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SANCTIONS AND RUSSIAN ONLINE PRICES

by Jonathan Benchimol* and Luigi Palumbo**

Abstract

This study leverages web-scraped daily data to evaluate the impact of the economic sanctions following Russia's invasion of Ukraine on consumer prices and product availability across different goods categories in Russia. We find that international sanctions significantly disrupted Russian price dynamics, with the exchange rate serving as the primary transmission mechanism. Utilizing granular online data allows us to circumvent potential misreporting and to track real-time economic indicators at a high frequency. Our analysis uncovers heterogeneous effects across product groups, with sanctions associated with an average increase of 11.7 percentage points in the Russian CPI. The results highlight how trade policies and geopolitical events can rapidly propagate through retail markets, underscoring the importance of timely price monitoring during periods of economic turbulence. More broadly, we demonstrate the value of online data for evaluating policy shocks, paving the way for similar applications in other contexts.

JEL Classification: E21, E31, F13, F38, F51.

Keywords: political economy, online prices, product availability, sanctions, conflict, Russia, Ukraine.

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1 Introduction[1]

Sanctions can increase import costs, reduce product availability, and create inflationary pressures. They can also disrupt the supply chain, lead to devaluation and increased volatility of the local currency (Wang et al., 2019), and increase borrowing costs for the targeted country. However, the exact effect of sanctions on the exchange rate (Itskhoki and Mukhin, 2022) and on prices depends on a variety of factors, including the specific nature of the sanctions, the size and structure of the economy, and the political and economic response of the targeted country. Moreover, movements in the exchange rate, by themselves, are a poor measure of the welfare effect of sanctions (Lorenzoni and Werning, 2023). Disruptions to domestic price movements, however, can significantly impact welfare, particularly for those with less disposable income and limited ability to adjust their earnings to the new pricing dynamics.

International political and economic orders may influence the evolution of sanctions. Considering the increasing importance of sanctions, which have been extensively used as a foreign policy tool in the post-World War II era, it is crucial to understand how targeted states react to them, including the economic and security consequences (Morgan et al., 2023). These actions, taken by one state or collectively to influence another's behavior, typically involve restricting foreign trade, either of all goods or specific commodities, with mixed results (Davis and Engerman, 2003). As a component of international diplomacy, financial sanctions can effectively restrict entities' access to financial assets or services and limit their use of the international payment system, including the SWIFT network (Cipriani et al., 2023). Furthermore, sanctions are found to strengthen the interdependence among sanctioning countries, while simultaneously weakening the interdependence between the sanctioned country and the rest of the world (Jin and Meng, 2024).

The severe international sanctions imposed in response to Russia's invasion of Ukraine on February 24, 2022, mark a novel development in contemporary economic history due to their intensity and the number of countries involved. US and EU sanctions targeted about 19% of Russia's total imports (Hausmann et al., 2022), severely affecting its GDP (Simola, 2023) and industrial production

[1] The views expressed in this paper are those of the authors and do not necessarily represent the views of the Bank of Israel, the Bank of Italy, or the Eurosystem. The authors thank the Editor and the referees, Noam Ben-Ze'ev, Fabio Busetti, Giovanni Caggiano, Paolo Del Giovane, Konstantin Kosenko, Sasha Talavera and participants at the Joint National Bank of Ukraine and National Bank of Poland 2023 Annual Research Conference, the 2023 RCEA-Europe International Conference on Global Threats to the World Economy, the 10th SIdE-Italian Econometric Association WEEE, and the 136th American Economic Association annual conference (ASSA/AEA) for their helpful comments. The authors also thank Maxim Chupilkin, Beata Javorcik, and Alexander Plekhanov for kindly sharing the full list of European Union trade sanctions and related Harmonized System Codes.

(Simola, 2022). These sanctions have significantly disrupted global supply chains, and the full impact remains to be determined. The Ukraine conflict caused an estimated 1.5% reduction in global GDP and a 1.3 percentage point increase in global inflation (Caldara et al., 2022). Additionally, the conflict has led to unprecedented calls for major corporations to take proactive measures beyond the sanctions, such as ceasing operations in Russia (Sonnenfeld et al., 2023). Others suggest that sanctions have caused a much greater welfare loss in Russia than in the countries imposing them (Hausmann et al., 2022), even if Russia realized substantial trade gains from the increased prices of its exported commodities (Steinbach, 2023). The effects on sanctioning countries widely vary depending on their level of interdependence with Russia (Mahlstein et al., 2022).

The confluence of economic sanctions, corporate actions, fluctuating commodity prices, post-COVID-19 stimulus packages, and exchange rate movements have significantly impacted the Consumer Price Index (CPI) in Russia and other countries since the full-scale invasion. In the context of this ongoing conflict, access to reliable economic data takes on strategic importance beyond just economic considerations. Monitoring global consumer price trends can provide insights into the strengths and weaknesses of both allied and rival nations, as well as the effectiveness of political decisions.

While concerns about the overall quality of Russian official statistics have existed for some time (Gibson et al., 2008; Khanin, 2013), the current question is whether intentional misreporting is occurring. The manipulation of official statistics is a rarely discussed topic, despite documented cases of deceit throughout history (von der Lippe, 1999; Coremberg, 2014; Frey, 2021; Aragão and Linsi, 2022). Recently, media outlets have criticized Rosstat, Russia's National Statistical Service, for a perceived lack of independence from the government (Ostroukh and Winning, 2017; Wiśniewska, 2017). Following the invasion and subsequent sanctions, Russian authorities halted publication of numerous statistical indicators, raising concerns among analysts about the reliability of remaining publicly available data (Starostina, 2022). It seems reasonable to assume that Russian authorities have an incentive to manipulate data that opponents might use to inform further sanctions, with this incentive increasing for more critical economic indicators (Campbell, 1979).

To address this concern, we investigate the alignment between online and official prices for different categories of goods, both before and during the war. By analyzing disaggregated price patterns, we can determine whether price components and trends are consistent, assess how the war and its consequences have impacted pricing trends in Russia, and ultimately, evaluate the reliability of official CPI data.

High frequency and openly available data are increasingly used to track economic activity and validate official statistics, with web data (Cavallo, 2013; Faryna et al., 2018) and satellite imagery (Martínez, 2022) being popular sources. The Billion Prices Project is one of the pioneering initiatives in the field of price statistics that utilizes these new tools, collecting daily prices from hundreds of online retailers from over eighty countries and providing daily CPIs (Cavallo and Rigobon, 2016). This automated method of extracting and structuring information from websites is also becoming increasingly popular among National Statistical Institutes for calculating official price statistics (Eurostat, 2020).

The COVID-19 pandemic further intensified the use of online data in academic research for real-time tracking of economic activity and price changes (Jaworski, 2021; Hillen, 2021; Macias et al., 2023), since pandemic control policies significantly disrupted traditional data collection processes. We also collect the number of products available for sale, therefore we are able to identify supply disruptions for consumer goods, contributing to this growing field of study (Cavallo et al., 2014; Cavallo and Kryvtsov, 2023; Nikolsko-Rzhevskyy et al., 2023). Antoniades et al. (2022) propose a method to construct price indices without quantity data, reducing bias in the frequency of price changes and inflation measurement. Collecting and analyzing high-frequency product price and quantity data allows for a more comprehensive analysis of product price and stock dynamics following economic sanctions.

This contribution leverages data obtained through web scraping (Cavallo, 2013) from the e-commerce website of a prominent Russian multichannel retailer with a network of (offline) megastores in the Moscow region. Our research aims to evaluate the accuracy of official Russian CPI figures following the war's outbreak, and assess the impact of sanctions on the CPI and consumer product availability. As an initial step, we verified the consistency of our web-scraped data with pre-war official CPI figures, assuming minimal incentive for data manipulation by Russian authorities at that time. Product availability is approximated by the number of units in stock of each item on the retailer's website.

Building on the established link between online and offline price fluctuations (Cavallo, 2017, 2018; Strasser et al., 2023), online prices have proven valuable for constructing official CPIs (Harchaoui and Janssen, 2018), forecasting official statistics (Aparicio and Bertolotto, 2020), detecting shifts in inflation trends (Cavallo and Zavaleta, 2023), and anticipating official data releases (Jaworski, 2021; Macias et al., 2023). Gorodnichenko and Talavera (2017) emphasize the flexibility and pass-through of online prices in response to exchange rate movements. Our paper extends this research by investigating how trade and financial sanctions influence pricing patterns in both online and traditional markets, as well as how they impact product quantities during geopolitical turmoil.

International sanctions, frequently used in international policymaking, have come under increased scrutiny for their effectiveness and consequences. Research by Ngo et al. (2022) reveals a significant disparity between public perceptions of sanctions and official governmental positions on their implementation and outcomes. Itskhoki and Mukhin (2023) establish Lerner symmetry as a framework to understand how import and export sanctions impact allocations and welfare. Our study expands on their work by incorporating the timing of sanctions, the interplay between trade and financial restrictions, and the effects of financial sanctions, allowing for a more comprehensive understanding of how sanctions influence pricing and consumption patterns during wartime. Specifically, we examine how the ongoing war in Ukraine and subsequent international trade and financial sanctions impacted Russian consumer prices across good categories, revealing significant differences in price dynamics. Bělín and Hanousek (2021) utilize a quasi-natural experiment of bilateral trade sanctions between Russia and the EU since 2014 to analyze the effectiveness of narrow versus broadly defined sanctions, and sanctions imposed on exports and imports. Our study complements this perspective by examining the impact of international economic sanctions on Russian consumer prices, emphasizing the disruptions on CPI levels caused by sanctions and considering financial sanctions. While Imbs and Pauwels (2024) estimate the costs of trade sanctions for various sanctioning and sanctioned countries or sectors, our approach contributes to the literature on the economic repercussions of sanctions by providing granular insights into the evolution of prices across different product categories in Russia. Our findings contribute to the growing literature on using online data to monitor real-time economic activity, and highlight the significant influence of political events and economic sanctions on pricing dynamics and consumption patterns.

Financial sanctions have emerged as powerful tools in the current geopolitical landscape, impacting key macroeconomic variables. Bianchi and Sosa-Padilla (2023) use a graphical framework to explore the macroeconomic effects of financial sanctions, sovereign debt crises, and capital flow fragmentation. Our study complements their research by empirically analyzing the impact of international trade sanctions on Russian prices. Leveraging daily data obtained through web scraping, we generate high-frequency signals to assess policy effects, particularly how the war in Ukraine and subsequent sanctions influence pricing dynamics, demonstrating how they contributed to an average excess CPI level of 11.7% in Russia. Gaur et al. (2023) highlight the use of adaptation strategies by Russian firms to counter the economic impacts of targeted sanctions.

Our findings show that the Russian economy has gradually absorbed the initial impact of sanctions and realigned with the pre-existing WS-CPI trend, offering a nuanced perspective on product price and stock-level consequences of this war.

The remainder of this paper is organized as follows. Section 2 describes the methodology used to analyze the data presented in Section 3. Section 4 presents the results, and Section 5 concludes.

2 Methodology

2.1 Calculation of Indices

To calculate the CPI from our web-scraped data (WS-CPI) we employed a multilateral unweighted index method with time-product dummies (TPDs). This choice balances complexity with methodological consistency, as the same TPDs are used to calculate the Product Stock Index from web scraping (WS-PSI). While the CPI is a well-established concept, the WS-PSI is a novel addition to the field. This index is constructed based on the quantities available for sale within each COICOP (1999) category for every product. A higher WS-PSI indicates greater product availability, suggesting well-stocked shelves, while a lower index might signal potential shortages.

The term TPD was introduced by de Haan and Krsinich (2014), as this model adapts the country-product dummy model (Summers, 1973) for spatial comparison to comparison across time. The following Equation 1 refers to the TPD specification (Aizcorbe et al., 2003) applied to time series[2]

$$\ln P_{it} = \sum_{i=1}^{N} a_i D_i + \sum_{t=1}^{T} \gamma_t T_t + \mu_{it}, \tag{1}$$

where, for each product aggregate, $\ln P_{it}$ is the log of the price of good i at time t, D_i and T_t are the dummy variables for good i and time t, respectively, with $i = 1, ..., N$ and $t = 1, ..., T$.

Differences in the γ_t coefficients are interpreted as measures of WS-CPI change over time, and we can then derive the CPI levels for each time t by exponentiating

[2]As noted in the literature (Melser, 2005; de Haan et al., 2021), TPD presents some limitations. It implicitly adjusts for differences in quality across sampled items. However, this implicit mechanism can lead to overfitting and bias, especially when there is a substantial lack of matching items across time periods. We chose this method due to its simplicity in handling moderate fluctuations in sampled products and data collection interruptions. Additionally, the substantial number of matching items across time mitigates the risk of degeneration mentioned earlier. Furthermore, being a multilateral index allows for direct comparison of WS-CPI and WS-PSI levels at different points in time without any adjustments.

them:

$$WS\text{-}CPI_t = e^{\gamma_t}. \tag{2}$$

For the analysis of WS-PSI, we use the same methodology applied to product stock levels, such as

$$\ln S_{it} = \sum_{i=1}^{N} b_i D_i + \sum_{t=1}^{T} \delta_t T_t + \varepsilon_{it}, \tag{3}$$

where, for each product aggregate, $\ln S_{it}$ is the log of the stock available for sale of good i at time t, and all other parameters follow the convention of Equation 1. In this case, differences in the δ_t coefficients are interpreted as measures of WS-PSI change over time, and we can then derive the WS-PSI levels for each time t by exponentiating them:

$$WS\text{-}PSI_t = e^{\delta_t}. \tag{4}$$

To align with official CPI releases, we use February 28, 2021 (period t_2) as the reference point for both WS-CPI and WS-PSI, excluding the relative dummy from the equation. Consequently, all $WS\text{-}CPI_t$ and $WS\text{-}PSI_t$ for $t \neq 2$ represent relative levels compared to the reference period. We opted for an unweighted index method for computational efficiency and lack of representative weights for each product. This method is also commonly used by National Statistical Institutes for constructing price indices of elementary aggregates (International Monetary Fund et al., 2020).

2.2 Web Scraping and Official CPI

Retailer characteristics alone are insufficient to determine the usefulness and representativeness of web-scraped price data. Following Macias et al. (2023), we employ an empirical approach to validate the accuracy of online prices in tracking the official CPI. We utilize correlation, as in Cavallo (2013), alongside adherence metrics used in model validation and forecasting. Additionally, we use cointegration-based time series models to confirm a long-term relationship between online and official price index levels, thereby reinforcing the robustness of our analysis.

We choose this approach for two main reasons. First, official CPIs often have a significant delay in publication. This makes our WS-CPI metrics, available immediately, valuable for nowcasting or short-term projections. Second, our time series are relatively short (only 20 months) and contain missing values and several regime shifts. These characteristics can be challenging for standard econometric methods used to confirm cointegration. Therefore, we analyzed monthly CPI levels from both web-scraped and official indices using a combination of model validation and econometric techniques. To address missing data points in our web-scraped data,[3] we apply Kalman Smoothing (Gómez and Maravall, 1994).

2.2.1 Model Validation Metrics

This section presents the tools we use to evaluate the adherence between web-scraped and official data. First, we calculate the Pearson's correlation coefficient between the WS-CPI and the official CPI, performing a simple Student's t-test (Gosset, 1908) to assess the null hypothesis of no correlation. Following Mayer and Butler (1993), we employ modeling efficiency (a dimensionless metric based on the coefficient of determination) to compare the adherence between web-scraped and official data. As suggested by Willmott and Matsuura (2012), we use the Nash and Sutcliffe (1970) model efficiency. Finally, we visually analyze the differences by comparing plots of the official data with the predicted data (web scraping) model efficiency formula. The Nash-Sutcliffe efficiency formula is

$$E = 1 - \frac{\sum_{i=1}^{n} (F_i - O_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}, \tag{5}$$

where E is the Nash-Sutcliffe coefficient of efficiency, n is the number of observations, F_i are the predictions from the model for observations $i = 1, ..., n$, O_i are the paired observations for $i = 1, ..., n$, and $\bar{O}$ is the "true" mean of all observations.

While Mayer and Butler (1993) criticize certain summary metrics, other studies (Rayer, 2007; Swanson, 2015) emphasize the value of additional indicators. Rayer (2007) proposes the Mean Absolute Percentage Error (MAPE), which is the arithmetic mean of all Absolute Percentage Errors (APE), and the Mean Algebraic Percentage Error (MALPE), which is the arithmetic mean of all Algebraic Percentage Errors (ALPE), for assessing accuracy and bias, respectively. We favor these metrics over others (e.g., Root Mean Square Error) because evaluating MAPE and MALPE together allows for a comprehensive evaluation of both accuracy and bias in our results. In most cases, the difference between the MAPE-MALPE pair and alternative metrics is negligible (Rayer, 2007). Following Swanson (2015), we consider 5% for MAPE and ±5% for MALPE as indicative of satisfactory performance.

Additionally, we perform a simple Student t-test (Gosset, 1908) to compare MAPE and MALPE values before and after the war's outbreak. This simple test, alongside the other analyses, helps us identify potential divergences in the patterns of the two time series following this event.

Finally, we employ the Bayesian Estimator of Abrupt change, Seasonal

[3] Data from two time periods, June 2021 and June 2022, were imputed for the WS-CPI.

change, and Trend (BEAST) proposed by Zhao et al. (2019) to identify potential shifts in the underlying trends of APE and ALPE, estimate the probability slope of the trend, and pinpoint potential change points in the underlying time series, especially around the start of the war.

2.2.2 Econometric Approach

To validate the relationship between our WS-CPI and the official CPI for each product COICOP (1999) category under investigation, we use tests that can handle time series with unknown fractional integration orders due to many of our series exhibiting regime shifts and nonstationarity at typical differencing levels. As Nielsen and Shimotsu (2007) point out, this is a frequent characteristic of economic time series.

To assess the relationship between our WS-CPI and the official CPI, we employ econometric tests that can handle time series with unknown integration orders. First, we utilize the pairwise test (Robinson and Yajima, 2002; Nielsen and Shimotsu, 2007) to determine if both WS-CPI and the official CPI exhibit the same order of integration. The null hypothesis for this test is that both series have the same order of integration.

Second, we employ the semiparametric test proposed by Marmol and Velasco (2004) to assess the presence of cointegration between the two series without requiring prior knowledge about specific characteristics of the data, such as memory of the original series, short-run dynamics, the cointegrating vector, or the degree of cointegration itself. The null hypothesis for this test is the absence of cointegration.

Finally, we leverage two additional tests to obtain a consistent estimate of the cointegration rank between our WS-CPI and the official CPI. The first test, introduced by Nielsen and Shimotsu (2007), utilizes the exact local Whittle estimator, originally proposed by Shimotsu and Phillips (2005), to provide a consistent estimate.

The second one, proposed by Zhao et al. (2019), uses eigenanalysis to determine the cointegration rank between time series, and relaxes many of the underlying hypotheses compared to other tests. The time series under analysis can be of different and unknown integration order, integer or fractional.

Our analysis faces a challenge due to the relatively short length of our time series, with only 20 monthly observations. The tests we employ are typically validated with much larger samples, often exceeding 100 observations. While applications of these methods for small datasets, like ours, are not documented in the literature, we complement our analysis with additional tools.

We implement a bootstrap procedure to assess the stationarity of the differences between the official CPI and WS-CPI levels for each COICOP (1999) category. If the stationarity hypothesis is satisfied, alongside the Robinson and Yajima (2002) test indicating the same integration order for both series, this would suggest cointegration between the two time series (Engle and Granger, 1987).

To generate an empirical distribution of the differences between official CPI and WS-CPI, we employ the maximum entropy bootstrap methodology (Vinod, 2006; Vinod and Lopez-de Lacalle, 2009). This approach is particularly suitable for time series as it preserves the original data's characteristics, including shape, periodicity, mass, and mean, regardless of their stationarity.

Our procedure is articulated in four steps. First, we generate 100 sets of resampled data using the maximum entropy bootstrap method for both the CPI and WS-CPI time series and for each COICOP (1999) category. Second, we calculate the difference between the CPI and WS-CPI values for each of the 10,000 possible combinations arising from these 100 replicates in each category. Third, we employ the ADF (Dickey and Fuller, 1979, 1981) and the KPSS (Kwiatkowski et al., 1992) tests on each of those combinations. The KPSS test is particularly useful for short time series like ours because the ADF test can be weak with limited data points (Arltová and Fedorová, 2016). The ADF model can be written as

$$\Delta y_t = \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + ... + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_t \tag{6}$$

and we can reject the null hypothesis of nonstationarity if $\gamma < 0$.

From each combination, we record the standard errors and γ values from the ADF test, as well as the KPSS statistics, and leverage the methodology described in Davison and Hinkley (1997) to build 95% confidence intervals for bootstrap estimates following Canty and Ripley (2022). If the upper limit of the bootstrap confidence interval for γ is negative, we can reject the null hypothesis of nonstationarity according to the ADF test. On the other side, if the upper limit of the bootstrap confidence interval for the KPSS test value is below the critical value, we cannot reject the null hypothesis of stationarity.

Finally, we leverage the Autoregressive Distributed Lag (ARDL) bound test proposed by Pesaran et al. (2001) to assess the presence of a level relationship between WS-CPI and official CPI, performing a Wald bounds-test for no cointegration between them. As noted by Pesaran et al. (2001), if the test statistic falls within the critical region, we can reject the null hypothesis of no cointegration without further information on the time series under analysis. Conversely, if the test statistic falls outside the critical region, inference is inconclusive, and knowledge of the order of the integration for the time series under analysis is required to draw conclusive inferences. For the ARDL test, we consider both CPI and WS-CPI as autoregressive time series with an order equal to one.

2.3 WS-CPI and WS-PSI Trend Changes

To identify potential trend shifts in the indices we calculated from the web-scraped data (Equations 1 and 3), we need a method robust to missing values due to significant breaks in our time series. We opted for the Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) proposed by Zhao et al. (2019) and implemented in the R package Rbeast.

The BEAST model, a Bayesian statistical model that performs time series decomposition into an additive model incorporating multiple trend and seasonal signals, is also used to detect trend changes in WS-CPI and WS-PSI. This model, which has primarily been employed in the field of geographical sciences, demonstrates a high degree of resilience towards missing values, can identify an unknown number of trend changes, and provides an estimated probability of trend change for each time point. Given the presence of missing data and relevant unknown structural changes within our time series, these characteristics lead us to select BEAST for our analysis over competing methodologies more commonly used in the economic literature, such as Bai and Perron (1998, 2003). The general form of the model is:

$$y_i = S\left(t_i; \Theta_s\right) + T\left(t_i; \Theta_t\right) + \varepsilon_i, \tag{7}$$

where y_i is the observed value at time t_i, Θ_s and Θ_t are respectively the season and trend signals, and ε_i is noise with an assumed Gaussian distribution. Given the relatively short length of our time series, we removed the seasonal component from the model, giving us the formalization:

$$y_i = T\left(t_i; \Theta_t\right) + \varepsilon_i. \tag{8}$$

Trend change points are implicitly encoded in Θ_t, and the trend function is modeled as a piecewise linear function with m knots and $m+1$ segments. In each segment, the trend is built as follows:

$$T\left(t\right) = a_j + b_j t \text{ for } \tau_j \leq t < \tau_{j+1}, j = 0, ..., m \tag{9}$$

where a_j and b_j are parameters for the linear trend in the j segment, which spans from τ_j to τ_{j+1}.

Further details about the Bayesian formulation of BEAST, its Markov Chain Monte Carlo inference and posterior inference of change points, seasonality, and trends can be found in Zhao et al. (2019). According to this model, the estimated trend, trend slope (positive, neutral, or negative), and change point likelihoods are provided for each point in time.[4]

[4]By construction, the probability of being a trend change point is additive over time. In other

2.4 Sanctions and Structural Breaks

To investigate the causal relationship between sanctions and the probability patterns of structural breaks in the WS-CPI and WS-PSI, we use a modified Wald test on the results of a Vector Autoregression (VAR) analysis, using WS-CPI and WS-PSI structural break series, in succession, with the sanctions time series. We only selected positive structural breaks for WS-CPI, as the sanctions have a punitive aim toward the targeted country, and that may only be achieved with an increase in its domestic price level. On the other side, we analyze both positive and negative breaks for WS-PSI since sanctions may have contrasting effects on product availability and inventory decisions by retailers. Proposed by Toda and Yamamoto (1995), we selected this method to circumvent potential issues with the traditional Granger (1969, 1988) causality test that may arise due to nonstationarity in the time series under examination.

To carry out the Toda-Yamamoto (TY) causality test, we first determine the maximum integration order of the time series under examination[5] through an autoregressive wild bootstrap methodology (Friedrich et al., 2020). We then use the Akaike Information Criteria (AIC) on a preliminary VAR analysis to select the appropriate lag for inclusion in the TY VAR equation (Akaike, 1969, 1971, 1998). According to Toda and Yamamoto (1995), we implemented the VAR with a lag equal to the sum of the maximum integration order and the recommended lag from the AIC, in order to eliminate any potential autocorrelation in the VAR residuals. We repeated the process for each COICOP (1999) category, testing different modeling of the causal relationship between sanctions on the one side and WS-CPI and WS-PSI structural breaks on the other. We also divide the sanctions between financial-related and trade-related.

The effect of sanctions on excess WS-CPI is also investigated using the TY test, where excess WS-CPI represents the difference between the effective WS-CPI (i.e., following sanctions) and the expected WS-CPI level without sanctions. Our investigation examines the relationship between sanctions and trend shifts in the WS-PSI to determine whether sanctions caused positive or negative changes in the trend of product availability.

Recognizing the exchange and interest rates as potential factors in the transmission channel between sanctions and prices and product inventories, we analyze exchange and interest rate trend shifts using the BEAST model and perform additional TY causality tests to explore the interplay between sanctions, exchange and interest rate shifts, WS-CPI, and WS-PSI.

The effect of sanctions on exchange and interest rate trend shifts is analyzed

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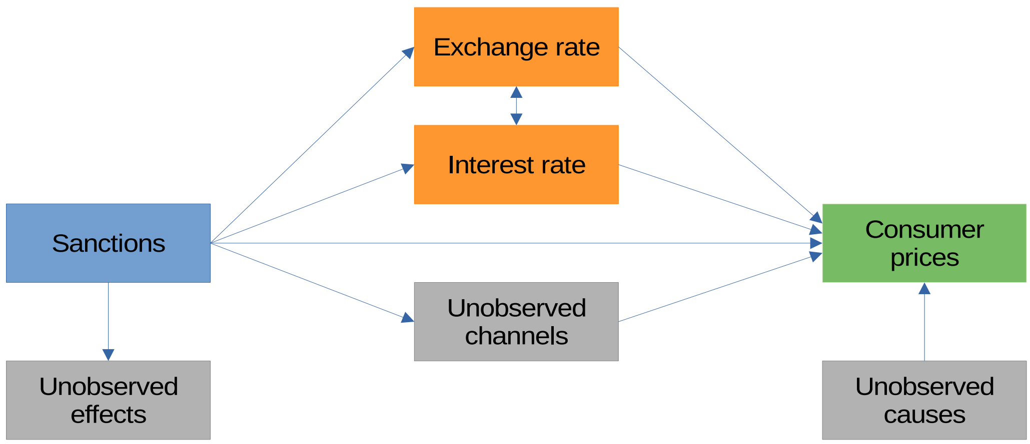
words, the total probability of encountering a trend change point between time *t* and *s* equals the sum of all probabilities for time points between *t* and *s*.

[5]WS-CPI positive structural break probability, WS-PSI structural break probability, and sanctions.

using TY causality tests to determine whether sanctions induced upward shifts exclusively or both upward and downward shifts in the rates.[6] This analysis aims to ascertain whether upward shifts in exchange and interest rates resulting from sanctions correspond to excess WS-CPI and upward WS-CPI shift changes, allowing us to gain insights into the interconnectedness of exchange and interest rates, sanctions, and prices. TY causality tests also analyze the connection between exchange and interest rates and WS-PSI upward and downward shifts resulting from sanctions. Finally, we also use the TY causality test to explore the interaction between exchange and interest rate breaks. Figure 1 shows a stylized representation of the causal interconnections under examination. We added placeholders for unobserved variables for completeness, as we are aware that the dimensions included in this study do not cover all possible implications of the sanctions nor all possible causes for disruption in consumer price levels.

Figure 1. Causal Model



Notes: Gray squares represent unobserved effects and causal factors exogenous to the interest rate or the exchange rate.

The resulting VAR equation is

$$y_t = A_1 y_{t-1} + ... + A_{p+dmax} y_{t-(p+dmax)} + CD_t + u_t, \tag{10}$$

where y_t is a vector with the value of the variables under examination for time t. The coefficient matrices $A_1 ... A_{p+dmax}$ have a 2×2 dimension, the term CD_t captures constant and trend, u_t is the error term, p is the lag selected according to AIC, and $dmax$ is the maximum order of integration for the time series in y.

To further validate the absence of residual autocorrelation, we use the

[6] We express the exchange rate in units of local currency per US dollar. An upward shift means the local currency is devaluating vis-à-vis the US dollar.

Breusch-Godfrey test (Breusch, 1978; Godfrey, 1978) on the VAR residuals. Additionally, we examine the VAR roots to confirm the stability of the model (Lütkepohl, 2005). Finally, we apply the Wald test to the potential-causing variable (for instance, sanctions time series) coefficient in the $A_1 ... A_{p+dmax}$ coefficient matrices for each VAR equation, under the null hypothesis of no causal effects of the aforementioned time series on the potentially influenced variable (for instance, WS-CPI and WS-PSI probability of structural break time series). The Wald test uses the variance-covariance matrix from the VAR equation (Equation 10) in order to jointly test the significance of the potential-causing variable coefficients, calculated as

$$W = \left(\hat{\beta}\right)' \left[V\left(\hat{\beta}\right)\right]^{-1} \left(\hat{\beta}\right) \tag{11}$$

where $\hat{\beta}$ is the vector of coefficients related to the potential-causing variable (for instance, sanctions), lagged effects on the potentially influenced variable (for instance, WS-CPI or WS-PSI break probability) extracted from the coefficients matrices $A_1 ... A_{p+dmax}$ from Equation 10, and $V(\hat{\beta})$ is their variance-covariance matrix. W is distributed as a χ^2 with degrees of freedom equal to the number of tested parameters, in this case, $p + dmax$. If the test rejects the null hypothesis, we can conclude there is Granger-Causality between the first and the second variable.

The final step in our analysis is to evaluate how much sanctions have affected WS-CPI levels in Russia. To do so, we establish a baseline by projecting the average WS-CPI trend extracted from the BEAST model before the beginning of the war and calculate the deviation of this baseline from our WS-CPI level. We repeat the same exercise on monthly official CPI levels and perform correlation tests between the two metrics to check whether the impact measured on data from web scraping is consistent with official figures. Finally, we perform the TY causality test described above using excess inflation as a target variable and sanctions, exchange and interest rate breaks as potentially causing ones.

2.5 Product-Level Analysis

To complement our macroeconomic analysis of CPI dynamics, we conduct three micro-level studies. First, we evaluate the impact of the ban on Champagne exports to Russia on its price and availability, using other sparkling wines not affected by specific sanctions as a comparison group. Second, we classify brands according to their country of origin in four COICOP (1999) categories, and use a Time-interaction Classification Dummy (TiClD) approach to evaluate price and availability dynamics for products with different origins and exposures to sanctions. Third, we compare the evolution of prices for matching products of selected brands in Russia and Italy.

2.5.1 Difference-in-Differences

We conduct a targeted Difference-in-Differences (DiD) analysis focused on a specific subcategory, namely, sparkling wine. On March 15, 2022, sanctions were imposed specifically on Champagne, leading to a ban on its export to Russia. In contrast, other sparkling wines, such as Prosecco, remained unaffected by these sanctions. While distinctions in price points and consumer motivations for purchasing may exist between Champagne and Prosecco, their potential to be perceived as substitutable goods warrants investigation. Additionally, both products originate in the Euro area, subjecting them to similar impacts from currency fluctuations. Therefore, we see the opportunity to analyze whether there was a difference in the price dynamics and availability of Champagne and Prosecco following the specific sanctions on Champagne export to Russia.

We follow the DiD methodology proposed by Callaway and Sant'Anna (2021), using the doubly-robust method from Sant'Anna and Zhao (2020), which allows for treatment effect heterogeneity and dynamic effect, improving on the standard two-way fixed effects model. Using Prosecco as a nontreated control group, we estimate the average treatment effect on the treated (ATT) for Champagne prices following the sanctions. Our panel data is unbalanced as different products were added and dropped over time.

Additionally, our analysis is augmented by a collection of descriptive statistics. Utilizing the TPD formula as in Equations 2 and 4, we calculate price and product stock indices for Champagne and Prosecco. Furthermore, we calculate the average price of products available weekly and assess the count of individual products and brands available for sale each week within each category.

2.5.2 Disaggregated WS-CPI and WS-PSI

While many countries imposed trade sanctions on Russia, significant exceptions like China, India, and Turkey remained. Additionally, only certain goods or categories of goods faced export bans. Understanding how these sanctions impacted consumer prices and product availability and how these effects differ based on the product's country of origin (sanctioning, nonsanctioning, or domestic) and sanction status (sanctioned or nonsanctioned) is necessary.

To this end, we classify each product in our dataset according to the Harmonized System (HS) Codes by calculating cosine similarity on vectorized text embeddings (Farouk, 2020) between the product names and the HS Code descriptions. For each product we selected the HS Code with the highest similarity, saving the similarity score as a measure of confidence for the classification. We then matched the HS Codes with the list of trade sanctions implemented by the European Union towards Russia, as in Chupilkin et al. (2023).

We manually classify all brands in four COICOP (1999) categories – 05.3.1 Major household appliances whether electric or not, 05.3.2 Small electric household appliances, 05.5.1 Major tools and equipment, and 05.5.2 Small tools and miscellaneous accessories – according to the country of origin of the ultimate brand owner. In the limited cases where we are unable to identify the owner of the brand, we use the prevailing manufacturing country for products belonging to the brand as a proxy. Each country is classified according to its stance on trade sanctions towards Russia as sanctioning or nonsanctioning. Russian brands are classified as domestic.

Finally, we employ a variation of the TPD index that allows for simultaneous comparability across time and classifications to calculate WS-CPI and PSI for the selected COICOP (1999) categories. The basic concept underlying this variation was first proposed by Aizcorbe and Aten (2004) as the TiCPD approach for pooled comparison across space and time, and used with the same purpose in several works (Hill, 2004; Hill et al., 2009; Benedetti et al., 2022). Here we present a novel formulation of this method, in which the time dummy variable interacts with another dummy that captures the product's classification according to brand origin and sanction status, and removes the product dummies to prevent collinearity.

We call this index formula the Time-interaction-Classification Dummy (TiClD), which is expressed as:

$$\ln P_{it} = \sum_{t=1}^{T} \sum_{k=1}^{K} \gamma_{tk} T_t C_k + \mu_{it}, \tag{12}$$

where for each product aggregate, P_{it} is the price of good i at time t, and C_k and T_t are the dummy variables for the classification of good i and time t, respectively, with $k = 1, ..., K$, $i = 1, ..., N$, and $t = 1, ..., T$.

The differences between the γ_{tk} coefficients measure the WS-CPI change over time for goods with classification k. We can derive the respective CPI levels for each time t and classification k by exponentiating them:

$$WS\text{-}CPI_{tk} = e^{\gamma_{tk}}. \tag{13}$$

The TiClD is not a general purpose index formula, and its results may reflect the changing mix of products classified in each category, given the removal of the product dummy variables. Since there is no overlapping data across the different categorizations, comparisons may lack properties desirable in indices for official statistics. However, we find the TiClD suitable for our purposes of qualitatively studying the evolution of prices and product availability in the specific case at hand, enabling direct comparisons across time and categorizations for index levels within sufficiently narrow categories.

2.5.3 Matching Products Dynamics

The final step in our micro-level investigation involves a comparative analysis of price evolution for identical products in Italy and Russia. We used web scraping to gather data from 20 shops belonging to the largest supermarket chain in Italy.[7] We were able to find products matching those sold in Russia belonging to seven different brands: Barilla, Campari, Ferrero, Head & Shoulders, Pepsi, Schwepps, and Tampax.

For each brand, we compute the WS-CPI in the local currency following Equation 1 using the TPD index. For Russian prices, we also convert the prices into US dollars using the average exchange rate for each week, and calculate the WS-CPI in the foreign currency.

This Italian retailer cannot be considered a canonical control group to perform causal inference on the impact of sanctions, as the Italian and Russian CPIs experienced widely different trends in the recent past. However, by comparing the relative evolution of prices for specific international brands with consistent global positioning, we can gain additional insights into the evolution of the CPI level in Russia using an external reference point.

3 Data

The dataset used for this paper has been collected via web scraping techniques. Data on consumer product prices and quantities have been collected daily from a prominent Russian multichannel retailer, since February 15, 2021. This retailer operates an e-commerce website that ships products across Russia, as well as a network of megastores in major cities, mostly in Western Russia. The operating company behind the retailer brand was established in 1993 and reported over 47 billion rubles in revenue in 2022, an increase of 7.41% from the previous year. This retailer mainly carries goods oriented toward middle-class customers, but has a significant share of entry-level and luxury items, providing additional relevance to our work.

As delineated in Banerjee and Duflo (2008), the middle class is a demographic segment exerting significant influence in shaping the economic and social well-being of a nation. Consequently, examining the dynamics of prices and product

[7] Shops are located in seven different Italian regions.

availability within this economic stratum should yield more pertinent insights into a country's economic perspectives.

According to self-reported company data, approximately 1 million shoppers visit the company's physical retail establishments monthly, and the e-commerce website has over 500,000 monthly visitors. Public information available online about its website shows that the user base is predominantly female (63%), concentrated in Moscow and the surrounding region (78%), and mainly in the 25-44 age range (60%).

The fact that this retailer has both an online presence and physical shops in the Moscow area, which is the largest region in Russia by population and total volume of economic activity, adds additional value to the dataset. The adherence between online and offline price levels for multichannel retailers has already been proven across multiple countries (Cavallo, 2017, 2018). Strasser et al. (2023) has confirmed this relationship, showing a contemporaneous correlation between offline and online prices of well above 60% in France and the United Kingdom. Moreover, we can draw additional anecdotal confirmations of this phenomenon in the course of our overall web scraping operations, which span across several countries.[8] There were two significant data collection breaks originating from website structure updates that caused failures in the web scraping routine. The first break started on May 27, 2021, and ended on July 12, 2021. The second break started on May 26, 2022, and ended on July 24, 2022.

We capture the name, brand, category, price, and quantity of each product in the retailer's warehouse. We map the commercial categories defined by the retailer to the Classification of Individual Consumption by Purpose, 1999 version (COICOP, 1999). We selected COICOP (1999) among all classification standards since the OECD uses it for reporting Russian CPI data, and - to the best of our knowledge - the Federal State Statistics Service in Russia (Rosstat) also uses the same taxonomy. Table 1 reports the Level 4 categories where we collected data, along with the number of unique items and the total number of observations recorded.

Given the nature of the multichannel retailer from which we gather data, we notice excellent coverage of categories in furnishings and household equipment, as well as goods for recreation and culture. Food is also well-represented, along with goods for personal care. In total, we have almost 8 million weekly records, aggregated from the collected daily ones, and about 250,000 unique items. Our daily web scraping routines collect approximately 120,000 records every day.

[8] While there is some evidence that online-only retailers may adjust their pricing faster than offline-only ones in response to exogenous shocks (Gorodnichenko and Talavera, 2017), we found no evidence in the literature suggesting that multichannel retailers may react to shocks by adjusting prices differently in their online and offline stores. In the case of large shocks, there is a stronger argument that offline prices may be less rigid than during usual times (Karadi and Reiff, 2019), and thus online prices may become an even better indicator of offline price changes.

Table 1. Classification of Collected Data According to COICOP (1999)

COICOP (1999) Category		Items	Records
01.1	Food *	9742	296405
01.1.2	Meat	1530	40019
01.1.3	Fish and seafood	1120	31447
01.1.4	Milk, cheese and eggs	3949	116689
01.1.8	Sugar, jam, honey, chocolate and confectionery	4861	131279
01.1.9	Food products n.e.c.	4264	129686
01.2.1	Coffee, tea and cocoa	8822	324178
01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	2390	77966
02.1	Alcoholic beverages *	4464	155984
03.1.2	Garments	6165	133832
03.1.3	Other articles of clothing and clothing accessories	658	27414
04.3.1	Materials for the maintenance and repair of the dwelling	19490	437812
05.1.1	Furniture and furnishings	24218	760297
05.1.2	Carpets	2044	66280
05.2.0	Household textiles	12272	431860
05.3.1	Major household appliances whether electric or not	2771	86232
05.3.2	Small electric household appliances	30834	934541
05.4.0	Glassware, tableware and household utensils	32861	1188091
05.5.1	Major tools and equipment	2351	97974
05.5.2	Small tools and miscellaneous accessories	4712	195688
05.6.1	Nondurable household goods	7989	300823
06.1.2	Other medical products	75	3381
07.2.1	Spare parts and accessories for personal transport equipment	1280	43027
08.2.0	Telephone and telefax equipment	635	18254
09.1.1	Equipment for the reception, recording and reproduction of sound and pictures	729	20718
09.1.2	Photographic and cinematographic equipment and optical instruments	15	467
09.1.3	Information processing equipment	1682	52221
09.2.1	Major durables for outdoor recreation	611	13906
09.3.1	Games, toys and hobbies	9250	333979
09.3.2	Equipment for sport, camping and open-air recreation	1083	30739
09.3.3	Gardens, plants and flowers	13617	434477
09.3.4	Pets and related products	4889	158111
09.4.5	Books	2689	114126
12.1.2	Electric appliances for personal care	413	15165
12.1.3	Other appliances, articles and products for personal care	12456	438015
12.3.1	Jewellery, clocks and watches	328	11140
12.3.2	Other personal effects	7220	226852

Notes: The star (*) denotes items in commercial categories that span more than one Level 4 COICOP (1999) category and have been listed in the appropriate Level 3 classification. The second column reports the number of unique items, and the third column the total records available.

We collected data regarding sanctions from the Peterson Institute for International Economics (Bown, 2023) and further elaborated on it. From a set of countries, we selected sanctions related to import, export, and financial activities.

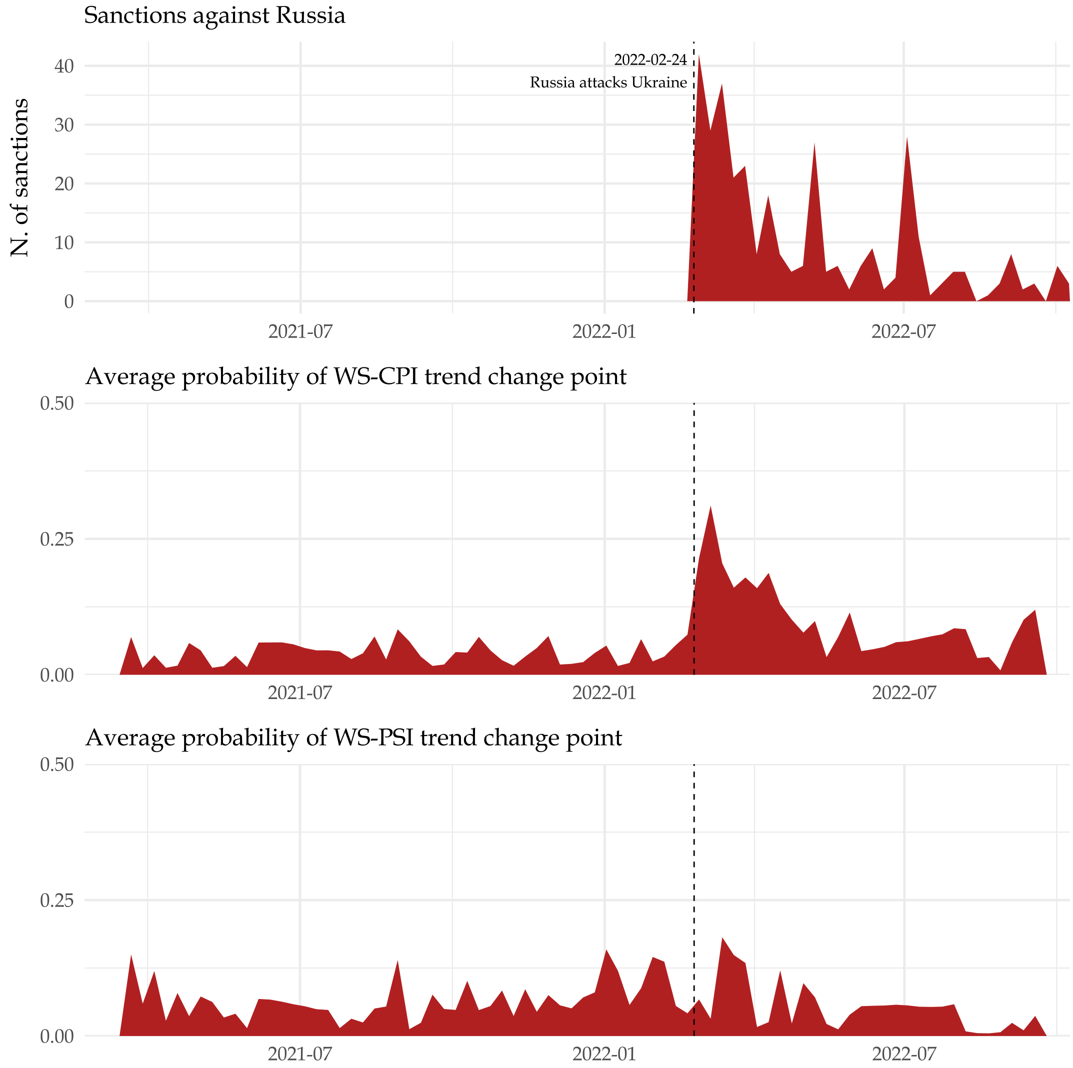
Finally, we collected the time series for the Ruble Overnight Index Average (RUONIA) from the Bank of Russia website to represent the prevailing interest rate in Russia, and the daily ruble to US dollar exchange rates from *The Wall Street Journal* website.

4 Results

4.1 WS-CPI and WS-PSI Dynamics

Figure 2 shows that the WS-CPI underwent a significant increase in the number of trend change points following Russia's attack on Ukraine and the subsequent waves of international sanctions, compared to other periods. Conversely, the pattern of structural breaks in the WS-PSI does not appear to have been significantly affected by these events.

Figure 2. Sanctions and Break in Trends



Notes: Data from web scraping and Bown (2023).

Figures 3 and 4 present the results for selected COICOP (1999) categories for WS-CPI and WS-PSI as examples of the dynamics we uncovered.

Figure 3. Consumer Price Indices

Notes: Data from web scraping are denoted by the color blue, and official data sourced from the Federal Service for State Statistics (Russian Government) is represented by the color red. The areas shaded in green, violet, and orange indicate positive, zero, and negative slopes, respectively.

Figure 4. Product Stock Indices

Notes: Data from web scraping are denoted by the color red. The areas shaded in green, violet, and orange indicate positive, zero, and negative slopes, respectively.

Results for WS-CPI are compared with official CPI figures, while we have no other source of information for WS-PSI.

Figure 3 shows that after Russia invaded Ukraine on February 24, 2022, both online and official meat prices increased significantly, with slight differences between them. However, fish prices display a significant gap between online and official prices following the invasion of Ukraine, with an increase in the likelihood of changepoints. Figure 3 also shows that the gap between online and official major tools and equipment prices is even greater than for fish.

Furthermore, Figure 3 highlights an increasing difference between online and official prices for the "jewelry, clocks and watches" category. However, in this case, WS-CPI over time decreases below the pre-war price levels, while the official CPI does not.

Figure 4 presents the evolution of product stocks over time. Overall, the availability of products decreased since the war started, except with regard to major tools and equipment stocks, where an interesting increase occurred a couple of weeks before the war started.

For WS-PSIs, differentiating between the potential impact of trade sanctions and commercial strategies put in place by the retailer is challenging. In the case of jewelry and watches, Figure 4 shows a long downward trend in inventory that predates any hint of potential war. A peak appears around the turn of the year and the corresponding holiday period for meat and fish product availability, which corresponds to standard commercial practices in retail. Unfortunately, the lack of more extended time series makes it impossible to disentangle seasonal variations from variations caused by sanctions.

However, the turn of the year cannot explain the increase in product availability of major tools and equipment, as this stock increase occurred in January and February 2022. The increase in stock also seems not related to prices (Figure 3), as prices declined from March to April 2022, along with the decrease in stocks (Figure 4).

4.2 Model Validation Metrics

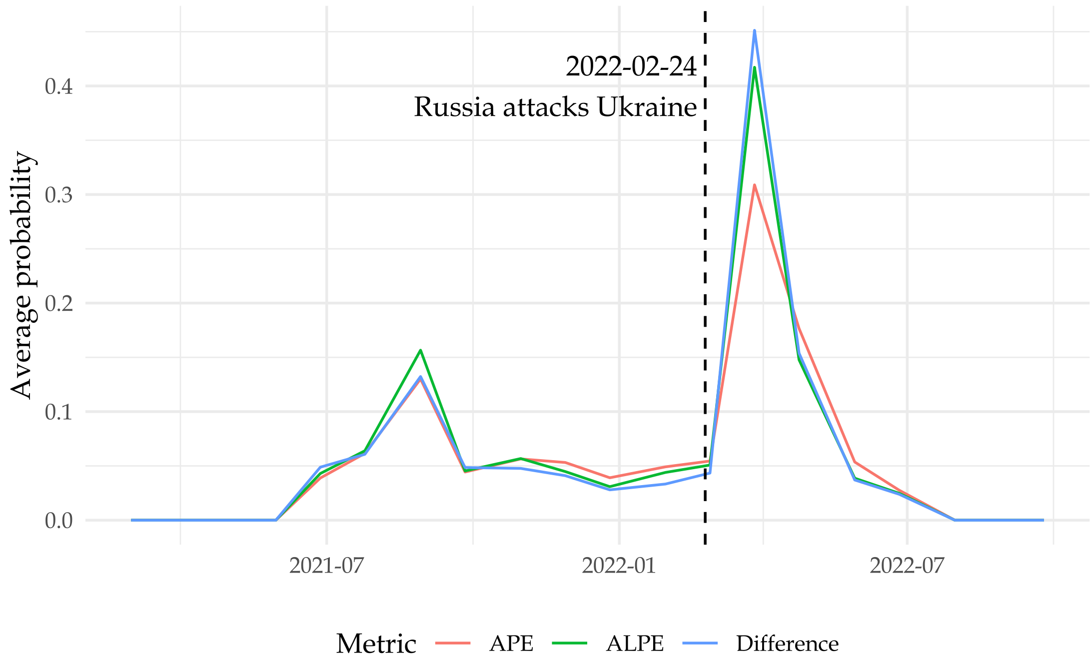
Table 9 in Appendix A shows the correlation coefficients of the official CPI and WS-CPI over the full sample, together with the p-value for the null hypothesis of no correlation. In 20 and 30 cases out of 37 the correlation is above 90% and 70%, respectively. There are only 2 cases in which we cannot reject the null hypothesis of no correlation.

Table 10 in Appendix A shows the model validation metrics over the full sample. In 21 out of 37 cases, overall MAPE is below 5%, which indicates a good tracking performance, and MALPE is within $\pm5\%$, indicating the absence of relevant bias (Swanson, 2015). In 14 cases, the Nash-Sutcliffe modeling efficiency scores above 0.8, confirming the satisfactory tracking performance between WS-CPI and the official CPI.

These results, combined with the findings presented in Section 4.3, establish that online prices are reliable sources of real-time CPI data throughout the analyzed period.

Figure 5 shows the average probability distribution for structural breaks in APE, ALPE and differences between web scraping and official CPI across all categories. We observe peaks in all metrics during the weeks immediately following the outbreak of the full-scale war.

Figure 5. Probability of Structural Break



Notes: This figure presents the probability of a structural break in APE, ALPE, and absolute difference.

Table 2 illustrates the difference in web-scraped data tracking performance before and after the onset of the war. At a 95% confidence level, we note that in 21 cases, the tracking accuracy, measured by the MAPE, degrades significantly, while in 18 cases, there is a significant increase in bias measured by the MALPE. Before the war, the MAPE was less than 5% for 28 series, and the MALPE was within $\pm$5% for 29 of them. However, according to both metrics, only 15 series delivered satisfactory tracking performance after the war started. Table 2 shows the sudden increase in average breakpoint probability in MAPE, MALPE, and differing trends after the start of the war.

While a perfectly possible explanation is that prices from our source became less representative of the overall Russian CPI level in certain (COICOP, 1999)

Table 2. Pre- and In-War Summary Metrics: Forecasting and Model Validation Analysis

COICOP (1999)	*Pre-War*				*In-War*				*Difference p-value*	
Category	**MAPE**	**SD APE**	**MALPE**	**SD ALPE**	**MAPE**	**SD APE**	**MALPE**	**SD ALPE**	**MAPE**	**MALPE**
01.1	1.91	1.13	-1.91	1.13	1.97	1.84	0.56	2.74	0.93	0.04
01.1.2	1.15	1.01	-1.13	1.03	0.93	0.70	-0.73	0.93	0.58	0.38
01.1.3	1.27	0.75	-1.27	0.75	1.80	2.25	0.92	2.80	0.54	0.06
01.1.4	1.65	1.16	1.23	1.63	1.38	0.66	1.38	0.66	0.52	0.77
01.1.8	2.12	1.53	-2.11	1.55	5.52	2.27	-5.52	2.27	0.00	0.00
01.1.9	3.53	1.70	-3.53	1.70	3.47	1.33	-3.29	1.78	0.93	0.77
01.2.1	0.67	0.54	-0.11	0.88	3.74	3.48	2.92	4.29	0.04	0.09
01.2.2	1.12	0.90	-0.12	1.47	1.25	0.63	0.55	1.35	0.72	0.31
02.1	0.45	0.30	0.35	0.42	9.37	4.20	9.37	4.22	0.00	0.00
03.1.2	2.63	1.68	-2.63	1.68	13.37	5.47	-13.37	5.47	0.00	0.00
03.1.3	2.10	1.39	-2.10	1.39	7.18	3.63	7.14	3.73	0.00	0.00
04.3.1	11.47	5.97	-11.47	5.97	9.28	3.82	-9.28	3.82	0.33	0.33
05.1.1	2.89	2.65	-2.81	2.75	2.38	1.75	0.30	3.07	0.61	0.04
05.1.2	9.06	6.05	-9.05	6.07	11.32	2.17	-11.32	2.17	0.26	0.25
05.2.0	2.74	2.11	-2.62	2.28	4.79	3.11	-0.22	5.98	0.13	0.31
05.3.1	1.04	0.78	1.04	0.78	3.34	1.66	-2.96	2.34	0.01	0.00
05.3.2	1.08	0.66	1.08	0.66	3.75	2.21	3.05	3.21	0.01	0.13
05.4.0	2.22	1.51	-2.22	1.51	9.63	4.13	8.87	5.77	0.00	0.00
05.5.1	0.88	0.61	0.56	0.93	10.51	3.74	10.51	3.74	0.00	0.00
05.5.2	0.84	0.62	-0.75	0.73	2.93	1.54	2.17	2.61	0.01	0.02
05.6.1	2.97	1.67	-2.97	1.67	5.78	2.98	-5.78	2.98	0.04	0.04
06.1.2	2.97	1.73	1.77	3.03	9.60	5.12	9.60	5.12	0.01	0.00
07.2.1	4.54	4.17	-4.54	4.17	22.61	6.10	-22.61	6.10	0.00	0.00
08.2.0	7.63	5.28	-7.63	5.28	7.94	3.89	-7.90	3.98	0.88	0.90
09.1.1	6.88	4.43	-6.88	4.43	3.46	3.51	-0.47	5.08	0.07	0.01
09.1.2	12.58	5.89	-12.58	5.89	25.87	2.92	-25.87	2.92	0.00	0.00
09.1.3	18.29	14.02	-18.22	14.12	30.59	5.09	-30.59	5.09	0.01	0.01
09.2.1	8.92	6.96	-8.92	6.96	15.15	10.45	-13.42	12.87	0.17	0.39
09.3.1	4.15	2.49	-4.15	2.49	8.49	1.99	-8.49	1.99	0.00	0.00
09.3.2	5.81	3.33	-2.39	6.46	6.73	7.40	-6.55	7.58	0.75	0.22
09.3.3	3.29	2.96	-2.86	3.42	3.14	3.50	-3.10	3.54	0.92	0.88
09.3.4	0.83	0.65	-0.29	1.04	7.22	7.52	6.94	7.81	0.05	0.03
09.4.5	1.27	0.97	-0.16	1.64	8.52	3.00	-8.52	3.00	0.00	0.00
12.1.2	2.69	2.04	-2.44	2.35	14.82	8.36	-11.40	13.13	0.00	0.10
12.1.3	2.57	1.86	-2.57	1.86	1.97	1.72	-1.97	1.72	0.47	0.47
12.3.1	6.36	4.99	-6.11	5.33	18.80	5.75	-18.80	5.75	0.00	0.00
12.3.2	4.28	3.49	-4.28	3.49	8.87	0.78	-8.87	0.78	0.00	0.00

Notes: We use 2022-02-24 as the cutoff date between Pre- and In-War. The category names related to the COICOP (1999) reference numbers are available in Table 1.

categories after the start of the war, we cannot completely discount the possibility that the official CPI failed to capture some of the price evolutions that happened during that period. In fact, we should note that the methodology used by Rosstat for the official CPI involves collecting data on a single day each month, between the 21st and the 25th. The limited sampling in time for price data can cause substantial uncertainty for month-over-month CPI changes (Palumbo and Laureti, 2024), especially during periods characterized by strong price variability. In Appendix C, we provide, as a robustness check, an alternative calculation of the WS-CPI using a methodology more closely aligned with Rosstat's approach. The results confirm that the choice of methodology has virtually no impact on the outcomes and, overall, our WS-CPI can continue to be considered an excellent tracker of the official CPI. Therefore, we continue the analysis with our WS-CPI calculated weekly and using data from all days in the month to benefit from maximum data coverage.

4.3 Econometric Adherence Measures

The results presented in Table 3 show that several cointegration relationships exist between the official CPI and WS-CPI across the various COICOP (1999) categories we collected.

In only 2 cases out of 37 the Robinson and Yajima (2002) test rejects the null hypothesis that paired time series are integrated of the same order. The Marmol and Velasco (2004) test rejects the null hypothesis of no cointegration between paired time series in 22 cases out of 37. The Nielsen and Shimotsu (2007) test finds evidence of cointegration of order one in 36 series, while the test proposed by Zhang et al. (2019) finds evidence of cointegration of order two in all of them.

The bootstrapped ADF test only confirms the stationarity of differences in 11 cases out of 37, while the bootstrapped KPSS test does not reject the null hypothesis of stationarity in any case. The ARDL test confirms the relationship in levels between CPI and WS-CPI in 12 COICOP (1999) categories.

These results, considered together with the excellent tracking performance discussed in Section 4.2, indicate that, with a few exceptions in specific product categories, there is a strong correspondence between WS-CPI and official CPI over the entire analyzed period. This supports the reliability of our online price data for Russia as a source of information for these product categories, thereby corroborating the use of WS-CPI as a relevant tool for monitoring the official CPI and the overall level of consumer prices in Russia.

4.4 Predictive Causal Analysis

The results from our Toda and Yamamoto (1995) causality tests for the sanctions, divided into financial- and trade-related sanction effects on each COICOP (1999) category in terms of WS-CPI positive breaks, WS-PSI breaks, and excess WS-CPI, are reported in Tables 4 to 6. The level of significance we selected for our hypothesis test is 95%.

We find that financial sanctions influence WS-CPI upward trend shifts more than trade sanctions. Table 4 shows that TY causality tests confirm that financial and trade sanctions cause upward trend shifts in 28 and 24 COICOP (1999) categories, respectively.

WS-CPI upward trend shifts in certain COICOP (1999) categories are only caused by financial sanctions: coffee, tea, and cocoa; materials for the maintenance and repair of dwellings; carpets; and equipment for the reception,

Table 3. Econometric Analysis Summary

COICOP (1999)	RY2002	MV2004	NS2007	ZRY2019	ADF	KPSS	ARDL
01.1			1	2	Reject		
01.1.2		Reject	1	2	Reject		
01.1.3		Reject	1	2	Reject		Reject
01.1.4			1	2	Reject		
01.1.8		Reject	1	2			Reject
01.1.9			1	2			
01.2.1		Reject	1	2			Reject
01.2.2			1	2	Reject		
02.1		Reject	1	2			Reject
03.1.2	Reject	Reject	0	2			
03.1.3			1	2			
04.3.1			1	2			Reject
05.1.1		Reject	1	2	Reject		
05.1.2		Reject	1	2			
05.2.0		Reject	1	2	Reject		
05.3.1			1	2			
05.3.2			1	2			Reject
05.4.0		Reject	1	2			
05.5.1		Reject	1	2			
05.5.2		Reject	1	2			
05.6.1		Reject	1	2			Reject
06.1.2			1	2			
07.2.1		Reject	1	2			
08.2.0			1	2			
09.1.1			1	2	Reject		Reject
09.1.2		Reject	1	2			Reject
09.1.3			1	2			
09.2.1	Reject	Reject	1	2			
09.3.1			1	2			
09.3.2		Reject	1	2			
09.3.3			1	2	Reject		Reject
09.3.4			1	2	Reject		Reject
09.4.5		Reject	1	2			
12.1.2			1	2			Reject
12.1.3		Reject	1	2	Reject		
12.3.1		Reject	1	2			
12.3.2		Reject	1	2			

Notes: RY2002 stands for Robinson and Yajima (2002), where the null hypothesis is that time series are integrated of the same order. MV2004 stands for Marmol and Velasco (2004), where the null hypothesis is that there is no cointegration between the two time series. NS2007 and ZRY stand for Nielsen and Shimotsu (2007) and Zhang et al. (2019), respectively, which report the cointegration rank between time series according to the respective tests. The category names related to the COICOP (1999) reference numbers are available in Table 1.

recording, and reproduction of sound and pictures. This implies that financial sanctions have a pronounced influence on the prices of goods within these specific categories of products.

Conversely, WS-CPI upward trend shifts of the ”other articles of clothing and clothing accessories” category are only caused by trade sanctions.

Table 4. Causality Analysis: Sanctions and WS-CPI Positive Breaks

COICOP (1999) Category	Financial Sanctions VAR Lag	MIO	Resid	Unit Root	Sanctions	Trade Sanctions VAR Lag	MIO	Resid	Unit Root	Sanctions
01.1	9	1	Not reject	Stable	Reject	9	1	Not reject	Stable	Reject
01.1.2	4	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Reject
01.1.3	3	1	Not reject	Stable	Reject	9	1	Not reject	Stable	Reject
01.1.4	12	1	Not reject	Stable	Reject	11	1	Not reject	Stable	Reject
01.1.8	4	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Reject
01.1.9	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
01.2.1	3	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Not reject
01.2.2	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
02.1	10	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
03.1.2	2	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Reject
03.1.3	1	1	Not reject	Stable	Not reject	11	1	Not reject	Not stable	Reject
04.3.1	2	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Not reject
05.1.1	10	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
05.1.2	3	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Not reject
05.2.0	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
05.3.1	8	1	Not reject	Stable	Not reject	8	1	Not reject	Stable	Not reject
05.3.2	10	1	Not reject	Stable	Reject	12	1	Not reject	Not stable	Reject
05.4.0	2	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
05.5.1	10	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
05.5.2	10	1	Not reject	Stable	Reject	11	1	Not reject	Stable	Reject
05.6.1	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
06.1.2	10	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
07.2.1	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
08.2.0	10	1	Not reject	Stable	Reject	11	1	Not reject	Stable	Reject
09.1.1	9	1	Not reject	Stable	Reject	9	1	Not reject	Stable	Not reject
09.1.2	2	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Reject
09.1.3	11	1	Not reject	Stable	Reject	11	1	Not reject	Stable	Reject
09.2.1	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
09.3.1	12	1	Not reject	Stable	Not reject	12	1	Not reject	Stable	Not reject
09.3.2	10	1	Not reject	Stable	Not reject	11	1	Not reject	Stable	Not reject
09.3.3	12	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
09.3.4	10	1	Not reject	Stable	Reject	11	1	Not reject	Stable	Reject
09.4.5	1	1	Not reject	Stable	Not reject	5	1	Not reject	Stable	Not reject
12.1.2	12	1	Not reject	Stable	Not reject	11	1	Not reject	Stable	Not reject
12.1.3	11	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
12.3.1	11	1	Not reject	Stable	Reject	11	1	Not reject	Stable	Reject
12.3.2	12	1	Not reject	Not stable	Reject	12	1	Not reject	Stable	Reject

Notes: This table presents the causality tests from sanctions to WS-CPI positive structural breaks. Category indicates the COICOP (1999) category, Sanction type the type of sanctions used in the analysis, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Sanctions for the absence of causality from sanctions. The category names related to the COICOP (1999) reference numbers are available in Table 1.

The instability of the VAR model in one particular category (small electric household appliances) may signal a complex relationship between trade sanctions and the prices of small electric household appliances.

Financial sanctions have a much more considerable influence on WS-PSI trend shifts than trade sanctions. Table 5 shows that financial and trade sanctions cause WS-PSI trend shifts in 15 and 6 COICOP (1999) categories, respectively.

WS-PSI trend shifts in the following COICOP (1999) categories are also caused by trade sanctions: alcoholic beverages; small electric household appliances; small tools and miscellaneous accessories; information processing equipment; equipment for sport, camping, and open-air recreation; other articles of clothing and clothing accessories.

Table 5. Causality Analysis: Sanctions and WS-PSI Breaks

COICOP (1999) Category	Financial Sanctions					Trade Sanctions				
	VAR Lag	MIO	Resid	Unit Root	Sanctions	VAR Lag	MIO	Resid	Unit Root	Sanctions
01.1	8	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
01.1.2	12	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Not reject
01.1.3	5	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
01.1.4	11	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Not reject
01.1.8	2	1	Not reject	Stable	Not reject	2	1	Not reject	Stable	Not reject
01.1.9	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
01.2.1	2	1	Not reject	Stable	Reject	11	1	Not reject	Stable	Not reject
01.2.2	2	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Not reject
02.1	10	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
03.1.2	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
03.1.3	10	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
04.3.1	8	1	Not reject	Stable	Reject	11	1	Not reject	Stable	Not reject
05.1.1	3	1	Not reject	Stable	Not reject	2	1	Not reject	Stable	Not reject
05.1.2	4	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
05.2.0	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
05.3.1	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Not reject
05.3.2	4	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
05.4.0	12	1	Not reject	Not stable	Not reject	12	1	Not reject	Stable	Not reject
05.5.1	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
05.5.2	5	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
05.6.1	7	1	Not reject	Stable	Not reject	8	1	Not reject	Stable	Not reject
06.1.2	3	1	Not reject	Stable	Not reject	11	1	Not reject	Stable	Not reject
07.2.1	4	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Not reject
08.2.0	5	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
09.1.1	6	1	Not reject	Stable	Reject	1	1	Not reject	Stable	Not reject
09.1.2	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
09.1.3	8	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
09.2.1	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
09.3.1	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
09.3.2	8	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
09.3.3	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
09.3.4	2	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
09.4.5	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
12.1.2	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
12.1.3	12	1	Not reject	Stable	Reject	8	1	Not reject	Stable	Not reject
12.3.1	1	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject
12.3.2	3	1	Not reject	Stable	Not reject	1	1	Not reject	Stable	Not reject

Notes: This table presents the causality tests from sanctions to WS-PSI structural breaks. Category indicates the COICOP (1999) category, Sanction type the type of sanctions used in the analysis, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Sanctions for the absence of causality from sanctions. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Our findings suggest that financial sanctions, compared to trade ones, have a comparatively more substantial impact on WS-PSI structural breaks than on WS-CPI. The effects of financial sanctions on WS-PSI are observed across a broad range of COICOP (1999) categories, indicating a pervasive influence on WS-PSI structural breaks. In contrast, the effects of trade sanctions are relatively limited in terms of the number of categories impacted.

A potential explanation for this pattern is that Russian retailers could find alternative sources for products affected by trade sanctions (Chupilkin et al., 2023), except for a limited set of categories listed above, while financial sanctions had a more substantial effect on purchasing decisions and on the desirable level of financial resources devoted to inventory.

Trade sanctions influence more excess WS-CPI than financial sanctions. Table 6 shows that trade and financial sanctions cause excess WS-CPI in 26 and 22 COICOP (1999) categories, respectively. In cases where causality could not be proven, the instability of unit roots in the VAR model was the contributing factor.

Table 6. Causality Analysis: Sanctions and Excess WS-CPI

COICOP (1999)	Financial Sanctions					Trade Sanctions				
Category	VAR Lag	MIO	Resid	Unit Root	Sanctions	VAR Lag	MIO	Resid	Unit Root	Sanctions
01.1	11	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
01.1.2	12	1	Not reject	Not stable	Reject	12	1	Not reject	Not stable	Reject
01.1.3	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
01.1.4	12	2	Not reject	Stable	Reject	12	2	Not reject	Stable	Reject
01.1.8	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
01.1.9	12	2	Not reject	Not stable	Reject	12	2	Not reject	Not stable	Reject
01.2.1	5	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
01.2.2	9	2	Not reject	Stable	Reject	9	2	Not reject	Stable	Reject
02.1	11	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
03.1.2	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
03.1.3	8	1	Not reject	Stable	Reject	12	1	Not reject	Not stable	Reject
04.3.1	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
05.1.1	12	1	Not reject	Not stable	Reject	12	1	Not reject	Stable	Reject
05.1.2	12	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
05.2.0	12	1	Not reject	Not stable	Reject	12	1	Not reject	Not stable	Reject
05.3.1	11	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
05.3.2	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
05.4.0	5	1	Not reject	Stable	Reject	8	1	Not reject	Stable	Reject
05.5.1	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
05.5.2	12	2	Not reject	Not stable	Reject	12	2	Not reject	Not stable	Reject
05.6.1	12	2	Not reject	Not stable	Reject	10	2	Not reject	Stable	Reject
06.1.2	12	2	Not reject	Stable	Reject	12	2	Not reject	Stable	Reject
07.2.1	12	2	Not reject	Not stable	Reject	12	2	Not reject	Not stable	Reject
08.2.0	12	1	Not reject	Not stable	Reject	12	1	Not reject	Stable	Reject
09.1.1	11	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
09.1.2	2	1	Not reject	Stable	Reject	9	1	Not reject	Stable	Reject
09.1.3	11	1	Not reject	Stable	Reject	10	1	Not reject	Stable	Reject
09.2.1	12	1	Not reject	Not stable	Reject	12	1	Not reject	Stable	Reject
09.3.1	12	1	Not reject	Not stable	Reject	12	1	Not reject	Stable	Reject
09.3.2	11	2	Not reject	Not stable	Reject	12	2	Not reject	Not stable	Reject
09.3.3	12	2	Not reject	Not stable	Reject	12	1	Not reject	Not stable	Reject
09.3.4	12	1	Not reject	Stable	Reject	12	1	Not reject	Stable	Reject
12.1.2	11	1	Not reject	Stable	Reject	9	1	Not reject	Stable	Reject
12.1.3	11	1	Not reject	Stable	Reject	11	1	Not reject	Not stable	Reject
12.3.1	12	1	Not reject	Not stable	Reject	12	1	Not reject	Not stable	Reject
12.3.2	12	2	Not reject	Not stable	Reject	12	2	Not reject	Not stable	Reject

Notes: This table presents the causality tests from sanctions to excess WS-CPI. Category indicates the COICOP (1999) category, Sanction type the type of sanctions used in the analysis, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Sanctions for the absence of causality from sanctions. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Tables 7 and 8 report the results from Toda and Yamamoto (1995) causality tests for financial- and trade-related sanctions' effects on the exchange and interest rates. In all cases, the test validates the presence of a causal effect from sanctions to disruptions in the exchange rate and interest rate, and the VAR estimation results are stable with the absence of autocorrelation in their residuals.

In Appendix B (Tables 11 to 13), we report the results from our Toda and Yamamoto (1995) causality tests for the exchange rate effects on each COICOP

Table 7. Causality Analysis: Sanctions and the Exchange Rate

SB	Sanction type	VAR Lag	MIO	Resid	Unit Root	Sanctions
All	Financial	10	1	Not reject	Stable	Reject
All	Trade	12	1	Not reject	Stable	Reject
Increase	Financial	11	1	Not reject	Stable	Reject
Increase	Trade	11	1	Not reject	Stable	Reject

Notes: This table presents the causality tests from sanctions to currency exchange. SB indicates the type of structural break (only positive or all), Sanction type the type of sanctions used in the analysis, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Sanctions for the absence of causality from sanctions.

Table 8. Causality Analysis: Sanctions and the Interest Rate

SB	Sanction type	VAR Lag	MIO	Resid	Unit Root	Sanctions
All	Financial	12	1	Not reject	Stable	Reject
All	Trade	12	1	Not reject	Stable	Reject

Notes: This table presents the causality tests from sanctions to interest rate. SB indicates the type of structural break (only positive or all), Sanction type the type of sanctions used in the analysis, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Sanctions for the absence of causality from sanctions.

(1999) category regarding WS-CPI positive breaks, WS-PSI breaks, and excess WS-CPI.

Table 11 (Appendix B) shows that abrupt positive exchange rate changes cause abrupt positive changes in WS-CPI across 27 COICOP (1999) categories, suggesting that the exchange rate contributes to price movements in various product categories. Interestingly, when comparing the impact of abrupt positive exchange rate changes to that of financial sanctions, we found that the former had a slightly lower but still considerable effect on abrupt positive changes in WS-CPI.

These findings shed light on the significance of exchange rate dynamics in driving WS-CPI dynamics. Understanding the causal relationship between exchange rate fluctuations and WS-CPI can provide valuable insights for policymakers to assess and forecast the effects of financial and trade sanctions.

Table 12 (Appendix B) highlights that exchange rate dynamics may cause WS-PSI changes across a subset of COICOP (1999) categories. Specifically, abrupt exchange rate changes, encompassing positive and negative shifts, cause abrupt changes in WS-PSI in 11 COICOP (1999) categories. This implies that fluctuations in the exchange rate can significantly impact the inventory of goods within these specific categories.

A noteworthy finding is that the impact of exchange rate changes on WS-PSI changes was observed to be slightly smaller, though still substantial, compared to that of financial sanctions. However, it is worth noting that the causal effect of exchange rate changes on WS-PSI changes was found to be more widespread than the impact of trade sanctions. These findings highlight the crucial role of exchange rate fluctuations in influencing changes in stocks of products.

Table 13 (Appendix B) shows that abrupt positive changes in the exchange rate cause excess WS-CPI for 13 COICOP (1999) categories, providing new insights into the transmission channels of exchange rate fluctuations.

Notably, the effect of abrupt positive changes in the exchange rate on excess WS-CPI variations is smaller than that of trade or financial sanctions. The causal effect of exchange rate movements on excess WS-CPI was found to be less pronounced than the effects of sanctions, highlighting the complex relationship between exchange rates, sanctions, and excess WS-CPI.

Finally, Appendix B (Tables 14 to 16) shows the results from our Toda and Yamamoto (1995) causality tests for the interest rate effects on each COICOP (1999) category regarding WS-CPI positive breaks, WS-PSI breaks, and excess WS-CPI. We can see that breaks in the interest rates are connected with WS-CPI positive breaks in 19 COICOP (1999) categories, with WS-PSI breaks in 14 categories, and with excess inflation in 16 categories. Overall, the effects of interest rate breaks seem comparable to the effects of exchange rate breaks.

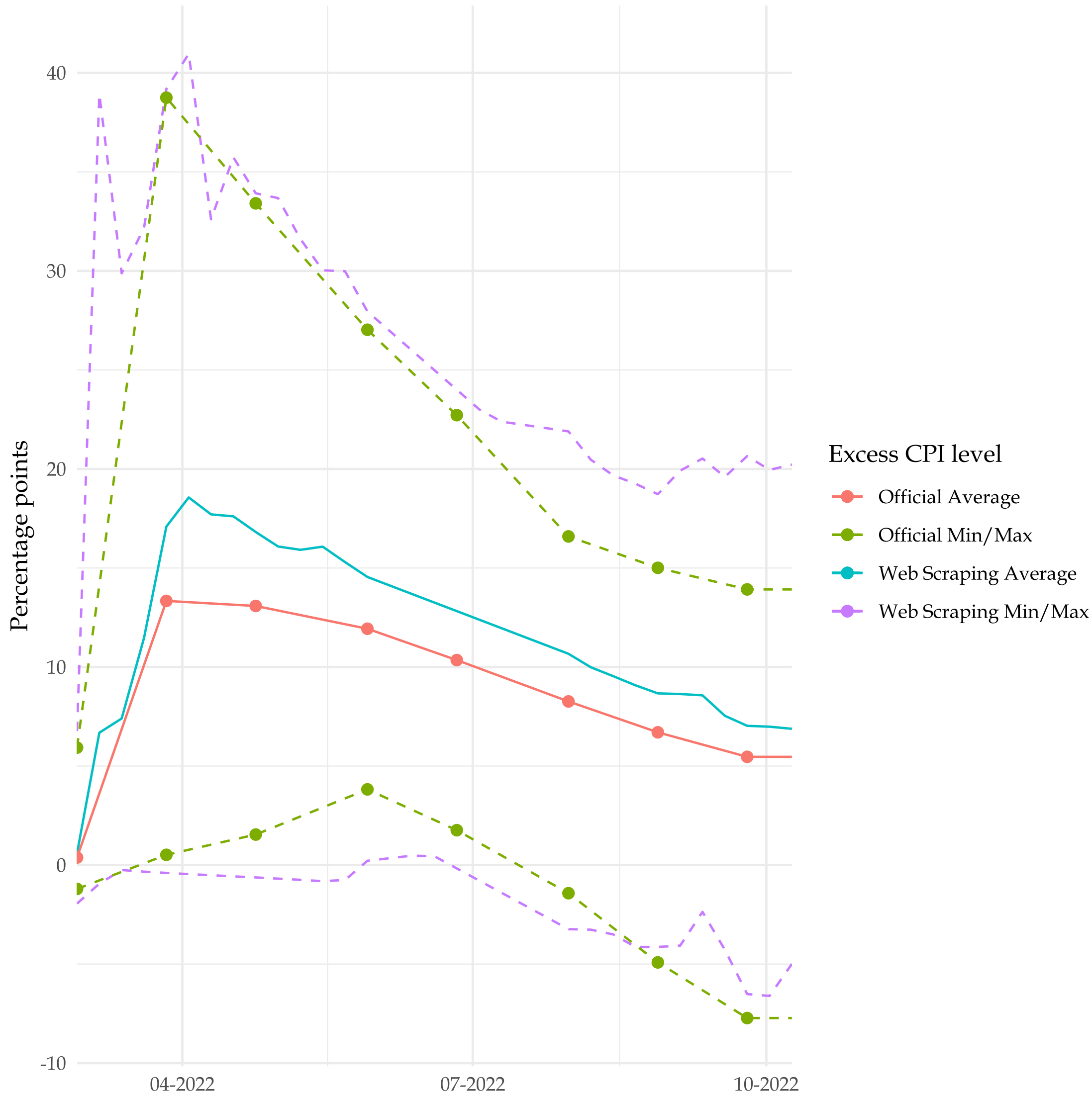
It was impossible to assess the potential interrelation between exchange rate and interest rate breaks in either direction since the TY VAR unit roots were not stable.

Figure 6 shows the difference between the average measured WS-CPI level and its projection based on the pre-war trend for all COICOP (1999) categories we collected each week, together with the minimum and maximum impact. We consider this difference ”excess WS-CPI”, as it signals that the prices we collect deviated from their precedent trend. We also calculate the same indicators on monthly official CPI values, defining it as ”excess CPI”.

We note that excess WS-CPI peaked at about 18% in April 2022. It then steadily declined to just below 7% in October 2022. On average, we measure the excess WS-CPI level for Russia at 11.7% for each COICOP (1999) category after the sanctions. In comparison, the average excess CPI calculated on official data is only 8.7%, with a value of 5.5% at the end of September 2022. In our analysis, the excess WS-CPI level is consistently above the excess measured on official data, averaging 2.3% more for each COICOP (1999) category. These are simple averaging values across COICOP (1999) categories, and should not be confused with an aggregate CPI or WS-CPI.

The observed attenuation of sanctions’ impact on consumer prices aligns with existing literature in the field. For instance, Huynh et al. (2022) demonstrate that

Figure 6. Excess CPI and the Average Effect of Sanctions



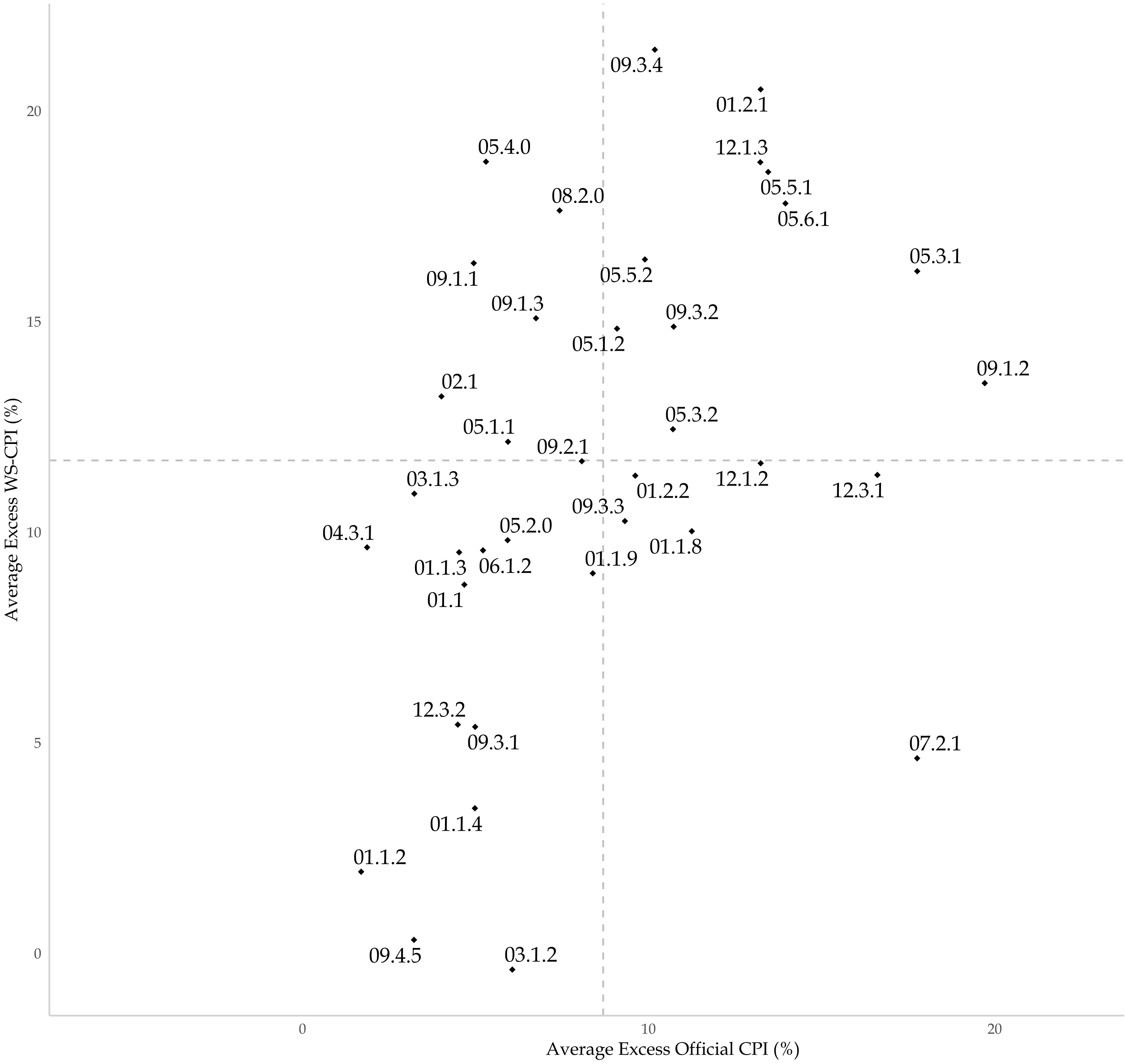
Notes: The dashed lines represent the maximum and minimum impact across all COICOP (1999) categories, which can belong to different categories over time.

Russian firms, having experienced sanctions following the Crimea invasion in 2014, exhibited a degree of preparedness, suggesting a potential mechanism that mitigated the impact of subsequent sanctions. Furthermore, Gaur et al. (2023) show how firms employ adaptation strategies to limit the effects of international sanctions.

Moving the analysis to a more granular level, we compare excess CPI and WS-CPI for each COICOP (1999) category. Figure 7 presents each COICOP (1999) category according to these two metrics. While most categories show a similar path, there are some outliers. Spare parts and accessories for personal transport equipment (07.2.1) category shows a much higher excess in official CPI than in

WS-CPI, while - to a lesser extent - Telephone and telefax equipment (08.2.0), Information processing equipment (09.1.2), and Equipment for the reception, recording, and reproduction of sounds and pictures (09.1.1) show the opposite pattern.

Figure 7. Excess Official CPI and Excess WS-CPI by COICOP (1999) category



Notes: The dashed lines represent the average Excess Official CPI and WS-CPI across COICOP (1999) categories. The category names related to the COICOP (1999) reference numbers are available in Table 1.

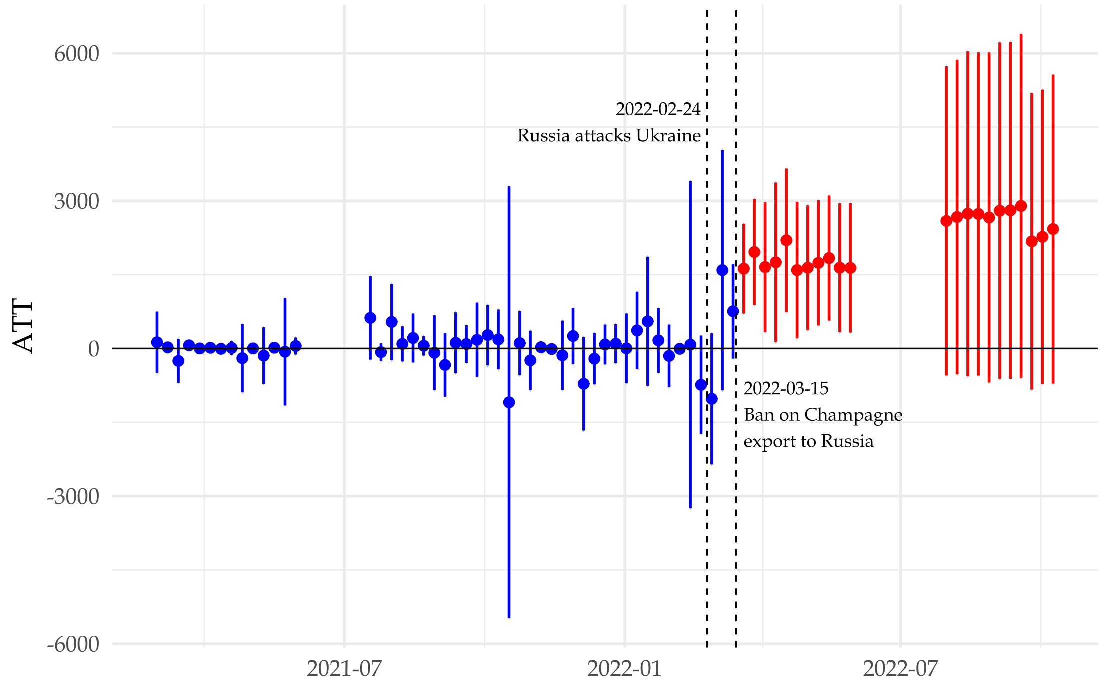
We check for correlations between excess official CPI and excess WS-CPI in absolute values and ranking across COICOP (1999) categories, using Pearson's correlation in the first case and Spearman's rank correlation in the second. In both cases, we use a two-sided test with the null hypothesis being the absence of correlation. Correlation tests to examine the relationship between excess official CPI and excess WS-CPI show a significant positive correlation between the two variables. Pearson's correlation coefficient yielded a value of 0.411 (p-value: 0.012), indicating a significant positive association. Similarly, Spearman's rank correlation coefficient yielded a value of 0.498 (p-value: 0.002), further supporting this significant and positive relationship.

In summary, we conclude that excess official CPI and excess WS-CPI present a significant and substantial correlation both in terms of quantity of impact and identification of the most impacted categories.

4.5 Champagne and Prosecco

Results from our DiD analysis show a significant treatment effect on the price of Champagne in contrast to Prosecco in the weeks immediately after the imposition of the ban on Champagne export. However, after July 2022, the effect appears to no longer be statistically significant. Figure 8 shows the DiD analysis of sanctions effects on Champagne prices.

Figure 8. Effects of Sanctions on Champagne Prices

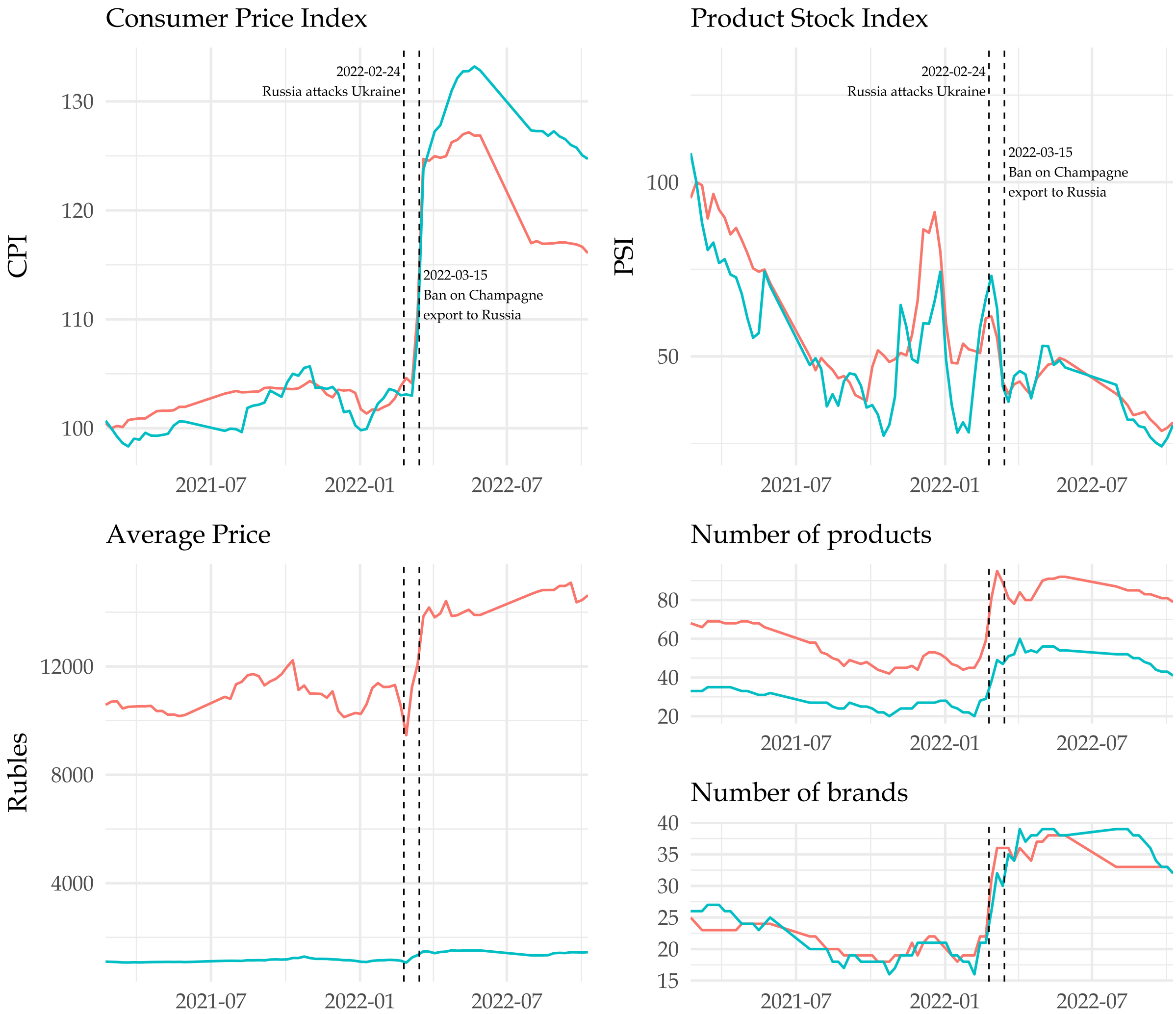


Notes: ATT indicates the average treatment effect on the treated for the price of Champagne in rubles. Time points are colored in blue before the ban on Champagne export and red afterward. Vertical lines represent the 95% confidence interval for ATT.

The descriptive statistics presented in Figure 9 show a substantial increase in Champagne and Prosecco price indices after the imposition of sanctions on

Champagne. Prosecco, which was not directly sanctioned, exhibits a more pronounced price escalation than Champagne. However, it is crucial to underscore that the average price of Champagne is approximately ten times higher than that of Prosecco.

Figure 9. Champagne Price and Product Stock Indices



Notes: Red and blue lines denote data from web scraping for Champagne and Prosecco, respectively.

Concerning product availability, Figure 9 shows that the WS-PSI for both products increased before the start of the full-scale war, subsequently maintaining a level below historical averages. In contrast, the count of distinct individual products and brands witnessed a marked increase between the onset of the full-scale invasion and the imposition of sanctions on champagne. Following this period, the count stabilized at a level surpassing historical averages.

This suggests that the retailer expanded its product offerings with diverse items and suppliers yet concurrently maintained relatively low inventories for each. These findings support the assertion that the flow of sanctioned goods into Russia continued, potentially involving intermediate trade routes (Chupilkin et al., 2023).

4.6 Brand Origin and Sanction Effects

Classifications of products into sanctioned and nonsanctioned HS Codes was successfully achieved, with an average confidence score above 63%. A manual check on a random subset of products also confirmed the satisfactory classification performance.[9] Almost all COICOP (1999) categories are composed of a mix of sanctioned and nonsanctioned products, with the exception of photograpic and cinematographic equipment and optical instruments, where all products were classified as subject to sanctions. A detailed breakdown is presented in Figure 15 in Appendix D.

Manual classification of the brand origin, presented in Figure 10, shows that most of the products in the four selected COICOP (1999) categories belong to Russian brands. The three top foreign countries for brand origin are Italy, Germany, and China. A majority of products across categories is classified as subject to sanctions.

In Figure 11 we present the pattern of WS-CPI and WS-PSI for the four selected COICOP (1999) categories. WS-CPI for all imported products increased substantially after the start of the full-scale war and the resulting sanctions. Price growth for domestic brands was substantially lower, with the exception of nonsanctioned products in the Small electric household appliances category, which presented a WS-CPI growth roughly in line with imported products.

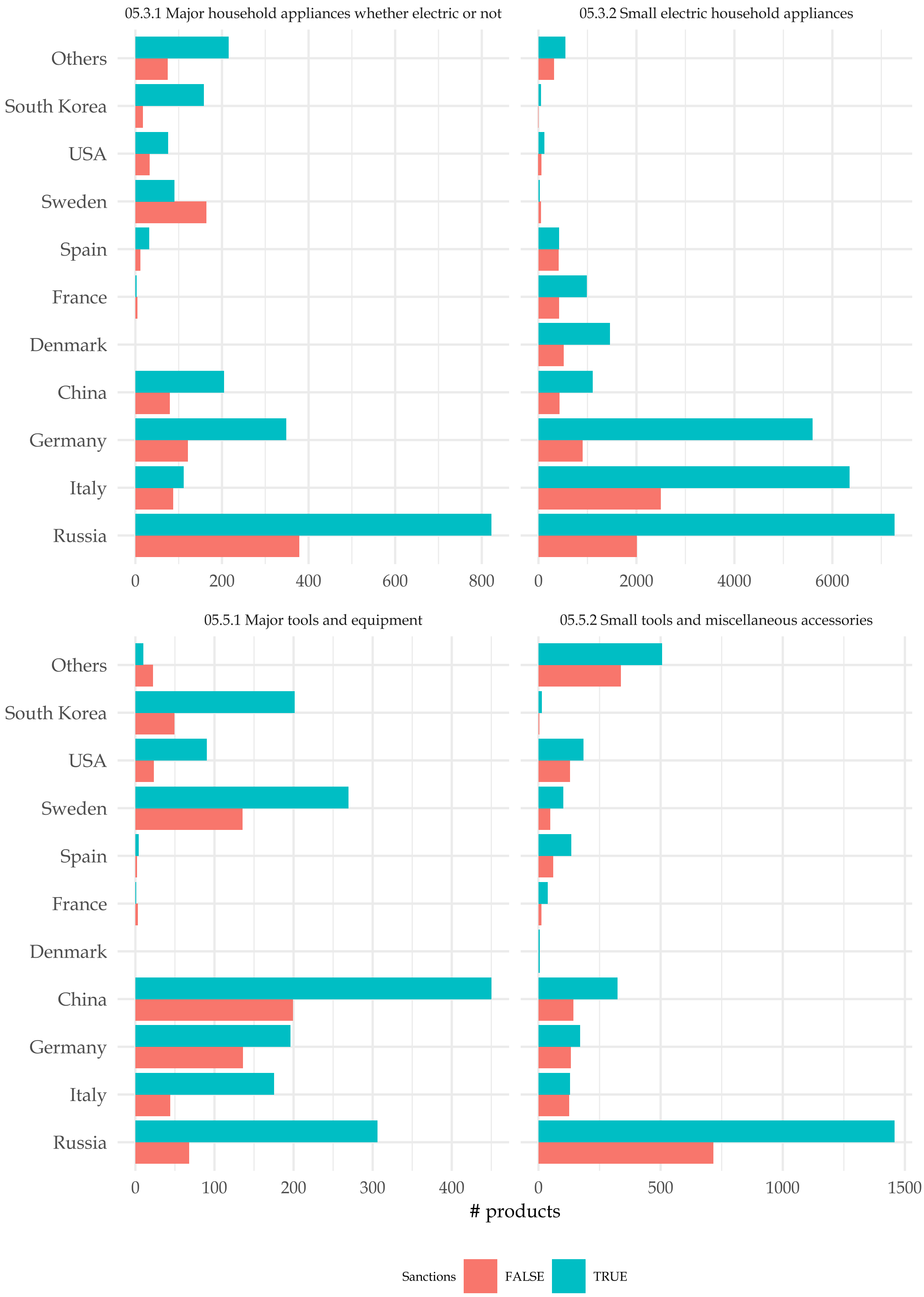
The dip in WS-CPI for imported Major household appliances and the corresponding peak in WS-PSI in March 2022 can be attributed to the temporary disappearance of imported products with high prices, and low stock levels in that period. The change of product mix, as noted in the methodology, had a disruptive impact on the TiClD index stability.

Another noteworthy pattern is the slow increase of WS-CPI for domestic products in the Small tools and miscellaneous equipment category. A potential explanation is a progressive pass-through of higher import cost for subcomponents and materials involved in the production of such products, while imported final products in the same category experienced a sudden shift towards higher price levels.

These findings corroborate our identification of the exchange rate as the

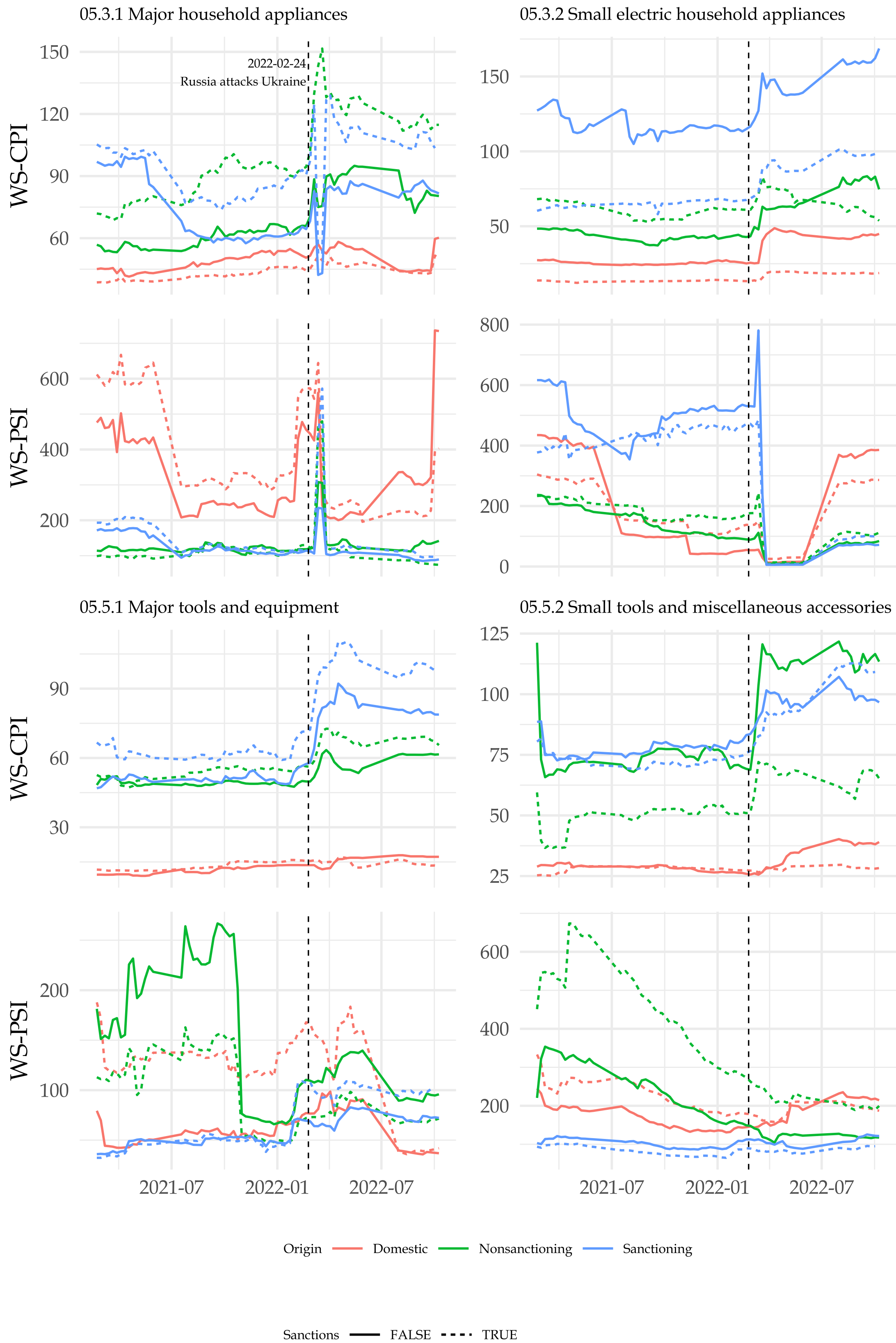
[9] Details for each COICOP (1999) category are presented in Figure 14 in Appendix D.

Figure 10. Brand origin



Notes: Blue and red bars indicate the number of sanctioned and nonsanctioned products, respectively, in each COICOP (1999) category divided by country of origin of the product brand.

Figure 11. WS-CPI and WS-PSI by brand origin and sanctions status



Notes: Dotted and solid lines indicate the index level for products subject and not subject to sanctions, respectively. Red indicates brands of Russian origin, while blue and green denote brands from sanctioning and nonsanctioning countries, respectively.

primary transmission channel of sanctions' effects on Russian consumer prices.

4.7 Comparison to Italian Prices

By comparing the price evolution of selected brands in Russia and Italy, as illustrated in Figure 12, we observe that, prior to the onset of the full-scale war in Ukraine, the price trends were quite similar in both countries. Our weekly indices, particularly for Barilla, Head & Shoulders, and Tampax, exhibit significant noise. This is primarily due to the reliance on a single retailer in each country for the data, making indices susceptible to short-term fluctuations caused by price discounts on specific brands.

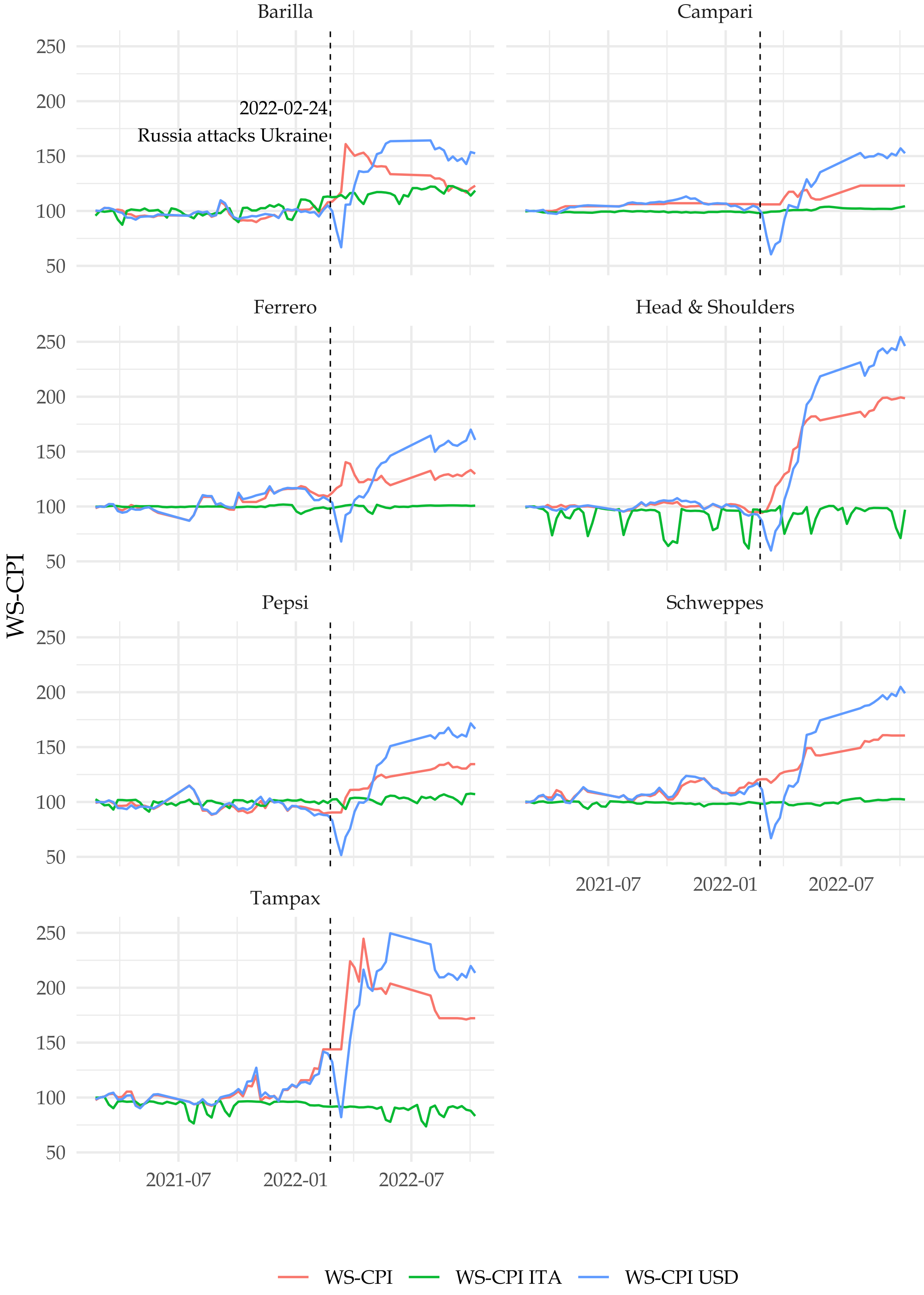
For most brands, there is a noticeable increase in prices denominated in rubles following the start of the war, which coincides with the depreciation of the ruble exchange rate. However, the strengthening of the ruble – indicated by the WS-CPI calculated with prices converted to US dollars surpassing the one calculated with ruble prices – resulted in a decrease in nominal prices only for Tampax and Barilla products. For other brands, prices remained elevated at the levels reached during the currency crisis.

In Italy, prices did not experience substantial inflation during the examined period, except for Barilla. Notably, Tampax prices in Italy actually experienced mild deflation, which can be attributed to the reduction of VAT on tampons implemented in January 2022.

The price evolution of Barilla follows a distinct pattern. In Russia, prices began to rise immediately after the onset of the war, following the depreciation of the Russian ruble exchange rate. However, as the exchange rate strengthened, Barilla's prices decreased significantly. Conversely, in Italy, Barilla prices began to increase substantially after the war started, mostly due to the rise in grain prices caused by the conflict. By the end of the studied period, the relative price growth in domestic currency for both countries was substantially equivalent.

The qualitative insight we derive from this focus is that the impact on Russian consumer prices was more limited for products where Russia is a net exporter of the underlying commodities. This finding further reinforces our identification of the exchange rate as the primary transmission channel of sanctions to consumer prices. However, it is also important to note that the benefits from the strengthening of the exchange rate do not appear to have been substantially passed on to consumers.

Figure 12. Matching brand WS-CPI in Russia and Italy



Notes: Red and blue lines indicate the WS-CPI in Russia in local currency and with prices converted in US dollars, respectively. Green lines indicate WS-CPI in Italy. Base date for all indices is February 28, 2022.

5 Conclusion

This study emphasizes the critical importance of real-time monitoring of economic activity to inform evidence-based policy decisions. The examination of consumer price levels for various product categories in Russia reveals significant fluctuations and changes in trends after the invasion of Ukraine and the imposition of international sanctions.

Firstly, our analysis shows a substantial alignment between the WS-CPI and the official CPI figures for most COICOP (1999) categories, as determined by statistics computed over the entire analyzed period. However, this correspondence seems to have declined slightly but significantly for a considerable number of COICOP (1999) series following the onset of the war. These differences can be attributed to the increase in price volatility, which the official CPI methodology may fail to capture due to its limited data collection window. Overall, the WS-CPI can be considered an accurate proxy for the official CPI, and there are no evident signs of manipulation in the official figures.

Secondly, we highlight that waves of economic sanctions against Russia effectively disrupted the WS-CPI pattern for a large number of COICOP (1999) categories, effectively increasing the level of consumer prices above the previous long-term trend. The WS-PSI seems to have been impacted, but to a much lower extent. All our results point to the exchange rate as the main transmission channel between sanctions and consumer prices. The interest rate also appears to play a significant role in this transmission, albeit marginally less relevant than the exchange rate. There are multiple transmission channels that we are unable to control for, as is common in macroeconomic analysis. However, the complementary micro-level analysis corroborates our findings.

Finally, we provide an assessment of the impact of sanctions on WS-CPI levels. While we confirmed that the sanctions effectively disrupted the WS-CPI pattern, we show that the Russian economy is slowly absorbing the effect of sanctions and realigning with the pre-existing WS-CPI trend. Moreover, it seems the official CPI is marginally underreporting the impact of sanctions in terms of excess CPI level. In this case as well, the limited data collection window of the official CPI methodology seems to have impaired its capability to completely capture the evolution of consumer prices during a period characterized by extremely high price volatility.

Our economic modeling exercise presents a simplified representation of reality, and the data we used come from only a single large retail chain. The causality established through the Toda-Yamamoto test pertains to the concept of Granger causality, thus implying predictability rather than a conclusive causal relationship. Nevertheless, we offer a unique contribution to the existing literature by providing a flash analysis of consumer price levels and stock dynamics at a granular level, leveraging real-time web-scraped data.

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6 Appendix

A Model Validation Metrics: Full Sample

Table 9 shows the correlation coefficients of the official CPI and WS-CPI over the full sample. Table 10 shows the model validation metrics over the full sample.

Table 9. Correlation Analysis

Category	Correlation	p-value
01.1	0.97	0.00
01.1.2	0.99	0.00
01.1.3	0.98	0.00
01.1.4	0.99	0.00
01.1.8	0.98	0.00
01.1.9	0.99	0.00
01.2.1	0.97	0.00
01.2.2	0.99	0.00
02.1	0.97	0.00
03.1.2	-0.53	0.02
03.1.3	0.96	0.00
04.3.1	0.79	0.00
05.1.1	0.95	0.00
05.1.2	0.82	0.00
05.2.0	0.85	0.00
05.3.1	0.99	0.00
05.3.2	0.96	0.00
05.4.0	0.96	0.00
05.5.1	0.97	0.00
05.5.2	0.99	0.00
05.6.1	0.98	0.00
06.1.2	0.79	0.00
07.2.1	0.85	0.00
08.2.0	0.82	0.00
09.1.1	0.85	0.00
09.1.2	0.68	0.00
09.1.3	0.08	0.76
09.2.1	0.37	0.13
09.3.1	0.80	0.00
09.3.2	0.65	0.00
09.3.3	0.92	0.00
09.3.4	0.93	0.00
09.4.5	0.85	0.00
12.1.2	0.49	0.04
12.1.3	0.99	0.00
12.3.1	0.63	0.01
12.3.2	0.74	0.00

Notes: This table presents correlation coefficients between official CPI and WS-CPI for all dates, together with p-values for the null hypothesis of no correlation. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Table 10. Forecasting and Model Validation Analysis

Category	MAPE	SD APE	MALPE	SD ALPE	NSME
01.1	1.94	1.41	-0.92	2.24	0.91
01.1.2	1.06	0.89	-0.97	0.99	0.95
01.1.3	1.49	1.5	-0.40	2.10	0.92
01.1.4	1.54	0.98	1.29	1.30	0.95
01.1.8	3.48	2.49	-3.47	2.49	0.82
01.1.9	3.51	1.52	-3.44	1.69	0.86
01.2.1	1.90	2.65	1.10	3.09	0.90
01.2.2	1.17	0.79	0.15	1.43	0.98
02.1	4.02	5.17	3.95	5.22	-1.72
03.1.2	6.93	6.47	-6.93	6.47	-2.56
03.1.3	4.13	3.53	1.59	5.27	-0.72
04.3.1	10.59	5.22	-10.59	5.22	-0.90
05.1.1	2.69	2.29	-1.56	3.21	0.81
05.1.2	9.97	4.92	-9.96	4.93	-0.51
05.2.0	3.56	2.68	-1.66	4.20	0.51
05.3.1	1.96	1.64	-0.56	2.53	0.95
05.3.2	2.15	1.96	1.87	2.24	0.85
05.4.0	5.19	4.63	2.21	6.68	-0.18
05.5.1	4.73	5.37	4.54	5.54	0.28
05.5.2	1.67	1.48	0.42	2.23	0.93
05.6.1	4.09	2.62	-4.09	2.62	0.84
06.1.2	5.62	4.74	4.90	5.52	-5.54
07.2.1	11.77	10.31	-11.77	10.31	-0.19
08.2.0	7.75	4.66	-7.74	4.69	-1.72
09.1.1	5.51	4.34	-4.31	5.59	0.37
09.1.2	17.89	8.24	-17.89	8.24	-1.65
09.1.3	23.21	12.71	-23.17	12.79	-17.19
09.2.1	11.41	8.84	-10.72	9.70	-2.64
09.3.1	5.88	3.13	-5.88	3.13	-0.57
09.3.2	6.18	5.17	-4.06	7.05	0.01
09.3.3	3.23	3.10	-2.95	3.38	0.73
09.3.4	3.39	5.60	2.60	6.03	0.62
09.4.5	4.17	4.14	-3.50	4.74	-0.08
12.1.2	7.54	8.08	-6.03	9.33	-0.05
12.1.3	2.33	1.78	-2.33	1.78	0.95
12.3.1	11.34	8.10	-11.18	8.32	-0.60
12.3.2	6.12	3.54	-6.12	3.54	-0.85

Notes: This table presents the summary metrics for all dates. The category names related to the COICOP (1999) reference numbers are available in Table 1.

B Predictive Causality Analysis: Exchange and Interest Rates

Table 11 presents the results of the TY causality tests from positive structural breaks in the exchange rate to positive structural breaks in the WS-CPI. Table 12 presents the results of the TY causality tests from structural breaks in the exchange rate to structural breaks in the WS-PSI. Table 13 presents the results of the TY causality tests from positive structural breaks in the exchange rate to excess WS-CPI. Table 14 presents the results of the TY causality tests from structural breaks in the interest rate to positive structural breaks in the WS-CPI. Table 15 presents the results of the TY causality tests from structural breaks in the interest rate to structural breaks in the WS-PSI. Table 16 presents the results of the TY causality tests from structural breaks in the interest rate to excess WS-CPI.

C CPI Methodology: Rosstat Procedure

Rosstat performs price data collection for the CPI in Russia once per month, between the 21st and 25th day of the month, on a selected basket of products and services. Prices are collected in 282 cities, involving over 86,000 retail and services organizations. CPI for elementary aggregates is calculated using a unweighted Jevons index formula, and then aggregated using a weighted Laspeyres index formula which takes into account the expenditure shares as weights.

We calculated the CPI using a procedure that resembles the one described above. Since we do not know the exact day when Rosstat collected data in each month, we use the arithmetic mean of daily prices between the 21st and 25th day to represent the price of each product. Also, since we perform our calculations at a higher level of aggregation than Rosstat and we do not have information on expenditure shares or on the inclusion of specific products in the official basket, we assign equal weights to all products in a COICOP (1999) category. We call this measure RWS-CPI.

Figure 13 illustrates our results for selected categories, including the WS-CPI calculated using the TPD index formula and the official CPI as references. The patterns of the different indices are substantially coherent, and the index calculated with the TPD formula seems to better approximate official data.

We calculate MAPE and MALPE of RWS-CPI versus our references for all COICOP (1999) categories, in order to analytically assess the potential impact of the different CPI methodologies. As expected, the results presented in Table 17 confirm that there is virtually no impact from the change in index calculation methodology. MAPE and MALPE compared to the WS-CPI are less than +/-5% in 30 and 31 cases, respectively. The categories where there is less adherence are

Table 11. Causality Analysis: Exchange Rate Positive Breaks and WS-CPI Positive Breaks

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1	5	1	Not reject	Stable	Reject
01.1.2	3	1	Not reject	Stable	Reject
01.1.3	6	1	Not reject	Stable	Reject
01.1.4	12	1	Not reject	Stable	Reject
01.1.8	2	1	Not reject	Stable	Reject
01.1.9	10	1	Not reject	Stable	Reject
01.2.1	2	1	Not reject	Stable	Reject
01.2.2	1	1	Not reject	Stable	Not reject
02.1	12	1	Not reject	Stable	Reject
03.1.2	1	1	Not reject	Stable	Not reject
03.1.3	1	1	Not reject	Stable	Not reject
04.3.1	4	1	Not reject	Stable	Reject
05.1.1	12	1	Not reject	Not stable	Reject
05.1.2	1	1	Not reject	Stable	Reject
05.2.0	1	1	Not reject	Stable	Not reject
05.3.1	11	1	Not reject	Stable	Not reject
05.3.2	10	1	Not reject	Stable	Reject
05.4.0	5	1	Not reject	Stable	Not reject
05.5.1	12	1	Not reject	Stable	Reject
05.5.2	10	1	Not reject	Stable	Reject
05.6.1	12	1	Not reject	Stable	Reject
06.1.2	7	1	Not reject	Stable	Reject
07.2.1	11	1	Not reject	Stable	Reject
08.2.0	12	1	Not reject	Stable	Not reject
09.1.1	11	1	Not reject	Stable	Reject
09.1.2	1	1	Not reject	Stable	Not reject
09.1.3	12	1	Not reject	Stable	Reject
09.2.1	12	1	Not reject	Stable	Reject
09.3.1	12	1	Not reject	Stable	Reject
09.3.2	8	1	Not reject	Stable	Not reject
09.3.3	11	1	Not reject	Stable	Reject
09.3.4	12	1	Not reject	Stable	Reject
09.4.5	12	1	Not reject	Stable	Reject
12.1.2	11	1	Not reject	Stable	Reject
12.1.3	12	1	Not reject	Stable	Reject
12.3.1	12	1	Not reject	Stable	Reject
12.3.2	6	1	Not reject	Stable	Reject

Notes: This table presents the causality tests from exchange rate positive structural breaks to WS-CPI positive structural breaks. Category indicates the COICOP (1999) category, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Exchange rate for the absence of causality from exchange rate positive structural breaks. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Table 12. Causality Analysis: Exchange Rate Breaks and WS-PSI Breaks

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1	1	1	Not reject	Stable	Not reject
01.1.2	10	1	Not reject	Stable	Reject
01.1.3	4	1	Not reject	Stable	Not reject
01.1.4	10	1	Not reject	Stable	Reject
01.1.8	1	1	Not reject	Stable	Not reject
01.1.9	1	1	Not reject	Stable	Not reject
01.2.1	12	1	Not reject	Stable	Not reject
01.2.2	11	1	Not reject	Stable	Not reject
02.1	12	1	Not reject	Stable	Reject
03.1.2	1	1	Not reject	Stable	Not reject
03.1.3	9	1	Not reject	Stable	Reject
04.3.1	12	1	Not reject	Stable	Reject
05.1.1	4	1	Not reject	Stable	Not reject
05.1.2	12	1	Not reject	Stable	Not reject
05.2.0	1	1	Not reject	Stable	Not reject
05.3.1	12	1	Not reject	Stable	Not reject
05.3.2	5	1	Not reject	Stable	Reject
05.4.0	12	1	Not reject	Stable	Not reject
05.5.1	1	1	Not reject	Stable	Not reject
05.5.2	3	1	Not reject	Stable	Not reject
05.6.1	12	1	Not reject	Stable	Not reject
06.1.2	12	1	Not reject	Stable	Not reject
07.2.1	4	1	Not reject	Stable	Not reject
08.2.0	1	1	Not reject	Stable	Not reject
09.1.1	3	1	Not reject	Stable	Not reject
09.1.2	1	1	Not reject	Stable	Not reject
09.1.3	9	1	Not reject	Stable	Reject
09.2.1	4	1	Not reject	Stable	Reject
09.3.1	4	1	Not reject	Stable	Not reject
09.3.2	9	1	Not reject	Stable	Reject
09.3.3	6	1	Not reject	Stable	Reject
09.3.4	4	1	Not reject	Stable	Not reject
09.4.5	1	1	Not reject	Stable	Not reject
12.1.2	1	1	Not reject	Stable	Not reject
12.1.3	5	1	Not reject	Stable	Reject
12.3.1	1	1	Not reject	Stable	Not reject
12.3.2	4	1	Not reject	Stable	Not reject

Notes: This table presents the causality tests from exchange rate structural breaks to WS-PSI structural breaks. Category indicates the COICOP (1999) category, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Exchange rate for the absence of causality from exchange rate structural breaks. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Table 13. Causality Analysis: Exchange Rate and Excess WS-CPI

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1	12	1	Not reject	Not stable	Reject
01.1.2	12	1	Not reject	Not stable	Reject
01.1.3	11	1	Not reject	Stable	Reject
01.1.4	12	2	Not reject	Not stable	Reject
01.1.8	11	1	Not reject	Stable	Reject
01.1.9	10	2	Not reject	Stable	Reject
01.2.1	12	1	Not reject	Not stable	Reject
01.2.2	12	2	Not reject	Not stable	Reject
02.1	12	1	Not reject	Stable	Reject
03.1.2	12	1	Not reject	Stable	Not reject
03.1.3	2	1	Not reject	Stable	Reject
04.3.1	12	1	Not reject	Not stable	Reject
05.1.1	12	1	Not reject	Not stable	Reject
05.1.2	10	1	Not reject	Stable	Reject
05.2.0	10	1	Not reject	Not stable	Reject
05.3.1	12	1	Not reject	Stable	Reject
05.3.2	12	1	Not reject	Not stable	Reject
05.4.0	12	1	Not reject	Not stable	Reject
05.5.1	12	1	Not reject	Stable	Reject
05.5.2	10	2	Not reject	Not stable	Reject
05.6.1	11	2	Not reject	Not stable	Reject
06.1.2	8	2	Not reject	Stable	Reject
07.2.1	7	2	Not reject	Stable	Reject
08.2.0	12	1	Not reject	Not stable	Reject
09.1.1	12	1	Not reject	Stable	Reject
09.1.2	12	1	Not reject	Not stable	Reject
09.1.3	12	1	Not reject	Stable	Reject
09.2.1	12	1	Not reject	Not stable	Reject
09.3.1	11	1	Not reject	Not stable	Reject
09.3.2	12	2	Not reject	Not stable	Reject
09.3.3	12	1	Not reject	Not stable	Reject
09.3.4	12	1	Not reject	Not stable	Reject
12.1.2	12	1	Not reject	Stable	Reject
12.1.3	11	1	Not reject	Not stable	Reject
12.3.1	10	1	Not reject	Stable	Not reject
12.3.2	12	2	Not reject	Not stable	Reject

Notes: This table presents the causality tests from exchange rate positive structural breaks to excess WS-CPI. Category indicates the COICOP (1999) category, Sanction type the type of sanctions used in the analysis, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Exchange rate for the absence of causality from exchange rate positive structural breaks. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Table 14. Causality Analysis: Interest Rate Breaks and WS-CPI Positive Breaks

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1	4	1	Not reject	Stable	Reject
01.1.2	6	1	Not reject	Stable	Reject
01.1.3	6	1	Not reject	Stable	Reject
01.1.4	6	1	Not reject	Stable	Reject
01.1.8	4	1	Not reject	Stable	Reject
01.1.9	6	1	Not reject	Stable	Reject
01.2.1	1	1	Not reject	Stable	Reject
01.2.2	1	1	Not reject	Stable	Not reject
02.1	12	1	Not reject	Stable	Reject
03.1.2	1	1	Not reject	Stable	Not reject
03.1.3	12	1	Not reject	Not stable	Reject
04.3.1	6	1	Not reject	Stable	Reject
05.1.1	12	1	Not reject	Not stable	Reject
05.1.2	1	1	Not reject	Stable	Reject
05.2.0	1	1	Not reject	Stable	Not reject
05.3.1	12	1	Not reject	Stable	Not reject
05.3.2	10	1	Not reject	Stable	Reject
05.4.0	6	1	Not reject	Stable	Not reject
05.5.1	6	1	Not reject	Stable	Reject
05.5.2	12	1	Not reject	Not stable	Reject
05.6.1	11	1	Not reject	Stable	Reject
06.1.2	6	1	Not reject	Stable	Reject
07.2.1	12	1	Not reject	Stable	Not reject
08.2.0	10	1	Not reject	Stable	Not reject
09.1.1	12	1	Not reject	Stable	Not reject
09.1.2	1	1	Not reject	Stable	Not reject
09.1.3	9	1	Not reject	Stable	Not reject
09.2.1	12	1	Not reject	Not stable	Reject
09.3.1	12	1	Not reject	Stable	Not reject
09.3.2	9	1	Not reject	Stable	Not reject
09.3.3	10	1	Not reject	Stable	Reject
09.3.4	11	1	Not reject	Stable	Reject
09.4.5	12	1	Not reject	Stable	Reject
12.1.2	12	1	Not reject	Stable	Not reject
12.1.3	12	1	Not reject	Stable	Reject
12.3.1	10	1	Not reject	Stable	Not reject
12.3.2	6	1	Not reject	Stable	Reject

Notes: This table presents the causality tests from interest rate structural breaks to WS-CPI positive structural breaks. Category indicates the COICOP (1999) category, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Exchange rate for the absence of causality from exchange rate positive structural breaks. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Table 15. Causality Analysis: Interest Rate Breaks and WS-PSI Breaks

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1	1	1	Not reject	Stable	Not reject
01.1.2	10	1	Not reject	Stable	Reject
01.1.3	4	1	Not reject	Stable	Not reject
01.1.4	10	1	Not reject	Stable	Reject
01.1.8	1	1	Not reject	Stable	Not reject
01.1.9	1	1	Not reject	Stable	Not reject
01.2.1	12	1	Not reject	Stable	Not reject
01.2.2	11	1	Not reject	Stable	Not reject
02.1	12	1	Not reject	Stable	Reject
03.1.2	1	1	Not reject	Stable	Not reject
03.1.3	9	1	Not reject	Stable	Reject
04.3.1	12	1	Not reject	Stable	Reject
05.1.1	4	1	Not reject	Stable	Not reject
05.1.2	12	1	Not reject	Stable	Not reject
05.2.0	1	1	Not reject	Stable	Not reject
05.3.1	12	1	Not reject	Stable	Not reject
05.3.2	5	1	Not reject	Stable	Reject
05.4.0	12	1	Not reject	Stable	Not reject
05.5.1	1	1	Not reject	Stable	Not reject
05.5.2	3	1	Not reject	Stable	Not reject
05.6.1	12	1	Not reject	Stable	Not reject
06.1.2	12	1	Not reject	Stable	Not reject
07.2.1	4	1	Not reject	Stable	Not reject
08.2.0	1	1	Not reject	Stable	Not reject
09.1.1	3	1	Not reject	Stable	Not reject
09.1.2	1	1	Not reject	Stable	Not reject
09.1.3	9	1	Not reject	Stable	Reject
09.2.1	4	1	Not reject	Stable	Reject
09.3.1	4	1	Not reject	Stable	Not reject
09.3.2	9	1	Not reject	Stable	Reject
09.3.3	6	1	Not reject	Stable	Reject
09.3.4	4	1	Not reject	Stable	Not reject
09.4.5	1	1	Not reject	Stable	Not reject
12.1.2	1	1	Not reject	Stable	Not reject
12.1.3	5	1	Not reject	Stable	Reject
12.3.1	1	1	Not reject	Stable	Not reject
12.3.2	4	1	Not reject	Stable	Not reject

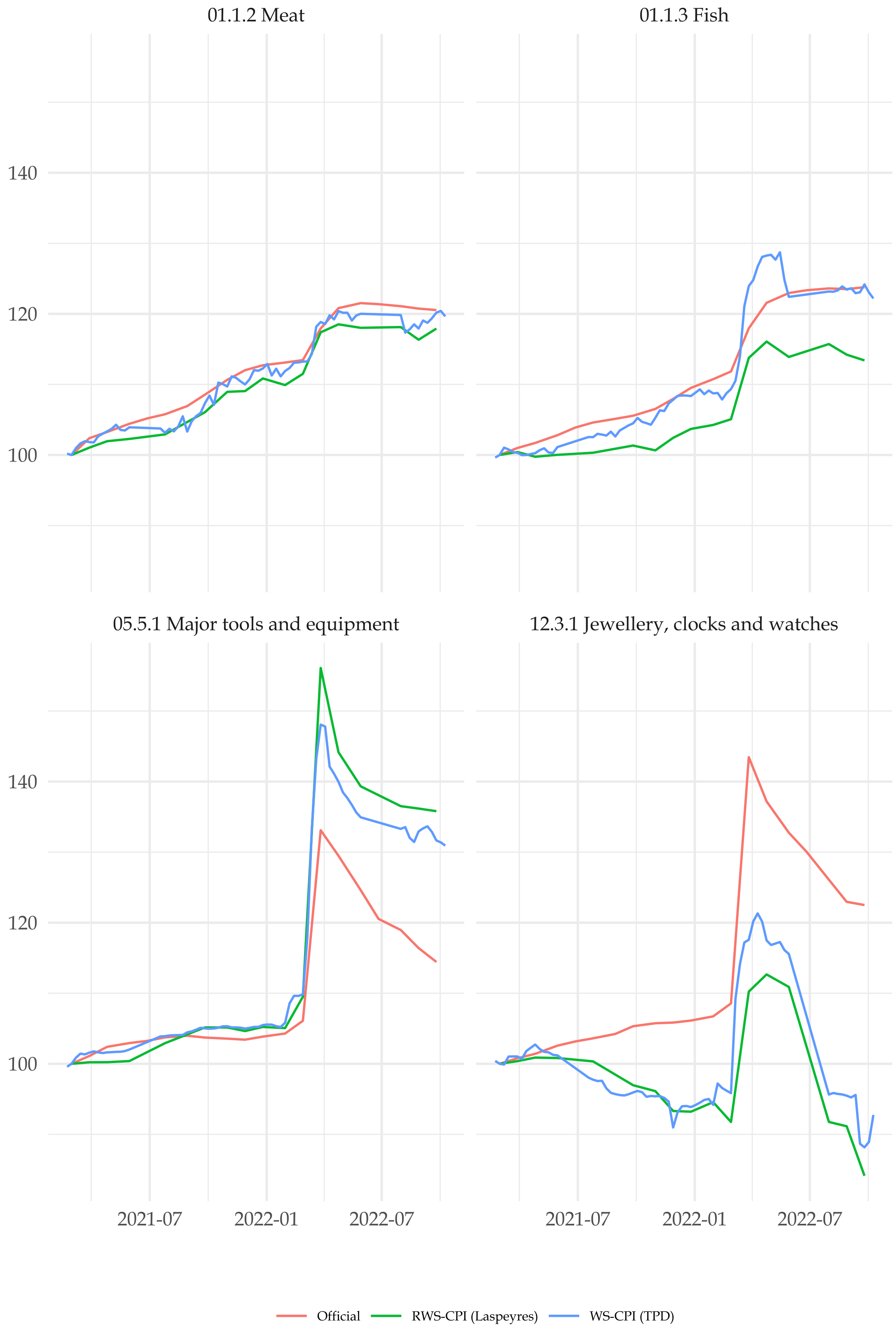
Notes: This table presents the causality tests from interest rate structural breaks to WS-PSI structural breaks. Category indicates the COICOP (1999) category, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Exchange rate for the absence of causality from exchange rate structural breaks. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Table 16. Causality Analysis: Interest Rate and Excess WS-CPI

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1	12	1	Not reject	Stable	Reject
01.1.2	7	1	Not reject	Stable	Reject
01.1.3	12	1	Not reject	Stable	Reject
01.1.4	12	2	Not reject	Not stable	Reject
01.1.8	12	1	Not reject	Stable	Reject
01.1.9	12	2	Not reject	Not stable	Reject
01.2.1	12	1	Not reject	Not stable	Reject
01.2.2	11	2	Not reject	Not stable	Reject
02.1	12	1	Not reject	Stable	Reject
03.1.2	12	1	Not reject	Stable	Not reject
03.1.3	12	1	Not reject	Not stable	Reject
04.3.1	12	1	Not reject	Not stable	Reject
05.1.1	12	1	Not reject	Stable	Reject
05.1.2	12	1	Not reject	Not stable	Reject
05.2.0	12	1	Not reject	Not stable	Reject
05.3.1	12	1	Not reject	Stable	Reject
05.3.2	12	1	Not reject	Stable	Reject
05.4.0	12	1	Not reject	Not stable	Reject
05.5.1	12	1	Not reject	Not stable	Reject
05.5.2	11	2	Not reject	Stable	Reject
05.6.1	11	2	Not reject	Not stable	Reject
06.1.2	12	2	Not reject	Not stable	Reject
07.2.1	12	2	Not reject	Not stable	Reject
08.2.0	10	1	Not reject	Stable	Not reject
09.1.1	10	1	Not reject	Stable	Reject
09.1.2	9	1	Not reject	Stable	Not reject
09.1.3	10	1	Not reject	Stable	Reject
09.2.1	12	1	Not reject	Stable	Reject
09.3.1	12	1	Not reject	Stable	Reject
09.3.2	8	2	Not reject	Not stable	Reject
09.3.3	7	1	Not reject	Stable	Reject
09.3.4	12	1	Not reject	Stable	Reject
12.1.2	12	1	Not reject	Stable	Reject
12.1.3	12	1	Not reject	Not stable	Reject
12.3.1	12	1	Not reject	Stable	Not reject
12.3.2	12	2	Not reject	Not stable	Reject

Notes: This table presents the causality tests from interest rate structural breaks to excess WS-CPI. Category indicates the COICOP (1999) category, Sanction type the type of sanctions used in the analysis, VAR Lag for the lag selection from AIC, MIO for the maximum integration order, Resid, for the absence of autocorrelation in VAR residuals, Unit Root for the presence of unit root in the VAR, and Exchange rate for the absence of causality from exchange rate positive structural breaks. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Figure 13. CPI Methodologies: Comparison



Notes: Official data are denoted in red. Data from web scraping are represented in blue and green for calculations with TPD and Laspeyres index formulas, respectively.

also the ones where WS-CPI has a relatively poor performance in tracking the official CPI, as presented in Table 10. The tracking of RWS-CPI versus the official CPI for those categories seems even worse.

The RWS-CPI somehow adheres less to the official CPI, with MAPE and MALPE less than +/-5% in 15 and 20 cases, respectively. In this respect, RWS-CPI seems to track official CPI less than WS-CPI calculated using the TPD index formula. Significant differences may arise between official CPI and indices derived from web scraping data when their aggregation and weighting methodologies are inconsistent (Strasser et al., 2023)

D Sanction Status and Product Category

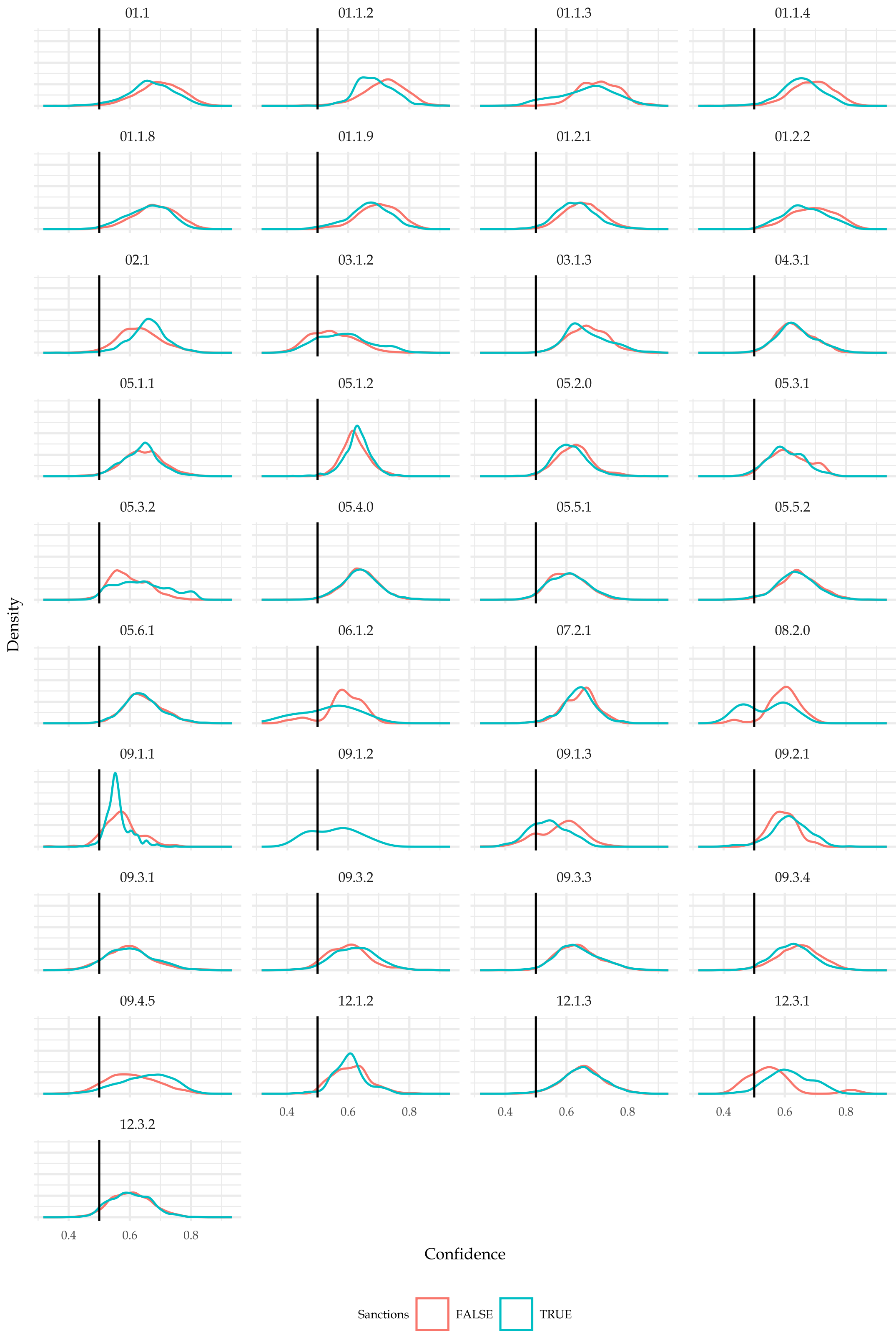
Figure 14 presents the density distribution of confidence scores for the classification of all our products, divided into different COICOP (1999) categories, in HS Codes affected or not affected by sanctions. Figure 15 shows the distribution of sanctioned and nonsanctioned products in each COICOP (1999) category.

Table 17. Causality Analysis: Interest Rate and Excess WS-CPI

COICOP (1999)	*WS-CPI (TPD)*		*Official CPI*	
Category	**MAPE**	**MALPE**	**MAPE**	**MALPE**
01.1	3.79	3.79	4.73	4.73
01.1.2	1.20	1.20	1.99	1.99
01.1.3	4.44	4.42	4.65	4.65
01.1.4	1.06	1.06	1.13	-0.19
01.1.8	6.41	6.37	9.91	9.87
01.1.9	3.87	3.70	6.98	6.98
01.2.1	3.22	-2.12	4.94	-3.23
01.2.2	0.67	0.47	1.05	0.28
02.1	1.69	0.23	3.35	-3.35
03.1.2	1.68	-1.00	7.12	7.12
03.1.3	3.84	-3.82	5.42	-5.14
04.3.1	1.51	-0.08	11.42	11.42
05.1.1	3.09	2.88	5.14	4.59
05.1.2	13.42	13.42	24.56	24.56
05.2.0	1.98	1.34	5.55	2.98
05.3.1	2.60	2.50	3.53	3.08
05.3.2	2.54	-2.41	4.22	-4.12
05.4.0	1.16	-0.62	5.86	-2.48
05.5.1	1.58	-0.75	5.69	-4.94
05.5.2	2.03	1.46	2.12	1.15
05.6.1	2.66	-0.57	3.93	3.74
06.1.2	1.41	1.14	3.88	-3.24
07.2.1	2.60	2.57	18.05	18.05
08.2.0	3.24	1.21	10.65	10.65
09.1.1	14.04	-1.90	20.06	3.13
09.1.2	9.83	-9.83	12.61	12.61
09.1.3	13.78	-12.75	21.43	21.43
09.2.1	11.78	11.71	25.12	25.12
09.3.1	2.27	2.21	8.73	8.73
09.3.2	4.77	2.95	9.10	8.15
09.3.3	2.62	2.59	6.12	6.05
09.3.4	3.75	3.71	4.61	1.38
09.4.5	5.33	-5.27	4.13	-1.24
12.1.2	3.80	3.80	11.09	11.09
12.1.3	3.39	1.29	3.86	3.73
12.3.1	2.52	1.64	15.50	15.50
12.3.2	3.71	2.93	9.72	9.72

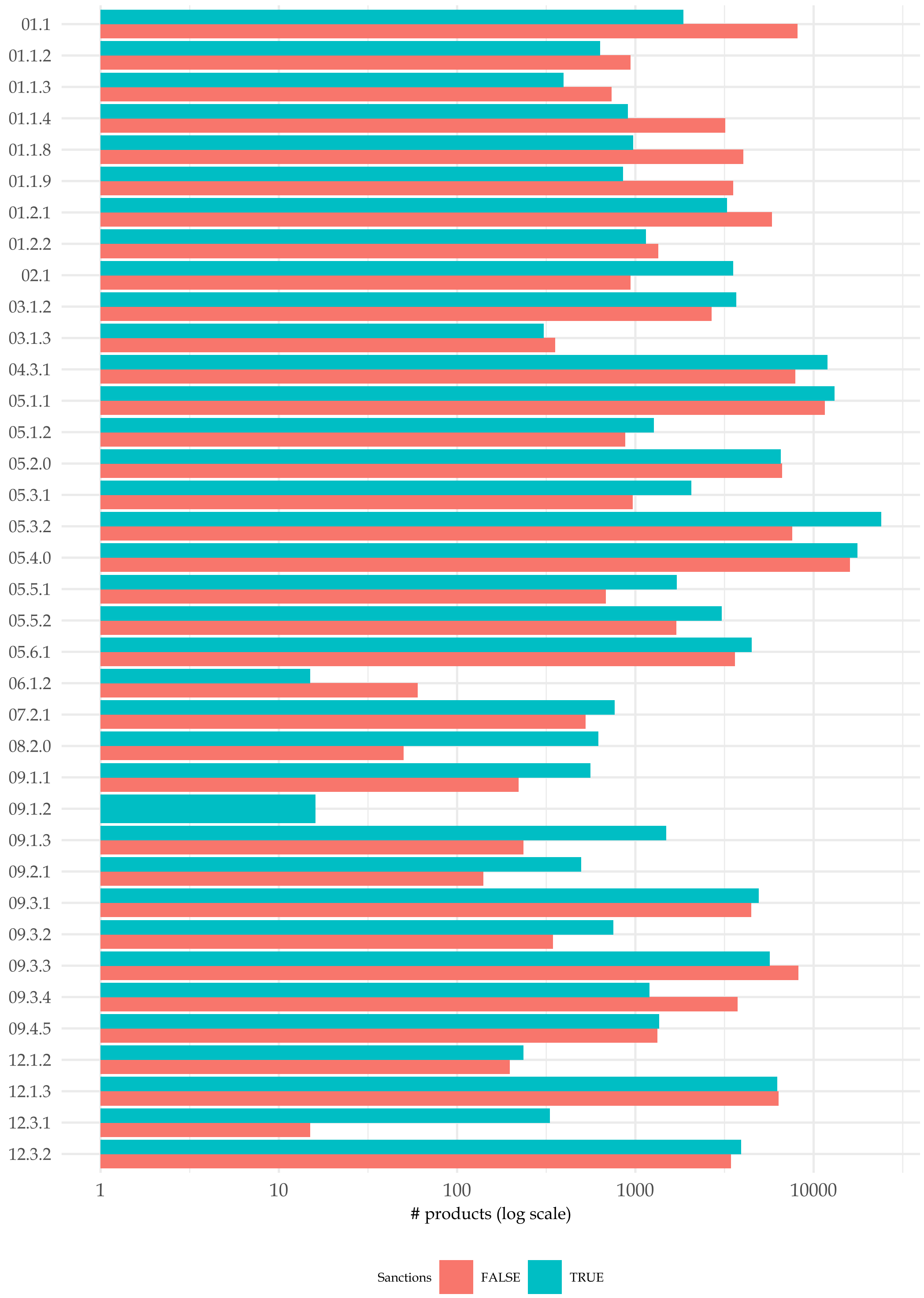
Notes: This table presents the summary model validation metrics for the CPI calculated on our web scraping data according to the Rosstat methodology against the WS-CPI calculated with the TPD formula and the official CPI. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Figure 14. Sanctions status classification confidence



Notes: Blue and red lines indicate classification confidence for individual products in sanctioned and nonsanctioned categories, respectively. The category names related to the COICOP (1999) reference numbers are available in Table 1.

Figure 15. Sanctioned products by COICOP (1999) category



Notes: Blue and red bars indicate the number of sanctioned and nonsanctioned products in each COICOP (1999) category, respectively. The category names related to the COICOP (1999) reference numbers are available in Table 1.

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