010-12-28	0.717^{***} (0.092)
2011-03-28	0.736^{***} (0.092)
2011-06-28	1.212^{***} (0.092)
2011-09-28	1.115^{***} (0.092)
2011-12-28	0.946^{***} (0.092)
2012-03-28	0.911^{***} (0.092)
2012-06-28	0.784^{***} (0.092)
2012-09-28	0.863^{***} (0.092)
2012-12-28	0.833^{***} (0.092)
2013-03-28	0.595^{***} (0.092)
2013-06-28	0.967^{***} (0.092)
2013-09-28	0.633^{***} (0.092)
2013-12-28	0.593^{***} (0.092)
2014-03-28	0.792^{***} (0.092)
2014-06-28	0.846^{***} (0.092)
2014-09-28	0.870^{***} (0.092)
2014-12-28	2.760^{***} (0.092)
2015-03-28	3.631^{***} (0.092)
2015-06-28	3.399^{***} (0.092)
2015-09-28	1.257^{***} (0.092)
2015-12-28	1.364^{***} (0.092)
2016-03-28	0.999^{***} (0.092)
2016-06-28	0.831^{***} (0.092)
2016-09-28	0.783^{***} (0.092)
2016-12-28	0.873^{***} (0.092)
2017-03-28	0.746^{***} (0.092)
2017-06-28	0.615^{***} (0.092)
2017-09-28	2.027^{***} (0.092)
2017-12-28	1.090^{***} (0.092)
2018-03-28	0.858^{***} (0.092)
2018-06-28	0.575^{***} (0.092)
2018-09-28	1.009^{***} (0.092)
2018-12-28	0.803^{***} (0.092)
2019-03-28	1.175^{***} (0.092)
2019-06-28	0.765^{***} (0.092)
2019-09-28	1.082^{***} (0.092)
2019-12-28	0.809^{***} (0.092)
2020-03-28	0.739^{***} (0.092)
2020-06-28	2.206^{***} (0.092)
Observations	13,980,375
R^2	0.780
Adjusted R^2	0.780
Residual Std. Error	0.606 (df = 13980257)
F Statistic	$419{,}497.700^{***}$ (df = 118; 13980257)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 12: The dummy regression of predictors' presence in an equation on RMSE, controlling for the date of prediction and the number of coefficients present in the model.
Part 2/3: coefficients of the predictors.

	Dependent variable:
	RMSE
CPI1	0.001 (0.004)
CPI2	0.011*** (0.004)
CPI3	0.020*** (0.004)
CPI4	0.027*** (0.004)
expect1	−0.046*** (0.004)
expect2	0.017*** (0.004)
expect3	0.041*** (0.004)
expect4	0.051*** (0.004)
HP_gdp_Rus1	0.042*** (0.004)
HP_gdp_Rus2	0.025*** (0.004)
HP_gdp_Rus3	0.038*** (0.004)
HP_gdp_Rus4	0.051*** (0.004)
effrate_HP_gap1	0.078*** (0.004)
effrate_HP_gap2	−0.016*** (0.004)
effrate_HP_gap3	0.027*** (0.004)
effrate_HP_gap4	0.058*** (0.004)
urals1	0.014*** (0.004)
urals2	0.030*** (0.004)
urals3	0.023*** (0.004)
urals4	0.031*** (0.004)
OECD_gap1	0.026*** (0.004)
OECD_gap2	0.057*** (0.004)
OECD_gap3	0.063*** (0.004)
OECD_gap4	0.055*** (0.004)
cargo1	0.025*** (0.004)
cargo2	0.033*** (0.004)
cargo3	0.0001 (0.004)
cargo4	0.065*** (0.004)
capacity1	0.039*** (0.004)
capacity2	0.008** (0.004)
capacity3	−0.002 (0.004)
capacity4	0.012*** (0.004)
PMI_Rus1	0.025*** (0.004)
PMI_Rus2	0.033*** (0.004)
PMI_Rus3	0.022*** (0.004)
PMI_Rus4	0.026*** (0.004)
BCOM1	0.016*** (0.004)
BCOM2	0.016*** (0.004)
BCOM3	0.024*** (0.004)
BCOM4	0.027*** (0.004)
trade_gap1	0.063*** (0.004)
trade_gap2	0.009** (0.004)
trade_gap3	0.041*** (0.004)
trade_gap4	0.038*** (0.004)
BDI1	0.007* (0.004)
BDI2	0.022*** (0.004)
BDI3	0.008** (0.004)
BDI4	0.022*** (0.004)
Kilian1	0.016*** (0.004)
Kilian2	0.025*** (0.004)
Kilian3	0.027*** (0.004)
Kilian4	0.039*** (0.004)
Observations	13,980,375
R^2	0.780
Adjusted R^2	0.780
Residual Std. Error	0.606 (df = 13980257)
F Statistic	419,497.700*** (df = 118; 13980257)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 13: The dummy regression of predictors' presence in an equation on RMSE, controlling for the date of prediction and the number of coefficients present in the model.
Part 3/3: coefficients of the dummies standing for the number of predictors in a model.

	Dependent variable:
	RMSE
number_of_predictors_2	-0.150 (0.092)
number_of_predictors_3	-0.250^{***} (0.085)
number_of_predictors_4	-0.325^{***} (0.081)
number_of_predictors_5	-0.377^{***} (0.077)
number_of_predictors_6	-0.417^{***} (0.073)
number_of_predictors_7	-0.447^{***} (0.069)
number_of_predictors_8	-0.472^{***} (0.066)
number_of_predictors_9	-0.491^{***} (0.062)
number_of_predictors_10	-0.506^{***} (0.058)
number_of_predictors_11	-0.519^{***} (0.054)
number_of_predictors_12	-0.531^{***} (0.051)
number_of_predictors_13	-0.541^{***} (0.047)
number_of_predictors_14	-0.550^{***} (0.043)
number_of_predictors_15	-0.559^{***} (0.040)
number_of_predictors_16	-0.568^{***} (0.036)
number_of_predictors_17	-0.575^{***} (0.033)
number_of_predictors_18	-0.582^{***} (0.029)
number_of_predictors_19	-0.585^{***} (0.026)
number_of_predictors_20	-0.585^{***} (0.023)
number_of_predictors_21	-0.578^{***} (0.021)
number_of_predictors_22	-0.562^{***} (0.019)
number_of_predictors_23	-0.528^{***} (0.017)
number_of_predictors_24	-0.438^{***} (0.017)
Observations	13,980,375
R^2	0.780
Adjusted R^2	0.780
Residual Std. Error	0.606 (df = 13980257)
F Statistic	$419{,}497.700^{***}$ (df = 118; 13980257)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 8: Mean values of coefficients across all the models by predictor's lag order.
(1) - AR(1), (2) - AR(2), (3) - AR(3), (4) - AR(4)

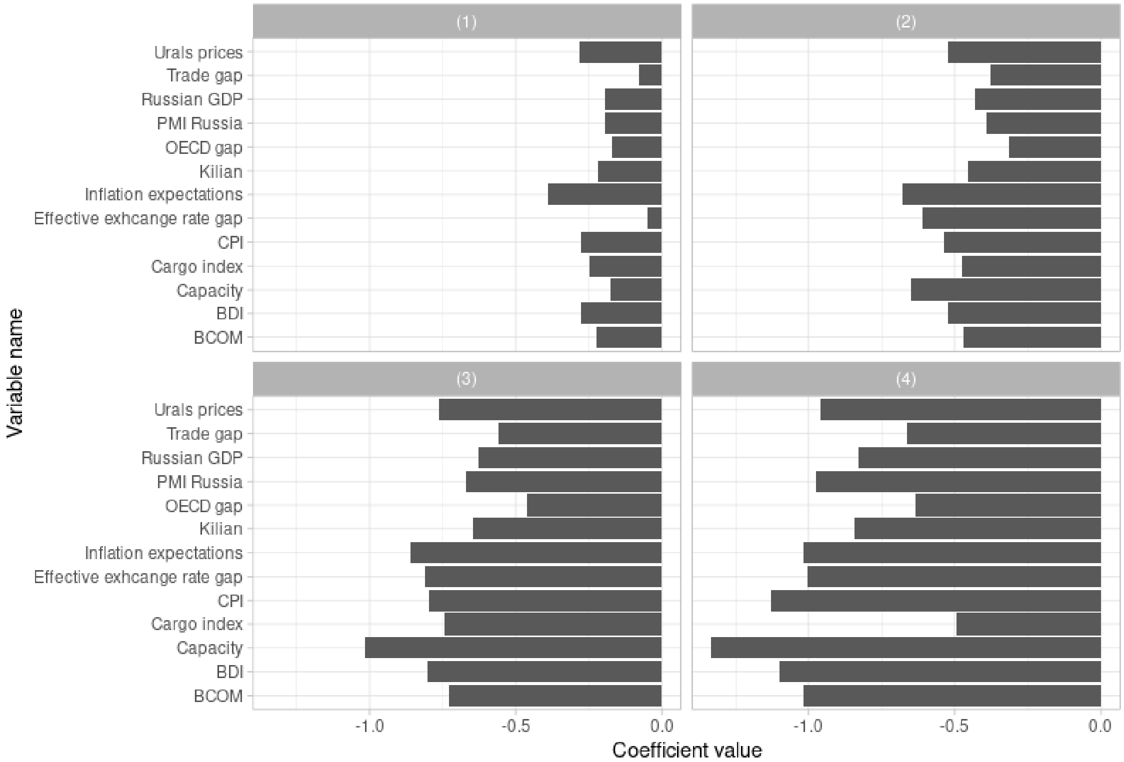

Figure 9: Coefficients of the dummies corresponding to the date of prediction (based on the results from table 11)

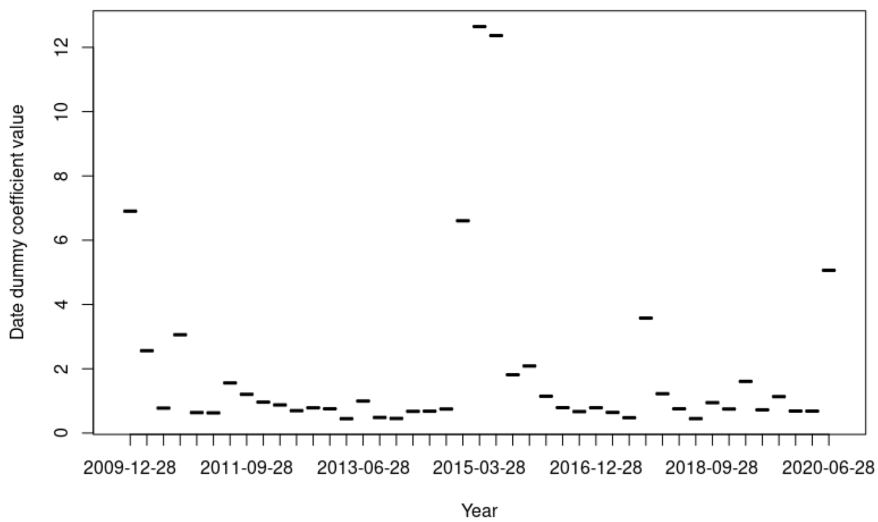

Figure 10: Proportion of models falling in a given percentile rank depending on the presence of a predictor, colour standing for the number of lags included