Russia

10 December 2009

Renaissance Capital

NES New Economic School

Konstantin Styrin, PhD
+7 (495) 956-9508 ext 254
kstyrin@nes.ru

Valentina Potapova (Krylova), CFA
+7 (495) 258-7770 ext 4274
vkrylova2@rencap.com

RenCap-NES Leading GDP Indicator

Forecasts - better and earlier

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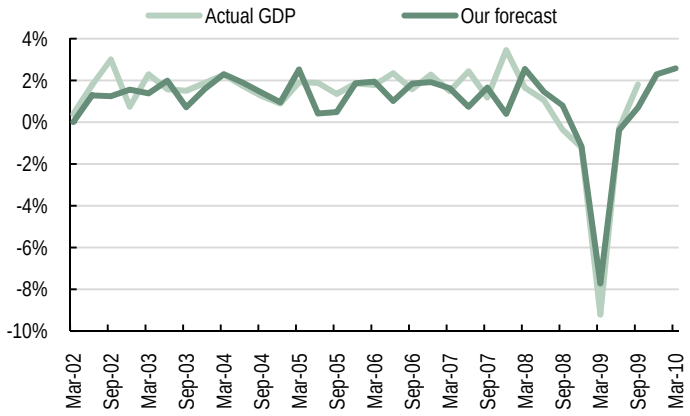
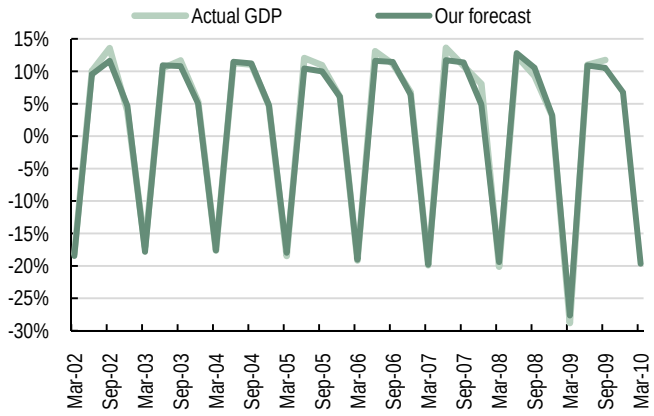
- In this note, we present the RenCap-NES leading GDP indicator, a model that seeks to forecast real GDP growth. We will publish monthly reports on our results.
- Using our model, we forecast QoQ real GDP to grow 6.8% in 4Q09 and drop 19.6% in 1Q10. Seasonally adjusted figures are 2.3% and 2.6%, respectively. In comparison with the previous year, real GDP is expected to decline 5.7% this quarter vs 4Q08, and increase 6.4% in 1Q10 vs 1Q09.
- Our model outperforms naïve benchmarks and competing models provided by the Development Center and Russia's Ministry of Economic Development (MED). MED's GDP forecast is our toughest competitor, but our model beats it in two ways:
  1. Our GDP estimate is more accurate, as it has a lower forecast error
  2. Our final estimate of GDP growth is released well before the ministry publishes its forecast

Figure 1: Seasonally adjusted GDP growth, QoQ



Source: Rosstat, NES estimates, Renaissance Capital estimates

Figure 2: Unadjusted GDP growth, QoQ



Source: Rosstat, NES estimates, Renaissance Capital estimates

Introduction

The main idea behind the construction of our model is that real GDP growth represents a good summary measure of economic activity. Most people typically look at GDP dynamics in order to judge a country's economic health and the phases of the business cycle. Investors and government officials make their decisions depending on what they expect the economic situation will be in the short and medium term. However, GDP data are published with a considerable delay. The first official release is published by Rosstat approximately 1.5 months after the end of the reference quarter. From this point of view, it is difficult to overestimate the importance of accurate and timely GDP forecasting. Our model makes it possible to obtain a reasonably accurate real GDP forecast well before the actual data are published (our first estimate of GDP is released as much as six months before official data). We base our methodology on the same approach as the US Federal Reserve and the European Central Bank adopted to construct similar indices. Overall, the methodology relies on relatively recent advances in modern time-series econometrics (please see Appendix 5).

According to our model, we expect seasonally adjusted QoQ real GDP growth of 2.3% in 4Q09 and 2.6% in 1Q10. In terms of unadjusted figures, this represents 6.8% growth this quarter and a 19.6% drop next quarter. In comparison with the previous year, real GDP is expected to decline 5.7% this quarter vs 4Q08 and increase 6.4% in 1Q10 vs 1Q09.

Our core forecasting procedure can be summarised as follows: we use 108 monthly time series (among which are surveys, commodity prices, exchange rates, real activity, labour market and money market data) as input variables. The data cover a time interval from Jan 1996 until Nov 2009, although most variables are now available to Oct 2009.

First, we transform all input time series to obtain stationarity by removing seasonality and trends. Second, we smooth data outliers. Then, we split the sample into balanced and unbalanced parts, where the former contains observations with all monthly predictors available for the whole quarter. The balanced part is standardised.

Second, if necessary, we select predictors by using a targeted predictors' procedure or weigh them by using the Boivin and Ng method, the purpose of which is to reduce the fraction of noise in the data and isolate a subset of predictors that better forecast GDP growth.

Third, we exploit the static factor approach. On the balanced part, we estimate factors as regular principal components of input time series. Thereby the forecasting content of multiple input variables is summarised in just a few factors.

Fourth, applying the Kalman filter, we solve the so-called 'jagged edge' problem, whereby some variables are unavailable due to their publication lags, and we estimate the factor values for the rest of the sample.

Finally, given these factors and GDP lags (if necessary), we predict real GDP growth for the next quarter. We have constructed our forecasting model as a projection of real GDP growth on the space of own lags and factors.

We forecast a quarter of GDP growth at the end of each month as soon as monthly releases of the Federal State Statistics Service and Russian Economic Barometer

survey data (REB; a project run by the Institute of World Economy and International Relations since the early 1990s) are published. Commodity and financial market data become available immediately. Forecasts for the later months of a quarter can be viewed as an updated forecast for earlier months of the same quarter since the arrival of a new piece of monthly data provides a natural occasion to revise the GDP growth forecast.

Thus, we have five consecutive estimates of a quarter of GDP growth. The first estimate is released in the first month of the previous quarter (six months before the actual figure is published by Rosstat) and is based on just a few market series (RTS, overnight interest rate MOSIBOR, and others) available for that quarter as well as historical observations for preceding months. We make a final revision in the second month of the quarter of interest (or almost a quarter before the official GDP data for that quarter are released).

Based on a pseudo out-of-sample performance, our model beats our rivals and the naïve benchmarks. Among the competing models, the Ministry of Economic Development (MED) is our toughest rival. Nevertheless, our model outperforms its forecasts in two respects. First, our GDP estimate is more accurate, as it has a lower mean squared forecast error (measured by the root mean squared forecast error [RMSFE]). Second, our final revision of the GDP estimate is available seven weeks before the ministry publishes its ultimate forecast.

GDP forecast for 1Q10 and 4Q09

As of the beginning of Dec 2009, we will produce two GDP forecasts, the fifth vintage for 4Q09 and the second vintage for 1Q10. Both of them are based on market variables up to the end of November, most Rosstat series up to October, and REB survey data up to September. According to our model, we expect seasonally adjusted QoQ real GDP growth of 2.3% in 4Q09 and 2.6% in 1Q10. In terms of unadjusted figures, this represents 6.8% growth this quarter and a 19.6% drop next quarter. In comparison with the previous year, real GDP is expected to decline 5.7% this quarter vs 4Q08 and increase 6.4% in 1Q10 vs 1Q09.

Input data

Unlike for the US and many other developed countries, where prolonged histories of observations are available for very diverse economic indicators, in Russia, data availability and their time span are limited. Few economic indicators have data available prior to 1999. Nevertheless, we have managed to collect more than 100 time series and plan to increase this in the future.

The initial data panel used in our model comprises 108 input variables covering the period from Jan 1996 to Nov 2009. Among these are surveys, commodity prices, exchange rates, economic indicators from the real sector, labour market, money market data and so on. Most data are released with delays and we explicitly account for this in our model.

Before running analyses, we transform the input variables in the following way. First, we transform predictors in order to remove their trends (please see Appendix 1). Second, we remove seasonality from each series by using the US Census X-11 filter. Third, we smooth data outliers. Then we split the sample into balanced and unbalanced parts, where the balanced part contains observations with all monthly predictors available for the whole quarter. The series in the balanced part are standardised by subtracting their mean and dividing them for their standard deviation.

GDP forecast model methodology

Our model forecasts quarterly GDP growth h quarters ahead (actual GDP data are released with approximately a 1.5-month lag after the end of the respective quarter). A large panel of macroeconomic time series, which become available at monthly frequencies, serve as input variables. Our model produces a forecast at the end of each month, as soon as the Federal State Statistics Service and REB publishes monthly data. Revisions (vintages) of the forecast made in the later months of a quarter can be viewed as updated forecasts for the same quarter, conditional on more recent information. The arrival of a new piece of monthly data provides a natural occasion to revise the GDP growth forecast.

We have five consecutive estimates of GDP growth for a given quarter. For instance, if we forecast the next quarter's (i.e. 1Q10) GDP growth at the end of October - beginning of November, we make our first estimate of 1Q10 GDP growth on the basis of a few market variables available for the preceding quarter 4Q09 and almost all data available for 3Q09. As of the end of November, most Rosstat data become available for October, the first month of 4Q09, and we are able to revise our preliminary GDP forecast. As of the end of December, the third estimate (vintage) of the GDP forecast will take place, etc. We make our last revision of the 1Q10 GDP forecast at the end of February – when all data for 4Q09 become available. Such an abundance of data allows us to produce our best forecast.

Thus, in the first month of any given quarter, we will publish a preliminary estimate of the next quarter's GDP growth, and in the second month, we will release a final GDP forecast for that quarter. For example, in this report, we will produce a final revision of 4Q09 GDP growth and a second estimate of 1Q10 GDP growth.

The basic idea behind our approach is that the movements observed in a large set of economic indicators are forced by a few common sources or shocks (please see Appendix 3). Therefore, all time series in our dataset can be viewed as being driven by a small number of common factors. In addition, each variable contains an idiosyncratic component (or noise). The aggregate effect of noise declines as more input variables are included into the model. If the number of input time series is large enough, as in our data sample, then idiosyncratic error terms tend to be mutually cancelled out.

Technically, by applying a principal components method, we convert a large number of input variables (108) into a small number of several common factors, which describe the bulk of variability of the initial data set. According to Bai-Ng criteria, the number of static factors in our dataset is estimated at two. To be on the safe side, we also consider specifications of the forecasting equation that involve one and

three factors. We use these factors as predictors in the GDP forecast h quarters ahead. It is conventional in macro forecasting literature to include lags of the target variable (i.e. GDP) as extra predictors in addition to the factors (if needed).

$GDP_{t+h} = \mu + \sum_{j=1}^{r} factor_{j,t} + \sum_{i=1}^{q} GDP_{t-i}$, where

q –a number of GDP lags (GDP lag with i=0 is available for 2-5 vintages)

r – a number of factors

Before running the analysis, we transform all input time series to obtain stationarity (i.e. trends and seasonality are removed) and smooth data outliers. Since all of the time series we use to forecast quarterly GDP growth are available at monthly frequencies, we implement the following procedure to combine GDP growth at quarterly frequencies and data at monthly frequencies. Monthly observations for all series are transformed to obtain stationarity and aggregated to quarterly averages. Then, these quarterly series are standardised (so that the sample means are zeros and standard deviations are ones).

Applying the principal component method to the input series, we usually encounter uneven availability of the most recent data or the so-called ‘jagged edge’ problem. For example, by the end of November we have most of the economic indicators up to October, but REB survey indicators only up to September. One solution is based on the Kalman filter (please see Appendix 4). In brief, we apply principal components to the largest balanced part of the sample (i.e. the time series up to the quarter when all of the series are available). Then we obtain the up-to-date estimate of the vector of factors by applying Kalman filter formulas and using values of only those variables for which the most recent data are available. As a result, we have values for static factors for the whole of the analysed period, including the quarter(s) when some of the predictors have missing values.

One-quarter-ahead model produces the best forecast

A conventional way to evaluate the quality of a forecast is to check its out-of-sample performance. Suppose that we have a sample of data covering periods t=1,…,T. Starting with subsample t=1,…,P-h (P<T), we estimate factors and the forecasting equation and produce the forecast for period P, GDP_P. Adding one observation period to the sample (i.e. t=P-h+1), we re-estimate factors and the forecasting equation on the updated sample and produce the GDP forecast for period P+1, GDP_{P+1}. We continue until the final time observation t=T-h is reached. The RMSFE is defined as:

RMSFE=$\sqrt{\frac{1}{T-P+1}\sum_{t=P}^{T}(GDP\ actual_t - GDP\ forecast_t)^2}$

We set a period from 1Q96 to 1Q02-h quarters as a subsample for the first forecast (i.e. for h=1 the subsample ends in 4Q01 and for h=2 in 3Q01). Given this subset of data, we forecast GDP growth in 1Q02. Next, we add 2Q02 data (1Q02 if h=1) to the initial subsample, re-estimate factors and the forecasting equation and forecast 2Q02. Thus, for each quarter we use data that was available by that time and forecast a quarter GDP h quarters ahead. Current quarter GDP nowcast implies

h=0; h=1 indicates that we do a GDP forecast for the next quarter; h=3 means that we forecast GDP growth in three quarters from now with help from the current quarter of economic indicators (i.e. in March we forecast GDP changes for 4Q of that year). A deviation of our forecast from the actual GDP growth is measured by RMSFE. Between two alternative forecasts, we view the one with the lowest RMSFE as the most accurate.

Note that, for different vintages of our forecast, the best specifications of the forecasting equation will be different, in general. We distinguish between a vintage of the forecast and the forecast horizon. These are completely different dimensions. The vintage is related to the information set on which we condition our forecast. For example, vintage 5 of the forecast means that we forecast GDP for quarter t using information available as of the end of the second month of that quarter. At the same time, we can try different specifications of the forecasting equation for the vintage 5 forecast, each corresponding, in particular, to a certain choice of h: quarter t GDP on contemporaneous factors and own lags (i.e. h=0), quarter t GDP on the first lags of factors and own lags (i.e. h=1), etc. We believe this makes perfect sense as we encounter a trade-off. On the one hand, for a given vintage, higher h implies that factor values at t-h that predict the GDP for quarter t are more accurately estimated. The reason is that, as of the end of the second month of t, more relevant data are available for quarter t-h than for quarter t-h+1, etc. On the other hand, higher h increases forecast uncertainty.

To our surprise, a model for the one-quarter-ahead forecasting equation (h=1) performs much better than the current quarter forecasting equation (h=0). One possible interpretation is that our dataset is dominated by the variables that are mostly driven by the shock that affects GDP with a lag. This explanation is consistent with the fact that a substantial part of our dataset comprises survey variables, which presumably contain a non-negligible forward-looking component. For the time being, the models with no GDP lags have the lowest RMSFE among different forecast specifications.

Figure 3: RMSFE for h periods ahead GDP forecast (multiplied by 100)

Model	No GDP lags	One GDP lag	Two GDP lags	Three GDP lags	Four GDP lags
h=0					
One factor	2.15	2.13	2.15	2.21	2.26
Two factors	1.71	1.73	1.81	1.80	1.81
Three factors	1.56	1.55	1.58	1.61	1.58
h=1					
One factor	1.11	1.17	1.19	1.13	1.17
Two factors	1.12	1.32	1.34	1.42	1.49
Three factors	0.95	1.08	1.10	1.20	1.29
h=2					
One factor	2.27	2.27	2.30	2.42	2.40
Two factors	2.25	2.23	2.19	2.34	2.34
Three factors	2.68	2.72	2.68	2.80	2.87
h=3					
One factor	2.22	2.23	2.28	2.28	2.31
Two factors	2.26	2.26	2.30	2.30	2.32
Three factors	2.28	2.29	2.35	2.33	2.35

Source: NES estimates, Renaissance Capital estimates

Thus, the one-quarter-ahead GDP forecasting equation (h=1) with no GDP lags will be used in further analysis. Although a three-factor model has the lowest RMSFE, we also experiment with those involving one and two factors.

It is also worth pointing out that the contribution of factors to our GDP forecast is quite high: RMSFE for zero-factor models (GDP lags only) are much higher than those for one-factor models.

Figure 4: Contribution of factors in GDP forecast, RMSFE. (multiplied by 100)

Model	One GDP lag	Two GDP lags	Three GDP lags	Four GDP lags
Zero factor	2.22	2.22	2.24	2.29
One factor	1.17	1.19	1.13	1.17

Source: NES estimates, Renaissance Capital estimates

More data are not necessarily a good thing

There are two important assumptions behind the factor model. First, every time series has a non-zero common component. Second, error terms are weakly correlated. If we include into the dataset a variable that is not correlated with the rest of the data then no useful information is added, only noise. If a group of variables in the dataset has highly correlated error terms then these error terms will reinforce rather than attenuate each other and this will deteriorate the estimate of factors. A practical solution is offered by Boivin and Ng (2006) and Bai and Ng (2008), who suggest, accordingly, to re-weigh and pre-select input series before running factor analysis.

Boivin and Ng (2006): Weighted input variables

Boivin and Ng (2006) propose assigning weights to variables. A series gets the lower weight the higher the fraction of variance explained by its idiosyncratic component and/or the higher its average absolute correlation with the other variables. The purpose of the re-weighting procedure is to downsize the contribution of variables with a high degree of noise and high degree of cross-correlation in the error term.

Rule SWa weights are set as reciprocals of diagonal elements of the covariance matrix of idiosyncratic terms. The rule SWb weight for each series inversely depends on a sum of absolute values of covariances of this variable with all others including itself.

Boivin and Ng's data re-weighting scheme does not seem to improve the RMSFE of our model, probably because it only pays attention to noise-to-signal ratios and cross-correlations of idiosyncratic errors, entirely ignoring relative forecasting content of individual predictors with respect to GDP. Targeted predictors methods, on the contrary, form factors using a subset of those variables (predictors) that have a high predictive power for GDP growth.

Figure 5: RMSFE for Boivin and Ng methods (multiplied by 100; weighted predictors)

Model	No GDP lags	One GDP lag	Two GDP lags	Three GDP lags	Four GDP lags
SWa (h=1)					
One factor	1.20	1.28	1.30	1.23	1.28
Two factors	1.23	1.37	1.37	1.40	1.47
Three factors	0.98	1.10	1.10	1.18	1.27
SWb (h=1)					
One factor	1.17	1.23	1.25	1.18	1.23
Two factors	1.19	1.33	1.34	1.39	1.45
Three factors	0.97	1.08	1.10	1.19	1.28

Source: NES estimates, Renaissance Capital estimates

Bai and Ng (2008): Targeted predictors procedure

Bai and Ng (2008) suggest a so-called targeted predictors procedure. In terms of theoretical considerations, the importance of different kinds of macroeconomic shocks (monetary, fiscal, productivity, terms of trade) is different for different variables. For example, monetary shocks tend to explain a high fraction in the variability of prices and a low fraction in that of sectoral outputs while the opposite is true about productivity shocks. This implies that different variables are helpful to a different extent in estimating a particular factor of interest. Ideally, we would like to keep in our dataset only those series that are driven mostly by the same factors that are important for GDP.

Proceeding variable by variable, one can rank all time series according to their ability to forecast GDP, then only variables with the highest rankings are used to estimate factors. Effectively, this approach removes from the information set all data that are irrelevant for explaining the dynamics of GDP.

One implementation of the targeted predictors approach is the so-called hard thresholding (HT) procedure, which ranks predictors based on their forecasting content (as measured by the absolute values of respective t-statistics) in single-predictor forecasting regressions.

The results of the HT method indicate that a state of the Russian economy is closely interconnected with the level of activity in the banking sector and banks' ability and willingness to finance the real economy. According to HT ranking (please see Appendix 2), REB index 11: Diffusion index of credit terms, industry, actual and Money supply M2, predict one-quarter-ahead change in real GDP best of all. Money supply M2 indirectly points at the level of activity in the banking sector, since M2 can be represented as a product of M0 (or the monetary base adopted for Russia) and money multiplier. When the economy's prospects are good, banks are optimistic and expand credit to the economy, which raises the money multiplier and inflates M2. When expectations are not so good, credit institutions prefer to decrease their loan exposure and accumulate excess reserves. As a result, the money multiplier decreases, thus shrinking the money supply.

Another possible interpretation relates to oil revenues. When the price of oil is high, the inflow of petrodollars to the economy is high, which allows the central bank to accumulate foreign reserves in exchange for newly created money. Lower oil prices imply worse prospects for the economy as a whole and depreciation of the rouble. The latter gives agents incentives to rebalance their portfolios by increasing foreign asset holdings. Under the sort of managed float we have in Russia, this leads to an endogenous shrinkage of the monetary base and money supply. We can highlight the importance of the link between affordability of banking credit and a state of the economy by using 2008 as an example. In 2008, the financial crisis was followed by an economic recession.

Ranking by their predictive power, the REB index of credit terms and M2 are followed by oil prices (Urals) and industrial production.

Figure 6: RMSFE for hard thresholding method (multiplied by 100)

Model	30 predictors	50 predictors	70 predictors	80 predictors	90 predictors	100 predictors	All predictors
No GDP lags							
One factor	1.30	1.15	1.15	1.16	1.13	1.12	1.11
Two factors	1.40	1.15	1.22	1.16	1.15	1.11	1.12
Three factors	1.39	1.14	1.13	1.07	1.02	1.00	0.95

Source: NES estimates, Renaissance Capital estimates

According to out-of-sample forecast performance evaluation, the HT method does not help us improve our model.

In addition, in applying HT we can end up selecting variables that are too similar and miss information in other predictors. The least angle regression (LARS) method provides more flexible alternatives as it performs subset selection and shrinkage simultaneously.

Figure 7: RMSFE for least angle regression method (multiplied by 100)

Model	10 predictors	20 predictors	30 predictors	40 predictors
No GDP lags				
One factor	1.36	1.07	1.02	0.98
Two factors	1.34	0.97	0.91	0.90
Three factors	1.12	1.02	0.99	0.93
One GDP lag				
One factor	1.36	1.05	0.98	0.94
Two factors	1.37	1.00	0.95	0.94
Three factors	1.12	1.02	1.00	0.92
Two GDP lags				
One factor	1.28	0.98	0.93	0.86
Two factors	1.28	0.99	0.93	0.86
Three factors	1.10	1.05	0.99	0.91
Three GDP lags				
One factor	1.24	0.99	0.91	0.86
Two factors	1.26	1.00	0.93	0.86
Three factors	1.07	1.08	1.00	0.90

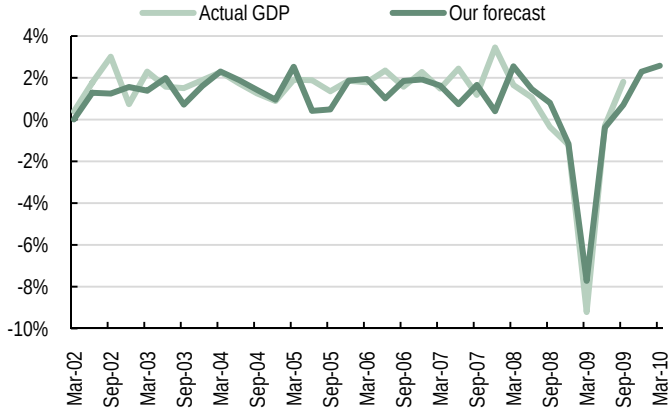
Source: NES estimates, Renaissance Capital estimates

However, out-of-sample forecast performance evaluation indicates that the LARS method does not improve results either. Thus, this time we use all predictors with no weights for GDP forecasting.

Our final choice: Three-factor model with no GDP lags

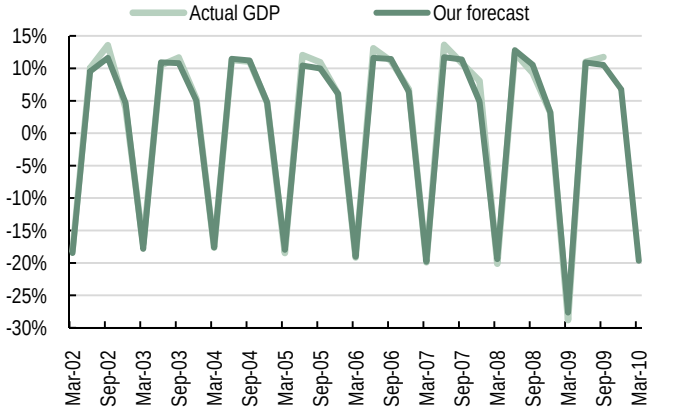
According to out-of-sample forecast performance evaluation, the three-factor model with no GDP lags and all predictors involved outperforms all other specifications, therefore, this time, we consider it as our baseline forecasting model. In the future, however, we plan to test all other specifications and methods of variable selection routinely to check whether our model still outperforms them.

Figure 8: Seasonally adjusted GDP growth, QoQ



Source: Rosstat, NES estimates, Renaissance Capital estimates

Figure 9: Unadjusted GDP growth, QoQ



Source: Rosstat, NES estimates, Renaissance Capital estimates

Our model outperforms the rivals and naïve benchmarks

We evaluate the quality of our forecasting model by looking at its ability to forecast out of sample. A model is considered superior if it produces forecasts with lower RMSFE statistics compared with its rivals, or benchmark forecasts. Based to the RMSFE comparison, our model beats naïve models and the performance of competing models, among which the MED is the toughest.

Random walk and univariate autoregression are naïve models that serve as conventional benchmarks in macro-forecasting literature. All specifications of our model with h=1 considerably outperform them both. Most specifications with h=0 have a lower RMSFE than those for the naïve benchmarks but not remarkably so.

Figure 10: Performance of naïve benchmarks for one-quarter-ahead forecast (RMSFE multiplied by 100)

Naïve benchmark	RMSFE
Random walk with drift	2.23
AR(1)	2.22
AR(2)	2.22
AR(3)	2.24
AR(4)	2.29

Source: NES estimates, Renaissance Capital estimates

The Development Center produces the coincident, leading, and lagging indices for the Russian economy. Although not directly comparable with GDP growth figures, these indices can be used as inputs for a GDP growth forecast. Specifically, the best forecast based on Development Center indices is constructed in the following way: take the leading index and its lags as well as lags of GDP growth and try several alternatives. Pick the best specification based on the out-of-sample performance and call it the Development Center forecast. RMSFE for a quarter-ahead GDP forecast (multiplied by 100) is 1.97, which exceeds the respective statistic of 0.95 in our model.

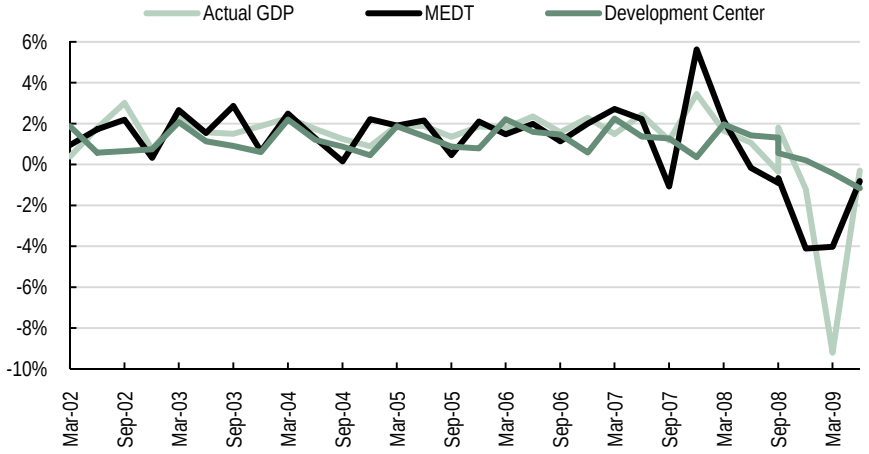
Figure 11: Performance of forecast based on Development Center's indices (RMSFE multiplied by 100)

Model	No GDP lags	One GDP lag	Two GDP lags	Three GDP lags	Four GDP lags
Nowcast (h=0)					
Only contemporaneous CLI	2.22	2.15	2.17	2.17	2.19
Contemporaneous CLI and one lag	2.12	2.04	2.06	2.06	2.07
Contemporaneous CLI and two lags	1.92	1.92	1.93	1.94	1.93
Forecast one quarter ahead (h=1)					
Only contemporaneous CLI	2.14	2.19	2.19	2.21	2.26
Contemporaneous CLI and one lag	2.02	2.05	2.06	2.07	2.12
Contemporaneous CLI and two lags	1.97	2.01	2.02	2.03	2.07

Source: Development Center, NES estimates, Renaissance Capital estimates

The MED is the toughest rival for our model. The ministry produces monthly GDP proxies and typically publishes it within three weeks after the end of a respective month. The monthly GDP estimates are aggregated to quarterly data to compare them with actual GDP changes. GDP forecasts by the MED have a RMSFE (multiplied by 100) equal to 1.48, which means that our model outperforms it. Another advantage of our GDP forecast is that we release our final revision about seven weeks earlier than the ministry publishes its ultimate estimate.

Figure 12: Performance of MED forecast and Development Center index (data is s/a)



Source: Rosstat, MED, Development Center

Implementation details

GDP forecast monthly revisions

We produce five vintages of the GDP forecast for a given quarter. They represent GDP forecasts made in the first-to-third months of the preceding quarter (representing one-to-three vintages), and the first-to-second months of the quarter of interest (representing four-to-five vintages).

Apparently, the first and second vintages use the smallest information set, which results in the highest RMSFE. For the third-to-fifth vintages, the RMSFE gradually declines reaching the lowest values for the fifth vintage when all required data are available.

Figure 13: RMSFE for different vintages (multiplied by 100)

Model	No GDP lags	One GDP lag	Two GDP lags	Three GDP lags	Four GDP lags
vintage 1					
One factor	1.86	1.86	1.87	1.84	1.82
Two factors	1.88	1.88	1.89	1.76	1.91
Three factors	1.84	1.84	1.86	1.76	1.81
vintage 2					
One factor	2.43	2.43	2.80	3.02	3.07
Two factors	2.38	2.38	2.75	2.91	2.99
Three factors	2.12	2.12	2.27	2.36	2.35
vintage 3					
One factor	1.67	1.67	1.88	2.01	2.05
Two factors	1.66	1.66	1.85	1.98	2.05
Three factors	1.53	1.53	1.64	1.76	1.76
vintage 4					
One factor	1.45	1.45	1.52	1.57	1.61
Two factors	1.48	1.48	1.50	1.67	1.71
Three factors	1.21	1.21	1.29	1.42	1.43
vintage 5					
One factor	1.11	1.17	1.19	1.13	1.17
Two factors	1.12	1.32	1.34	1.42	1.49
Three factors	0.95	1.08	1.10	1.20	1.29

Source: NES estimates, Renaissance Capital estimates

It is worth noting that the model specification with three factors and no GDP lags outperforms the other specifications for all vintages. Consequently, we will use this model to forecast 4Q09 GDP growth (this is the fifth vintage) and 1Q10 (second vintage).

Appendix 1: Input variables

Figure 14: Input time series and their treatment methods

N	Variable	Source	Publication lag	Data transformation	Seasonally adjusted
1	Consumer price index	Federal State Statistics Service	1	Differences in logs	Yes
2	Producer price index	Federal State Statistics Service	1	Differences in logs	Yes
3	Money supply M2, end of period	Federal State Statistics Service	1	Differences in logs	Yes
4	Money M0, end of period	Federal State Statistics Service	1	Differences in logs	Yes
5	Real effective exchange rate	IMF(CBR if IMF data is missing)	1	Differences in logs	No
6	USD/RUB RER, end of period	Central Bank of Russia	0	Differences in logs	No
7	CBR USD/RUB, end of period	Central Bank of Russia	0	Differences in logs	No
8	CBR GBP/RUB, end of period	Central Bank of Russia	0	Differences in logs	No
9	CBR CAD/RUB, end of period	Central Bank of Russia	0	Differences in logs	No
10	RTS index, end of period	"RTS" Stock Exchange	0	Differences in logs	No
11	CBR refinancing rate, end of period	Central Bank of Russia	0	Differences	No
12	Overnight interest rates on bank loans (O/N Mosibor), end of period	Bloomberg	0	Differences	No
13	Eurobond YtM (Russia-30 YTM and MinFin V prior February 2006), end of period	Bloomberg	0	Differences	No
14	USD Libor 6m, end of period	Bloomberg	0	Differences	No
15	Unemployment	Federal State Statistics Service	1	Differences	Yes
16	Labour requirements, K	Federal State Statistics Service	1	Differences in logs	Yes
17	Retail sales real	Federal State Statistics Service	1	Differences in logs	Yes
18	Retail service	Federal State Statistics Service	1	Differences in logs	Yes
19	Wholesale sales	Federal State Statistics Service	1	Differences in logs	Yes
20	Investment in productive capacity	Federal State Statistics Service	1	Differences in logs	Yes
21	Real disposable income	Federal State Statistics Service	1	Differences in logs	Yes
22	Real wages	Federal State Statistics Service	1	Differences in logs	Yes
23	Nominal wage due	Federal State Statistics Service	1	Differences in logs	Yes
24	New house building	Federal State Statistics Service	1	Differences in logs	Yes
25	Cargo shipment	Federal State Statistics Service	1	Differences in logs	Yes
26	Cargo shipment tariffs	Federal State Statistics Service	1	Differences in logs	Yes
27	Accounts payable, RUBbn	Federal State Statistics Service	2	Differences in logs	Yes
28	Accounts payable due, RUBbn	Federal State Statistics Service	2	Differences in logs	Yes
29	Accounts receivable, RUBbn	Federal State Statistics Service	2	Differences in logs	Yes
30	Accounts receivable due, RUBbn	Federal State Statistics Service	2	Differences in logs	Yes
31	Merchandise export	Federal State Statistics Service	1	Differences in logs	Yes
32	Trade balance	Federal State Statistics Service	1	Level	Yes
33	Fed budget exp	Federal State Statistics Service	1	Differences in logs	Yes
34	Fed budget balance	Federal State Statistics Service	1	Level	Yes
35	Urals Mediterranean crude oil spot price, USD/barrel, end of period	Bloomberg	0	Differences in logs	No
36	Aluminium A7e MB CIS, USD/tonne, end of period	Metal Bulletin	0	Differences in logs	No
37	Russia Black Sea export hot rolled steel, USD/tonne, end of period	Steel Business Briefing Commodities	0	Differences in logs	No
38	Russia Black Sea export cold rolled steel, USD/tonne, end of period	Steel Business Briefing Commodities	0	Differences in logs	No
39	LME Copper, USD/MT, end of period	London Metal Exchange	0	Differences in logs	No
40	LME Tin, USD/MT, end of period	London Metal Exchange	0	Differences in logs	No
41	LME Nickel, USD/MT, end of period	London Metal Exchange	0	Differences in logs	No
42	LME Aluminium, USD/MT, end of period	London Metal Exchange	0	Differences in logs	No
43	1. Diffusion index of output prices, industry, actual (percent rising over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
44	2. Diffusion index of input prices, industry, actual (percent rising over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
45	4. Diffusion index of wages, industry, actual (percent rising over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
46	5. Diffusion index of employment, industry, actual (percent rising over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
47	6. Diffusion index of output, industry, actual (percent rising over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
48	7. Diffusion index of order-book level, industry, actual (percent rising over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
49	8. Diffusion index of stocks of finished products, industry, actual (percent rising over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
50	10. Diffusion index of output/input prices ratio, industry, actual (percent improving over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
51	11. Diffusion index of credit terms, industry, actual (percent improving over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
52	14. Diffusion index of expenditures for equipment, industry, actual (percent rising over 1-month spans)	Russian Economic Barometer (REB)	2	Differences	Yes
53	21. Diffusion index of output prices, industry, anticipated (percent rising over 3-month spans)	Russian Economic Barometer (REB)	0	Differences	Yes
54	22. Diffusion index of input prices, industry, anticipated (percent rising over 3-month spans)	Russian Economic Barometer (REB)	0	Differences	Yes
55	24. Diffusion index of wages, industry, anticipated (percent rising over 3-month spans)	Russian Economic Barometer (REB)	0	Differences	Yes
56	25. Diffusion index of employment, industry, anticipated (percent rising over 3-month spans)	Russian Economic Barometer (REB)	0	Differences	Yes
57	26. Diffusion index of output, industry, anticipated (percent rising over 3-month spans)	Russian Economic Barometer (REB)	0	Differences	Yes
58	27. Diffusion index of expenditures for equipment, industry, anticipated (percent rising over 3-month spans)	Russian Economic Barometer (REB)	0	Differences	Yes
59	28. Diffusion index of financial situation, industry, anticipated (percent improving over 3-	Russian Economic Barometer (REB)	0	Differences	Yes

N	Variable	Source	Publication lag	Data transformation	Seasonally adjusted
	month spans)				
60	29. Diffusion index of order-book level, industry, anticipated (percent rising over 3-month spans)	Russian Economic Barometer (REB)	0	Differences	Yes
61	30. Diffusion index of bank loans, industry, anticipated (percent rising over 3-month spans)	Russian Economic Barometer (REB)	0	Differences	Yes
62	13. Capacity utilisation rate, industry (normal monthly level = 100)	Russian Economic Barometer (REB)	2	Differences	Yes
63	15. Labour utilisation rate, industry (normal monthly level = 100)	Russian Economic Barometer (REB)	2	Differences	Yes
64	16. Stocks of finished products, industry (normal monthly level = 100)	Russian Economic Barometer (REB)	2	Differences	Yes
65	17. Order-book level, industry (normal monthly level = 100)	Russian Economic Barometer (REB)	2	Differences	Yes
66	19. Share of enterprises in 'good' or 'normal' financial conditions , industry (%)	Russian Economic Barometer (REB)	2	Differences	Yes
67	20. Share of enterprises not buying equipment for 2 and more months, industry (%)	Russian Economic Barometer (REB)	2	Differences	Yes
68	31. Anticipated interest rates on bank credits (in roubles) to be received in the course of 3 months, industry (% on annual basis)	Russian Economic Barometer (REB)	2	Differences	Yes
69	32. Share of enterprises not indebted to banks and not going to be indebted in the course of 3 months, industry (%)	Russian Economic Barometer (REB)	2	Differences	Yes
70	33. Indebtedness to banks, industry (normal monthly level = 100)	Russian Economic Barometer (REB)	2	Differences	Yes
71	34. Share of enterprises not going to make new bank borrowings in the next 3 months, industry (%)	Russian Economic Barometer (REB)	2	Differences	Yes
72	Industrial production (total)	The Higher School of Economics	1	Differences in logs	Yes
73	Fuel-energy complex	The Higher School of Economics	1	Differences in logs	Yes
74	Utilities	The Higher School of Economics	1	Differences in logs	Yes
75	Fuel industry	The Higher School of Economics	1	Differences in logs	Yes
76	Oil-producing industry	The Higher School of Economics	1	Differences in logs	Yes
77	Oil-refining industry	The Higher School of Economics	1	Differences in logs	Yes
78	Gas industry	The Higher School of Economics	1	Differences in logs	Yes
79	Coal industry	The Higher School of Economics	1	Differences in logs	Yes
80	Ferrous metallurgy	The Higher School of Economics	1	Differences in logs	Yes
81	Nonferrous metallurgy	The Higher School of Economics	1	Differences in logs	Yes
82	Engineering and	The Higher School of Economics	1	Differences in logs	Yes
83	Chemical and petrochemical industry	The Higher School of Economics	1	Differences in logs	Yes
84	Timber industry	The Higher School of Economics	1	Differences in logs	Yes
85	Building materials industry	The Higher School of Economics	1	Differences in logs	Yes
86	Food industry	The Higher School of Economics	1	Differences in logs	Yes
87	Textile industry	The Higher School of Economics	1	Differences in logs	Yes
88	Mining	The Higher School of Economics	1	Differences in logs	Yes
89	Fuel-energy mining	The Higher School of Economics	1	Differences in logs	Yes
90	Coal mining	The Higher School of Economics	1	Differences in logs	Yes
91	Crude oil and gas mining	The Higher School of Economics	1	Differences in logs	Yes
92	Metal mining	The Higher School of Economics	1	Differences in logs	Yes
93	Other minerals mining	The Higher School of Economics	1	Differences in logs	Yes
94	Manufacturing industry	The Higher School of Economics	1	Differences in logs	Yes
95	Food manufacturing	The Higher School of Economics	1	Differences in logs	Yes
96	Textile and clothing manufacture	The Higher School of Economics	1	Differences in logs	Yes
97	Pulp and paper manufacture	The Higher School of Economics	1	Differences in logs	Yes
98	Output of oil and coke	The Higher School of Economics	1	Differences in logs	Yes
99	Output of coke	The Higher School of Economics	1	Differences in logs	Yes
100	Output of petrochemicals	The Higher School of Economics	1	Differences in logs	Yes
101	Output of chemicals	The Higher School of Economics	1	Differences in logs	Yes
102	Metallurgical industry	The Higher School of Economics	1	Differences in logs	Yes
103	Output of machines and equipment	The Higher School of Economics	1	Differences in logs	Yes
104	Output of electrical equipment	The Higher School of Economics	1	Differences in logs	Yes
105	Output of transport means	The Higher School of Economics	1	Differences in logs	Yes
106	Production and distribution of electricity gas and water	The Higher School of Economics	1	Differences in logs	Yes
107	Intensity of structural reforms	The Higher School of Economics	2	Differences	Yes
108	Quality of structural reforms	The Higher School of Economics	1	Differences	Yes

Source: Rosstat, REB, Bloomberg, HSE, NES estimates, Renaissance Capital estimates

Appendix 2: Hard thresholding method results

Figure 15: Predictors ranked by their ability to forecast GDP

N of predictor	Short description	Average rank	Min	Max
51	11. Diffusion index of credit terms, industry, actual (percent improving over 1-month spans)	2	1	17
3	Money supply M2, end of period	3	1	3
72	Industrial production (total)	3	1	7
85	Building materials industry	6	3	9
88	Mining	6	3	13
102	Metallurgical industry	7	4	23
94	Manufacturing industry	7	4	16
82	Engineering and	8	4	12
2	Producer price index	9	4	17
95	Food manufacturing	13	6	39
81	Nonferrous metallurgy	14	4	29
59	28. Diffusion index of financial situation, industry, anticipated (percent improving over 3-month spans)	15	9	31
4	Money M0, end of period	15	9	25
80	Ferrous metallurgy	16	11	38
105	Output of transport means	18	12	28
66	19. Share of enterprises in 'good' or 'normal' financial conditions , industry (%)	18	11	29
89	Fuel-energy mining	21	10	42
90	Coal mining	21	14	35
79	Coal industry	23	16	37
108	Quality of structural reforms	23	3	36
87	Textile industry	23	15	38
56	25. Diffusion index of employment, industry, anticipated (percent rising over 3-month spans)	24	3	37
73	Fuel-energy complex	25	13	48
35	Urals Mediterranean crude oil spot price, USD/barrel, end of period	25	9	33
55	24. Diffusion index of wages, industry, anticipated (percent rising over 3-month spans)	27	7	37
75	Fuel industry	27	14	57
30	Accounts receivable due, RUBbn	28	13	81
52	14. Diffusion index of expenditures for equipment, industry, actual (percent rising over 1-month spans)	28	15	43
19	Wholesale sales	29	18	71
63	15. Labour utilisation rate, industry (normal monthly level = 100)	31	15	38
9	CBR CAD/RUB, end of period	32	15	79
41	LME Nickel, USD/MT, end of period	33	22	50
86	Food industry	35	16	55
18	Retail service	35	26	49
67	20. Share of enterprises not buying equipment for 2 and more months, industry (%)	35	6	61
62	13. Capacity utilisation rate, industry (normal monthly level = 100)	36	9	50
45	4. Diffusion index of wages, industry, actual (percent rising over 1-month spans)	37	14	46
25	Cargo shipment	37	22	45
42	LME Aluminium, USD/MT, end of period	37	13	55
91	Crude oil and gas mining	40	28	58
103	Output of machines and equipment	40	27	50
99	Output of coke	40	32	50
28	Accounts payable due, RUBbn	40	28	59
10	RTS index, end of period	44	30	51
107	Intensity of structural reforms	45	12	53
104	Output of electrical equipment	46	33	55
13	Eurobond YtM (Russia-30 YTM and MinFin V prior February 2006), end of period	47	22	74
39	LME Copper, USD/MT, end of period	48	14	61
65	17. Order-book level, industry (normal monthly level = 100)	50	26	59
96	Textile and clothing manufacture	51	46	65
1	Consumer price index	52	30	85
93	Other minerals mining	52	47	63
23	Nominal wage due	53	37	62
58	27. Diffusion index of expenditures for equipment, industry, anticipated (percent rising over 3-month spans)	54	27	71
26	Cargo shipment tariffs	55	41	93
36	Aluminium A7e MB CIS, USD/tonne, end of period	55	34	80
20	Investment in productive capacity	55	42	71
92	Metal mining	57	42	72
76	Oil-producing industry	58	46	84
27	Accounts payable, RUBbn	60	52	96
31	Merchandise export	62	28	75
57	26. Diffusion index of output, industry, anticipated (percent rising over 3-month spans)	63	44	80
74	Utilities	64	54	86
46	5. Diffusion index of employment, industry, actual (percent rising over 1-month spans)	64	47	72
106	Production and distribution of electricity gas and water	65	57	85

N of predictor	Short description	Average rank	Min	Max
29	Accounts receivable, RUBbn	65	55	104
12	Overnight interest rates on bank loans (O/N Mosibor), end of period	67	61	88
16	Labour requirements, K	70	41	78
21	Real disposable income	70	62	78
40	LME Tin, USD/MT, end of period	72	31	93
83	Chemical and petrochemical industry	73	33	82
33	Fed budget exp	73	63	108
11	CBR refinancing rate, end of period	73	63	97
38	Russia Black Sea export cold rolled steel, USD/tonne, end of period	73	56	91
71	34. Share of enterprises not going to make new bank borrowings in the next 3 months, industry (%)	75	68	91
8	CBR GBP/RUB, end of period	76	64	90
24	New house building	76	55	98
54	22. Diffusion index of input prices, industry, anticipated (percent rising over 3-month spans)	78	41	86
53	21. Diffusion index of output prices, industry, anticipated (percent rising over 3-month spans)	79	59	90
78	Gas industry	80	70	88
84	Timber industry	81	67	90
98	Output of oil and coke	81	73	94
7	CBR USD/RUB, end of period	82	53	108
60	29. Diffusion index of order-book level, industry, anticipated (percent rising over 3-month spans)	82	63	93
32	Trade balance	84	21	94
77	Oil-refining industry	85	76	97
6	USD/RUB RER, end of period	86	68	99
15	Unemployment	86	73	103
101	Output of chemicals	87	49	95
47	6. Diffusion index of output, industry, actual (percent rising over 1-month spans)	87	66	94
100	Output of petrochemicals	88	81	101
48	7. Diffusion index of order-book level, industry, actual (percent rising over 1-month spans)	89	56	98
37	Russia Black Sea export hot rolled steel, USD/tonne, end of period	90	68	105
22	Real wages	90	83	106
43	1. Diffusion index of output prices, industry, actual (percent rising over 1-month spans)	92	76	99
34	Fed budget balance	95	40	108
50	10. Diffusion index of output/input prices ratio, industry, actual (percent improving over 1-month spans)	96	75	107
64	16. Stocks of finished products, industry (normal monthly level = 100)	98	91	103
5	Real effective exchange rate	98	93	108
69	32. Share of enterprises not indebted to banks and not going to be indebted in the course of 3 months, industry (%)	99	92	105
17	Retail sales real	100	82	108
68	31. Anticipated interest rates on bank credits (in roubles) to be received in the course of 3 months, industry (% on annual basis)	101	93	108
61	30. Diffusion index of bank loans, industry, anticipated (percent rising over 3-month spans)	102	89	107
14	USD Libor 6m, end of period	102	69	108
44	2. Diffusion index of input prices, industry, actual (percent rising over 1-month spans)	103	75	108
70	33. Indebtedness to banks, industry (normal monthly level = 100)	103	100	108
97	Pulp and paper manufacture	103	87	106
49	8. Diffusion index of stocks of finished products, industry, actual (percent rising over 1-month spans)	105	96	108

Source: NES estimates, Renaissance Capital estimates

Appendix 3: Common factors

Macroeconomic shocks and common factors

Macroeconomists tend to think of aggregate business fluctuations in terms of random shocks occasionally hitting the economy with the effects propagated over time. Mathematically, it can be summarised by a moving average process of infinite order. For simplicity, we assume that the only kind of shock that matters for the Russian economy is an unexpected change in the global oil price ϵ_t^{OIL}. Then the dynamics of the GDP growth rate, denoted as y_t, can be expressed as:

$$y_t = \mu + \sum_{i=0}^{\infty} a_i \, \epsilon_{t-i}^{OIL} \qquad (1)$$

We can interpret equation (1) in the following way: an unexpected increase in the oil price of 1% will induce a change in GDP growth of $a_0$percent on impact, a_1 percent in one month, a_2 percent in two months after the shock and so on. Sequence $\{a_h\}_{h=0}^{\infty}$ is called the impulse response function and describes how the effect of a unit shock propagates through time. One important assumption that we make in (1) is that series y_t is stationary. Stationarity means that the effect of the shock ϵ_t^{OIL} on y_t is temporary and dies out over time; GDP growth thus tends to return to its mean level μ in the long run. Mathematically, this implies that the effect of the shocks a_h becomes negligibly small at long horizons h.

If we re-write (1) in a more laconic way and define the lag operator as Ly_t= y_{t-1},. it follows that $L^2 y_t$ = L(Ly_t) = Ly_{t-1}= y_{t-2} and, similarly, $L^i y_t$= y_{t-i}.

Then (1) is equivalent to:

$$y_t = \mu + \sum_{i=0}^{\infty} a_i \epsilon_{t-i}^{OIL} = \mu + \sum_{i=0}^{\infty} a_i L^i \epsilon_t^{OIL} \equiv \mu + a(L)\, \epsilon_t^{OIL} \qquad (2)$$

where:

$a(L) \equiv \sum_{i=0}^{\infty} a_i L^i$ is a lag polynomial of infinite order.

Examples of macroeconomic disturbances other than oil shocks include unexpected changes in monetary policy, government spending, productivity, expectations, and export/import prices. In general, relatively few kinds of shocks are believed to be important from an empirical standpoint. This implies that numerous available macroeconomic time series can be driven by a relatively small number of common shocks. Empirically, macro aggregate variables feature a high degree of comovement (Stock and Watson, 1999). Mathematically, such a comovement can be accounted for through a generalisation of (2):

$$x_{it} = \sum_{j=0}^{\infty} a'_{ij} \epsilon_{t-j} + \xi_{it} \equiv a_i(L)' \epsilon_t + \xi_{it} \qquad (3)$$

where ϵ_t is a q×1 vector of common shocks and a'_{ij} is a q×1 vector of impulse responses of variables x_{it} to respective shocks at horizon j and ' means: transpose of. Term ξ_{it} is called the idiosyncratic component as opposite to the common component

χ_{it} = $a_i(L)' \epsilon_t$

so that

$$x_{it} = \chi_{it} + \xi_{it} \quad (4)$$

The idiosyncratic term appears in (4) due to measurement errors that are inevitably present in data. The common and idiosyncratic components are assumed uncorrelated at all leads and lags.

One problem with the infinite-order moving average representations (1) and (3) is that each of them involves an infinite number of parameters that cannot be estimated given a finite size of available data samples. One way to overcome this difficulty is to approximate the infinite-order moving average representation of the common component by a parsimonious specification characterised by a finite number of parameters:

$$\chi_{it} = \tilde{\lambda}(L)' f_t \equiv \sum_{l=0}^{p} \lambda'_{il} f_{t-l} \quad (5)$$

$$f_t = \Gamma(L) f_{t-1} + \eta_t \equiv \sum_{l=1}^{s} \Gamma_l f_{t-l} + \eta_t \quad (6)$$

Effectively, equations (4), (5) and (6) impose a dynamic factor structure on the data: they assume that each time series x_{it} contains a common component χ_{it} and idiosyncratic component ξ_{it} and that the common component is a distributed lag of the vector of dynamic factors f_t. = $(f_{1t}, \ldots, f_{qt})$'. The presence of idiosyncratic term ξ_{it} is caused by measurement errors and other non-systematic features in behavior of x_{it}. The error term ξ_{it} can be correlated over time and across different time series. Cross correlation is assumed sufficiently weak (Stock and Watson, 2002a, provide details). The time evolution of x_{it}'s is thus described by an approximate factor model in the sense of Chamberlain and Rothschild (1983) as opposed to the classical factor model where ξ_{it}'s are assumed uncorrelated across variables.

The number of dynamic factors q equals the number of major shocks that affect the economy. For example, if we believe that there are two major shocks for Russia, changes in world oil prices and changes in domestic money supply, then q = 2. In practice, the number of dynamic shocks as well as the lag order of (5), p, are not known a priori but can be determined by statistical methods (Amengual - Watson, 2007, method and Akaike and Schwartz information criteria accordingly). Dynamic factors f_t thus serve as sources of shocks in the model. They are assumed to follow a vector autoregression (VAR) process (6) where η_t is the vector of common shocks. The lag order of the dynamic factor VAR (6), s, can be determined by standard statistical methods (Akaike and Schwartz information criteria).

One way to isolate common components and estimate factors is to re-write equation (5) in terms of static factors and then apply the method of principal components. Define the vector of static factors F_t as one consisting of f_t and their first p lags:

$$F_t = (f'_t, f'_{t-1}, \ldots, f'_{t-p})'$$

Then equations (4) and (5) imply

$$x_{it} = \lambda'_i F_t + \xi_{it} \quad (7)$$

where $\lambda_i = (\tilde{\lambda}'_{io}, \ldots, \tilde{\lambda}'_{ip})'$.

The benefit of switching from dynamic to static factors is straightforward. In equation (7), x_{it} depends only on contemporaneous values of F_t and, hence, the method of principal components can be applied to estimate F_t.

By construction, principal components are orthogonal linear combinations of x_{it}'s that explain the bulk of data variability. This method allows to reduce the dimensionality of the data in the sense that it summarises statistical properties of a panel of variables in a few linear combinations of data, principal components. In the context of factor analysis, principal components are a particular way to estimate factors.

Static factors F_t are not observed but can be consistently estimated as first r principal components of data (see Stock and Watson, 2002a). Intuitively, the reason why principal components serve as a consistent estimate of F_t is a weak correlation across different ξ_{it}'s. If this is the case, gathering a large number of time series in a single data set will make a version of the Law of Large Numbers work and, as a result, only common components should survive.

Note that, effectively, the dimensionality of F_t, r, can be less than (p+1)q since not all lags of dynamic factors will appear on the right-hand side of (5) in general. The VAR describing the evolution of static factors F_t is derived from the dynamic factor VAR, equation (6):

$$F_t = \Phi(\mathrm{L})\, F_{t-1} + \mathrm{G}\eta_t \equiv \sum_{l=1}^{s} \Phi_l F_{t-l} + \mathrm{G}\eta_t \qquad (8)$$

where $\{\Phi_l\}_{l=1}^{s}$ are r×r matrices and G is an r×q matrix of rank q. The number of static factors r is determined by statistical methods (Bai - Ng, 2002, information criterion applied to equation (7)).

Appendix 4: Kalman filter

Recall the factor model introduced in Appendix 3:

$$x_t = \Lambda F_t + \xi_t \tag{1}$$

$$F_t = \Phi F_{t-1} + G\eta_t \tag{2}$$

Where

$$E(\xi_t) = 0, \qquad Var\,(\xi_t) = H, \qquad E(\eta_t) = 0, \qquad Var(\eta_t) = Q$$

The model can be viewed as a model in the so-called state space form where, for simplicity, we assume that the evolution of static factors is governed by the first-order VAR: $\Phi(L) \equiv \Phi$. Equation (1) is called the measurement equation whereas (2) is the transition equation. The vector of unobserved static factors F_t completely describes the state of the economy. Each of the observed variables $x_t \equiv \{x_{it}\}_{i=i}^{N}$ is measured with some noise and equals a linear combination of the state variables up to an additive measurement error (noise term) ξ_{it}.

Given that parameter matrices Λ, H, Φ, and Q as well as the joint probability distribution of disturbance vectors ξ_t and η are known, one can solve the so-called signal extraction problem using the Kalman filter: unobserved factors F_t are estimated based on noisy measurements of observed x_t. It is common in econometrics literature to assume that ξ_t and η are serially uncorrelated Gaussian disturbances and

$$E(\xi_t \eta_t^{i}) = 0 \qquad \text{for all } t = 1, \dots, T$$

The estimation procedure can be split into two stages: updating and forecasting. Denote the history of measurements as

$$X_t \equiv \{x_s\}_{s=1}^{t}$$

At the beginning of each date t, we have some prior knowledge about the distribution of F_t conditional on the last period's information:

$$F_{t|t-1} \equiv E(F_t | X_{t-1})$$

$$P_{t|t-1} \equiv E\big((F_t - F_{t|t-1})(F_t - F_{t|t-1})' \big| X_{t-1}\big)$$

After observing x_t, we can update our beliefs about F_t in Bayesian fashion and the posterior distribution of $F_t$conditional on X_t is fully characterised by

$$F_{t|t} \equiv E(F_t | X_t)$$

$$P_{t|t} \equiv E\big((F_t - F_{t|t})(F_t - F_{t|t})' \big| X_t\big)$$

Now, using transition equation (2), we can forecast $F_{t+1|t}$ and $P_{t+1|t}$ which will serve as parameters of the prior distribution of F_t for the next period.

Forecasting formulas for the Gaussian Kalman filter are given by

$$F_{t|t-1} = \Phi F_{t-1|t-1} \tag{3}$$

$$P_{t|t-1} = \Phi P_{t-1|t-1} \Phi' + GQG' \quad (4)$$

Updating is done as

$$F_{t|t} = F_{t|t-1} + P_{t|t-1}\Lambda^{i}\Psi_{t}^{-1}(x_t - \Lambda F_{t|t-1}) \quad (5)$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}\Lambda^{i}\Psi_{t}^{-1}\Lambda P_{t|t-1} \quad (6)$$

where

$\Psi_t = \Lambda P_{t|t-1}\Lambda^{i} + H$

The Kalman filter is normally initialised by setting

$F_{0|0} = 0$

$\mathrm{vec}(P_{0|0}) = (I - \Phi \oplus \Phi)^{-1}\,\mathrm{vec}(GQG')$

where I is the identity matrix, $\oplus$ denotes Kronecker product and 'vec' vectorisation operator. Chapter four in Harvey (1993) provides derivation details.

We follow Giannone, Reichlin, and Small (2008) in treating the so-called jagged edge problem by the Kalman filter. Such a situation occurs when different pieces of data become available unevenly so that, on a given date, for some variables, we have data up to that date, and for some others only up to the previous period. In our case, the financial time series and commodity prices are available immediately; most Goskomstat indicators are published with a one-month lag, and some REB survey indicators with a two-month lag.

The procedure works as follows: the whole sample is split into two parts – balanced and unbalanced. The balanced part is the longest subsample with no missing values. For example, in our dataset, as of end-Nov 2009, most REB survey data for October and November, as well as Goskomstat data for November, are missing. Hence, the balanced part of the sample is the subsample ending in Sep 2009, the last month when all predictors are observed; while the unbalanced part includes the past two months of data – October and November. We apply principal components to the balanced part of the sample to estimate factors up to September. Then we estimate parameters of the state space model (1)-(2) using factor estimates and observed variables. Given parameter matrices, we apply the Kalman filter (3)-(6) to the unbalanced subsample and estimate factor values for October and November. The lack of some observations for the last two months is accounted for by adjusting the covariance matrix of ξ_{it} in an appropriate way. Specifically, if a value of variable x_i is missing, say, for October then the ith diagonal element of H is replaced by ∞ when the October value of $F_{t|t}$ is computed from (5). The latter substitution means that we treat the signal conveyed by variable x_i in that month as having zero precision. The idea is that a missing value brings in no new information about factors and, hence, it should be discarded from the updating stage.

Appendix 5: GDP forecast model methodology

Core methodology

We exploit the static factor approach (Stock and Watson, 2002a and 2002b). This method estimates factors as regular principal components of input data. In addition to the factors, in the forecasting model we include GDP lags as extra predictors.

The core forecasting procedure is summarised as follows.

1. Transform all input time series to obtain stationarity before running analyses. First, stochastic trends are removed in the course of data transformation (find detail in Appendix 1). Second, all predictors and GDP data are seasonally adjusted by US Census X-11 filter. Third, data outliers are smoothed.

2. Split the sample into balanced and unbalanced parts, where the balanced part contains observations with all monthly predictors available for the whole quarter. In the unbalanced part, some of the predictors may not be observed for the most recent months. For instance, when we update our model in January most of the data will be available for Dec 2009, nevertheless the balanced part should be cut up to Sep 2009, which is the last quarter when all of the predictors are observed.

3. Standardise the balanced part so that the sample means are zeros and standard deviations are ones. Apply principal components method to the balanced subsample and estimate static factors as first r principal components of non-GDP data , t=1,…,T-k, i=1,…,N. The number of static factors r is determined using Bai-Ng (2002) information criterion. This criterion trades off the goodness-of-fit against the number of factors. Common factors can be estimated either on the set of all predictors, or a subset of targeted variables, or weighted predictors.

4. Estimate static factors F_t for t=T-k+1, …,T applying the Kalman filter (please see Appendix 4). As a result, we get factor values for the whole analysed period from t= 1 to T.

5. Given historical data t=1,…,T-h, we estimate the forecasting equation hereinafter, i.e. OLS regression of GDP on own lags and the factors. The number of lags is determined using Akaike and Schwartz information criteria. The estimated coefficients are μ, β and γ.

$$GDP_t = \mu + \beta F_{t-h} + \gamma(L)\, GDP_{t-1-h} + e_t$$

6. Given the values of static factors F_T for quarter T estimated by the Kalman filter and the parameters of the forecasting equation estimated in the bullet above, we compute the forecast of GDP for quarter T+h.

$$GDP_{T+h} = \mu + \beta F_T + \gamma(L)\, GDP_{T-1} + e_{T+h}$$

Appendix 6: References

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Renaissance
Capital

Renaissance Securities (Cyprus) Ltd.
Alpha Business Centre, 8th Floor
27 Pindarou Street
1060 Nicosia
Republic of Cyprus
T +357 (22) 505 800
F + 357(22) 676 755

Renaissance Capital
Moscow City
Naberezhnaya Tower, Block C
10, Presnenskaya Nab.
Moscow 123317 Russia
T + 7 (495) 258 7777
F + 7 (495) 258 7778
www.rencap.com

Renaissance Capital Ltd.
One Angel Court
Copthall Avenue
London EC2R 7HJ
United Kingdom
T + 44 (20) 7367 7777
F + 44 (20) 7367 7778

Renaissance Capital Kazakhstan
Esentai Tower
77/7 Al-Farabi Avenue
Almaty 050060 Kazakhstan
T + 7 (727) 244 1544
F + 7 (727) 244 1545

Renaissance Securities (Nigeria) Ltd
5th Floor, Professional Centre
Plot 1B, Bank PHB Crescent
Victoria Island, Lagos
Nigeria
T +234 (1) 448 5300
F +234 (1) 448 5353

Renaissance Capital
6th Floor, Purshottam Place
Westlands Road
P.O. Box 40560-00100
Nairobi, Kenya
T +254 (20) 368 2000
F +254 (20) 368 2339

Renaissance Capital Ukraine
Parus Business Center,
2 Mechnykova Street,14th Floor
Kyiv 01601, Ukraine
T +38 (044) 492-7383
F +38 (044) 492-7393

Renaissance Capital Research

Head of Research
Roland Nash
+ 7 (495) 258 7916
RNash@rencap.com

Head of Equity Research
Alexander Burgansky
+ 7 (495) 258 7904
ABurgansky@rencap.com

Head of Macro/Fixed Income Research
Alexei Moisseev
+ 7 (495) 258 7946
AMoisseev@rencap.com

Head of Russia Research
Natasha Zagvozdina
+ 7 (495) 258 7753
NZagvozdina@rencap.com

Head of Central Asia Research
Milena Ivanova-Venturini
+ 7 (727) 244 1544
MIvanovaVenturini@rencap.com

Banking
+ 7 (495) 258 7748
David Nangle
DNangle@rencap.com
Milena Ivanova-Venturini
Armen Gasparyan

Chemicals/Engineering/Building materials
+ 7 (495) 783 5653
Marina Alexeenkova
MAlexeenkova@rencap.com

Consumer/Retail/Agriculture
+ 7 (495) 258 7753
Natasha Zagvozdina
NZagvozdina@rencap.com
Ulyana Tipsina

Central Asia
+ 7 (727) 244 1544
Milena Ivanova-Venturini
Tatyana Kalachova

Equity Strategy
+ 7 (495) 258 7916
Roland Nash
RNash@rencap.com
Tom Mundy
Ovanes Oganisian

Metals & Mining
+ 44 (20) 7367 7781
Rob Edwards
REdwards@rencap.com
Boris Krasnojenov

Oil & Gas
+ 7 (495) 258 7904
Alexander Burgansky
ABurgansky@rencap.com
Irina Elinevskaya
Ildar Davletshin
Tatyana Kalachova (Central Asia)

Media/Technology/Real Estate
+ 7 (495) 258 4350
David Ferguson
DFerguson@rencap.com

Telecoms/Transportation
+ 7 (495) 258 7902
Alexander Kazbegi
AKazbegi@rencap.com
Ivan Kim

Utilities
+ 44 (20) 7367 7793
Derek Weaving
DWeaving@rencap.com
Vladimir Sklyar

Ukraine
+38 (044) 492-7383
Anastasiya Golovach

Macro & Fixed Income Research
+ 7 (495) 258 7946
Alexei Moisseev
AMoisseev@rencap.com
Nikolai Podguzov
Petr Grishin
Maxim Raskosnov
Andrey Markov
Anastasiya Golovach (Ukraine)
Anton Nikitin

Africa Macro & Strategy
+234 1 448 5300
Samir Gadio
SGadio@rencap.com

Africa Financials
+234 1 448 5300
Kato Mukuru
KMukuru@rencap.com

East Africa
+263 (11) 634-463
Dzika Danha
DDanha@rencap.com
Eric Musau

Southern Africa
+263 (11) 634-463
Dzika Danha
DDanha@rencap.com
Anthea Alexander

West Africa
+ 234 1 271 91 33
Esili Eigbe
EEigbe@rencap.com