DOI: 10.46541/978-86-7233-443-2_468

XXX International Scientific Conference
Strategic Management
and Decision Support Systems
in Strategic Management
SM2025
Subotica (Serbia), 16 May, 2025

Aleksandr Chernykh
PhD Student,
European University at St.Petersburg
Saint-Petersburg, Russia

achernykh@eu.spb.ru
Participation: virtual
JEL: C58, F51, G12

Estimation of Risk Spillovers Between Russian Financial Markets in the 2022-2023 Sanctions Period by Wavelet Coherence Analysis

Abstract: This paper investigates the impact of European Union sanctions on Russian economy during 2022–2023, with a focus on the oil and gas sector. Given the limited availability of Russian macroeconomic data, financial markets serve as key indicators of economic responses to sanctions. Utilizing wavelet coherence analysis (WCA), this study examines contagion effects between the Russian stock market, government bond market, and foreign exchange market to identify vulnerability and transmission of uncertainty. Unlike traditional econometric models such as GARCH, WCA captures the time-varying nature and statistical significance of co-movements between markets across different time horizons, offering a nuanced perspective on short- and medium-term dynamics. The findings reveal that the sixth EU sanctions package in mid-2022 triggered short-term volatility spillovers from the bond market to both equities and the exchange rate. A more complex pattern emerged in autumn 2022, where coherence between equity and debt markets intensified, though it remains difficult to disentangle the effects of the eighth sanctions package from concurrent political developments. In early 2023, the oil price cap introduced renewed volatility, primarily transmitted from the foreign exchange market to the bond and equity markets within days. However, by the end of 2023, markets showed signs of stabilization, suggesting a degree of adaptation by the Russian economy. This study highlights the evolving nature of sanctions' impact and the effectiveness of WCA in tracing financial contagion in turbulent geopolitical contexts.

Keywords: financial markets, wavelet coherence, economic sanctions, Russia

1. INTRODUCTION

The Russian economy has faced international sanctions since 2014, with the most stringent measures imposed by the United States and the European Union since 2022. These measures vary in effectiveness, causing different levels of economic disruption.

While the overall economy has remained stable, key export sectors, particularly oil and gas, have faced short-term adverse effects. Due to restricted access to trade and macroeconomic data, movements in the Russian stock market serve as an indicator of these effects, reflecting traders' reactions. As more data becomes available, medium-term market responses can be analyzed.

As negotiations may progress, the question of lifting or tightening sanctions will arise. Both sides of the sanctions conflict need to understand which sanctions have caused the most damage. Assessing the impact of economic events requires identifying the financial markets most affected, as these markets propagate risk and uncertainty to others.

To estimate risk transfer during negative shocks, researchers typically use the generalized autoregressive conditional heteroskedasticity (GARCH) family of models (Syriopoulos et al., 2015; Afanasyev et al., 2021; Fedorova et al., 2024). However, GARCH models either fail to show the direction of shock transmission in univariate models or require estimation of multiple parameters with unclear interpretations (Aganin & Peresetsky, 2018). Wavelet Coherence Analysis (WCA), introduced by Torrence and Compo (1998), addresses these issues. Initially applied in physics, WCA detects significant shocks in the relationship between two time series and assesses the persistence of their correlation. Applied to sanctions, WCA allows for the analysis of contagion effects across markets over various time horizons, including the medium term. Unlike regression analysis, WCA reveals insights into the relationships between different components of time series, differentiating short- and medium-term responses.

Unlike GARCH models, WCA captures the time-varying dynamics of correlation and its statistical significance at any point in time. This method is widely used to evaluate the economic consequences of prolonged adverse events on financial markets, such as the impact of COVID-19 (Szczygielski et al., 2023), economic sanctions on Iran (Samadi et al., 2021; Omidi et al., 2021), and sanctions on Russia (Panazan & Gheorghe, 2024).

This study uses WCA to examine Russian financial markets from 2022 to 2023 and identify the most vulnerable sectors. After determining the leading market, contagion effects will be analyzed through uncertainty spillovers, with the strongest shifts in variable coherence indicating the most severe effects of sanctions. The strongest shifts in variable coherence are expected to indicate the most severe effects of sanctions imposed by the European Union, Russia's former main trading partner.

2. METHODOLOGY

Financial market contagion refers to the abnormal transfer of uncertainty between markets. Volatility is commonly used as a measure of risk or uncertainty in financial market literature. There are several methods to estimate the volatility of returns, with the non-parametric realized volatility method being one of the simplest to compute. Despite its simplicity, the realized volatility method provides reliable results for the Russian market, yielding values comparable to those from other parametric methods (Aganin & Peresetsky, 2018). Realized volatility is defined as the squared return for each index's return:

$$V_{i,t} = R_{i,t}^2 \tag{1}$$

where:

$R_{i,t}$ is the logarithmic return of the i index.

The Continuous Wavelet Transform (CWT) decomposes a time series into time-frequency space using a "mother wavelet." CWT projects the series onto wavelets of different scales and positions, revealing how volatility behaves across various time horizons. The main equation of the CWT is given by equation (1):

$$W_x(s,\tau) = \int_{-\infty}^{\infty} x\,(t)\,\frac{1}{\sqrt{s}}\,\psi^*\left(\frac{t-\tau}{s}\right) dt \tag{2}$$

where:

$W_x(s,\tau)$ is the wavelet coefficient at scale s and time τ;

$x(t)$ is the time series (volatility of an index);

$\frac{1}{\sqrt{s}}$ is the normalizing agent;

$\psi(t)$ is the mother wavelet. For financial analysis, the Morlet wavelet is commonly used (Szczygielski et al., 2022) because it balances time and frequency resolution;

s is the time scale, related to frequency or time horizon, e.g., 2, 4, 8... days;

τ is the time position, or the shift of the wavelet along the series.

The Morlet wavelet, a wave-like function modulated by a Gaussian, is defined as:

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2} \tag{3}$$

where:

ω_0 is the central non-dimensional frequency, set to 6 for optimal time-frequency localization (Farge, 1992).

The CWT can be computed efficiently using the Fast Fourier Transform (FFT), which is computationally faster than direct integration. The FFT accelerates the process by converting the convolution into a multiplication in the frequency domain:

$$W_x(s,\tau) = \mathcal{F}^{-1}\left[\mathcal{F}\big(x(t)\big)\mathcal{F}\big(\psi(s,t)\big)\right] \tag{4}$$

where:

$\mathcal{F}$ and $\mathcal{F}^{-1}$ are the Fourier Transform and Inverse Fourier Transform, respectively.

By implementing equation (2) and applying the FFT through equation (4) to both volatility series for each pair of indices, we can obtain the Cross-Wavelet Spectrum to examine the relationship between each pair of indices:

$$W_{xy}(s,\tau) = W_x(s,\tau) W_y^*(s,\tau) \tag{5}$$

where:
$W_{xy}(s,\tau)$ is the cross-wavelet transform;
W_x, W_y are the CWTs of the two time series (volatilities of the indices);
W_y^* is the complex conjugate of W_y.
The Cross-Wavelet Spectrum measures the joint power (magnitude) and phase (direction) of the two volatilities at each scale and time.
Wavelet Coherence (WTC) normalizes the cross-wavelet power to quantify the strength of the relationship between the two time series. It is calculated as follows:

$$R^2(s,\tau) = \frac{\left|S\left(s^{-1}W_{xy}(s,\tau)\right)\right|^2}{S(s^{-1}|W_x(s,\tau)|^2)S\left(s^{-1}\left|W_y(s,\tau)\right|^2\right)} \tag{6}$$

where:
$R^2(s,\tau)$ is the wavelet coherence, ranging from 0 (no coherence) to 1 (perfect coherence);
S is the smoothing operator (which averages over time and scale to reduce noise), ensuring that the result is not overly noisy;
$|W_x|^2, \left|W_y\right|^2$ are the wavelet power spectra of each series;
$\left|S(W_{xy})\right|^2$ is the smoothed cross-wavelet power.
WTC measures the co-movement of two time series in the time-frequency domain. WTC can be viewed as a correlation coefficient in linear regressions, but it operates at different frequencies. If $R^2(s,\tau)$ is high at a particular scale s, the two indices exhibit strong co-movement at that time horizon. Therefore, WTC illustrates how closely the volatilities of two indices align at a given time and scale.
In Wavelet Coherence Analysis (WCA), the phase difference helps determine whether one financial variable leads or lags another at a given time scale. The phase angle from $W_{xy}(s,\tau)$ reveals the lead-lag relationship. It is computed as:

$$\phi(s,\tau) = tan^{-1}\left(\frac{\Im\left(S\left(W_{xy}(s,\tau)\right)\right)}{\Re\left(S\left(W_{xy}(s,\tau)\right)\right)}\right) \tag{7}$$

where:
$\phi(s,\tau)$ is the phase difference at scale and time;
$\Im, \Re$ are the real and imaginary parts, respectively.
The phase difference can be interpreted by the following angles:

- $\phi = 0$, In-phase: both indices volatilities move together at a time scale;
- $\phi = \pi$, Anti-phase: the volatilities move in opposite directions;
- $\phi = -\pi/2$, Lagging indicator: the first index lags behind the second;
- $\phi = \pi/2$, Leading indicator: the first index leads the second;

The hypothesis of the research is that high coherence with a phase lag might indicate the spillover of risk from one market to another. Changes in coherence over time could reflect the impact of sanctions on the risk level of the Russian financial markets.
The computation code is written in the Python programming language with the help of the Krieger & Freij (2023) package.

3. DATA

The study examines contagion effects in three markets: the equity market, the government bond market, and the foreign exchange market. The returns of the Moscow Exchange Oil & Gas Sectoral Index (MOEXOG) are used to represent the equity market. This is motivated by the fact that companies in the oil and gas industry account for approximately half of the total weight of the main Russian stock exchange index, the RTSI[1]. Furthermore, the oil and gas industry, along with the financial sector, was the primary sector affected by sanctions. The yield of the Moscow Exchange Government Bond Index (RGBITR), which reflects the Russian government bond market (Moscow Stock Exchange, 2025), is used to represent the government bond market. The yield of the USD/RUB currency pair is used to represent the currency market. Given the multitude of sanctions imposed on Russia, it is appropriate to limit the sample of sanction events. This study considers only those sanctions from the EU that were targeted at the oil and gas industry (Bown, 2023) and that have demonstrated significance through event-driven analysis (Chernykh, 2024). The list of sanctions is presented in Table 1.

Table 1: List of sanction events imposed by the EU on Russia's oil and gas industry

	Announcement date	Event description
(1)	03 June, 2022	6th package: imposition of sanctions
(2)	02 September, 2022	8th package: announcement of the oil price ceiling
(3)	06 October, 2022	8th package: imposition of sanctions

[1] Moscow Exchange Indices: RTS Index. https://www.moex.com/en/index/RTSI/constituents

(4)	05 December, 2022	8th package: setting of the price ceiling for Russian crude oil of $60
(5)	04 February, 2023	8th package: setting of the price ceiling for Russian oil products
(6)	23 June, 2023	11th package: ban on servicing Russian oil tankers in third countries
(7)	18 December, 2023	12th package: enforcement of the oil price cap

Source: Bown, 2023.

The sample of sanction events excludes those imposed before March 28, 2022, due to the suspension of trading on the Moscow Exchange.
Table 2 presents the descriptive statistics for the returns of the three financial variables.

Table 2: Descriptive statistics of financial variable returns

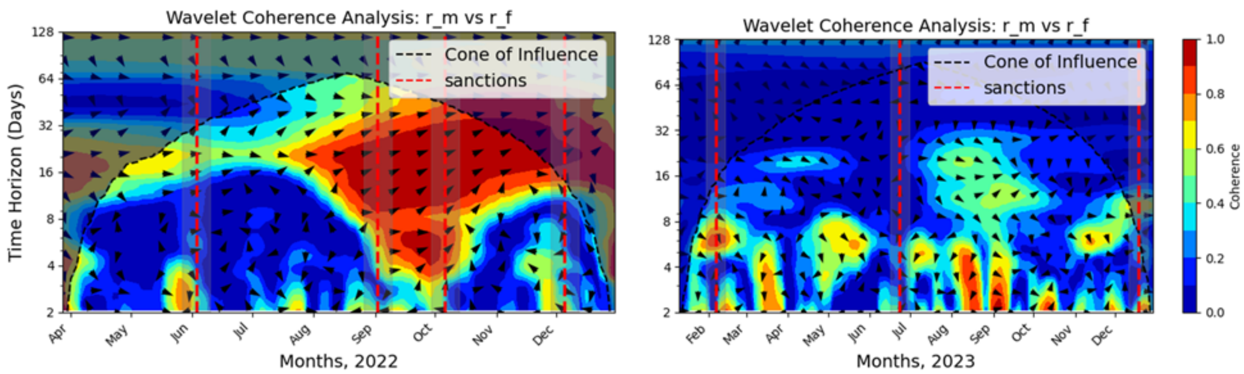
	MOEXOG			RGBITR			USD/RUB		
Year	2021	2022	2023	2021	2022	2023	2021	2022	2023
Count	242	190	246	242	190	246	242	190	246
Mean, %	0.04	-0.06	0.18	-0.02	0.13	0.00	0.00	-0.06	0.08
Std, %	1.20	2.01	0.93	0.25	0.65	0.24	0.54	1.91	0.78
Minimum, %	-3.69	-8.72	-2.70	-0.86	-2.18	-1.00	-2.05	-8.26	-3.65
Maximum, %	3.32	7.13	3.68	1.01	4.24	1.07	1.86	9.73	2.84

Source: Calculated by the author.

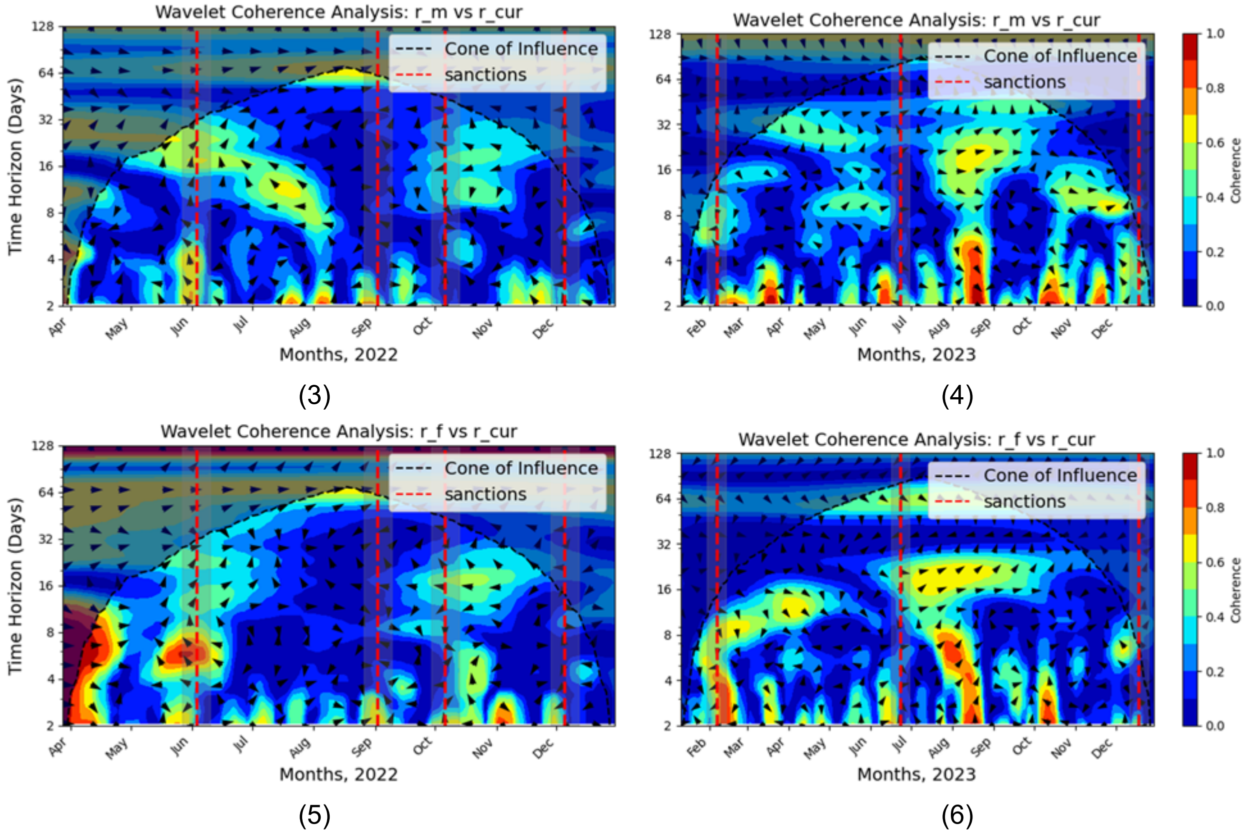
The sampling for 2022 begins on March 28, resulting in only 190 observations for that year. The average value of stock market returns becomes negative at the onset of the sanctions period but returns to a positive value in 2023. The foreign exchange market exhibits a similar pattern in its mean. For the bond market, the rebound occurs as early as 2022. Regarding the standard deviation, which serves as a proxy for risk, the peak values also occur in 2022. Risk decreases in 2023: for both the stock and bond markets, the standard deviation values in 2023 are even lower than those observed in the relatively calm year of 2021. These average returns and standard deviation values may indirectly suggest that Russian financial markets are adapting to the sanctions regime. However, more reliable conclusions require further analysis through the WCA calculations.

4. RESULTS

In the last relatively calm year, 2021, just before the imposition of large-scale sanctions, the main contagion effects occurred between the government bond market and the ruble exchange rate. The estimation results are presented in the Appendix (Picture A.3). Coherence reaches its peak at the end of March and continues throughout April. During this period, the Key Rate of the Bank of Russia was increased by a total of 75 basis points.
The WCA estimation results for each index pair across the two sanction years are presented in Picture 1. In contrast to 2021, as shown in the Appendix, the main contagion effects are observed between the stock market and the bond market (Picture 1.1).



(1) (2)



Picture 1: Wavelet Coherence Analysis for each pair of index volatilities in 2022–2023 year
Source: Calculated by the author.

The coherence between the MOEXOG and RGBITR indices in 2022 reaches its maximum in late August to early September, across time horizons ranging from 8 days to 1 month (Picture 1.1). This corresponds to the boundary between short- and medium-term effects. Sanction 2 (Table 1), the announcement of sanctions within the eighth package, coincides with this time period. The arrows in this area of the spectrogram indicate a phase difference in the range $0 < \phi = \pi/4$, suggesting that contagion spreads from the stock index to the bond index with a positive relationship. Between sanctions 2 and 3 (Table 1), another reciprocal reaction of the indices is observed at the 4–6-day horizon. However, this reaction might not be economically driven. The September-October 2022 period corresponds to Ukraine's counter-offensive, which has a long-term impact that cannot be captured by the WCA method, as the area of increased dependence extends beyond the cone of influence.

In 2023, the coherence between stock and bond market volatilities decreases significantly (Picture 1.2). For the most part, the spectrogram shows no contagion effects, except for the fifth sanction event (Table 2)—the imposition of a price ceiling on petroleum products. During the fifth event window, contagion reaches 0.9 on a six-day time horizon, with contagion spreading from government bonds to oil and gas stocks.

Regarding volatility co-movements between the stock market and the exchange rate, only the window of the first sanction event shows an increase in coherence to 0.6. The directions of the phase difference arrows point upward-left, indicating that contagion spreads from the stock market to the ruble exchange rate, with the volatilities moving in opposite directions. For the subsequent sanction events, the spectrogram shows no significant contagion effects between the two financial variables.

Finally, for the pair of the bond market and the foreign exchange market in 2022, there is an increase in volatility on a 5–6-day time horizon during the first sanction event window (Picture 1.5). The angle of the arrows, $\phi \approx 3\pi/4$, suggests that bond index volatility leads currency market volatility with a negative correlation. The beginning of the observations also corresponds to a significant area of the spectrogram with increased coherence. The contagion effects between the markets arise from the onset of the military and sanctions conflicts. The arrows are horizontal and point to the right, indicating a simultaneous reaction of shocks in the two financial markets with positive coherence. However, the boundaries of the cone of influence prevent drawing medium-term conclusions from this observation period.

In the 2023 spectrogram (Picture 1.6), there is also a reaction from the bond market to the increase in ruble exchange rate volatility during the fifth sanction event. The contagion effect extends no further than a four-day time horizon.

A spike is observed in all three WCA spectrograms for mid-August 2023. This period corresponds to an increase in the Key Rate from 8.5% to 12%. The stock market is the first to react, triggering contagion that spreads to the bond market and the currency market. The ruble exchange rate reacts last of the three markets. However, this reaction is not as pronounced as the market responses observed in pre-sanctions 2021, which may indicate that the markets are becoming accustomed to macroeconomic shocks.

5. CONCLUSION

This paper examined Russian financial markets, represented by the respective indices: the stock market, the government bond market, and the foreign exchange market. Using wavelet coherence analysis, a method that has proven effective in assessing sanctions, the contagion effects between markets during the period of announcement and implementation of European Union sanctions against the Russian oil and gas sector in 2022–2023 were analyzed.

Among the sanction events analyzed, the introduction of the sixth sanctions package had a short-term impact. Over the course of a week, there were volatility spillovers from the debt market to the equity market and the exchange rate. In the fall of 2022, significant contagion effects were observed between the equity and debt markets. However, the WCA method was unable to distinguish between the effects of the announcement and implementation of sanctions under the eighth package and those of military and political events. The imposition of a price ceiling on Russian oil products in February 2023 also resulted in a transfer of volatility from the ruble exchange rate to the bond market and then to the equity market, with a duration of less than a week. Additionally, 2023 appears to be characterized by a gradual stabilization of all three Russian financial markets, suggesting that the Russian economy may be adapting to the sanctions regime.

REFERENCES

Afanasyev, D., Fedorova, E., & Ledyaeva, S. (2021). Strength of words: Donald Trump's tweets, sanctions and Russia's ruble. Journal of Economic Behavior & Organization, 184, 253-277. Retrieved from https://doi.org/10.1016/j.jebo.2021.02.002

Aganin, A. D., & Peresetsky, A. A. (2018). Volatility of ruble exchange rate: Oil and sanctions. Applied Econometrics, 52, 5-21. Retrieved from https://ideas.repec.org/a/ris/apltrx/0353.html

Bown, C. (2023). Russia's war on Ukraine: A sanctions timeline. Peterson Institute for International Economics. Retrieved March 27, 2025, from https://www.piie.com/blogs/realtime-economics/russias-war-ukraine-sanctions-timeline

Chernykh, A. (2024). Event-Driven Analysis of the Effectiveness of European Economic Sanctions Against Russia (2022–2024). International Scientific Conference Strategic Management and Decision Support Systems in Strategic Management, 73-79. Retrieved from https://doi.org/10.46541/978-86-7233-428-9_399

Farge, M., 1992: Wavelet transforms and their applications to turbulence. Annu. Rev. Fluid Mech., 24, 395–457.

Fedorova E., Nevredinov A., & Chernikova L. (2023). The Impact of Sanctions on the Capitalization of Russian Companies: The Sectoral Aspect. Journal of Corporate Finance Research, 17(2), 50-67. Retrieved from https://doi.org/10.17323/j.jcfr.2073-0438.17.2.2023.50-67

Krieger S. & Freij N. PyCWT: wavelet spectral analysis in Python. V. 0.4.0-beta. Python. 2023. Retrieved March 27, 2025, from https://github.com/regeirk/pycwt

Omidi, Z., Farazmand, H., Anvari, E., & Arman, S. A. Investigating the Relationship between Exchange Rates and Oil Prices on Iranian Steel Exports to China with Emphasis on Sanctions: A wavelet and multivariate-GARCH approach. International Journal of ISSI, Vol. 18(2021), No. 1, pp. 98-105. Retrieved from https://doi.org/10.22034/ijissi.2021.540392.1209

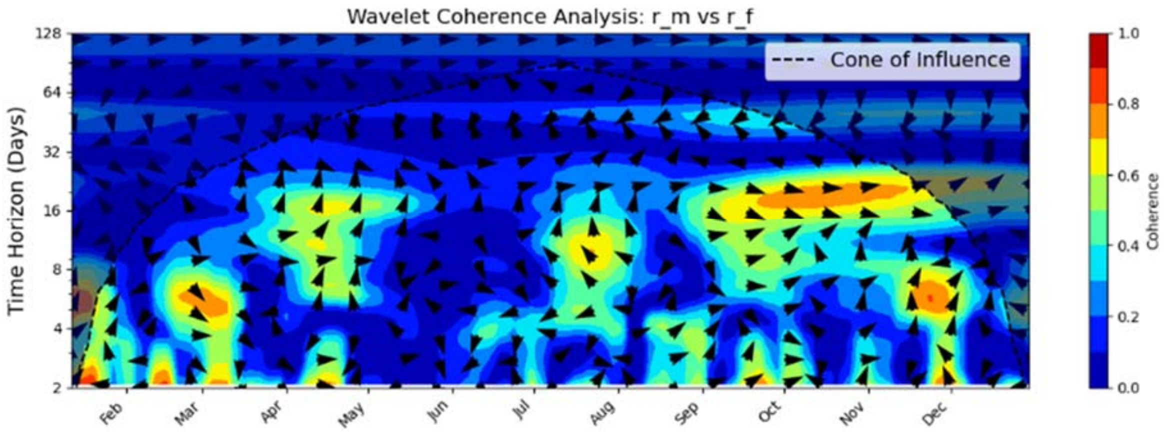
Samadi A., Owjimehr S. & Halafi Z. (2021). The cross-impact between financial markets, Covid-19pandemic, and economic sanctions: The case of Iran. Journal of Policy Modeling, 43 (1), 34-55. Retrieved from https://doi.org/10.1016/j.jpolmod.2020.08.001

Syriopoulos, T., Makram, B., & Boubaker, A. (2015). Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. International Review of Financial Analysis, 39, 7-18. https://doi.org/10.1016/j.irfa.2015.01.015

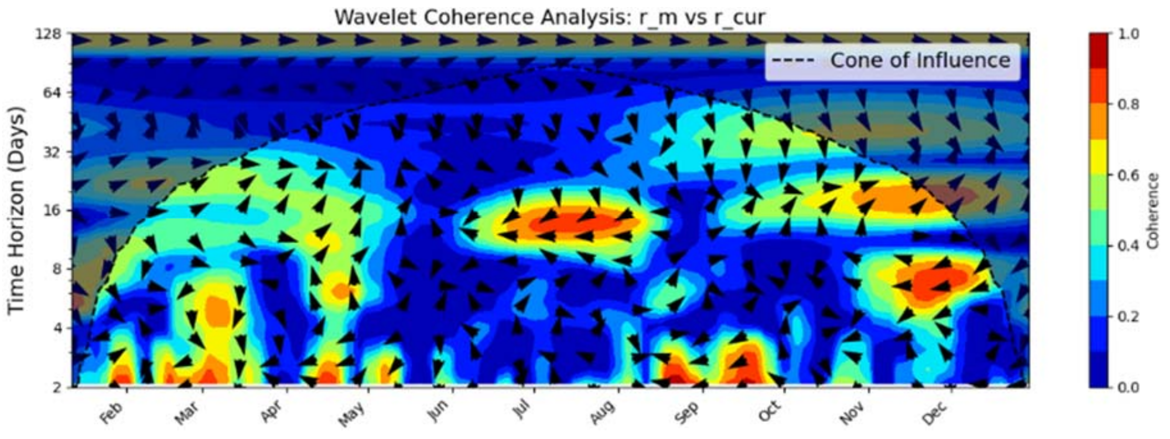
Szczygielski J., Charteris A. & Obojska L. (2022). Do commodity markets catch a cold from stock markets? Modelling uncertainty spillovers using Google search trends and wavelet coherence. International Review of Financial Analysis, 87, 102304. Retrieved from https://doi.org/10.1016/j.irfa.2022.102304

Torrence, C., & Compo, G. P. (1998). A practical guide to wavelet analysis. Bulletin of the American Meteorological Society, 79, 61–78. Retrieved from https://doi.org/10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO;2

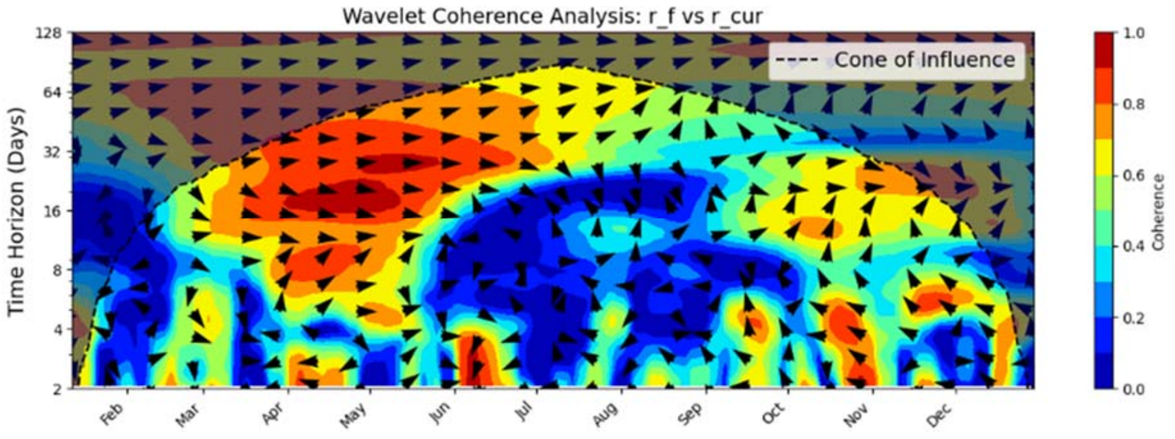
APPENDIX



(1)



(2)



(3)

Picture A: Wavelet Coherence Analysis for each pair of index volatilities in 2021
Source: Calculated by the author