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SHORT-TERM INFLATION PROJECTIONS: THE NEW BOG'STIP MODEL

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ABSTRACT

This paper outlines the operational framework of the new Short-Term Inflation Projections model for the Greek economy - BoG'STIP model (hereafter) currently employed by the Bank of Greece within the context of the Eurosystem's inflation projection exercises. The new BoG'STIP model is designed to produce monthly projections for the Greek inflation over a 36-month horizon, providing a critical input for monetary policy decisions. It consists of a set of short-term dynamic equations for the Harmonised Index of Consumer Prices (HICP) and its main components, estimated with emphasis on both the statistical fit and the economic plausibility of the estimated coefficients. Using a pseudo real-time forecasting setup, the model is estimated over the period 1995–2021 and generates projections for 2022–2024. The findings indicate that BoG'STIP model outperforms benchmark models such as AR and ARIMA across most HICP components, except for energy, confirming its robustness and practical value despite certain limitations. The model also exhibits strong forecasting performance for headline inflation, particularly at the 12-month horizon, and effectively captures broader inflationary trends even over longer horizons (up to 36 months). The paper contributes both operationally, by documenting a projection framework compatible with the Broadly Eurosystem Macroeconomics Projections Exercise ((B)MPE) and the Eurosystem Narrow Inflation Projections Exercise (NIPE) and empirically, by providing a transparent and policy-ready inflation forecasting tool tailored to the Greek economy.

Keywords*:* BMPE, Greek economy, Inflation forecasting, NIPE, STIP model
JEL Classification**:** C32; C51; C52; C53; E31

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1. Introduction

Inflation sits at the heart of euro area monetary policy. The Eurozone's policy operating model is anchored to inflation, with the ECB defining price stability as a symmetric two percent medium term objective and setting rates based on expected, not current, inflation, a stance clarified in the 2021 strategy statement and reiterated in subsequent strategy summaries and projection disclosures by the ECB (European Central Bank, 2021, 2025a, 2025b, 2025c). Recent episodes such as the pandemic crisis, the following energy price shock and supply bottlenecks stemming from the war between Russia and Ukraine have reaffirmed that credible policy and communication rely on timely, accurate projections. Accurate and timely forecasts are crucial for both monetary policy decisions and the credibility of the ECB (Banerjee et al., 2023; Giannellis et al., 2024).

Extensive literature has responded with both econometric and machine-learning tools (Angelopoulos et al., 2025). Recent work shows that parts of euro area core inflation react measurably to policy impulses, that outcomes differ with country characteristics such as fiscal stance, energy exposure, and labor market structure, and that forecast errors during 2021 to 2022 were state dependent and larger when inflation was already high. Cross-country heterogeneity in fiscal policy, energy exposure, and labor markets reshapes national inflation dynamics, which argues for architectures that fuse area-wide signals with country-level features and that remain robust across regimes through combinations and adaptive windows (Delle Monache and Pacella, 2024), Hubrich and Skudelny, 2017, Hall et.al. (2023,2024).

The ECB has since expanded transparency around projections and their historical accuracy, reinforcing the case for model diversification and combinations, particularly in turbulent regimes. Three methodological directions are especially relevant: a) Factor approaches extracting area-wide common components and testing the incremental value of national data for aggregate HICP, b) Forecast combinations, especially with disciplined weighting, improve robustness during structural change, and c) Short-term inflation projection frameworks that target salient components such as energy and food enhance real-time performance. Together, these strands point toward designs that integrate global and component-level drivers while retaining operational clarity.

In particular, the short-term inflation projections are central to the Eurosystem policy process; they inform near-term risk assessments, support communication, and anchor scenario design. The recent inflation cycle in Greece and the euro area, muted dynamics through the late 2010s, followed by sharp price pressures between 2022 and 2024, has stress-tested legacy toolchains and created a clear case for an upgraded operational framework for monthly HICP projections.

In this paper, we introduce the new Bank of Greece Short-Term Inflation Projections model for the Greek economy - BoG'STIP model (hereafter). The contribution of this paper is therefore twofold: operational and empirical. Operationally, we codify a forecast pipeline that is compatible with B(M)PE and NIPE timetables while preserving real-time replicability, consistent with national implementations elsewhere in the Eurosystem (see also Bessonovs and Krasnopjorovs, 2021). Empirically, we deliver a transparent, modular template that is Greece-specific yet Eurosystem-ready, suitable for live policy use, and robust to heterogeneous shocks such as those observed in 2022 to 2024 (Cuadro-Sáez et al., 2025).

We build on the earlier operational framework established at the Bank of Greece (see Albani, Bragoudakis, and Zonzilos, 2007), where a component-based, bottom-up framework for monthly inflation forecasting was formalized and embedded in routine policy workflows. The new BoG'STIP model emphases the process discipline in the context of the Eurosystem Broadly Eurosystem Macroeconomics Projections Exercise ((B)MPE) and the Eurosystem Narrow Inflation Projections Exercise (NIPE), the use of judgment alongside data, and the need for forecasts to be explainable to decision-makers and the public, priorities that remain pertinent in a high-volatile environment. Since forecasting is a core input to economic policy decisions, the paper contributes to integrating fully automated econometric projections with strictly data-driven assessments, and to render the inflation-forecasting workflow more open and intelligible, so that projections can function as a practical instrument in policy design.

The main purpose of the new BoG'STIP model is to enhance monthly inflation projections for Greece through an operational framework that preserves methodological discipline while allowing the systematic incorporation of expert judgment. The intention is to combine mechanical econometric projections with empirical assessments in a way that makes the forecasting process more transparent and comprehensible, thereby increasing its usefulness for scenario analysis and policy formulation and addressing the skepticism with which such models are sometimes viewed. The new BoG'STIP model contributes to a better monthly inflation forecast in Greece by creating a forecasting framework, which, without sacrificing methodological rigour, could improve inflation forecasting by allowing the incorporation of expert judgments.

In the context of the new BoG'STIP, inflation forecasting remains unavoidably judgment-based because the econometric forecaster confronts imperfect knowledge of the economy's structure, limited real-time information on cyclical conditions, and the non-stationary character of macroeconomic data that renders future shocks intrinsically hard to anticipate. These realities elevate the role of informed expert assessment alongside formal models. At the same time, forecasts must be intelligible and fully defensible, both to the public, in order to anchor expectations, and to policy makers, so they can be incorporated into decisions. Transparency, therefore, becomes a prerequisite for credibility (see ECB, 2025b).

Against this backdrop, we re-engineer Greece's short-term inflation projection model as a suite of monthly equations for headline HICP and five strategic components, non-energy industrial goods, energy, services, unprocessed food, and processed food, estimated in a pseudo-real-time procedure that mirrors information sets at each forecast vintage. The new BoG'STIP model combines intrinsic price dynamics with a disciplined set of exogenous drivers, including international commodity prices, the euro exchange rate, producer prices, capacity utilization, and labor-cost indicators, in order to reduce omitted-variable risk and enable scenario conditioning consistent with Eurosystem practice.

Our empirical findings provide evidence that headline accuracy is strong at the 12-month horizon, with a persistent signal up to 36 months. The model outperforms AR and ARIMA benchmarks across most components at the 12-month horizon, with a persistent signal up to 36 months, with energy exhibiting the expected volatility-driven exceptions. The evaluation also reveals areas for refinement, most notably services, and a tendency to under-predict during the initial phase of the 2022 shock, findings that guide the roadmap for further model governance and extension.

The remainder of the paper is organized as follows. Section 2 situates the work in the literature and institutional context. Section 3 details the model architecture, data, and estimation protocol. Sections 4 and 5 present empirical results and the forecasting ability of the model against AR and ARIMA benchmarks and discuss the scenario-conditioned paths. Section 6 summarizes the concluding remarks and highlights the usefulness and the valuable contribution of the new BoG'STIP model to the inflation forecasting toolkit used by the Bank of Greece.

2. Literature review

Forecasting inflation remains a central task for economic policy and planning, with ongoing debates regarding the relative effectiveness of disaggregated versus aggregated approaches. A growing body of theoretical and empirical literature suggests that a bottom-up, or disaggregated modelling strategy, where forecasts are generated for individual components and then aggregated, can outperform direct aggregate forecasting under certain conditions. This approach is grounded in the theoretical proposition that, when data-generating processes are correctly specified, the forecast errors across disaggregated components may partially offset one another, leading to improved accuracy for the aggregate (Clements and Hendry, 2002; Lütkepohl, 1984, 1987).

However, this theoretical superiority is contingent upon a set of ideal conditions that are rarely met in empirical practice. As Hendry and Hubrich (2011) caution, model misspecification, selection and estimation uncertainty, changing collinearity, structural breaks, and measurement errors can all degrade forecasting performance. The disaggregated approach can also be vulnerable to exogenous shocks that affect multiple sub-components in the same direction, as demonstrated by Hubrich (2005) in the case of oil and food price shocks affecting euro area inflation.

Despite these caveats, empirical studies across various countries provide evidence in favour of the disaggregated method. For instance, Espasa et al. (2002) report that for simple differenced ARIMA models in the USA, disaggregation can lead to more than a 20% improvement in the relative root mean squared error (RMSE) for one-year-ahead forecasts. Similarly, studies on Austria (Fritzer et al., 2002; Moser et al., 2007), Spain (Álvarez and Sánchez, 2017), Portugal (Duarte and Rua, 2007), France (Bruneau et al., 2007) and Latvia (Bessonovs and Krasnopjorovs, 2020; 2021) all report gains in forecast accuracy using disaggregated models.

NCBs frequently adopt a partial disaggregation approach by isolating volatile components such as unprocessed food and energy, a practice supported by multiple studies including those by Espasa et al. (2002b), den Reijer and Vlaar (2006), Albani et al. (2007) and Bermingham and D'Agostino (2014). While there is no consensus on the optimal degree of disaggregation, researchers have explored a wide range from breaking the CPI or HICP into 5 to over 180 components (Aron & Muellbauer, 2012; Stakėnas, 2015, Bessonovs and Krasnopjorovs, 2020; 2021).

A significant development in the literature is the incorporation of long-run equilibrium relationships via cointegration analysis. Traditional forecasting models, such as ARIMA, VAR, and dynamic factor models, are effective at capturing short-term dynamics (Marcellino et al., 2006; Giannone et al., 2014; Stock and Watson, 1999), but they often neglect the long-run forces that anchor inflation. Aron and Muellbauer (2012) argue that cointegrated relationships between prices and their determinants introduce valuable equilibrium correction mechanisms that improve forecasting accuracy. Although historically underutilized, cointegration methods are gaining traction. Notable applications include Espasa and Albacete (2007) for the euro area, Peach et al. (2004) for the U.S., and Stakėnas (2015) for Lithuania.

Interestingly, empirical studies provide mixed evidence regarding the superiority of the disaggregated approach, especially across different forecast horizons. Hubrich (2005) finds that while the indirect (disaggregated) method underperforms the direct approach for 12-month-ahead forecasts of total euro area inflation, it performs better for core inflation (HICPX) when volatile components are excluded. Similar findings are reported in Austria (Fritzer et al., 2002; Moser et al., 2007) and by Benalal et al. (2004), who find that the indirect approach outperforms the direct approach for HICPX, but not for total HICP at longer horizons. This suggests that disaggregation may be particularly useful in improving forecasts for less volatile inflation measures or when volatile elements are treated separately.

The bottom-up approach also allows for the inclusion of sector-specific variables, enhancing model flexibility and relevance. For example, Moser et al. (2007) use a rich set of sectoral determinants to improve inflation forecasting in Austria, while Aron and Muellbauer (2012, 2013) apply cointegration analysis in constructing inflation models for South Africa and the U.S., capturing both sectoral and macroeconomic interactions. It is noteworthy mentioning that as forecasting practices continue to evolve, further research into optimal disaggregation strategies and the integration of long-run information remains a promising avenue for enhancing inflation forecast accuracy.

3. Methodology-Description of new BoG'STIP model

The new BoG'STIP model consists of a set of short-term dynamic equations for the HICP and its components. The empirical model is specified as follows:

$$dlogI_t = a + \sum_{i=1}^{p} \beta_i dlogI_{t-i} + \sum_{j=1}^{k} \sum_{l=0}^{q_j} \gamma_j X_{j,t-l} + \sum_{s=1}^{11} \delta_s D_{st} + \varepsilon_t \qquad (1)$$

where I_t is the corresponding price index of period t, $X_{j,t}$ is a set of explanatory variables in period t and D_{st} is a set of seasonal and other time variables and with $E(\varepsilon_t) = 0, Var(\varepsilon_t) = \Omega, \Omega\ HAC$.

Specifically, forecasting equations are also formulated for non-energy industrial goods (NEIG), energy goods (HEG), services (SERV), unprocessed (UNPROC) and processed food (PROC) as presented in Table 1. Following Albani et al. (2007), the model exploits the autocorrelation structure of the data, as well as the key inflation determinants. Hence, exogenous variables are also included as explanatory variables. The exogenous variables used in the models are the following: oil prices (POILU) in US dollars, the US dollar/euro exchange rate, foreign price indices of food and non-food commodities, the producer price index for the domestic market (PPI), the capacity utilization rate in industry (CAP), and total economy unit labour cost (ULC) or, alternatively, compensation per employee (WUN).

In line with Albani et al. (2007), we formulate the equations based on a pseudo real-time forecasting procedure, taking also into account the goodness of fit of the equations, the statistical significance and the plausibility of the estimated coefficients. In this analysis, we expand the estimation period to Jan. 1995 – Dec. 2021. This period includes also a so-called 'low-inflation' era (2012 – 2020) but not the inflationary crisis that broke out after the COVID pandemic and was reinforced by the crisis caused from the war in Ukraine (early 2022). One of the objectives of the present paper is to find out whether the inflationary crisis would be forecasted by the STIP model and in which extent. Another extension of the paper of Albani et al. (2007) is the inclusion of VAT rates in the equations. Having VAT rates for each HICP component, we are able to study the impact of VAT on price indices and inflation.

The innovation of the proposed new BoG'STIP model is twofold. By incorporating VAT rates, a new set of explanatory variables is introduced while equations for all HICP subcomponents are re-estimated yielding updated elasticities for the exogenous variables. The inclusion of VAT rates in the estimated equations allows for estimating the impact of indirect taxes on inflation. This update is crucial as it refers to a low-inflation era while the structural relationships between fundamentals of the economy might have changed.

Further, we obtain projections for the 2022 – 2024 period and we compare the results with the real values of the HICP and its components. Since the evaluation sample is limited especially for larger out-of-sample periods, we extend the out-of-sample estimation by restricting the sample used for estimating the models' equation so as to increase the evaluation metrics' reliability. Hence, as a robustness check, the sample is restricted to January 1995 to December 2019. This datapoint has also been selected as this period does not include both the pandemic and the following inflationary crisis.[1] By extending the forecasting period, more degrees of freedom are obtained especially for the longer forecasting horizons.

[Insert Table 1 here]

4. Empirical results and forecasting ability of model

In this section, we present the main results of the model, estimating the HICP using two ways[2]. Firstly, we estimate directly the HICP and compare the forecasted values obtained from the model with the real HICP values[3]. Secondly, we use an indirect methodology of projecting the HICP by getting projections for its components. Then, we calculate the projected values of the HICP by synthesizing the components' indices using also the respective annual weights. Forecasted values are obtained from rolling estimations of equations described in Table 1. The estimations are conducted in a 60-month rolling window and forecasted values are produced for a 36-month period ahead.

In order to assess the forecasting ability of the new BoG'STIP model, we calculate the projected-to-real-value ratio. The closer to 1 is the value of this ratio, the better the estimation. If the ratio is lower than 1, then the respective index is underestimated and vice

[1] The Relative Root Mean Squared Errors (RRMSE) for the extended out-of-sample period are provided in Annex.

[2] The results from estimated equations are presented in Annex II.

[3] Further, a comparison with the forecasted HICP values produced in the context of the December 2021 Broad Macroeconomic Projections Exercise (BMPE) has been held, but the results cannot be published for confidentiality reasons.

versa. This ratio is calculated both for the HICP and its components for the entire projection period (2022 – 2024).

The ratio for the HICP using both the direct and indirect approach is shown in Figure 1. During the entire projection period, the ratio takes values below or slightly above (when using the indirect approach) 1, indicating that the STIP model mostly underestimates HICP index regardless of the approach employed. However, as information is included in the model the ratio increases in both cases. This happens because there are autoregressive features included in the model and as higher values of HICP are introduced, the projected values are being adjusted to higher levels. Hence, we could argue that the STIP model, using either the direct or the indirect approach, achieves to reach real values of HICP (and inflation) as it gets more information about the inflationary period.

The same ratio is calculated for all the HICP components and shown in Figure 2. A very first finding is that since 2022 the model overestimates the energy price index (HEG) and hence energy inflation. This overestimation reaches almost 25% in June 2024. This can probably be attributed to the autoregressive nature of the estimated equation. Hence, the model takes into account higher values of the energy price index and estimates a continuous increase in the projection period. This projection has not been confirmed since energy prices deescalated in some extent. At this point, we obtain the most significant shortcoming of models based on autoregression which is that these models cannot forecast turning points and non-linear features should probably be included.

[Insert Figure 1 here]

As for the other indices, results obtained are better. Despite the fact that all other price indices are mainly underestimated, the projected-to-real-value ratio is closer to 1. In general, a declining trend is observed for all ratios indicating that the model tends to underestimate more the prices indices as we go further into the projection period. Better results are obtained for the non-energy industrial goods prices (NEIG) and services' price (SERV) indices. The underestimation of processed food prices index (PROC) is quite larger during the projection period, while stronger fluctuations are observed for the ratio of unprocessed food (UNPROC). The last result may be linked to higher volatility of unprocessed food prices which reduces forecasting ability.

[Insert Figure 2 here]

5. Forecast evaluation

One of the most important issues related to forecasting models is whether such a model produces better results than simple linear benchmark models. As Albani et al. (2007) note, linear autoregressive models meet the minimum properties that a good benchmark model should contain.

In this section, we test the forecasting performance of the new BoG'STIP model comparing it with that of simple AR and ARIMA (Autoregressive Integrated Moving Average) models. We employ an ARIMA model selected automatically among several models with different orders of autoregression and moving average. Competitive models are compared in terms of Relative Root Mean Square Errors (RRMSE) and for several forecasting horizons (from 1 month to 36 months). The Root Mean Square Errors for each model are calculated using the following formula:

$$RMSE = \sqrt{\sum_{t=T_0+1}^{T_0+h} \frac{(\hat{\pi}^i_{t+h|t} - \pi_{t+h})^2}{h}} \qquad (2)$$

where *h* denotes the number of out-of-sample observations, T_0 is the end of the in-sample period, π_t+h|t is the h-step-ahead forecast generated by the i-th model, and π^_t+h is the realized inflation rate. Following the standard practice, inflation is calculated on an annual basis.

The relative RMSE (RRMSE) of the i-th model relative to a benchmark model for the h-step-ahead forecast horizon is given by:

$$RRMSE^i_h = \frac{RMSE^i_h}{RMSE^{benchmark}_h}$$

In Table 2 the relative values of RMSE for the BoG'STIP model over the competitive models are reported. When the relative value is lower than 1, the BoG'STIP model performs better than the respective competitive model. Comparison between STIP and the competitive models is also conducted both for the HICP and its components separately (see Table 2).

Obtaining the relative values of RMSE, we can conclude that the new BoG'STIP model performs better than all competitive models in forecasting the HICP index (and hence the headline inflation) for all forecasting horizons with the exception of the 1-month horizon. At the same time, when comparing the AR1 and the ARIMA model, we get that the second performs better except from the very short-term forecasting horizons (1 and 3 months).

However, results significantly differ when comparing forecasts for HICP components. Starting from Non-Energy Industrial Goods (NEIG), we get that the new BoG'STIP model performs better than the AR1 up to the 12-months horizon. On the contrary, the ARIMA model performs better than both the new BoG'STIP and AR1 for all forecasting horizons.

As for Energy Goods (HEG), the new BoG'STIP model performance is better than both AR1 and ARIMA for all forecasting horizons except that of 36 months. As expected, it is found that ARIMA model performs better than AR1 due to the fact that the first is much more sophisticated and can produce better predictions.

Our findings conclude that forecasting of Services (SERV) inflation using STIP seems to be problematic. It is found that the new BoG'STIP does not perform better than either AR1 or ARIMA for all forecasting horizons. Among the two, ARIMA produces better results in terms of RRMSE. This finding might suggest that the components related to Services in the BoG'STIP model need to be reviewed.

On the contrary, the new BoG'STIP model is estimated to perform better than AR1 as far as unprocessed food price index is concerned for all forecasting horizons despite the fluctuations observed previously when comparing real values of unprocessed food price index versus projected values. The result remains the same when comparing with ARIMA but only for forecasting horizon up to 9 months. From 12 months onwards, ARIMA performs better than new BoG'STIP model. Further, ARIMA seems to beat AR1 for all forecasting horizons except the very short-term (1 month).

[Insert Table 2 here]

Finally, as for processed food, the new BoG'STIP model performs better than both AR1 and ARIMA except for the long-term projections (24 and 36 months), while ARIMA seems to beat AR1 for all forecasting horizons.

All in all, the new BoG'STIP model is estimated to have higher forecasting ability when compared to a simple AR1 or a more sophisticated ARIMA model regarding headline inflation. The higher predictive accuracy of the new BoG'STIP model is also confirmed by a Diebold-Mariano test. With the exception of services component, the new BoG'STIP model is estimated to beat the other two competitive models for all other HICP components and especially for up to 12-month forecasting horizon. Hence, the new BoG'STIP model is reliable when producing projections in the short-term.

As previously noted, to obtain sufficiently stable and reliable RMSE estimates, the number of out-of-sample observations, *N*, must definitely exceed 20 for relatively stable RMSE results. Hence, an extended out-of-sample period is employed. Under this framework, the new BOG'STIP model outperforms the competing models, with two exceptions. First, for the energy component, its superior performance emerges only at longer projection horizons (exceeding nine months). Second, for the unprocessed food component, the model outperforms only the ARIMA benchmark and only for projection horizons up to 12 months. Figure 3 presents the projections of the overall HICP index produced from each of the models used in the present paper compared to the real HICP index. The sample used in this analysis is from January 1995 to December 2021. The projection horizon is defined at 36 months for the time period: January 2022 – December 2024 and the new BoG'STIP model uses the technical assumptions[4] as of December 2021.

[Insert Figure 3 here]

The new BoG'STIP model projections (illustrated with the orange dashed line) achieve to follow the trend of the real HICP but they seem to fail in forecasting the sharp rise of HICP in 2022. However, STIP projection converge to the real values of HICP close to the 24-month forecasting horizon. On the other hand, projections produced from the

[4]At the beginning of every projection exercise a set of initial technical assumptions is derived, covering market interest rates (short, long and global rates), oil prices, exchange rates, stock market prices and international non-oil commodity prices. The assumptions are regularly reviewed and updated in the course of the exercise until the final cut-off date.

ARIMA model underestimate HICP values up to the mid-2023, but they overestimate HICP for the second half of the forecasting period, probably due to the autoregressive and moving average features included. Moreover, the AR1 model just catches the upward trend of the HICP while fails on forecasting turning points or sharp increases.

Summing up, the above illustration confirms that the new BoG'STIP model produces better results as for headline inflation especially for forecasting horizons up to 12 months and despite that there are still challenges to be faced, it remains the best predictive model between those presented.

6. Conclusions

This paper presents the new BoG'STIP model, which is an updated version of the Short-Term Inflation Projections model for the Greek economy. The new BoG'STIP model employed by the Bank of Greece in the context of the Eurosystem forecasting framework. Building on the earlier structure of Albani et al. (2007), the model incorporates an extended estimation sample period (1995–2021), pseudo real-time estimation techniques and new explanatory variables such as VAT rates. The new BoG'STIP model produces projections for the period 2022–2024, allowing for an assessment of its forecasting accuracy during the recent inflationary episode.

The empirical results confirm that the new BoG'STIP model performs well in forecasting headline inflation, particularly over short-term horizons (up to 12 months). It outperforms benchmark models such as AR and ARIMA across most HICP components, notably for non-energy industrial goods, processed and unprocessed food, and energy (except in long-term horizons). The model exhibits an ability to adapt as new information becomes available, gradually converging toward actual inflation values even during periods of elevated volatility.

The recent war in the Middle East further underscores the practical relevance of the new BoG'STIP model. The escalation of the conflict in March 2026 has already generated sharp volatility in oil and gas prices, disruptions to shipping routes and energy infrastructure, and renewed uncertainty over the duration and intensity of supply bottlenecks. In its March 2026 projections, the ECB explicitly revised up the near-term inflation outlook for the euro area because of higher energy prices associated with the war, while also stressing the unusually high uncertainty surrounding the inflation path. This environment highlights precisely why a policy-oriented short-term inflation model such as the new BoG'STIP model is needed. The new BoG'STIP model which is a component-based framework complemented by disciplined expert judgment, is better suited to capture the rapid pass-through of geopolitical shocks to energy, food, and transport-related prices than purely mechanical benchmark models. In this sense, the new BoG'STIP model provides a forecasting framework capable of incorporating abrupt external shocks of the kind currently affecting the inflation process in Greece and the euro area.

However, the analysis reveals some limitations. The new BoG'STIP model tends to underestimate inflation during the period of the 2022 inflation shock and overestimates energy prices due to its autoregressive structure, which lacks mechanisms to anticipate turning points. Moreover, forecasting performance for the services component is notably weaker than for other indices, highlighting areas where model refinements are needed.

Comparative evaluation using relative RMSE metrics reinforces the model's robustness for headline inflation, while pointing to mixed results across components and horizons. Notably, while ARIMA models sometimes outperform STIP in longer-term or highly volatile components, STIP remains the most reliable model overall for short-term inflation projections. Future extensions of the BoG'STIP model could focus on several directions. First, its application could be expanded to a more detailed COICOP classification, beyond its current use for rents and energy sub-components, to capture finer price dynamics across categories. Second, incorporating interactions between components, such as the effect of unprocessed food prices on restaurant prices, could enhance the model's structural framework and improve predictive power. Third, developing a more detailed forecasting framework for the services sector would improve coverage of one of the most volatile and policy-relevant components of inflation.

Despite the current limitations, the BoG'STIP model is consider a valuable contribution to the inflation forecasting toolkit used by the Bank of Greece and reinforces the utility of disaggregated approaches within the Eurosystem's projection framework.

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TABLES AND FIGURES

Table 1: Explanatory variables included in the new BoG'STIP model

HICP	Energy (HEG)	Non-energy industrial goods (NEIG)	Processed food (PROC)	Unprocessed food (UNPROC)	Services (SERV)
AR (4, 5, 6, 12)	AR (1)	AR (1, 2, 3, 4, 6, 11, 12)	AR (1)	AR (1, 2, 4)	AR (1, 4, 5, 6, 7, 9, 11, 12)
SD	SD	SD	SD	SD	SD
DV	DV	DV	DV	DV	DV
Unit Labour Cost (12)	Oil prices (in EUR) (1)	Compensation per employee (5)	Non-energy commodity prices (5)		Compensation per employee (2)
Oil prices (in EUR)	Electricity Producer Prices (12)	Non-energy commodity prices (4)	Compensation per employee (5)		Unprocessed Food (1)
Producer Price Index (3)	Non-energy commodity prices (non-agriculture) (2)	Capacity Utilisation Rate (9)			
Capacity Utilisation Rate (9)					

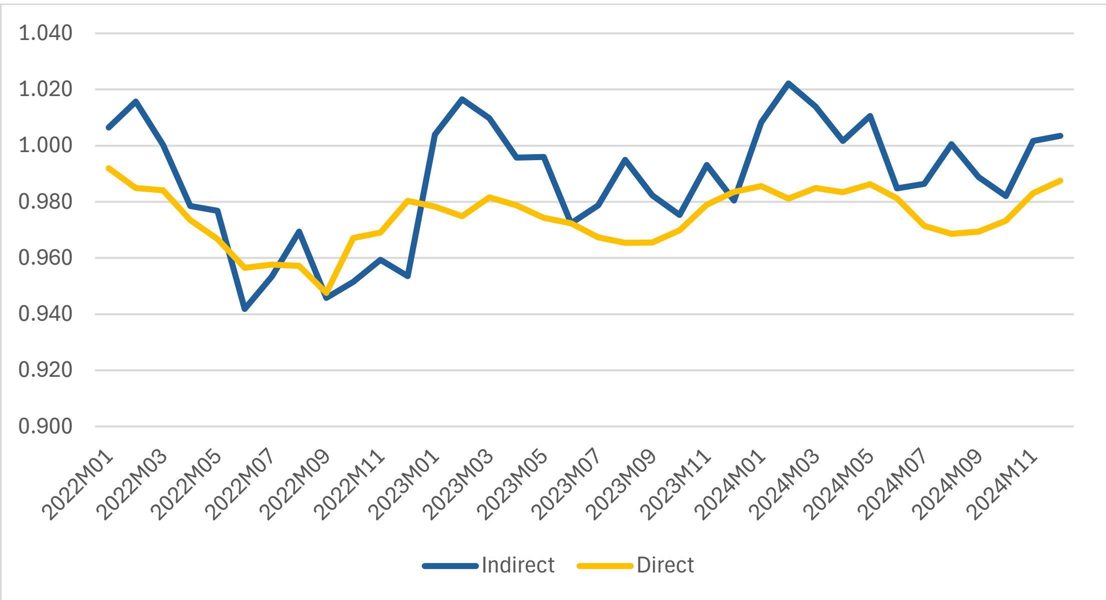
Source: Bank of Greece

Notes: The respective VAT rates are used in all equations. Numbers between brackets are the lags included in the models. All variables were transformed into first log differences, except for unit labor cost and wages, which are expressed as rates of change and were therefore transformed into simple first differences.
SD denotes for Seasonal Dummies. DV denotes Dummy Variables.
The Akaike Information Criterion (AIC) is employed for selecting the number of lags in each equation.

Table 2. Relative root mean square error (RRMSE) values							
	1 month	**3 months**	**6 months**	**9 months**	**12 months**	**24 months**	**36 months**
HICP							
STIP/AR1	1.909	0.817	0.637	0.706	0.651	0.517	0.462
STIP/ARIMA	1.096	0.770	0.756	0.829	0.853	0.997	0.843
AR1/ARIMA	0.574	0.943	1.187	1.173	1.310	1.930	1.825
NEIG							
STIP/AR1	0.170	0.135	0.366	0.666	0.884	1.259	1.332
STIP/ARIMA	2.001	1.730	1.437	1.430	1.280	1.406	1.492
AR1/ARIMA	11.774	12.824	3.927	2.148	1.448	1.117	1.120
HEG							
STIP/AR1	0.489	0.426	0.494	0.473	0.493	0.919	1.124
STIP/ARIMA	0.454	0.411	0.482	0.461	0.480	0.905	1.121
AR1/ARIMA	0.927	0.964	0.975	0.974	0.973	0.985	0.997
SERV							
STIP/AR1	9.761	1.870	1.229	1.210	1.276	1.435	1.492
STIP/ARIMA	5.072	1.954	1.290	1.264	1.328	1.578	1.772
AR1/ARIMA	0.520	1.045	1.050	1.044	1.041	1.100	1.187
UNPROC							
STIP/AR1	0.224	0.308	0.646	0.845	0.874	0.929	0.906
STIP/ARIMA	0.194	0.316	0.713	0.976	1.017	1.018	0.988
AR1/ARIMA	0.867	1.024	1.104	1.155	1.164	1.096	1.091
PROC							
STIP/AR1	0.596	0.813	0.867	0.924	0.962	1.007	1.011
STIP/ARIMA	0.623	0.769	0.828	0.895	0.945	0.999	1.005
AR1/ARIMA	1.045	0.945	0.955	0.968	0.983	0.992	0.994

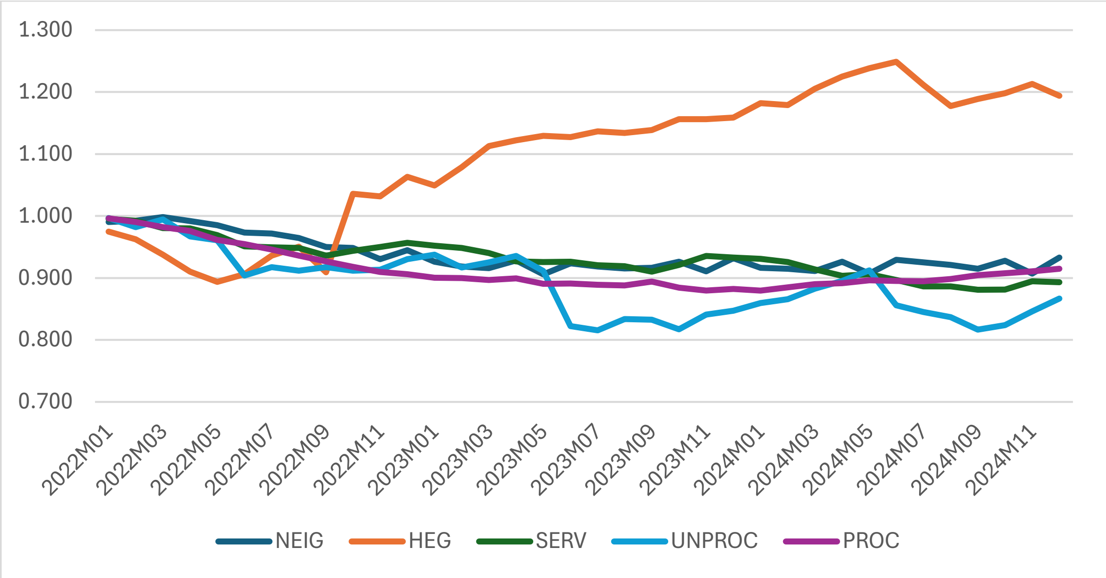
Source: Authors' calculations

Figure 1. Ratio of projected to real values of HICP, 2022 – 2024



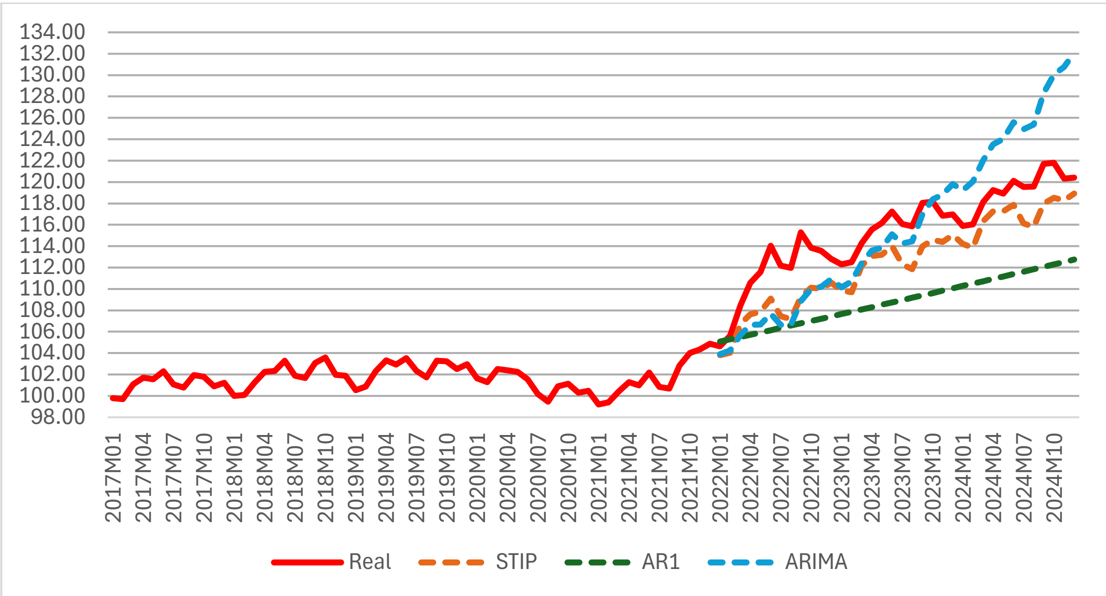
Source: Authors' calculations

Figure 2. Ratio of projected to real values of HICP components, 2022 – 2024



Source: Authors' calculations

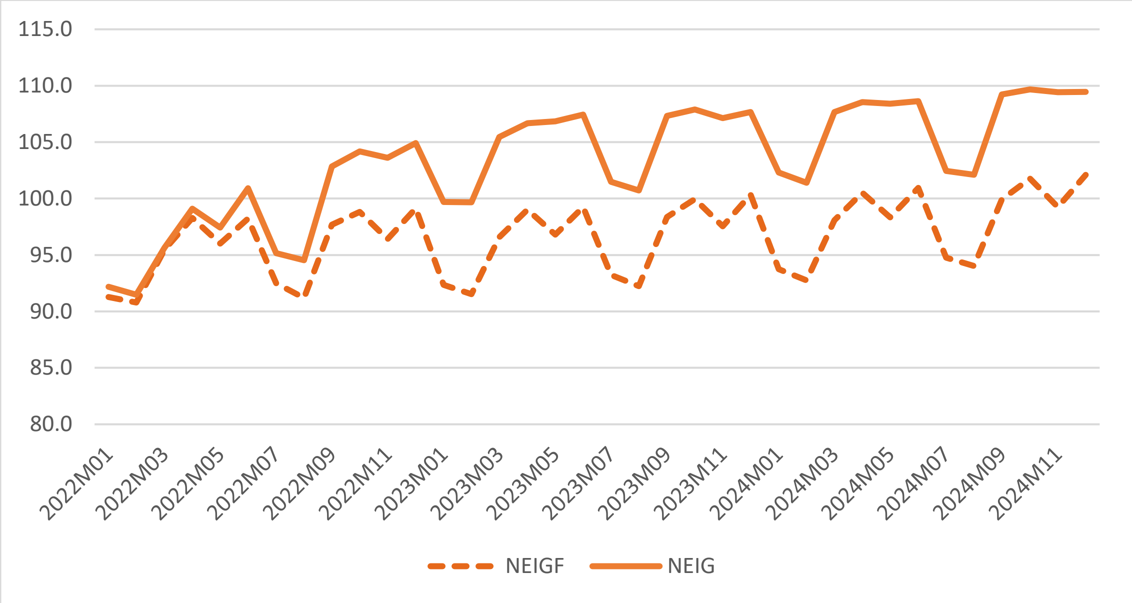
Figure 3. HICP real and projected values using different projections methods.



Source: Authors' calculations

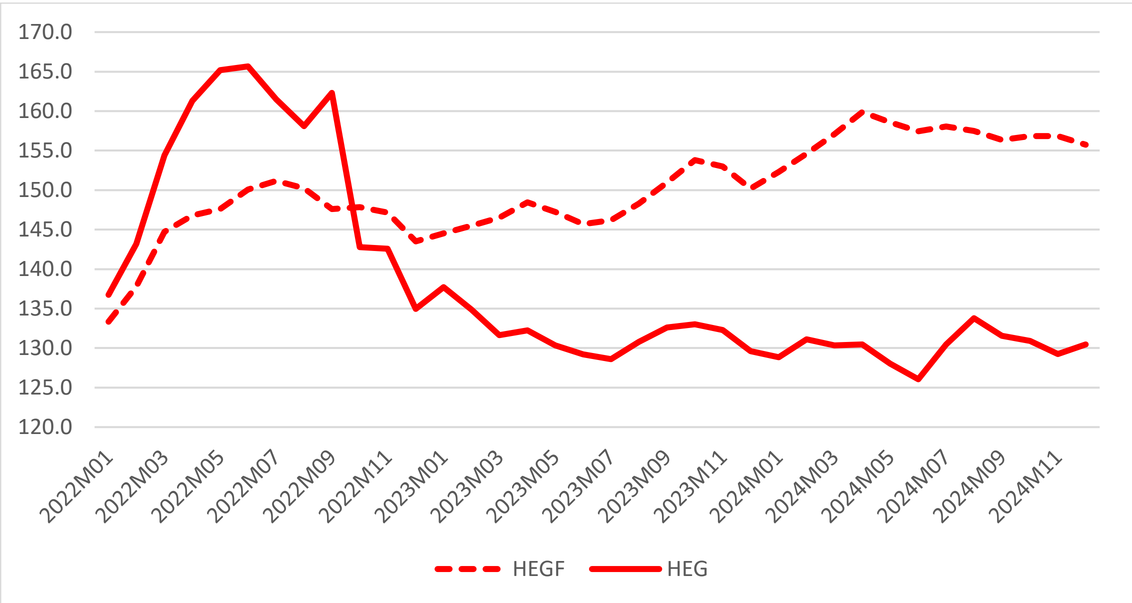
APPENDIX I

Graph A.1. Non-Energy Industrial Goods price index, comparison between real and projected values.



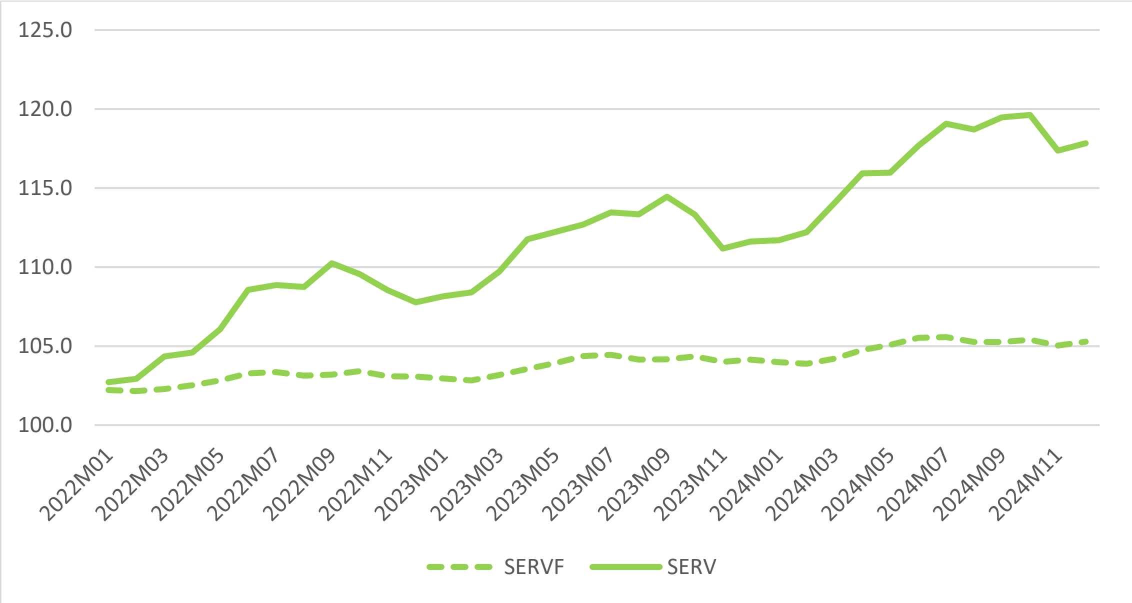
Source: Authors' calculations

Graph A.2. Energy Goods price index, comparison between real and projected values.



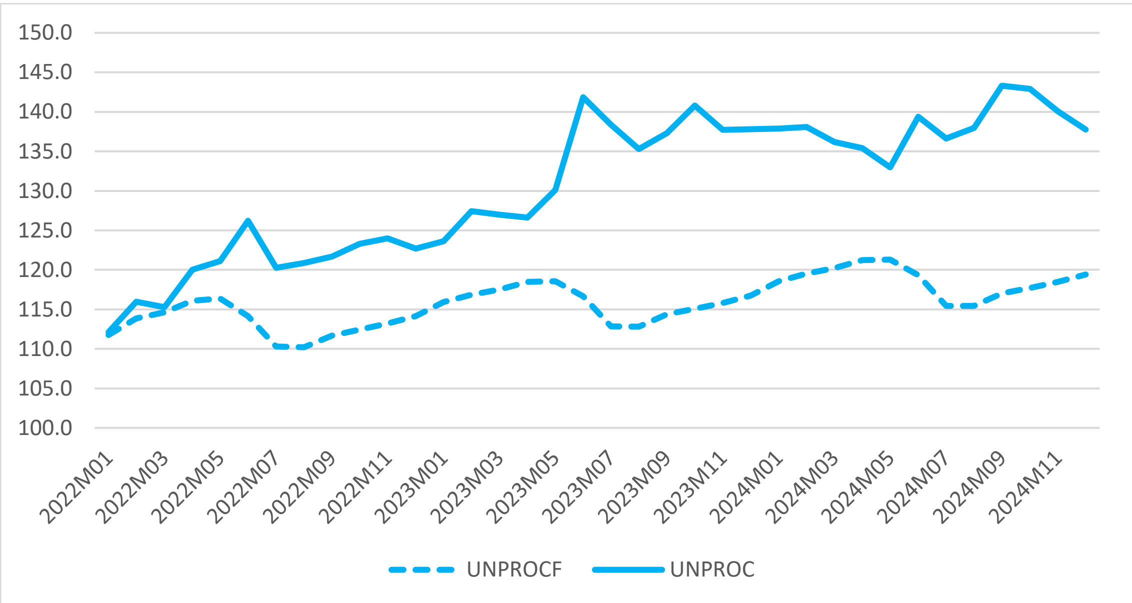
Source: Authors' calculations

Graph A.3. Services price index, comparison between real and projected values.



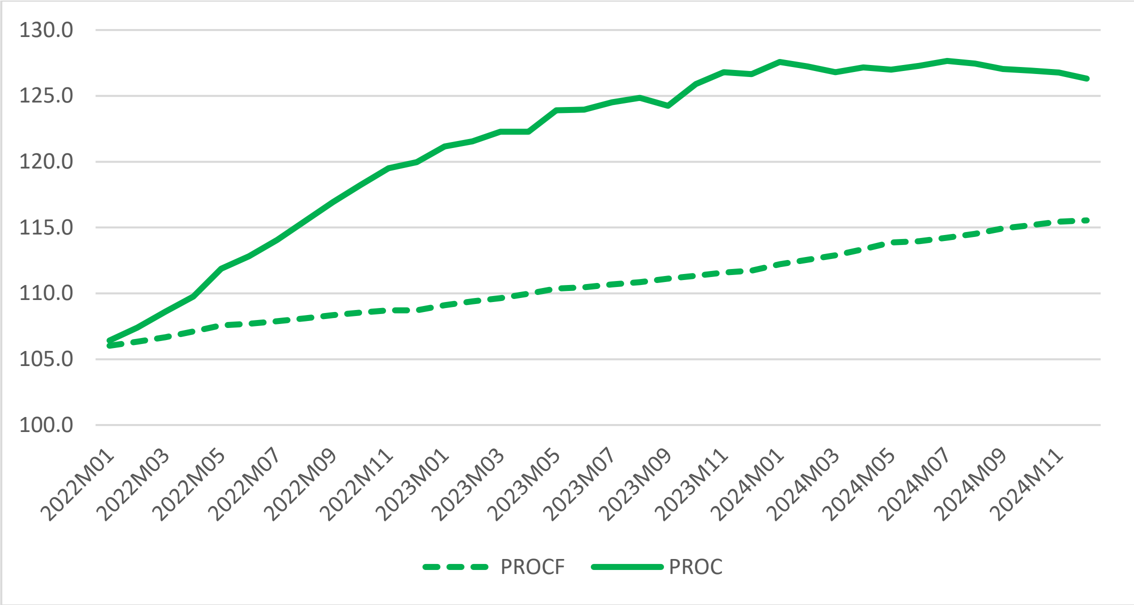
Source: Authors’ calculations

Graph A.4. Unprocessed food price index, comparison between real and projected values.



Source: Authors’ calculations

Graph A.5. Processed food price index, comparison between real and projected values.



Source: Authors' calculations

APPENDIX II[5]

Headline inflation

Dependent Variable: DLOG(HICP)
Sample (adjusted): 1997M02 2021M12
Included observations: 299 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000	0.001	0.481	0.631
DLOG(HICP(-4))	0.085	0.044	1.957	0.051
DLOG(HICP(-5))	-0.074	0.043	-1.738	0.083
DLOG(HICP(-6))	0.157	0.047	3.358	0.001
DLOG(HICP(-12))	0.525	0.047	11.119	0.000
SEASDV01	-0.005	0.002	-2.620	0.009
SEASDV02	-0.001	0.002	-0.613	0.540
SEASDV03	0.007	0.002	4.124	0.000
SEASDV04	0.001	0.001	1.056	0.292
SEASDV05	0.000	0.001	0.020	0.984
SEASDV06	0.000	0.001	-0.206	0.837
SEASDV07	-0.009	0.002	-4.568	0.000
SEASDV08	-0.001	0.002	-0.513	0.608
SEASDV09	0.005	0.002	3.053	0.002
SEASDV10	0.000	0.001	-0.110	0.913
SEASDV11	0.000	0.001	0.149	0.882
DV199804	0.009	0.004	2.351	0.019
DV200006	-0.009	0.004	-2.303	0.022
DV200010	0.008	0.004	2.169	0.031
DV200202	-0.009	0.004	-2.427	0.016
DV200502	-0.012	0.004	-3.112	0.002
D(ULC1)	0.590	0.204	2.897	0.004
D(ULC1(-12))	0.522	0.217	2.409	0.017
DLOG(POILU/EXR)	0.013	0.002	6.384	0.000
DLOG(PPI_HAT(-3))	0.077	0.019	4.110	0.000
D(CAP_HAT(-9))	0.000	0.000	2.286	0.023

R-squared	0.906	Mean dependent var	0.002
Adjusted R-squared	0.898	S.D. dependent var	0.011
S.E. of regression	0.004	Akaike info criterion	-8.296
Sum squared resid	0.004	Schwarz criterion	-7.975
Log likelihood	1266.319	Hannan-Quinn criter.	-8.168
F-statistic	105.869	Durbin-Watson stat	1.986
Prob(F-statistic)	0.000		

[5] Multicollinearity was examined using the Variance Inflation Factor (VIF). The centered VIF values for all explanatory variables are well below the commonly accepted threshold, indicating the absence of serious multicollinearity in all estimated models. Therefore, the estimated coefficients can be considered stable and reliable with respect to multicollinearity.
To account for potential serial correlation and heteroskedasticity, all models were estimated using OLS using Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors.

Non-energy industrial goods

Dependent Variable: DLOG(NEIG)
Sample (adjusted): 1996M09 2021M12
Included observations: 304 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005	0.004	1.521	0.129
DLOG(NEIG(-1))	-0.388	0.047	-8.211	0.000
DLOG(NEIG(-2))	-0.279	0.049	-5.720	0.000
DLOG(NEIG(-3))	-0.226	0.049	-4.587	0.000
DLOG(NEIG(-4))	-0.132	0.044	-2.974	0.003
DLOG(NEIG(-6))	0.224	0.042	5.294	0.000
DLOG(NEIG(-11))	-0.189	0.042	-4.447	0.000
DLOG(NEIG(-12))	0.368	0.051	7.227	0.000
WUN1(-5)	0.451	0.121	3.714	0.000
D(NEIG_VAT)	0.177	0.249	0.711	0.478
SEASDV01	-0.022	0.005	-4.833	0.000
SEASDV02	-0.024	0.006	-4.082	0.000
SEASDV03	-0.001	0.006	-0.220	0.826
SEASDV04	0.007	0.006	1.146	0.253
SEASDV05	0.003	0.005	0.557	0.578
SEASDV06	0.001	0.002	0.227	0.821
SEASDV07	-0.018	0.005	-4.000	0.000
SEASDV08	-0.017	0.006	-2.897	0.004
SEASDV09	0.003	0.006	0.534	0.594
SEASDV10	0.006	0.006	0.973	0.331
SEASDV11	0.002	0.005	0.379	0.705
DV200501	0.047	0.008	5.616	0.000
DV200502	-0.016	0.009	-1.847	0.066
DLOG(COMFD(-4)/EXR(-4))	0.015	0.013	1.187	0.236
D(CAP_HAT(-9))	0.001	0.000	1.683	0.093

R-squared	0.962	Mean dependent var	0.001
Adjusted R-squared	0.958	S.D. dependent var	0.040
S.E. of regression	0.008	Akaike info criterion	-6.703
Sum squared resid	0.019	Schwarz criterion	-6.398
Log likelihood	1043.896	Hannan-Quinn criter.	-6.581
F-statistic	291.571	Durbin-Watson stat	2.262
Prob(F-statistic)	0.000		

Energy

Dependent Variable: DLOG(HEG)
Sample (adjusted): 2007M02 2021M12
Included observations: 179 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.006	0.005	-1.203	0.231
DLOG(HEG(-1))	0.350	0.068	5.134	0.000
DLOG(POILU/EXR)	0.110	0.012	9.160	0.000
DLOG(POILU(-1)/EXR(-1))	0.032	0.015	2.128	0.035
DLOG(ELECTRIC(-12))	-0.001	0.013	-0.063	0.950
DLOG(COMFDX(-2)/EXR(-2))	-0.033	0.037	-0.893	0.373
D(HEG_VAT)	0.636	0.364	1.746	0.083
SEASDV01	0.021	0.007	3.132	0.002
SEASDV02	0.010	0.007	1.495	0.137
SEASDV03	0.016	0.007	2.394	0.018
SEASDV04	0.012	0.007	1.741	0.084
SEASDV05	0.001	0.007	0.087	0.931
SEASDV06	0.003	0.007	0.500	0.617
SEASDV07	0.008	0.007	1.256	0.211
SEASDV08	0.007	0.007	1.096	0.275
SEASDV09	0.003	0.007	0.495	0.622
SEASDV10	0.015	0.007	2.214	0.028
SEASDV11	0.006	0.007	0.901	0.369

R-squared	0.574	Mean dependent var	0.005
Adjusted R-squared	0.529	S.D. dependent var	0.026
S.E. of regression	0.018	Akaike info criterion	-5.101
Sum squared resid	0.052	Schwarz criterion	-4.780
Log likelihood	474.531	Hannan-Quinn criter.	-4.971
F-statistic	12.747	Durbin-Watson stat	2.130
Prob(F-statistic)	0.000		

Services

Dependent Variable: DLOG(SERV)
Sample (adjusted): 1996M04 2021M12
Included observations: 309 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001	0.001	1.572	0.117
DLOG(SERV(-1))	-0.129	0.044	-2.900	0.004
DLOG(SERV(-4))	0.170	0.043	3.933	0.000
DLOG(SERV(-5))	-0.095	0.040	-2.352	0.019
DLOG(SERV(-6))	-0.074	0.042	-1.770	0.078
DLOG(SERV(-7))	-0.064	0.042	-1.524	0.129
DLOG(SERV(-9))	0.196	0.044	4.476	0.000
DLOG(SERV(-11))	0.146	0.040	3.697	0.000
DLOG(SERV(-12))	0.546	0.042	13.039	0.000
D(WUN1(-2))	0.718	0.214	3.359	0.001
DLOG(UNPROC_HAT(-1))	0.032	0.015	2.193	0.029
D(SERV_VAT)	0.160	0.075	2.139	0.033
SEASDV01	-0.003	0.001	-1.992	0.047
SEASDV02	-0.004	0.001	-3.095	0.002
SEASDV03	-0.001	0.001	-1.100	0.272
SEASDV04	0.001	0.001	0.598	0.550
SEASDV05	0.000	0.001	0.322	0.748
SEASDV06	0.001	0.001	0.399	0.690
SEASDV07	-0.001	0.001	-0.680	0.497
SEASDV08	-0.002	0.001	-1.359	0.175
SEASDV09	-0.002	0.001	-1.729	0.085
SEASDV10	0.000	0.001	-0.379	0.705
SEASDV11	-0.002	0.001	-1.625	0.105

R-squared	0.634	Mean dependent var	0.002
Adjusted R-squared	0.606	S.D. dependent var	0.007
S.E. of regression	0.004	Akaike info criterion	-8.005
Sum squared resid	0.005	Schwarz criterion	-7.727
Log likelihood	1259.729	Hannan-Quinn criter.	-7.894
F-statistic	22.548	Durbin-Watson stat	2.152
Prob(F-statistic)	0.000		

Unprocessed food

Dependent Variable: DLOG(UNPROC)
Sample (adjusted): 1995M06 2021M12
Included observations: 319 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.008	0.003	2.416	0.016
DLOG(UNPROC(-1))	0.122	0.055	2.222	0.027
DLOG(UNPROC(-2))	-0.171	0.055	-3.096	0.002
DLOG(UNPROC(-4))	-0.257	0.055	-4.653	0.000
D(UNPROC_VAT)	0.505	0.240	2.101	0.036
SEASDV01	0.011	0.005	2.312	0.021
SEASDV02	0.001	0.005	0.261	0.794
SEASDV03	0.001	0.005	0.185	0.854
SEASDV04	0.003	0.005	0.612	0.541
SEASDV05	-0.003	0.005	-0.716	0.474
SEASDV06	-0.021	0.005	-4.428	0.000
SEASDV07	-0.038	0.005	-7.741	0.000
SEASDV08	-0.005	0.005	-0.950	0.343
SEASDV09	0.000	0.005	0.026	0.979
SEASDV10	-0.008	0.005	-1.673	0.095
SEASDV11	-0.009	0.005	-1.689	0.092

R-squared	0.420	Mean dependent var	0.002
Adjusted R-squared	0.392	S.D. dependent var	0.022
S.E. of regression	0.017	Akaike info criterion	-5.235
Sum squared resid	0.090	Schwarz criterion	-5.047
Log likelihood	851.044	Hannan-Quinn criter.	-5.160
F-statistic	14.640	Durbin-Watson stat	2.022
Prob(F-statistic)	0.000		

Processed food

Dependent Variable: DLOG(PROC)
Sample (adjusted): 1996M10 2021M12
Included observations: 303 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000	0.001	-0.198	0.843
DLOG(PROC(-1))	0.276	0.050	5.542	0.000
DLOG(COMFD(-5)/EXR(-5))	0.007	0.006	1.237	0.217
D(PROC_VAT)	0.327	0.064	5.100	0.000
SEASDV01	0.003	0.001	3.248	0.001
SEASDV02	0.001	0.001	1.148	0.252
SEASDV03	0.001	0.001	1.321	0.187
SEASDV04	0.003	0.001	2.361	0.019
SEASDV05	0.003	0.001	2.526	0.012
SEASDV06	-0.001	0.001	-0.566	0.572
SEASDV07	0.001	0.001	0.760	0.448
SEASDV08	0.001	0.001	0.655	0.513
SEASDV09	0.001	0.001	1.148	0.252
SEASDV10	0.001	0.001	0.956	0.340
SEASDV11	0.001	0.001	0.893	0.373
DV200010	0.016	0.004	4.041	0.000
DV200204	0.013	0.004	3.245	0.001
DV200309	0.012	0.004	3.113	0.002
DV200106	0.015	0.004	3.961	0.000
WUN1(-5)	0.169	0.052	3.214	0.001

R-squared	0.371	Mean dependent var	0.002
Adjusted R-squared	0.329	S.D. dependent var	0.005
S.E. of regression	0.004	Akaike info criterion	-8.247
Sum squared resid	0.004	Schwarz criterion	-8.002
Log likelihood	1269.488	Hannan-Quinn criter.	-8.149
F-statistic	8.784	Durbin-Watson stat	1.889
Prob(F-statistic)	0.000		

Relative root mean square error (RRMSE) values with extended out-of-sample period (2020-2024).

	1 month	**3 months**	**6 months**	**9 months**	**12 months**	**24 months**	**36 months**
HICP							
STIP/AR1	0.386	0.386	0.386	0.387	0.352	0.353	0.391
STIP/ARIMA	0.069	0.066	0.064	0.063	0.057	0.052	0.051
AR1/ARIMA	0.180	0.171	0.166	0.161	0.163	0.147	0.132
NEIG							
STIP/AR1	0.247	0.247	0.247	0.247	0.247	0.248	0.250
STIP/ARIMA	0.044	0.043	0.042	0.041	0.040	0.037	0.034
AR1/ARIMA	0.177	0.174	0.170	0.166	0.162	0.149	0.137
HEG							
STIP/AR1	1.023	1.020	1.011	0.999	0.986	0.972	0.932
STIP/ARIMA	1.026	1.023	1.013	1.001	0.988	0.974	0.934
AR1/ARIMA	1.003	1.003	1.002	1.002	1.002	1.002	1.002
SERV							
STIP/AR1	0.405	0.405	0.405	0.406	0.406	0.411	0.412
STIP/ARIMA	0.242	0.238	0.233	0.228	0.223	0.208	0.190
AR1/ARIMA	0.598	0.589	0.574	0.561	0.549	0.506	0.461
UNPROC							
STIP/AR1	1.008	1.008	1.007	1.007	1.008	1.010	1.014
STIP/ARIMA	0.998	0.998	0.999	0.999	0.999	1.003	1.010
AR1/ARIMA	0.991	0.991	0.991	0.992	0.992	0.993	0.997
PROC							
STIP/AR1	0.230	0.230	0.230	0.230	0.231	0.234	0.267
STIP/ARIMA	0.294	0.293	0.292	0.291	0.290	0.285	0.327
AR1/ARIMA	1.279	1.276	1.270	1.263	1.255	1.217	1.227

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