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Decomposition of inflation in Azerbaijan into supply and demand components according to supermarket data

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Abstract

The balance between supply and demand influences inflation and understanding whether one factor predominates the other has significant implications for economic policy. Distinguishing the contributions of supply and demand factors to inflation offers insight into the primary drivers of inflation during economic shocks and is especially important for monetary policymaking. Decomposition serves as a tool for testing theoretical frameworks and enables policymakers and practitioners to monitor the factors contributing to inflation in real-time. In this context, the paper aims to decompose inflation into supply- and demand-driven components using an alternative micro-founded approach. It relies on a fundamental theory of price formation: the relationship between price and quantity, based on monthly data for 2,559 goods sold in one of the largest supermarket chains in Azerbaijan from 2020 and 2025. For each item, a structural vector autoregression (SVAR) model is estimated individually, resulting in 2,559 SVAR models used to identify whether observed inflation is driven by demand or supply shocks.

Preliminary findings from SVAR models highlight that demand is one of the main contributors to inflation, particularly in the post-COVID recovery period, which macro-founded models had previously underestimated. Consequently, this study contributes to the Central Bank of Azerbaijan by providing a tool to estimate the importance of demand-pulled inflation, helping policymakers stay ahead of the curve.

Keywords: Supply and demand driven inflation, SVAR model, supermarket data

***JEL classification*:** E30, E31, E52, E58

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Introduction

Understanding the demand-supply relationship is the core of all price behavior analysis and the functioning of an economy in general. Inflation, often defined as a persistent rise in the overall level of prices for goods and services, is never initiated by one factor. Most of the time, it is the compounding of supply-side issues and changes in consumer demand. Breaking down inflation into supply-driven and demand-driven components helps us better understand how different shocks affect the economy and how prices move in the long run.

On the supply side, inflation may arise when the economy faces disruptions that restrict the flow of goods and services. These disruptions can stem from a wide range of sources such as natural disasters that damage infrastructure, geopolitical tensions that alter trade flows, or logistical bottlenecks that delay shipments. Any such constraint reduces the effective supply of products, placing upward pressure on prices, particularly when demand remains unchanged or increases. Demand-pull inflation, on the other hand, arises when consumer spending increases. If aggregate demand rises faster than the economy is capable of producing due to government incentives, higher incomes for household budgets, or changing consumer tastes, firms will raise prices to manage the imbalance between strong demand and tight supply.

Between 2020 and 2025, Azerbaijan's inflation trends showed the complexity of price movements. At the beginning of this period, the COVID-19 pandemic and, later, the Russia–Ukraine war caused intense supply chain imbalances in global markets. Food prices shot up rapidly to a record 21.8% inflation in September 2022. But by 2023, general inflation had started to slow down. New research conducted by the Central Bank of Azerbaijan reports that only 16% of total inflation during this time was driven by demand. Most inflation was caused by supply-side factors. The findings suggest that there must be better ways of really knowing what is driving inflation, to enable more effective and targeted economic policy.

To address this need, this study proposes a new decomposition methodology specifically applied to supermarket price data. Based on category level inflation rates, the method generates two distinct data series measuring the monthly supply and demand factor contributions to inflation. The series enable identification of price movement that is caused by unexpected supply shocks or demand surges, based on traditional economic principles of supply and demand curve shift.

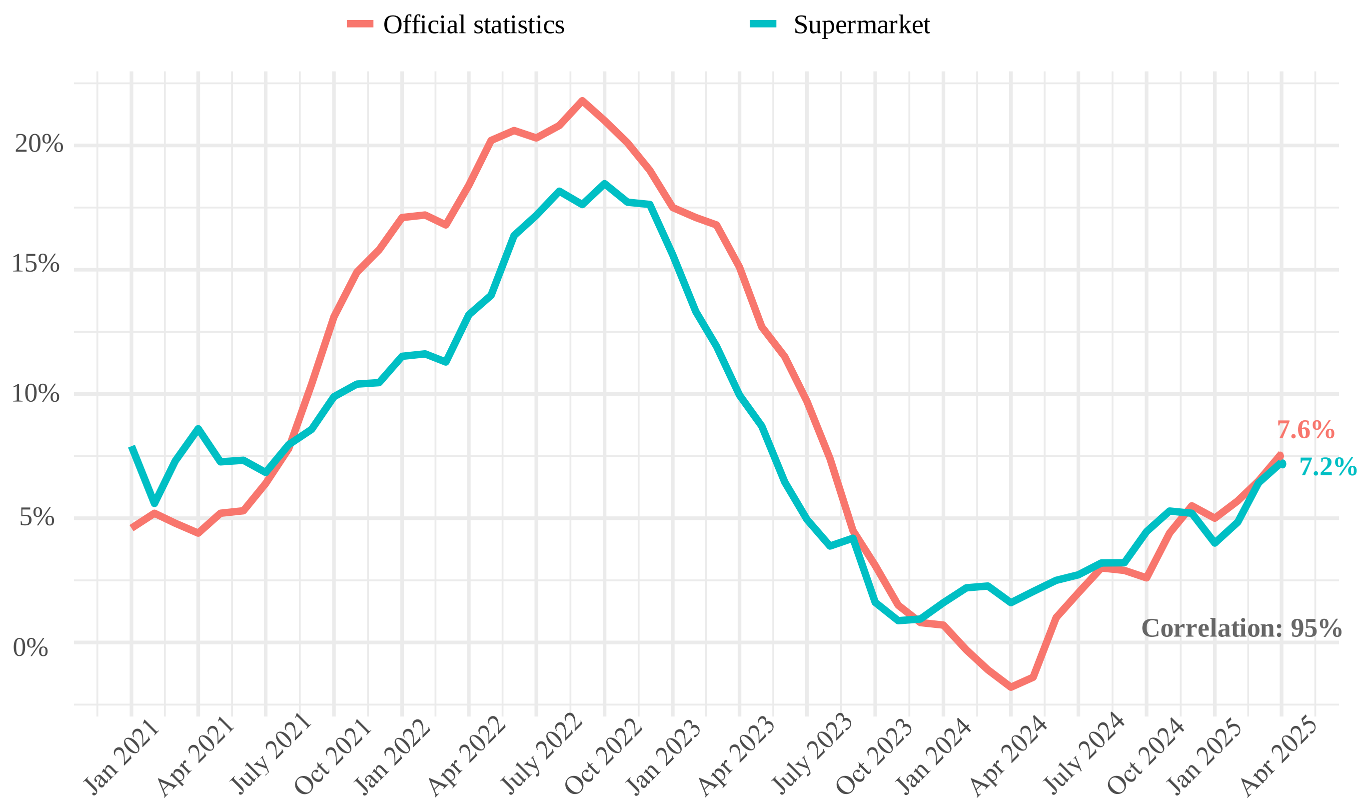
This analytical approach builds on core concepts of microeconomic theory. When inflation is demand-driven, price and quantity tend to increase together, reflecting movement along an upward-sloping supply curve. However, when inflation is supply-side driven, prices usually increase as quantities decrease, reflecting movement along a downward-sloping demand curve. By analyzing how prices and quantities move in tandem over time, an inference can be made regarding whether shocks are supply-constraint driven or driven by shifts in consumer demand. Extending the same technique to high-quality supermarket data on 2,559 individual goods makes it possible to identify disaggregated drivers of inflation, hence yielding a finer view of the structural forces at play.

This framework not only improves measurement precision. It provides policymakers, researchers, and market participants with a more informative understanding of inflation drivers.

By providing monthly measures of supply- and demand-driven inflation, this study provides timely diagnostics that are likely to inform monetary and fiscal policy calibration. In practice, distinguishing the sources of inflation means that tighter interest rates, subsidies, or supply-side reforms are the appropriate response.

Learning what's really driving inflation isn't just for academics it's essential to successful management of the economy. In today's unpredictable world, where real events tend to move faster than traditional models of inflation can keep pace, we need pragmatic instruments based on current, detailed data. This research takes that course of action, offering a peek at inflation in Azerbaijan and also supporting the broader aim of making economic policy more responsive, adaptive, and attuned to what is happening on the ground.

Figure 1: Annual food inflation



The decomposition of inflation in this study relies on supermarket data, which offers a robust and timely source for analyzing food price dynamics. Unlike survey-based estimates, supermarket data captures actual retail transactions, reflecting real behavior in the goods market through observed price and quantity changes. As illustrated in Figure 1, annual food inflation calculated from supermarket-level data closely mirrors the official figures reported by the State Statistical Committee of the Republic of Azerbaijan, with a strong correlation of 95%.

This alignment is especially notable during periods of heightened inflationary pressure. In the aftermath of the Russia–Ukraine conflict, countries across the region including Azerbaijan faced considerable supply chain disruptions, which contributed to higher inflation. Food prices climbed steadily, peaking at 22.5% in September 2022. Since then, inflation has gradually eased, reflecting the diminishing impact of external shocks and a partial normalization in supply conditions. The close tracking of official inflation figures by supermarket data throughout this period highlights its reliability for monitoring inflation trends.

Supermarket data has the advantage of being regularly updated and highly accurate, for conducting real-time analysis of price movements. It also allows for detailed examination by product and by retail outlet, providing a more developed understanding of the drivers of inflation. By disaggregating data to distinguish demand pressures and supply-side constraints, there is improved ability to conduct timely and focused policy measures.

Literature review

Shapiro's (2022) paper presents a new, empirically grounded methodology for distinguishing between the demand- and supply-side components of inflation. Using a three-decade view of U.S. inflation, Shapiro develops a taxonomy based on price and quantity regression residuals by sector. The method provides historical insights into inflation. Its relevance to policy lies in its capacity to inform differentiated monetary and fiscal policy responses, particularly during inflationary times. Further, the method allows for more effective identification of inflationary effects from exogenous shocks, thereby refining the precision of macroeconomic forecasts. Above all, Shapiro's method has real-time application, informing policymakers promptly regarding the nature of inflationary forces. More generally, the research makes an important theoretical and practical contribution by providing an open tool to underpin decision-making in an increasingly complicated post-pandemic economic context.

A growing body of literature has expanded on this analytical distinction between supply- and demand-driven inflation, particularly in response to the unique inflation dynamics observed after the COVID-19 pandemic. One notable contribution comes from Sheremirov (2022), who presents a rigorous decomposition of inflation using disaggregated consumption data. His study develops a novel method to estimate the contributions of both persistent and transitory supply and demand shocks. The findings indicate that although both shocks have contributed to the recent inflation outbreak, supply shocks have had a quantitatively greater impact. Nevertheless, the persistence of demand shocks particularly in their contribution to the persistent component of inflation poses fundamental implications for monetary policy. If demand shocks are more persistent, this could potentially require a more aggressive policy stance. Sheremirov’s research improves our understanding of inflation dynamics and provides a model timely for informing effective policy responsesin times of economic instability.

Based on such understanding, Melih (2023) presents a cross-country investigation of inflation dynamics in 32 economies over a 30-year period. Drawing on Shapiro and Sheremirov's methodologies, the article uses sectoral personal consumption expenditure (PCE) data instead of the conventional consumer price index (CPI) to enhance measurement precision. The research shows that both demand and supply forces have played a significant role in global inflation to surge enormously after 2021, highlighting the insufficiency of simple explanations. Regional variations are significant findings: whereas demand-driven inflationary pressures appear to have reached their peak in the US and large parts of Asia, Europe is stuck with chronic supply-side tensions. The decomposition also shows supply-driven inflation to be more responsive to external shocks like oil prices and supply chain disturbances, while demand-driven inflation is more sensitive to adjustments in domestic monetary policy. These results highlight the need for policy interventions to be calibrated according to the type and source of inflationary shocks. Melih's decomposition series also provides a rich dataset that can be used in future empirical research to improve the modeling of inflation.

In the same tradition of methodology, Carlomagno et al. (2023) offer an accurate inflation decomposition for Chile from high-frequency electronic payment data. Using a Structural Vector Autoregression (SVAR) model and sign restrictions, the study decomposes inflation into demand and supply shocks across various categories of goods. This allows for finer detail in identifying the sources of inflation than in standard models. Their outcomes show that demand shocks—the effects of the "pandemic-related fiscal and liquidity interventions" were the primary drivers of inflation in Chile during 2021. Supply shocks, particularly external supply disruptions, were a larger factor in 2022. The payments data's real-time quality contributes to the model's policy relevance in delivering actionable information regarding sectoral sources of inflationary pressure. Carlomagno's work not only sheds light on the inflation record of Chile but also shows the utility of applying this framework to other countries to improve inflation forecasting and the effectiveness of policy.

Shapiro's decomposition method based on the direction of simultaneous price and activity movements has also seen broader usage in other regional contexts. Gonçalves and Koester (2022), for example, extend this method to the euro area using turnover indices as proxies for economic activity for 72 sub-items of the Harmonized Index of Consumer Prices excluding food and energy (HICPX). Their findings are that the initial inflation jumps in non-energy industrial goods (NEIG) and services were chiefly supply-driven, stoked by input shortages and production bottlenecks. With the easing of pandemic restrictions, though, demand-side pressures—particularly in the services sector—began to assume a more driving role. While the framework offers greater transparency and granularity, the authors also acknowledge its limitations, particularly quantifying effect sizes and addressing anomalies caused by the pandemic. This calls for continuous methodological enhancement to deliver accurate inflation analysis during periods of turbulence.

Eickmeier and Hofmann (2022) offer a broader historical perspective, analyzing the drivers of inflation in both the United States and the euro area over the past five decades, including the most recent inflation surge since 2021. They employ a framework that decomposes inflation into demand-driven and supply-driven components, offering a narrative of key historical episodes. The findings reveal that major inflationary episodes, such as the Great Inflation of the 1970s and the post-pandemic surge, were driven by strong demand and tight supply. Recent inflation dynamics, especially since 2021, were attributed to extraordinarily expansionary demand alongside restrictive supply conditions, with a more pronounced role for tight supply in the euro area due to energy constraints. The paper suggests that tighter monetary policy primarily reduces demand. However, financial shocks such as higher risk aversion impact both demand and supply, reducing economic activity but offering little help in curbing inflation. Therefore, central banks may control inflation more effectively through tightening monetary policy, though adverse financial shocks can complicate this process.

Data description

The dataset used in this research comprises 3,918 food items sourced from multiple supermarket establishments. Following the exclusion of seasonal goods, characterized by either zero sales quantities or missing price data, the dataset was refined to include 2,559 goods, to ensure data consistency and reliability. Each item is accompanied by a time series spanning from January 2020 to April 2025, providing a comprehensive view of sales and pricing trends over the specified period.

Table 1: Product Categories and Counts by COICOP Classification[4]

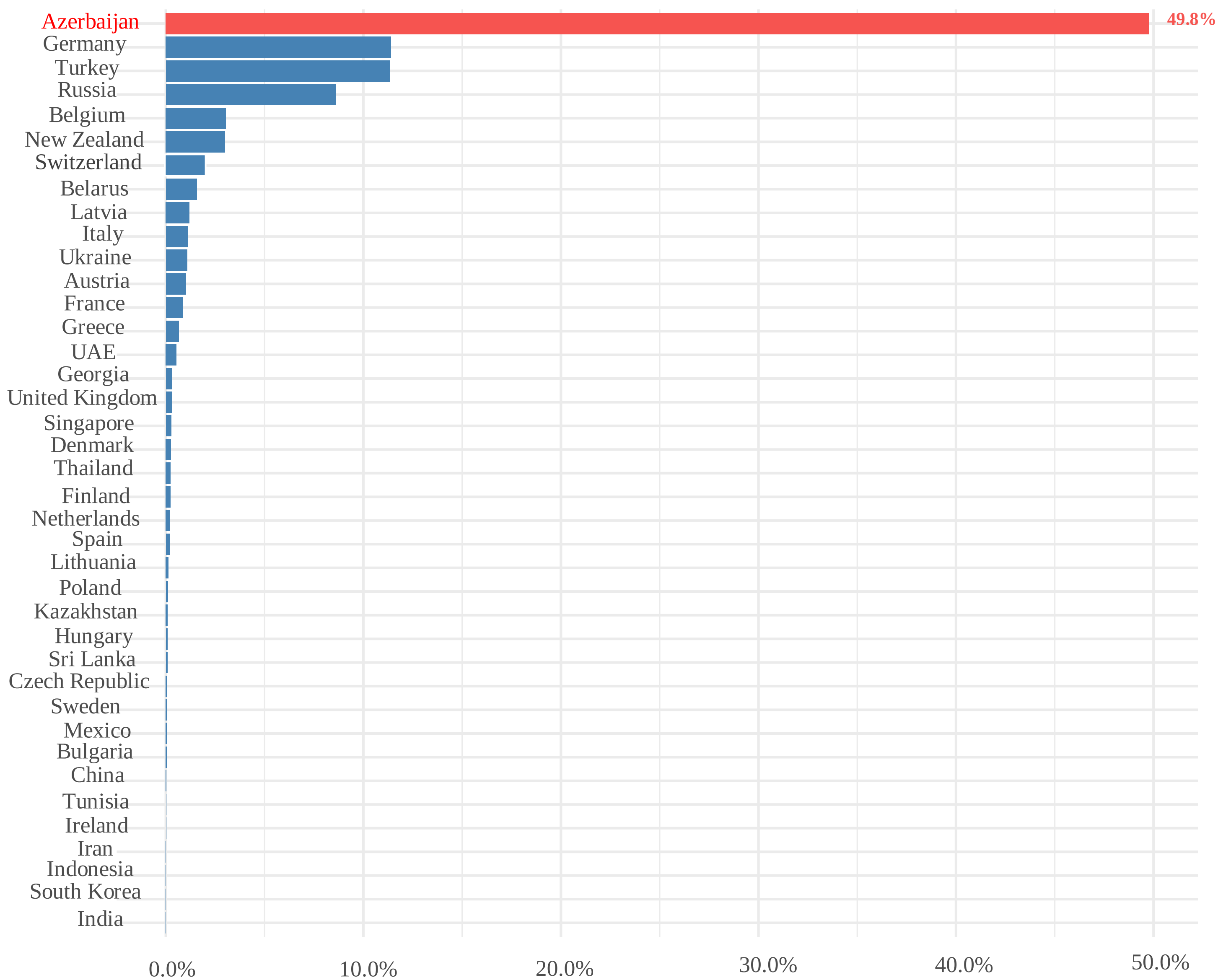
COICOP	Product	Number of Products
1	***Food products, beverages, and tobacco products***	***2559***
101	Food and non-alcoholic beverages	2299
1011	Food products	1769
10111	Bread, bakery products, and groats	507
10112	Meat and meat products	127
10113	Fish and fish products	57
10114	Milk, dairy products, and eggs	252
10115	Butter and vegetable oils	92
10116	Fruits	73
10117	Vegetables	123
10118	Sugar, jam, honey, chocolate, and sweets	327
10119	Other food products	211
1012	Non-alcoholic beverages	530
10121	Tea, coffee, and cocoa	137
10122	Mineral waters, soft drinks, and juices	393
102	Alcoholic beverages and tobacco	260
1021	Alcoholic beverages	191
10211	Vodka and brandy (cognac)	115
10212	Wine	50
10213	Beer	26
1022	Tobacco products	69

Table 1 presents a detailed breakdown of the 2,559 food and beverage products included in the final dataset, classified according to the Classification of Individual Consumption by Purpose (COICOP) structure. The majority of products (2,299) fall under the category of "Food and non-alcoholic beverages," with 1,769 items specifically classified as food products. These items are further subdivided into categories such as bakery products, meat, dairy, fruits, vegetables, and sweets, providing a granular view of consumption patterns. Notably, the largest subcategory is

[4] Product units vary across and within categories. Although standardizing to common units (e.g., grams or liters) was considered, lack of consistent conversion data across all items limited its implementation. See Limitations section for further discussion.

“Bread, bakery products, and groats” with 507 items, followed by “Sugar, jam, honey, chocolate, and sweets” with 327 items. The dataset also includes 260 items from the “Alcoholic beverages and tobacco” category[5], allowing for a broader perspective on food-related inflation dynamics. This detailed categorization supports robust disaggregated analyses, enabling the identification of inflationary pressures across specific product types.

Figure 2: Share of Food goods sold in Supermarket by country of origin



[5] In the *Alcoholic beverages and tobacco* category, tobacco products constitute roughly 80% of the items. Barcode analysis indicates that most of these products originate from Germany.

Figure 2 presents the share of food goods sold in supermarket chains by country of origin. Products of Azerbaijani origin account for approximately 49.8% of the total, indicating a significant, though not exclusive, reliance on domestic supply. German goods account for about 11.4%, largely due to tobacco products, which dominate Germany's contribution. Turkey and Russia follow with shares of 11.3% and 8.6%, respectively, mainly exporting chocolate and bakery products. Other notable contributors include Belgium (3.0%), New Zealand (3.0%), and Switzerland (2.1%). The remaining share is distributed among a wide range of countries, reflecting both the diversity and specialization of imported food products.

This dataset offers a solid empirical foundation for analyzing the decomposition of inflation into its supply- and demand-driven components. Through this lens, it becomes possible to assess the relative influence of supply-side constraints and demand-side pressures on overall inflation trends. Such insights can serve as practical proxies in constructing official inflation weights, enabling policymakers to more accurately identify the underlying drivers of inflation. In doing so, the dataset not only enhances our understanding of inflationary dynamics but also contributes to the formulation of more targeted and effective policy responses.

Methodology

The methodology developed by Shapiro (2022) and extended by Melih (2023) is applied to classify inflation at the level of individual expenditure items as either supply-driven or demand-driven. This framework relies on fundamental economic principles: when the price of a good rises, suppliers are generally willing to produce more reflecting an upward-sloping supply curve while consumers tend to reduce their purchases, consistent with a downward-sloping demand curve. By observing the co-movement of price and quantity changes for each good *i*, the method infers whether price dynamics are primarily driven by shifts in supply or demand conditions.

$$\text{Supply curve:} \quad q_i = \gamma_i p_i + \alpha_i \tag{1}$$

$$\text{Demand curve:} \quad p_i = -\delta_i q_i + \beta_i \tag{2}$$

q_i represents the quantity (or real consumption) of a good, p_i represents the price level, γ_i is the slope of the supply curve, δ_i is the slope of the demand curve, while α_i and β_i represent the intercepts. A shift in the intercept of curve (1) is commonly termed a "supply shock," while a shift in the intercept of curve (2) is referred to as a "demand shock." Therefore, alterations to the supply and demand curves for each good i can be represented as shifts or shocks. The supply and demand shock functions for good i can be expressed as:

$$\text{Supply shock:} \quad \varepsilon_i^s = (q_{i,t} - \gamma_i p_{i,t}) - (q_{i,t-1} - \gamma_i p_{i,t-1}) \tag{3}$$

$$\text{Demand shock:} \quad \varepsilon_i^d = (p_{i,t} + \delta_i q_{i,t}) - (p_{i,t-1} + \delta_i q_{i,t-1}) \tag{4}$$

where $\varepsilon_i^s = \Delta a_i$ and $\varepsilon_i^d = \Delta\beta_i$. This model's estimation with time-series data involves transforming it into a SVAR:

$$A^i z_{i,t} = \sum_j^N A^i z_{i,t-j} + \varepsilon_{i,t} \tag{5}$$

where $z_i = \begin{bmatrix} q_i \\ p_i \end{bmatrix}$, $A_i = \begin{bmatrix} 1 & -\gamma_i \\ \delta_i & 1 \end{bmatrix}$, and it follows that $\varepsilon_i = \begin{bmatrix} \varepsilon_i^s \\ \varepsilon_i^d \end{bmatrix}$ represent the structural supply and demand shocks in period t. Recovering the structural shocks entails running a reduced-form estimation of price and quantity (z_i). The reduced form of the model is as follows:

$$z_{i,t} = [A_i]^{-1} \sum_j^N A^i z_{i,t-j} + v_{i,t} \tag{6}$$

$$v_{i,t} = [A_i]^{-1} \varepsilon_{i,t} \tag{7}$$

where $v_i = \begin{bmatrix} v_i^q \\ v_i^p \end{bmatrix}$, v_i^q and v_i^p are reduced form residuals. The signs of the reduced-form residuals indicate the type of shock.

$$\text{Demand shock} = \begin{matrix} v_{i,t}^q > 0, v_{i,t}^p > 0 \\ v_{i,t}^q < 0, v_{i,t}^p < 0 \end{matrix}$$

$$\text{Supply shock} = \begin{matrix} v_{i,t}^q > 0, v_{i,t}^p < 0 \\ v_{i,t}^q < 0, v_{i,t}^p > 0 \end{matrix}$$

When both the price and quantity residuals move in the same direction, it signals a demand shock. This means that if both the price and quantity regressions show positive (or negative) reduced-form residuals at time t, it implies a positive (or negative) demand shock occurred at that time, without specifying the direction of the supply shock. Conversely, if the residuals show opposite signs, it indicates a supply shock. For example, if the price regression shows a positive (or negative) reduced-form residual while the quantity regression shows a negative (or positive) one at time t, it suggests a negative (or positive) supply shock occurred then, again without specifying the direction of the demand shock.

After categorizing each item, the demand- and supply-driven inflation series is calculated using supermarket data. This is done by taking the weighted sum of the inflation rates for individual items (9), where each item's weight is determined by its share of total sales (8)[6].

$$\omega_i = \frac{p_i * q_i}{\sum_{i=1}^{i=2559} p_i * q_i} \tag{8}$$

$$\pi_t^d = \sum_i 1_{i \in demand,t} \omega_{i,t} \pi_{i,t} \text{ – Demand driven inflation rate}$$

$$\pi_t^s = \sum_i 1_{i \in supply,t} \omega_{i,t} \pi_{i,t} \text{ – Supply driven inflation rate} \tag{9}$$

Each SVAR model is estimated with a lag length of one. Although lag selection is guided by the Akaike Information Criterion (AIC), the relatively short sample period—from February 2020 to April 2025—makes it impractical to include additional lags. Longer lag structures risk overfitting and reduce estimation reliability. All models are estimated in first differences (log-differences) to account for potential non-stationarity in the price and quantity series, which is common in high-frequency retail data.

The decision to restrict the lag length also reflects the high dimensionality of the dataset. With 2,559 individual SVAR models estimated at the product level, parsimony is essential for computational feasibility and consistency across models. Attempts to include additional lags often result in convergence issues or unstable estimates, particularly for goods with limited price or quantity variation. Moreover, using a uniform lag structure ensures comparability in shock classification and inflation decomposition, which would otherwise be compromised by heterogeneous model specifications across products.

Robustness Checks

To enhance the robustness of the inflation decomposition results, an alternative classification method has been introduced. Goods are classified as *ambiguous* when the residuals of their price or quantity regressions fall within specified thresholds around zero. Specifically, a good is ambiguous if the residuals lie in the range of 0.025, 0.05, or 0.5 standard deviations above and below zero[7]. Accommodates cases in which minor price or quantity fluctuations are inadequate to certainly indicate whether a shock is demand or supply motivated. With the inclusion of the

[6] This is done by taking the weighted sum of the inflation rates for individual items, where each item's weight is determined by its Paasche weight, which is the share of consumption expenditures in period t.

[7] This classification takes the subjective approach formulated by Shapiro, a relative mode of treating residuals that display minimal changes, but which may not provide clear evidence of supply or demand shocks.

ambiguity range, the method avoids over-attribution and enhances the robustness of the inflation decomposition framework[8].

For classification:

$$\text{Demand shock } = \begin{matrix} v_{i,t}^{q} > Threshold, v_{i,t}^{p} > Threshold \\ v_{i,t}^{q} < -Threshold, v_{i,t}^{p} < -Threshold \end{matrix}$$

$$\text{Supply shock } = \begin{matrix} v_{i,t}^{q} > Threshold, v_{i,t}^{p} < -Threshold \\ v_{i,t}^{q} < -Threshold, v_{i,t}^{p} > Threshold \end{matrix}$$

$$\text{Ambiguous shock} = \begin{matrix} Threshold > v_{i,t}^{q}, Threshold > v_{i,t}^{p} \\ -Threshold < v_{i,t}^{q}, -Threshold < v_{i,t}^{p} \\ Threshold > v_{i,t}^{q}, -Threshold < v_{i,t}^{p} \\ -Threshold < v_{i,t}^{q}, Threshold > v_{i,t}^{p} \end{matrix}$$

By applying these ambiguity thresholds, the risk of misclassifying minor price or quantity shocks as significant is minimized. Goods exhibiting minimal price or quantity movements are classified as *ambiguous*, allowing the analysis to focus on more substantial shocks that more clearly signal supply or demand-driven inflation. By filtering out items with only marginal deviations, this approach sharpens the classification process and ensures that only meaningful variations are attributed to specific inflationary forces. As a result, the overall accuracy and reliability of the decomposition are improved. This strategy also accommodates the presence of noise and measurement errors, which are more likely to affect small residuals. It strengthens the interpretability of results, particularly in volatile market conditions where weak signals can be misleading. Furthermore, it provides a more cautious and credible approach to categorizing shocks when the signals are not clear-cut.

Results

Following the overlap of changing consumer demand, supply chain disruptions in international markets, and geopolitical conflicts, inflation has been a leading economic issue for most nations in recent times. For policymakers to create effective fiscal and monetary policy measures, they must have a firm grasp of the causative roots of inflation. Inflation has been broken down into two

[8] This method helps to handle minor deviations (residuals close to zero) and provides a clear decomposition of inflation.

principal components in this report: supply-driven inflation, which is the result of production limitations, cost, and external shocks, and demand-driven inflation, which reflects the shifts in consumer buying and overall economic activity. The trajectory of these two components from April 2020 to April 2025 is illustrated in Figure 3, with highlights around periods of significant change and upheaval in the inflation forces.

Figure 3: Supply and demand-driven inflation

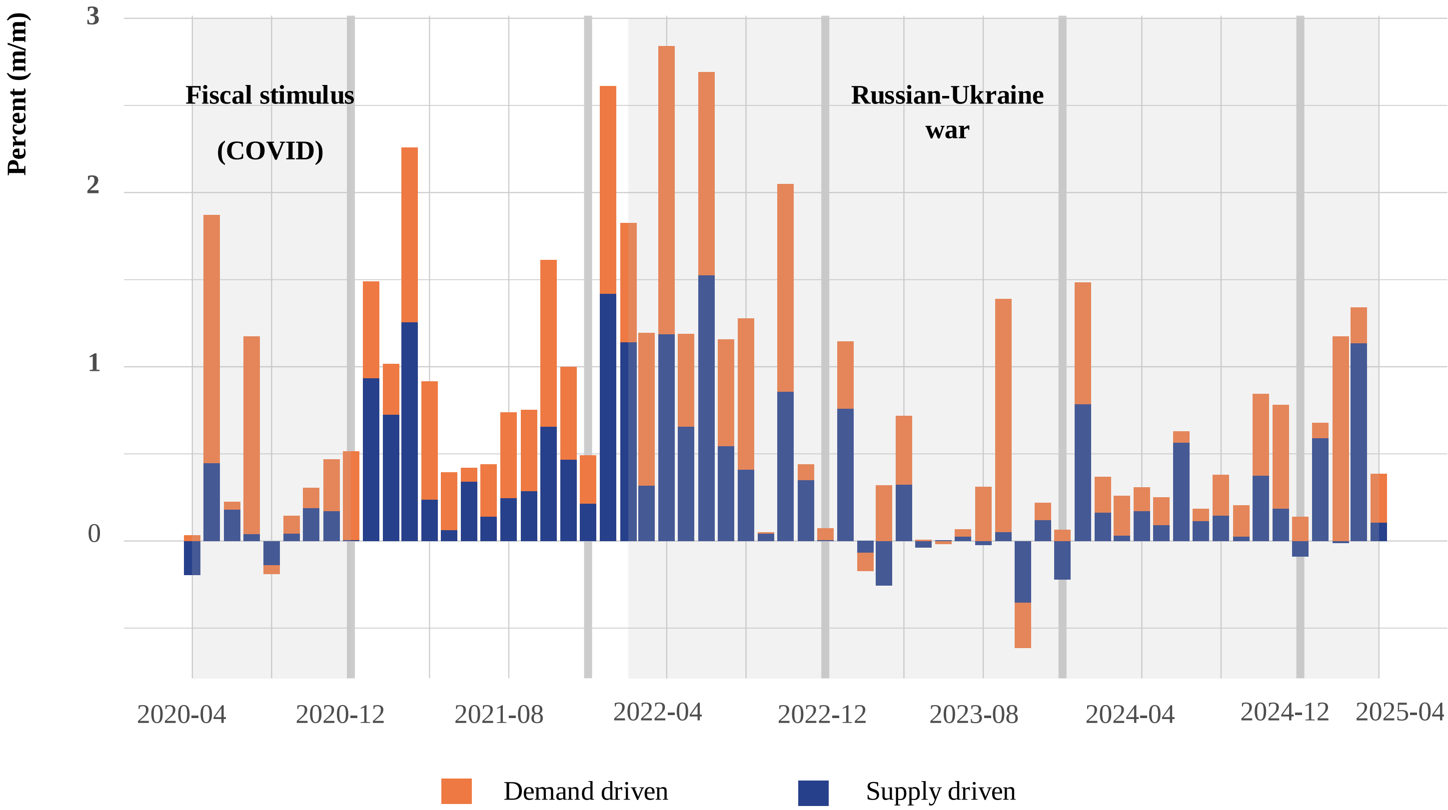


Figure 3 shows the past inflation development from April 2020 to April 2025, distinguishing supply-driven and demand-driven ones. The chart mirrors significant shifts in inflation dynamics closely associated with key world events such as the COVID-19 pandemic and the Russia–Ukraine war. They influenced which type of inflation dominated, particularly during periods when there were fiscal stimulus measures and geopolitical unrest. During the early part of 2020, when the pandemic gained hold, governments issued huge fiscal stimulus to support economies, feeding through to a sharp spike in demand-led inflation as consumers went out and spent. During the latter half of 2020 and 2021, demand-led inflation ran far and away ahead of supply-led inflation, the latter of which was comparatively tame, demonstrating that supply chain breakages had yet to rise to crisis levels.

By December 2021, once the world economy began to get back on track from the pandemic, inflation pressures shifted dramatically. Both demand-pull and supply-side inflation were present, but supply-side started gaining predominance. Supply chain shortages, rising input costs, and logistics took a turn for the worse as demand started surpassing supply. The breakpoint was in early 2022 with the outbreak of the Russia–Ukraine war. This war caused a sharp increase in supply-led inflation due to large disturbances in the global supply of energy and large commodities. The war restricted the supply of critical goods such as oil, gas, and grains, thereby increasing prices. Even demand-led inflation persisted, but its relative importance diminished as supply shocks came to characterize the inflation environment. Between late 2022 and 2025, inflation pressure on both sides slowed down gradually. Demand-led inflation declined as monetary policy was tightened by central banks, raising interest rates to curb consumer spending. Meanwhile, supply-led inflation softened as world supply chains gradually rebounded from the pandemic and war-related disruptions to provide a more stable inflation backdrop.

Conclusion

Summarily, this research provides an integrated platform for understanding inflation dynamics by decomposing inflation into supply-driven and demand-driven elements. Using Structural Vector Autoregression (SVAR) models and stringent classification processes, this research successfully isolates the key shocks that stimulate inflationary movements. The findings point to the primary contribution of international events such as the COVID-19 pandemic and the Russia–Ukraine conflict in shaping inflation trends, with demand-side determinants taking the lead initially before being overshadowed by supply-side pressures.

Ambiguity thresholds were also implemented to further refine the classification, such that only meaningful shocks were detected, hence allowing a more nuanced interpretation of the complex drivers of inflation. This is an advance over standard methods that can fail to capture subtle yet significant economic signals and offers more precise insights into how individual shocks, whether as a result of consumers' demand changes or supply chain disruptions, affect price levels over time.

Lastly, this study offers beneficial information to policymakers as well as economic analysts by availing a more precise tool for the management of inflation. The model has the potential to improve forecasting and inform targeted policy measures that address both demand and supply-side factors and thus boost the efficacy of monetary and fiscal policy measures to stabilize the economy against uncertainty and exogenous shocks.

Limitations

While this method of decomposition is helpful, several limitations warrant consideration. First, supermarket prices are more sticky in nature because retailers often maintain fixed prices for extended periods as part of their price policies and only change them from time to time. For instance, a supermarket might maintain fixed prices for an entire month before changing them once, unlike changing continuously. This price stickiness can conceal short-run supply or demand shocks that otherwise would be more apparent.

A second issue concerns the grouping products. Most product classes have products with dissimilar measurement units, and thus it is not easy to aggregate prices meaningfully. For example, in the confectionery class, some chocolates are priced per kilogram, but others, like single bars of chocolate, are unit priced. This diversity makes it hard to form truly homogeneous sets for analysis, which could affect the reliability of decomposition results.

Finally, the relative shares of supply- and demand-side determinants of inflation may vary significantly over time. Rapid changes pose challenges in establishing stable trends, thereby weakening the vigor and relevance of inferences based on the decomposition. However, the implementation of robustness checks such as alternative classification thresholds and unit consistency tests helps mitigate this limitation by ensuring that the main findings are not overly sensitive to short-term fluctuations or classification noise.

Despite all these limitations, this research offers a fresh perspective on inflation dynamics, providing us with improved price behavior insights in the supermarket sector and with a richer depiction of inflation drivers.

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Appendix

Figure 3A: Inflation Decomposition with 0.05 Standard Deviation Precision Cutoff

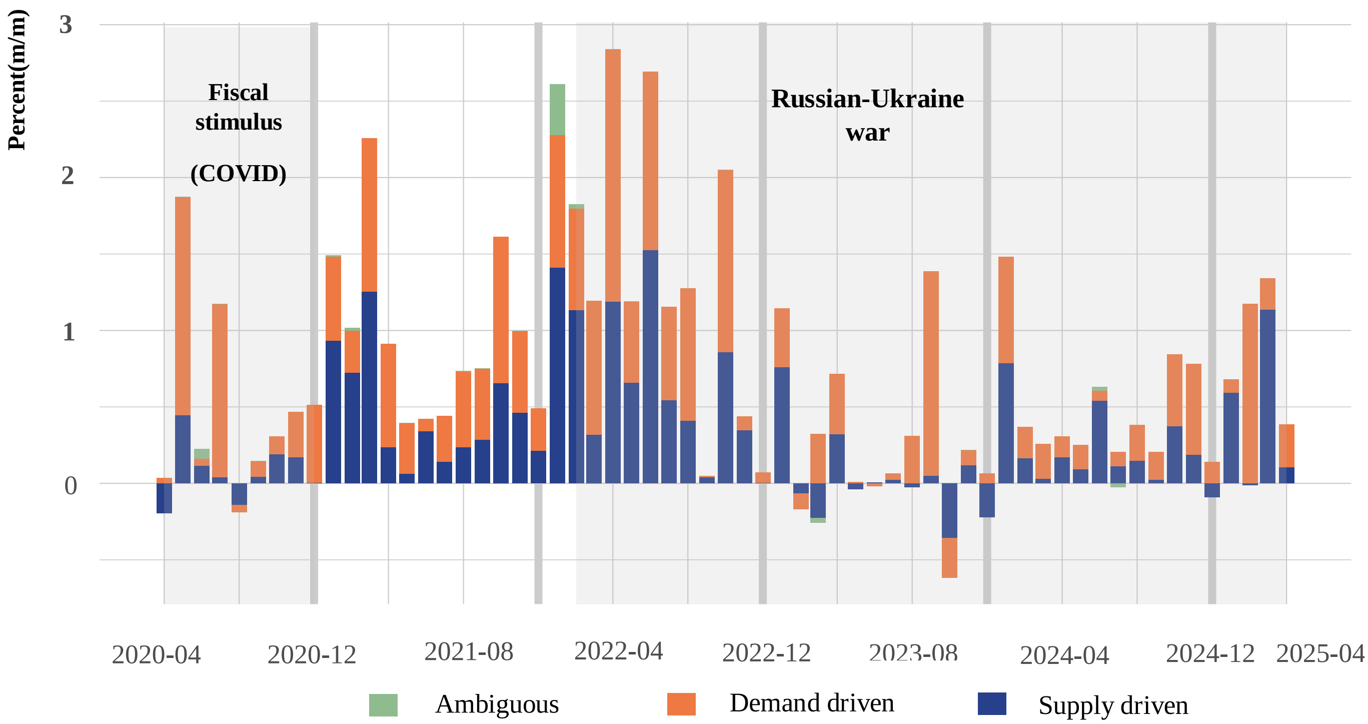

Figure 3B: Inflation Decomposition with 0.1 Standard Deviation Precision Cutoff

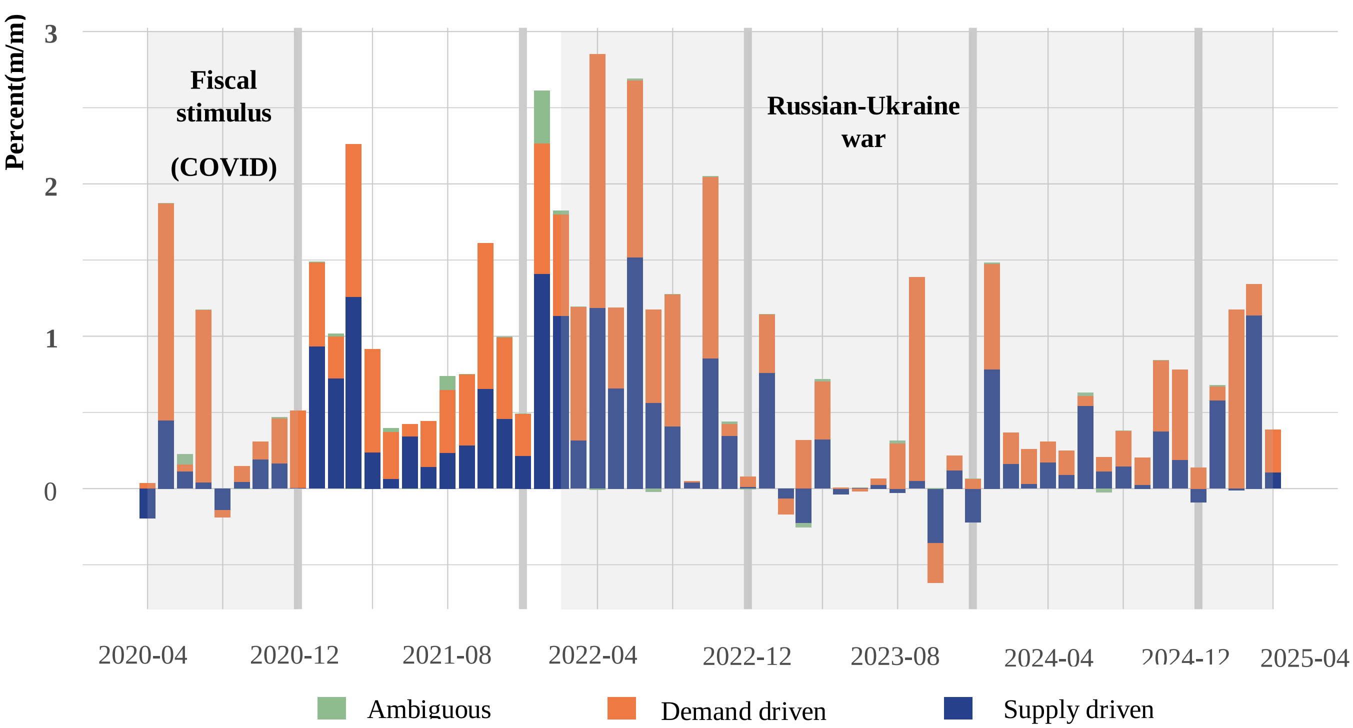

Figure 3C: Inflation Decomposition with One Standard Deviation Precision Cutoff

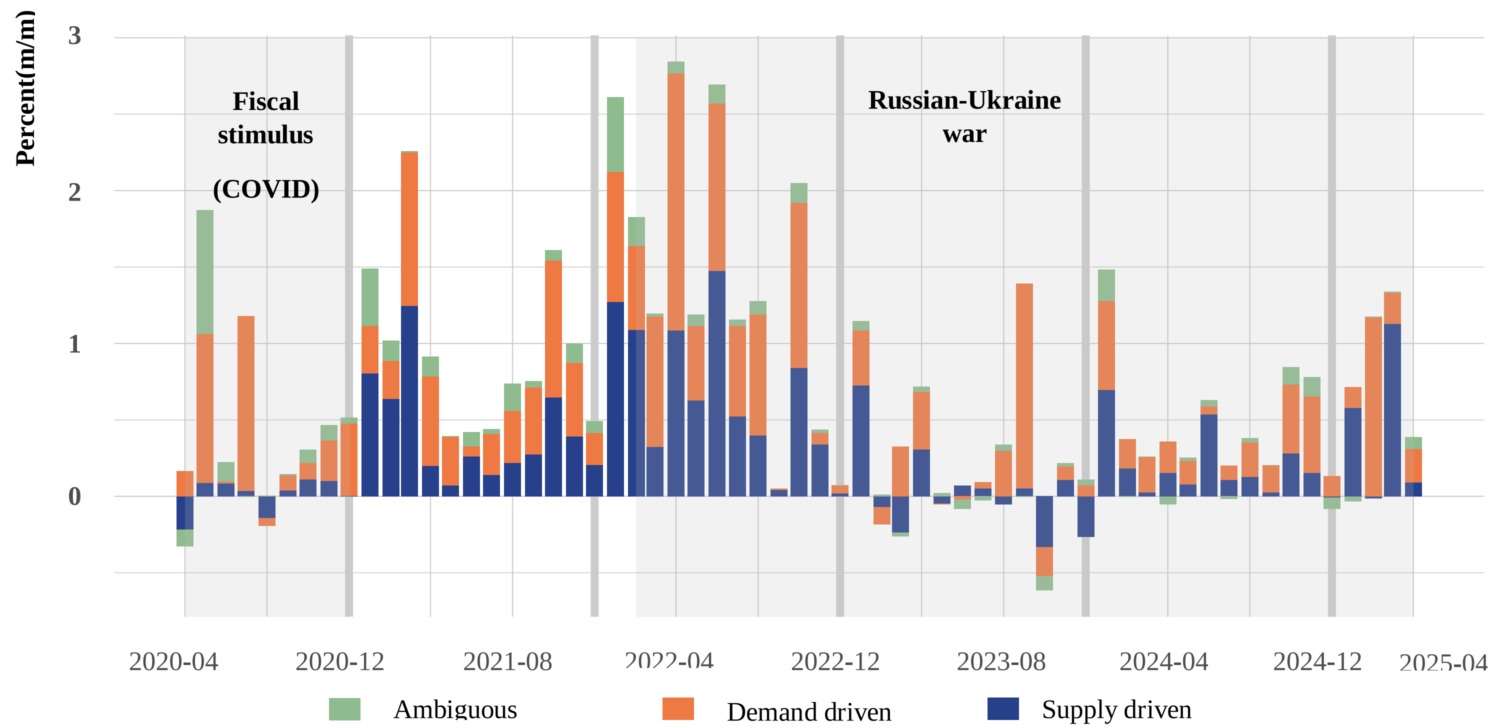

Figure 4A: Inflation Decomposition

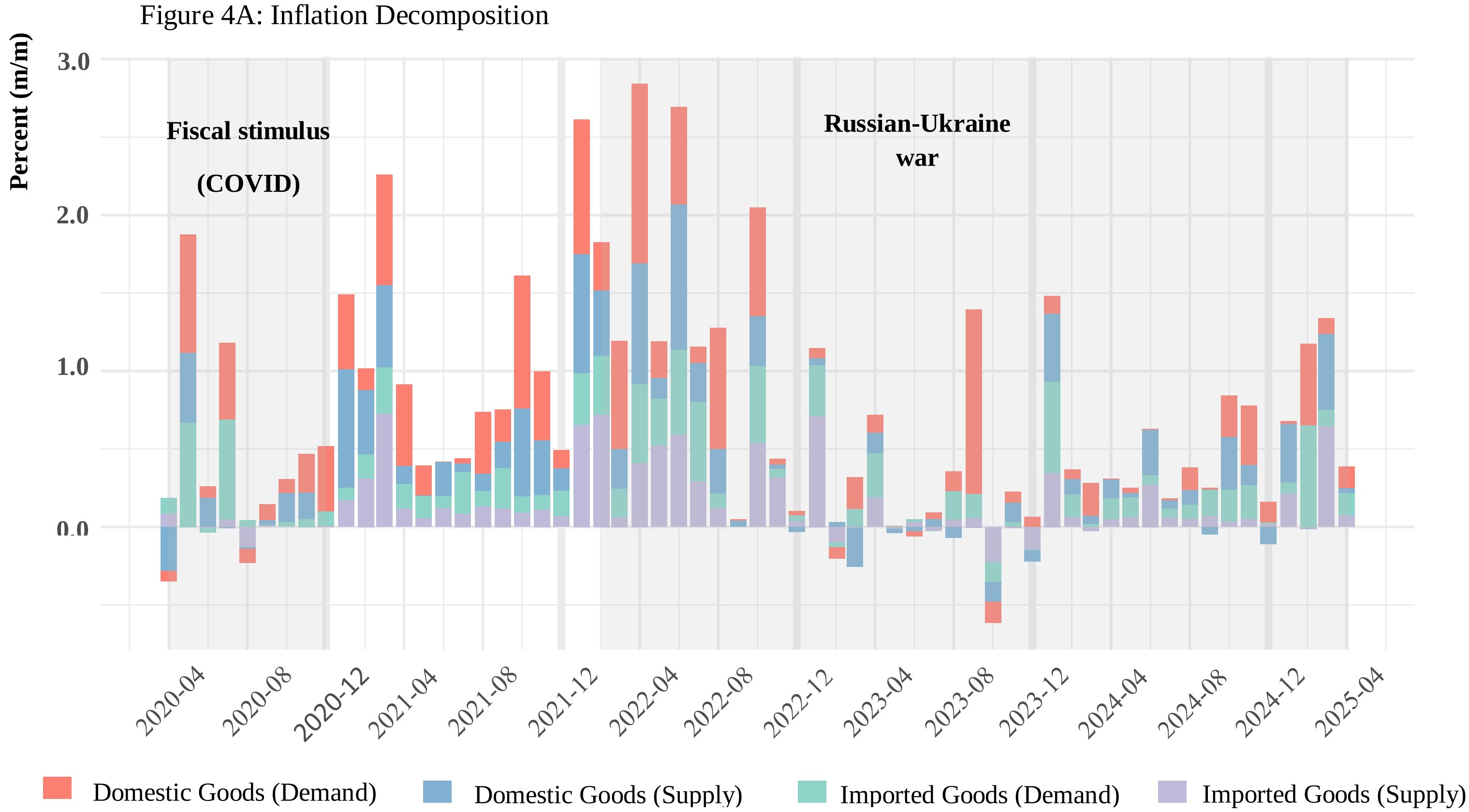

Table 2: Inflation Metrics by COICOP Category – April 2025 (Full Dataset Before Filtering)

COICOP	Product	Weight	Monthly inflation	Year to date inflation	Annual inflation
1	**Food products, beverages, and tobacco products**	**100.0%**	**0.3%**	**3.5%**	**7.2%**
101	**Food and non-alcoholic beverages**	**82.8%**	**0.4%**	**3.5%**	**8.1%**
1011	Food products	71.6%	0.4%	3.6%	8.5%
10111	Bread, bakery products, and groats	13.4%	0.1%	2.3%	4.9%
10112	Meat and meat products	14.3%	-0.3%	2.9%	2.9%
10113	Fish and fish products	1.2%	0.0%	-2.2%	-2.2%
10114	Milk, dairy products, and eggs	8.3%	1.0%	-0.4%	8.1%
10115	Butter and vegetable oils	13.7%	1.2%	5.2%	21.7%
10116	Fruits	4.8%	2.7%	12.5%	1.7%
10117	Vegetables	6.0%	-2.5%	1.2%	3.4%
10118	Sugar, jam, honey, chocolate, and sweets	7.3%	0.6%	6.9%	14.1%
10119	Other food products	2.5%	0.2%	0.9%	1.7%
1012	Non-alcoholic beverages	11.2%	0.3%	3.0%	6.0%
10121	Tea, coffee, and cocoa	2.5%	1.4%	3.3%	7.2%
10122	Mineral waters, soft drinks, and juices	8.6%	0.0%	2.9%	5.6%
102	**Alcoholic beverages and tobacco**	**17.2%**	**0.0%**	**3.2%**	**3.5%**
1021	Alcoholic beverages	3.1%	0.1%	1.6%	3.8%
10211	Vodka and brandy (cognac)	1.7%	0.0%	1.5%	4.2%
10212	Wine	0.3%	0.0%	4.1%	5.8%
10213	Beer	1.1%	0.2%	0.4%	2.8%
1022	Tobacco products	14.1%	0.0%	3.6%	3.5%