Bank of Russia

Monetary Policy REVIEW

RETROSPECTIVE ASSESSMENT OF THE EFFECTIVENESS OF MONETARY POLICY

Working paper

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INTRODUCTION

The Bank of Russia has performed a retrospective analysis of the economic situation in the period of *inflation targeting* as part of its Monetary Policy Review. One of the objectives of the Monetary Policy Review is to establish the degree to which the current monetary policy is optimal in terms of social welfare. This analysis helps determine the timeliness of the Bank of Russia's response to unexpected changes in economic conditions and to what extent the monetary policy it has followed has been in agreement with the stages of the business cycle.

Such retrospective studies use counterfactual analysis as the key method. In this method, the paths of the variables in the basic specification of the model are compared with the counterfactual paths in modified model simulations (for example, with other values of the monetary rule ratios). The criterion of effectiveness in linearised models is the *loss function*, the monetary regulator's target function, which as a rule consists of the weighted sum of the squared deviations of the macrovariables from their values in a steady state.

One example of such studies is the work of X, which relies on a small semi-structural model to compare a number of variations of monetary policy rules in stylised Asian economies. As they compare the results obtained with optimal policies and linear rules, the authors argue that the results of a more flexible inflation targeting regime (based on, for instance, a target range instead of a point) are similar to those of an optimal discretionary policy.

X distinguish the effects of exogenous oil price shocks and of monetary policy and consider a small neo-Keynesian DSGE model of the US economy which takes oil prices into account. The authors draw on counterfactual simulations to measure the effect of a positive oil price shock on output with a fixed interest rate and find that the two variables are directly correlated. Further, the authors compare the *Wicksellian* monetary rule (which smooths out nominal rigidities in the economy) with other rules and make the case that it is output gap neutral.

X explore the credibility of the US Fed's policy and estimate a New Keynesian DSGE model which enables changes in the policy regime. The work assumes that, in every time period, the US Fed chooses between meeting its recent commitments and optimising them. The counterfactual analysis finds that the US Federal Reserve has clearly failed to fully follow through on its commitments since the second half of the 1960s but has refrained from foregoing them altogether with the passage of time. X also use the same method with a focus on the euro area: the work posits that that the monetary regulator adheres to an optimal discretionary policy.

The work of X uses a small log-linearised New Keynesian DSGE model with a monetary regulator loss function. The small number of parameters in the model makes it possible to clearly estimate the parameters of the loss function using the maximum likelihood method. The authors argue that a model featuring an optimal discretionary policy describes the historical data better than a model that includes commitments. X rely on the same approach to examine the effectiveness of central bank policy in China.

Another important problem pertaining to the effectiveness of monetary regulator policy is the availability of data at the time of decision making. The most vivid example is the unavailability of fresh data on GDP. The workaround in most cases is *nowcasting* and the use of *pseudo real-time* time series – data derived from a model predicting the current values of the variable using the known values of other factors. Highlighting this problem and drawing on the example of *vintage* and *ex-post* data on output and inflation, X demonstrates a significant revision of the interest rate in retrospect.

The work of X examines the quality of various methods for estimating the output gap on *pseudo real-time* data. It is argued that a reliable assessment of the output gap is impossible owing to the errors of GDP nowcasting. Furthermore, the frequently used statistical methods to measure the cyclical component of the time series and its trend (a linear trend, the unobservable components model, and the Hodrick–Prescott filter) fail to produce a correct estimate of the non-cyclical component. The authors warn of potential problems in monetary policy decision making stemming from the inaccuracy of the available data.

The work of X continues the study of the accuracy of measuring the output gap based on pseudo *real-time* data. According to the authors, the predictive capabilities of inflation forecasting models relying on the output gap as an explanatory variable are inferior to simple models based on the growth rate in predicting *out-of-sample* observations (a sample that is not used in model estimation).

X examine various specifications of a real-time forecast and stress the importance of *vintage* data (used at the time the forecast is made) in the specification and model estimation processes. The work of X is a similar study which makes use of New Zealand output data.

In exploring the impact of oil prices on the quality of estimates of GDP growth, X note minimal differences in forecast accuracy with the use of *pseudo real-time* data and *ex-post* time series for output. At the same time, oil prices are a key factor in forecasts for four quarters ahead. On that point, the authors argue that the improvement in the forecast is hardly meaningful. X also note that the GDP data used at the time of decision making are not characterised by systematic differences from *ex-post* time series. The authors make the case for the use of *vintage* data in forecasting, though they admit that there is a certain bias in US output data.

X analyse data for the euro area and advocate the use of *pseudo real-time* data. I should stress here, however, that different model specifications and different forecast horizons may lead to conflicting conclusions. The paper discusses the choice between the use of a good model specification based on accurate data and the use of time series obtained by *nowcasting*.

This work is a retrospective study of the effectiveness of the monetary policy conducted in the period of inflation targeting up to 2022. The remainder of the paper is organised as follows. I begin with a discussion of the definition of the model framework, proceed with a presentation of three studies on the subject, and thereafter present the conclusion. Section 2 includes a brief description of the model I employ and the definition of the monetary regulator loss function and of two types of optimal policies in the rational expectations models.

The first study (Section 3) considers the analysis of welfare in the conditions of the historical monetary policy, a simple linear policy free of exogenous interest rate shocks with different responses to the output gap, and an optimal policy, one under commitment and a discretionary one. The paths for the optimal policies are calculated for the 2015–2021 period, and thereafter the values of the loss function are determined for each of the specifications. The difference between the actual value of the loss function and the value of an optimal policy under commitment is significantly less than compared to a confidence-free policy, and it is close to a simple linear policy involving no response to the output gap.

Since there is no formal criterion for the closeness of the historical policy to any of the optimal policies, solutions to the optimal policy problem will be classified using the *k-nearest* neighbours algorithm. Namely, the loss function problems are solved for 230 different parameterisations starting from 2015, with each solution characterised by three values: the average root-mean-square (RMS) gap of the deviation of inflation from target, output, and the rate increase. With any positive value of k <230, the actual mean square gaps are closer to those obtained for a policy under commitment.

The second part of the work examines the impact of errors in the measurement of vintage GDP data on the model's predictive capabilities and the accuracy of smoothing of the paths of unobservable variables. Consistent with the iterative procedure discussed in Section 4, I obtain the paths of the variables in a decision-making environment marked by incomplete information. For 2015–2020, the output gap is underestimated, but in terms of the loss function, decision making based on vintage data proves better. Deviations in the predicted values over various horizons affect the forecast quality of only the output variables, while different aggregation methods show significant forecast deviations over various horizons.

The third study (Section 5) is an effectiveness analysis in terms of the loss function of the fiscal rule that was in place between 2017 and 2021. I rely on a modified set of observations of primary federal budget expenditure to obtain counterfactual simulations for the period under study. The results show that the fiscal rule did indeed boost public welfare as measured by the significance of the loss function for the monetary regulator. Section 6 concludes.

METHODS AND DATA

Model

The working model is an enhanced version of the Quarterly Projection Model (QPM) of the Bank of Russia with a temporal structure of market interest rates. This model is used in the making of decisions on the key rate and on other monetary policy instruments, and so it is the obvious choice for this paper. Using the Kalman filter, I extract the smoothed historical values of the unobservable variables and use the shocks identified conditional on the data and the model in further analysis.

The QPM is a linear semi-structural model which imposes restrictions on the methods of analysis that can be used, since its initial linearity drives the choice of the ad-hoc loss function in this work. The inherent non-linearity of DSGE models allows the use of the approximation of the higher-order model solution (including non-linearities) and of the direct result of the linear-square approximation of the household utility function.

The monetary rule is an enhanced Taylor rule which responds to a deviation of expected inflation from target in three quarters. This rule is known as the *forecasted inflation targeting (FIT)* rule:

$$R_t = \gamma_R R_{t-1} + (1-\gamma_R)\left(R^* + \gamma_{\tilde{\pi}}\mathbb{E}_t\tilde{\pi}_{t+3} + \gamma_{\tilde{Y}}\tilde{Y}_t\right) + \varepsilon_t^R, \quad (1)$$

where R_t is the nominal interest rate in period t, R^* is the neutral nominal interest rate, $\mathbb{E}_t\tilde{\pi}_{t+3}$ is the expected deviation of inflation from a steady state, $\tilde{Y}_t$ is the output gap, $\gamma_R, \gamma_{\tilde{\pi}}, \gamma_{\tilde{Y}}$ are the parameters setting the response of the nominal interest rate under the corresponding variables, and $\varepsilon_t^R \sim \mathcal{N}(0, \sigma^2_{\varepsilon_R})$ is the exogenous dispersive shock of monetary policy $\sigma^2_{\varepsilon_R}$.

In this work, the specified rule of zero response to the output gap ($\gamma_{\tilde{Y}} = 0$) is used as the basic rule in identifying shocks in the model. This is due to the fact that it was difficult to measure the output gap (that is, to obtain a smoothed series of appropriate accuracy) following the severe shocks of the crisis in late 2014. The comparisons with the optimal policies are also based on the same linear rule, but the latter includes a response to the gap ($\gamma_{\tilde{Y}} = 1$).

Loss function

The concept of the monetary regulator loss function is introduced to describe the historical monetary policy from the standpoint of social welfare. This function consists of the weighted sum of the variances of the deviation of inflation from target, the output gap, and the increase of the nominal interest rate in the current period compared to the past:

$$\mathcal{L}_{cb} = w_{\tilde{\pi}}\bar{\sigma}^2_{\tilde{\pi}} + w_{\tilde{Y}_t}\bar{\sigma}^2_{\tilde{Y}} + w_{\Delta_R}\bar{\sigma}^2_{\Delta R}, \quad (2)$$

where $\tilde{\pi}$ is the deviation of inflation from target, $\tilde{Y}$ is the output gap, $\Delta R = R_t - R_{t-1}$ is the first difference of the nominal interest rate, $\bar{\sigma}^2_{\tilde{\pi}}$, $\bar{\sigma}^2_{\tilde{Y}}$, $\bar{\sigma}^2_{\Delta R}$ is the unconditional variance of the corresponding variable, and $w_{\tilde{\pi}} > 0, w_{\tilde{Y}} > 0, w_{\Delta R} > 0$ are the weighing parameters. An important factor enabling the interpretation of the loss function is that the weights of the squared deviations are normalised relative to the inflation-related indicator. Although the literature uses weight value $w_{\tilde{\pi}} = 1$, I take the value below.

To account for the inflation dynamics in the period in the loss function without irrelevant (past or future) information, I use an annualised inflation indicator calculated as the log of the consumer price index (CPI) in the quarter to its previous value,

$$\pi_t^{QoQ} = \ln \frac{CPI_t}{CPI_{t-1}}, \tag{3}$$

$$\pi_t^{QoQ,ar} = 4\pi_t^{QoQ}, \tag{4}$$

$$\tilde{\pi}_t = \pi_t^{QoQ,ar} - \pi^*, \tag{5}$$

where CPI_t is the CPI in the current period, π_t^{QoQ} is QoQ inflation in the period, $\pi_t^{QoQ,ar}$ is QoQ annualised inflation in the period, and π^* is the inflation target.

However, the volatility of the indicator in this case increases by a factor of 16:

$$\sigma^2_{\pi_t^{QoQ,ar}} = \tilde{\pi}_t^2 = \left(\pi_t^{QoQ,ar} - \pi^*\right)^2 = 16\sigma^2_{\pi_t^{QoQ}}. \tag{6}$$

To capture this property, the corresponding weight is set before the volatility of deviation from target: $w_{\tilde{\pi}} = 1/16$. This sets off the effects of the calculation of the annualised inflation and allows comparable results to be obtained.

In the strict sense of the problem, the loss function is deduced from the second-order approximation of the household utility function or from the weighted utility sums of heterogeneous households in the vicinity of the steady state. In this case, the use of an *ad-hoc* utility function is a consequence of the original linearity of the Bank of Russia's QPM.

The counterfactual studies are limited to the observable time interval, prohibiting the use of unconditional variances. To calculate the *ex-post* values of the loss function, I use the sum of the average squares of the discontinuities of the variables (mean square gap):

$$\mathcal{L}_{cb}^{ex-post} = w_{\tilde{\pi}} MSG_{\tilde{\pi}} + w_{\tilde{Y}} MSG_{\tilde{Y}} + w_{\Delta_R} MSG_{\Delta R}, \tag{7}$$

$$MSG_{\tilde{\pi}} = \sum_{t \in T} \frac{(\pi_t - \pi^*)^2}{N_T}, \tag{8}$$

$$MSG_{\tilde{Y}} = \sum_{t \in T} \frac{\tilde{Y}_t^2}{N_T}, \tag{9}$$

$$MSG_{\Delta R} = \sum_{t \in T} \frac{(R_t - R_{t-1})^2}{N_T}, \tag{10}$$

where π^* is the inflation target, ΔR is the rate increase from the previous period (the first difference), T is the set of quarterly dates with number of elements N_T, T_i is the i-th element of set $T, i \in [1, N_T]$.

Of note, I use the terms *mean square gap, volatility*, and *variance* (σ^2) interchangeably. It is also important to note that the mean square gap is equivalent to the uncorrected variance.

Based on research taking a similar approach to the assessment of policy effectiveness, I choose weights $w_{\tilde{Y}} = w_{\Delta R} = 0{,}5$. I intentionally overestimate the weighing parameter of the rate increase relative to the values used in the above-mentioned articles. This is due to the fact that, in the articles exploring advanced economies, the interest rate volatility is limited by the high probability that the lower zero bound is reached, which is a deterrent to a rate change per se. In what follows, the relatively high weight of the first difference limits its volatility in an optimal policy and is a factor in the more consistent policy of the monetary regulator.

A formal comparison between the loss function values for the different model specifications with the help of a statistical criterion is impossible due to the absence of such criteria in the literature. However, X propose two measures for the difference of the values of the loss functions with no conclusion about statistical significance: *relative increase in welfare* and an *inflation equivalent*. Importantly, in the original work, the above measures are used only to compare the values of the loss function under an optimal policy under commitment and an optimal discretionary policy:

1. Relative increase in welfare: $\Omega = 100 \cdot \left(1 - \frac{\mathcal{L}_1}{\mathcal{L}_2}\right)$;

Inflation equivalent: $\hat{\pi}_{0+} = \sqrt{\mathcal{L}_2 - \mathcal{L}_1}$,

where $\mathcal{L}_1$ ($\mathcal{L}_2$) is the value of the loss function of the best/worst model, $\mathcal{L}_1 \leqslant \mathcal{L}_2$.

The inflation equivalent takes the appropriate form only if the ratios of the loss functions are normalised relative to the mean square gap of inflation. In this work, the inflation equivalent is given as the quarter-on-quarter growth rate of inflation after the multiplication of the mean square gap of annualised quarter-on-quarter inflation by the corresponding weight.

Additionally, for ease of understanding, the inflation equivalent can be defined as follows:

$$\hat{\pi} = \operatorname{sgn}(\mathcal{L}_2 - \mathcal{L}_1)\sqrt{|\mathcal{L}_2 - \mathcal{L}_1|} \equiv \left|\sqrt{\mathcal{L}_2 - \mathcal{L}_1}\right|. \quad (11)$$

In this case, at negative values $\hat{\pi}$, $\mathcal{L}_1 > \mathcal{L}_2$.

Optimal policy

To determine the effectiveness of monetary policy, I compare the value of the loss function and the change in macroeconomic variables with the solutions of the problem of an optimal policy *under commitment* and a *discretionary* optimal policy.

In the case of an optimal policy under commitment, the monetary regulator minimises the discounted sum of the values of the loss function in each period for all endogenous variables, with agent effectiveness and market equilibrium factored in and without a clearly specified monetary rule. The regulator conducts optimisation only within the initial period and induces the private sector to develop an understanding of the importance of monetary policy tools in every economic state, which allows the use of agent expectations.

Having said this, a regulator conducting a discretionary optimal policy re-optimises the problem in each period and accepts private sector expectations as given. While its action may be efficient in a given period, its overall operations lack dynamic coordination and ultimately result in a bias towards growth in inflation expectations and in equilibrium inflation.

Therefore, the values of the loss function with a discretionary optimal policy are expected to be higher than those with an optimal policy under commitment. It is worth mentioning works (namely, the work of X) which show how, under certain conditions, a discretionary optimal policy can outperform an optimal policy under commitment. However, this can occur only in rather specific conditions (for example, a low discount factor).

The above are the basic approaches to the understanding of effectiveness as a monetary policy objective in the existing academic literature. In reality, it seems impossible to imagine that there is an economy in which the monetary regulator fully follows through on its previously announced stance without making adjustments for the current state of affairs. A similar logic may be applied to a regulator conducting a discretionary policy. Under a mixed approach, which appears more natural, the work of X presents a New Keynesian DSGE model with loose commitments, in which the regulator can fall short of its commitments with a certain fixed probability and recommit to the implementation of a new optimisation. In addition, the works referred to in the introduction are based on general equilibrium models with mode switches for the same purposes. This study is limited to only two extreme cases of optimal policy.

Optimal policy problems require the loss function to converge to infinity. To this end, the value of the loss function for each specific period is discounted by corresponding discount factor X:

$$\mathcal{L}_{cb}^{obj} = \sum_{t=T_1}^{\infty} \beta^{(t-T_1)} \left[w_{\tilde{\pi}} (\pi_t - \pi^*)^2 + w_{\tilde{Y}} \tilde{Y}_t^2 + w_{\Delta_R} (R_t - R_{t-1})^2 \right], \quad (12)$$

where β is the loss flow discount factor. For comparability, I normalise the loss function value by the number of periods in the sum (T). Based on the assumptions in X, I set the value of the discount factor at $\beta = 0{,}997$. The value of the loss function on historical data is estimated in a similar fashion.

It is assumed that the value of the loss function on historical data is never better than that under an optimal policy under commitment. The existence of solutions resulting in a lower loss than with a policy under commitment speaks either to the incorrect specification of the monetary regulator's optimisation problem in the model or to forthcoming shocks in the future alongside incorrect specifications of the model equations overall.

Data

To identify the unobservable variables, I use the following observable 2004 Q1 series:

- Urals price per barrel (spot market) and the base price for the fiscal rule, USD
- Consumer price index (on the whole and by component)
- GDP in constant prices, RUB
- Interbank rate, pp
- OFZ yields with maturities of 1, 2, 3, 5, 7, and 10 years, pp
- Interest rate on loans to non-financial companies with maturities of 1 and 3 years, pp
- Revenue (oil and gas, non-oil and gas) and expenditure of the consolidated and federal budgets of the Russian Federation, RUB
- Composite indicators of the external sector: GDP, inflation, interbank rate, USD exchange rate USD/EUR exchange rate
- Estimated risk premium on OFZ bonds at short/long ends, pp

The variables suspected of having seasonal factors are seasonally adjusted with X-13 ARIMA-SEATS, a US Census Bureau technique.

MONETARY POLICY RULES

This section considers counterfactual simulations for two solutions to the optimal policy problem: a policy under commitment and a discretionary policy, as well as for two linear rules: one with and one without the output gap response.

I obtain smoothed series for the unobservable variables in the 2015–2021 period based on data beginning from 2004 Q1. The exogenous shocks thus identified throughout the path under study help in obtaining the simulations in the model with the modified monetary policy rule (that is, with the corresponding linear rule free of discretionary shocks or a result with a solution to the optimal policy problem). My counterfactual scenarios exclude monetary policy shocks, which ensures strict adherence to the linear rule and rules out temporary discretionary effects.

I also calculate the mean square gap for counterfactual simulations with optimal rules based on weight chart $w_{\tilde{Y}}$ (the coefficient of the output gap in the loss function) and $w_{\Delta R}$ (the coefficient of the rate change in the same place) and obtain a sample from two distributions. To describe the actual mean square gaps in terms of proximity to one or another distribution (a policy under commitment or a discretionary policy), I use the k-nearest neighbours algorithm for various values of *k*.

Comparison with optimal policy

Figure 1 shows the key rate, output gap, and inflation dynamics on historical data and for optimal policy rules beginning from 2015 Q1. The actual value of the loss function is much closer to the same value under an optimal policy under commitment than under a discretionary optimal policy.

Counterfactual simulations of output gap ( ), nominal interest rates (), and inflation beginning from 2015 under optimal policy (policy under commitment or discretionary policy) compared to historical paths

The smooth descent in the nominal interest rate after the spike in 2015 Q1 was caused by the inertia of the indicator in the loss function. With comparable output gaps and inflation under the policy under commitment and the actual policy, high inflation is reported in 2015 alongside a highly volatile output gap, while the rate under the discretionary policy is higher. This difference is explained by the inconsistency of the monetary regulator's actions, leading to high inflation expectations in the private sector. The growth of the above variables in 2021 is explained in a similar fashion: with the interest rate close to historical readings, an optimal discretionary policy results in accelerated inflation and an expanding output gap.

While on the subject of overall movements in the key rate, I note that the Bank of Russia's monetary policy in the aftermath of the 2015 shocks was tougher than the optimal discretionary policy. The exception is the 2019 Q2–2020 Q1 period, when the regulator began a systematic reduction in the key rate.

It is of note that there was a jump in inflation in 2020 Q2 in the conditions of an optimal policy under commitment: the strong reduction in the interest rate at the time helped reduce the deviation from potential output. At the same time, private sector confidence helped return inflation back to target, reducing the gap in absolute terms by the following quarter.

LOSS FUNCTION VALUES FOR OPTIMAL POLICY SIMULATIONS *Table 1*

$\mathcal{L}$ (commitment)	$\mathcal{L}$ (discretionary)	$\mathcal{L}$ (actual)	$\hat{\pi}$ (commitment/ discretionary)	$\hat{\pi}$ (actual/commitment)	$\hat{\pi}$ (discretionary/actual)
3.3911	5.9501	3.7175	1.5997	0.5713	1.4942

Note: The last three columns contain the inflation equivalent (% QoQ, annualised average) of the difference in the values of the loss functions in parentheses.

To gain more insight into the effects of the weights in the loss function on the solution to the optimisation problem, I run simulations for each pair on the parameter grid:

$$\overline{w}_{\tilde{Y}} \times \overline{w}_{\Delta_R} : \ \overline{w}_{\tilde{Y}} = (0{,}003; 0{,}03; 0{,}1; 0{,}2; \ldots ; 2),\ \overline{w}_{\Delta_R} = (0; 0{,}003; 0{,}3; 0{,}1; 0{,}2; \ldots ; 0{,}9).$$

A non-zero $\overline{w}_{\tilde{Y}}$ is a prerequisite for a stable solution to the model (the strict inequality shown in X). I also add weights of 0.03 and 0.003. The first number can be obtained from X for $\varkappa = 0{,}3$ ($\varkappa$ is the Phillips curve slope factor, before output), which is used in the QPM, and $\theta = 10$ (θ is the demand elasticity factor for a commodity in terms of price). This is consistent with the result discussed by X. The second value is taken from X. The remaining range of weights is consistent with X.

Figure 2 shows the RMS gaps that constitute the loss function in 2015–2021. Under an optimal discretionary policy, the mean square gaps of inflation and output have a greater spread than in the case of a policy under commitment. At the same time, the RMS gap of the nominal interest rate is slightly lower. Figure 7 in the Appendix shows the orthogonal projections of this graph.

Root graph of RMS gaps: different weights in loss function for optimal policies (under commitment and discretionary)

As a criterion for the proximity of a historical point to one or the other distribution, I rely on a non-parameter method: the k-nearest neighbours algorithm. The Mahalanobis distance is used to capture the differences in the variance of the different dimensions. It normalises the values of the variance of each RMS gap. The probability[1] of correspondence to the distribution of a policy under commitment is equal to one with k. It can therefore be argued that, in efficiency, the Bank of Russia's policy is more similar to decision making with a policy under commitment than with a discretionary policy.

The results of the historical monetary policy are particular in the extremely low volatility of the inflation gap. This fact is of interest when compared with the RMS deviations of inflation from the target obtained from counterfactual paths with linear rules. The discretionary monetary policy shocks identified under a linear rule with zero response to the output gap result in significantly lower volatility of inflation on account of the immaterially higher output-gap volatility.

The chart of the dependence of the deviations of the mean square gaps from target and the output gap also demonstrate a *Pareto policy frontier*. It is obvious that the frontier of the distribution of a policy under commitment is closer to the origin of the coordinates than that of a discretionary policy. In addition, there is a discretionary policy 'mode' defined by a set of weights, the property of which is the co-direction of the mean square gaps of inflation and the output gap (the path of points from 3, 2 to 9, 10 on the corresponding projection). The frontier is also present in the dependence of the deviations of inflation from the target and interest rate increases. However, this relationship is more characteristic of a discretionary policy. Under a commitment policy, the volatility of the rate increase has little effect on the volatility of the output gap.

The correlation between inflation volatility and interest rate increments is also of interest: Whereas the *Pareto frontier* is traced in the mean square gaps of an optimal discretionary policy, the distribution of a policy under commitment does not contain a frontier in this plane. In addition, a certain co-directionality of the magnitudes of the volatility of these two variables can be seen.

Linear rule without exogenous monetary policy shocks

Counterfactual simulations which exclude exogenous monetary policy shocks are run to describe past monetary policy from the point of view of a linear rule. The exogenous variable in equation ε_t^R is taken as the source of monetary policy shocks.

This experiment is intended to determine how the judgments of Bank of Russia board members influence the current monetary policy stance in comparison with the model rule and how they influence the dynamics of inflation and the output gap.

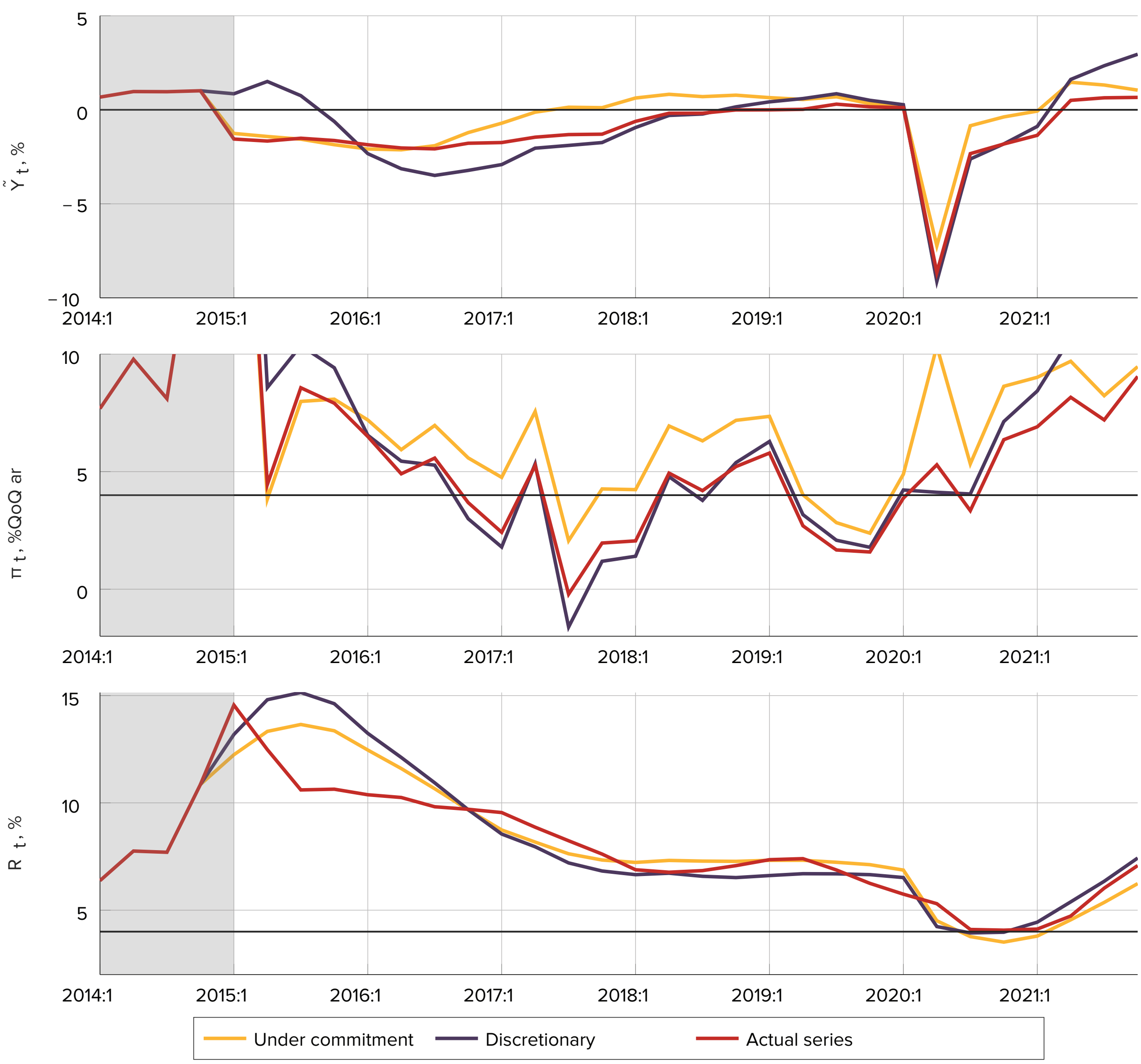
[1] Fig. 6 displays dependence of the probability on the number of nearest neighbour points (k) up to the whole point set.

Figure 3 shows the actual paths of the output gap, the nominal interest rate, and inflation (quarter-on-quarter (QoQ), annualised), as well as the paths without exogenous monetary policy shocks. I do not see significant deviations in the actual rate from the strictly linear rule until the second half of 2020. However, immediately after the beginning of the pandemic, the no-shock rule suggested a tougher monetary policy.

There are two intervals in which the actual monetary policy was tougher than the linear rule assumes: between 2015 Q4 and 2017 Q1 and between 2018 Q3 and 2020 Q1. In the first case, the deviation is probably due to the rise in inflation in 2015 Q3 and the concerns at the time that it would accelerate. The second period is more informative: the no-shock rule suggests a softer monetary policy despite the positive output gap beginning from 2018 Q3.

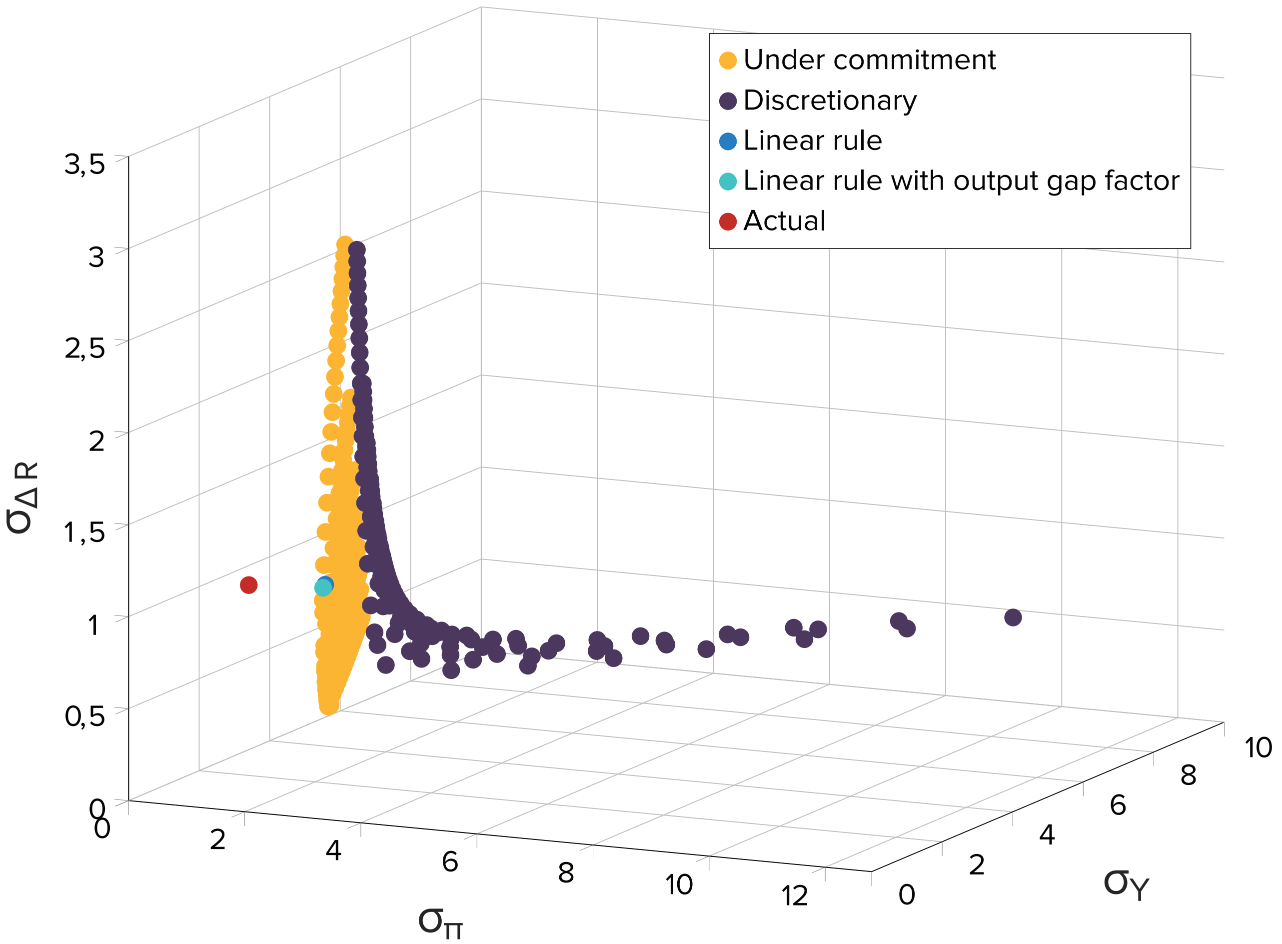
Comparisons between the values of the loss function from the actual paths and the paths without exogenous monetary shocks yield the following outcome: The no-shock rule leads to a more optimal result in terms of losses, though the difference is insignificant (0.42% in a quarter-on-quarter annualised inflation equivalent, on average).

COUNTERFACTUAL SIMULATIONS OF OUTPUT GAP ($\tilde{Y}_t$), NOMINAL INTEREST RATE (R_t) AND INFLATION π_t WITH OPTIMAL MONETARY POLICIES (DISCRETIONARY, UNDER COMMITMENT) AND ACTUAL TRAJECTORY FROM 2015 TO 2021 *Chart 1*



DISTRIBUTION OF MSG ROOTS (INFATION, OUTPUT GAP, INTEREST RATE INCREMENT) OBTAINED IWTH DIFFERENT WEIGHTS IN THE LOSS FUNCTION

Chart 2



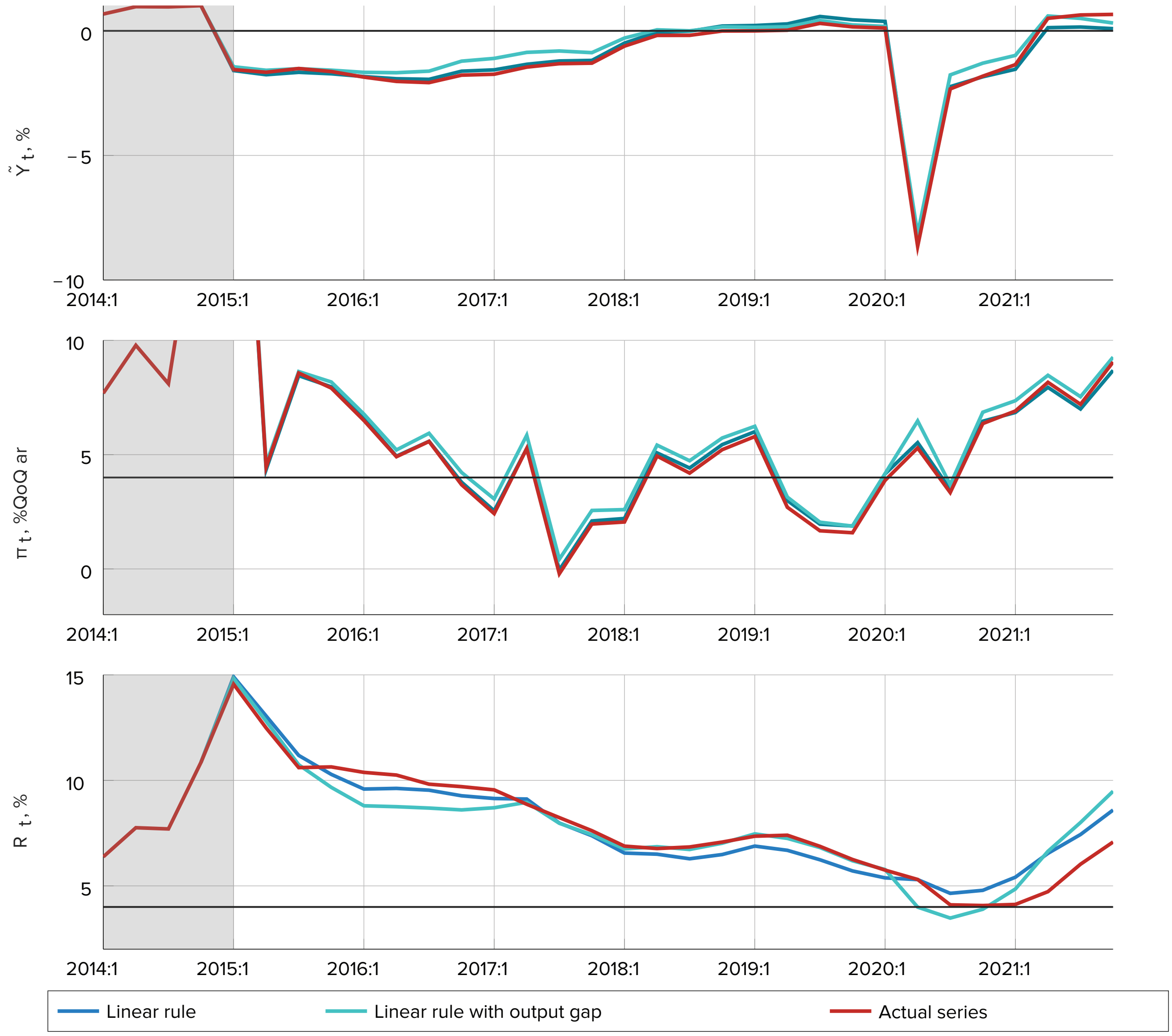
VALUES OF LOSS FUNCTION FOR SIMULATIONS WITH LINEAR MONETARY POLICY RULES

Table 1

$\mathcal{L}\,(\gamma_{\tilde{Y}} = 0)$	$\mathcal{L}\,(\gamma_{\tilde{Y}} = 1)$	$\mathcal{L}$ (actual)	$\hat{\pi}$ (actual/$(\gamma_{\tilde{Y}} = 0)$)	$\hat{\pi}$ (actual/$(\gamma_{\tilde{Y}} = 1)$)
3.6559	3.5436	3.7175	0.2482	0.4170

Note: The last two columns contain the inflation equivalent (% quarter-on-quarter annualised on average) of the difference in the values of the loss function in parentheses.

COUNTERFACTUAL SIMULATIONS OF OUTPUT GAP ($\tilde{Y}_t$), NOMINAL INTEREST RATE (R_t), AND INFLATION π_t WITHOUT EXOGENOUS MONETARY POLICY SHOCKS BEGINNING FROM 2015 COMPARED TO HISTORICAL PATHS *Chart 2*



Vintage data on output

In its medium-term forecasting, the Bank of Russia is confronted with the lack of flash data, in particular on output. To address the challenge of the limited availability of time series, nowcasting is used as a technique for predicting the current values of time series based on historical and incomplete current data. Subsequently revised macrovariables may have a retrospective impact on the effectiveness of monetary policy: a nowcasting error may well lead to a significant deviation from the optimal path of the monetary rule.

The Federal State Statistics Service (Rosstat) publishes GDP estimates with a significant lag (of up to three quarters). For forecasting purposes, the Bank of Russia uses the available information to nowcast the output. A GDP estimate for the current quarter is certain to include a statistical error. This may affect both the predicted values of the other variables and the effectiveness of a monetary policy decision in the current period.

This section considers the impact of the error of real GDP nowcasting on the effectiveness of the linear monetary rule, analysed with the help of *vintage* time series of the variable used in the core forecast rounds between 2015 and 2021. The design of the study is based on the work of X, although I place more emphasis on the limited availability of data. The GDP series start from 2004 Q1, and the current time series are shown as of 2021 Q4.

First, I obtain the smoothed series of the output gap using the vintage GDP series for each forecast round to show historically how a change in the data entails a change in the gap. Then, on an iterative basis, I calculate the predicted values of the macrovariables series beginning from 2015 and compare them with the iterative forecast based on the actual data, using the Diebold-Mariano test.

Data and methods

In the QPM, the output indicator (y_t) is the log of the current real GDP in 2016 prices (GDP_t):

$$y_t = \log(GDP_t). \tag{13}$$

I use the last available data (as of 2022 Q1) as the information set in each quarter between 2015 and 2021 for all the variables except real output. Real output, in turn, is represented by the quarterly vintage time series between 2015 and 2021 and the actual time series for 2022 Q1. The actual time series includes the nowcasting for 2021 Q3–Q4. The interval under study includes the path of the Russian economy's transition to inflation targeting and the transformation process following the foreign currency crisis in late 2014.

The vintage (*pseudo real-time*) $\hat{y}_t^{(\tau)}$ output value for period t which exists at time τ can be represented as the difference between the true value (which is not observable in real time y_t) and the error $\tilde{\varepsilon}_t^{(\tau)}$:

$$\hat{y}_t^{(\tau)} = y_t + \tilde{\varepsilon}_t^{(\tau)}. \tag{14}$$

To determine the accuracy of forecasting variables on different horizons, the RMS is calculated for the forecast for h quarters ahead:

$$RMSFE_h^{(x)} = \sqrt{\frac{\sum_{t=T_1}^{T_2-h} \left(x_{t+h} - \hat{x}_{t+h|t}\right)^2}{T_2 - T_1 - h}}, \tag{15}$$

where h is the forecast horizon in the periods, T_1 is the number of first observations of the time series used to build the model, T_2 is the number of observations in the whole time series (including the observations used to validate the predictive capability), $\hat{x}_{t+h|t}$ is the predicted value of variable x in period $t+h$ obtained from the information set available in period t, and x_{t+h} is the actual value of the variable in period $t+h$.

This study is grounded in a basic specification model with a linear monetary rule. The impact of an exogenous monetary shock is intentionally excluded in the assumption of strict adherence to the simple monetary policy rule. I compare the predicted values of the variables and of the loss function from the model assuming fully available information at the time of the decision, with the value from the counterfactual model assuming "lagged" information where output data are nowcast. This helps determine how much the quality of decisions changes when *pseudo real-time* output data are used.

To compare the predicted values of the variables derived from the two models, I calculate Diebold–Mariano statistics for one quarter-ahead forecasts:

$$DM_h = \frac{\bar{d}_h^{1,2}}{\sqrt{\sigma_d^2/(T_2 - T_1 - h)}}, \tag{16}$$

$$\bar{d}_h^{1,2} = \frac{\sum_{t=T_1}^{T_2-h} l(\varepsilon_{t+h}^{(1)}) - l(\varepsilon_{t+h}^{(2)})}{T_2 - T_1 - h}, \tag{17}$$

$$\varepsilon_{t+h}^{(i)} = y_{t+h}^{(i)} - \hat{y}_{t+h|t}^{(i)}, \tag{18}$$

where $\varepsilon_t^{(i)}$ is the forecast error for period t from model i, $\bar{d}_t^{1,2}$ is the average model error differential (1 and 2), $l(\cdot)$ is the loss function, σ_d^2 is the unconditional variance of the model error differentials, $DM_h^{(1,2)}$ is the Diebold–Mariano (DM) statistic for the models (1 and 2) on forecasts for h periods ahead from T_1 to $T_2 - h$. The DM statistics have a standard normal distribution: $DM_h^{(1,2)} \sim \mathcal{N}(0,1)$. Loss function l is the deviation of the RMSs from zero: $l(\varepsilon) = \varepsilon^2$.

The main difference between the above statistics and the generally accepted definitions of RMSFE and DM is that error aggregation does not occur along the entire length of the horizon period, but for all forecasts (as incoming data are put to use) at the end of the forecast horizon. This provides more detailed insight into the quality of the forecast over different horizons: a short-term forecast is of more value in the making of current decisions, while longer-term forecasts influence the long-term strategy of overall monetary policy.

The RMSFE and DM statistics are calculated for each point, starting from forecast round 1 (in 2015) and ending with the latest available data for each horizon period (2021 Q4 minus *h* quarters). Therefore, the number of observations in the validation sample drops as the forecast horizon expands.

A more detailed analysis of the stability of the GDP forecast is enabled by the calculated ratio of the predicted GDP values to the current values. This ratio makes it possible to understand the difference, in percentage equivalent, between the predicted increase in output based on vintage data and the real value:

$$Y_{t,h}^{\text{ratio}} = \frac{Y_{t+h|t}^{\text{vint}}}{Y_{t|t}^{\text{vint}}} : \frac{Y_{t+h}}{Y_t}, \tag{19}$$

where $Y_{t+h|t}^{\text{vint}}$ is the predicted output in period $t+h$ obtained using the output data available at time t, $Y_{t|t}^{\text{vint}}$ is the output value available in period t, Y_{t+h} is the actual observable output in period $t+h$, and Y_t is the actual observable value in period t.

Taking the logarithm, this expression has the form:

$$\log\left(Y_{t,h}^{\text{ratio}}\right) = \left(\log Y_{t+h|t}^{\text{vint}} - \log Y_{t|t}^{\text{vint}}\right) - \left(\log Y_{t+h} - \log Y_t\right). \tag{20}$$

To simulate monetary policy decision making with the assumption of limited data availability, I perform the following procedure[2]:

1. Obtain the solution of model $\mathcal{M}_i$ with a specified monetary policy rule and prescribe the value of initial period t to current period t_0.
2. Calculate vintage data error $u_t = y_t^{\text{actual}} - y_t^{\text{vint}}$, where y_t^{actual} is the current (last known) data series.
3. Obtain the smoothed values of unobservable variables $(\widehat{x_\tau}, \widehat{\varepsilon_\tau})$, , for the period from t_0 to t: $\tau \in [t_0, t]$, by using the Kalman smoothing method on simulated observable data, with the vintage error taken into account: $y_\tau^{\text{sim, u}}(-R_t) = y_\tau^{\text{sim}}(-R_t) + u_\tau(-R_t)$, where y_τ^{sim} is the vector of values of observable variables (y) in period τ, $(-R_t)$ is the index of the exclusion of value R_t from the observable variables in the Kalman filter in the last step, $y_\tau^{\text{sim, u}}$ is the vector of the sum of the observable variables and the corresponding vintage series errors for the forecast round τ.

[2] Schematic illustration of the algorithm is contained in Appendix (fig. 8).

The last value of nominal interest rate R_t in y_t^{obs} must be omitted so that it can be obtained using the filter. For $t = t_0$: $y_{t_0}^{\text{sim}} = y_t^{\text{vint}}(-R_{t_0})$.

4. Using the exogenous shocks $\hat{\varepsilon}_t$ obtained by smoothing the unobservable variables on the last available time series $\mathcal{F}_T$ and nominal interest rate values $\hat{R}_t$ from the previous step, obtain the paths of variables $(x_{t+1}^{\text{sim}}, y_{t+1}^{\text{sim}} | \hat{R}_t, \hat{\varepsilon}_{(t,-R)})$ by representing nominal interest rate $\hat{R}_t$ as an exogenous variable through the representation of monetary policy shock ε_t^R as endogenous[3].
5. End if current period t is equal to final period T; otherwise, move period t forward by one unit of measurement (quarter): $t = t + 1$ and proceed to Step 2.

This procedure is used to transfer the estimated error of the vintage data to the simulated series. Therefore, the counterfactual monetary policy is subject to the influence of this error, which in reality leads to deviations from the linear rule. However, my assumption is that the error in this algorithm is idiosyncratic: $\varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon)$. A more complete solution to the problem of measuring the counterfactual vintage error would be an assessment of its dependence on the variables in the current and previous periods: $\varepsilon_t = (\varepsilon_t | \mathcal{F}_t)$.

At this time, I am not using the solutions of the optimal policy problems discussed in the previous section: the iterative procedure for obtaining a counterfactual policy of strict adherence to the rule implies a change in the lag of the state variables. This violates the conditions for dynamic consistency: the decisions misfit the state plan, and the resulting paths are meaningless. Nevertheless, the discretionary policy model has no technical problems, but its results are also interpreted as less univalent: high inflation expectations emerge as a result of the dynamic inconsistency in the design of the problem and on the back of the incompleteness of the data.

Estimation of accuracy of smoothing and forecasting

For ease of comparison of the RMSFE indicators, Table 3 presents the correlations of these statistics (from the *pseudo real-time* forecasts and those based on *post-hoc* data). The original RMSFE values are presented in the tables in the Appendix. Table includes the Diebold–Mariano criterion statistics with a square loss function for both forecasts.

RMSFE RATIOS FOR VINTAGE (IN NOMINATOR) AND THE LATEST (2021, IN DENOMINATOR) OUTPUT DATA *Table 3*

Variable	1Q	2Q	4Q	6Q	8Q
Output gap	1.1185	0.9990	0.9854	1.0127	1.0271
GDP, QoQ	1.1400	1.0373	1.0102	1.0012	1.0006
GDP, YoY	1.0925	1.1614	1.4553	1.0555	1.0220
REER gap	0.9573	0.9653	0.9937	1.0224	1.0167
NEER, QoQ	0.9631	1.0019	0.9914	1.0001	0.9999
NEER, log. rub	0.9631	0.9713	0.9933	1.0024	0.9923
Inflation, QoQ	1.0660	1.0601	1.0314	0.9991	1.0050
Inflation, YoY	1.0694	1.0877	1.0766	0.9928	0.9960
CPI	1.0660	1.0810	1.0724	0.9939	0.9690

Remark: (> 1) –> rightarrow post-hoc data forecast is superior.

[3] In other words one has to choose ε_t^R in decision rule: $\hat{R}_t = d_R(Y_{t-1}, \varepsilon)$ such that $\hat{R}_t = \bar{\hat{R}}_t$, where $\bar{\hat{R}}_t$ is a value that variable $\hat{R}_t$ is set exogenously, Y_{t-1} is a lagged state variable values vector, ε_t is an exogenous shock innovations vector. $d.(\cdot)$ can be reperesented as a computable function of any complexity. In this considered model $d.(\cdot)$ is a sum of weighted arguments (lagged state variables and shock innovations).

DIEBOLD-MARIANO STATISTICS WITH QUADRATIC LOSS FUNCTION: FORECASTS WITH PSEUDO REAL-TIME DATA VS. POST-HOC SERIES *Table 4*

Variable	1Q	2Q	4Q	6Q	8Q
Output gap	1.4752	-0.0221	-1.2329	3.1841***	2.8660***
GDP, QoQ	3.1823***	2.7947***	1.9611**	0.8354	1.0639
GDP, YoY	1.4463	2.7820**	4.1853***	3.1232***	2.4215**
REER gap	-1.4132	-0.9836	-0.2035	0.6560	0.7241
NEER, QoQ	-1.4620	0.3608	-1.1342	0.0147	-0.0070
NEER, log. rub.	-1.4620	-1.0754	-0.3805	0.2936	-1.0843
Inflation, QoQ	1.3015	1.1197	0.7076	-0.0532	0.6554
Inflation, YoY	1.3933	1.3374	0.9917	-0.2570	-0.1427
CPI	1.3015	1.2606	0.9378	-0.2021	-0.5865

Remark: two-sided alternative hypothesis.
**= $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.*
Positive (negative) value $\Rightarrow$ post-hoc (pseudo out-of-sample) forecast is superior.

As can be seen, the quarter-on-quarter GDP forecast for 1–4 quarters ahead based on the *pseudo real-time* data is seriously inferior (at the 1% level) to the *post-hoc* forecast. However, over a short-term horizon (up to four quarters ahead), the difference between the two is statistically insignificant.

Persistent error is seen particularly for the year-on-year GDP forecast: the deviation remains significant at the 1% level from Q2 through Q8. This result is explained by the particularities of the year-on-year calculations: with the indicator in this form, the error accumulates over a long period. Table 4 presents the percentage deviation of predicted output growth to its actual value (equation). The difference increases as the forecast horizon expands. The forecast on *pseudo real-time* data is, on average, overestimated.

It is rather interesting to observe the change in the accuracy of the forecast of the real output gap. The statistical significance (0.1%) of the differences comes into focus only over horizons of six or more quarters ahead. However, the change in the sign of the difference in the forecast for two and four quarters ahead argues for the forecast based on *pseudo real-time* data, on the one hand.

On the other hand, the rest of the macroeconomic variables presented are under much weaker influence if there is a measurement error in the *pseudo real-time* data on output: there are no significant discrepancies in the forecast estimates on all horizons except for the 12-quarter-ahead forecast of year-on-year inflation and the real exchange rate gap at the 0.1% level.

Figure 4 shows the smoothed historical output gap estimates for each forecast quarter. The smoothing is based on the Kalman filter with observable variables that are up to date at the time of writing, except for those on output. Each new quarter uses the corresponding vintage *pseudo real-time* series of output as was used in the creation of the forecast. I conclude that after the currency crisis of late 2014, the use of data available at the time led to a significant underestimation of the output gap, with the deviation subsequently receding through 2020.

There are two more sources of underestimation in addition to the nowcasting error: the lack of observations at the beginning of the period under study (the earliest observations for the model are from 2004 Q1) and the structural changes in the Russian economy after the switch to inflation targeting. The influence of the first source recedes as the length of the series and the number of observable variables increase. The process of adjusting to inflation targeting is also taken into account in the QPM; however, other non-linear effects may also play a role in the distorted smoothing of the output gap time series.

In conclusion, I note that the use of *pseudo real-time* data significantly distorts the forecasts of the GDP and the output gap on horizons of up to eight quarters. The predicted values of other variables change insignificantly. I next assess the degree of influence the distortions have on monetary policy.

Assessment of policy effectiveness

In what follows, I describe the effectiveness of an endogenous monetary policy governed by the rule of equation, but with zero monetary policy shock, similarly to the previous section. The Kalman filter is applied on an iterative basis to extract the endogenous interest rate in the current period. Next, the exogenous shocks identified from the most recently observed data are used to calculate the counterfactual simulations, which include endogenous variables for the next iteration with the corresponding vintage series of output.

Overall, the process of making decisions on the interest rate according to a linear rule based on vintage *pseudo real-time* output data is characterised by higher volatility of inflation with a comparable variance of the rate change, while the volatility of output is lower. It is of note that decision making based on *pseudo real-time* data is better in terms of minimising the loss function, though the difference between the two values is not critical (a quarter-on-quarter annualised inflation equivalent ~0,63% on average).

In view of the stochastic nature of the errors in the *pseudo real-time* data, the comparative benefit of using them to make decisions is hardly systematic; furthermore, the result may indirectly evince the nature of the model's monetary rule and the optimisation of its parameters. Over the course of 2015–2020, the underestimation of the output gap resulted in a looser monetary policy stance in comparison with *post-hoc* smoothing. The underestimation of the gap can be supposed to have led to a greater softening of monetary policy, resulting in a reduction in the output gap in absolute terms with a weaker inflation response.

Therefore, the statistical errors in the vintage output data do not result in a significant deterioration in the model's predictive capability over the medium-term horizon, but they markedly distort the estimate of the output gap. In terms of the loss function, although the use of *pseudo real-time* data over the course of 2015–2021 helped yield a value more optimal than the actual value, this is hardly a systematic benefit.

DEVIATION OF CUMULATIVE GDP FORECAST CHANGES ON VINTAGE DATA FROM CURRENT DATA *Table 5*

Quarters	1	2	4	6	8
Deviation, sum, QoQ	1.7319	2.9878	4.8509	5.9383	6.9310

OUTPUT GAP ESTIMATES OBTAINED BY SMOOTHING BASED ON VINTAGE OUTPUT DATA AS OF HORIZON QUARTER *Chart 4*

VALUES OF LOSS FUNCTION FOR COUNTERFACTUAL SIMULATIONS WITH ASSUMPTION OF DECISIONS MADE ON VINTAGE AND LAST AVAILABLE DATA *Table 5*

Output data	$\mathcal{L}$	σ_π^2	$\sigma_{\tilde{Y}}2$	$\sigma_{\Delta R}^2$	Inflation equivalent ($\tilde{\pi}$)
Vintage	3.4491	1.0764	3.7046	1.0407	0.63% QoQ
Up to date	3.8508	1.0469	4.5107	0.0971	

Remark: estimated sqare roots of MSG for 2015–2021.

EFFICACY OF 2017–2021 FISCAL RULE

In this concluding section, I assess the effectiveness of the fiscal rule between 2017 and 2021 in terms of the loss function. The fiscal rule was intended to boost the counter-cyclicality of federal budget spending, helping deliver a more balanced federal budget and reduce the dependence of budget expenditure on the prices of fossil fuel exports. The stabilisation of spending is expected to lower the impact of the fiscal sector on the volatility of the variables, and the actual value of the monetary regulator loss function therefore should be lower than it is without a rule.

I run counterfactual simulations to measure the difference between the actual values (under the current fiscal rule of 2017–2021) and the counterfactual values (rule-free) of the loss function. The QPM includes a stylised fiscal sector to simulate cash flows in the federal, representative regional, and consolidated budgets. The modified model I use as a counterfactual model assumes that all additional oil and gas revenues are spent as soon as they are received. This eliminates the effect of the fiscal rule on the dependence of expenditure on current oil prices.

Data and methods

The model simulates federal budget spending according to equation:

$$E_t^{p,fed} = \rho_{E^{p,fed}} E_{t-1}^{p,fed} + (1-\rho_{E^{p,fed}})\left(E_t^{p.rule} + \tilde{E}_t^{fed}\right) - \psi_{cycl}^{fed}\left(\frac{\sum_{\tau=0}^{3}\hat{y}_{t-\tau}}{4}\right) + \varepsilon^{E^{p,fed}}, \quad (21)$$

where $E_t^{p,fed}$ is (primary) federal budget expenditure (% of GDP) in period t, $E_t^{p.rule}$ is basic oil and gas revenues according to the fiscal rule, $\tilde{E}_t^{fed}$ is the discretionary deviation from the fiscal rule (in terms of the random walk process), $\hat{y}_t$ is the output gap, and $\varepsilon^{E^{p,fed}}$ is the discretionary shock of federal budget expenditure. $\rho_{E^{p,fed}}$ is the autoregression parameter for federal budget expenditure, and ψ_{cycl}^{fed} is a coefficient for the impact of the counter-cyclical component on federal budget expenditure.

Equation is given in stylised form, has a component for the counter-cyclical adjustment of budget expenditure, and depends on basic oil revenues:

$$\bar{R}_t^o = \bar{R}_{t-1}^o + \frac{\bar{R}^{o,ss}}{4}\left(\Delta^4\hat{p}_t^{oil,base} + \Delta^4\hat{s}_t - \Delta^4\hat{y}_t^{nom}\right) + e_t^{\bar{R}^o}, \quad (22)$$

where $\bar{R}_t^o$ is basic oil and gas revenues (% of GDP) in period t, $\hat{p}_t^{oil,base}$ is the gap of the nominal base oil price, $\hat{s}_t$ is the nominal rate gap, and $e_t^{\bar{R}^o}$ is the discretionary shock with the AR(1) process and parameter and innovation $\rho_{e^{\bar{R}^o}}$:

$$e_t^{\bar{R}^o} = \rho_{e^{\bar{R}^o}} e_{t-1}^{\bar{R}^o} + \varepsilon_t^{\bar{R}^o}. \quad (23)$$

$\bar{R}^{o,ss}$ is the parameter determining the basic oil and gas revenues in a steady state, and Δ^4 is the operator of the logarithmic year-on-year growth rate of the variable.

The observable series in this sub-block are total oil and gas revenues ($\bar{R}_t^o$), basic oil and gas revenues ($\bar{R}_t^{o,base}$), total federal budget expenditure (E_t), and debt servicing costs (E_t^d). Therefore, the counterfactual series of primary federal budget expenditure can be simulated net of fiscal rule effects as follows:

$$E_{t,cf}^{p,fed} = \underbrace{\left(E_t - E_t^d\right)}_{E_t^p} + \underbrace{\left(\bar{R}_t^o - \bar{R}_t^{o,base}\right)}_{\bar{R}_t^{o,extra}}, \quad (24)$$

where $\bar{R}_t^{o,extra}$ is the additional oil and gas revenues of the federal budget. This produces a counterfactual observable series in which fiscal policy is free of fiscal rule effects and all oil and gas revenues are instantly spent.

Similarly to the previous sections, the loss function is equation with weights $w_{\tilde{\pi}}$, equivalent to the unitary weight of un-annualised quarter-on-quarter inflation, $w_{\tilde{Y}} = 0{,}5$, and $w_{\Delta_R} = 0{,}5$. To make the results more comparable, I specify the mean square gap values for each variable. The comparison makes it possible to assume that the analysis of social welfare in terms of the implementation or forgoing of a fiscal rule should be conducted using the fiscal regulator's assumed loss function, given that its remit includes the introduction of various methods for the enforcement of fiscal discipline. This loss function would probably have an equal or greater effect on the output gap than on inflation, and the contribution of the nominal interest rate change would be eliminated or replaced by the mean square gap of the debt-to-GDP ratio or another relevant measure. This work assumes that fiscal and monetary regulators have the same targets. In addition, further analysis shows that the difference in the mean square gap of the rate increase between the two models (fiscal rule/fiscal rule-free) under the same parameters in the linear rule is negligibly small.

In this part of the work, as in the previous sections, I use a linear FIT rule with zero ($\gamma_{\tilde{Y}} = 0$) and unitary ($\gamma_{\tilde{Y}} = 1$) coefficients for the output gap. The exogenous shocks are identified with the help of the standard model specification, which provides for a fiscal rule and a zero response from the monetary policy rule to the output gap. To avoid the influence of discretionary shocks on monetary policy, which may depend on current fiscal policy, I exclude exogenous shocks in the linear rule in the timeframe under consideration.

The simulations which use the historical values of primary federal budget expenditure are simulations of the *fiscal rule model*, while the counterfactual series simulations are simulations of the *fiscal rule-free model*. This clarification is due to the fact that the model itself is not modified, but the observable series of variables are.

The mean square gap values of the variables are calculated over 20 periods between 2017 and 2021, which is a rather short timeframe for the statistical assessment of the variance. Given that the mean square gaps are estimated using known observable data, I believe that the results are reliable.

Results

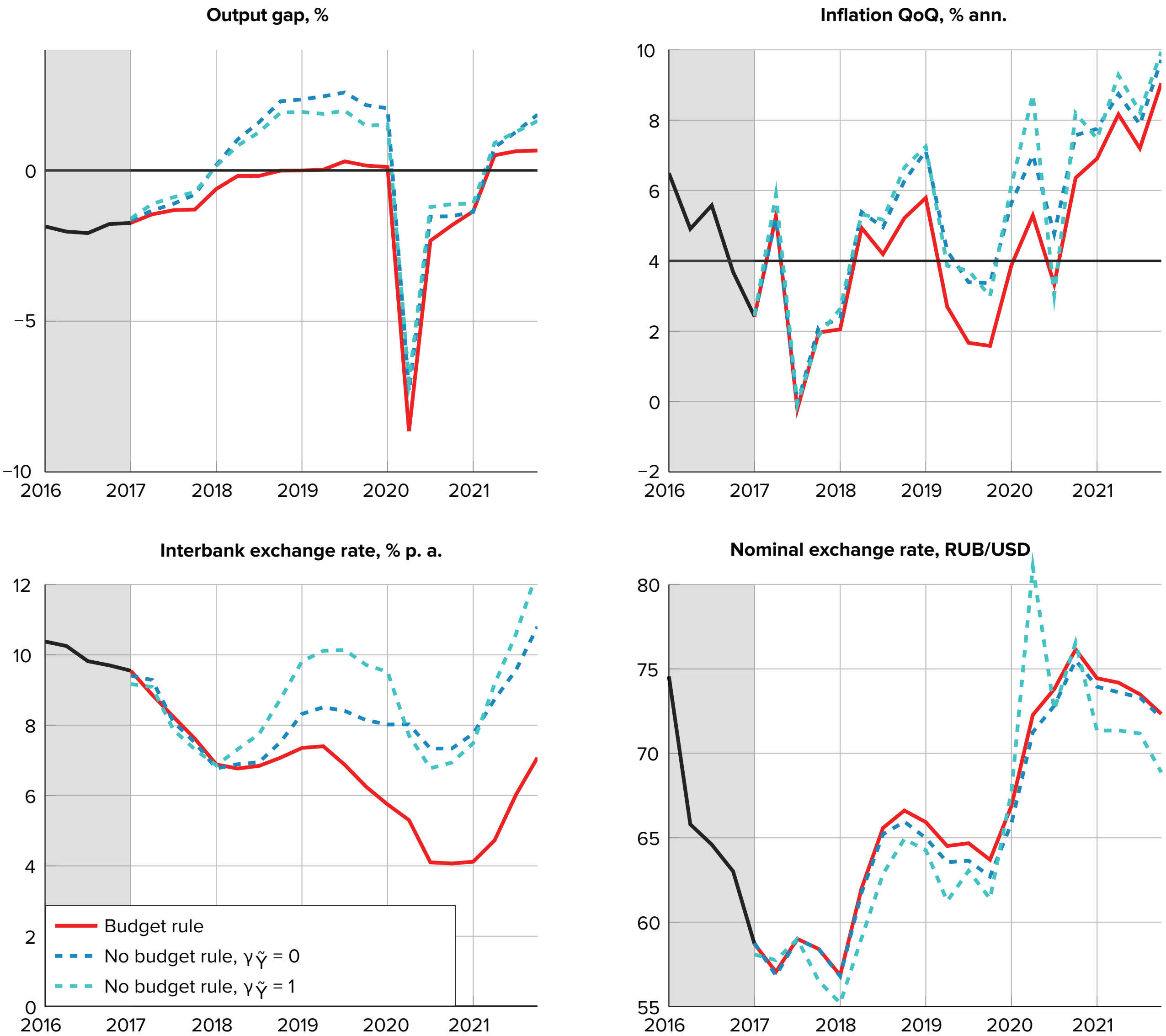
Figure 5 shows the counterfactual paths of the variables: the output gap, quarter-on-quarter inflation, the nominal interest rate, and the US dollar exchange rate. The fiscal rule-free simulation ($\gamma_{\tilde{Y}} = 0$) is marked by a substantially higher output gap (up to+2%), higher inflation, and a tightening monetary policy over the course of the counterfactual interval. The results also show a slight strengthening of the US dollar exchange rate, and this reduces the additional disinflationary effect.

Let me now focus on dynamics in the fiscal rule-free simulation ($\gamma_{\tilde{Y}} = 1$). The regulator responds to the overheating of the economy that emerges between mid-2018 and late 2019 with a yet higher rate increase (of up to +1.8pp), while slightly narrowing the output gap. Inflation in the period is essentially the same as the path obtained in fiscal rule-free stimulation ($\gamma_{\tilde{Y}} = 0$). At the onset of the pandemic (2020 Q2), simulation ($\gamma_{\tilde{Y}} = 1$) is marked by a drop in the output gap and the nominal rate, which is comparable to simulation ($\gamma_{\tilde{Y}} = 0$), but the dynamics of the exchange rate and inflation are drastically different. The exchange rate falls sharply by ₽15 (~20% QoQ), pushing inflation up by almost 2pp relative to simulation ($\gamma_{\tilde{Y}} = 0$).

Table 6 shows the values of the loss function and its decomposition for the three models under study. The fiscal rule proves beneficial from the point of view of social welfare in the period under study, while the non-zero response of the monetary policy rule to the output gap only makes the result worse. This leads to a significant stabilisation effect on inflation close to the target compared to the rule-free simulations, giving up only a slight increase in the mean square gap of the output gap. In fiscal rule-free simulation ($\gamma_{\tilde{Y}} = 1$) the reduction in the gap variance is greater, but it is offset by greater volatility in the interest rate increase and, to a lesser extent, inflation.

The results therefore show that the fiscal rule did help impart a further counter-cyclicality to the fiscal sector, thereby lowering social welfare losses compared to the fiscal rule-free models.

COUNTERFACTUAL PATHS WITH/WITHOUT FISCAL RULE, WITH MONETARY POLICY SHOCKS EXCLUDED. THE SHADED AREA DENOTES HISTORICAL DATA *Chart 5*



LOSS FUNCTION AND MEAN SQUARE GAP VALUES OF VARIABLES FOR COUNTERFACTUAL PATHS, WITH/WITHOUT FISCAL RULE *Table 7*

Model	$\mathcal{L}$	$\sigma^2_{\tilde{\pi}}$	$\sigma^2_{\tilde{Y}}$	$\sigma^2_{\Delta R}$	In relation to fiscal rule ($\tilde{\pi}$)
Fiscal rule	2.9552	0.3716	4.7824	0.3846	–
Without fiscal rule, $\gamma_{\tilde{Y}} = 0$	3.1844	0.6277	4.7182	0.3952	0.3723% QoQ
Without fiscal rule, $\gamma_{\tilde{Y}} = 1$	3.2785	0.7121	4.2483	0.8845	0.4666% QoQ

CONCLUSION

This analytical note compares the historical dynamics of the Russian economy with counterfactual simulations on the assumption of an optimal policy under commitment and a discretionary optimal policy. Comparing the values of the monetary regulator loss function, I conclude that the Bank of Russia's policy since 2015 may be described as being close to a policy under commitment. This conclusion is confirmed by the calculation of the components of the loss functions of different parameter values. I also conduct counterfactual simulations of a linear monetary rule free of exogenous monetary policy shocks. The results of the comparison show that, since the second half of 2020, the Bank of Russia has conducted a softer monetary policy than the linear rule assumes. As a result, the output gap is positive in this timeframe.

I assume that the Bank of Russia's transition to inflation targeting has strengthened the private sector's confidence in it as a regulator and has helped lower overall inflation expectations, since it has brought the monetary policy stance much closer to the optimal policy with confidence. Having said this, I note that *post-hoc* analysis may fail to capture the conditions in which the monetary regulator makes decisions given the limited availability of time series for this timeframe.

I draw on the example of vintage output data to infer that the output gap was underestimated in 2015–2020 owing to the inaccuracies of real GDP nowcasting. Further, I calculate the deviation of the model forecast based on *pseudo real-time* output series from that based on *post-hoc* data. It is notable that there is a certain deviation from the *post-hoc* forecast, and it is particularly significant for the output gap. Therefore, I succeed in using Russian macroeconomic data to validate the conclusions drawn by X. One finding of interest is that, in terms of the significance of the loss function, decision making using pseudo *real-time* data proves better than that based on *post-hoc* time series. However, this is hardly a systematic result. Further research in this area may envisage a more systematic approach towards the estimation of the forecast error for the output gap and the methods of correction. This could enhance forecast accuracy and help in the making of optimal monetary policy decisions.

Furthermore, I conduct an analysis of the effectiveness of the fiscal rule that was in place between 2017 and 2021. I conclude that the fiscal rule helped reduce the value of the monetary regulator loss function and, accordingly, increased the welfare of the private sector. Separately, if there is a response to the output gap in the linear rule and there is no fiscal rule, the value of the loss function is higher due to the higher volatility of the increase in the interest rate and inflation, but the effect of the stabilisation of the output gap remains.

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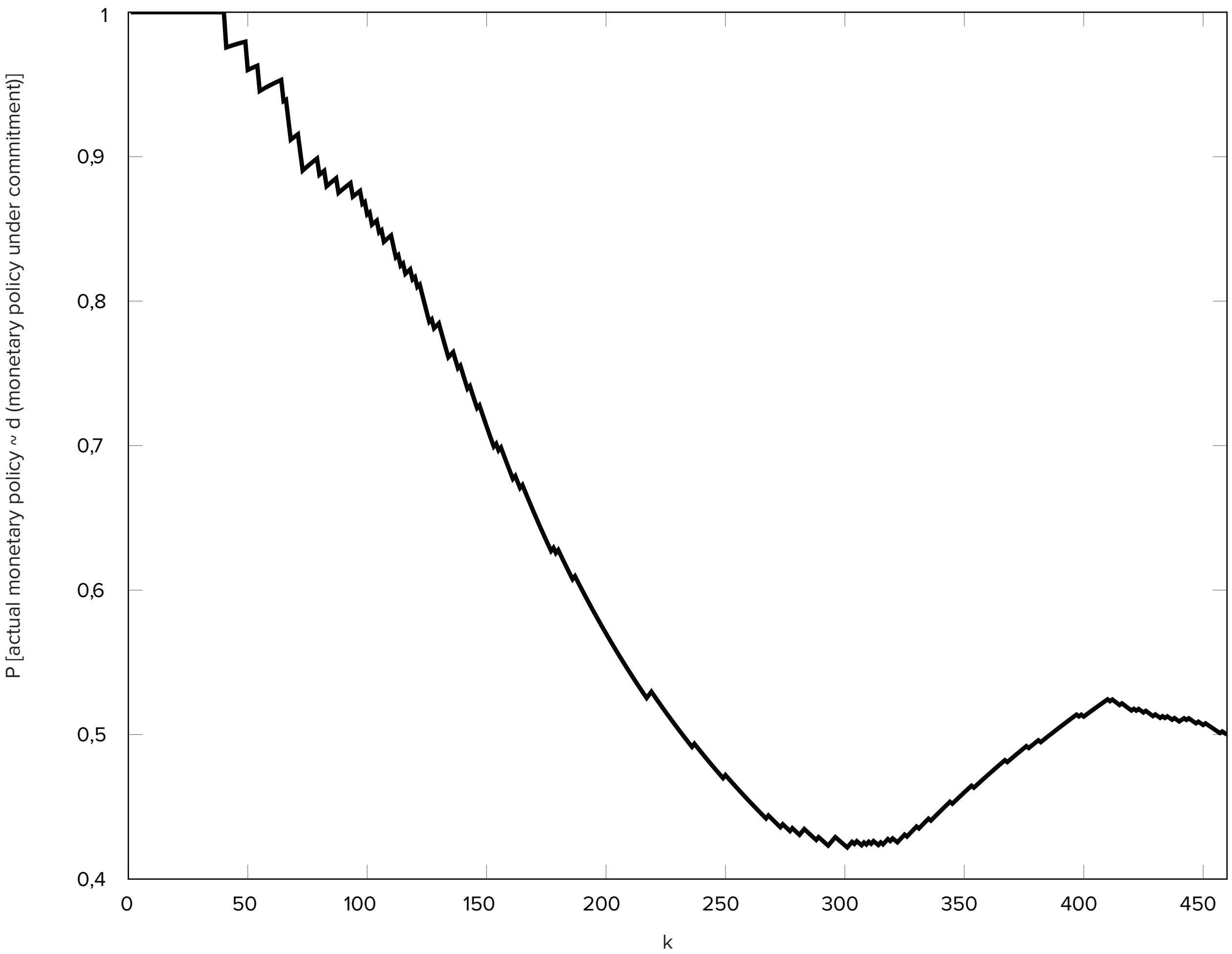
APPENDIX

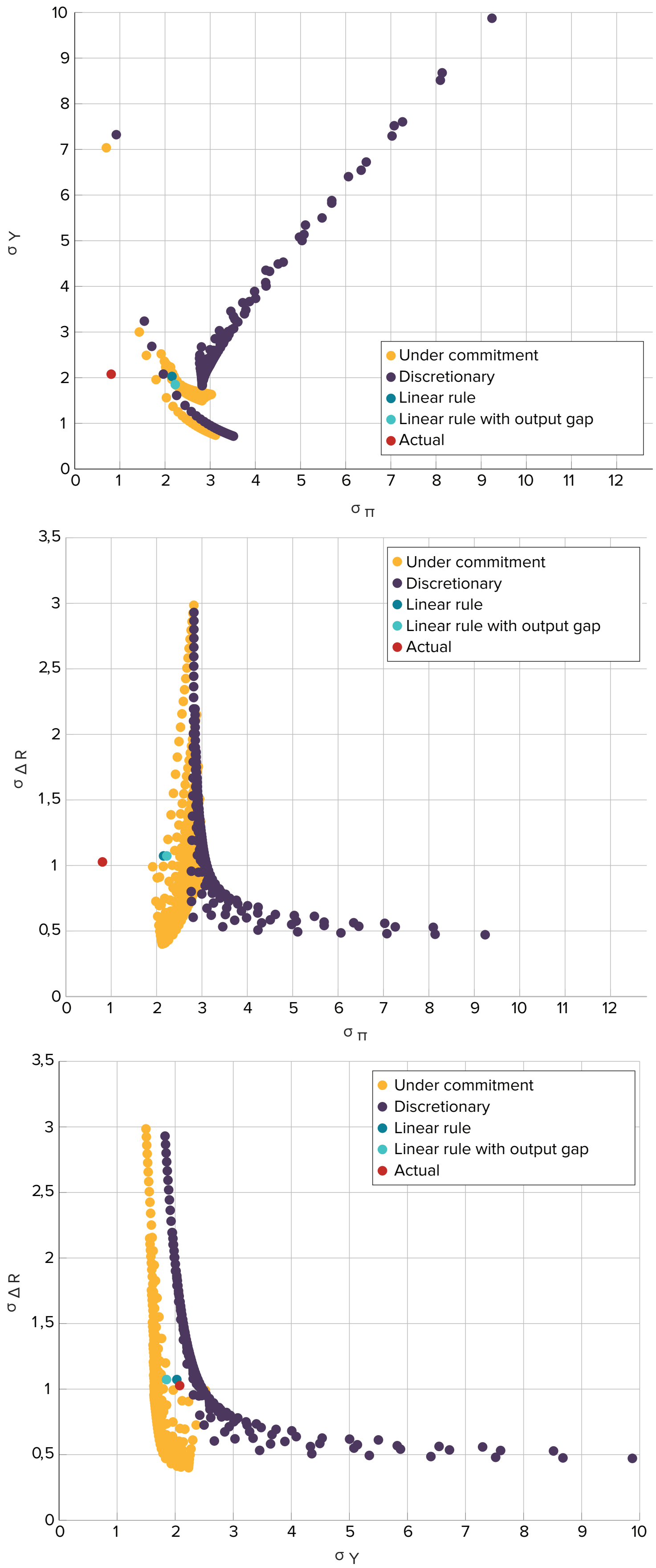
DECOMPOSITION OF LOSS FUNCTION VALUES FOR DIFFERENT POLICIES: $\tilde{\pi}$ IS INFLATION QOQ, $\tilde{Y}$ IS THE OUTPUT GAP, AND ΔR IS THE RATE CHANGE IN CURRENT PERIOD *Table 7*

Policy	$\sigma^2_{\tilde{\pi}}$	$\sigma^2_{\tilde{Y}}$	$\sigma^2_{\Delta R}$
Commitment	1.5637	3.0599	0.5947
Actual	1.0327	4.3156	1.0541
Discretionary	2.3749	6.2385	0.9120

PROBABILITY CURVE OF RATIO OF ACTUAL MEAN SQUARE GAPS TO DISTRIBUTION GENERATED BY CHANGE IN WEIGHTS IN PROBLEM OF OPTIMAL POLICY UNDER COMMITMENT. ALTERNATIVE CLASS – DISCRETIONARY POLICY DISTRIBUTION *Chart 6*

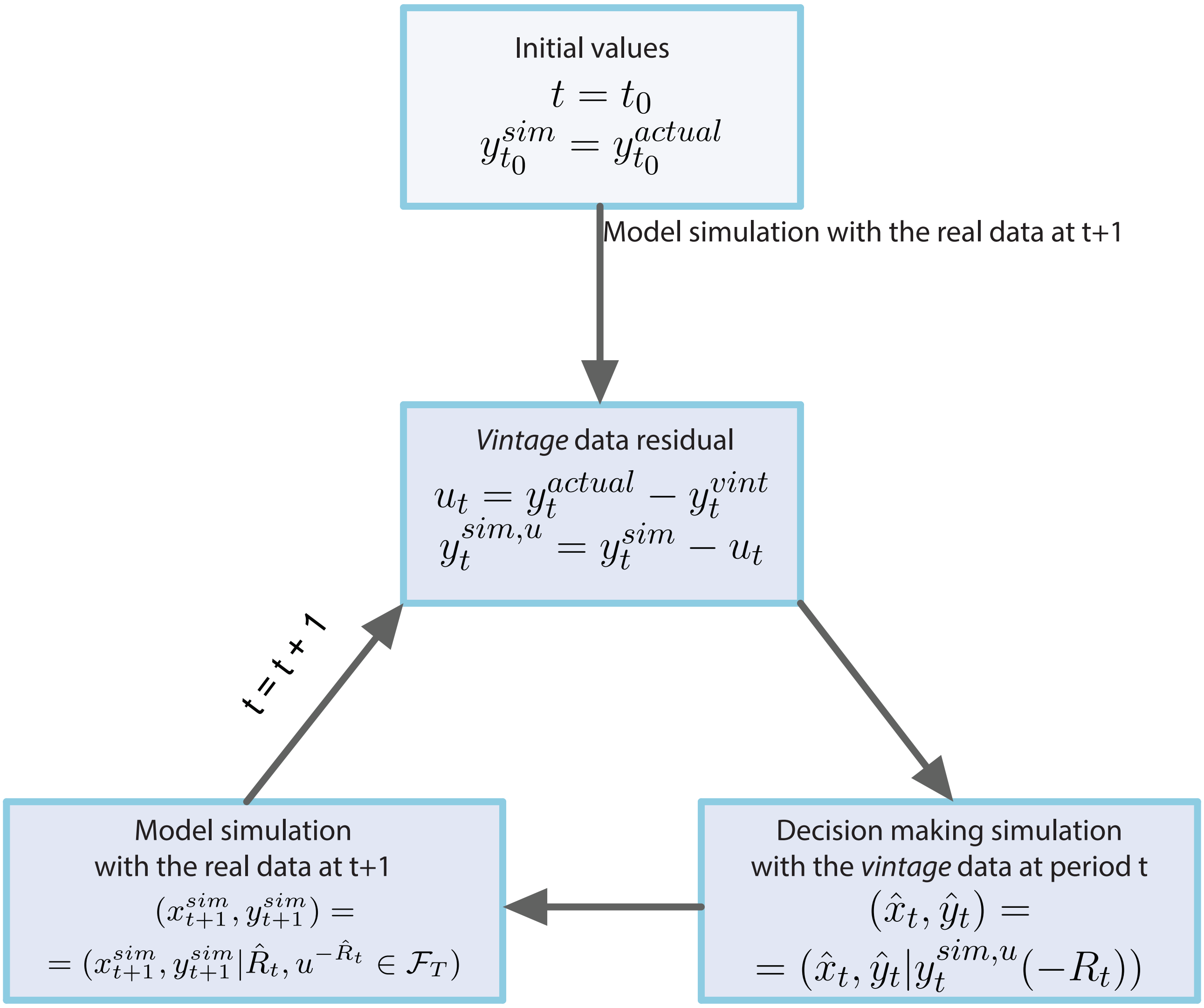


PROJECTIONS OF RMS GAP GRAPHS FOR DIFFERENT WEIGHTS IN LOSS FUNCTION FOR HISTORICAL POLICY AND OPTIMAL POLICIES (UNDER COMMITMENT AND DISCRETIONARY) *Chart 7*



DECISION SIMULATION ALGORITHM BASED ON VINTAGE DATA: BLOCK DIAGRAM

Chart 8



ROOT MEAN SQUARED FORECAST ERROR (RMSFE): FORECAST WITH VINTAGE PSEUDO REAL-TIME OUTPUT DATA VS. ACTUAL TIME SERIES *Table 9*

Variable	K1	K2	K4	K6	K8	K10	K12
Output gap, %	1.9971	1.8419	1.4517	1.9366	2.1362	2.2315	2.2568
GDP QoQ, log-% ann.	9.8695	9.9449	7.0043	10.2370	10.5570	11.0780	11.6780
GDP YoY, log-%	2.3690	2.9645	3.5498	3.0785	2.8701	3.1142	3.3259
REER gap, %	6.7007	8.2406	9.5521	7.2948	6.518	5.6743	6.3820
NEER QoQ, log-%	26.8610	20.809	17.752	16.178	17.135	14.456	13.8530
NEER, 100*log rub.	6.7151	8.3421	9.6859	7.6167	7.6886	7.5469	8.7593
Inflation, QoQ, log-% ann.	3.0249	2.7091	2.7393	2.426	2.3204	2.5303	2.7286
Inflation YoY, log-%	0.77289	1.3165	2.3211	1.8856	1.6447	1.7227	1.9710
CPI, 100*log	0.7562	1.3138	2.3204	2.4002	2.0985	2.0835	2.7738

ROOT MEAN SQUARED FORECAST ERROR (RMSFE): FORECAST WITH POST-HOC OUTPUT DATA VS. ACTUAL TIME SERIES *Table 10*

Variable	K1	K2	K4	K6	K8	K10	K12
Output gap, %	1.7856	1.8436	1.4732	1.9123	2.0799	2.1873	2.2211
GDP QoQ, log-% ann.	8.6578	9.5873	6.9339	10.2250	10.55	11.0760	11.6790
GDP YoY, log-%	2.1684	2.5526	2.4393	2.9166	2.8083	3.1102	3.3283
REER gap, %	6.9994	8.5369	9.6125	7.1352	6.4111	5.6725	6.4026
NEER QoQ, log-%	27.8890	20.7700	17.9050	16.1760	17.136	14.357	13.8560
NEER, 100*log rub.	6.9722	8.5883	9.7518	7.5987	7.748	7.6204	8.8764
Inflation, QoQ, log-% ann.	2.8376	2.5555	2.6560	2.4282	2.3089	2.5268	2.7283
Inflation YoY, log-%	0.7227	1.2103	2.1506	1.8994	1.6514	1.7215	1.9672
CPI, 100*log	0.7094	1.2154	2.1637	2.4149	2.1656	2.2296	2.9061