Sanctions and Russian Online Prices*

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Abstract

Daily data obtained through web scraping allows for generating high-frequency signals for evaluating the effects of policies and supporting decision-making processes. The reliability of official price data in Russia has been questioned during the ongoing war in Ukraine. This study investigates the influence of this war and related sanctions on Russian official and online prices for different categories of goods before and after the war. A disaggregated analysis of price patterns finds significant differences in price dynamics following Russia's invasion of Ukraine, which may be attributed to the following international economic sanctions. In light of disruptions to traditional channels related to conflicts and political decisions, we contribute to the growing literature using online data to monitor real-time economic activity, price, and quantity evolution. We highlight the importance of political events and economic sanctions on pricing and consumption patterns in times of war and show that sanctions may have contributed to an average excess CPI level for Russia of 11.7%.

Keywords: Political economy, Online prices, Product availability, Sanctions, Conflict, Russia, Ukraine.

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

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1 Introduction

The reliability of Russian official price data has been questioned during the war in Ukraine. We investigate the influence of the war in Ukraine and related sanctions on the Russian Consumer Price Index (CPI). To do so, we examine whether online and official prices are aligned and whether this alignment changed for different categories of goods before and during the war. Price patterns in a disaggregated view help us determine whether the decompositions (components, trends) are aligned, whether the war in Ukraine and its consequences have impacted pricing trends in Russia, and whether official data were reliable.

Sanctions can increase the costs of imports, reduce the availability of certain products, and create inflationary pressures. Sanctions can also disrupt the supply chain, lead to devaluation and increased volatility of the local currency (Wang et al., 2019), and increase the costs of borrowing 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). However, disruption of domestic price evolution may effectively impact welfare, especially for the population with less disposable income and limited means to adjust their earnings according to the new price dynamic.

International political and economic orders may influence the evolution of sanctions. The increasing importance of sanctions, extensively used as a foreign policy tool in the post-World War II era, accentuates the necessity of understanding how targets react to them, with their economic and security consequences (Morgan et al., 2023). However, these actions taken by one state or collectively to influence another state's behavior typically restrict foreign trade, either of all goods or specific commodities, and have had mixed results (Davis and Engerman, 2003). Financial sanctions as a component of international diplomacy, could effectively restrict entities from accessing financial assets or services, and limit access to the international payment system, including the SWIFT network (Cipriani et al., 2023).

The imposition of severe international sanctions in response to Russia's invasion of Ukraine on February 24, 2022, represents a novel occurrence in the realm of contemporary economic history in terms of intensity and number of countries involved. Sanctions by US and EU affected about 19% of total Russian imports (Hausmann et al., 2022). The disruption to global supply chains resulting from these sanctions has been substantial, and the full extent of their impact is yet to be determined. Some studies estimate that the conflict in Ukraine caused a reduction of 1.5 percent in the global GDP level and led to a rise in global inflation of about 1.3 percentage points (Caldara et al., 2022). Additionally, there have been unprecedented calls for major corporations to take proactive measures amid the conflict, such as ceasing operations in Russia beyond the limitations imposed by sanctions (Sonnenfeld et al., 2023). According to other streams of research, sanctions caused a much more significant welfare loss in Russia than in the imposing countries (Hausmann et al., 2022).

The combination of economic sanctions, corporate actions, commodity prices, post-COVID19 economic stimulus, and exchange rate fluctuations have generated significant fluctuations in consumer prices in Russia and several other countries in the following months. In the context of the ongoing conflict, access to reliable information on economic indicators assumes a strategic importance beyond solely economic considerations. Monitoring the evolution of consumer price levels globally can provide insight into the strengths and weaknesses of both friendly and opposing countries, as well as the effectiveness of political decisions. In the case under examination, Russian authorities have already ceased the publication of several statistical indicators, raising concerns about the reliability of figures that are still publicly available (Starostina, 2022).

Our objective is to monitor CPI changes in Russia at various levels of granularity, using daily data obtained through web scraping. Web scraping is an automated method of extracting and structuring information from websites, becoming increasingly prevalent among National Statistical Institutes for calculating official price statistics (Eurostat, 2020). This approach enables the generation of high-frequency signals for evaluating the effects of policies and supporting decision-making processes at various levels.

Recent studies have established that changes in online prices are indicative of fluctuations in offline retail prices, and this has led to the recognition of the utility of online prices for constructing official CPIs (Harchaoui and Janssen, 2018), for providing accurate forecasts of official statistics (Aparicio and Bertolotto, 2020), and for anticipating official data releases (Jaworski, 2021; Macias et al., 2023). The Billion Prices Project at MIT 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).

The effectiveness and consequences of international sanctions have gained significant attention due to their frequent use as tools of international policymaking. Itskhoki and Mukhin (2023) establish Lerner symmetry as a benchmark to understand the impact of import and export sanctions on allocations and welfare. Our study builds upon their work by incorporating the timing of sanctions, interactions between trade and financial restrictions, and the effects of the financial sanctions, providing a comprehensive understanding of the implications of sanctions on pricing and consumption patterns in times of war. Specifically, we investigate the influence of the ongoing war in Ukraine and the subsequent international trade and financial sanctions on Russian official and online prices for different categories of goods, revealing significant differences in price dynamics. Our findings contribute to the growing literature on online data monitoring real-time economic activity and highlight the importance of political events and economic sanctions on pricing dynamics and consumption patterns.

Financial sanctions have emerged as powerful tools in the current geopolitical landscape, with implications for macroeconomic variables. Bianchi and Sosa-Padilla (2023) employ a graphical framework to examine the macroeconomic effects of financial sanctions, sovereign debt crises, and the fragmentation of capital flows. 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 evaluate policy effects, particularly the influence of the war in Ukraine and subsequent sanctions on pricing dynamics.

The use of economic sanctions as a foreign policy instrument has substantially increased since the post-World War II era. Morgan et al. (2023) adopt an interdisciplinary perspective to explore the historical evolution and patterns of economic sanctions, emphasizing their connection to the contemporaneous international political and economic orders. Our study aligns with their call for interdisciplinary research and contributes empirical insights to the discussion. By utilizing online data to monitor real-time economic activity, price dynamics, and quantity evolution, we contribute to the literature on alternative data sources to document price and product availability changes (Cavallo and Kryvtsov, 2023). Specifically, we provide evidence of the impact of the ongoing war in Ukraine and the subsequent international economic sanctions, demonstrating how they may have contributed to an average excess CPI level of 11.7% in Russia. These results highlight the disruptive effects of conflicts on traditional channels and the relevance of online data for monitoring economic activity during times of war.

Furthermore, academic research using online data to track economic activity and price evolution in real time intensified, particularly during the COVID19 (Jaworski, 2021; Hillen, 2021; Macias et al., 2023), since pandemic control policies severely impacted traditional data collection processes. Our contribution leverages a novel data source from web scraping the e-commerce website of a prominent Russian multichannel retailer. Our research aims to evaluate the accuracy of Russia's official CPI figures following the onset of the war, as well as the effect of sanctions on CPI and consumer product availability. As an initial step, we verify the consistency of our web-scraped data with official CPI figures before the start of the war. The availability of products is approximated by the number of units the retailer has in stock for each item.

The remainder of the paper is organized as follows. Section 2 describes the methodology used to analyze the data presented in Section 3. Section 4 presents the results, Section 5 draws key policy implications, and Section 6 concludes.

2 Methodology

2.1 Indexes Calculation

We selected a multilateral unweighted index method to calculate CPI levels from web scraping (WS-CPI), the time-product dummy (TPD) method, in order to reduce complexity and keep a consistent methodology with Product Stock Index from web scraping (WS-PSI) calculation. While the CPI is a familiar concept for economists, the WS-PSI is quite a novelty in the literature. This index is built according to the quantities available for sale of each product in each COICOP (1999) category. A higher WS-PSI means more products are available for sale, and the retailer's shelves are full, while a lower index may indicate shortages.

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

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

where, for each product aggregate, lnP_{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 them:

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

For the analysis of WS-PSI, we use the same methodology applied to product

[1] As noted in the literature (Melser, 2005; de Haan et al., 2021), TPD presents some limitations, since it implicitly adjusts for different quality across the sampled items and, in case of substantial lack of matching items across time, this implicit mechanism may degenerate in overfitting and bias. However, we selected this index calculation methodology due to the simplicity in addressing moderate fluctuations in the sampled products and the interruptions in data collection. The number of matching items across time is also substantial, preventing the degeneration noted above. Furthermore, being a multilateral index enables us to directly compare WS-CPI and WS-PSI levels at different times without any adjustment.

stock levels, such as

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

where, for each product aggregate, lnS_{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:

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

In both WS-CPI and WS-PSI, we use the period t_2 as a reference, corresponding to February 28, 2021, to facilitate matching with official CPI releases over time, excluding the relative dummy from the equation. Therefore, all $WS\text{-}CPI_t$ and $WS\text{-}PSI_t$ for $t \neq 2$ should be interpreted as level relative to the reference period. We selected an unweighted index method in order to reduce the computational burden. Unweighted index methodologies are also commonly used in price indexes for elementary aggregates by most National Statistic Institutes (International Monetary Fund et al., 2020)

2.2 Web Scraping and Official CPI

In this section, we augment the conventional cointegration-based time series model with additional metrics frequently employed in forecasting and model validation. The primary justification for this approach is twofold: first, official indexes are often released with a significant lag. Thus our WS-CPI metrics can be considered as "nowcasting" projections; second, the time series under examination are of relatively limited length (comprising only 20 monthly observations) and exhibit missing values and multiple regime shifts, which can pose challenges for standard econometric approaches aimed at validating cointegration. To this end, we have analyzed monthly CPI levels for both the web-scraped index and the official index and applied Kalman Smoothing (Gómez and Maravall, 1994) to our web-scraped index for imputation over periods where data collection was unavailable.[2]

2.2.1 Econometric Approach

To establish the validity of the relationship between our WS-CPI and the official CPI, we use a suite of tests drawn from recent literature that is capable of accommodating unknown fractional integration orders in the underlying time series, as many of our time series exhibit several regime shifts and are not found to be

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

stationary at any discrete level of differencing. This is a common characteristic among economic time series, as Nielsen and Shimotsu (2007) noted.

We use a set of different tests to validate the cointegration of our WS-CPI index with the official CPI in each of the COICOP (1999) categories under examination.

First, we leverage the pairwise test suggested by Robinson and Yajima (2002) and Nielsen and Shimotsu (2007) to validate that the two time series are integrated to the same order. The null hypothesis for this test is that the two time series have the same order of integration.

Secondly, we have performed the semiparametric test suggested by Marmol and Velasco (2004) on our time series. This test allows for consistent testing of the spurious regression hypothesis against the alternative of fractional cointegration without prior knowledge of the memory of the original series, their short-run properties, the cointegrating vector, or the degree of cointegration. The null hypothesis is the absence of cointegration between the time series under examination.

Finally, we have performed two further tests that provide a consistent estimate for the cointegration rank between our two time series.

The first one is introduced by Nielsen and Shimotsu (2007), and leverages the exact local Whittle estimator – first introduced by Shimotsu and Phillips (2005) – in order to provide a consistent estimate of the cointegration rank.

The second one, proposed by Zhao et al. (2019), leverages eigenanalysis to identify the cointegration rank between time series and relaxes most of the underlying hypothesis compared to other tests. The time series under analysis are allowed to be of different and unknown integration order, integer or fractional.

Unfortunately, our time series are relatively short, with only 20 monthly observations. The approaches we leverage have presented numeric validations for their test statistics for much larger samples, usually above 100 observations. To the best of our knowledge, there are no published applications of those methodologies with a small number of observations as in our case. Hence we complement the analysis with additional tools, performing the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979, 1981) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests (Kwiatkowski et al., 1992) on the differences between official CPI and WS-CPI levels for each COICOP (1999) category to check for their stationarity. Satisfying the stationarity hypothesis, combined with the Robinson and Yajima (2002) test, which warrants that the two time series have the same integration order, would also be an indicator of cointegration between the two time series (Engle and Granger, 1987). The KPSS test is suggested for checking ADF results on short time series like the ones we have, as the power of the ADF test is substantially reduced when the time series is relatively short (Arltová and Fedorová, 2016).

2.2.2 Forecasting and Model Validation

The set of tools from the fields of forecasting and model validation we use to evaluate the adherence between official data and data obtained through web scraping is presented in this section. Following Mayer and Butler (1993), we use a dimensionless metric, the modeling efficiency – a statistic based on the coefficient of determination – in order to compare the adherence between official data and data from web scraping. We use the Nash-Sutcliffe model efficiency (Nash and Sutcliffe, 1970), as suggested in Willmott and Matsuura (2012). We also compare the official vs. predicted (web scraping) plots for visual analysis of the differences.

The Nash-Sutcliffe modeling efficiency formula is

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

where E is the Nash-Sutcliffe coefficient of efficiency, n is the number of observations, P_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.

Although Mayer and Butler (1993) have a critical view towards other summary metrics, a wide body of literature (Rayer, 2007; Swanson, 2015) also consider other indicators as effective guidelines. Rayer (2007) suggests the use of the Mean Absolute Percentage Error (MAPE), which is the arithmetic mean of all Absolute Percentage Errors (APE), to estimate the accuracy, and the Mean Algebraic Percentage Error (MALPE), which is the arithmetic mean of all Algebraic Percentage Errors (ALPE), to estimate the bias. We prefer those metrics over other commonly used in the literature, such as the Root Mean Square Error, as a combined examination of MAPE and MALPE allows us to immediately perceive both accuracy and bias in our metrics. The difference between the MAPE-MALPE pair and alternative metrics is marginal in most cases (Rayer, 2007). We evaluate MAPE and MALPE results as Swanson (2015) suggested, using 5% for MAPE and $\pm 5\%$ for MALPE as limits for satisfactory performance.

Additionally, we perform a simple Student T-test (Gosset, 1908) to check the difference between MAPE and MALPE before and after the start of the war. While very simple, combined with the other tests it helps us to identify possible divergence in the pattern of the two time series after the event.

Finally, we analyze APE and ALPE using a Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) proposed by Zhao et al. (2019) to obtain a probability slope for its trend and identify potential change points that may signal a divergence in the underlying time series, particularly around the start of the war.

2.3 WS-CPI and WS-PSI Trend Changes

The next step in our analysis was the selection of a methodology for detecting changes in trends for the indexes we calculated on our data from web scraping according to equations 1 and 3. One crucial criterion is the robustness to missing values due to significant breaks in our time series. The selected model was 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 in our time series data, those 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:

$$y_i = S(t_i; \Theta_s) + T(t_i; \Theta_t) + \varepsilon_i, \tag{6}$$

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, which is then formalized as:

$$y_i = T(t_i; \Theta_t) + \varepsilon_i. \tag{7}$$

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:

$$T(t) = a_j + b_j t \text{ for } \tau_j \leq t < \tau_{j+1}, j = 0, ..., m \tag{8}$$

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.[3]

[3] 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, alternatively, 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 non-stationarity 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[4] 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 rate as a potential factor in the transmission channel between sanctions and prices and product inventories, we analyze exchange rate trend shifts using the BEAST model and perform additional TY causality tests to explore the interplay between sanctions, exchange rate shifts, WS-CPI and WS-PSI.

The effect of sanctions on exchange rate trend shifts is analyzed using TY

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.

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

causality tests to determine whether sanctions induced upward shifts exclusively or both upward and downward shifts in the exchange rate.[5] This analysis aims to ascertain whether upward shifts in the exchange rate resulting from sanctions correspond to excess WS-CPI and upward WS-CPI shift changes, allowing us to gain insights into the interconnectedness of exchange rates, sanctions, and prices. The connection between the exchange rate and WS-PSI upward and downward shifts resulting from sanctions is also analyzed with TY causality tests.

The resulting VAR equation is

$$y_t = A_1 y_{t-1} + ... + A_{p+dmax} y_{t-(p+dmax)} + CD_t + u_t, \tag{9}$$

where y_t is a vector with the value of the variables under examination for time t. The coefficient matrices $A_1...A_{p+dmax}$ are of dimension 2×2, 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 Breusch-Godfrey test (Breusch, 1978; Godfrey, 1978) on the VAR residuals. Additionally, we examined the VAR roots to confirm the stability of the model (Lütkepohl, 2005). Finally, we apply the Wald test to the sanctions coefficient in the $A_1...A_{p+dmax}$ coefficient matrices for each VAR equation, under the null hypothesis of no causal effects of the sanctions time series on the WS-CPI and WS-PSI probability of structural break time series. The Wald test uses the variance-covariance matrix from the VAR equation 9 in order to jointly test the significance of sanctions coefficients, calculated as

$$W = (\hat{\beta})'[V(\hat{\beta})]^{-1}(\hat{\beta}) \tag{10}$$

where $\hat{\beta}$ is the vector of coefficients related to the potential causing variable (sanctions), lagged effects on the potentially influenced variable (WS-CPI or WS-PSI break probability) extracted from the coefficients matrices $A_1...A_{p+dmax}$ from equation 9 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

Our 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 web scraping

[5] We express the exchange rate in units of local currency per US Dollar. An upward shift means the local currency is devaluating towards the US Dollar.

data is consistent with official figures.

3 Data

The dataset used for this paper has been collected via web scraping techniques. Data on consumer product prices have been collected daily from Your House (*tvoydom.ru*), a major Russian multichannel retailer since February 15, 2021. This retailer operates an e-commerce website that ships products across Russia and a network of physical shops in major cities mostly in Western Russia. This retailer belongs to a conglomerate group with over $3 billion in annual revenue. While its product portfolio is mostly oriented toward middle-class customers, this retailer also carries a significant share of the economy and luxury goods. Approximately 1 million shoppers visit the company's retail establishments every month, and the e-commerce website has over 500 thousand monthly visitors. Two significant data collection breaks originated from website structure updates that caused web scraping routine failures. The first break started on May 27, 2021, and ended on July 12, 2021. The second one started on May 26, 2022, and ended on July 24, 2022.

We capture the name, category, price, and quantity of each product in the retailer's warehouse. As presented by the multichannel retailer, we map commercial categories to the Classification of Individual Consumption by Purpose, 1999 version (COICOP, 1999). We selected COICOP (1999) amongst all classification standards since OECD uses the same for reporting Russian CPI data, and - to the best of our knowledge - also the Federal Service of State Statistics in Russia uses the same taxonomy. Table 1 reports the Level 4 categories where we collected data, 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 can see an excellent coverage of categories in the furnishing and household equipment, as well as goods for recreation and culture. Food is also well represented, together with goods for personal care. All in all, we currently have almost 8 million weekly records as an aggregation of the collected daily ones and about 250.000 unique items. Daily web scraping routines collect about 120.000 records every day.

We collected data regarding sanctions from the Peterson Institute for International Economics (Bown, 2023) and further elaborated. We selected sanctions related to import, export, and financial activities from a set of countries and classified those sanctions according to the expected impact magnitude (high or low).

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	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	Non-durable 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

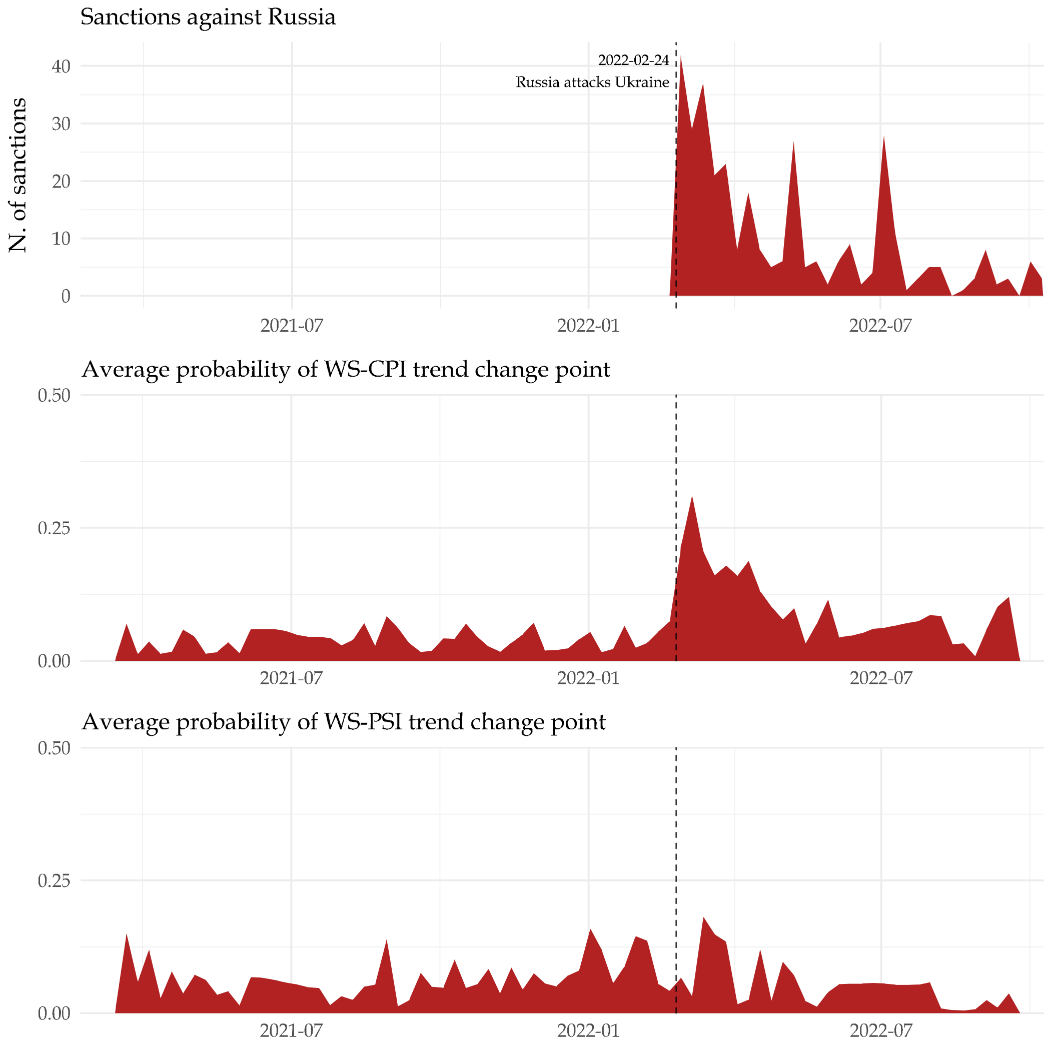
Notes: * denotes items in commercial categories that span over more than one Level 4 COICOP (1999) category and have been listed in the appropriate Level 3 classification. The second column reports the unique items, and the third column the total records available.

4 Results

4.1 WS-CPI and WS-PSI Dynamics

Figure 1 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 1. Sanctions and Break in Trends



Notes: data from web scraping and (Bown, 2023).

Figures 2 and 3 present the results for selected COICOP (1999) categories for WS-CPI and WS-PSI as examples of the dynamics we uncovered. Results for WS-CPI are compared with official CPI figures, while we have no other source of information for WS-PSI.

Figure 2. Consumer Price Index

Notes: Data from web scraping is 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 3. Product Stock Index

Notes: Data from web scraping is 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 2 shows that after Russia invaded Ukraine on February 24, 2022, online and official meat prices significantly increased together, with slight differences between online and official prices. 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 2 also shows that the gap between online and official major tools and equipment prices is even greater than for fish.

Furthermore, Figure 2 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 price levels available before the war, while the official CPI does not.

Figure 3 presents the evolution of product stocks over time. Overall, the availability of products decreased since the war started, except concerning 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 3 shows a long downward trend in the inventory that predates any hint of potential war. A peak appears around the New Year and the corresponding holiday period for meat and fish product availability, which resound with standard commercial practices in retail. However, the lack of more extended time series disallows disentangling seasonal variations from variations caused by sanctions.

However, the New 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 stocks also seems not related to prices (Figure 2), as prices declined from March-April 2022, along with the decrease in stocks (Figure 3).

4.2 Econometric Adherence Measures

Results presented in Table 2 show that several cointegration relationships exist between the official CPI and WS-CPI across the various COICOP (1999) categories we collected.

Only in 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 ADF test only confirms the stationarity of differences in 5 cases out of 37, while the KPSS test does not reject the null hypothesis of stationarity in any case.

Table 2. Econometric Analysis Summary

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

Notes: RY2022 stands for Robinson and Yajima (2002), where the null hypothesis is: time series are integrated of the same order. MV2004 stands for Marmol and Velasco (2004), where the null hypothesis 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.

These results indicate that, with a few exceptions in specific product categories, there is a strong correspondence between WS-CPI and official CPI over the complete analyzed period. This supports the reliability of 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.

4.3 Forecasting and Model Validation

Table 8 in Appendix A shows the forecasting results and model validation metrics over the full sample. In 21 cases out of 37 overall MAPE is below 5% and MALPE within $\pm 5\%$, which indicates a good tracking performance and the absence of relevant bias Swanson (2015), respectively.

In 14 cases, the Nash-Sutcliffe modeling efficiency scores above 0.8, indicating a satisfactory tracking performance between WS-CPI and the official CPI.

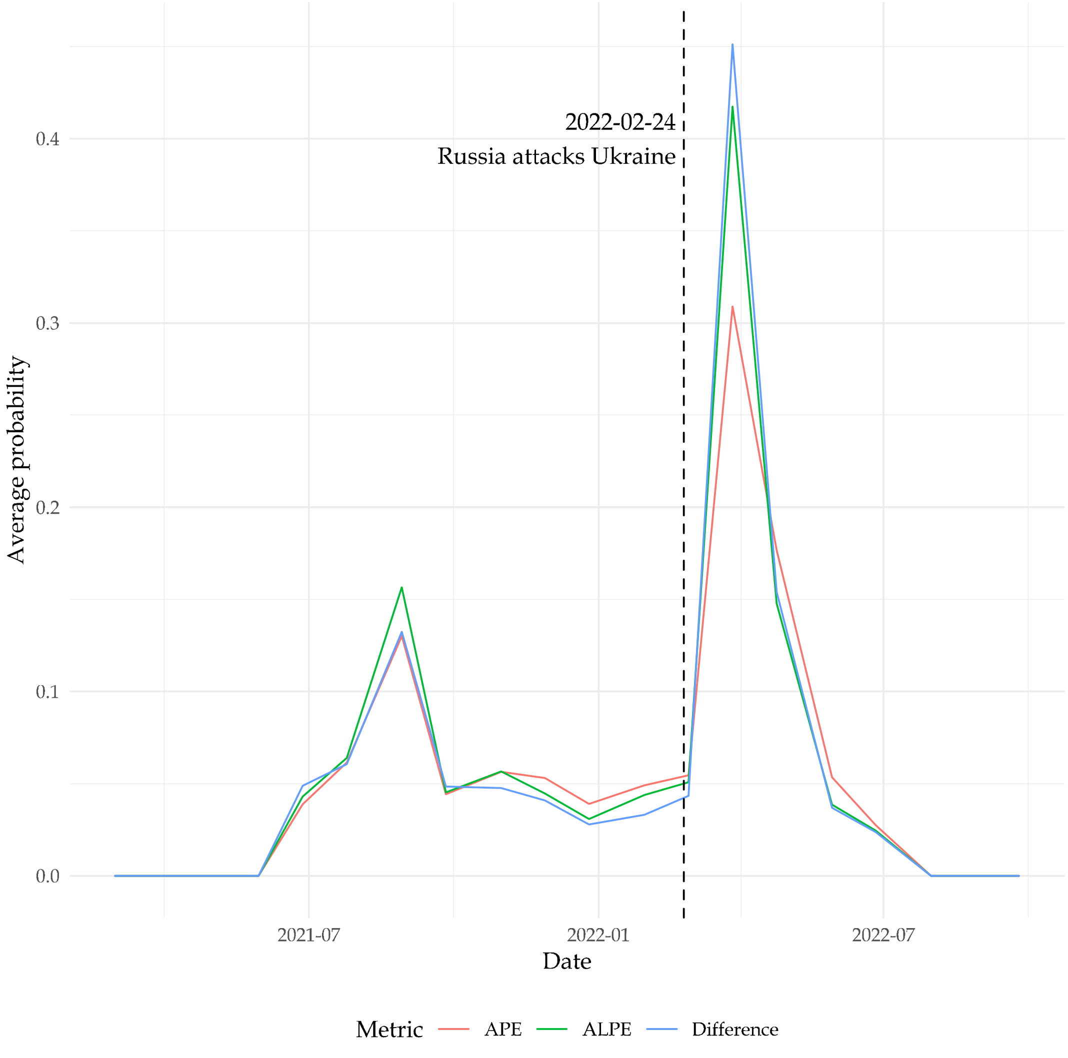
These results, combined with the previous findings in Section 4.2, establish that online prices are reliable sources of real-time CPI data throughout the analyzed period.

Figure 4 shows the average probability distribution for structural breaks in APE, ALPE and differences between web scraping and official CPI across all categories.

Table 3 shows the difference in web-scraped data tracking performance before and after the war started. At 95% confidence level we note that in 21 cases the tracking accuracy, measured by MAPE, degrades significantly, while in 18 cases we report a significant increase in bias, measured by MALPE. Before the war, MAPE was less than 5% for 28 series, and 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. Figure 3 shows the sudden increase in average breakpoint probability in MAPE, MALPE, and differences trends after the start of the war.

Whilst a perfectly possible explanation is that prices from our source - for some reason - became less representative of the overall Russian CPI level in certain (COICOP, 1999) categories after the start of the war, we cannot completely discount the possibility that official CPI failed to capture some of the prices evolutions that happened in that period.

Figure 4. Probability of Structural Break



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

Table 3. Pre- and Post-War Summary Metrics: Forecasting and Model Validation Analysis

COICOP (1999)	*Pre-War*				*Post-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	0.7	-0.73	0.93	0.58	0.38
01.1.3	1.27	0.75	-1.27	0.75	1.8	2.25	0.92	2.8	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	0
01.1.9	3.53	1.7	-3.53	1.7	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	0.9	-0.12	1.47	1.25	0.63	0.55	1.35	0.72	0.31
02.1	0.45	0.3	0.35	0.42	9.37	4.2	9.37	4.22	0	0
03.1.2	2.63	1.68	-2.63	1.68	13.37	5.47	-13.37	5.47	0	0
03.1.3	2.1	1.39	-2.1	1.39	7.18	3.63	7.14	3.73	0	0
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	0.3	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
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	0
05.5.1	0.88	0.61	0.56	0.93	10.51	3.74	10.51	3.74	0	0
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	9.6	5.12	9.6	5.12	0.01	0
07.2.1	4.54	4.17	-4.54	4.17	22.61	6.1	-22.61	6.1	0	0
08.2.0	7.63	5.28	-7.63	5.28	7.94	3.89	-7.9	3.98	0.88	0.9
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	0
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	0
09.3.2	5.81	3.33	-2.39	6.46	6.73	7.4	-6.55	7.58	0.75	0.22
09.3.3	3.29	2.96	-2.86	3.42	3.14	3.5	-3.1	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	-8.52	3	0	0
12.1.2	2.69	2.04	-2.44	2.35	14.82	8.36	-11.4	13.13	0	0.1
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	18.8	5.75	-18.8	5.75	0	0
12.3.2	4.28	3.49	-4.28	3.49	8.87	0.78	-8.87	0.78	0	0

Notes: We use 2022-02-24 as the cutoff date between Pre-War and Post-War

4.4 Causal Analysis and the Effect of Sanctions

In Tables 4 to 6 we report 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. The level of significance we selected for our hypothesis test is 95%.

We find that financial sanctions influence more WS-CPI upward trend shifts 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, 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.

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 considerably influence WS-PSI trend shifts compared to 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.

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, except for a limited set of categories listed above, while financial sanctions affected more substantially the purchasing decisions and the desirable level of financial resources devoted to inventory.

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

Category	Sanction type	VAR Lag	MIO	Resid	Unit Root	Sanctions
01.1 Food	Financial	9	1.00	Not Reject	stable	Reject
	Trade	9	1.00	Not Reject	stable	Reject
01.1.2 Meat	Financial	4	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Reject
01.1.3 Fish	Financial	3	1.00	Not Reject	stable	Reject
	Trade	9	1.00	Not Reject	stable	Reject
01.1.4 Milk, cheese and eggs	Financial	12	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	stable	Reject
01.1.8 Sugar, jam, honey, chocolate and confectionery	Financial	4	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Reject
01.1.9 Food products n.e.c.	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
01.2.1 Coffee, tea and cocoa	Financial	3	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
01.2.2 Mineral waters, soft drinks, fruit and vegetable juices	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
02.1 Alcoholic beverages	Financial	10	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
03.1.2 Garments	Financial	2	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Reject
03.1.3 Other articles of clothing and clothing accessories	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	11	1.00	Not Reject	not stable	Reject
04.3.1 Materials for the maintenance and repair of the dwelling	Financial	2	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
05.1.1 Furniture and furnishings	Financial	10	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
05.1.2 Carpets	Financial	3	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
05.2.0 Household textiles	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
05.3.1 Major household appliances whether electric or not	Financial	8	1.00	Not Reject	stable	Not Reject
	Trade	8	1.00	Not Reject	stable	Not Reject
05.3.2 Small electric household appliances	Financial	10	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	not stable	Reject
05.4.0 Glassware, tableware and household utensils	Financial	2	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
05.5.1 Major tools and equipment	Financial	10	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
05.5.2 Small tools and miscellaneous accessories	Financial	10	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	stable	Reject
05.6.1 Non-durable household goods	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
06.1.2 Other medical products	Financial	10	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
07.2.1 Spare parts and accessories for personal transport equipment	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
08.2.0 Telephone and telefax equipment	Financial	10	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	stable	Reject
09.1.1 Equipment for the reception, recording and reproduction of sound and pictures	Financial	9	1.00	Not Reject	stable	Reject
	Trade	9	1.00	Not Reject	stable	Not Reject
09.1.2 Photographic and cinematographic equipment and optical instruments	Financial	2	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Reject
09.1.3 Information processing equipment	Financial	11	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	stable	Reject
09.2.1 Major durables for outdoor recreation	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
09.3.1 Games, toys and hobbies	Financial	12	1.00	Not Reject	stable	Not Reject
	Trade	12	1.00	Not Reject	stable	Not Reject
09.3.2 Equipment for sport, camping and open-air recreation	Financial	10	1.00	Not Reject	stable	Not Reject
	Trade	11	1.00	Not Reject	stable	Not Reject
09.3.3 Gardens, plants and flowers	Financial	12	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
09.3.4 Pets and related products	Financial	10	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	stable	Reject
09.4.5 Books	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	5	1.00	Not Reject	stable	Not Reject
12.1.2 Electric appliances for personal care	Financial	12	1.00	Not Reject	stable	Not Reject
1	Trade	11	1.00	Not Reject	stable	Not Reject
12.1.3 Other appliances, articles and products for personal care	Financial	11	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
12.3.1 Jewellery, clocks and watches	Financial	11	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	stable	Reject
12.3.2 Other personal effects	Financial	12	1.00	Not Reject	not stable	Reject
	Trade	12	1.00	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.

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

Category	Sanction type	VAR Lag	MIO	Resid	Unit Root	Sanctions
01.1 Food	Financial	8	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
01.1.2 Meat	Financial	12	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Not Reject
01.1.3 Fish	Financial	5	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
01.1.4 Milk, cheese and eggs	Financial	11	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Not Reject
01.1.8 Sugar, jam, honey, chocolate and confectionery	Financial	2	1.00	Not Reject	stable	Not Reject
	Trade	2	1.00	Not Reject	stable	Not Reject
01.1.9 Food products n.e.c.	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
01.2.1 Coffee, tea and cocoa	Financial	2	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	stable	Not Reject
01.2.2 Mineral waters, soft drinks, fruit and vegetable juices	Financial	2	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
02.1 Alcoholic beverages	Financial	10	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
03.1.2 Garments	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
03.1.3 Other articles of clothing and clothing accessories	Financial	10	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
04.3.1 Materials for the maintenance and repair of the dwelling	Financial	8	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	stable	Not Reject
05.1.1 Furniture and furnishings	Financial	3	1.00	Not Reject	stable	Not Reject
	Trade	2	1.00	Not Reject	stable	Not Reject
05.1.2 Carpets	Financial	4	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
05.2.0 Household textiles	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
05.3.1 Major household appliances whether electric or not	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Not Reject
05.3.2 Small electric household appliances	Financial	4	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
05.4.0 Glassware, tableware and household utensils	Financial	12	1.00	Not Reject	not stable	Not Reject
	Trade	12	1.00	Not Reject	stable	Not Reject
05.5.1 Major tools and equipment	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
05.5.2 Small tools and miscellaneous accessories	Financial	5	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
05.6.1 Non-durable household goods	Financial	7	1.00	Not Reject	stable	Not Reject
	Trade	8	1.00	Not Reject	stable	Not Reject
06.1.2 Other medical products	Financial	3	1.00	Not Reject	stable	Not Reject
	Trade	11	1.00	Not Reject	stable	Not Reject
07.2.1 Spare parts and accessories for personal transport equipment	Financial	4	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
08.2.0 Telephone and telefax equipment	Financial	5	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
09.1.1 Equipment for the reception, recording and reproduction of sound and pictures	Financial	6	1.00	Not Reject	stable	Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
09.1.2 Photographic and cinematographic equipment and optical instruments	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
09.1.3 Information processing equipment	Financial	8	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
09.2.1 Major durables for outdoor recreation	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
09.3.1 Games, toys and hobbies	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
09.3.2 Equipment for sport, camping and open-air recreation	Financial	8	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
09.3.3 Gardens, plants and flowers	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
09.3.4 Pets and related products	Financial	2	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
09.4.5 Books	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
12.1.2 Electric appliances for personal care	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
12.1.3 Other appliances, articles and products for personal care	Financial	12	1.00	Not Reject	stable	Reject
	Trade	8	1.00	Not Reject	stable	Not Reject
12.3.1 Jewellery, clocks and watches	Financial	1	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	Not Reject	stable	Not Reject
12.3.2 Other personal effects	Financial	3	1.00	Not Reject	stable	Not Reject
	Trade	1	1.00	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.

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.

In Table 7 we report the results from our Toda and Yamamoto (1995) causality tests for financial- and trade-related sanctions' effects on exchange rate. We can note that in all cases, the test validates the presence of a causal effect from sanctions to disruptions in the exchange rate, and the VAR equations results are stable with the absence of autocorrelation in their residuals.

Finally, we report in Appendix B (Tables 9 to 11) the results from our Toda and Yamamoto (1995) causality tests for the exchange rate effects on each COICOP (1999) category in terms of WS-CPI positive breaks, WS-PSI breaks, and excess WS-CPI.

Table 9 (Appendix B) shows that abrupt exchange rate positive changes cause WS-CPI abrupt positive changes across 27 COICOP (1999) categories, suggesting that the exchange rate contributes to price movements in various product categories. Interestingly, when comparing the impact of exchange rate abrupt positive changes to that of financial sanctions, we found that the former had a slightly lower but still considerable effect on WS-CPI abrupt positive changes.

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 financial and trade sanctions' effects.

Table 10 (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 WS-PSI abrupt changes in 11 COICOP (1999) categories. This implies that fluctuations in the exchange rate can significantly impact the inventory of goods within these specific categories.

Interestingly, when comparing the impact of exchange rate changes to that of financial sanctions, we observed a slightly smaller, albeit still substantial, effect on WS-PSI changes. However, it is worth noting that the causal effect of exchange rate changes on WS-PSI changes was found to be more significant compared to the impact of trade sanctions. These findings highlight the crucial role of exchange rate fluctuations in influencing changes in stocks of products.

Table 11 (Appendix B) exhibits that exchange rate abrupt positive changes cause excess WS-CPI for 13 COICOP (1999) categories, providing new insights into the transmission channels of exchange rate fluctuations.

Notably, the effect of exchange rate positive abrupt changes on excess WS-CPI variations is smaller than that of trade or financial sanctions. The causal effect

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

Category	Sanction type	VAR Lag	MIO	Resid	Unit Root	Sanctions
01.1 Food	Financial	11	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
01.1.2 Meat	Financial	12	1.00	Not Reject	not stable	Reject
	Trade	12	1.00	Not Reject	not stable	Reject
01.1.3 Fish	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
01.1.4 Milk, cheese and eggs	Financial	12	2.00	Not Reject	stable	Reject
	Trade	12	2.00	Not Reject	stable	Reject
01.1.8 Sugar, jam, honey, chocolate and confectionery	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
01.1.9 Food products n.e.c.	Financial	12	2.00	Not Reject	not stable	Reject
	Trade	12	2.00	Not Reject	not stable	Reject
01.2.1 Coffee, tea and cocoa	Financial	5	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
01.2.2 Mineral waters, soft drinks, fruit and vegetable juices	Financial	9	2.00	Not Reject	stable	Reject
	Trade	9	2.00	Not Reject	stable	Reject
02.1 Alcoholic beverages	Financial	11	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
03.1.2 Garments	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
03.1.3 Other articles of clothing and clothing accessories	Financial	8	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	not stable	Reject
04.3.1 Materials for the maintenance and repair of the dwelling	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
05.1.1 Furniture and furnishings	Financial	12	1.00	Not Reject	not stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
05.1.2 Carpets	Financial	12	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
05.2.0 Household textiles	Financial	12	1.00	Not Reject	not stable	Reject
	Trade	12	1.00	Not Reject	not stable	Reject
05.3.1 Major household appliances whether electric or not	Financial	11	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
05.3.2 Small electric household appliances	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
05.4.0 Glassware, tableware and household utensils	Financial	5	1.00	Not Reject	stable	Reject
	Trade	8	1.00	Not Reject	stable	Reject
05.5.1 Major tools and equipment	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
05.5.2 Small tools and miscellaneous accessories	Financial	12	2.00	Not Reject	not stable	Reject
	Trade	12	2.00	Not Reject	not stable	Reject
05.6.1 Non-durable household goods	Financial	12	2.00	Not Reject	not stable	Reject
	Trade	10	2.00	Not Reject	stable	Reject
06.1.2 Other medical products	Financial	12	2.00	Not Reject	stable	Reject
	Trade	12	2.00	Not Reject	stable	Reject
07.2.1 Spare parts and accessories for personal transport equipment	Financial	12	2.00	Not Reject	not stable	Reject
	Trade	12	2.00	Not Reject	not stable	Reject
08.2.0 Telephone and telefax equipment	Financial	12	1.00	Not Reject	not stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
09.1.1 Equipment for the reception, recording and reproduction of sound and pictures	Financial	11	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
09.1.2 Photographic and cinematographic equipment and optical instruments	Financial	2	1.00	Not Reject	stable	Reject
	Trade	9	1.00	Not Reject	stable	Reject
09.1.3 Information processing equipment	Financial	11	1.00	Not Reject	stable	Reject
	Trade	10	1.00	Not Reject	stable	Reject
09.2.1 Major durables for outdoor recreation	Financial	12	1.00	Not Reject	not stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
09.3.1 Games, toys and hobbies	Financial	12	1.00	Not Reject	not stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
09.3.2 Equipment for sport, camping and open-air recreation	Financial	11	2.00	Not Reject	not stable	Reject
	Trade	12	2.00	Not Reject	not stable	Reject
09.3.3 Gardens, plants and flowers	Financial	12	2.00	Not Reject	not stable	Reject
	Trade	12	1.00	Not Reject	not stable	Reject
09.3.4 Pets and related products	Financial	12	1.00	Not Reject	stable	Reject
	Trade	12	1.00	Not Reject	stable	Reject
12.1.2 Electric appliances for personal care	Financial	11	1.00	Not Reject	stable	Reject
	Trade	9	1.00	Not Reject	stable	Reject
12.1.3 Other appliances, articles and products for personal care	Financial	11	1.00	Not Reject	stable	Reject
	Trade	11	1.00	Not Reject	not stable	Reject
12.3.1 Jewellery, clocks and watches	Financial	12	1.00	Not Reject	not stable	Reject
	Trade	12	1.00	Not Reject	not stable	Reject
12.3.2 Other personal effects	Financial	12	2.00	Not Reject	not stable	Reject
	Trade	12	2.00	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.

Table 7. Causality Analysis: Sanctions and Exchange Rate

SB	Sanction type	VAR Lag	MIO	Resid	Unit Root	Sanctions
All	Financial	10.00	1.00	Not Reject	stable	Reject
All	Trade	12.00	1.00	Not Reject	stable	Reject
Increase	Financial	11.00	1.00	Not Reject	stable	Reject
Increase	Trade	11.00	1.00	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.

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.

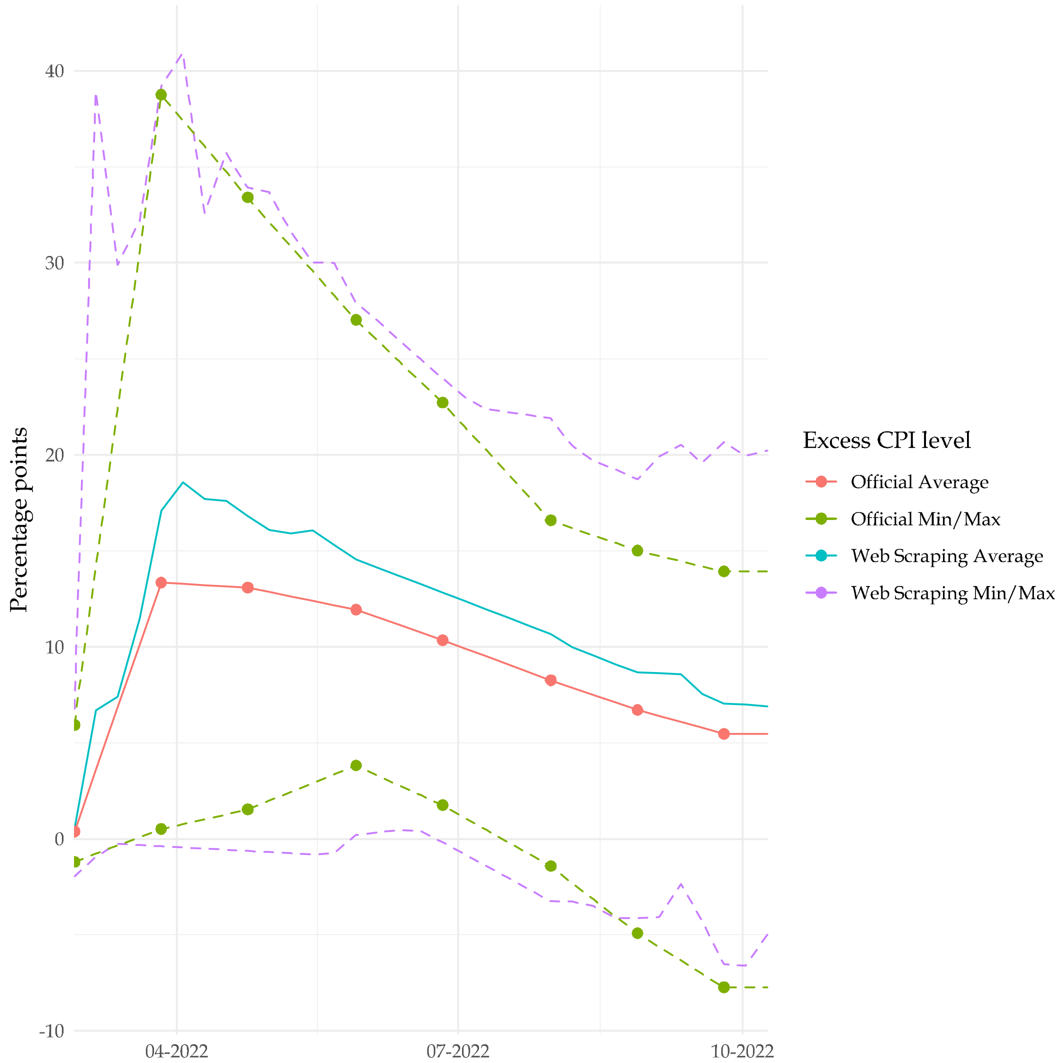
Figure 5 shows the average impact of sanctions over WS-CPI levels for all COICOP (1999) categories we collected each week, together with the minimum and maximum impact. We also calculate the same indicators on monthly official CPI values.

Figure 5 shows that the difference between the average measured WS-CPI level and its projection based on the pre-war trend peaked at about 18% in April 2022. It then steadily declined until just below 7% in October 2022. On average, we measure the excess WS-CPI level for Russia at 11.7% per 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, on average 2.3% more for each COICOP (1999) category. Please note that we are simply averaging values across COICOP (1999) categories, and this should not be confused with an aggregate CPI or WS-CPI.

Moving the analysis to a more granular level, we compare excess CPI and WS-CPI for each COICOP (1999) category. Figure 6 presents each COICOP (1999) category according to those two metrics. While most categories show a similar path, we can note some outliers. Spare parts and accessories for personal transport equipment (07.2.1) show 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.

We checked 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 cor-

Figure 5. Excess CPI and the Average Effect of Sanctions

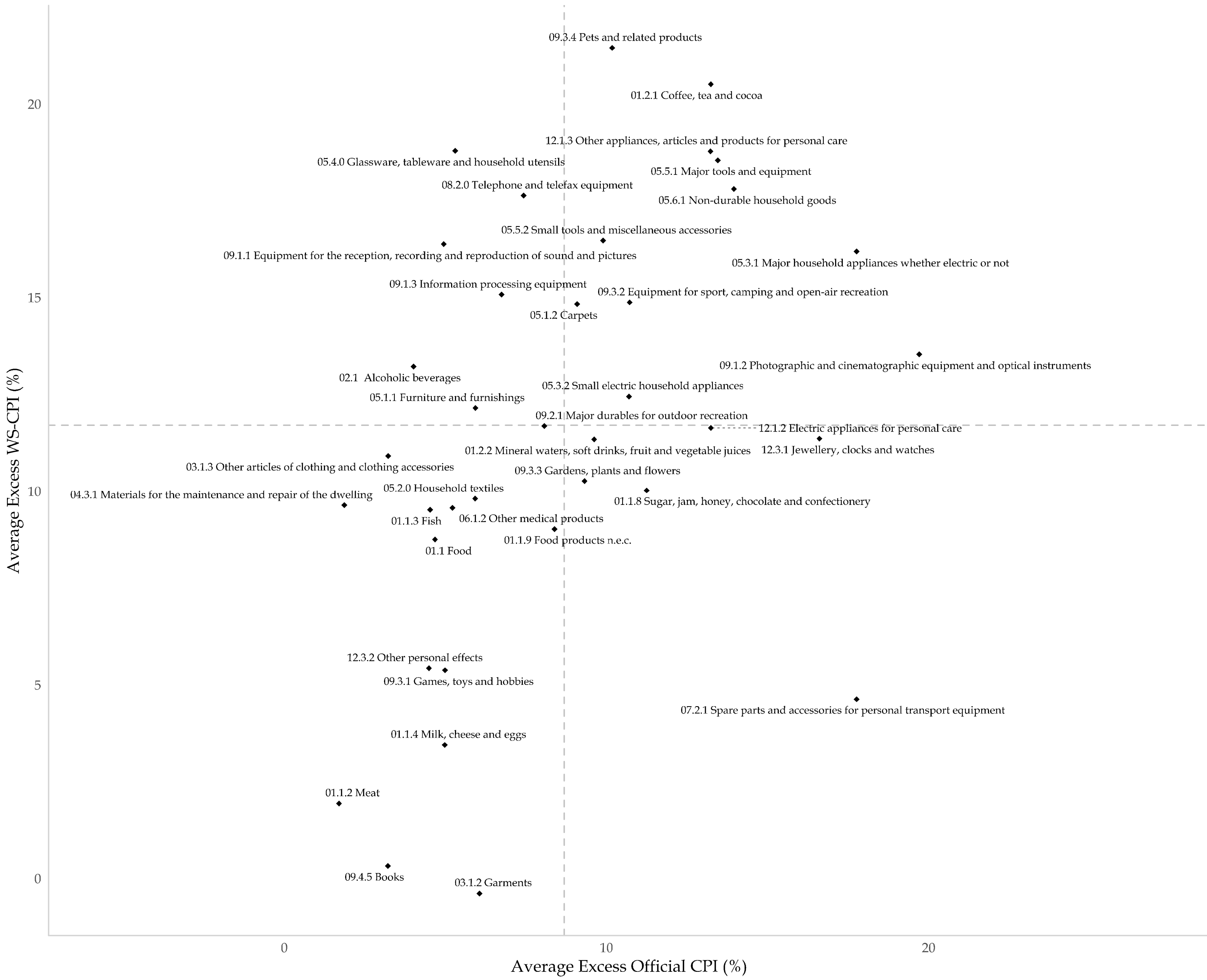


Notes: The dashed lines represent the maximum and minimum impact across all COICOP (1999) categories, which can belong to different categories over time.

relation. 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 can conclude that excess Official CPI and excess WS-CPI present a significant and substantial, albeit moderate, correlation both in terms of quantity of impact and identification of the most impacted categories.

Figure 6. 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.

5 Policy Implications

This paper examines the complex relationship between war, economic sanctions, and online and official price indexes in Russia. By analyzing the impact of conflicts and international sanctions on pricing and consumption patterns, we highlight the need for reliable and timely data on foreign countries' economic activity to understand the effects of sanctions on product pricing and availability and potential policy responses in times of war.

Furthermore, we emphasize the importance of real-time monitoring of economic activity to inform evidence-based policy decisions. Real-time information can show immediately when a sanction has a strong impact and when it stops working. For instance, while financial sanctions were very effective in driving up domestic prices in Russia in the first phase of the war, they progressively lost effectiveness, and the excess inflation they created was progressively reabsorbed by the economy. Policymakers intensively rely on reliable and accurate price data in times of crisis to make informed decisions regarding economic policies and interventions. Therefore, investing in robust data collection mechanisms, such as web scraping, that ensure direct access to raw and granular economic data in foreign countries becomes a critical policy consideration.

While the long-term effect of trade and financial sanctions on the Russian economy cannot be assessed from our data, we note that in the short term, after an initial turmoil, the effect on consumer prices has gradually faded. This should be taken into consideration by countries that want to use economic leverage to impose a penalty on Russia as a result of the war for their next actions.

Our paper also contributes to understanding war and sanctions' effects on product prices and stocks at the product category level. As not all product categories have the same relevance in impacting the welfare of the targeted country, granular information on the effects of sanctions is critical.

Our findings highlight the significant impact of economic sanctions on pricing dynamics and the exchange rate, which was strongly affected in the first phase but gradually returned to pre-war levels. Imposing sanctions can increase import costs, disrupt supply chains, and create inflationary pressures. Policymakers must carefully evaluate the potential consequences of imposing or lifting sanctions, as they directly influence the availability and affordability of products in the targeted market and the exchange rates. A nuanced understanding of the intricate relationship between sanctions and pricing dynamics is crucial for formulating effective policies that target specific economic outcomes.

Using alternative data sources like web scraping can offer policymakers valuable insights into real-time economic activity, price dynamics, and product availability. Incorporating these innovative approaches enables policymakers to monitor economic trends, evaluate the effectiveness of policies, and make timely decisions. By embracing interdisciplinary research and leveraging technological advancements, policymakers can enhance their capacity to respond swiftly and effectively to evolving economic conditions and help governments to calibrate trade and financial sanctions in times of war.

Finally, policymakers must carefully evaluate the potential consequences of sanctions and consider the expected target of sanctions, which is also crucial for governments during wars.

6 Conclusion

The examination of consumer price levels for various product categories in Russia reveals significant fluctuations and alterations in trends subsequent to the invasion of Ukraine and the imposition of international sanctions.

First, our analysis reveals a substantial alignment between WS-CPI and official CPI figures for the majority of (COICOP, 1999) categories, as determined by statistics computed over the entire period analyzed. However, this correspondence appears to decline significantly for a substantial number of (COICOP, 1999) series following the onset of war.

Second, we highlight that economic sanctions waves 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. Also, WS-PSI seems to have been impacted, even to a much lower extent. The exchange rate appears to be a relevant transmission channel, but there are numerous causal effects explained by the sanctions and not directly impacted by the exchange rate, implying the sanctions impact Russian prices through other channels in addition to the exchange rate.

Finally, we provide an assessment of sanctions' impact on WS-CPI levels. While we confirmed that the sanctions effectively disrupted the WS-CPI pattern, we show that the Russian economy is slowly reabsorbing the effect of sanctions and realigning with the pre-existing WS-CPI trend. Moreover, it seems official CPI is consistently underreporting - even if only marginally - the impact of sanctions in terms of excess CPI level.

Our economic modeling exercise presents a simplified representation of reality, and the data we used only comes from 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 on the flash analysis of consumer price level and stock dynamics at a granular level, leveraging real-time and web-scraped data.

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7 Appendix

A Forecasting and Model Validation: Full Sample

Table 8. Forecasting and Model Validation Analysis

COICOP (1999) 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	-0.4	2.1	0.92
01.1.4	1.54	0.98	1.29	1.3	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	1.9	2.65	1.1	3.09	0.9
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	-0.9
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	4.2	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	4.9	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	9.7	-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	3.1	-2.95	3.38	0.73
09.3.4	3.39	5.6	2.6	6.03	0.62
09.4.5	4.17	4.14	-3.5	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	8.1	-11.18	8.32	-0.6
12.3.2	6.12	3.54	-6.12	3.54	-0.85

Notes: This table presents the summary metrics for all dates.

B Causality Analysis: Exchange Rate

Table 9. Causality Analysis: Exchange Rate Positive Breaks and WS-CPI Positive Breaks

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1 Food	5	1.00	Not Reject	stable	Reject
01.1.2 Meat	3	1.00	Not Reject	stable	Reject
01.1.3 Fish	6	1.00	Not Reject	stable	Reject
01.1.4 Milk, cheese and eggs	12	1.00	Not Reject	stable	Reject
01.1.8 Sugar, jam, honey, chocolate and confectionery	2	1.00	Not Reject	stable	Reject
01.1.9 Food products n.e.c.	10	1.00	Not Reject	stable	Reject
01.2.1 Coffee, tea and cocoa	2	1.00	Not Reject	stable	Reject
01.2.2 Mineral waters, soft drinks, fruit and vegetable juices	1	1.00	Not Reject	stable	Not Reject
02.1 Alcoholic beverages	12	1.00	Not Reject	stable	Reject
03.1.2 Garments	1	1.00	Not Reject	stable	Not Reject
03.1.3 Other articles of clothing and clothing accessories	1	1.00	Not Reject	stable	Not Reject
04.3.1 Materials for the maintenance and repair of the dwelling	4	1.00	Not Reject	stable	Reject
05.1.1 Furniture and furnishings	12	1.00	Not Reject	not stable	Reject
05.1.2 Carpets	1	1.00	Not Reject	stable	Reject
05.2.0 Household textiles	1	1.00	Not Reject	stable	Not Reject
05.3.1 Major household appliances whether electric or not	11	1.00	Not Reject	stable	Not Reject
05.3.2 Small electric household appliances	10	1.00	Not Reject	stable	Reject
05.4.0 Glassware, tableware and household utensils	5	1.00	Not Reject	stable	Not Reject
05.5.1 Major tools and equipment	12	1.00	Not Reject	stable	Reject
05.5.2 Small tools and miscellaneous accessories	10	1.00	Not Reject	stable	Reject
05.6.1 Non-durable household goods	12	1.00	Not Reject	stable	Reject
06.1.2 Other medical products	7	1.00	Not Reject	stable	Reject
07.2.1 Spare parts and accessories for personal transport equipment	11	1.00	Not Reject	stable	Reject
08.2.0 Telephone and telefax equipment	12	1.00	Not Reject	stable	Not Reject
09.1.1 Equipment for the reception, recording and reproduction of sound and pictures	11	1.00	Not Reject	stable	Reject
09.1.2 Photographic and cinematographic equipment and optical instruments	1	1.00	Not Reject	stable	Not Reject
09.1.3 Information processing equipment	12	1.00	Not Reject	stable	Reject
09.2.1 Major durables for outdoor recreation	12	1.00	Not Reject	stable	Reject
09.3.1 Games, toys and hobbies	12	1.00	Not Reject	stable	Reject
09.3.2 Equipment for sport, camping and open-air recreation	8	1.00	Not Reject	stable	Not Reject
09.3.3 Gardens, plants and flowers	11	1.00	Not Reject	stable	Reject
09.3.4 Pets and related products	12	1.00	Not Reject	stable	Reject
09.4.5 Books	12	1.00	Not Reject	stable	Reject
12.1.2 Electric appliances for personal care	11	1.00	Not Reject	stable	Reject
12.1.3 Other appliances, articles and products for personal care	12	1.00	Not Reject	stable	Reject
12.3.1 Jewellery, clocks and watches	12	1.00	Not Reject	stable	Reject
12.3.2 Other personal effects	6	1.00	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.

Table 10. Causality Analysis: Exchange Rate Breaks and WS-PSI Breaks

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1 Food	1	1.00	Not Reject	stable	Not Reject
01.1.2 Meat	10	1.00	Not Reject	stable	Reject
01.1.3 Fish	4	1.00	Not Reject	stable	Not Reject
01.1.4 Milk, cheese and eggs	10	1.00	Not Reject	stable	Reject
01.1.8 Sugar, jam, honey, chocolate and confectionery	1	1.00	Not Reject	stable	Not Reject
01.1.9 Food products n.e.c.	1	1.00	Not Reject	stable	Not Reject
01.2.1 Coffee, tea and cocoa	12	1.00	Not Reject	stable	Not Reject
01.2.2 Mineral waters, soft drinks, fruit and vegetable juices	11	1.00	Not Reject	stable	Not Reject
02.1 Alcoholic beverages	12	1.00	Not Reject	stable	Reject
03.1.2 Garments	1	1.00	Not Reject	stable	Not Reject
03.1.3 Other articles of clothing and clothing accessories	9	1.00	Not Reject	stable	Reject
04.3.1 Materials for the maintenance and repair of the dwelling	12	1.00	Not Reject	stable	Reject
05.1.1 Furniture and furnishings	4	1.00	Not Reject	stable	Not Reject
05.1.2 Carpets	12	1.00	Not Reject	stable	Not Reject
05.2.0 Household textiles	1	1.00	Not Reject	stable	Not Reject
05.3.1 Major household appliances whether electric or not	12	1.00	Not Reject	stable	Not Reject
05.3.2 Small electric household appliances	5	1.00	Not Reject	stable	Reject
05.4.0 Glassware, tableware and household utensils	12	1.00	Not Reject	stable	Not Reject
05.5.1 Major tools and equipment	1	1.00	Not Reject	stable	Not Reject
05.5.2 Small tools and miscellaneous accessories	3	1.00	Not Reject	stable	Not Reject
05.6.1 Non-durable household goods	12	1.00	Not Reject	stable	Not Reject
06.1.2 Other medical products	12	1.00	Not Reject	stable	Not Reject
07.2.1 Spare parts and accessories for personal transport equipment	4	1.00	Not Reject	stable	Not Reject
08.2.0 Telephone and telefax equipment	1	1.00	Not Reject	stable	Not Reject
09.1.1 Equipment for the reception, recording and reproduction of sound and pictures	3	1.00	Not Reject	stable	Not Reject
09.1.2 Photographic and cinematographic equipment and optical instruments	1	1.00	Not Reject	stable	Not Reject
09.1.3 Information processing equipment	9	1.00	Not Reject	stable	Reject
09.2.1 Major durables for outdoor recreation	4	1.00	Not Reject	stable	Reject
09.3.1 Games, toys and hobbies	4	1.00	Not Reject	stable	Not Reject
09.3.2 Equipment for sport, camping and open-air recreation	9	1.00	Not Reject	stable	Reject
09.3.3 Gardens, plants and flowers	6	1.00	Not Reject	stable	Reject
09.3.4 Pets and related products	4	1.00	Not Reject	stable	Not Reject
09.4.5 Books	1	1.00	Not Reject	stable	Not Reject
12.1.2 Electric appliances for personal care	1	1.00	Not Reject	stable	Not Reject
12.1.3 Other appliances, articles and products for personal care	5	1.00	Not Reject	stable	Reject
12.3.1 Jewellery, clocks and watches	1	1.00	Not Reject	stable	Not Reject
12.3.2 Other personal effects	4	1.00	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.

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

Category	VAR Lag	MIO	Resid	Unit Root	Exchange rate
01.1 Food	12	1.00	Not Reject	not stable	Reject
01.1.2 Meat	12	1.00	Not Reject	not stable	Reject
01.1.3 Fish	11	1.00	Not Reject	stable	Reject
01.1.4 Milk, cheese and eggs	12	2.00	Not Reject	not stable	Reject
01.1.8 Sugar, jam, honey, chocolate and confectionery	11	1.00	Not Reject	stable	Reject
01.1.9 Food products n.e.c.	10	2.00	Not Reject	stable	Reject
01.2.1 Coffee, tea and cocoa	12	1.00	Not Reject	not stable	Reject
01.2.2 Mineral waters, soft drinks, fruit and vegetable juices	12	2.00	Not Reject	not stable	Reject
02.1 Alcoholic beverages	12	1.00	Not Reject	stable	Reject
03.1.2 Garments	12	1.00	Not Reject	stable	Not Reject
03.1.3 Other articles of clothing and clothing accessories	2	1.00	Not Reject	stable	Reject
04.3.1 Materials for the maintenance and repair of the dwelling	12	1.00	Not Reject	not stable	Reject
05.1.1 Furniture and furnishings	12	1.00	Not Reject	not stable	Reject
05.1.2 Carpets	10	1.00	Not Reject	stable	Reject
05.2.0 Household textiles	10	1.00	Not Reject	not stable	Reject
05.3.1 Major household appliances whether electric or not	12	1.00	Not Reject	stable	Reject
05.3.2 Small electric household appliances	12	1.00	Not Reject	not stable	Reject
05.4.0 Glassware, tableware and household utensils	12	1.00	Not Reject	not stable	Reject
05.5.1 Major tools and equipment	12	1.00	Not Reject	stable	Reject
05.5.2 Small tools and miscellaneous accessories	10	2.00	Not Reject	not stable	Reject
05.6.1 Non-durable household goods	11	2.00	Not Reject	not stable	Reject
06.1.2 Other medical products	8	2.00	Not Reject	stable	Reject
07.2.1 Spare parts and accessories for personal transport equipment	7	2.00	Not Reject	stable	Reject
08.2.0 Telephone and telefax equipment	12	1.00	Not Reject	not stable	Reject
09.1.1 Equipment for the reception, recording and reproduction of sound and pictures	12	1.00	Not Reject	stable	Reject
09.1.2 Photographic and cinematographic equipment and optical instruments	12	1.00	Not Reject	not stable	Reject
09.1.3 Information processing equipment	12	1.00	Not Reject	stable	Reject
09.2.1 Major durables for outdoor recreation	12	1.00	Not Reject	not stable	Reject
09.3.1 Games, toys and hobbies	11	1.00	Not Reject	not stable	Reject
09.3.2 Equipment for sport, camping and open-air recreation	12	2.00	Not Reject	not stable	Reject
09.3.3 Gardens, plants and flowers	12	1.00	Not Reject	not stable	Reject
09.3.4 Pets and related products	12	1.00	Not Reject	not stable	Reject
12.1.2 Electric appliances for personal care	12	1.00	Not Reject	stable	Reject
12.1.3 Other appliances, articles and products for personal care	11	1.00	Not Reject	not stable	Reject
12.3.1 Jewellery, clocks and watches	10	1.00	Not Reject	stable	Not Reject
12.3.2 Other personal effects	12	2.00	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.