Sanctions and Russian Online Prices

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ASSA/AEA San Antonio 2024

January 5, 2024

This presentation does not necessarily reflect the views of the Bank of Israel, the Bank of Italy, or the Eurosystem.

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Origins

2022-02-24: Russia invades Ukraine

▶ The US, EU, and other countries impose economic sanctions on Russia due to the invasion of Ukraine

▶ Russia suspends the publication of several official statistics

▶ Timely information on the Russian economy becomes key to policymakers

Objectives

Our research questions:

- ▶ How reliable are current Russian official price statistics?
- ▶ Did sanctions affect Russian consumer prices?
- ▶ Can we quantify this effect in real-time?

Results preview

Our findings:

▶ Russian official price statistics appear to be reliable

▶ Sanctions substantially affected the pattern of Russian consumer prices

▶ Exchange and interest rates likely transmission channels

▶ Peak effect on April 2022 with 18% excess inflation, largely reabsorbed over time

Data

Web scraping Source

▶ Consumer prices and product inventory[3] information since Feb 2021 from a major Russian multi-channel retailer

▶ Daily data, aggregated in $\sim$8M weekly observations on $\sim$120k unique daily products covering 37 CPI categories

Official Sources

▶ Monthly CPI from Rosstat for COICOP 1999[4] Level 4 aggregates

▶ Sanctions data from Peterson Institute for International Economics (Bown, 2023)

▶ RUB/USD exchange rate (WSJ Markets)

▶ RUONIA interest rate (Central Bank of Russia)

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[3]Detail not visible on the webpage but included in the page metadata

[4]Classification of individual consumption according to purpose, 1999 version

Time-Product Dummy

Unweighted multilateral index methodology to calculate CPI

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

lnP_{it}: log of the price of good i at time t
D_i, T_t: dummy variables for good i and time t, respectively, with
$i = 1, ..., N$ and $t = 1, ..., T$

Differences in the γ_t coefficients $=>$ measures of CPI change over time

CPI levels:

$$CPI_t = e^{\hat{\gamma}_t} \tag{2}$$

The same methodology applies to the Product Stock Index (PSI), using the quantity of products available for sale

Tracking CPI - Econometric Approach

▶ Check that web scraping and official CPI have the same order of integration (Robinson and Yajima, 2002)

▶ Test for absence of cointegration (Marmol and Velasco, 2004) and estimate the integration order (Nielsen and Shimotsu, 2007; Zhang et al., 2019)

▶ ARDL[5] (Pesaran et al., 2001) bound test for relationship in levels

Limitation: only 20 monthly observations

▶ Vinod (2006) maximum entropy bootstrap and test for stationarity of differences (Dickey and Fuller, 1979; Kwiatkowski et al., 1992)

▶ Complement the econometric approach with model validation

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[5]Autoregressive distributed lag

Tracking CPI - Model Validation Approach

Given the small number of official data points, we complement the econometric approach

- ▶ Calculate MAPE[6] and MALPE[7] on differences (Rayer, 2007; Swanson, 2015)
- ▶ T-test on MAPE and MALPE levels before and after the invasion start (Gosset, 1908)
- ▶ Identify breakpoints in MAPE and MALPE series with BEAST (Zhao et al., 2019) ▸ BEAST

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[6]Mean absolute percentage error

[7]Mean algebraic percentage error

Sanctions Effect - CPI and PSI Trend Change

BEAST: Bayesian ensemble algorithm that performs time series decomposition into an additive model (Zhao et al., 2019)

$$y_i = S(t_i; \Theta_s) + T(t_i; \Theta_t) + \varepsilon_i \tag{3}$$

y_i: observed value at time t_i

Θ_s: seasonal signal

Θ_t: trend signal

ε_i: noise, assumed Gaussian distribution

Estimation of trend and trend change point probability for CPI and PSI

Sanctions Effect - Causality Analysis

Toda and Yamamoto (1995) test for Granger-Causality

- Estimate VAR equation

$$y_t = A_1 y_{t-1} + ... + A_{p+dmax} y_{t-(p+dmax)} + CD_t + u_t \quad (4)$$

  y_t: vector with the values of CPI (or PSI) trend change probability and sanctions in time t
  CD_t: intercept and trend

- Wald Test on $A_1...A_{p+dmax}$ coefficients to validate Granger-Causality
- Same approach repeated between sanctions and trend change points in the exchange and interest rates, and between trend change points in those rates and trend change points in CPI and PSI

Sanctions Effect - Counterfactual

- ▶ Project pre-war web scraping CPI trend from BEAST to derive expected CPI levels in the absence of sanctions

- ▶ Calculate differences with observed web scraping CPI levels

- ▶ **Excess inflation**

Difference-in-Differences

- ▶ March 2022: ban on Champagne export to Russia
- ▶ Was there an effect on prices compared to alternative products?
- ▶ DiD on Champagne price patterns compared to Prosecco
- ▶ Methodology by Callaway and Sant'Anna (2021) using the doubly-robust method by Sant'Anna and Zhao (2020)

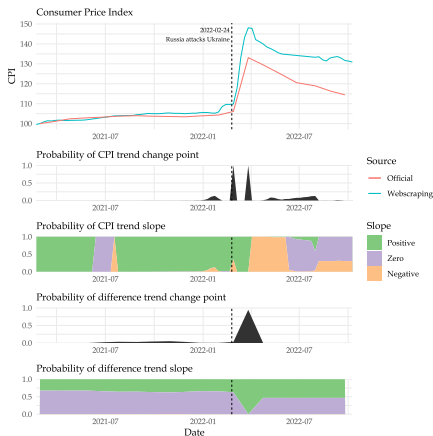# CPI from web scraping tracks well official data...
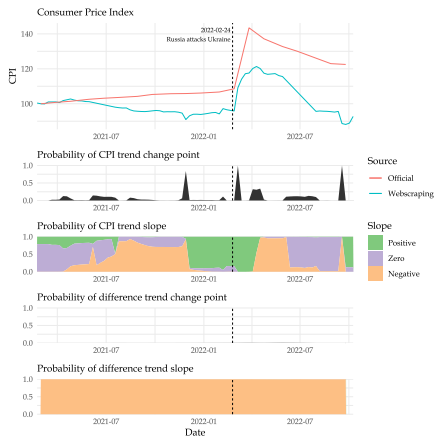
Meat prices

Fish prices
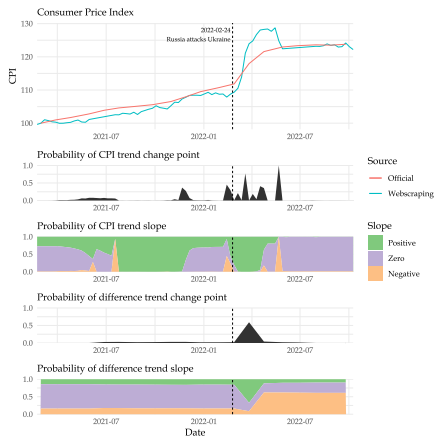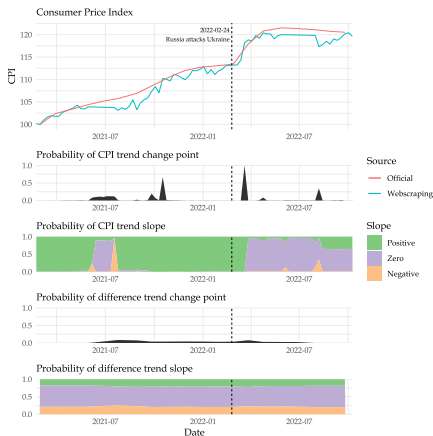
...but not in all aggregates

Major tools prices

Accessories prices

Econometrics tools confirm the tracking...

Web scraping and official CPI time series are:

- integrated of the same order: Reject 2/37
- not cointegrated: Reject 22/37
- stationary in their differences after bootstrap:
    - ADF: 11/37 (Reject non-stationarity)
    - KPSS: 37/37 (Not reject stationarity)
- related in levels: 12/37 (Reject absence of relationship)

Web scraping data is a solid tracker for official CPI

...but tracking degraded after the invasion

Structural break probability

- MAPE below 5% and
  MALPE within ±5%: 21/37
  cases
- After the invasion:
  - MAPE degrades in 21
    cases
  - MALPE degrades in 18
    cases
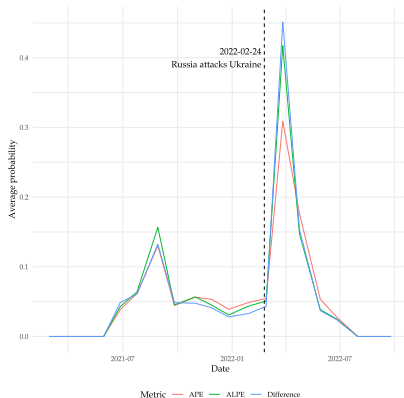
Sanctions and CPI Disruptions

Metric	Financial Sanctions	Trade Sanctions	Exchange rate SB	Interest rate SB
CPI +SB	28	24	27	19
Excess CPI	22	26	13	16
PSI SB	15	6	11	14

- ▶ Granger-causality from sanctions to exchange and interest rates structural breaks
- ▶ Relatively larger impact on CPI compares to PSI
- ▶ Exchange and interest rates seem to explain a large share of sanctions' impact on CPI and PSI
- ▶ Unstable VAR roots between exchange and interest rates hinder further causal analysis
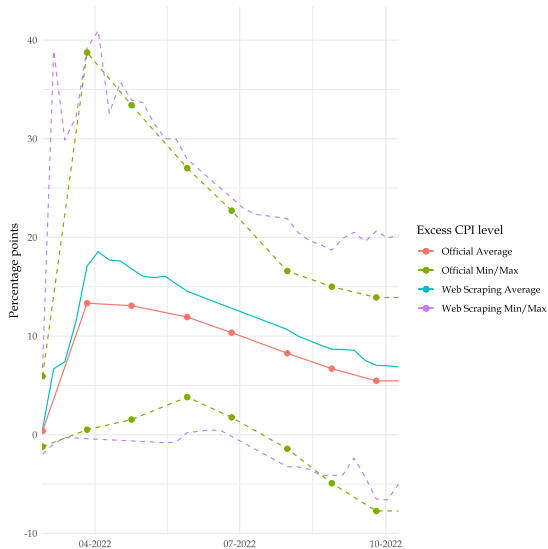
Figure 6. Excess Official CPI and Excess WS-CPI by COICOP (1999) category
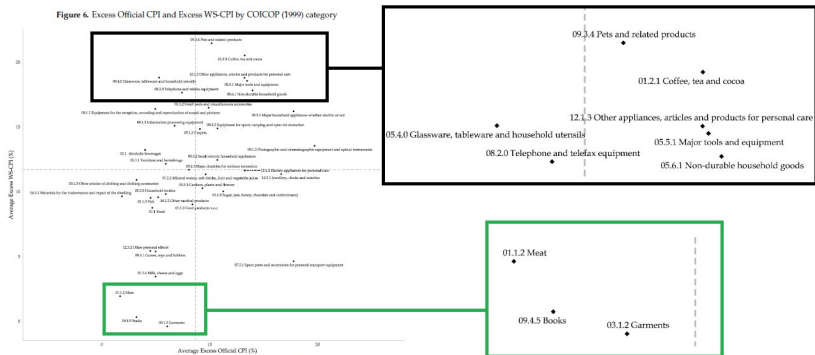
Notes: The dashed lines represent the average Excess Official CPI and WS-CPI across COICOP (1999) categories.

Substantially aligned between web scraping and official data

Relevant impact on CPI, but slowly reabsorbing

DiD on Champagne confirms the impact decay over time

Conclusion

- ▶ Online prices can effectively track official CPI and **inform decision-makers in real-time**
- ▶ Sanctions effectively impacted CPI patterns in Russia
  - ▶ Excess CPI level peaked around 18% in April 2022
- ▶ The Russian economy **slowly reabsorbed this increase**
- ▶ PSI impacted to a much lower extent
- ▶ **Financial sanctions had a wider impact than trade ones**, but trade sanctions are linked to more excess inflation
- ▶ Exchange and interest rates are plausible transmission channels of sanctions to CPI and PSI

Thanks

▶ Thank you for your attention

▶ Working paper available on ResearchGate

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