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Forecasting Emerging Market Indicators: Brazil and Russia *

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Abstract

The adoption of inflation targeting in emerging market economies makes accurate forecasting of inflation and output growth in these economies of primary importance. Since only short spans of data are available for such markets, autoregressive and small-scale vector autoregressive models can be suggested as forecasting tools. However,these models include only a few economic time series from the whole variety of data available to forecasters. Therefore dynamic factor models, extracting information from a large number of time series, can be suggested as a reasonable alternative. In this paper two approaches are evaluated on the basis of data available for Brazil and Russia. The results allow us to suggest that the forecasting performance of the models considered depends on the statistical properties of the series to be forecast, which are affected by structural changes and changes in operating regime. This interaction between the statistical properties of the series and the forecasting performance of models requires more detailed investigation.

JEL codes: C53, C32, E37
Keywords: forecasting, emerging markets, factor models

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1 Introduction: Monetary Policy and Forecasting

Forecasts of inflation and output growth provide the basis for the development of monetary policy within an inflation targeting framework. According to Svensson (1999) an inflation targeting framework is characterized by (1) an explicit quantitative inflation target; (2) an operating procedure that can be described as inflation-forecast targeting, namely the use of an internal conditional inflation forecast as an intermediate target variable; and (3) a high degree of transparency and accountability.

The operating procedure can be described as inflation-forecast targeting in the following sense: the central bank's internal conditional inflation forecast is used as an intermediate target variable. An instrument path is selected which results in a conditional inflation forecast in line with a target for the inflation forecast. This instrument path then constitutes the basis for the current instrument setting.

In the theoretical literature (Svensson (1999), Woodford (2003)) this procedure is referred to as a targeting rule as opposed to an instrumental (Taylor) rule that expresses an interest rate as a prescribed function of predetermined or forward-looking variables, or both. The targeting rule does not specify a formula for the central bank's interest-rate operating target. Rather, an interest rate is set at whatever level may turn out to be required in order for the bank's conditional forecast to be in line with an inflation target.

During the 1990s several advanced industrial countries (United Kingdom, Sweden, Norway, Canada, Australia, and New Zealand) introduced inflation targeting as a framework for the conduct of monetary policy. Towards the end of the 1990s a few post-Soviet countries (Czech Republic (1997), Poland (1998), and Hungary (2001)) also shifted to inflation targeting. Brazil adopted an inflation targeting framework in 1999 and the Central Bank of Russian Federation started announcing inflation targets in 2003.

A classical example of inflation-forecast targeting is the procedure used by the Bank of England. The Bank of England adopts a given operating target i_t for the overnight interest rate at date t if and only if the Bank's forecast of the evolution of inflation over the next two years, conditional upon the interest rate remaining at the level i_t, implies an inflation rate of 2.5 percent per annum (the Bank's current inflation target) two years after date t (Vickers (1998)). In the development of the conditional inflation forecast the Bank of England uses a suite of models rather then a single model (Hatch (2001)). The Bank's large-scale core model of the UK economy is supplemented by small-scale macroeconometric models, Phillips-curve models, vector autoregressive models, and survey data. The final inflation projection published in the Inflation Report is the result of the collective judgement of the Monetary Policy Committee.

The experience of the Bank of England and the central banks of other industrial countries has been used by central banks of emerging market economies. In the second half of the 1990s the central banks in many emerging markets have abandoned fixed exchange rate regimes and replaced them with more flexible exchange rate arrangements. The fixed exchange rate was used as a nominal anchor to achieve a rapid stabilization of the price level. However, while inflation did decline significantly, it did not decline enough to prevent a large real appreciation of national currencies. This real appreciation eroded relative competitiveness of emerging market economies and ultimately created significant current account deficits. Under these conditions the central banks of these economies were forced to abandon fixed exchange rates. When abandoning the exchange rate peg, the central banks had to decide which nominal anchor to use instead of a fixed exchange rate. The successful experience of advanced industrial countries suggested the adoption of inflation targeting.

The most serious objection raised against the adoption of inflation targeting in emerging market economies is the limited ability to forecast inflation in these economies (Jonas and Mishkin (2003)). This is partly the result of the relatively frequent occurrence of shocks and the large degree of openness of emerging markets. Mainly due to an inability to forecast inflation and economic growth accurately, the countries that opted for the inflation targeting regime had significant deviations from their chosen targets. The central banks of these countries (Czech Republic, Poland) responded by the widening of target bands and the introduction of exceptional events into their monetary programs. But they also tried to improve their conditional inflation forecasts by the development of forecasting tools and the incorporation of a growing amount of information.

In this paper we look at the experience of Brazil and Russia, two of the largest emerging market economies. The IMF and the World Bank include them in the ten largest economies in the world with respect to the dollar estimates of GDP, which are computed using purchasing power parity (PPP). Therefore the investigation of these economies is of particular interest.

We focus on forecasting CPI inflation and GDP growth in Brazil and Russia. Forecasts from autoregressive (AR) models and small-scale vector autoregressive (VAR) models are compared with those from dynamic factor models. Given the small time span of reliable data for Brazil and Russia, AR and small-scale VAR models, including only few variables and few parameters, can be considered as a reasonable forecasting tool. On the other hand, dynamic factor models extract information from a large number of time series, despite the small time span of data. We provide evidence on the relative forecasting performance of AR, VAR, and dynamic factor models in small sample in the presence of structural changes.

The presence of structural changes in forecast variables and many predictors raises the important question about the correction of models for these non- stationarities. Since the complexity of the structural changes and lack of observations complicate the modeling of these changes explicitly, forecasts can be robustified by application of methods proposed by Clements and Hendry (1998, 1999). Among these methods are intercept correction of the forecast and additional differencing of the variable to be forecast. Their efficiency is going to be evaluated in application to autoregressive models.

The paper is organized as follows. In section 2 we briefly consider economic developments and monetary policy in Brazil and Russia over the last ten years, and evaluate the role of forecasting in implementation of monetary policy. Section 3 describes the forecasting models, data sets, and criteria for forecast comparison. In Section 4 the results of forecast comparison are reported. In Section 5 we propose some general conclusions and suggestions for further research.

2 Inflation Targeting in Brazil and Russia

2.1 Brazil

The crawling peg regime in Brazil, initiated in mid-1994, successfully brought annual inflation to one-digit figures in less than three years. However, it led to the overvaluation of the national currency and a growing current account deficit. Trade imbalances and accumulated public debt left Brazil vulnerable to a confidence crisis, which became a reality with the international financial turmoil of 1997-1998 culminating with the Russian moratorium in August 1998. The Russian crisis generated a capital flight from Brazil, and the Central Bank of Brazil was forced to abandon the crawling peg regime: the real was forced to float on January 1999.

The new exchange rate regime required a new anchor for monetary policy and in July 1999 Brazil adopted inflation targeting as the monetary policy framework. The Broad Consumer Price Index (IPCA) was chosen for measuring inflation. The targets were set at 8% for 1999, 6% for 2000 and 4% for 2001. Tolerance intervals of 2% for each year were also defined.

In order to support the monetary policy decision process, the Research Department of the Central Bank of Brazil has developed a set of tools which include a structural model of the transmission mechanism of monetary policy to prices, short-term inflation forecasting models, leading inflation indicators, and surveys of market expectations (Bogdanski, Tombini and Werlang (2000)). The structural model includes an IS-type equation, a Phillips curve, an uncovered interest parity condition, and monetary policy rules. This model is complemented by a set of short-term models including Autoregressive Moving Average (ARMA) and Vector Autoregressive (VAR) models. The forecasts of the structural and time-series models are complemented by survey data-based forecasts and used for the projection of CPI inflation and GDP growth.

Bogdanski, Tombini and Werlang (2000) emphasize that monetary policy decisions in the Bank of Brazil are taken on the basis of the widest information set available. This information includes dynamics of production, investment, and consumption; developments in the labour market; state of public finance; dynamics of disaggregated price indices; exports, imports, and exchange rate dynamics; changes in the international economy; and market expectations. Using this data, the Monetary Policy Committee of the Bank of Brazil develops the baseline scenario and decides on the inflation target and the interest rate path.

Implementing inflation targeting, the Central Bank of Brazil succeeded in keeping the inflation rate within the tolerance intervals in 1999 and 2000 (Table 1). However, the Argentine crisis and the terrorist attacks to the United States in September 2001 generated large capital outflows from the Brazilian economy and rapid depreciation of the real. Together with the accelerated growth of administered prices it implied an increase of the CPI inflation rate above the tolerance interval. In 2002 the confidence crisis continued. It was triggered by concerns that the new president, who had been elected that year, would default on the national debt. Therefore the depreciation of the real continued and inflation accelerated. As a result, despite the upward shift of the inflation targets and expanding of the tolerance intervals (up to 2.5%) the Central Bank of Brazil failed to hit the inflation targets in 2002 and 2003: inflation reached levels well above the tolerance intervals. Only in 2004 did the Central Bank of Brazil succeed in decelerating inflation and bringing the inflation rate within the tolerance interval.

Table 1 Forecast and actual inflation in Brazil and Russia

Year	Brazil		Russia	
	Target	Actual	Forecast/Target	Actual
1999	8 (6 -10)	8.9	30	35.5
2000	6 (4 - 8)	6	18.6	20.2
2001	4 (2 - 6)	7.7	12 - 14	18.6
2002	3.5 (1.5 - 5.5)	12.5	12 - 14	15.1
2003	4 (1.5 - 6.5)	9.3	10-12	12
2004	5.5 (3 - 8)	5.7	8-10	11.7

2.2 Russia

The Central Bank of Russia has started announcing inflation targets much later than the Bank of Brazil. From 1995 onwards Russia had the crawling band regime. As in Brazil, the introduction of the crawling band allowed inflation to decrease significantly but it did not decrease sufficiently to prevent the real appreciation of the national currency. In 1998, the Asian crisis and decrease of oil prices in the international market led to large capital outflows from the Russian economy. The adverse external factors combined with the growing public debt led to a currency crisis and default on national obligations in August 1998. The crawling band regime was abandoned, the exchange rate of rouble devaluated more than 3 times and the inflation rate reached 84.4% per annum at the end of 1998.

In the aftermath of the currency crisis the Central Bank of the Russian Federation applied a discretionary, "just-do-it" approach to monetary policy without an explicit nominal anchor. The Central Bank of Russia tried to slow down inflation and protect the exchange rate of the rouble from sharp changes by making significant interventions in the foreign exchange market.

Inflation forecasts, produced in 1999-2002 by the Central Bank of the Russian Federation, systematically underestimated actual inflation (Table 1). These inflation forecasts were conditioned by expectations of relatively low oil prices in the international markets and moderate economic growth in Russia. However, high oil prices together with improved relative competitiveness of domestic producers after the devaluation of the rouble implied higher than expected rates of economic growth. In addition, large interventions of the Bank of Russia in the foreign exchange market under the conditions of growing capital inflows led to significant an increase of inflation rates well above forecast levels.

In 2002 the Central Bank of the Russian Federation announced for the first time an inflation target for the next year. The Bank of Russia decided to target the CPI. The inflation target for 2003 was set by the Bank of Russia at 10-12 %. This target was met as the inflation rate amounted to 12 %.

In 2003 the Bank of Russia announced inflation targets for the next three years. According to Monetary Policy Guidelines for 2004 the rate of inflation had to be reduced to 8-10 % in 2004, 6.5-8.5 % in 2005, and 5.5-7.5 % in 2006. However, in 2004 the inflation rate amounted to 11.7 % well above the target range. This overshoot was conditioned by a level of economic activity higher than the level that was supposed in any scenario of economic development for 2004.

From 2002 onwards two principal scenarios of economic development have been considered by the Bank of Russia when setting an inflation target and selecting instruments for the following year. These two scenarios differ in their different prospects for global economic development, including oil price dynamics in the international markets, world economic growth rates, world interest rates and exchange rates of major world currencies. The first (pessimistic) scenario is based on assumptions of relatively low oil prices and high dollar-denominated interest rates. In the second (basic) scenario stable oil prices and low interest rates are assumed. The main internal factors taken into account in the development of monetary program are labour market dynamics, consumer and investment demands, the state of public finance. On the basis of these two scenarios variants of monetary program for the next year are developed.

According to the basic scenario for 2004 the growth rate of national product would amount to 5.2 % while according to the pessimistic scenario the growth rate would amount to 3.8 %. However, the growth rate of national product has in fact amounted to 7.1 %. This high growth was associated with good external prospects and growing consumer and investment demands inside of country, which were not assumed in any scenario. Consequently, the inflation rate was pushed above the target range.

This early inflation targeting experience indicates that the success or failure of inflation targeting in Brazil and Russia in the coming years will depend in large degree on the ability to produce accurate forecasts of economic developments inside of these countries and abroad. It raises the issue of development of accurate forecasting tools.

The Brazilian and Russian economies have passed through large transformations and structural changes. In particular, the currency crisis in 1998 - 1999 and the following change in the policy regime have affected significantly the dynamics of many macroeconomic time series in these economies.

The 1998 - 1999 crisis implied a change in the slope of inflation both in Brazil and Russia (Figures 1 and 3, Appendix C). In both countries inflation was declining over 1995 - 1997, but in 1998 the trend was broken. The currency crisis in August 1998 implied an explosion of inflation in Russia over the last two quarters of 1998 and the first quarter of 1999 with the following slow adjustment to the lower levels, while in Brazil the abandoning of the crawling peg in January 1999 did not lead to a large one-time shock but implied a shift to a higher level of inflation.

Turning to output growth, the 1998 crisis affected it significantly in Russia and led to a sharp fall in the rate of output growth in 1998. In the aftermath of the crisis, the rate of output growth shifted to a higher level (Figure 4, Appendix C). In Brazil the dynamics of output growth was similar to that of output growth in Russia, but the effect of the currency crisis on output growth was not as large as in Russia (Figure 2, Appendix C).

In the aftermath of the crisis, inflation and output growth stabilized in Russia. However, in Brazil a new confidence crisis in 2002-2003 provoked a large shock to inflation with the following slow adjustment to a lower level.

This preliminary analysis suggests that the dynamics of CPI inflation and GDP growth in Brazil and Russia is not only subject to one-time shocks and shifts but also to nonlinear adjustment processes. This raises the issue about the ability of different forecasting models to accommodate structural changes and fit the non-linear dynamics of the series of interest. Lack of data does not allow us to estimate efficiently non-linear models which include many parameters. On the other hand, presence of structural changes can imply instability of estimated parameters for linear models and failure in forecasting.

In this paper we evaluate the forecasting performance of different linear models in the small sample in the presence of structural changes. We also evaluate efficiency of some methods which were proposed by Clements and Hendry (1999) in order to robustify forecasts from linear models in the presence of structural changes.

3 Methodology

In this section forecasting approaches and criteria for the evaluation of their relative merits are represented briefly. Given the small time span of data available, small-scale linear models (AR, VAR) can be suggested as forecasting tools, because of their parsimonious specification and good performance. However, small-scale models include only few economic time series of the whole variety of data available to policy makers.

Another approach, combining information from a large number of time series with parsimonious specification has been the topic of investigation in the last years. Dynamic factor models, as developed by Stock and Watson (1998), have been successfully used to forecast macroeconomic variables in the US, UK and Euro-area, (Stock and Watson (2002), Marcellino, Stock, and Watson (2003), Artis, Banerjee and Marcellino (2003)). Some evidence in favour of dynmic factor models was found for transition economies (Banerjee, Marcellino and Masten (2004)). There have also been attempts to incorporate the information extracted by factor models into traditional small-scale models with the purpose of forecasting and policy analysis (Stock and Watson (1999), Favero and Marcellino (2001), Bernanke and Boivin (2003)).

The primary justification for the use of factors models in data sets for emerging economies, as described in Banerjee, Marcellino and Masten (2004), is their usefulness as a particular efficient means of extracting information from a large number of time series, albeit of short time span. Forecasts of key macroeconomic variables may be improved significantly, not least because in a rapidly changing economy the ranking of variables as good leading indicators for inflation or output growth is not clear a priori. Therefore factor models provide a methodology that remains "agnostic" about the structure of economy, by employing as much information as possible in the construction of forecasting exercise.

The design of this forecasting exercise replicates one developed in Artis, Banerjee and Marcellino (2003). All forecasting models are specified and estimated as a linear projection of an one-step ahead forecast variable, y_{t+1}, onto t-dated predictors. More precisely, the forecasting models all have the form,

$$y_{t+1} = \mu + \alpha(L)y_t + \beta(L)'Z_t + \varepsilon_{t+1}, \tag{1}$$

where μ is a constant, $\alpha(L)$ is a scalar lag polynomial, $\beta(L)$ is a vector lag polynomial, and Z_t is a vector of predictor variables.

The construction of the forecast variable y_t depends on whether the original series is modelled as *I(0), I(1)* or *I(2)*. Recall that series integrated of order d, denoted *I(d)* are those for which the d-th difference (Δ^d) is stationary. Denoting by x the original series (usually in logs) in the *I(0)* case the forecast series $y_{t+1} = x_{t+1}$. In the *I(1)* case, the forecast series y is the growth in the original series x between time period t and *t+1*: $y_{t+1} = \Delta x_{t+1} = x_{t+1} - x_t$. In the *I(2)* case, y is the difference of growth in x between t and *t+1*: $y_{t+1} = \Delta^2 x_{t+1} = \Delta x_{t+1} - \Delta x_t = x_{t+1} - 2x_t + x_{t-1}$. This is a convenient formulation because, given that x_t and its lags are known when forecasting, the unknown component of y_{t+1} conditional on the available information is equal to x_{t+1} independently of the choice of the order of integration. This makes the mean square forecast error (MSFE) from models for a twice differenced variable directly comparable with that from models for first differences.

3.1 Forecasting Models

Various forecasting models, which are compared, differ in their choice of Z_t. Let us list the forecasting models and briefly discuss their main characteristics.

Autoregressive forecast (ar_aic). A univariate autoregressive forecast is taken as a benchmark. It is based on (1) excluding Z_t. The lag length is chosen by the Akaike Information Criteria (AIC) with a maximum of 4 lags.

Autoregressive forecast with second differencing (ar_i2_aic). Clements and Hendry (1999) showed that the second differencing of the forecast variable can improve the forecasting performance of autoregressive models in the presence of structural changes, even in the case of over-differencing. Hence, this model corresponds to (1), excluding Z_t and treating the variable of interest as *I(2)*.

Autoregressive forecast with intercept correction (ar_ic_aic). An alternative remedy in the presence of structural changes is to put the forecast back on track by adding past forecast errors to the forecast. Clements and Hendry (1999) show that simple addition of the forecast error can be useful. Hence, the forecast is given by $\hat{y}_{t+1} + \varepsilon_t$, where $\hat{y}_{t+1}$ is the AR forecast and ε_t is the forecast error made when forecasting y_t in period *t-1*. However, both intercept correction and second differencing increase the MSFE, when not needed, by adding a moving average component to the forecast error, and thus are not costless.

Random walk forecast (rw). Since random walk forecast is found to be a robust benchmark in many forecasting exercises, it is also included in this exercise. This model correspond to (1), excluding Z_t and setting $\alpha(L)$ to be equal to 1.

VAR forecast (var_aic). VAR forecasts are constructed using equation (1) with different regressors Z_t . In particular, for GDP growth Z_t includes the money market interest rate and for CPI inflation Z_t includes the nominal exchange rate and GDP growth. The lag length is chosen by the Akaike Information Criteria (AIC) with the maximum of 4 lags.

Factor-based forecasts. These forecasts are based on setting Z_t in (1) to be estimated factors from a dynamic factor model. Stock and Watson (1998) show that, if the set of predictor variables can be described by an approximate dynamic factor model, then under certain assumptions (restrictions on moments and stationarity conditions) the space spanned by the latent factors can be estimated consistently by the principal components of the covariance matrix of the predictor time series. Stock and Watson (1998) also provide conditions under which these estimated factors can be used to construct asymptotically efficient forecasts. The dynamic factor model is briefly reviewed in Appendix A.

For each of the factor-based models, factors can be extracted from the unbalanced panel (prefix *fnbp*), or from the balanced panel (prefix *fbp*). The former contains more variables than the latter, and therefore more information. The only drawback is that missing observations have to be estimated in a first stage, which can introduce noise in the factor estimation.

Two types of factor-based forecasts are considered. First, we consider the model which includes both factors and lags of forecast variable (*fnbp_ar_aic* and *fbp_ar_aic*). The selection of a number of factors and lags is based on AIC. The maximum number of factors is equal to 6 and the maximum number of lags of dependent variable is equal to 4. Second, we consider the model where only up to 6 factors appear as regressors, but not lags of dependent variable (*fnbp_aic* and *fbp_aic*).

In order to evaluate the role of each factor in forecasting, for the unbalanced panel we also consider forecasts using a fixed number of factors, from 1 to 4 (*fnbp_ar_1* to *fnbp_ar_4* and *fnbp_1* to *fnbp_4*).

3.2 Forecast Comparison

The forecast comparison is performed in a simulated out-of-sample framework where all statistical calculation are done using a fully recursive methodology. The models are first estimated using data from 1995:1 to 2002:2, and one-quarter ahead forecasts are computed. Then the estimation sample is augmented by one quarter and the corresponding one-quarter ahead forecasts are computed again. The forecast period for one-quarter ahead forecasts is 2002:3 - 2004:4 for a total of 10 quarters, and the final estimation sample for one-quarter ahead forecasts is therefore 1995:1 - 2004:3.

Every quarter (i. e. every augmentation of the sample) all standardization of data and model estimation are repeated. A simulated out of sample MSFE is then computed as an average of the sum of squares of all comparisons between an actual value of the variable and its forecast (under any methods given in section 3.1 above).

The forecasting performance of the described methods is examined by comparing their simulated out-of-sample MSFE relative to the benchmark AR forecast. West (1996) standard errors are computed around the relative MSFE.

It is worth noting that the reported comparison criteria are based on averaging forecast errors, whose magnitude can differ substantially over forecasting period. They also do not provide information about the directional accuracy of forecasts which can be of particular importance.

The choice of the forecast horizon is conditioned by the availability of the data and small sample size, and the chosen forecast horizon, one quarter, is of rather limited relevance for the decisions about the monetary policy. Since the the inflation target is set one year in advance, it requires one-year ahead forecasts. However, the Monetary Policy Committee meets every month in order to adjust its forecasts and decide on interest rate path, and every quarter it issues inflation report and produce forecasts for the next quarter. Thus, the one-quarter ahead forecasting is relevant for the monitoring economy and adjusting monetary policy over the year.

3.3 Data

The data sets for Brazil and Russia include respectively 41 and 47 quarterly series over the period 1995:1 - 2004:4. These series are extracted from the OECD database (Main Economic Indicators), the IMF database (International Financial Statistics), the database of the Central Bank of Brazil, and the database of the Russian Statistical Agency. They include series characterizing real output and income (GDP and its main components, production indices), labour market indicators (employment, unemployment, vacancies); interest rates (money market rates, lending and deposit rates); stock price indices; producer and consumer price indices; money aggregates; survey data; miscellaneous (exports, imports, exchange rates, international oil prices etc.). A complete list of series for both countries is reported in the Appendix B.

Following Banerjee, Marcellino and Masten (2004) the data are pre-processed in four stages before being modelled with a factor representation. First, all series excluding financial (interest rates, stock prices and exchange rates) are seasonally adjusted using original X-11 ARIMA procedure.

Second, logarithms are taken of all nonnegative series that are not already in rates or percentage points, and the series are transformed to account for stochastic or deterministic trends. The same transformation is applied to all the series of the same type.

The main choice is whether prices and nominal variables are *I(1)* or *I(2)*. Given the small time span of the sample and adjustment processes ongoing over the period under consideration it is hard to rely upon formal tests in deciding whether prices and other nominal series are *I(1)* or *I(2)*. Even if the price series are not generated by *I(2)* processes, second differencing can robustify the forecasts in the presence of structural breaks (see Clements and Hendry(1999)). In order to evaluate the role of second differencing in the forecasting performance of the factor models, this exercise is performed both under the assumption of *I(1)* prices and under the assumption of *I(2)* prices. In the first case all prices are treated as series generated by *I(1)* processes, and differenced only once. In the second case all prices and other nominal series are treated as series generated by *I(2)* processes, and differenced twice.

Third, all series are standardized before being used for factors estimation, e. g. they are transformed to series with zero mean and with the standard deviation equal to one.

Finally, the transformed seasonally adjusted series are screened for large outliers (outliers exceeding six times the interquartile range). Each outlying observation is recorded as missing data, and the EM algorithm (Stock and Watson (1998)) is used to estimate the factor model for the resulting unbalanced panel.

This procedure implies that the factors, which are estimated using differenced series, do not have large outliers. Large outliers in differenced series are generated by shifts in mean in original series. This type of structural break is excluded from the estimated factors, which are then used in forecasting.

Using the cumulative trace R^2 from the regressions of individual series on the estimated factors we find that the estimated factors fit the data quite well both for nominal series treated as *I(1)* and for nominal series treated as *I(2)* (Tables 1 and 2, Appendix D). If nominal series are differenced once, the first six factors explain 56% of the variability of the 41 series for Brazil and 63% of the variability of the 47 series for Russia. If nominal series are differenced twice, the first six factors explain

54% of the total variability of the data for Brazil and 62% of the total variability of the data for Russia.

For Brazil the first estimated factor explains real variables including production, consumption, and labour market indicators, while the second and the third factors explain interest rates and prices. This result for Brazil does not depend on the order of differencing of nominal series. For Russia, if nominal series are differenced once, the first factor explains consumer prices and exchange rates, the second factor loads on production series and producer prices, while the third factor explains interest rates. If nominal series are differenced twice, the first factor explains production variables as well as consumer prices and exchange rates, the second factor explains some production series and producer prices, and the third factor loads on the interest rates and money aggregates.

In Tables 1–2 (Appendix D) we report the R^2 in the regression of each variable to be forecast on the estimated factors. The first 3–4 estimated factors explain most of the variability of CPI inflation and GDP growth in Brazil in Russia. If nominal series are differenced once, the first three factors explain 50% of the variability of inflation in Brazil and 88% of the variability of inflation in Russia, and they also explain 76% of the variability of output growth in Brazil and 82% of the variability of output growth in Russia. This result does not change significantly, if nominal series are differenced twice.

Therefore the estimated factors are found to be informative about the data sets as whole, and about the variables to be forecast in particular. Let us now turn to their forecasting efficacy.

4 Forecasting Results

In this section the results of the forecast comparison for the Brazilian and Russian GDP growth and CPI inflation are reported. Forecasting is performed for one-quarter horizon for a total of 10 quarters. Relative MSFE are reported in Tables 3 – 4 in Appendix D.

4.1 Brazil

The results for Brazil are reported in Table 3 (Appendix D). In Figures 5 and 6 (Appendix C) we report actual values and one-quarter ahead forecasts from the best non-factor and factor models.

Let us consider the case when the price series are treated as *I(1)*. Both for GDP growth and CPI inflation, most of the factor forecasts do outperform the benchmark autoregressive forecast. On the other hand, most of the factor forecasts are outperformed by the VAR forecast. The VAR forecast is best for inflation, while for output growth there is a factor forecast (*fnbp_3*) that outperforms the VAR, but the gain provided by this factor forecast comparing to the VAR forecast is not large.

The random walk forecast, the intercept corrected AR forecast, and the AR forecast for the price series differenced twice outperform the benchmark for CPI, but they do not provide gains in the forecasting of GDP. This result corresponds to the evidence provided by the analysis of the dynamics of these series: while inflation was the subject of several structural changes, there is no certain evidence of non-stationarities in the dynamics of output growth in Brazil. Therefore the methods robustifying for structural changes appear to be efficient for inflation but not for output growth.

Figure 6 (Appendix C) shows that the VAR and the best factor model provide poor forecasts for GDP growth although they outperform the benchmark. The visual analysis of the graph of these forecasts allows us to suggest that they are biased downwards. This result requires further investigation and explanation.

The VAR and the best factor forecasts of CPI inflation (Figure 4, Appendix C) are biased downwards in the first three quarters of forecasting, but then they converge to the actual values of the series and perform well. In the case of CPI the forecast failure in the first quarters of the forecasting is conditioned by the large outlier in the inflation rate in 2002 triggered by the confidence crisis.

In order to evaluate the effect of additional differencing of the price series on the forecasting performance of the factor models the exercise is repeated under the assumption that all prices, money aggregates, wages, and exchange rates are generated by *I(2)* processes, and all these series are differenced twice. The AR forecast of the GDP growth and the AR forecast of the twice differenced CPI are compared with the factor forecasts (other non-factor forecasts are not considered in this case). Accordingly, the forecasting results for GDP can be compared directly with the results of the exercise performed under the assumption of *I(1)* prices, while this direct comparison with the *I(1)* case is not possible for CPI, since the forecast variable and the benchmark forecast are different in this case.

There is no obvious ranking of the factor forecasts performed under the assumption of *I(1)* prices and the factor forecasts performed under the assumption of *I(2)* prices: some factor models perform better under the assumption of *I(1)* prices while others perform better when prices are treated as *I(2)*. However, most of the factor forecasts do improve their performance for the GDP series under the assumption of the *I(2)* prices. This can be explained by the fact that the variance of the price series decreases after second differencing and the twice differenced prices do not dominate the dynamics of estimated factors, which are used for forecasting. Thus, the estimated factors become more informative about output series rather than about prices and provide additional gains in forecasting GDP growth.

4.2 Russia

The results for Russia are reported in Table 4 (Appendix D). In Figures 7 and 8 (Appendix C) we report actual values and one-quarter ahead forecasts from the best non-factor and factor models.

The graphs of GDP growth and CPI inflation (Figures 3 - 4, Appendix C) provide ample evidence of structural changes in these series. While output growth shifted to a higher mean in the aftermath of the 1998 crisis, inflation, which exploded in 1998, converged to a lower level in the following years.

High levels of inflation before the currency crisis and the explosion of inflation in 1998 implied the upward bias of the benchmark AR forecast for CPI. This forecast is outperformed by the random walk forecast, the intercept corrected AR forecast, and the AR forecast for the twice differenced series. The gains provided by the random walk forecasts and the corrected AR forecasts are large. They reach 84% for the random walk forecast and 82% for the AR forecast of second differences. It can mean that the CPI is better described as generated by *I(2)* process. On the contrary, there is no evidence that GDP is better treated as *I(2)* series: the random walk forecast and the corrected AR forecasts do not provide large gains in the forecasting of GDP comparing to the benchmark.

These differences in the efficiency of intercept correction and second differencing can be explained by differences in size and direction of structural changes in output and inflation as well as different persistence of these series.

There is at least one factor forecast for each forecast variable that provides gains comparing to the AR benchmark. These gains are not large for GDP, but they reach 76% for CPI (*fnbp_ar_1*). The VAR forecasts outperform the benchmark both for GDP and CPI. For GDP growth the VAR forecast is the best with the relative gain of 29% comparing to the AR benchmark.

Figure 8 (Appendix C) shows that, as in the case of Brazil, both VAR and factor models provide poor forecasts for output growth: both of them have lower volatility than actual values of the series and the factor forecasts appear to be biased downwards. On the contrary, the random walk forecast, which is the best forecast for the CPI inflation, and the best factor forecast follow closely the actual inflation (Figure 7, Appendix C).

Since intercept correction and second differencing appear to be so efficient for CPI, it is reasonable to consider the factor forecasts performed under the assumption of *I(2)* prices. The results of comparison of the AR forecast with the factor forecasts computed with the use of twice differenced price series are shown in Table 4 (Appendix D).

Because prices are differenced twice in this case, the benchmark forecast for CPI is the AR forecast of the second differences. This is a more robust benchmark than the AR forecast of the first differences and not one factor model outperforms it.

The benchmark forecast of GDP does not change under the assumption of the *I(2)* prices and the factor forecasts for output growth, evaluated under the assumptions of *I(1)* prices and *I(2)* prices, are directly comparable. Most of the factor forecasts of output growth do improve their performance significantly under the assumption of *I(2)* prices and provide significant gains compared to the benchmark. As in the case of Brazil this result can be explained by the decrease of the variance of price series after second differencing, which do not dominate the factor dynamics, and factors become more informative about output series.

5 Conclusions

In this paper the relative forecasting performance of autoregressive, vector autoregressive, and factor models was compared on the basis of data sets which are available for the Brazilian and Russian economies.

Both Brazil and Russia have passed through large transformations and structural changes. In particular, the currency crisis in 1998-1999 implied structural changes in CPI inflation, GDP growth and other macroeconomic variables in these countries. It raises the issue about the ability of different forecasting models to accommodate these structural changes.

Since only short spans of reliable time series are available for Brazil and Russia, AR and simple VAR models can be expected to perform comparatively well. On the other hand, the availability of the large set of macroeconomic indicators suggests factor models. The results of our forecasting exercise show that both VAR and factor models are useful in forecasting inflation and output growth, but their relative performance differs for different forecast series and different series treatment.

Because of the complexity of ongoing changes and short time spans of data, structural changes are not modelled explicitly. However, two types of corrections for structural changes are considered: intercept correction and second differencing as proposed by Clements and Hendry (1999). These methods, applied to AR forecasts, produce certain gains in forecasting inflation, but they are not efficient in forecasting output growth. The outcome may be explained by a higher persistence of inflation or larger breaks in its dynamics comparing to output growth.

The results of the exercise allow us to suggest that the efficiency of different forecasts models and the efficiency of their corrections depend on the statistical properties of the series under consideration, in particular, on the persistence of the series and on the type and size of the structural changes in the series. It also points the direction for future research which can be detailed Monte Carlo simulations in order to evaluate the effect of different structural breaks on the relative forecasting performance of the models under consideration.

Another interesting direction of research would be the evaluation of different forecast combinations in order to bring our forecasting exercise closer to the decision making process ongoing in the Central Banks. There decisions are not based on one best model, but the whole set of models is used to produce the final projection of output and inflation.

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Appendix A. Dynamic Factor Model

This appendix briefly reviews a dynamic factor model. The material draws on Stock and Watson (1998). Let y_t denote the scalar series to be forecast and let X_t be a N-dimensional multiple time-series of predictor variables, observed for $t = 1, ..., T$, where y_t and X_t are both taken to have mean 0. Suppose that (X_t, y_t) admit a dynamic factor model representation with $\bar{r}$ common dynamic factors f_t,

$$y_{t+1} = \beta(L)f_t + \gamma(L)y_t + \epsilon_{t+1,} \tag{A1}$$

$$X_{it} = \lambda_i(L)f_t + e_{it}, \tag{A2}$$

for $i = 1, ..., N$, where $e_t = (e_{1t}, ..., e_{Nt})'$ is the $N \times 1$ idiosyncratic disturbance, and $\lambda_i(L)$ and $\beta(L)$ are lag polynomials in nonnegative powers of L. It is assumed that $E(\epsilon_{t+1}|f_t, y_t, X_t, f_{t-1}, y_{t-1}, X_{t-1}, ...) = 0$. If the lag polynomials $\lambda_i(L)$, $\beta(L)$, and $\gamma(L)$ have finite orders of at most q, A1 and A2 can be rewritten as,

$$y_{t+1} = \beta' F_t + \gamma(L)y_t + \epsilon_{t+1}, \tag{A3}$$

$$X_t = \Lambda F_t + e_t, \tag{A4}$$

where $F_t = (f_t', ..., f_{t-q}')'$ is $r \times 1$, $r \leq (q+1)\bar{r}$, the ith row of Λ in A3 is $(\lambda_{i0}, ..., \lambda_{iq})$, and $\beta = (\beta_0, ..., \beta_q)'$.

Stock and Watson (1998) show that, under this finite lag assumption and some additional assumptions (restrictions on moments and stationarity), the column space spanned by the dynamic factors f_t can be estimated consistently by the principal components of the $T \times T$ covariance matrix of the X's.

The principal component estimator is computationally convenient, even for very large N. It can be generalized to handle data irregularities such as missing observations using the EM algorithm. The consistency of the estimated factors implies that they can be used to construct asymptotically efficient forecasts for the series y_{t+1}.

Appendix B Data Description

This appendix lists time series used to construct factor-based forecasts. The transformation codes are: 1 = no transformation; 2 = first differences; 3 = second differences; 4 = levels of logarithms; 5 = first differences of logarithms; and 6 = second differences of logarithms.

Brazil

No	Mnemonic	Code	Description
Output and income			
1.	gdp	5	gross domestic product, index, 1995=100, sa
2.	manuf	5	manufacturing, index, 1995=100, sa
3.	constr	5	construction, index, 1995=100, sa
4.	mining	5	mining, index, 1995=100, sa
5.	prodsteel	5	production of manufactured crude steel, index, 1995=100, sa
6.	publutil	5	public utilities, index, 1995=100, sa
7.	agr	5	agriculture, index, 1995=100, sa
8.	serv	5	services, index, 1995=100, sa
9.	transp	5	transport, index, 1995=100, sa
10.	commun	5	communication, index, 1995=100, sa
11.	trade	5	trade, index, 1995=100, sa
12.	conspriv	5	private consumption, index, 1995=100, sa
13.	consgov	5	government consumption, index, 1995=100, sa
14.	invest	5	gross investment, index, 1995=100, sa
Labour market			
15.	earning	5/6	real monthly earnings: all activities, index,1995, sa
16.	hours	5	monthly hours of work, index, 1995=100, sa
17.	unempl	2	unemployment rate, %, sa
Interest rates			
18.	irmm	2	money market rate, % pa
19.	irtb	2	treasury bill rate, % pa
20.	irdep	2	deposit rate, % pa
Stock prices			
21.	bovespa	5/6	BOVESPA stock price index, 1995=100

Prices

22.	ppagr	5/6	producer price index, agriculture, 1995=100, sa
23.	ppconstr	5/6	producer price index, construction, 1995=100, sa
24.	pws	5/6	whosale price index, 1995=100, sa
25.	cpi	5/6	cpi, total, 1995=100, sa

Money aggregates

26.	m0	5/6	monetary base M0, mln BRL, sa
27.	m2	5/6	monetary aggregate M2, mln BRL, sa

Survey data

28.	utiliz	2	manufacturing: rate of capacity utilization, %, sa
29.	utilicons	2	production: future tendency, % balance,sa
30.	utilcap	2	producer prices, future tendency, % balance, sa
31.	stock	2	manufacturing: finished good stock, % balance, sa
32.	ftprod	2	manufacturing: production, future tendency, % balance, sa
33.	ftprice	2/3	manufacturing: selling prices, future tendency, % balance, sa

Miscellaneous

34.	exp	5	exports, index, 1995=100, sa
35.	imp	5	imports, index, 1995=100, sa
36.	intprpetr	5	average price of crude petroleum, USD/barrel
37.	nomexr	5/6	nominal effective exchange rate, index,1995=100
38.	realexr	5/6	real effective exchange rate, index, 1995=100
39.	gdpus	5	gdp, USA, index, 1995=100, sa
40.	cpus	5/6	cpi, USA, index, 1995=100, sa
41.	irus	2	treasury bill rate, USA, % pa

Russia

No	Mnemonic	Code	Description
Output and income			
1.	gdp	5	gross domestic product, index, 1995=100, sa
2.	indtotal	5	industrial production, index, 1995=100, sa
3.	agr	5	agriculture, index 1995=100, sa
4.	constr	5	construction, index, 1995=100, sa
5.	servm	5	market services, index, 1995=100, sa
6.	transp	5	transport and communication, index 1995=100, sa
7.	trade	5	trade, index 1995=100, sa
8.	servnm	5	nonmarket services, index, 1995=100, sa
9.	conspriv	5	private consumption, index, 1995=100, sa
10.	consgov	5	government consumption, index, 1995=100, sa
11.	sav	5	gross savements, index, 1995=100, sa
12.	capital	5	gross fixed capital formation, index, 1995=100, sa
13.	indmain	5	industrial production, main industries, index, 1995=100, sa
14.	prodpetr	5	production, crude petroleum, mln tonnes, sa
15.	prodgas	5	production, natural gas, mln cub m, sa
16.	retail	5	retail sales, index, 1995=100, sa
17.	realinc	5	real income, index 1995=100, sa
18.	realdinc	5	real disposable income, index, 1995=100, sa
Labour Market			
19.	wage	5/6	real wage, index, 1995=100, sa
20.	empl	5	employment, mln persons, sa
21.	unempl	2	unemployment rate, %, sa
22.	vacan	5	unfilled vacancies, th persons, sa
Interest rates			
23.	irmm	2	money market rate, % pa
24.	irdep	2	deposit rate, % pa
25.	irlend	2	lending rate, % pa
Stock prices			
26.	rts	5/6	RTS stock price index, 1995=100

Prices

27.	pp	5/6	producer price index, industrial production, total, 1995=100, sa
28.	ppoil	5/6	produce price, crude petroleum, RUR/tonne, sa
29.	ppgas	5/6	produce price, natural gas, RUR/th cub m, sa
30.	ppconstr	5/6	producer price index, construction, 1995=100, sa
31.	trcost	5/6	transportation costs, index, 1995=100, sa
32.	cpiserv	5/6	cpi, services, 1995=100, sa
33.	cpifood	5/6	cpi, food, 1995=100, sa
34.	cpi	5/6	cpi, total, 1995=100, sa

Money aggregates

35.	money	5/6	money, mln RUR, sa
36.	qmoney	5/6	money + quasi money, mln RUR, sa

Survey data

37.	utiliz	2	manufacturing: rate of capacity utilization, %, sa
38.	ftprod	2	production: future tendency, % balance, sa
39.	ftconstr	2	construction: business situation, future tendency, %balance, sa
40.	ftprice	2	producer prices, future tendency, % balance, sa

Miscellaneous

41.	exp	5	exports, index, 1995=100, sa
42.	imp	5	imports, index, 1995=100, sa
43.	intprpetr	5	average price of crude petroleum, USD/barrel
44.	intprgas	5	price of russian natural gas, USD/ th cub m
45.	ofexr	5/6	official exchange rate, RUR/USD
46.	nomexr	5/6	nominal effective exchange rate, index, 1995=100
47.	realexr	5/6	real effective exchange rate, index, 1995=100

Appendix C Figures

Figure 1 Brazil: CPI inflation

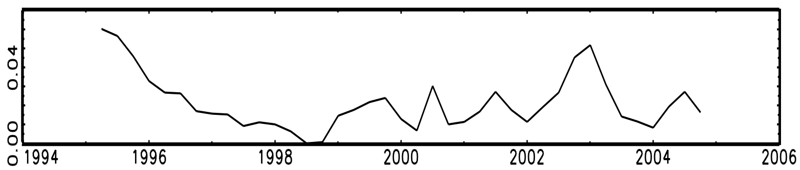


Figure 2 Brazil: GDP growth

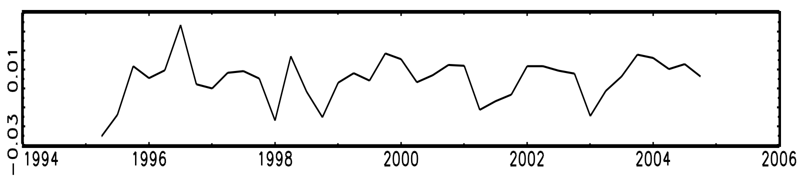


Figure 3 Russia: CPI inflation

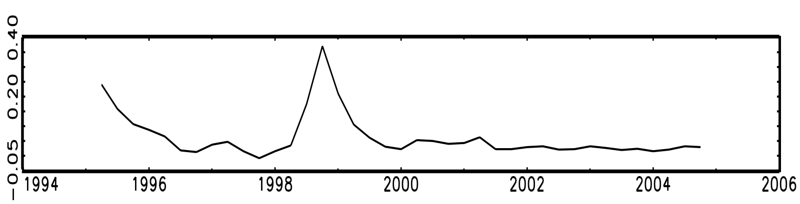


Figure 4 Russia: GDP growth

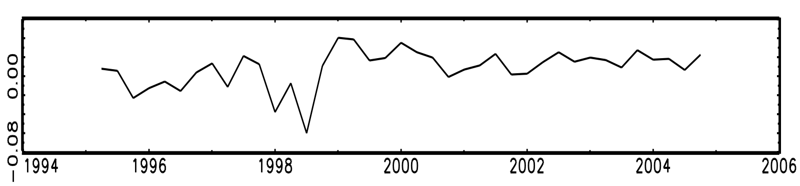


Figure 5 Brazil: CPI inflation forecasts

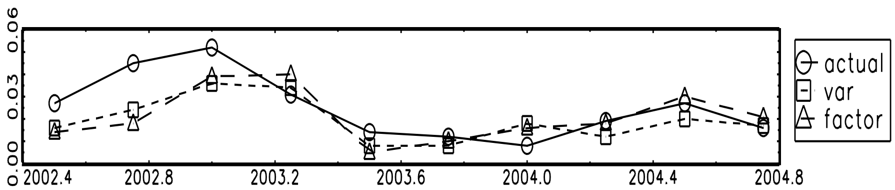


Figure 6 Brazil: GDP growth forecasts

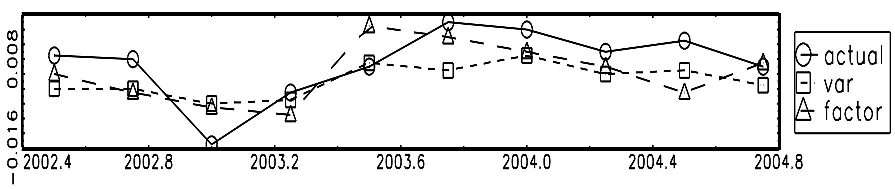


Figure 7 Russia: CPI inflation forecasts

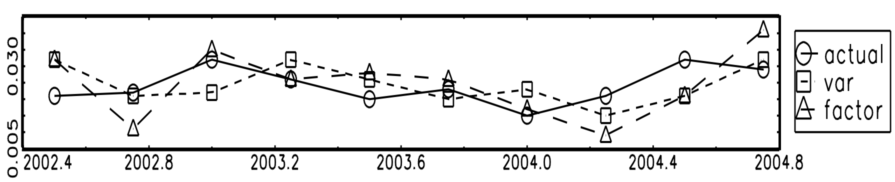
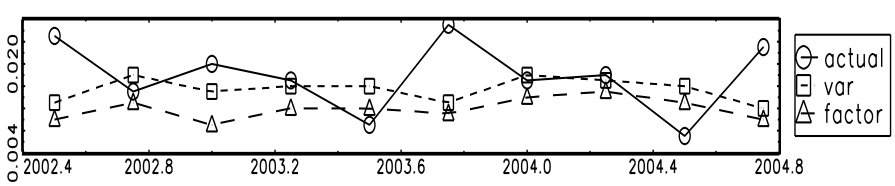


Figure 8 Russia: GDP growth forecasts



Appendix D Tables

Table 1 Brazil: cumulative R^2 from regressions of variables on factors

Factor	I(1) Prices			I(2)Prices		
	Total	CPI	GDP	Total	CPI	GDP
1	0.19	0.03	0.74	0.17	0.00	0.75
2	0.29	0.06	0.74	0.28	0.52	0.75
3	0.39	0.50	0.76	0.36	0.64	0.78
4	0.45	0.68	0.81	0.44	0.64	0.79
5	0.51	0.69	0.81	0.49	0.71	0.79
6	0.56	0.69	0.82	0.54	0.73	0.79

Table 2 Russia: cumulative R^2 from regressions of variables on factors

Factor	I(1) Prices			I(2)Prices		
	Total	CPI	GDP	Total	CPI	GDP
1	0.21	0.79	0.07	0.24	0.58	0.64
2	0.36	0.86	0.77	0.31	0.67	0.75
3	0.46	0.88	0.82	0.43	0.77	0.85
4	0.54	0.91	0.86	0.52	0.81	0.88
5	0.59	0.92	0.88	0.57	0.81	0.88
6	0.63	0.92	0.89	0.62	0.87	0.89

Table 3 Results for Brazil

Forecast Method	Relative MSFE			
	I(1) Prices		I(2)Prices	
	GDP growth	CPI inflation	GDP growth	CPI inflation
ar_aic	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)
ar_ic_aic	1.19 (0.36)	1.10 (0.67)	-	-
ar_i2_aic	1.55 (0.88)	0.90 (0.32)	-	-
rw	1.14 (0.32)	0.85 (0.30)	-	-
var_aic	0.73 (0.38)	0.64 (0.21)	-	-
fbp_ar_aic	1.32 (0.53)	0.97 (0.03)	0.92 (0.58)	1.13 (0.22)
fbp_aic	0.76 (0.23)	1.38 (0.81)	0.92 (0.58)	0.98 (0.02)
fnbp_ar_aic	1.26 (0.62)	0.83 (0.09)	0.76 (0.57)	0.92 (0.24)
fnbp_aic	0.83 (0.24)	0.79 (0.15)	0.76 (0.57)	0.88 (0.06)
fnbp_ar_1	1.11 (0.22)	1.04 (0.05)	0.94 (0.21)	1.28 (0.26)
fnbp_ar_2	0.90 (0.26)	0.85 (0.08)	1.09 (0.61)	1.01 (0.12)
fnbp_ar_3	0.84 (0.52)	0.76 (0.13)	1.12 (0.60)	1.08 (0.12)
fnbp_ar_4	1.21 (0.47)	0.78 (0.13)	0.81 (0.61)	0.67 (0.25)
fnbp_1	0.88 (0.08)	1.57 (0.91)	0.84 (0.10)	1.06 (0.07)
fnbp_2	0.88 (0.08)	1.09 (0.29)	0.72 (0.39)	0.96 (0.09)
fnbp_3	0.71 (0.47)	0.87 (0.13)	0.67 (0.42)	1.08 (0.23)
fnbp_4	1.09 (0.33)	0.74 (0.15)	0.81 (0.61)	0.68 (0.21)
RMSE for ar_aic	0.009	0.13	0.009	0.012

Table 4 Results for Russia

Forecast Method	Relative MSFE			
	I(1) Prices		I(2)Prices	
	GDP growth	**CPI inflation**	**GDP growth**	**CPI inflation**
ar_aic	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)
ar_ic_aic	1.80 (0.80)	0.38 (0.25)	-	-
ar_i2_aic	0.97 (0.26)	0.18 (0.26)	-	-
rw	1.23 (0.28)	0.16 (0.25)	-	-
var_aic	0.71 (0.22)	0.29 (0.26)	-	-
fbp_ar_aic	2.21 (1.07)	2.41 (1.33)	0.76 (0.34)	7.07 (15.33)
fbp_aic	2.19 (1.05)	2.67 (2.12)	0.76 (0.34)	5.76 (10.83)
fnbp_ar_aic	1.30 (0.46)	1.59 (1.01)	2.31 (1.88)	2.15 (1.39)
fnbp_aic	1.32 (0.25)	2.10 (1.43)	0.58 (0.31)	2.15 (1.39)
fnbp_ar_1	0.92 (0.10)	0.24 (0.26)	1.00 (0.05)	3.57 (3.61)
fnbp_ar_2	1.69 (0.60)	0.86 (0.20)	0.59 (0.27)	4.25 (6.51)
fnbp_ar_3	1.87 (0.66)	1.58 (0.68)	0.53 (0.31)	3.03 (4.96)
fnbp_ar_4	1.30 (0.46)	2.38 (1.62)	0.69 (0.41)	2.15 (1.39)
fnbp_1	0.92 (0.10)	0.78 (0.26)	1.14 (0.13)	1.86 (0.96)
fnbp_2	1.52 (0.43)	0.44 (0.24)	0.59 (0.27)	3.01 (3.07)
fnbp_3	1.87 (0.66)	0.79 (0.25)	0.53 (0.31)	2.07 (1.58)
fnbp_4	1.16 (0.18)	1.66 (0.81)	0.54 (0.32)	2.15 (1.39)
RMSE for ar_aic	0.009	0.18	0.009	0.007