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Estimation and forecasting with a Nonlinear Phillips Curve based on heterogeneous sensitivity between economic activity and CPI components

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Abstract

This study investigates the hypothesis of a nonlinear relationship between aggregate demand and inflation in the Russian economy. To detect the nonlinear effect, the aggregated Consumer Price Index was decomposed into cyclical (more sensitive to aggregate demand) and acyclical (less sensitive to aggregate demand) components. The decomposition methodology employed in the paper reveals a stable nonlinear link between aggregate demand and inflation. It is shown that the slope of the Phillips curve becomes significantly steeper, i.e., the sensitivity of inflation to economic activity increases, when two conditions are met simultaneously: 1) current general price growth rates exceed long-term inflation expectations; 2) the output gap is positive. Furthermore, it is established that the use of a nonlinear Phillips curve can significantly improve forecast accuracy if a preliminary decomposition of the CPI into cyclical and acyclical components is performed. The forecasting accuracy is asymmetric: inflation forecasts derived from Phillips curves (both linear and nonlinear) demonstrate higher precision during crisis periods. The obtained result proves robust to changes in the trend estimation method, alterations in the nonlinearity condition (using only a positive output gap), the exclusion of sharp CPI changes from the sample, and shifts in the left and right boundaries of the sample. The robustness of the result is also demonstrated with respect to the shock control procedure used in CPI decomposition: even without this procedure, the ability to detect the nonlinear relationship and the improved forecast accuracy (at least at the 9- to 12-month horizon) are preserved.

Key words: Phillips curve, inflation, business cycle, nonlinearity

JEL-codes: C22, C53, E31, E47

1. Introduction. Literature Review

In macroeconomic literature, the Phillips curve (hereinafter referred to as the PC), which describes the relationship between inflation and the level of economic activity, remains a cornerstone concept for analyzing price dynamics and monetary policy. Traditional linear PC specifications assume a symmetric influence of the output gap on inflation: positive and negative deviations of output from its potential level exert an impact that is equal in magnitude but opposite in direction. However, empirical studies challenge this hypothesis, revealing a nonlinear character of the relationship. The conditions enabling nonlinearity formation include:

- a high level of economic activity (Benigno & Eggertsson, 2023),
- high current inflation (Blanco et al., 2024).

Furthermore, as demonstrated by Forbes et al. (2021) using panel data, the nonlinearity is most pronounced under their joint presence.

Accounting for the nonlinear relationship between inflation and business activity is crucial for conducting effective monetary policy and interpreting economic data. As research shows (Huh et al., 2009; Karadi et al., 2025), a nonlinear Phillips curve implies the need for a nonlinear policy response from the regulator. Gagnon & Sarsenbayev (2022) emphasize that in a nonlinear environment, inflation may meet the central bank's target even with a significant negative output gap; consequently, stable low inflation at the target may not guarantee optimal macroeconomic outcomes.

In contrast to the thoroughly studied heterogeneity of exchange rate pass-through (Andreev, 2019; Zhurakovskiy et al., 2021), the nonlinear relationship between aggregate demand and inflation in the Russian economy remains understudied, at the time of writing this paper. Existing research analyzing the Phillips curve for the Russian economy is limited to its linear specification. Moreover, even estimating a linear Phillips curve on Russian data is not always successful. For instance, in Zubarev's (2018) study, the coefficient on economic activity turns negative when consumer prices are used as the dependent variable. Inozemtsev and Krotova (2024), examining the Phillips curve using panel data from Russian regions and spatial models, find no significant coefficient for the output gap.

Difficulties in detecting a significant and stable (both linear and nonlinear) relationship between demand and inflation arise from several features of Russian inflation data:

1) Concentration of large shocks within short time intervals;

2) Shift in the inflation trend following a change in the monetary policy regime;

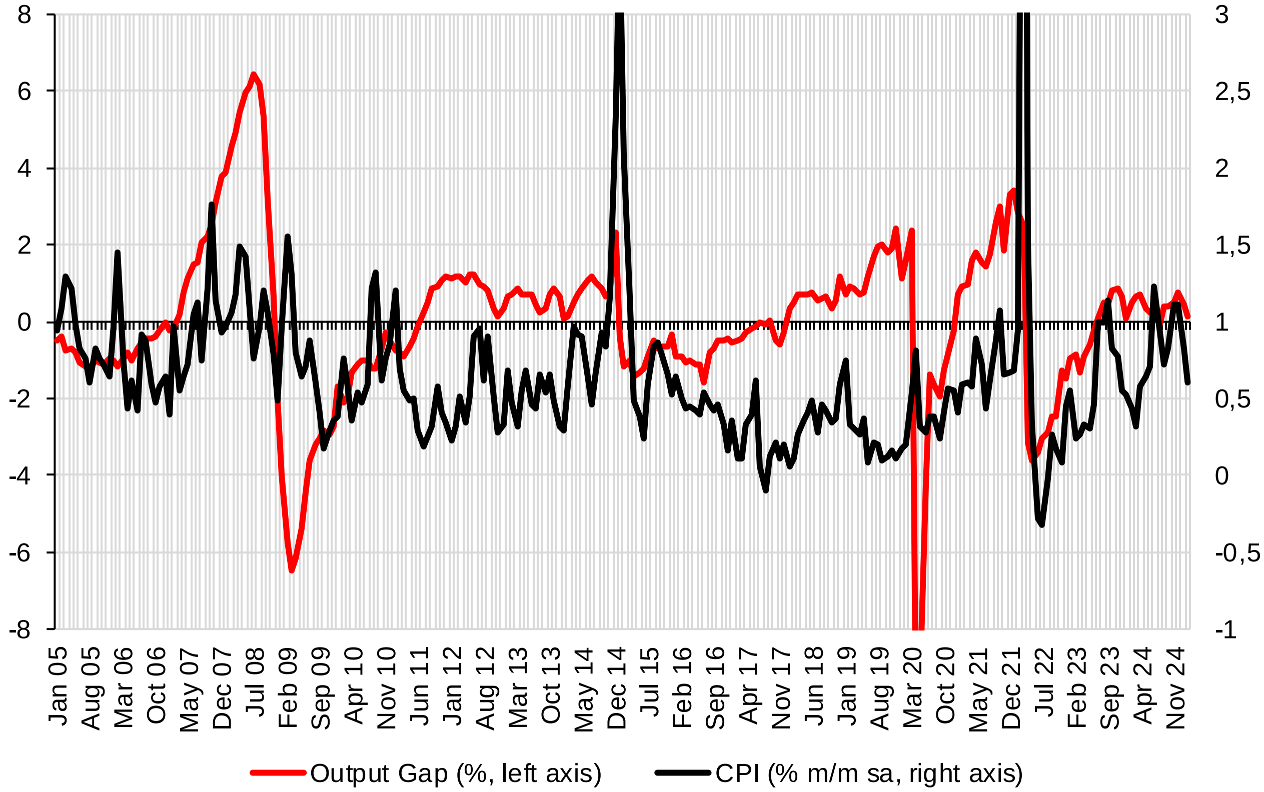
3) Significant nonlinear influence of other factors (as mentioned earlier, sufficient evidence has now accumulated regarding the nonlinear impact of the exchange rate);

4) Heterogeneous response of components within the aggregated price index to fluctuations in economic activity.

The aforementioned factors significantly distort the data and complicate the identification of stylized facts that would clearly demonstrate inflation's differential response to high versus low economic activity. As shown in Figure 1[1], Russian economic history contains a relatively small number of pronounced demand shocks where the output gap increased or decreased significantly, ceteris paribus.

[1] As the output indicator, a proxy measure calculated by the Bank of Russia's Research and Forecasting Department is used. The output gap is estimated using a two-sided Hodrick-Prescott filter. Here and elsewhere, the source for seasonally adjusted inflation data is the official website of the Bank of Russia.

Figure 1. Inflation and Output Gap in Russia



Nevertheless, analyzing specific periods reveals episodes of both high and low correlation between the output gap and the consumer price index. As shown in Figure 2, in the period from Jan 2005 to Dec 2006, when the output gap was somewhat below zero, the correlation between the CPI and economic activity was virtually absent. However, when the economy began to overheat (Jan 2007 - Dec 2009), a noticeable positive correlation emerged between the general price level inflation and economic activity.

Figure 2. Correlation between the output gap (%, vertical axis) and CPI (% m/m, sa, horizontal axis) in Jan 2005–Dec 2006 and Jan 2007–Dec 2008

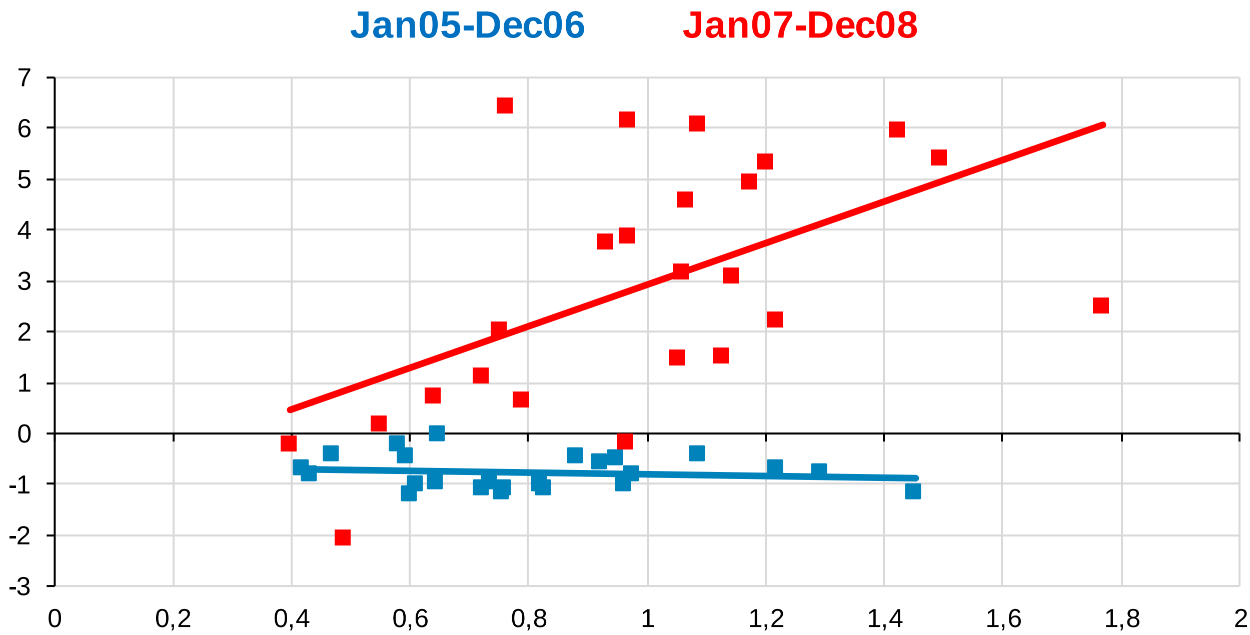


Figure 3 presents the period of the 2008-2009 crisis, as well as the subsequent recovery until the end of 2014. When the output gap is positive (Jan 2011-Dec 2014), a weak positive correlation between economic activity and inflation is observed. Conversely, when the output gap is negative (Jan 2009-Dec 2010), a negative correlation is found instead of a positive one.

Figure 3. Correlation between the output gap (%, vertical axis) and CPI (% m/m, sa, horizontal axis) in Jan 2009–Dec 2010 and Jan 2011–Dec 2014

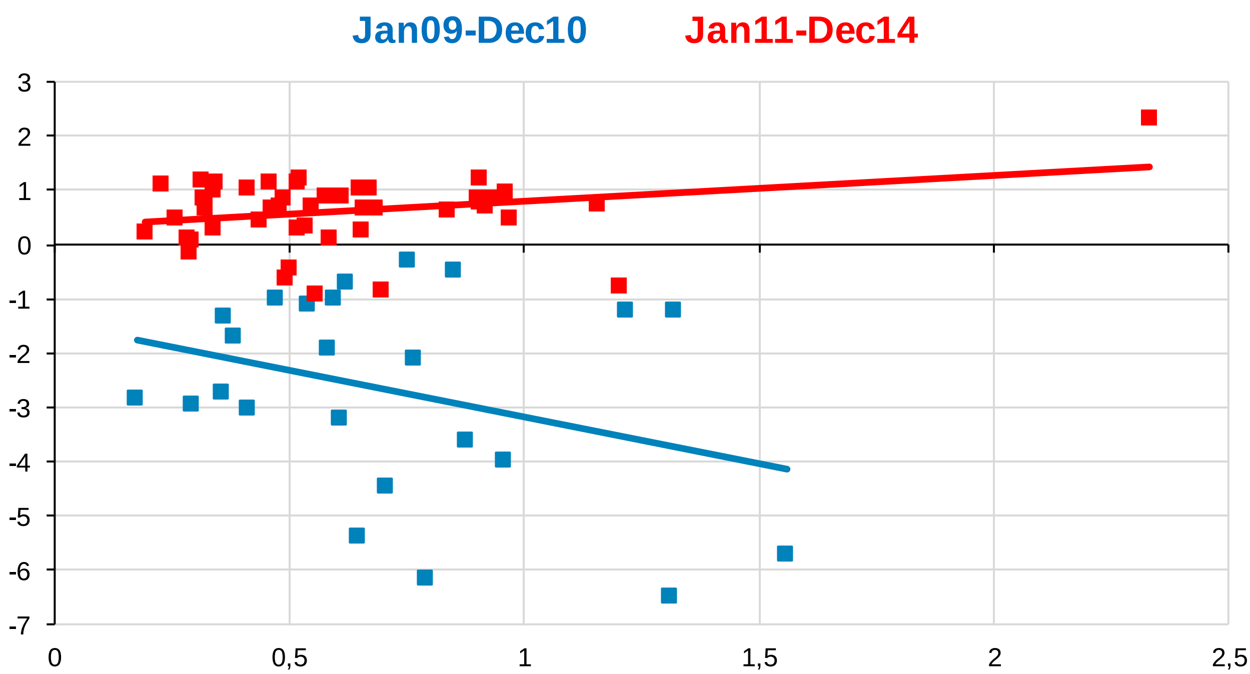
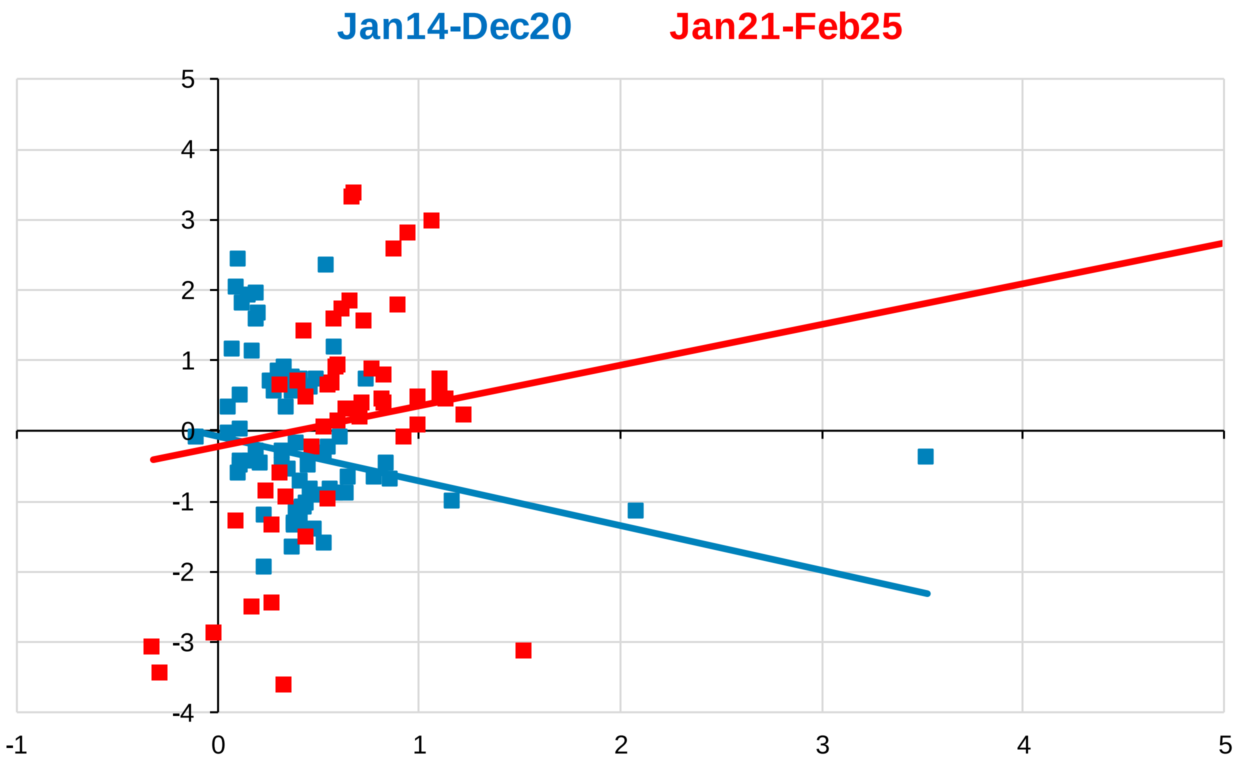


Figure 4 visualizes the correlation between the CPI and the output gap over the remaining time period. A negative relationship between economic activity and general price level inflation is observed from Jan 2015 to Dec 2020. From Jan 2021 to Feb 2025, the correlation became positive.

Figure 4. Correlation between the output gap (%, vertical axis) and CPI (% m/m, sa, horizontal axis) in Jan 2014–Dec 2020 and Jan 2021–Feb 2025



Thus, the hypothesis of a nonlinear relationship between inflation and economic activity is relevant for the Russian economy. As a solution to the aforementioned problems hindering the comprehensive model-based identification of this relationship, this paper proposes:

1) To split the CPI components into two groups: those more sensitive (cyclical) and those less sensitive (acyclical) to the output gap;

2) To estimate the nonlinear relationship with output separately for the cyclical and acyclical components.

As shown in a number of studies (Shapiro, 2022; Zaman, 2019; Lian and Freitag, 2022; Ehrmann et al., 2018; Ovechkin, 2025), decomposing the aggregate price index into cyclical and acyclical inflation can solve the problem of the "missing" linear correlation between inflation and economic activity. It can be hypothesized that this technique will also prove useful for detecting a nonlinear relationship.

In addition to estimating the nonlinear correlation between economic activity and inflation, this paper conducts an analysis of CPI forecast accuracy based on a nonlinear Phillips curve. The focus of this analysis will be a disaggregated CPI forecast, defined as a forecast of general price level inflation derived from separate equations for its components (in this study, from equations for the cyclical and acyclical components). Both international and domestic literature provides evidence of reduced forecasting error for aggregate price indices when they are forecasted component-by-component (Bermingham and D'Agostino, 2014; Faust and Wright, 2013; Kramkov, 2023).

A number of empirical studies question the superiority of the Phillips curve over simple alternatives that use only past inflation data (Atkeson & Ohanian, 2001; Ang et al., 2007). Khabibullin (2019) concludes that incorporating various proxies for economic activity does not improve the forecast accuracy for Russian inflation. According to the results of Saul (2021), adding domestic and external output gaps to a forecasting model worsens its predictive accuracy.

Regarding the comparison of forecasting accuracy between linear and nonlinear Phillips curves, the literature provides no clear consensus. Fuhrer and Olivei (2010) examine a Phillips curve with threshold effects and find that such an equation is more accurate than a naive model. However, Dotsey et al. (2018) analyze a broader sample and arrive at the opposite conclusion: for data from 1969 to 2014, a Phillips curve with threshold effects is less accurate than both a linear Phillips curve and a simple model containing only past inflation data.

Clark and McCracken (2006) analyze the reasons for unsatisfactory forecasting results and conclude that the forecasting accuracy of the Phillips curve deteriorates due to the instability of the coefficient on economic activity. Furthermore, some studies note that Phillips curve forecasting results are asymmetric. Dotsey et al. (2018) show that the accuracy of the Phillips curve may depend on the stage of the economic cycle: according to the authors' calculations, the Phillips curve is more accurate when the economy is in recession and less accurate during an economic expansion. Kartaev and Besedovskaya (2023) investigate the forecasting accuracy of linear Phillips curves for the period from 2019 to 2022 using Russian data and reach a conclusion similar to Dotsey et al. (2018): Phillips curves perform better in crisis years. This leads to the research questions that will be investigated in this paper:

1) Are the coefficients on economic activity in the nonlinear Phillips curve significant and stable?

2) Does a forecasting superiority of the Phillips curve exist when there is a clear nonlinearity in the relationship between economic activity and inflation?

3) Does forecasting accuracy improve if a preliminary decomposition of the CPI into cyclical and acyclical components is performed?

4) Does the forecasting accuracy of the nonlinear Phillips curve depend on the stage of the economic cycle?

The paper is structured as follows. Section 2 provides an overview of the methodology for decomposing inflation and estimating the coefficients of the nonlinear Phillips curve, while Section 3 presents the results. Section 4 discusses the forecasting methodology, and Section 5 reports the forecast accuracy assessment. Section 6 is devoted to robustness checks of the obtained results, and the Conclusion contains a summary of the paper's findings and directions for future research.

2. Methodology for CPI Decomposition and Nonlinear Phillips Curve Estimation

The standard decomposition methodology involves estimating the coefficients of a standard linear Phillips curve for each good and service included in the aggregate price index (Shapiro, 2022; Zaman, 2019; Lian and Freitag, 2022; Ehrmann et al., 2018). If the coefficient on economic activity is statistically significant (the significance level is determined by the researcher) and consistent with economic theory (positive for the output gap and negative for the unemployment gap), then that good or service is classified as cyclical; otherwise, it is classified as acyclical.

This paper will employ a slightly adjusted methodology for decomposition, as presented in the study by Ovechkin (2025). Unlike more standard methodologies, it is distinguished by the following features:

1) The dependent variable is not the level of inflation, but the deviation of the inflation rate from its trend. Using the inflation gap instead of the level is motivated by both theoretical and practical considerations. As shown by Cogley and Sbordone (2008), a Phillips curve with the level of inflation is merely a special case of a Phillips curve with the inflation gap. Both Cogley and Sbordone (2008) and Hasenzagl et al. (2022) demonstrate that including an inflation trend in the model helps estimate the relationship between inflation and economic activity more accurately. Furthermore, it should be noted that inflation data for some CPI components may be non-stationary over certain periods, including due to changes in the monetary policy regime by the Bank of Russia[2].

2) Additional regressors include the exchange rate and the relative price gap. The former is important for modeling Russian inflation; its significance and nonlinear relationship with inflation have been identified in many studies. As for the latter, it is necessary to capture the mechanism of

[2] As noted by Cogley and Sbordone (2008), trend inflation is not determined by demand and is shaped by actions of the central bank, such as a change in the monetary policy regime.

price adjustment of some goods and services relative to others, as well as to reflect possible supply shocks in individual markets.

3) Prior to the Phillips curve regression for individual CPI components (different goods and services, as well as cyclical and acyclical inflation), the dependent variables are adjusted for their sensitivity to a general price level inflation shock (accounting for potentially different responses to positive and negative shocks). This technique allows for obtaining more precise estimates of the coefficients on economic activity and reduces the likelihood of misclassifying CPI components (Ovechkin, 2025).

Thus, to perform the decomposition, Phillips curve coefficients are estimated separately for each good and service:

$$\hat{\pi}'_{it} = c + \beta_1^{\hat{\pi}'}\hat{\pi}_{it-1} + \beta_2^{\hat{\pi}'}\hat{x}_{t-1} + \beta_3^{\hat{\pi}'}\widehat{reer}_{t-1} + \beta_4^{\hat{\pi}'}\widehat{rel}_{it-1} \quad (1)$$

where:

$\hat{\pi}_{it}$ is the inflation gap (% m/m, SA, minus trend) for the i-th good or service in month t;

$\hat{\pi}'_{it}$ is the adjusted inflation gap for the i-th good or service in month t;

$\hat{x}_{t-1}$ is the indicator of economic activity in month t-1;

$\widehat{reer}_{t-1}$ is the real effective exchange rate gap in month t-1;

$\widehat{rel}_{it-1}$ is the relative price gap for the i-th good or service in month t-1.

The adjusted inflation gap is defined as the residual of the following equation:

$$\hat{\pi}_{it} = c + \rho_1^{\hat{\pi}} shkcpi_t DP_t + \rho_2^{\hat{\pi}} shkcpi_t DN_t \quad (2)$$

where:

$shkcpi_t$ is the CPI shock in month t;

DP_t is a dummy variable that equals 1 if the CPI shock is greater than 0, and 0 otherwise;

DN_t is a dummy variable that equals 1 if the CPI shock is less than 0, and 0 otherwise.

The CPI shock is defined as the residual of the following equation

$$\widehat{cpi}_t = c + \beta_2^{\widehat{cpi}}\hat{x}_{t-1} + \beta_3^{\widehat{reer}}\widehat{reer}_{t-1} \quad (3)$$

Equations (1)-(3) are estimated not simultaneously, but sequentially in the order (3), (2), and then (1).

Gaps are defined as deviations of actual values from their trends:

$$\hat{\pi}_{it} = \pi_{it} - \bar{\pi}_{it} \quad (4)$$

$$\hat{x}_t = x_t - \bar{x}_t \quad (5)$$

$$\widehat{rel}_{it} = rel_{it} - \overline{rel}_{it} \quad (6)$$

$$\widehat{cpi}_t = cpi_t - \overline{cpi}_t \tag{7}$$

where:

π_{it} is the actual monthly inflation of the i-th CPI component in month t;

$\bar{\pi}_{it}$ is the inflation trend of the i-th CPI component in month t;

x_t is the actual value of the economic activity indicator in month t;

$\bar{x}_t$ is the trend of the economic activity indicator in month t;

rel_{it} is the actual value of the logarithm of the relative price level in month t;

$\overline{rel}_{it}$ is the trend of the logarithm of the relative price level in month t.

cpi_t is the actual CPI value (actual general price level inflation) in month t;

$\overline{cpi}_t$ is the CPI trend.

The relative price level is calculated as follows:

$$REL_{it} = \frac{\prod_{t=1}^{n}(1+\pi_{it})}{\prod_{t=1}^{n}(1+cpi_t)} \tag{8}$$

where:

REL_{it} is the relative price level of the i-th CPI component in month t.

Although this method yields more precise estimates of the coefficients on economic activity compared to more standard approaches (Ovechkin, 2025), it requires an extension. At the decomposition stage, the Phillips curve equation for individual CPI components must be augmented to account for the nonlinear effects of the exchange rate and economic activity. The nonlinear effect of the exchange rate will be captured by a dummy variable that takes the value of 1 when the REER gap is negative (i.e., when the exchange rate is weaker relative to its trend), and 0 otherwise. Following Forbes et al. (2021), a dummy variable will be used to model the nonlinear effect of output; in this study, it equals 1 when both inflation and economic activity are high simultaneously. Thus, the Phillips curve equation that will form the basis for the CPI decomposition in this study is as follows:

$$\hat{\pi}'_{it} = c + \beta_1^{\hat{\pi}'}\hat{\pi}_{it-1} + \beta_2^{\hat{\pi}'}\hat{x}_{t-1} + \beta_{2D}^{\hat{\pi}'}D_{t-1}^{\hat{x}}\hat{x}_{t-1} + \beta_3^{\hat{\pi}'}\widehat{reer}_{t-1} + \beta_{3D}^{\hat{\pi}'}D_{t-1}^{\widehat{reer}}\widehat{reer}_{t-1} + \beta_4^{\hat{\pi}'}\widehat{rel}_{it-1} \tag{9}$$

where:

$D_{t-1}^{\hat{x}}$ is a dummy variable that equals 1 if both $\hat{x}$ and $\widehat{cpi}$ are greater than 0, and 0 otherwise;

$D_{t-1}^{\widehat{reer}}$ – is a dummy variable that equals 1 if $\widehat{reer}$ is less than 0, and 0 otherwise.

The CPI shock will be determined as the residual of a regression equation with the same dummy variables for economic activity and the exchange rate:

$$\widehat{cpi}_t = c + \beta_2^{\widehat{cpi}}\hat{x}_{t-1} + \beta_{2D}^{\widehat{cpi}}D_{t-1}^{\hat{x}}\hat{x}_{t-1} + \beta_3^{\widehat{reer}}\widehat{reer}_{t-1} + \beta_{3D}^{\widehat{reer}}D_{t-1}^{\widehat{reer}}\widehat{reer}_{t-1} \tag{10}$$

When distributing goods and services into "cyclical" and "acyclical" groups, attention must be paid not to 1, but to 2 coefficients for economic activity. To determine whether the combined effect of economic activity is significant, this study will employ a Wald test. The null hypothesis is that the sum of the coefficients $\beta_2^{\hat{\pi}'}$ and $\beta_{2D}^{\hat{\pi}'}$ is equal to 0. If the sign of the sum of these coefficients is consistent with economic theory and the null hypothesis is rejected at the 10% level, then the good or service will be classified as cyclical. In all other cases, they will be classified as acyclical.

After allocating goods and services into groups, cyclical and acyclical inflation can be calculated as the weighted sum of the monthly price growth rates of goods and services from the corresponding category. CPI weights are used as the weights:

$$ci_t = \frac{\sum_{i=1}^{n} \pi_{it}\, w_{it}}{\sum_{i=1}^{n} w_{it}} \tag{11}$$

$$ai_t = \frac{\sum_{j=1}^{m} \pi_{jt}\, w_{jt}}{\sum_{j=1}^{m} w_{jt}} \tag{12}$$

where:

ci_t is cyclical inflation (CI) in month t;

w_{it} is the weight of the i-th cyclical component in the CPI in month t;

π_{it} is the monthly price growth rate of the i-th cyclical CPI component in month t;

ai_t is acyclical inflation (AI) in month t;

π_{jt} is the monthly price growth rate of the j-th acyclical CPI component in month t;

w_{jt} is the weight of the j-th acyclical component in the CPI in month t.

After calculating cyclical and acyclical inflation, it is possible to estimate the influence of economic activity on CI and AI, as well as to perform disaggregated CPI forecasting using nonlinear Phillips curves whose coefficients are estimated for CI and AI.

When researchers focus on forecasting using the Phillips curve, Autoregressive Distributed Lag (ARDL) models are often employed instead of simple linear regressions to reduce the forecast error (e.g., Kartaev and Besedovskaya, 2023). In this work, the Phillips curves for CI and AI, used both for estimating and interpreting the influence of economic activity and for forecasting, will also be specified as ARDL models. As in the decomposition equations, the forecast equations will contain adjusted gaps on the left-hand side. Thus, the forecast equations for CPI via CI and AI will be as follows:

$$\widehat{ci}'_t = c + \beta_y^{\widehat{ci}'}(L)(\widehat{ci}'_{t-1}) + \beta_1^{\widehat{ci}'}\widehat{ci}_{t-1} + \beta_2^{\widehat{ci}'}\hat{x}_{t-1} + \beta_{2D}^{\widehat{ci}'}D_{t-1}^{\hat{x}}\hat{x}_{t-1} + \beta_3^{\widehat{ci}'}(L)\widehat{reer}_{t-1}$$
$$+\beta_{3D}^{\widehat{ci}'}(L)D_{t-1}^{\widehat{reer}}\widehat{reer}_{t-1} + \beta_4^{\widehat{ci}'}\widehat{rel}_{cit-1} \tag{13}$$

$$\widehat{ai}'_t = c + \beta_y^{\widehat{ai}'}(L)(\widehat{ai}'_{t-1}) + \beta_1^{\widehat{ai}'}\widehat{ai}_{t-1} + \beta_2^{\widehat{ai}'}\hat{x}_{t-1} + \beta_{2D}^{\widehat{ai}'}D_{t-1}^{\hat{x}}\hat{x}_{t-1} + \beta_3^{\widehat{ai}'}(L)\widehat{reer}_{t-1} + \beta_{3D}^{\widehat{ai}'}(L)D_{t-1}^{\widehat{reer}}\widehat{reer}_{t-1} + \beta_4^{\widehat{ci}'}\widehat{rel}_{ait-1} \quad (14)$$

where:

$\widehat{ci}'_t$ is the adjusted cyclical inflation gap in month t;

$\widehat{ai}'_t$ is the adjusted acyclical inflation gap in month t.

The models presented above are formulated such that the equations may include lags not only of the dependent variable but also of the exchange rate, which helps to eliminate residual autocorrelation. For other variables, only the first lag is retained.

As in the decomposition stage, the general price level shock will be determined as the residual of equation (10), and the adjusted CI and AI gaps as the residuals of the following equations:

$$\widehat{ci}_t = c + \rho_1^{\widehat{ci}} shkcpi_t DP_t + \rho_2^{\widehat{ci}} shkcpi_t DN_t \quad (15)$$

$$\widehat{ai}_t = c + \rho_1^{\widehat{ai}} shkcpi_t DP_t + \rho_2^{\widehat{ai}} shkcpi_t DN_t \quad (16)$$

It should be noted that such adjustment for shocks when estimating the coefficients of a nonlinear Phillips curve, while it has shown good results (Ovechkin, 2025), is not a common practice in estimating nonlinear Phillips curve coefficients. This is because in published works dedicated to the nonlinear relationship between inflation and economic activity, researchers typically do not perform decomposition and use the headline inflation rate as the dependent variable. For a model with such a dependent variable, a more suitable approximation of the inflation shock is the difference between the headline and core indices (e.g., Benigno & Eggertsson, 2023): the assumption is that if the headline index grew significantly faster than the core index in period t, then a positive inflation shock occurred in that period, and vice versa. Table 1 presents the most significant inflation shocks in the Russian economy, along with the corresponding CPI, core CPI, and the difference between them for those periods. According to the presented data, the difference between CPI and core CPI does not behave as assumed in international studies that use similar differences to control for shocks. No significant excess of CPI over core CPI is observed during shock periods. Moreover, in March 2023 and April 2023, this difference became noticeably negative. Thus, the discussed indicator (the difference between headline and core indices) is not suitable for controlling inflation shocks under Russian conditions.

Table 1

Inflation Shocks, CPI and Core CPI

Date	CPI (% m/m, SA)	Core CPI (% m/m, SA)	CPI minus Core CPI
Nov 2014	1,16	0,96	0,2
Dec 2014	2,33	2,57	-0,24
Jan 2015	3,53	3,42	0,11
Feb 2015	2,08	2,37	-0,28
Mar 2022	7,5	8,94	-1,44
Apr 2022	1,52	2,06	-0,54

3. Data and Methods for Estimating Trends, Gaps, and Regression Coefficients

The source of data for the seasonally adjusted CPI and its components, as well as for the real effective exchange rate index, is the Bank of Russia website. Monthly exchange rate growth rates have been converted into a base index (with December 2004 as the base period). The source of data for CPI component weights is Rosstat. The indicator of economic activity used is the monthly GDP proxy calculated by the Bank of Russia's Research and Forecasting Department.

A two-sided Hodrick-Prescott filter is applied to estimate the trend and gap for output, the exchange rate, and relative prices. These variables are logarithmized and multiplied by 100 prior to filtering.

As for the inflation trend estimation, The scientific literature suggests several methods for estimating the trend of general price level inflation, including statistical filters (Zubarev, 2018) and the median value of the components of the headline price index (Kramkov, 2023). Furthermore, analysts' long-term inflation expectations can be used as a proxy for the inflation trend (Faust and Wright, 2013). This latter approach offers a practical advantage for forecasting: when a monetary policy regime changes, analysts can quickly adjust their forecasts, whereas estimates from statistical filters would only converge to the central bank's announced target after the actual change in inflation has occurred. Therefore, following Faust and Wright (2013), this study approximates the headline inflation trend using analysts' long-term expectations. An additional argument for using this proxy is provided by the research of Hasenzagl et al. (2022), whose authors emphasize that correctly estimating the inflation-activity relationship requires a model to include an inflation trend derived from long-term expectations. The source for analysts' inflation expectations data is the HSE University Consensus Forecast[3]. Long-term expectations are defined as the most recent expectations

[3] https://dcenter.hse.ru/consensus_forecast

available in month t (converted to a monthly rate) for inflation at the end of the furthest survey year. For example, if the survey available for December 2024 shows expectations for the consumer price index on the longest horizon to be 3.9%, then the CPI trend is assumed to be 0.319%. Since the surveys are quarterly, months within the same quarter are assigned identical values.

In studies using disaggregated inflation statistics (Faust and Wright, 2013; Kramkov, 2023), the trend component of inflation for different price index components is often approximated by the same variable – the headline inflation trend. This approach simplifies modeling and forecasting but is unsatisfactory from the perspective of observed inflation dynamics. For instance, in many economies, services inflation is higher than goods inflation (Ferrara, 2019). This work will attempt to model the different dynamics of inflation trends. Thus, the inflation trends for different goods and services can be represented as the sum of the CPI trend (approximated by long-term inflation expectations) and a specific premium, which can be positive or negative for different price index components:

$$\overline{\pi}_{it} = \overline{cpi}_t + prem_{it} \tag{17}$$

where:

$\mathrm{prem}_{\mathrm{it}}$ is the trend premium for the i-th CPI component

To approximate this premium, this paper proposes the use of statistical filters on actual data. Trends obtained using statistical filters react with a lag to structural shifts in headline inflation but are presumed to capture the stable difference in inflation rates between different goods and services. Thus, the equation for the premium is as follows :

$$\mathrm{prem}_{\mathrm{it}} = \pi^*_{it} - cpi^*_t \tag{18}$$

where:

π^*_{it} is the statistically filtered (smoothed) value of inflation for the i-th good or service in month t;

cpi^*_t is the statistically filtered (smoothed) value of CPI in month t.

Trends for CI and AI are calculated in a similar manner:

$$\overline{ci}_t = \overline{cpi}_t + ci^*_t - cpi^*_t \tag{19}$$

$$\overline{ai}_t = \overline{cpi}_t + ai^*_t - cpi^*_t \tag{20}$$

where:

ci^*_t is the statistically filtered (smoothed) value of cyclical inflation in month t;

ai^*_t is the statistically filtered (smoothed) value of acyclical inflation in month t.

A two-sided Hodrick-Prescott filter is used in this study to obtain the values for π_{it}^*, cpi_t^*, ci_t^* and ai_t^*.

Ordinary Least Squares (OLS) estimation with standard errors in the Newey-West (Bermingham & D'Agostino, 2014) form is applied to estimate the coefficients for all equations. The "lag truncation parameter" (bandwidth) for estimating the covariance matrix is not set exogenously but is selected automatically using the Schwarz criterion. The number of lags in the ARDL models is also selected based on the Schwarz criterion.

4. Results of Estimating the Nonlinear Phillips Curve Coefficients

To test the robustness of the nonlinear influence of economic activity on inflation, the Phillips curves were estimated on three different samples. The first sample begins in January 2005 and ends in December 2013. Estimating coefficients on this sample is interesting because it focuses on the period when the Bank of Russia was actively preparing for, but had not yet transitioned to, inflation targeting. Furthermore, this sample does not yet include the major inflation shocks of late 2014. The second sample begins in January 2005 and ends in December 2019 (prior to the onset of the COVID-19 pandemic). The full sample begins in January 2005 and ends in February 2025. The decomposition procedure, as well as the estimation of gaps and trends, was conducted separately for each sample. The results of estimating the coefficients of the nonlinear Phillips curve for cyclical inflation (CI) and acyclical inflation (AI) separately are presented in Table 2.

Table 2

Estimates of Coefficients on the Output Gap for CI and AI (Equations (13) and (14))

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25
Coefficient $\beta_2^{\widehat{ci}'}$	-0,003	-0,008	0,0177**
Coefficient $\beta_{2D}^{\widehat{ci}'}$	0,079***	0,109***	0,0889***
Coefficient $\beta_2^{\widehat{ai}'}$	-0,037***	-0,007	-9,16E-05
Coefficient $\beta_{2D}^{\widehat{ai}'}$	0,059***	0,0327**	0,0203

Note: Significance levels are denoted by asterisks: *** - 1%, ** - 5%, * - 10%.*

A coefficient for the nonlinear influence of the output gap on cyclical inflation, significant at the 1% level, is observed in each of the studied samples. The coefficient for the nonlinear output gap for AI was statistically significant in two subsamples: Jan05-Dec13 and Jan05-Dec19. However, in the full sample, the statistical significance of the coefficient $\beta_{2D}^{\widehat{ai}'}$ disappears.

Thus, the nonlinear influence of output appears to be a stable characteristic of the Russian economy. It can be detected in data across different samples. For example, in the full sample, when the nonlinearity conditions are not met, a 1 percentage point (p.p.) increase in the output gap leads to a 0.0177 p.p. acceleration in monthly cyclical inflation. When the nonlinearity conditions are met, CI accelerates by an additional 0.0889 p.p., resulting in a total response of CI to the output gap increase (calculated as the sum of coefficients $\beta_2^{\widehat{ci}'}$ and $\beta_{2D}^{\widehat{ci}'}$, is equal to 0,1066). Conversely, monthly acyclical inflation does not respond significantly to an increase in the output gap when the nonlinearity condition is not met. If the nonlinearity condition is met, AI accelerates by an additional 0.0203 p.p. in response to a 1 p.p. increase in the output gap. The total response of AI to the output increase (the sum of the coefficients $\beta_2^{\widehat{ai}'}$ and $\beta_{2D}^{\widehat{ai}'}$) is also 0.0203 p.p.

The detection of a significant shift (at least in subsamples) in the slope of the Phillips curve for acyclical inflation is an interesting result. Unfortunately, it does not lend itself to comparison with existing studies, as, at the time of this publication, no estimations of a nonlinear Phillips curve using CI and AI as dependent variables have been conducted. If researchers do examine the relationship of CI and AI with the output gap, they do so by estimating coefficients of a linear Phillips curve (Lian and Freitag, 2022; Ovechkin, 2025). Nevertheless, when defining CI and AI, authors tend to adhere to a "soft" criterion: for instance, Shapiro (2022) defines cyclical and acyclical inflation as being more or less sensitive to economic activity, which does not preclude obtaining a significant coefficient for the output gap in a regression with AI. The results presented in Table 2 are consistent with this non-rigid definition: the output gap consistently has a stronger influence on CI and a weaker one on AI. In each sample, the sum of the coefficients $\beta_2^{\widehat{ci}'}$ and $\beta_{2D}^{\widehat{ci}'}$ is greater than the sum of the coefficients $\beta_2^{\widehat{ai}'}$ and $\beta_{2D}^{\widehat{ai}'}$. This may indicate that the decomposition was performed correctly. To further verify the decomposition, we estimate regressions of equations (13) and (14), excluding the output gap multiplied by the dummy variable. The results are presented in Table 3.

Table 3

Estimates of Coefficients on the Output Gap for CI and AI (Equations (13) and (14) with the variable $D_{t-1}^{\hat{x}}\hat{x}_{t-1}$ excluded)

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25
Coefficient $\beta_2^{\widehat{ci}'}$	0,045***	0,034*	0,039***

Coefficient $\beta_{2D}^{\widehat{ci}\prime}$	-	-	-
Coefficient $\beta_{2}^{\widehat{ai}\prime}$	0,0016	0,009	0,007
Coefficient $\beta_{2D}^{\widehat{ai}\prime}$	-	-	-

Note: Significance levels are denoted by asterisks: *** - 1%, ** - 5%, * - 10%.*

In accordance with (Lian and Freitag, 2022; Ovechkin, 2025), when estimating coefficients of a linear Phillips curve, CI shows a statistically significant relationship with the linear output gap. At the same time, the relationship for AI is insignificant. The alignment of these results with those in the published literature also supports the validity of the performed decomposition. The results presented in Table 2 can be explained by the assumption that during periods of simultaneously high inflation and a positive output gap, demand shocks are so substantial that "a rising tide lifts all boats," but to varying degrees: CI accelerates much more strongly than AI.

The influence of economic activity on the overall consumer price index can be estimated as the weighted sum (using the shares of CI and AI in the CPI as weights) of the coefficients $\beta_{2}^{\widehat{ci}\prime}$ and $\beta_{2}^{\widehat{ai}\prime}$, as well as $\beta_{2D}^{\widehat{ci}\prime}$ and $\beta_{2D}^{\widehat{ai}\prime}$. The results are presented in Table 4.

Table 4

Weighted Sum of Coefficients on Economic Activity

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25
Share of CI in CPI (last month of sample)	58,85%	52,06%	58,41%
Share of AI in CPI (last month of sample)	41,15%	47,94%	41,59%
Weighted sum of the coefficients $\beta_{2}^{\widehat{ci}\prime}$ and $\beta_{2}^{\widehat{ai}\prime}$ (linear link with CPI)	-0,017	-0,0075	0,0103
Weighted sum of the coefficients $\beta_{2D}^{\widehat{ci}\prime}$ and $\beta_{2D}^{\widehat{ai}\prime}$ (additional link under nonlinearity conditions)	0,071	0,0724	0,0604

As shown earlier, the absolute values of the coefficients $\beta_{2D}^{\widehat{ci}\prime}$ and $\beta_{2D}^{\widehat{ai}\prime}$ changed noticeably. One might have assumed that the nonlinear influence of economic activity on headline inflation would also be unstable. However, due to the variability in the weights of CI and AI within the CPI, the sum of the coefficients $\beta_{2D}^{\widehat{ci}\prime}$ and $\beta_{2D}^{\widehat{ai}\prime}$ remains relatively stable: 0.071 in the first sample, 0.0724 in the second, and 0.0604 in the third.

Next, let us compare the estimates of the Phillips curve coefficients for CI and AI (equations (13) and (14)) with estimates from a Phillips curve applied to the aggregate CPI. For comparability, the Phillips curve equation for the CPI will also be specified as an ARDL model, similar to those for CI and AI:

$$\widehat{cpi}_t = c + \beta_1^{\widehat{cpi}}(L)\widehat{cpi}_{t-1} + \beta_2^{\widehat{cpi}}\hat{x}_{t-1} + \beta_{2D}^{\widehat{cpi}} D_{t-1}^{\hat{x}}\hat{x}_{t-1} + \beta_3^{\widehat{cpi}}(L)\widehat{reer}_{t-1} + \beta_{3D}^{\widehat{cpi}}(L) D_{t-1}^{\widehat{reer}}\widehat{reer}_{t-1} \quad (21)$$

The results are presented in Table 5. The coefficient $\beta_{2D}^{\widehat{cpi}}$ showed statistical significance in the samples Jan 05-Dec 13 and Jan 05-Dec 19, but was insignificant in the sample Jan 05-Feb 25. Furthermore, its absolute value is unstable: $\beta_{2D}^{\widehat{cpi}}$ was 0.106 in the first sample, 0.0389 in the second, and 0.107 in the third. The behavior of the coefficient $\beta_2^{\widehat{cpi}}$. While the linear link of the output gap with the CPI, estimated separately for CI and AI, is close to zero across all considered samples, in the case of regression equation (21), the coefficient $\beta_2^{\widehat{cpi}}$ was significantly negative in the Jan 05-Dec 13 sample.

Table 5

Estimates of Coefficients on Economic Activity for CPI (Equation (21))

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25
Coefficient $\beta_2^{\widehat{cpi}}$ (linear link with CPI)	-0,059**	-0,0008	0,0112
Coefficient $\beta_{2D}^{\widehat{cpi}}$ (additional link under nonlinearity conditions)	0,106***	0,0389***	0,107

Note: Significance levels are denoted by asterisks: *** - 1%, ** - 5%, * - 10%.

Thus, this section confirms the hypothesis of a nonlinear relationship between economic activity and the CPI: the correlation between headline inflation and the dynamics of the output gap increases significantly when the output gap is positive and inflation exceeds analysts' long-term expectations. This result proves to be relatively stable across different samples if a CPI decomposition is performed and the relationship is estimated separately for CI and AI using the methodology presented in this study. Without preliminary decomposition, a nonlinear relationship between inflation and economic activity can also be detected; however, the estimates of the coefficients for the linear and nonlinear output gap do not exhibit the same stability when the sample is changed. Next, we will test whether accounting for nonlinearity can improve forecast quality.

5. Forecasting Methodology

This paper employs a recursive approach to forecasting. Within this approach, a model is estimated to forecast one period ahead, and inflation forecasts for more distant periods (in this study, up to 12 months) are obtained by iteratively feeding the model's previous forecasts back into it. The CPI decomposition (conducted according to the methodology outlined in Section 2) and the estimation of forecast equation coefficients are performed on a training sample, while the forecast and its evaluation are conducted on a test sample. The initial training sample covers the period from January 2005 to December 2011. The full sample includes data from January 2005 to February 2025.

After forecasts are generated for all horizons under study, the training sample is expanded by one month forward. This procedure yields: 158 forecast points for the 1-month-ahead forecast, 157 points for the 2-month-ahead forecast, 156 points for the 3-month-ahead forecast, 155 points for the 4-month-ahead forecast, 154 points for the 5-month-ahead forecast, 153 points for the 6-month-ahead forecast, 152 points for the 7-month-ahead forecast, 151 point for the 8-month-ahead forecast, 150 points for the 9-month-ahead forecast, 149 points for the 10-month-ahead forecast, 148 points for the 11-month-ahead forecast, and 147 points for the 12-month-ahead forecast.

The coefficients of the forecast equations are re-estimated each time the sample is expanded. However, performing the decomposition with such frequency seems somewhat excessive. In the author's opinion, conducting the CPI decomposition into CI and AI once a year, each December, is optimal.

This study will utilize the previously presented ARDL models with nonlinear economic activity effects: 1) the Phillips curve for CI and AI (equations (13) and (14)); and 2) the Phillips curve for the aggregate CPI (equation (21)). As shown earlier, the estimates of the nonlinear influence of the output gap on inflation differ substantially between these models. It is of particular interest to compare how these differences in estimating the nonlinear Phillips curve coefficients affect forecast accuracy.

To compare the forecasting accuracy of linear and nonlinear Phillips curves, forecasts will also be generated using an equation where the influence of the output gap on the CPI is strictly linear:

$$\widehat{cpi}_t = c + \beta_1^{\widehat{cpi}}(L)\widehat{cpi}_{t-1} + \beta_2^{\widehat{cpi}}\hat{x}_{t-1} + \beta_3^{\widehat{cpi}}(L)\widehat{reer}_{t-1} + \beta_{3D}^{\widehat{cpi}}(L)D_{t-1}^{\widehat{reer}}\widehat{reer}_{t-1} \quad (22)$$

Traditionally, the forecast accuracy of the Phillips curve is compared against simple models that use only past inflation information. Therefore, the final forecast model will not include economic activity or the exchange rate as regressors, and the inflation measure will be the standard consumer price index without trend subtraction:

$$cpi_t = c + \beta_1^{cpi}(L)cpi_{t-1} \quad (23)$$

The specification of the forecast equations above assumes the availability of forecast values for economic activity and the exchange rate. In works on inflation forecasting using Phillips curves, inflation drivers are often forecasted by separate simple autoregressive equations. Therefore, in this study, economic activity and the exchange rate gap will be forecasted by separate ARDL models, where the only regressors will be lags of the dependent variables:

$$\hat{x}_t = c + \beta_1^{\hat{x}}(L)\hat{x}_{t-1} \quad (24)$$

$$\widehat{reer}_t = c + \beta_1^{\widehat{reer}}(L)\widehat{reer}_{t-1} \quad (25)$$

Equations (13) and (14) describe the dynamics of the adjusted gaps for CI and AI. As noted in Section 2, adjusted CI and AI are the residuals of equations (15) and (16). To convert forecasts of adjusted gaps to forecasts of regular gaps, it is necessary, according to equations (15) and (16), to add the constants and the forecasts of the $shkcpi$ variable multiplied by the corresponding coefficients. Since the $shkcpi$ variable represents a CPI shock with zero expected value, its forecast values will be set to 0. Regarding the constants, their values obtained after estimating equations (15) and (16) on the training sample will be extended into the test sample.

To obtain forecasts of growth rates from forecasted gap values, forecasted trend values must be added to the former. No separate forecast equations are specified for the trends of CI, AI, and CPI: their forecast values for periods t+1 – t+12 will be set equal to their actual value in period t.

To obtain a forecast for the relative price gap, a separate forecast equation for the trend component is required, and the forecast for the relative price level can be calculated using forecast values for CI, AI, and CPI. The forecast equation for the relative price trend is the following ARDL model:

$$d(\overline{rel}_{cit}, 2) = c + \beta_1^{\overline{rel}_{ci}}(L)d(\overline{rel}_{cit-1}, 2) \quad (26)$$

$$d(\overline{rel}_{ait}, 2) = c + \beta_1^{\overline{rel}_{ai}}(L)d(\overline{rel}_{ait-1}, 2) \quad (27)$$

where:

$d(\overline{rel}_{cit}, 2)$ is the second difference of the logarithm of the relative price trend for cyclical components in month t;

$d(\overline{rel}_{ait}, 2)$ is the second difference of the logarithm of the relative price trend for acyclical components in month t.

Taking the second difference is necessitated by the fact that these variables are integrated of order two.

Thus, this study will compare several forecast models:

Model 1. Disaggregated (or component-wise for CI and AI) forecast using a nonlinear Phillips curve (hereinafter – DNPC), equations (13) and (14).

Model 2: Aggregate CPI forecast using a nonlinear Phillips curve (hereinafter – ANPC), equation (21).

Model 3: Aggregate CPI forecast using a linear Phillips curve (hereinafter – ALPC), equation (22).

Aggregate CPI forecast without the output gap and exchange rate in the forecast model (hereinafter – Benchmark), equation (23).

The forecast error metric used in this work is the Mean Absolute Error (MAE). To test the significance of differences in errors, the Diebold-Mariano test (Diebold and Mariano, 1995) with small-sample adjustments (HLN adjusted) will be conducted. The null hypothesis is that the benchmark and other forecast models have equal forecast accuracy (in terms of absolute error). The alternative hypothesis is that the accuracy of the benchmark and other forecast models differs. Since the benchmark model does not contain any inflation trends, for comparability, errors will be calculated for the forecasted CPI as % m/m, SA, not as the difference between CPI and its trend.

The coefficients of the forecast models will be estimated using OLS with Newey-West standard errors, and the number of lags in all forecast models will be selected automatically based on the Schwarz criterion.

6. Forecasting Results Using the Nonlinear Phillips Curves

The results of the forecast model comparison are presented in Table 6. The aggregate CPI forecast based on the linear Phillips curve and the simple ARDL model show no significant differences in accuracy at any forecast horizon. This result is consistent with studies whose authors find no significant superiority of the linear Phillips curve compared to simple autoregressive models.

The aggregate CPI forecast based on the model with a nonlinear influence of economic activity (ANPC) performs somewhat better. At longer-term horizons, the forecast based on the nonlinear Phillips curve proves to be significantly more accurate than the benchmark. Even at this stage of comparison, it can be concluded that accounting for the nonlinear relationship between the output gap and inflation has improved forecast accuracy, at least at the 10-12 month horizon.

The disaggregated CPI forecast based on CI shows the best results. Decomposition enhances the forecast accuracy of the Phillips curve with a nonlinear influence of the output gap on inflation: DNPC proves to be significantly more accurate than the benchmark at all forecast horizons except t+1. The relatively high accuracy of DNPC may be attributed to the fact that the disaggregated CPI forecast using nonlinear Phillips curves for CI and AI combines several advantages:

1) Accounting for the nonlinear relationship between inflation and the output gap increases relative forecast accuracy at longer horizons even without preliminary CPI decomposition;

2) The decomposition methodology used in this work allows for a more precise estimation of the coefficients on economic activity;

3) The estimates of the nonlinear influence of economic activity on the CPI obtained from separate Phillips curves for CI and AI demonstrated stability across different samples (Table 4). Clark and McCracken (2006) postulate the stability of coefficients on economic activity as a key condition for high forecast accuracy using the Phillips curve.

Table 6

Models and Their Forecast Accuracy MAE Metrics

Forecast points	Models			
	DNPC	ANPC	ALPC	Benchmark (ARDL)
t+1	0,256 (95,38%)	0,287 (106,76%)	0,290 (107,99%)	0,268
t+2	0,300* (85,01%)	0,370 (104,83%)	0,374 (106,04%)	0,353
t+3	0,318** (83,18%)	0,400 (104,61%)	0,407 (106,27%)	0,383
t+4	0,324** (82,13%)	0,405 (102,72%)	0,414 (105,01%)	0,395
t+5	0,336** (84,82%)	0,406 (102,51%)	0,408 (103,08%)	0,396
t+6	0,344** (87,28%)	0,408 (103,43%)	0,410 (104,07%)	0,394
t+7	0,342** (86,76%)	0,403 (102,22%)	0,409 (104,02%)	0,394
t+8	0,344** (87,20%)	0,389 (98,74%)	0,409 (103,70%)	0,394
t+9	0,344** (87,14%)	0,384 (97,19%)	0,402 (101,60%)	0,395
t+10	0,338*** (85,14%)	0,376** (94,66%)	0,398 (100,33%)	0,397
t+11	0,332*** (83,53%)	0,370*** (93,21%)	0,397 (100,00%)	0,397
t+12	0,328*** (82,50%)	0,373*** (93,89%)	0,395 (99,39%)	0,397

Note: Significance levels for the Diebold-Mariano test are denoted by asterisks: *** - 1%, ** - 5%, * - 10%. The figures in parentheses indicate the percentage ratio of the model's MAE to the benchmark's MAE.

Overall, a similar pattern is observed for all models: the MAE of the Phillips curves relative to the simple ARDL model decreases as the forecast horizon increases. This long-term gain can be explained by the fact that the Phillips curves proved more accurate in predicting the timing of inflation's convergence to its long-term trend. This result is documented in the literature. For example, according to the results presented in Table 1 of the work by Dotsey et al. (2018), at the 2-quarter horizon, the RMSE of the Phillips curve is 9.8% higher than the benchmark (IMA) (1.748 vs. 1.592), while at the 8-quarter horizon, it is only 1.6% higher (1.811 vs. 1.782).

To verify the hypothesis about the dependence of forecasting power on the business cycle phase, we will conduct a comparative analysis of model accuracy under conditions of positive and negative output gaps. For this, the output gap is estimated on the full sample using a two-sided Hodrick-Prescott filter. Then, the mean errors are recalculated so that only the forecast values that fell on periods with a positive/negative output gap are included in the MAE calculation formula.

The results for forecast points with a negative output gap are presented in Table 7. While no significant differences in accuracy between ALPC and the benchmark were observed on the entire sample, when the economy is in a downturn, the aggregate CPI forecast based on the linear Phillips curve wins at the long-term horizon (10 – 12 months). Adding nonlinearity somewhat improves forecast quality: ANPC proves to be more accurate than the benchmark at horizons of 9-12 months. The accuracy of the disaggregated CPI forecast based on CI and AI (DNPC) also increases when the economy is in a downturn.

Table 7

Models and Their Forecast Accuracy MAE Metrics (Negative Output Gap in Forecast Periods)

Forecast points	Models			
	DNPC	ANPC	ALPC	Benchmark (ARDL)
t+1	0,219 (71,11%)	0,344 (111,15%)	0,355 (114,83%)	0,309
t+2	0,299** (66,66%)	0,472 (105,07%)	0,487 (108,59%)	0,449
t+3	0,313*** (63,66%)	0,518 (105,51%)	0,542 (110,32%)	0,491
t+4	0,307*** (60,64%)	0,515 (101,72%)	0,539 (106,55%)	0,507
t+5	0,309*** (62,50%)	0,499 (100,98%)	0,519 (104,83%)	0,495
t+6	0,319*** (66,48%)	0,473 (98,48%)	0,504 (104,98%)	0,479
t+7	0,304*** (64,75%)	0,455 (96,73%)	0,486 (103,37%)	0,469
t+8	0,306*** (66,51%)	0,431 (93,74%)	0,461 (100,19%)	0,459
t+9	0,305*** (67,48%)	0,409** (90,39%)	0,429 (94,97%)	0,452
t+10	0,295*** (65,58%)	0,389*** (86,54%)	0,416* (92,46%)	0,449
t+11	0,285*** (63,70%)	0,377*** (84,23%)	0,408*** (91,23%)	0,447

t+12	0,279*** (62,62%)	0,381*** (85,28%)	0,413*** (92,55%)	0,447

Note: Significance levels for the Diebold-Mariano test are denoted by asterisks: *** - 1%, ** - 5%, * - 10%. The figures in parentheses indicate the percentage ratio of the model's MAE to the benchmark's MAE.

The results for forecast points with a positive output gap are presented in Table 8. When the economy is in an upswing, ALPC proves to be significantly less accurate compared to the simple ARDL model at horizons of 7-12 months. ANPC loses to the benchmark at horizons 6 and 7 months. DNPC showed significantly lower accuracy only at the very shortest horizon.

Table 8

Models and Their Forecast Accuracy MAE Metrics (Positive Output Gap in Forecast Periods)

Forecast points	Models			
	DNPC	ANPC	ALPC	Benchmark (ARDL)
t+1	0,279** (114,22%)	0,252 (103,36%)	0,251 (102,68%)	0,244
t+2	0,301 (102,34%)	0,307 (104,59%)	0,304 (103,63%)	0,294
t+3	0,321 (102,22%)	0,326 (103,73%)	0,322 (102,31%)	0,315
t+4	0,335 (103,36%)	0,336 (103,71%)	0,335 (103,49%)	0,324
t+5	0,352 (106,01%)	0,346 (103,96%)	0,337 (101,42%)	0,332
t+6	0,360 (106,28%)	0,366* (107,95%)	0,350 (103,23%)	0,339
t+7	0,366 (106,34%)	0,369** (107,11%)	0,360* (104,61%)	0,344
t+8	0,369 (105,04%)	0,362 (103,05%)	0,375*** (106,73%)	0,351
t+9	0,370 (103,75%)	0,368 (102,93%)	0,383** (107,19%)	0,357
t+10	0,367 (101,55%)	0,366 (101,48%)	0,386** (106,94%)	0,361
t+11	0,364 (100,20%)	0,366 (100,76%)	0,386** (106,26%)	0,363
t+12	0,364 (100,27%)	0,368 (101,18%)	0,382** (105,19%)	0,363

Note: Significance levels for the Diebold-Mariano test are denoted by asterisks: *** - 1%, ** - 5%, * - 10%. The figures in parentheses indicate the percentage ratio of the model's MAE to the benchmark's MAE.

7. Robustness Checks

This section will address the following questions: 1) Are the obtained results robust to changes in the trend estimation method; 2) Does the nonlinear relationship between the output gap and inflation, as well as the high predictive power of the nonlinear Phillips curve, persist if the conditions for nonlinearity are defined differently; 3) How sensitive are the estimates of the relationship between CI, AI, and economic activity to controlling for shocks; 4) Does the significant nonlinearity of the Phillips curve remain with a shift in the left boundary of the sample; 5) To what extent are the obtained results influenced by the inflationary outliers of 2014, 2015, and 2022.

To answer the first question, the procedures for coefficient estimation and forecasting described in sections 4 and 5 were repeated using an alternative method for extracting the trend component. Checking the robustness of the obtained results is necessary because the Hodrick-Prescott filter has a number of inherent drawbacks that could influence the findings: end-point bias, dependence on the choice of the smoothing parameter λ, and the ability to artificially create cyclical patterns in data that represent a random walk (Hamilton, 2018).

Despite the relevant criticism of the Hodrick-Prescott filter, the alternative proposed by Hamilton (2018) will not be used in this work. Moura (2024), using the same data as Hamilton (2018), showed that the Hamilton filter possesses similar drawbacks (e.g., it can also create cyclical patterns in data that represent a random walk). Moura (2024) also demonstrates that the trend obtained by the Hamilton filter can almost completely replicate the trend obtained by the Hodrick-Prescott filter, albeit with a two-year lag. Consequently, such a trend may appear implausible from an economic standpoint. For instance, Hall and Thomson (2021) and Dritsaki and Dritsaki (2022) apply the Hamilton filter to GDP and show that the estimated potential output persistently grows during deep crises and begins to decline only when the economy has already started recovering.

Thus, using the Hamilton filter not only fails to eliminate the shortcomings of the HP filter but also introduces new ones; therefore, it will not be applied in this study. As an alternative to the Hodrick-Prescott filter, this work will employ a polynomial trend. A uniform cubic specification is used for all variables:

$$y_t = c + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 \tag{28}$$

where:

y_t is the variable being detrended;

t is the time index.

The choice of a third-degree polynomial is based on it being a compromise between flexibility and stability. It can capture not only linear and quadratic trends but also more complex, S-shaped changes, while avoiding the excessive volatility inherent in higher-degree polynomials.

The estimates of the nonlinear Phillips curve coefficients for cyclical and acyclical inflation across the three samples are presented in Table 9. As in the baseline specification, both cyclical and acyclical inflation react significantly to changes in the output gap when nonlinearity conditions are met (with the former reacting much more strongly). Unlike the baseline specification, the coefficient $\beta_{2D}^{\widehat{ai}'}$ proved to be significant when the regression was run on the full sample.

Table 9

Estimates of Coefficients on the Output Gap for CI and AI (Equations (13) and (14)), Polynomial Trends

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25
Coefficient $\beta_{2}^{\widehat{ci}'}$	-0,0006	-0,003	0,003
Coefficient $\beta_{2D}^{\widehat{ci}'}$	0,095***	0,097***	0,098***
Coefficient $\beta_{2}^{\widehat{ai}'}$	-0,023***	-0,001	0,003
Coefficient $\beta_{2D}^{\widehat{ai}'}$	0,054***	0,027***	0,026***

Note: Significance levels are denoted by asterisks: *** - 1%, ** - 5%, * - 10%

Table 10 presents the influence of economic activity on the overall consumer price index as the weighted sum of the coefficients $\beta_{2}^{\widehat{ci}'}$ and $\beta_{2}^{\widehat{ai}'}$, as well as $\beta_{2D}^{\widehat{ci}'}$ and $\beta_{2D}^{\widehat{ai}'}$. Comparing the results presented in Tables 10 and 4, one can notice that changing the trend extraction method has a fairly noticeable impact on the decomposition results: when using a polynomial trend, the share of CI in the CPI grows more markedly. Overall, the sums of the beta coefficients do not show substantial differences compared to the baseline specification. The sum of $\beta_{2D}^{\widehat{ci}'}$ and $\beta_{2D}^{\widehat{ai}'}$ for the Jan05-Dec19 sample stands out, which equals 0.056 when using the polynomial trend, compared to 0.0724 when detrending with the Hodrick-Prescott filter.

Table 10

Weighted Sum of Coefficients on Economic Activity (Polynomial Trends)

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25
Share of CI in CPI (last month of sample)	44,37%	41,78%	61,24%
Share of AI in CPI (last month of sample)	55,63%	58,22%	38,76%
Weighted sum of the coefficients $\beta_{2}^{\widehat{ci}'}$ and $\beta_{2}^{\widehat{ai}'}$ (linear link with CPI)	-0,013	-0,0018	0,003

Weighted sum of the coefficients $\beta_{2D}^{\widehat{ci}'}$ and $\beta_{2D}^{\widehat{ai}'}$ (additional link under nonlinearity conditions)	0,072	0,056	0,07

Thus, the conclusion regarding the statistically significant nonlinear influence of the output gap on inflation is confirmed even when using a fundamentally different detrending method. The observed quantitative discrepancies in the coefficient estimates are expected and are due to differences in the methodology for extracting the trend component. However, their minor nature confirms the robustness of the obtained findings.

To verify whether changing the trend estimation method affects forecast accuracy, we compare the results of aggregated and disaggregated forecasts using linear and nonlinear Phillips curves, employing the same forecast models as in Section 5. We note that, similar to using the Hodrick-Prescott filter, using polynomial trends involves guarding against look-ahead bias. Equation (28) is estimated strictly on the training sample without "peeking" into the test sample. As before, trends and gaps are either forecasted by separate equations or fixed at their last observed value in the test sample. We also note that changing the trend estimation method required only one adjustment in the models: in equations (26) and (27), the trends of relative prices are represented as a fourth difference rather than a second difference. The results are presented in Table 11.

Table 11

Models and Their Forecast Accuracy MAE Metrics (Polynomial Trends)

Forecast points	Models			
	DNPC	ANPC	ALPC	Benchmark (ARDL)
t+1	0,258 (95,99%)	0,282 (104,97%)	0,280 (104,13%)	0,268
t+2	0,295* (83,65%)	0,343 (97,14%)	0,350 (99,13%)	0,353
t+3	0,308*** (80,42%)	0,347** (90,6%)	0,355 (92,67%)	0,383
t+4	0,314*** (79,65%)	0,361** (91,56%)	0,369 (93,39%)	0,395
t+5	0,313*** (79,2%)	0,363* (91,76%)	0,362* (91,52%)	0,396
t+6	0,325*** (82,37%)	0,374 (94,77%)	0,371 (94,05%)	0,394
t+7	0,323*** (81,93%)	0,376 (95,54%)	0,376 (95,39%)	0,394
t+8	0,319*** (80,83%)	0,375 (95,02%)	0,382 (96,82%)	0,394
t+9	0,319*** (80,77%)	0,379 (95,8%)	0,384 (97,07%)	0,395
t+10	0,321***	0,375**	0,389	0,397

	(80,96%)	(94,54%)	(98,04%)	
t+11	0,323*** (81,36%)	0,375** (94,43%)	0,391 (98,37%)	0,397
t+12	0,326*** (81,98%)	0,374*** (94,03%)	0,392 (98,75%)	0,397

Note: Significance levels for the Diebold-Mariano test are denoted by asterisks: *** - 1%, ** - 5%, * - 10%. The figures in parentheses indicate the percentage ratio of the model's MAE to the benchmark's MAE.

Compared to Table 6, the MAE metrics presented in Table 11 are lower for all forecast models. This may be related to the trend component estimation becoming more accurate. While changing the trend estimation method improved the forecast accuracy of all Phillips curves, it did not alter the hierarchy: the most accurate model relative to the simple ARDL benchmark was DNPC, the second most accurate was ANPC, and the aggregate forecast based on the linear Phillips curve (ALPC) showed a significantly lower error compared to the benchmark only at the 5-month horizon. Thus, the answer to the first question regarding robustness to the trend extraction method is positive.

To answer the second question, we repeat the procedure of CPI decomposition, Phillips curve coefficient estimation, and forecasting using the Hodrick-Prescott filter, but with altered nonlinearity conditions. Previously in the paper, it was assumed that the Phillips curve becomes steeper when the output gap is positive and inflation is high simultaneously. This section will investigate whether a positive output gap alone is sufficient for the Phillips curve to become steeper. That is, in all equations, the dummy variable $D^{\hat{x}}$ will take a value of 1 when $\hat{x}$ is greater than 0, and $\widehat{cpi}$ will not be taken into account.

Table 12 presents the estimates of the nonlinear Phillips curve coefficients for CI and AI when the dummy variable is based solely on the output gap. Changing the nonlinearity condition led to minor changes in the absolute coefficient estimates. Regarding their statistical significance, for $\beta_2^{\widehat{ci}'}$ and $\beta_{2D}^{\widehat{ci}'}$ no changes are observed compared to the baseline specification on any sample. The statistical significance of the coefficient $\beta_2^{\widehat{ai}'}$ decreased compared to the baseline specification on the Jan05-Dec13 sample and remained unchanged on other samples. The significance of the coefficient reflecting the nonlinear relationship between the output gap and acyclical inflation slightly decreased on the Jan05-Dec19 sample and increased on the Jan05-Feb25 sample. As in the baseline specification, when the nonlinearity conditions are met, CI accelerates much more strongly than AI.

Table 12

Estimates of Coefficients on the Output Gap for CI and AI (Equations (13) and (14)), Nonlinearity Condition – Only Positive Output Gap

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25

Coefficient $\beta_2^{\widehat{ci}'}$	-0,006	-0,008	0,026**
Coefficient $\beta_{2D}^{\widehat{ci}'}$	0,084***	0,096***	0,097***
Coefficient $\beta_2^{\widehat{ai}'}$	-0,023*	-0,006	-0,0001
Coefficient $\beta_{2D}^{\widehat{ai}'}$	0,048***	0,0399*	0,028*

Note: Significance levels are denoted by asterisks: *** - 1%, ** - 5%, * - 10%.

As presented in Table 13, the sensitivity coefficients $\beta_2^{\widehat{ci}'}$ and $\beta_2^{\widehat{ai}'}$, as well as $\beta_{2D}^{\widehat{ci}'}$ and $\beta_{2D}^{\widehat{ai}'}$ remained close to the baseline specification.

Table 13

Weighted Sum of Coefficients on Economic Activity (Nonlinearity Condition – Only Positive Output Gap)

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25
Share of CI in CPI (last month of sample)	48,47%	57,52%	47,09%
Share of AI in CPI (last month of sample)	51,53%	42,48%	52,91%
Weighted sum of the coefficients $\beta_2^{\widehat{ci}'}$ and $\beta_2^{\widehat{ai}'}$ (linear link with CPI)	-0,014	-0,007	0,012
Weighted sum of the coefficients $\beta_{2D}^{\widehat{ci}'}$ and $\beta_{2D}^{\widehat{ai}'}$ (additional link under nonlinearity conditions)	0,065	0,072	0,0605

The assessment of the forecast accuracy of the Phillips curves under the modified nonlinearity condition is presented in Table 14. The forecast accuracy of ALPC did not change, as altering the nonlinearity conditions by definition does not affect the forecast based on a linear Phillips curve. Regarding forecasts from nonlinear Phillips curves, no significant change in the accuracy of DNPC and ANPC is observed after modifying the nonlinearity condition. The hierarchy of the forecast models has been preserved: ANPC is more accurate than ALPC, and DNPC is more accurate than ANPC.

Table 14

Models and Their Forecast Accuracy MAE Metrics (Nonlinearity Condition – Only Positive Output Gap)

Forecast points	Models			
	DNPC	ANPC	ALPC	Benchmark (ARDL)
t+1	0,276 (102,78%)	0,291 (108,42%)	0,290 (107,99%)	0,268
t+2	0,316	0,374	0,374	0,353

	(89,47%)	(106,0%)	(106,04%)	
t+3	0,323** (84,36%)	0,407 (106,32%)	0,407 (106,27%)	0,383
t+4	0,324*** (82,03%)	0,411 (104,17%)	0,414 (105,01%)	0,395
t+5	0,335** (84,67%)	0,406 (102,59%)	0,408 (103,08%)	0,396
t+6	0,343** (87,03%)	0,409 (103,78%)	0,410 (104,07%)	0,394
t+7	0,339*** (86,10%)	0,404 (102,58%)	0,409 (104,02%)	0,394
t+8	0,340*** (86,14%)	0,393 (99,66%)	0,409 (103,70%)	0,394
t+9	0,340*** (86,15%)	0,387 (97,89%)	0,402 (101,60%)	0,395
t+10	0,333*** (83,95%)	0,378** (95,30%)	0,398 (100,33%)	0,397
t+11	0,329*** (82,92%)	0,373** (94,03%)	0,397 (100,00%)	0,397
t+12	0,330*** (83,03%)	0,376** (94,56%)	0,395 (99,39%)	0,397

Note: Significance levels for the Diebold-Mariano test are denoted by asterisks: *** - 1%, ** - 5%, * - 10%. The figures in parentheses indicate the percentage ratio of the model's MAE to the benchmark's MAE.

To answer the third question, it is necessary to estimate the coefficients of equations (13) and (14) such that the dependent variables are the CI and AI that are not adjusted for shocks (while the CI and AI series themselves are still obtained using the methodology outlined in section 2, which includes shock adjustment and uses the Hodrick-Prescott filter). The results are presented in Table 15.

Table 15

Estimates of Coefficients on the Output Gap for CI and AI (Equations (13) and (14) without adjustment of CI and AI for CPI shocks)

Sample	Jan 05 – Dec 13	Jan 05 – Dec 19	Jan 05 – Feb 25
Coefficient $\beta_2^{\widehat{ci}'}$	-0,021	-0,014*	0,002
Coefficient $\beta_{2D}^{\widehat{ci}'}$	0,088***	0,094***	0,105*
Coefficient $\beta_2^{\widehat{ai}'}$	-0,089**	0,001	-0,015
Coefficient $\beta_{2D}^{\widehat{ai}'}$	0,094**	0,015	0,074

Note: Significance levels are denoted by asterisks: *** - 1%, ** - 5%, * - 10%.

The absence of shock control, as expected, altered the absolute values of the coefficients. Despite this, the obtained conclusion about the presence of a significant nonlinear relationship between the output gap and inflation is confirmed. Cyclical inflation always accelerates more strongly in response to an increase in the output gap when it is greater than 0 and the CPI is above its long-term trend: the coefficient $\beta_{2D}^{\widehat{ci}}$ is statistically significant in all samples (its significance decreases to the 10% level in the Jan05-Feb25 sample), and its absolute value does not exhibit overly sharp fluctuations. The most noticeable changes from the absence of shock control are observed in the coefficient estimates for the acyclical inflation equation. A change in the slope of the Phillips curve for AI is still observed, as evidenced by the coefficient $\beta_{2D}^{\widehat{ai}}$ remaining positive. However, in the Jan05-Dec19 and Jan05-Feb25 samples, it ceased to be statistically significant.

The accuracy metrics for the disaggregated forecast based on the nonlinear Phillips curve without adjustment of CI and AI for shocks are presented in Table 16. The forecast error for DNPC increased noticeably compared to the results presented in Table 6. The disaggregated CPI forecast based on CI and AI without shock control on the training sample shows a significantly larger error relative to the benchmark at the t+1 horizon and a significantly smaller error at horizons t+9 – t+12.

Table 16

Models and Their Forecast Accuracy MAE Metrics (DNPC without adjustment of CI and AI for CPI shocks)

Forecast points	Models			
	DNPC	ANPC	ALPC	Benchmark (ARDL)
t+1	0,298* (111,02%)	0,287 (106,76%)	0,290 (107,99%)	0,268
t+2	0,359 (101,73%)	0,370 (104,83%)	0,374 (106,04%)	0,353
t+3	0,399 (104,35%)	0,400 (104,61%)	0,407 (106,27%)	0,383
t+4	0,409 (103,59%)	0,405 (102,72%)	0,414 (105,01%)	0,395
t+5	0,417 (105,37%)	0,406 (102,51%)	0,408 (103,08%)	0,396
t+6	0,409 (103,70%)	0,408 (103,43%)	0,410 (104,07%)	0,394
t+7	0,399 (101,28%)	0,403 (102,22%)	0,409 (104,02%)	0,394
t+8	0,378 (95,84%)	0,389 (98,74%)	0,409 (103,70%)	0,394
t+9	0,369*** (93,45%)	0,384 (97,19%)	0,402 (101,60%)	0,395

t+10	0,358*** (90,12%)	0,376** (94,66%)	0,398 (100,33%)	0,397
t+11	0,348*** (87,66%)	0,370*** (93,21%)	0,397 (100,00%)	0,397
t+12	0,347*** (87,41%)	0,373*** (93,89%)	0,395 (99,39%)	0,397

Note: Significance levels for the Diebold-Mariano test are denoted by asterisks: *** - 1%, ** - 5%, * - 10%. The figures in parentheses indicate the percentage ratio of the model's MAE to the benchmark's MAE

To answer the fourth question, CPI decomposition and the estimation of coefficients for equations (13) and (14) will be performed with a shift of the left boundary of the sample. As shown in the introduction, before conducting regression analysis, several periods of changing correlation between the CPI and the output gap can be visually identified:

1) Jan 05 - Dec 06 – period of near-zero correlation;

2) Jan 07 - Dec 08 – period of positive correlation;

3) Jan 09 - Dec 10 – period of negative correlation;

4) Jan 11 - Dec 14 – period of positive correlation;

5) Jan 15 - Dec 20 – period of negative correlation;

6) Jan 21 - Feb 25 – period of positive correlation.

The results are presented in Table 17.

Table 17

Estimates of Coefficients on the Output Gap for CI and AI (Equations (13) and (14)) with a Shift in the Left Boundary of the Sample

Sample	Jan 05 - Feb 25 (Full sample)	Jan 07 – Feb 25	Jan 09 – Feb 25	Jan 11 – Feb 25	Jan 15 – Feb 25
Coefficient $\beta_2^{\widehat{ci}'}$	0,0177**	0,017**	0,023*	0,023*	0,057
Coefficient $\beta_{2D}^{\widehat{ci}'}$	0,0889***	0,094***	0,167**	0,215***	0,299***
Coefficient $\beta_2^{\widehat{ai}'}$	-9,16E-05	0,006	0,005	0,009	0,0048
Coefficient $\beta_{2D}^{\widehat{ai}'}$	0,0203	0,02	0,014	-0,009	-0,0125

Note: Significance levels are denoted by asterisks: *** - 1%, ** - 5%, * - 10%.

The statistical significance of the coefficients on the nonlinear output gap ($\beta_{2D}^{\widehat{ci}\prime}$ and $\beta_{2D}^{\widehat{ai}\prime}$) does not change with the shift of the left boundary of the sample. However, as expected when changing the sample, the absolute values of the coefficients change: $\beta_{2D}^{\widehat{ci}\prime}$ consistently increases, while $\beta_{2D}^{\widehat{ai}\prime}$, on the contrary, decreases.

To answer the fifth question, we re-estimate the mean absolute errors, excluding those observations where the CPI was highest: Nov 2014, Dec 2014, Jan 2015, Feb 2015, Mar 2022, Apr 2022 (see Table 1). The results are presented in Table 18.

Table 18

Models and Their Forecast Accuracy MAE Metrics (Excluding Outliers from 2014, 2015, and 2022)

Forecast points	Models			
	DNPC	ANPC	ALPC	Benchmark (ARDL)
t+1	0,188 (106,59%)	0,198 (111,74%)	0,203* (114,7%)	0,177
t+2	0,223* (78,98%)	0,304 (107,56%)	0,31 (109,88%)	0,283
t+3	0,23*** (74,98%)	0,323 (105,35%)	0,333 (108,54%)	0,307
t+4	0,227*** (71,57%)	0,325 (102,38%)	0,336 (105,94%)	0,317
t+5	0,235*** (73,59%)	0,325 (101,69%)	0,330 (103,2%)	0,319
t+6	0,243*** (76,08%)	0,328 (102,8%)	0,333 (104,58%)	0,319
t+7	0,239*** (74,61%)	0,323 (102,24%)	0,335 (104,65%)	0,319
t+8	0,234*** (73,75%)	0,303 (95,49%)	0,330 (104,04%)	0,318
t+9	0,231*** (72,43%)	0,297* (93,12%)	0,322 (101,06%)	0,319
t+10	0,219*** (68,63%)	0,288*** (89,72%)	0,318 (99,22%)	0,321
t+11	0,212*** (66,04%)	0,282*** (87,85%)	0,315 (98,09%)	0,321
t+12	0,212*** (65,97%)	0,285*** (88,72%)	0,315 (98,26%)	0,321

Note: Significance levels for the Diebold-Mariano test are denoted by asterisks: *** - 1%, ** - 5%, * - 10%. The figures in parentheses indicate the percentage ratio of the model's MAE to the benchmark's MAE.

Excluding the outliers, as expected, reduced the forecast errors of all models. Nevertheless, the obtained conclusions regarding the relative accuracy of the models remained unchanged. The nonlinear specification of the Phillips curve is more accurate than the linear one. Furthermore, its forecast error decreases if a decomposition is performed and the CPI is forecasted separately for CI and AI using the forecast equations presented in the study.

Thus, it can be concluded that the obtained results are robust. When changing the method of estimating trends and the nonlinearity condition, a significant nonlinear relationship between inflation and economic activity, as well as the relatively high forecast accuracy of the nonlinear Phillips curve with preliminary CPI decomposition, persists. The regression results for CI and AI without shock control support the notion that the nonlinear correlation between inflation and economic activity is not a specific outcome of this adjustment procedure. Although a significant change in the slope of the Phillips curve (at least for CI) does not disappear, the coefficient estimates obtained without shock correction yield a significantly smaller error relative to the benchmark only at the 9-12 month horizon. With a shift in the left boundary of the sample, the nonlinear correlation between the output gap and inflation is detected, but the coefficient values change noticeably. Removing inflationary outliers makes all forecast models, as expected, more accurate while preserving their hierarchy: ANPC is more accurate than ALPC, and DNPC is more accurate than ANPC.

8. Conclusion

This paper estimates a Phillips curve with a nonlinear relationship between economic activity and inflation. A review of the existing literature indicates that nonlinearity can arise under conditions of a high level of economic activity and/or high inflation. The results obtained for other countries are confirmed using Russian data: the correlation between the output gap and consumer price inflation increases significantly if the output gap is positive and the CPI is above its long-term trend. Furthermore, this nonlinear relationship proves to be relatively stable across different samples. To detect it, a preliminary decomposition of the CPI into cyclical and acyclical components using the methodology presented in the study is necessary.

Accounting for the nonlinear relationship between inflation and economic activity helps improve forecast accuracy. Without decomposition, the nonlinear Phillips curve (ANPC) proves to be significantly more accurate than the benchmark only at the long-term horizon (10–12 months). If decomposition is performed, the nonlinear Phillips curve is more accurate than the simple ARDL model at almost all forecast horizons considered in the study.

Additionally, the hypothesis about the dependence of Phillips curve forecast accuracy on the business cycle phase was tested. Research shows that, compared to simple autoregressive models, forecasts based on the Phillips curve are more accurate when the economy is in a downturn and less accurate during an economic upswing. This hypothesis is confirmed for Russia. Moreover, during downturns, the hierarchy of the considered models is preserved: the nonlinear Phillips curve with CPI decomposition is the most accurate, while the linear Phillips curve is the least accurate.

The obtained results demonstrate robustness to changes in the baseline specification. A statistically significant change in the slope of the Phillips curve, as well as the superior accuracy of the disaggregated CPI forecast based on nonlinear Phillips curves, persist when the trend estimation method is altered (polynomial trend instead of the Hodrick-Prescott filter) and when the nonlinearity condition is modified (using only a positive output gap instead of the combination with a positive deviation of the CPI from its trend). A significant nonlinear relationship between the output gap and inflation (at least its cyclical component) is detected when shifting both the left and right boundaries of the sample. Excluding inflationary outliers does not alter the study's findings. Furthermore, a significant link between the output gap and cyclical inflation persists without the applied CPI shock control procedure, and the increased accuracy of the disaggregated forecast compared to alternatives is maintained over the 9 to 12-month horizon.

This research is limited by certain constraints and thus offers directions for further development. The presented approach to decomposition and estimation of nonlinear Phillips curve coefficients has the potential for integration into structural and semi-structural models. Furthermore, this study can be adapted to the regional level. The identified nonlinearity can also be integrated into a Kalman filter, which estimates the output or unemployment gap based on its relationship with inflation.

References

Andreev, A. (2019). Issledovanie asimmetrii i nelineynosti perenosa dinamiki obmennogo kursa v inflyatsiyu [A Study of Asymmetry and Nonlinearity in the Pass-Through of Exchange Rate Dynamics to Inflation]. Bank of Russia's Working Paper Series, (45).

Zhurakovskiy, V. P., Novopashina, A. N., & Tarantaev, A. D. (2021). Regional'naya raznorodnost' effekta perenosa valyutnogo kursa na inflyatsiyu [Regional Heterogeneity of the Exchange Rate Pass-Through Effect on Inflation]. Bank of Russia's Working Paper Series.

Zubarev, A.V. On the Estimation of the Phillips Curve for the Russian Economy. HSE Economic Journal, 2018, 22(1), p. 40–58. (in Russian)

Inozemtsev, E., & Krotova, Y. (2024). Phillips curve with spatial effects based on Russian regional data. Journal of the New Economic Association, 63(2), 35-56. (in Russian)

Kartaev, P. S., and M. N. Besedovskaya. (2023). Is the Phillips curve useful for forecasting inflation in Russia?. Moscow University Economics Bulletin 6: 24-43. (in Russian)

Kramkov, V. (2023). Does Including CPI Components Improve the Quality of Inflation Forecasts?. Bank of Russia's Working Paper Series, (112).

Ovechkin, D. (2025). Decomposition of the consumer price index into cyclical and acyclical components. Bank of Russia's Working Paper Series, (149).

Khabibullin R. (2019) What measures of real economic activity slack are helpful for forecasting Russian inflation? Bank of Russia's Working Paper Series, (50).

Ang, A., Bekaert, G., Wei, M. (2007). Do macro variables, asset markets, or surveys forecast inflation better?. Journal of monetary Economics, 54(4), 1163-1212.

Atkeson, A., Ohanian, L. E. (2001). Are Phillips curves useful for forecasting inflation?. Federal Reserve bank of Minneapolis quarterly review, 25(1), 2-11.

Benigno, P., Eggertsson, G. B. (2023). It's baaack: The surge in inflation in the 2020s and the return of the non-linear phillips curve (No. w31197). National Bureau of Economic Research.

Bermingham C., D'Agostino A., 2014. Understanding and forecasting aggregate and disaggregate price dynamics. Empirical Economics 46, 765–788.

Blanco, A., Boar, C., Jones, C., Midrigan, V. (2024). Non-linear inflation dynamics in menu cost economies (No. w32094). National Bureau of Economic Research.

Clark, T. E., McCracken, M. W. (2006). The predictive content of the output gap for inflation: Resolving in-sample and out-of-sample evidence. Journal of Money, Credit and Banking, 1127-1148.

Cogley T., Sbordone A. M. (2008). Trend inflation, indexation, and inflation persistence in the New Keynesian Phillips curve. American Economic Review, 98(5), 2101–2126.

Diebold, F. X., Mariano, R. S. (1999). Comparing predictive accuracy. Business Cycles: Durations, Dynamics, and Forecasting; Princeton University Press: Princeton, NJ, USA.

Dotsey, M., Fujita, S., Stark, T. (2018). Do Phillips curves conditionally help to forecast inflation?. 55th issue (September 2018) of the International Journal of Central Banking.

Dritsaki, M., & Dritsaki, C. (2022). Comparison of HP Filter and the Hamilton's Regression. Mathematics, 10(8), 1237.

Ehrmann M., Ferrucci G., Lenza M., O'Brien D. (2018). Measures of underlying inflation for the euro area. Economic Bulletin Articles, 4.

Faust J., Wright J., 2013. Forecasting Inflation (Handbook of Economic Forecasting). Elsevier.

Ferrara, L. (2019). What is behind the change in the gap between services price inflation and goods price inflation?. Economic Bulletin Boxes, 5.

Forbes, K., Gagnon, J., Collins, C. G. (2021). Low inflation bends the Phillips curve around the world (No. w29323). National Bureau of Economic Research.

Fuhrer, J. C., Olivei, G. (2010). The role of expectations and output in the inflation process: an empirical assessment. FRB of Boston Public Policy Brief, (10-2).

Gagnon, J., Sarsenbayev, M. (2022). 25 years of excess unemployment in advanced economies: Lessons for monetary policy. Peterson Institute for International Economics Working Paper, (22-17).

Hall, V. B., Thomson, R. G. (2021). "Does Hamilton's OLS Regression Provide a Better Alternative" to the Hodrick-Prescott Filter? A New Zealand Business Cycle Perspective." Journal of Business Cycle Research, 17(2), 151-183.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. Review of Economics and Statistics, 100(5), 831-843.

Hasenzagl, T., Pellegrino, F., Reichlin, L., Ricco, G. (2022). A Model of the Fed's View on Inflation. Review of Economics and Statistics, 104(4), 686–704.

Huh, H. S., Lee, H. H., Lee, N. (2009). Nonlinear Phillips curve, NAIRU and monetary policy rules. Empirical Economics, 37(1), 131-151.

Karadi, P., Nakov, A., Nuno, G., Pasten, E., Thaler, D. (2025). Strike while the iron is hot: optimal monetary policy with a nonlinear Phillips curve.

Lian W., Freitag A. (2022). Inflation Dynamics in Advanced Economies: A Decomposition into Cyclical and Non-Cyclical Factors. International Monetary Fund.

Moura, A. (2024). Why You Should Never Use the Hodrick-Prescott Filter. A Comment on Hamilton (The Review of Economics and Statistics, 2018). Journal of Comments and Replications in Economics (JCRE), 3, 1-17.

Saul, S. (2021). Do global output gaps help forecast inflation in Russia?. Bank of Russia working paper series, (85).

Shapiro A. H. (2022). A simple framework to monitor inflation. Federal Reserve Bank of San Francisco