THE EFFECT OF THE WAR ON MARKET PRICES IN METALLURGY SECTOR.

by

Yehor Vasyliev

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Thesis Supervisor: ______________________________ Professor Oleg Nivievskyi

Approved by ____

Head of the KSE Defense Committee, Professor [Type surname, name]

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Chapter 1. INTRODUCTION

1.1 Background

The war in Ukraine had an impact not only on the Ukrainian economy, but also on global markets. Commodity markets reacted strongly to the beginning of the war. Prices in the metal markets also showed sharp dynamics. There is no doubt among economists that oil and gas prices have changed significantly due to geopolitical factors, but there is no consensus on the dynamics of metal prices. Therefore, there is a problem of determining the statistical significance of the impact of war on metal prices.

1.2 Purpose

The purpose of this thesis is to identify the statistical impact of the fact of the beginning of the war between Russia and Ukraine on the prices of three metals: aluminum, iron ore and copper. For this purpose, global metal prices, as well as Ukrainian export and import prices and their ratio (terms of trade) should be analyzed.

The thesis proposes the following four hypotheses:

Hypothesis 1. The start of the Russian-Ukrainian war on February 24, 2022 had a statistically significant impact on world metal prices (aluminum, iron ore, copper).

Hypothesis 2. The start of the Russian-Ukrainian war on February 24, 2022 had a statistically significant impact on Ukrainian export prices of metals (aluminum and its products, ferrous metals, copper and its products - groups 76, 72 and 74 of the Classifier of Foreign Trade of Ukraine, respectively).

Hypothesis 3. The start of the Russian-Ukrainian war on February 24, 2022 had a statistically significant impact on Ukrainian export prices of metals (aluminum and its products, ferrous metals, copper and its products - groups 76, 72 and 74 of the Classifier of Foreign Trade of Ukraine, respectively).

Hypothesis 4. The start of the Russian-Ukrainian war on February 24, 2022 had a statistically significant impact on the tirms of Ukraine's trade in metals (aluminum and its products, ferrous metals, copper and its products - groups 76, 72 and 74 of the Classifier of Foreign Trade of Ukraine, respectively).

1.3 Methodology

Time series research methods are used to test the stated hypotheses. Using time series decomposition in the dynamics of metal prices, an outlier corresponding in time to the beginning of the war is identified. After removing the trend component and the cyclical component from the time series, the irregular component and the war beginning outlier remain in the time series. Identification of the trend component and cyclic component is performed using moving average smoothing. The stationarity of the irregular component is checked using the augmented Dickey-Fuller test. A linear regression containing a dummy variable is used to test the statistical significance of the effect of the war starting. If the effect of the beginning of the war dominates price dynamics, then the corresponding coefficient in the regression equation should be statistically significant.

1.4 Scope and Limitations

The paper focuses on the price dynamics of only three metals (aluminum, copper, iron) and the results cannot be extended to all other metals. The methodology used in this paper makes sense under the assumption that in the first months of the war the effect of the war was the dominant factor in the dynamics of metal prices. The identification of the period of influence of the war effect on metal prices in the work is justified in general terms, so it is possible that in some particular cases some individual factors were not taken into account. The historical data for the study includes metal prices from 2012 to 2023 and monthly indices from 2012 to 2023; the author does not exclude that expanding or narrowing the length of the time series may slightly change the results of the work.

1.5 Outline

The thesis is divided into six chapters. Chapter 2 describes the recent trends of the metal prices on the global market and in foreign trade of Ukraine. The ways in which the war affects the price of metals are presented here. The phases in the price dynamics of each metal are analysed. In chapter 3 the main components of the time series are analysed. The algorithm for isolating the war effect component is also described. This chapter also contains the justification for the period of influence of the war effect on metal prices. Chapter 4 describes the data used in the study. In chapter 5 the empirical results are presented and analysed. Chapter 6 presents and discusses the final conclusions and recommendations.

Chapter 2. INDUSTRY OVERVIEW AND RELATED STUDIES

2.1 Mechanisms of influence of the full-scale phase of the Russian-Ukrainian war (from 2022) on the prices of aluminum, copper and iron ore.

The war in Ukraine since the end of February 2022 have had uneven impacts on commodity markets. The effects were most pronounced in the oil, natural gas, fertilizer and grain markets. Metals markets have been under less pressure. The heterogeneity of the impact of the war on different commodities is due to a combination of the following factors:

- the possibility of redirecting sanctioned Russian exports through other countries;

- the amount of raw material stocks that can be used for the period of supply disruptions;

- the potential for an urgent increase in commodity production in other countries;

- market sensitivity to the war-induced decline in demand.

At the beginning of 2022, Russia's share in global aluminum exports was estimated at 4.2% (according to JPMorgan). In this regard, the sanctions imposed on Russian aluminum exports had an impact on global aluminum prices. Alumina imports were also restricted due to the refusal of supplies from Australia, the largest importer of alumina to Russia. In February, Rusal suspended production at its alumina refinery in Ukraine. Combined, these led to the loss of 2/3 of Russian imports Alumina.

Russian copper exports accounted for about 3.3% of global exports. Although the EU has not imposed sanctions on Russian copper, Russian producers have been subject to blocking sanctions by the United States. And the largest importer of copper in Europe, Aurubis, refused to extend contracts with Russian producers, as a result of which Russian copper exports to Europe fell from 27.9 thousand tons in January 2022 to 7.7 thousand tons by May 2023. However, the main decline in imports occurred in 2023, and in 2022, according to Eurostat, there was even a slight increase in imports (301.6 thousand tons in 2022 compared to 294.5 thousand tons in 2021). Thus, the shock in the medical market from the war and sanctions restrictions for 2022 was moderate or even weak.

According to the World Bank, in 2021, Ukraine ranked 4th in the world ($3.9 billion) in terms of the value of iron ore exports, second only to Australia ($115.2 billion), Brazil ($40.7 billion) and Canada ($5.4 billion). In 2022, Ukraine's exports decreased to $2.9 billion, behind South Africa, Sweden and China in addition to the three leaders. After the start Russia's armed invasion due to the blockade of seaports, exports have been restricted. Ukraine redirected part of its iron ore exports to European countries, however, due to increased logistics costs by rail and lower prices on the world market, production was reduced. On the other hand, the war caused a significant increase in energy costs for metal producers. Steel producers who import iron ore, in an effort to reduce increased costs, reduced production, or tried to find cheaper suppliers of ore, which pushed world iron ore prices down.

2.2 Literature review

Numerous studies have explored the economic consequences of armed conflicts on domestic markets, sector incomes, and world market prices in various contexts. These studies provide valuable insights and serve as a foundation for understanding the potential effects of the war on the metallurgy sector in Ukraine. The following are three relevant studies that shed light on similar themes:

"The Economic Impact of Armed Conflict and the Price of Violence" by Paul Collier and Anke Hoeffler (2004):

This study examines the economic consequences of armed conflicts, focusing on the impact on economic growth, domestic investment, and capital accumulation. It highlights the negative effects of conflict on various sectors, including manufacturing, agriculture, and trade. The study emphasizes the importance of restoring economic stability and rebuilding infrastructure in post-conflict situations to foster sustainable development.

"The Effects of Conflict on Local Taxation: Evidence from the War in Iraq" by Ryan S. Jablonski (2015):

This research investigates the effects of the war in Iraq on local tax revenues, a crucial source of income for local governments. The study finds that armed conflict disrupts tax collection mechanisms, leading to significant declines in revenue. It emphasizes the importance of understanding the fiscal implications of conflict and developing strategies to mitigate the adverse effects on local economies.

"The Impact of Political Conflict on Trade: Evidence from the Ukraine Crisis" by Sergey Kiselev and Philip Ushchev (2017):

This study analyzes the impact of the Ukraine crisis on international trade, focusing on the trade relationship between Ukraine and its major trading partners. The research finds substantial negative effects of the conflict on bilateral trade flows, highlighting the disruption of supply chains, increased trade costs, and reduced market access. The study emphasizes the importance of diversifying trade partners and developing resilient trade strategies in conflict-affected regions.

These studies offer insightful information about the financial effects of armed conflicts and market disruptions on both domestic and international markets. Although they might not particularly address the Ukrainian metallurgical industry, they do provide pertinent approaches, frameworks, and factors to take into account when analyzing how the war has affected domestic prices, sector earnings, and global market prices.

By concentrating on the influence of the conflict on domestic pricing and sector incomes in Ukraine's metallurgy industry, as well as its implications for world market prices, the current thesis seeks to close the knowledge gap by building on the findings and techniques of these research. This study aims to offer a thorough analysis of the economic effects of the war in the industry by taking into account the special context of Ukraine and its importance in the global metallurgical market.

Charper 3. METHODOLOGY

3.1 Hypotheses tested in this paper:

Hypothesis 1. The start of the Russian-Ukrainian war on February 24, 2022 had a statistically significant impact on world metal prices (aluminum, iron ore, copper).

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3.2 The main components of the time series of metal prices.

Cyclic component C_t. As the graphical analysis of the dynamics of prices for aluminum, copper and iron ore in 2013-2023 in the world market and in Ukraine's foreign trade showed, the cyclical component is the leading component of the time series. Particularly striking cycles stand out in the dynamics of world prices and the dynamics of export prices in Ukraine, where 3-4 major cycles are noted. According to the time series charts of the terms of trading in metals in Ukraine, cyclicality is not traced.

Seasonal component S_t. The study of autocorrelation functions for the initial world prices of aluminum, copper, and iron ore does not reveal monthly seasonality (lag = 12), since the corresponding ACF coefficients are not statistically significant at the significance level of 0.05 (Figure 1). Similar conclusions are made on the basis of the analysis of Ukraine's export prices according to the Paasche price index by the base year 2012. In import price indices, an autocorrelation with a lag of 12 is observed for iron, since in January 2015 there was an abnormal value of the import price index for this metal. At the same time, the nature of the anomaly of this value remains unclear.

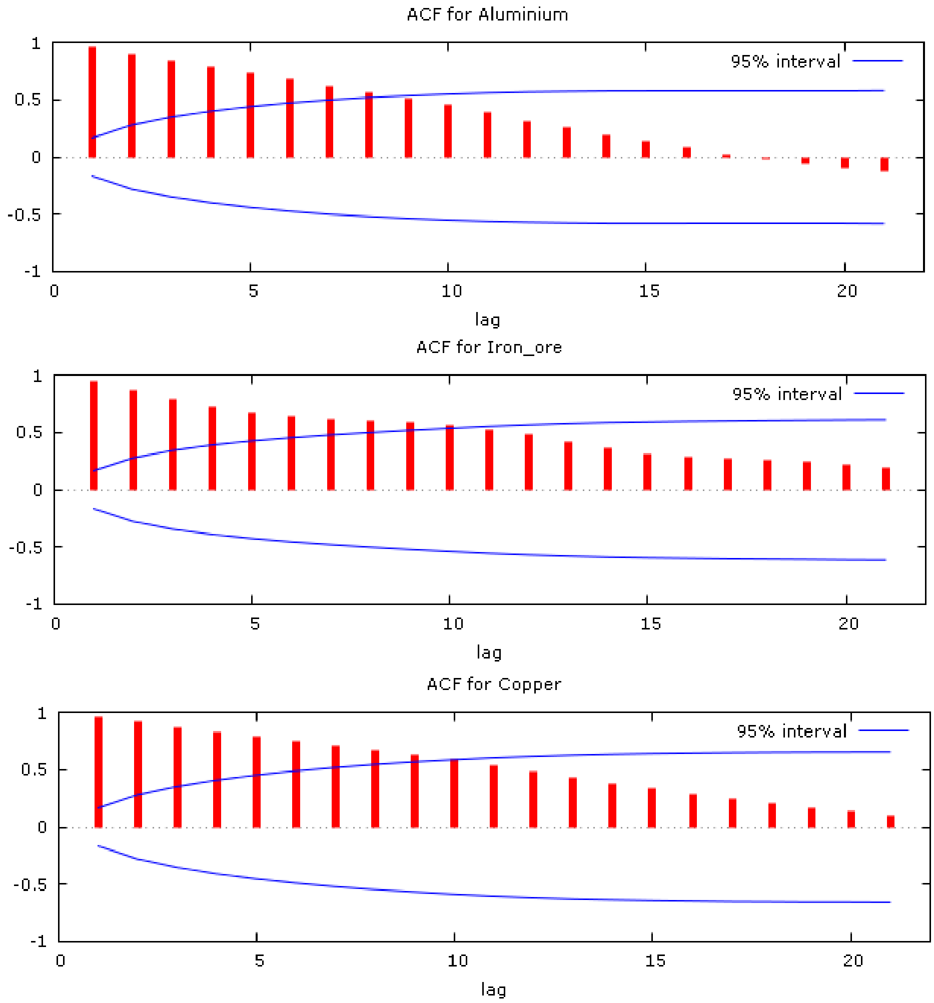


Figure 1. Autocorrelation functions for nominal metal prices with Bartlett 95% standard errors

Trend component T_t. It is not possible to identify a stable trend component that plays a leading role in the time series of metal prices (at least in the time interval 2013-2020). It is possible to consider short-term trends within a particular cycle, however, in this case, the trend component plays a secondary role, not the leading one. In the event that the trend component played a leading role and cyclical components are secondary, visually on the chart, cycles would follow the trend, and not vice versa.

Irregular component E_t. This component is counted as a residual component after excluding the cyclical, seasonal and trend components. Since seasonality and visible trend are not clearly observed in the time series, the main task is to filter the cyclic component.

3.3 The algorithm for identifying the shock component – the impact of the beginning of the large-scale phase of the Russian-Ukrainian war.

Along with the main components, metal prices can include shock components of individual geopolitical or other events that have a short-term but very significant impact on the price. Among such events in recent years, the COVID-19 pandemic (or, more precisely, the reaction of society to the pandemic in the form of restrictive measures, in particular, lockdowns, which have direct economic consequences), as well as Russia's armed invasion of Ukraine in February 2022, stand out. Both events are shocks to the economy, as they are unpredictable both in terms of the duration of the impact and the expected consequences. The reaction of markets to such shocks is most evident in commodity prices, in particular, metals, since market participants often factor in all possible risks of consequences, thereby multiplying the effect of the shock factor.

To assess the impact of the shock component, the following sequence of analysis seems appropriate:

Stage 1. Isolation of the cyclic component. It can be carried out in different ways. In this paper, a centered moving average with a smoothing period of t=12 months is used for filtering.

Stage 2. Testing of the residual component for stationarity. Since only the random and shock components should remain after the cyclic component is excluded, the part of the time series where the shock component should not occur chronologically is checked using the single root test (the Augmented Dickey-Fuller test). In the case of nonstationarity, the most appropriate filtering method is selected.

Stage 3. Estimation of the duration of the shock component. Typically, this is a relatively short period of time during which the shock factor is dominant in the markets.

Stage 4. Estimating the significance of the shock component using the following year's regression:

$$\hat{y}_t = a_0 + a_1 \cdot W + a_2 \cdot W \cdot t + \varepsilon_t,$$

where $\hat{y}_t$ is the time series of basic metal price indices with cyclical, trend and seasonal components excluded (i.e. stationary series + shock components);

W – fictitious variable of the war (equal to 0 in the period before and after the impact of the shock of the beginning of the war, 1 during the period of the market shock);

t – period number (month number in order, January 2013 t=1);

ε_t – irregular component, regression residuals;

a_0, a_1, a_2 - Least squares regression parameters.

The inclusion of the factor in the regression along with the W factor $(W \cdot t)$ is caused by the need to assess the impact of the shock for several periods (months) in case of uneven distribution of the impact within the estimated critical period.

Along with the extended form, abbreviated regressions $\hat{y}_t = a_0 + a_2 \cdot W \cdot t + \varepsilon_t$ and $\hat{y}_t = a_0 + a_1 \cdot W + \varepsilon_t$.

The statistical significance of at least one of the coefficients a_1, a_2 will be equivalent to the statistical significance of the impact of the war shock on the price of the corresponding metal.

3.4 Estimation of the duration of the shock component.

In order to assess the duration of the shock effect of the beginning of the war, it is necessary to select such a critical point (bifurcation point) at which the effect of other important factors in the dynamics of metal prices begins to outweigh the shock effect. These are, first of all, the following factors:

a) Inflationary consequences of excessive money printing as part of aid programs during the period of pandemic restrictions.

b) The second wave of lockdowns in China (the closure of Shanghai and some other cities), which sharply reduced economic activity in China, the largest consumer of metals in the world. China's industrial production index decreased by -2.9% in April 2022 (compared to April 2021). In March-April, the Shanghai Composite stock index lost about 12% of its capitalization.

c) Economic consequences of high energy prices for the industry of European developed countries. In particular, in Germany, industrial production in March 2022 decreased by -3.5% (compared to the previous year), in April it decreased by -2.2%, in May it decreased by -1.5%.

d) Decisive measures taken by central banks to combat high inflation. On March 16, the Fed began a cycle of rate hikes (to 0.5% on March 16, to 1% on May 4, to 1.75% on June 15 and beyond during the second half of 2022 and in 2023 to a high of 5.5% on July 26, 2023).

It is also necessary to take into account the methodological difference in the world prices used and the prices of Ukraine's foreign trade. World metal prices are exchange quotations of world commodity exchanges (in fact, momentary levels of the time series), so the shock effect of the beginning of the war began to be laid down at the end of February (that is, it was taken into account in the price index for February 2022). Ukraine's export and import prices are taken into account in the weighted average aggregate indices, and since only 5 out of 28 days in February fall on hostilities, the shock effect of February is reflected in the prices of Ukraine's foreign trade very insignificantly.

Taking into account the above factors, the interval from February to April 2022 (W_1) was taken as the time range for taking into account the shock component of the war for world prices, and the interval from March to May 2022 (W_2) was taken for foreign trade prices in Ukraine.

Chapter 4. DATA

4.1 Dynamics of world prices for aluminum, copper and iron ore in 2013-2023 and since the beginning of the war in 2022.

In 2013-2020, world aluminium prices showed relatively restrained volatility, deviating to +20% from 2012 prices when growing and up to -30% from 2012 prices when decreasing. Several price cycles in aluminium can be distinguished: a short cycle in 2013-2014 (up to 110% at the peak of 2014), a downward wave in 2015-2017 (to -30% at a low in 2016), The most significant volatility in aluminum prices was observed in the 2021-2023 cycle, when the price reached up to +60% at the 2022 high from 2012 levels, which can be considered the result of the influence of the global inflationary processes in conjunction with the Russian-Ukrainian war (Figure 2).

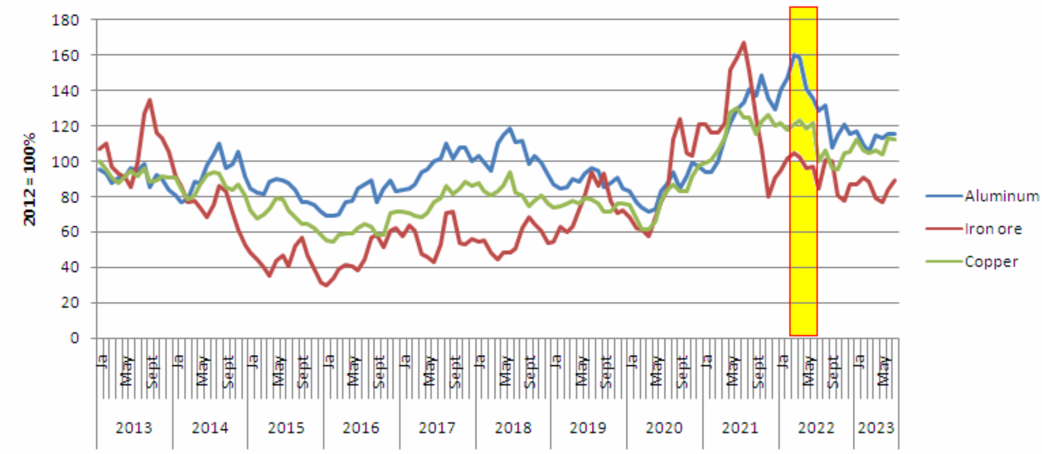


Figure 2. Global prices of the metals in the years 2013-2023, % to 2012 (the yellow area shows the first 4 months of the war)

The dynamics of global copper prices compared to aluminium have been more resilient to declines over the past decade. After a prolonged decline in 2013-2016, global copper prices fell below 60% of 2012 levels, then recovered to 90% of 2012 levels by 2018, and then fell significantly again to 60% levels at the beginning of the pandemic in 2020. Since 2021, copper prices have grown dynamically, reaching 130% of 2012 levels in mid-2021. In the second half of 2021, copper prices stabilized at around 120% before retreating to 100% in the second half of 2022. The beginning of the military conflict did not have a visible noticeable impact on world copper prices (or temporarily restrained them from falling).

Iron ore showed the most significant fluctuations in the dynamics of its world prices among the three metals under consideration (up to 30% at the lows and up to 160% at the highs from the 2012 levels). In 2013-2016, there was a phase of decline in world prices, in 2016-2021 - a phase of growth in world prices for iron ore, and from the second half of 2021 - a sharp decline in world prices.

In the first months of the war, world iron ore prices showed only a slight decline, while during 2022 as a whole, the price of copper stabilized at 80-90% of the base year of 2012. In general, the dynamics charts show a more significant impact of the war on world aluminum prices than on the prices of copper and iron ore.

4.2 Dynamics of export and import prices of Ukraine, as well as terms of trade of aluminum, copperand iron ores in 2013-2023 and since the beginning of the war in 2022.

In 2013-2020, export prices of all three metals showed a similar cyclicality: a decline by 2016, then an increase by 2018 and a decrease by 2020. Since 2021, aluminum export prices have shown an increase of up to 160% from 2012 levels, then decline by the beginning of 2022 and, with the beginning of the war, show a noticeable increase in the first half of 2022. Copper and iron ore in 2021 showed only moderate growth from 80% to 120% of 2012 levels, while in the first months of the war they moved with multidirectional monthly dynamics with a general downward trend. Thus, graphically, there is a noticeable impact of the war on the export prices of aluminum and, to some extent, iron ore, in the dynamics of copper export prices, the impact of the war is not discernible (Figure 3).

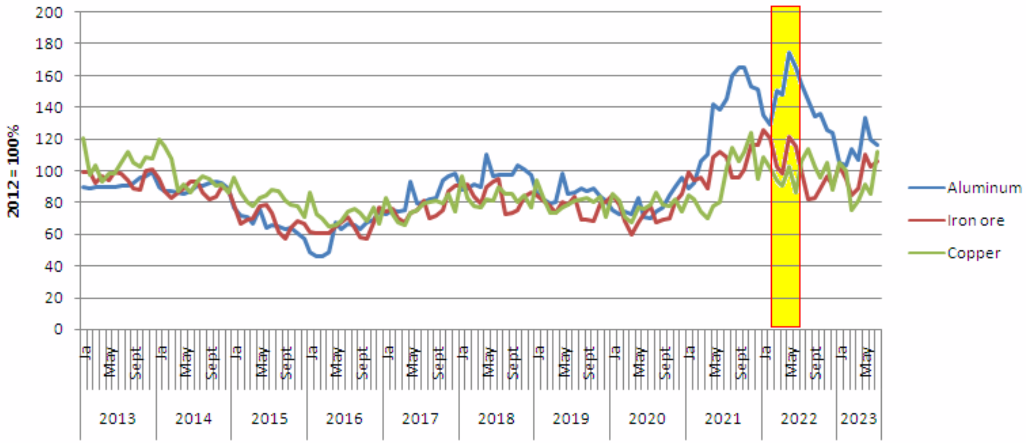


Figure 3. Export prices of the metals in Ukraine in the years 2013-2023, % to 2012 (the yellow area shows the first 4 months of the war)

Compared to exports, Ukraine's imports of metals show a much more significant price fluctuation with an upward trend in recent years. In general, the phases of growth and decline repeated the phases in export prices. However, the most noticeable dynamics since 2021 showed import prices not only for aluminum, but also for iron ore (up to 200% compared to the level of 2012). In the price dynamics, there is a noticeable impact of the war on import prices of aluminum, and to a lesser extent - in import prices of copper (Figure 4).

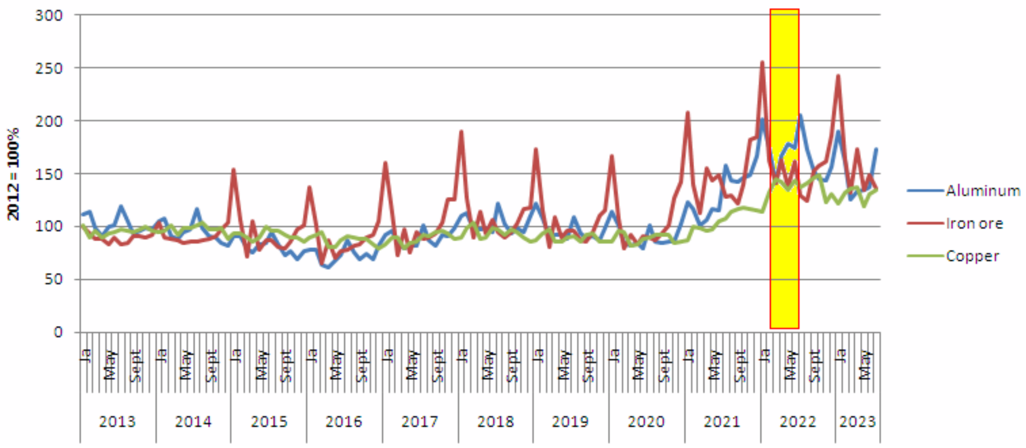


Figure 4. Import prices of the metals in Ukraine in the years 2013-2023, % to 2012 (the yellow area shows the first 4 months of the war)

The ratio of export prices of the metals under consideration to imports in Ukraine showed extremely high intra-year fluctuations between months, while since

2015 there has been a noticeable downward trend in the terms of trade for copper and ferrous metals. The effect of war on the terms of trade is difficult to determine graphically, and it is necessary to test the relevant statistical hypotheses (Figure 5).

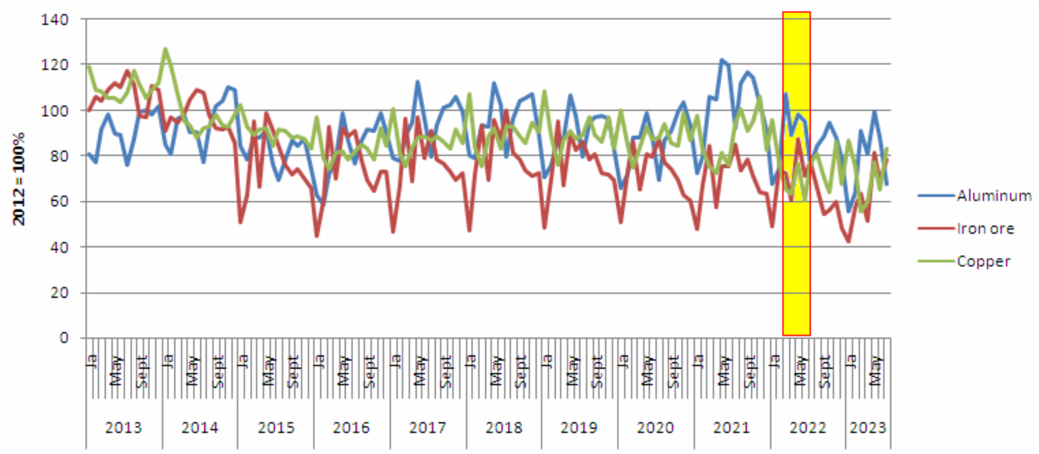


Figure 5. Terms of trade of the metals in Ukraine in the years 2013-2023, % to 2012
(the yellow area shows the first 4 months of the war)

Chapter 5. RESULTS

The market shock from the beginning of the large-scale phase of the Russian-Ukrainian war was statistically significant (at the 0.95 confidence level) for global aluminum prices (the impact is high because the P-level is very low). In the model y(W) for coefficient a_1 P-level is $7.6 \cdot 10^{-5}$, in the model y(Wt) for coefficient a_2 P-level is $7.2 \cdot 10^{-5}$, and in the model y(W,Wt) both coefficients a_1 and a_2 are statistically insignificant at the level of 0.05 (P-level 0.105 and 0.099 for parameters a_1 and a_2 respectively). Thus, one parameter was sufficient to identify the impact of the beginning of the war on world aluminum prices. The extremely low P-level value for the first two models indicates that world aluminum prices were very sensitive to the shock from the beginning of the war.

The contribution of the shock component of the beginning of the war to the dynamics of global iron ore prices cannot be recognized as statistically significant in any of the considered modifications of the models: in the model y(W) for the coefficient a_1 P-level is 0.511, in the model y(Wt) for the coefficient a_2 P-level is 0.510, and in the model y(W,Wt) both coefficients a_1 and a_2 turned out to be statistically insignificant at the level of 0.05 (P-level 0.735 and 0.731 for parameters a_1 and a_2 respectively). Thus, no significant effect of the war in the dynamics of global iron ore prices was found.

The contribution of the shock component of the beginning of the war to the dynamics of global copper prices also cannot be recognized as statistically significant in any of the considered modifications of the models: in the model y(W) for the coefficient a_1 P-level is 0.214, in the model y(Wt) for the coefficient a_2 P-level is 0.211, and in the model y(W,Wt) both coefficients a_1 and a_2 turned out to be statistically insignificant at the level of 0.05 (P-level 0.268 and 0.264 for parameters a1 and a2, respectively). Thus, no significant effect of the war in the dynamics of world copper prices was also found (Table 1).

Table 1. Levels of Significance of Metal Price Regression Coefficients (Global Market and Exports of Ukraine)

Regression	Options	Global Market			Export		
		Aluminum	Iron ore	Copper	Aluminum	Iron ore	Copper
y=a0+a1*W	P(a1)	$7,6*10^{-5}$	0,511	0,214	0,08	0,788	0,106
y=a0+a2*Wt	P(a2)	$7,2*10^{-5}$	0,510	0,211	0,077	0,766	0,108
y=a0+a1*W+a2*Wt	P(a1)	0,105	0,735	0,268	0,012	0,034	0,276
	P(a2)	0,099	0,731	0,264	0,011	0,034	0,281

Aluminum export prices in Ukraine were significantly affected by the effect of the beginning of the war. This is not reflected in the y(W) model, where the P-level of coefficient a_1 is 0.08 > 0.05, nor is it reflected in the y(Wt) model, where the P-level of coefficient a_2 was 0.077 > 0.05. However, in the y(W,Wt) model, both coefficients a_1 and a2 are statistically significant ($P_1 = 0.012 < 0.05$ and $P_2 = 0.011 < 0.05$). Moreover, since $a_2 = 14.44 > 0$, the war caused an upward effect in the export prices of aluminum in Ukraine.

Export prices of iron in Ukraine were significantly affected by the effect of the beginning of the war. This is not reflected in the y(W) model, where the P-level of the coefficient a_1 is 0.788 > 0.05, nor is it reflected in the y(Wt) model, where the P-level of the coefficient a_2 is 0.766 > 0.05. However, in the y(W,Wt) model, both coefficients a_1 and a_2 are statistically significant ($P_1 = 0.034 < 0.05$ and $P_2 = 0.034 < 0.05$). In this case, since $a_2 = 10.47 > 0$, the war caused an increase in iron export prices in Ukraine.

Export prices of copper in Ukraine did not react significantly to the beginning of the war: in the model y(W) p-level for coefficient a_1 is 0.106 > 0.05, in the model y(Wt) p-level for coefficient a_2 is 0.108 > 0.05, in the model y(W,Wt) both coefficients are not statistically significant, as $P_1 = 0.276 > 0.05$, $P_2 = 0.281 > 0.05$.

Import prices of aluminum in Ukraine changed significantly under the effect of the beginning of the war. This is not reflected in the model y(W), where the P-level of coefficient a_1 is 0.267 > 0.05, nor is it reflected in the model y(Wt), where the P-level of coefficient a_2 is 0.275 > 0.05. However, in the y(W,Wt) model, both coefficients a_1 and a_2 were statistically significant ($P_1 = 0.016 < 0.05$ and $P_2 = 0.016$

< 0.05). At the same time, since $a_2 = 18.54 > 0$, the war caused a growth effect in import prices of aluminum in Ukraine (Table 2).

Table 2. Levels of Significance of Metal Price Regression Coefficients (Ukraine's Imports and Terms of Trade)

Regression	Options	Import			Trading Condition		
		Aluminum	Iron ore	Copper	Aluminum	Iron ore	Copper
y=a0+a1*W	P(a1)	0,267	0,306	0,0088	0,200	0,350	0,028
y=a0+a2*Wt	P(a2)	0,275	0,305	0,0092	0,201	0,346	0,029
y=a0+a1*W+a2*Wt	P(a1)	0,016	0,877	0,039	0,726	0,299	0,144
	P(a2)	0,016	0,871	0,041	0,733	0,296	0,149

Import prices of iron in Ukraine did not react significantly to the beginning of the war: in the model y(W) p-level for coefficient a_1 is $0.306 > 0.05$, in the model y(Wt) p-level for coefficient a_2 is $0.305 > 0.05$, in the model y(W,Wt) both coefficients are not statistically significant as $P_1 = 0.877 > 0.05$, $P_2 = 0.871 > 0.05$.

Import prices of copper in Ukraine were found to be sensitive to the shock from the beginning of the war. In the model y(W) P-level for coefficient a_1 is $0.0088 < 0.05$, in the model y(Wt) P-level for coefficient a_2 is $0.0092 < 0.05$, and in the model y(W,Wt) the significance levels for the coefficients are $P_1 = 0.039 < 0.05$ and $P_2 = 0.041 < 0.05$. In this case, since the value of coefficient $a_2 = -7.11 < 0$, the war led to a decrease in import prices for copper in Ukraine.

The terms of trade shows the relationship between export and import prices. If export prices change unidirectionally together with import prices, then even if the war effect is statistically significant separately for export prices and separately for import prices, it is likely that these dynamics will cancel each other out for the value of the terms of trade. In case of differently directed significant changes in export and import prices, on the contrary, there will be an amplification of the effect for the terms of trade. If there is a significant change for one of the components (export prices or import prices), the effect for the terms of trade can be either statistically significant or statistically insignificant, it can be revealed only by testing the statistical hypothesis.

Ukraine's terms of trade for aluminum turned out to be insensitive to the shock from the beginning of the war, for the model y(W) P-level for coefficient a_1 is 0.200

> 0.05, for the model y(Wt) P-level for coefficient a_2 is $0.201 > 0.05$, for the model y(W,Wt) both coefficients turned out to be statistically insignificant as $P_1 = 0.726 > 0.05$ and $P_2 = 0.733 > 0.05$. Thus, the significant change (increase) in aluminum export prices and the significant change (increase) in aluminum import prices mutually offset the effect of war on the terms of trade for aluminum.

Ukraine's terms of trade for iron turned out to be insensitive to the shock from the beginning of the war, for the model y(W) P-level for coefficient a_1 is $0.350 > 0.05$, for the model y(Wt) P-level for coefficient a_2 is $0.346 > 0.05$, for the model y(W,Wt) both coefficients turned out to be statistically insignificant as $P_1 = 0.299 > 0.05$ and $P_2 = 0.296 > 0.05$. Thus, a significant change (increase) in iron export prices in the absence of a significant change in import prices did not result in a statistically significant change in the terms of trade for iron.

Under the influence of a significant increase in import prices for copper, at which export prices showed no significant dynamics in the first months of the war, the terms of trade for copper showed a significant decline. This is evidenced by a negative significant regression coefficient $a_1 = -9.86 < 0$ ($p = 0.028 < 0.05$) for the y(W) model and a negative significant regression coefficient $a_2 = -0.088 < 0$ ($p = 0.029 < 0.05$) for the y(Wt) model.

Chapter 6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Main conclusions of the study.

The hypothesis testing has shown that the war had a strong impact on global aluminum prices. This is consistent with the mechanisms of influence transmission described above (expectations of a sharp reduction in supplies due to sanctions and others). World iron ore and copper prices in February-April 2022 showed the expected dynamics within their cycle and did not show sharp changes associated with the Russian-Ukrainian war.

For Ukraine's foreign trade, the beginning of the war had a more dramatic impact on metal prices. A moderate impact is noted in export prices of aluminum and ferrous metals. The war also had a noticeable and statistically significant impact on the growth of import prices of copper. In this regard, the already long declining terms of trade for copper have been markedly reduced by the beginning of the war.

Comparison of sensitivity of world prices and prices of Ukraine's foreign trade to the shock of the beginning of the war allows us to draw the following conclusions:

1) Aluminum prices both on the world market and in Ukraine's foreign trade (exports and imports) were characterized by a significant sensitivity to the war shock, while the effect in world aluminum prices was noticeably higher. The direction of movement of aluminum prices in all markets is growth. The terms of trade for aluminum in Ukraine did not change significantly, as the growth in export and import prices was statistically comparable.

2) World prices for iron ore did not show noticeable dynamics, also import prices for iron in Ukraine did not show noticeable dynamics. However, export prices for iron showed significant growth. Such results show, on the one hand, the decreasing influence of Ukrainian iron ore exports on the world market, on the other hand, they demonstrate the severity of the problems that led to an increase in the price of iron exports directly due to the hostilities on the territory of the country.

3) The copper price has not been significantly affected by the beginning of the military conflict on the world market, nor has it affected Ukrainian copper export

prices. However, Ukraine's copper import prices reacted significantly to the war shock, which also affected Ukraine's copper terms of trade.

6.2 Significance of the Russian-Ukrainian military conflict against the background of other factors shaping metal prices on the world market.

Among the three metals under consideration, only aluminum reacted with a significant price increase on the world market as a result of the shock from the beginning of the Russian-Ukrainian war, no statistically significant changes in iron ore and copper prices were found. In addition, within the cyclical dynamics of world prices, the duration of the shock from the impact of the war is limited to approximately three months. In general, the dynamics of all three metals show the following phase patterns: (1) price declines or extremely weak dynamics in the first months of the coronavirus pandemic (February-April 2020; (2) significant price increases in 2021, driven by the global economic recovery and the injection of money by the Federal Reserve and the European Central Bank; (3) some acceleration of growth or delayed price declines in the first months of the war; and (4) declines in metal prices in the second half of 2022 to the first half of 2023, influenced by the slowdown in China's economy and the global economy. The graphs of dynamics (Appendix 1) show that the most significant change in metal prices occurs in phases (2) and (4), and the impact of the war in phase (3), firstly, short-term in time, and secondly, not sustainable in impact. Thus, the impact of global factors (changes in global demand, monetary factors in major economies and others) looks like a much more significant driver of metal prices than the Russian-Ukrainian war.

6.3 Ways of using the results obtained in the work.

The obtained results of the study can be applied in a number of directions, among which the following can be noted:

1) War risks insurance. Despite the fact that in property insurance of many countries military-political events are regarded as an extreme force majeure circumstance and serve as an exception for the payment of insurance compensation for loss or damage to property, the demand for war risk insurance is increasingly growing and stimulates the expansion of the list of insurance types by adding war risk insurance. An example of one of the largest organizations insuring direct investments

against military risks is the Multilateral Investment Guarantee Agency (MIGA), a member of the World Bank Group. During 2022, the agency provided guarantees for 54 projects worth $4.9 billion. The American International Development Finance Corporation (DFC) is also engaged in war risk insurance. It specializes in supporting investors who are willing to invest in high-risk countries. DFC was established in December 2019, since then it has provided guarantees for 4 thousand projects, the total amount of investments in which amounted to $200 billion. Such companies are usually professionally engaged in calculating the degree of military risk both for individual countries and for individual industries and groups of goods.

When assessing the risk of war, the coefficients with the dummy variable W can serve as a basis for taking into account the relative dynamics of metal prices. In this case, the coefficients are comparable for comparing the dynamics of metal prices among themselves, since all regression models are calculated by percentage changes to a single base period. For example, from Appendix 3, the obtained values of coefficients a1: 16.0 for aluminum, 4.7 for iron ore and 3.8 for copper show that the risk of war for world aluminum prices is about 3.4 times higher than for iron ore and 4.2 times higher than for copper.

2) Accounting for military risks in international contracts. Military risks are being incorporated into international export-import contracts more and more often, especially in the foreign trade practice of Ukraine, where a legislative basis is being created for this purpose. Ukrainian draft law No. 9015 amends the law "On Financial Mechanisms to Stimulate Export Activity" No. 1792-VIII and authorizes the Export Credit Agency (ECA) to insure and reinsure direct investments in Ukraine against risks that may be caused by armed aggression, hostilities and/or terrorism. ECA acts as a guarantor of fulfillment of foreign economic contracts, factoring agreements, letters of credit, etc. If, for example, a company wants to take out a loan to finance an export contract, the bank will not grant the loan without insurance, which ECA can provide. In order to assess risks and calculate insurance premiums, organizations such as ECAs may need industry-specific risk ratios, which can be derived from the results of this paper.

3) Accounting for military risks in metal exchange trading. In order to diversify investments in commodities and metals in particular, it may be necessary to calculate the mean square deviation of metal price quotations. The dynamics of metal prices, except for the trend and cyclical component, includes the variation caused by military and political factors. The coefficients calculated in this paper can be used to calculate the overall risk in exchange trading of metals and financial derivatives linked to metal prices.

ANNEX 1

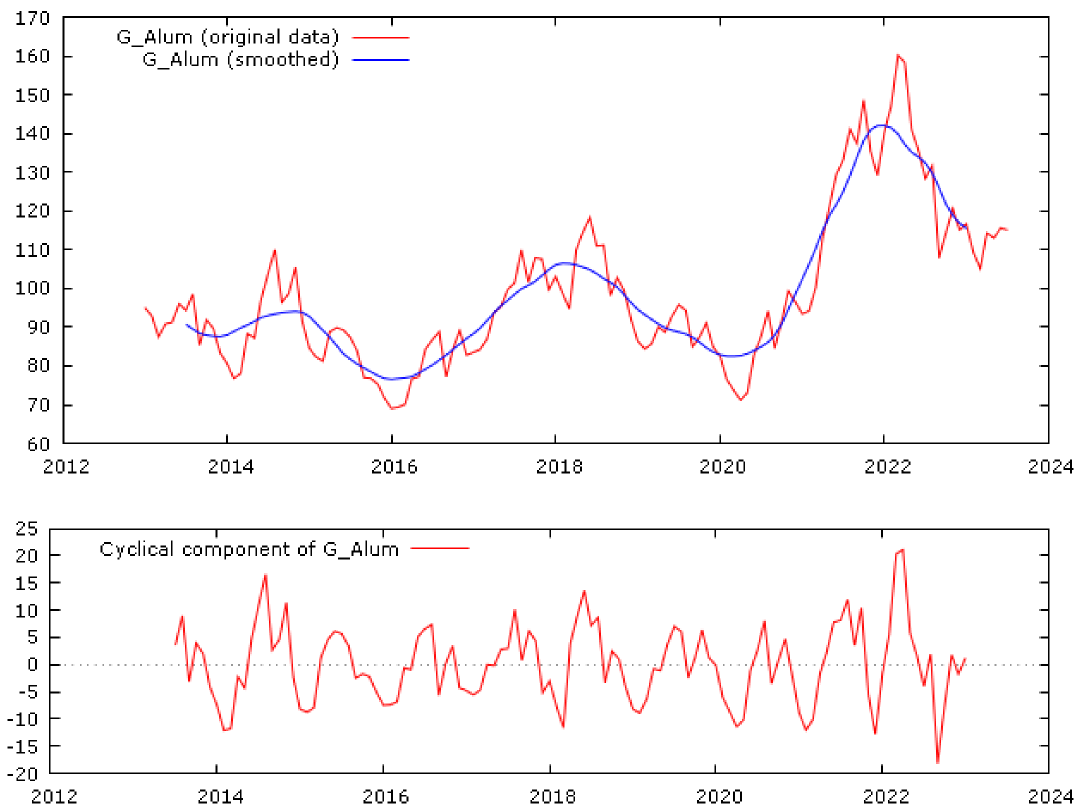
Smoothing Time Series with a 12-Month Centered Simple Moving Average

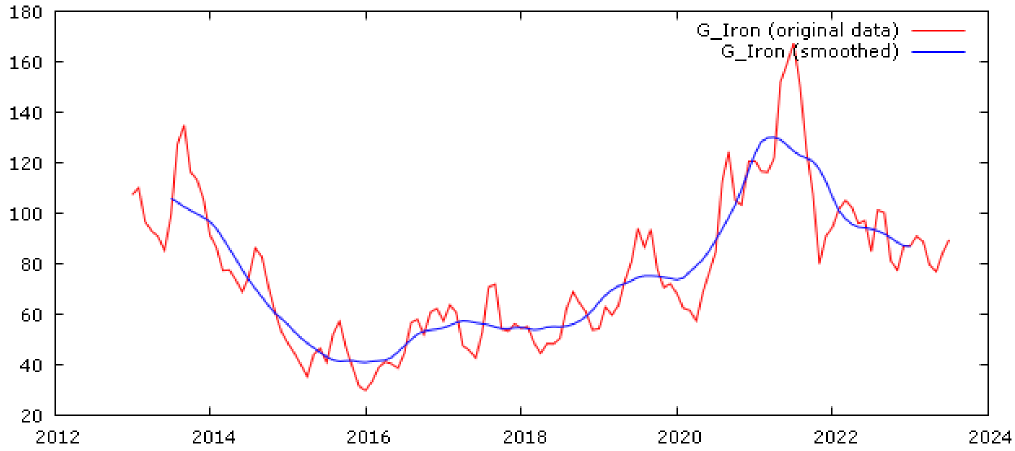
G_Alum, G_Iron, G_Co for basic indices of world prices;

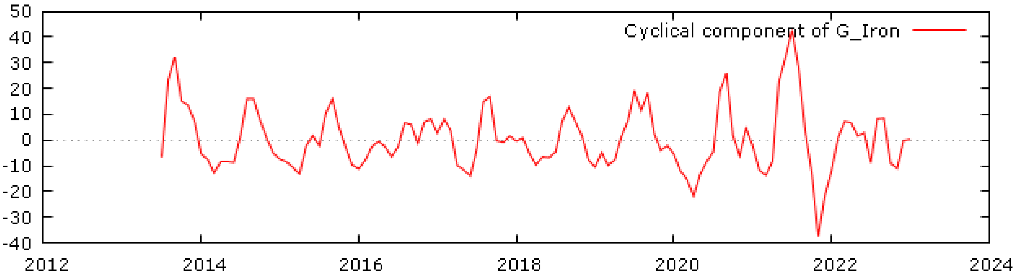
Exp_Alum, Exp _Iron, Exp _Co – for basic indices of export prices of Ukraine;

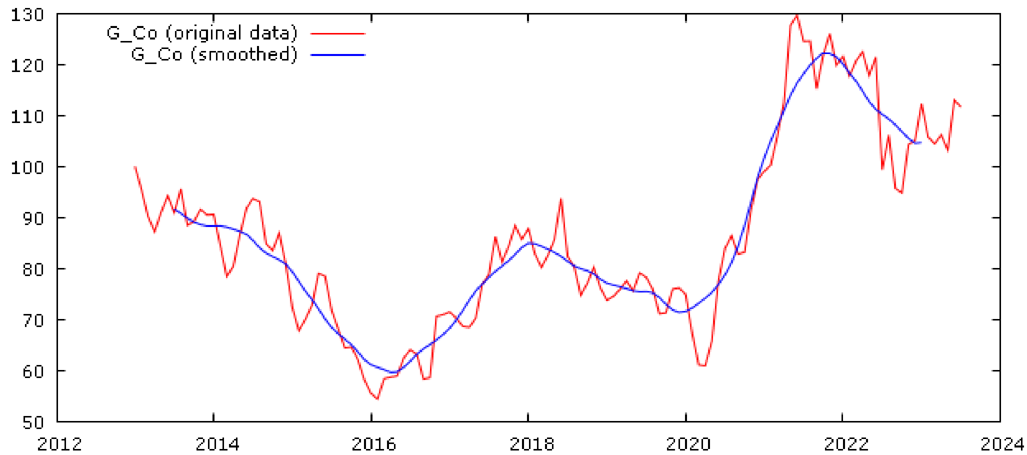
Imp_Alum, Imp _Iron, Imp _Co – for basic indices of import prices of Ukraine;

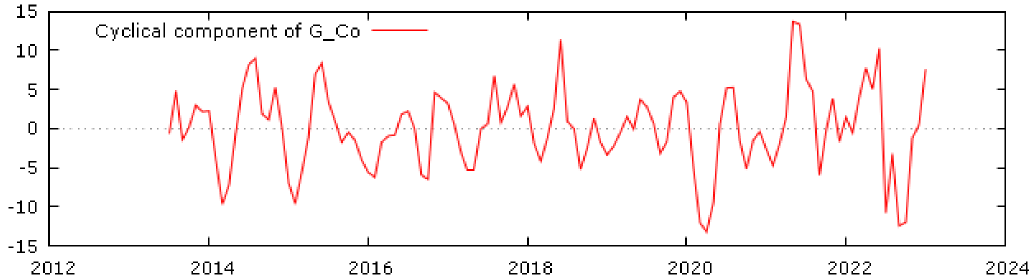
TT_Alum, TT _Iron, TT _Co – for basic indices of the terms of trade of Ukraine.

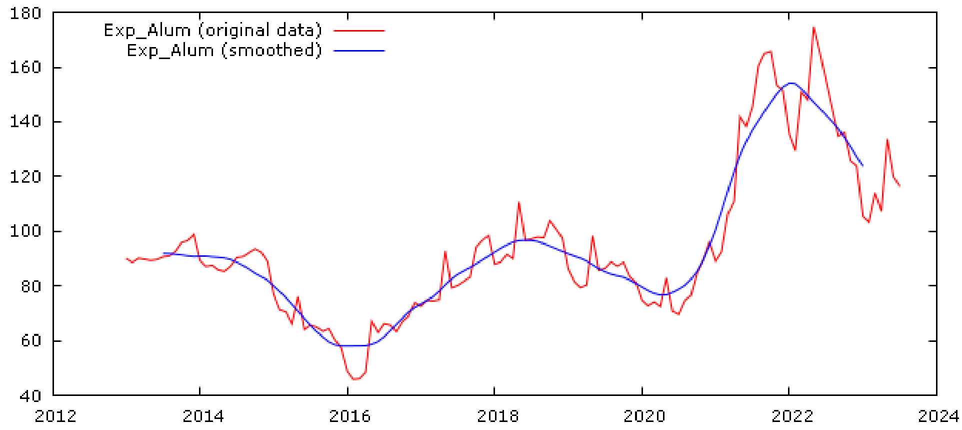


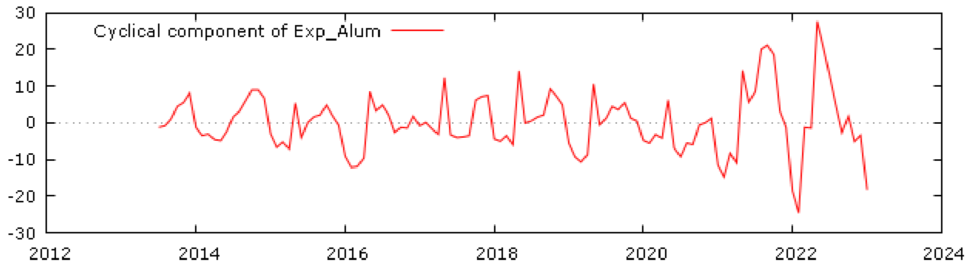

G_Iron (original data)
G_Iron (smoothed)
180
160
140
120
100
80
60
40
20
2012
2014
2016
2018
2020
2022
2024

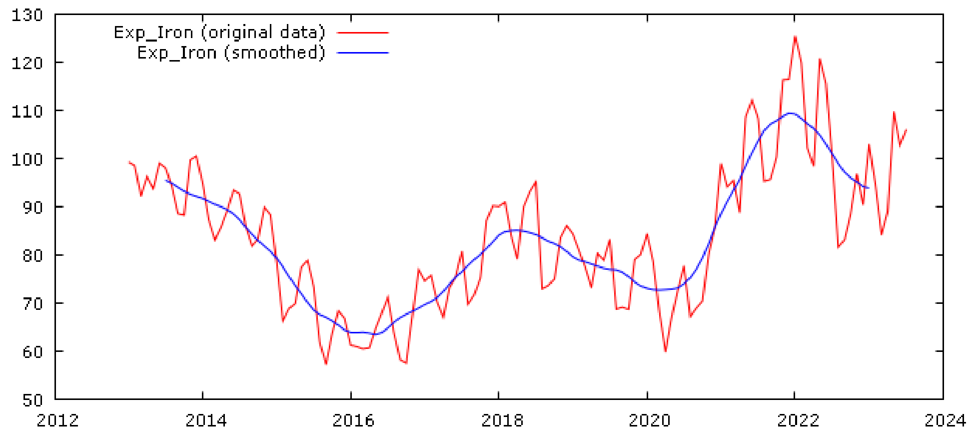

Cyclical component of G_Iron
50
40
30
20
10
0
-10
-20
-30
-40
2012
2014
2016
2018
2020
2022
2024

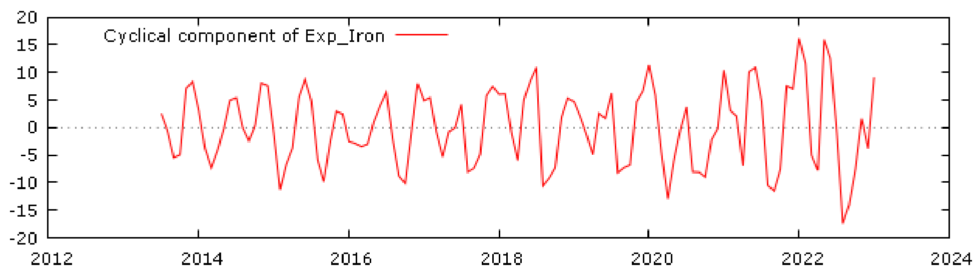

G_Co (original data)
G_Co (smoothed)
130
120
110
100
90
80
70
60
50
2012
2014
2016
2018
2020
2022
2024

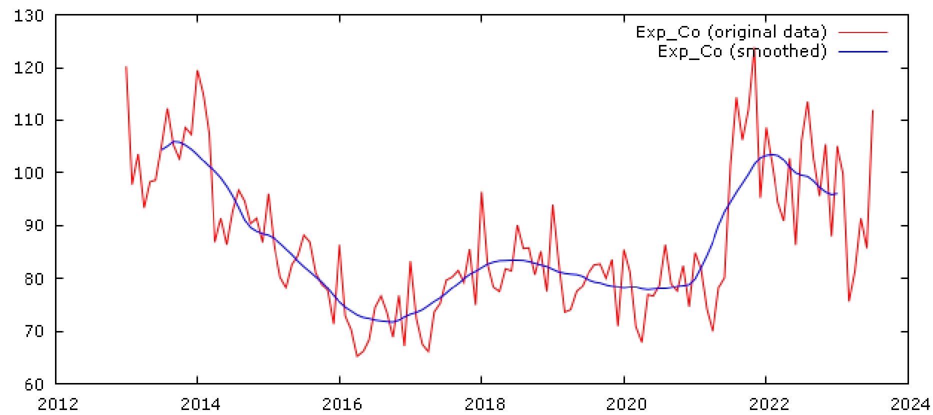

Cyclical component of G_Co
15
10
5
0
-5
-10
-15
2012
2014
2016
2018
2020
2022
2024

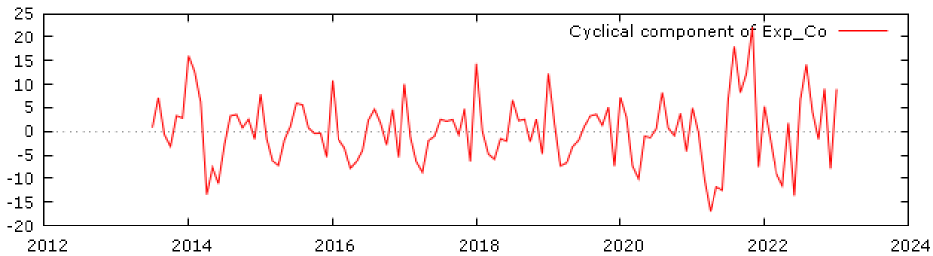

Exp_Alum (original data)
Exp_Alum (smoothed)
180
160
140
120
100
80
60
40
2012
2014
2016
2018
2020
2022
2024

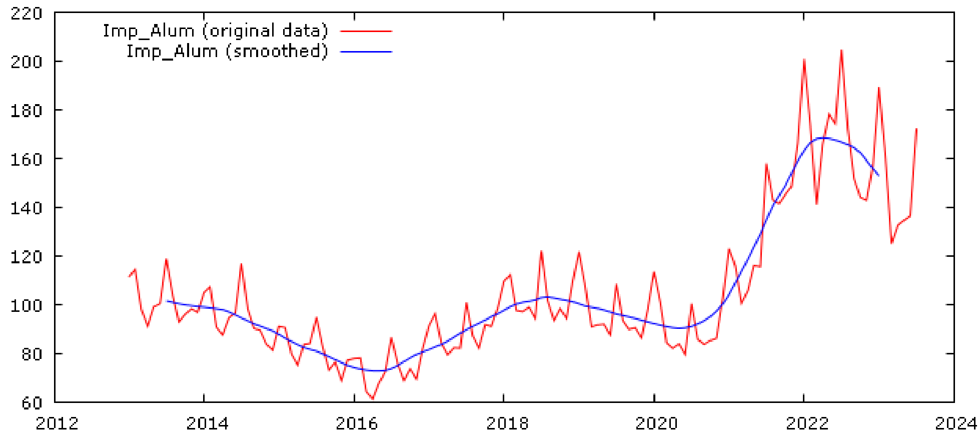

Cyclical component of Exp_Alum
30
20
10
0
-10
-20
-30
2012
2014
2016
2018
2020
2022
2024

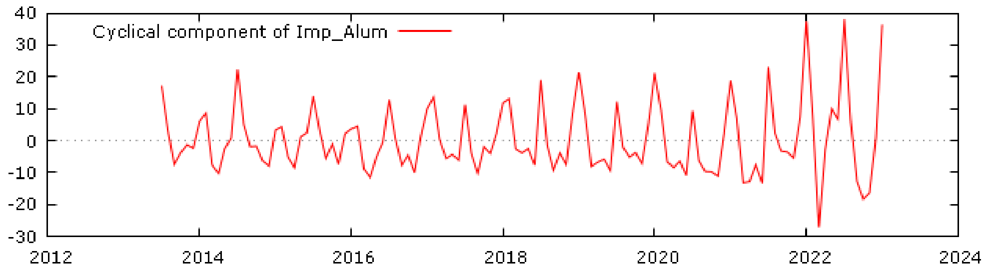

Exp_Iron (original data)
Exp_Iron (smoothed)
130
120
110
100
90
80
70
60
50
2012
2014
2016
2018
2020
2022
2024

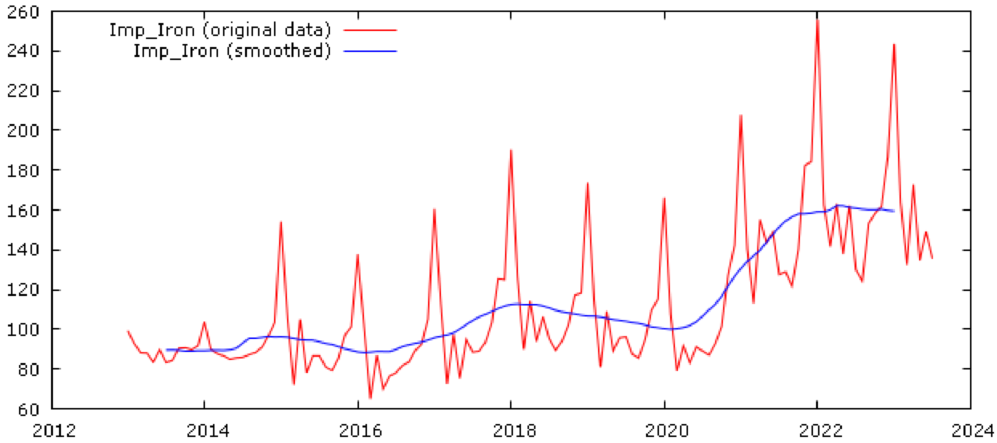

Cyclical component of Exp_Iron
20
15
10
5
0
-5
-10
-15
-20
2012
2014
2016
2018
2020
2022
2024

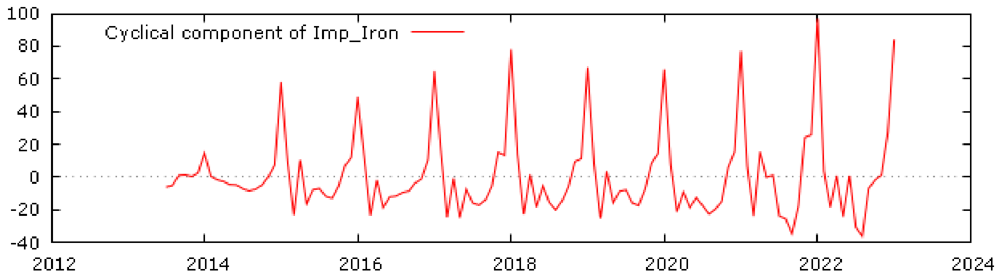

Exp_Co (original data)
Exp_Co (smoothed)
130
120
110
100
90
80
70
60
2012
2014
2016
2018
2020
2022
2024

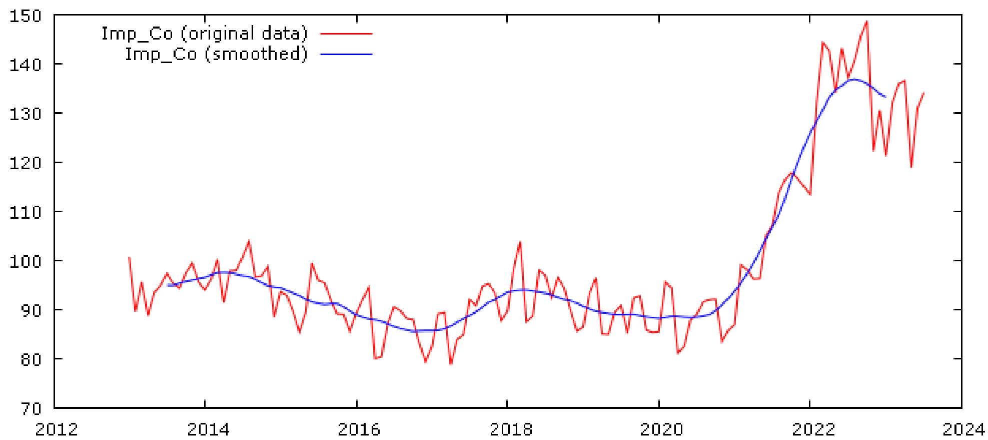

Cyclical component of Exp_Co
25
20
15
10
5
0
-5
-10
-15
-20
2012
2014
2016
2018
2020
2022
2024

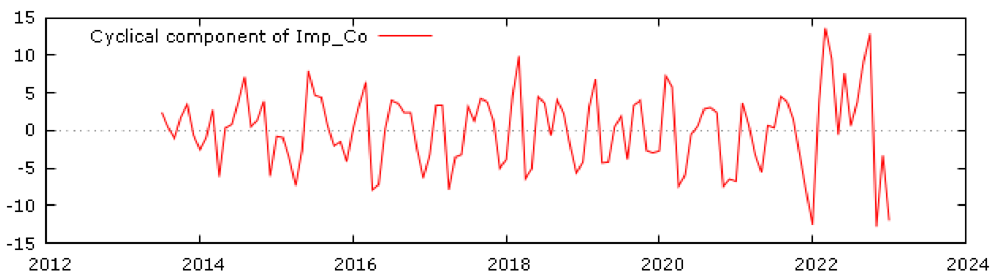

Imp_Alum (original data)
Imp_Alum (smoothed)
220
200
180
160
140
120
100
80
60
2012
2014
2016
2018
2020
2022
2024

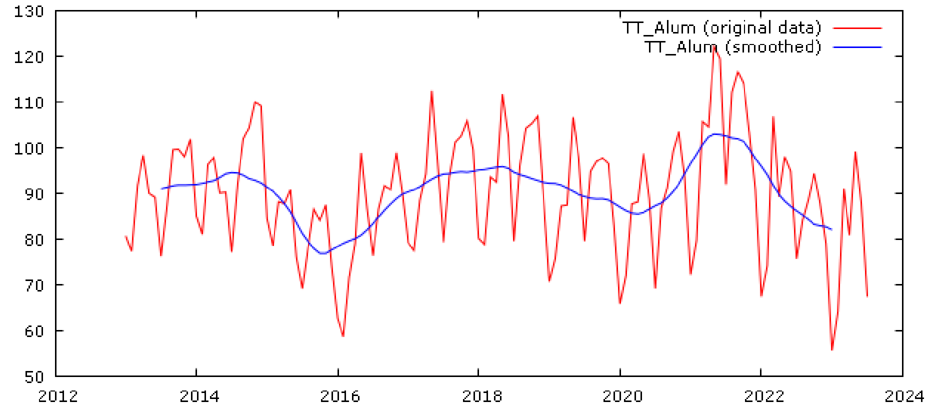

Cyclical component of Imp_Alum
40
30
20
10
0
-10
-20
-30
2012
2014
2016
2018
2020
2022
2024

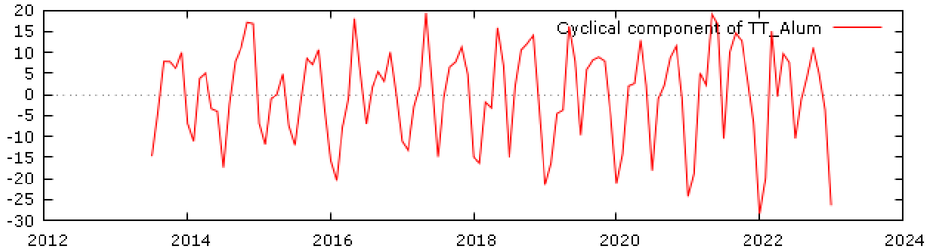

Imp_Iron (original data)
Imp_Iron (smoothed)
260
240
220
200
180
160
140
120
100
80
60
2012
2014
2016
2018
2020
2022
2024

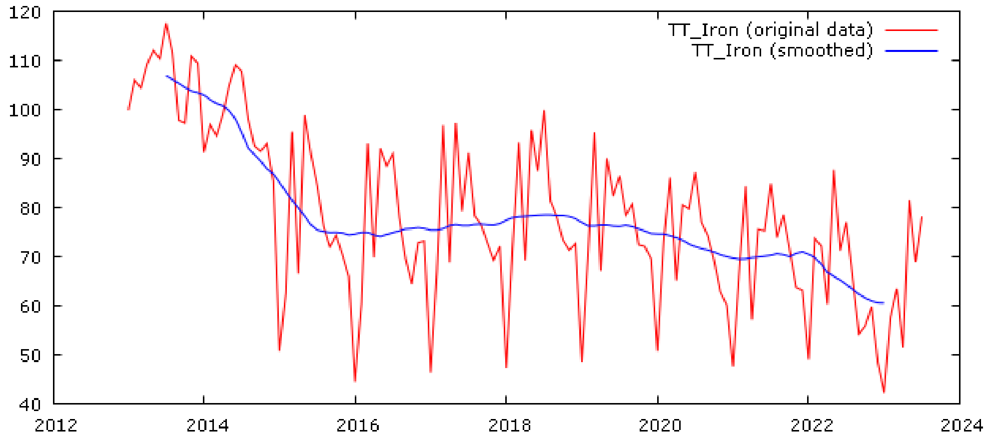

Cyclical component of Imp_Iron
100
80
60
40
20
0
-20
-40
2012
2014
2016
2018
2020
2022
2024

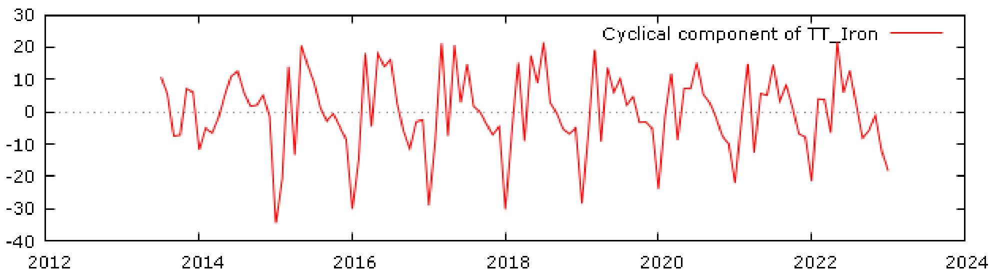

Imp_Co (original data)
Imp_Co (smoothed)
150
140
130
120
110
100
90
80
70
2012
2014
2016
2018
2020
2022
2024

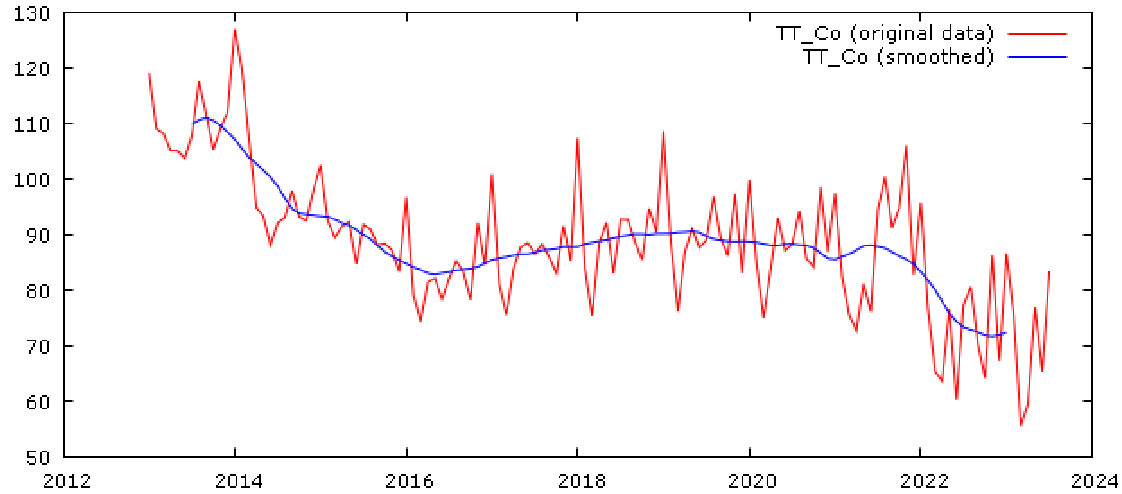

Cyclical component of Imp_Co
15
10
5
0
-5
-10
-15
2012
2014
2016
2018
2020
2022
2024

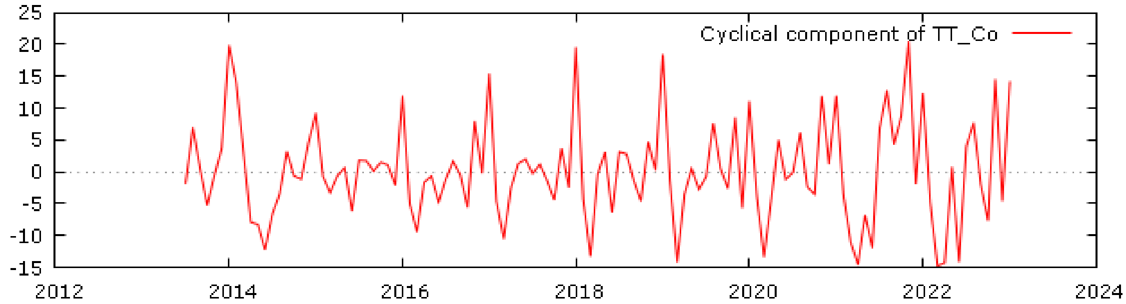

TT_Alum (original data)
TT_Alum (smoothed)
130
120
110
100
90
80
70
60
50
2012
2014
2016
2018
2020
2022
2024


Cyclical component of TT_Alum
20
15
10
5
0
-5
-10
-15
-20
-25
-30
2012
2014
2016
2018
2020
2022
2024


TT_Iron (original data)
TT_Iron (smoothed)
120
110
100
90
80
70
60
50
40
2012
2014
2016
2018
2020
2022
2024


Cyclical component of TT_Iron
30
20
10
0
-10
-20
-30
-40
2012
2014
2016
2018
2020
2022
2024


TT_Co (original data)
TT_Co (smoothed)
130
120
110
100
90
80
70
60
50
2012
2014
2016
2018
2020
2022
2024


Cyclical component of TT_Co
25
20
15
10
5
0
-5
-10
-15
2012
2014
2016
2018
2020
2022
2024

ANNEX 2

Checking the Stationarity of Smoothed Series Using the Dickey-Fuller Test

```
Augmented Dickey-Fuller test for mc_G_Alum
including 2 lags of (1-L)mc_G_Alum
sample size 112
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.599611
  test statistic: tau_nc(1) = -6.20842
  asymptotic p-value 1.505e-009
  1st-order autocorrelation coeff. for e: -0.037
  lagged differences: F(2, 109) = 4.236 [0.0169]
```

```
Augmented Dickey-Fuller test for mc_G_Iron
including 2 lags of (1-L)mc_G_Iron
sample size 112
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.539739
  test statistic: tau_nc(1) = -6.88651
  asymptotic p-value 3.394e-011
  1st-order autocorrelation coeff. for e: -0.037
  lagged differences: F(2, 109) = 15.755 [0.0000]
```

```
Augmented Dickey-Fuller test for mc_G_Co
including 2 lags of (1-L)mc_G_Co
sample size 112
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.773628
  test statistic: tau_nc(1) = -7.90826
  asymptotic p-value 8.236e-014
  1st-order autocorrelation coeff. for e: -0.040
  lagged differences: F(2, 109) = 12.422 [0.0000]
```

```
Augmented Dickey-Fuller test for mc_Exp_Alum
including 2 lags of (1-L)mc_Exp_Alum
sample size 112
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.684518
  test statistic: tau_nc(1) = -6.85064
  asymptotic p-value 4.166e-011
  1st-order autocorrelation coeff. for e: -0.109
  lagged differences: F(2, 109) = 8.700 [0.0003]
```

```
Augmented Dickey-Fuller test for mc_Exp_Iron
including 2 lags of (1-L)mc_Exp_Iron
sample size 112
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.15572
  test statistic: tau_nc(1) = -10.1997
  asymptotic p-value 5.484e-020
  1st-order autocorrelation coeff. for e: 0.087
  lagged differences: F(2, 109) = 28.924 [0.0000]
```

```
Augmented Dickey-Fuller test for mc_Exp_Co
including 5 lags of (1-L)mc_Exp_Co
sample size 109
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.02658
  test statistic: tau_nc(1) = -4.5805
  asymptotic p-value 5.28e-006
  1st-order autocorrelation coeff. for e: 0.076
  lagged differences: F(5, 103) = 5.081 [0.0003]
```

```
Augmented Dickey-Fuller test for mc_Imp_Alum
including 2 lags of (1-L)mc_Imp_Alum
sample size 112
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.33275
  test statistic: tau_nc(1) = -9.08046
  asymptotic p-value 6.098e-017
  1st-order autocorrelation coeff. for e: -0.123
  lagged differences: F(2, 109) = 15.279 [0.0000]
```

```
Augmented Dickey-Fuller test for mc_Imp_Iron
including 5 lags of (1-L)mc_Imp_Iron
sample size 109
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.4625
  test statistic: tau_nc(1) = -7.03689
  asymptotic p-value 1.428e-011
  1st-order autocorrelation coeff. for e: -0.057
  lagged differences: F(5, 103) = 5.473 [0.0002]
```

```
Augmented Dickey-Fuller test for mc_Imp_Co
including 2 lags of (1-L)mc_Imp_Co
sample size 112
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.1843
  test statistic: tau_nc(1) = -7.60477
  asymptotic p-value 5.086e-013
  1st-order autocorrelation coeff. for e: 0.000
  lagged differences: F(2, 109) = 7.806 [0.0007]
```

```
Augmented Dickey-Fuller test for mc_TT_Alum
including 2 lags of (1-L)mc_TT_Alum
sample size 112
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.06238
  test statistic: tau_nc(1) = -8.15514
  asymptotic p-value 1.843e-014
  1st-order autocorrelation coeff. for e: -0.075
  lagged differences: F(2, 109) = 14.655 [0.0000]
```

```
Augmented Dickey-Fuller test for mc_TT_Iron
including 5 lags of (1-L)mc_TT_Iron
sample size 109
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.82615
  test statistic: tau_nc(1) = -9.57219
  asymptotic p-value 2.815e-018
  1st-order autocorrelation coeff. for e: -0.148
  lagged differences: F(5, 103) = 10.991 [0.0000]
```

```
Augmented Dickey-Fuller test for mc_TT_Co
including 5 lags of (1-L)mc_TT_Co
sample size 109
unit-root null hypothesis: a = 1

  test without constant
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -1.33055
  test statistic: tau_nc(1) = -5.31004
  asymptotic p-value 1.641e-007
  1st-order autocorrelation coeff. for e: 0.007
  lagged differences: F(5, 103) = 2.942 [0.0160]
```

ANNEX 3

Regression $\hat{y}_t = a_0 + a_1 \cdot W + \varepsilon_t$

```
Model 1: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Alum

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       -0.337257     0.629565    -0.5357   0.5932
  W1          16.0088       3.89788      4.107    7.61e-05 ***

Mean dependent var   0.080364   S.D. dependent var   7.111283
Sum squared resid    5016.227   S.E. of regression   6.662687
R-squared            0.129885   Adjusted R-squared   0.122185
F(1, 113)            16.86794   P-value(F)           0.000076
Log-likelihood      -380.2693   Akaike criterion     764.5385
Schwarz criterion    770.0284   Hannan-Quinn         766.7668
rho                  0.523956   Durbin-Watson        0.949131
```

```
Model 3: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Iron

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       0.202294      1.15072      0.1758   0.8608
  W1          4.69314       7.12455      0.6587   0.5114

Mean dependent var   0.324724   S.D. dependent var   12.14779
Sum squared resid    16758.49   S.E. of regression   12.17806
R-squared            0.003825   Adjusted R-squared  -0.004990
F(1, 113)            0.433922   P-value(F)           0.511411
Log-likelihood      -449.6273   Akaike criterion     903.2546
Schwarz criterion    908.7445   Hannan-Quinn         905.4829
rho                  0.672372   Durbin-Watson        0.652485
```

```
Model 4: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Co

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       -0.116830     0.495198    -0.2359   0.8139
  W1           3.83107      3.06596      1.250    0.2140

Mean dependent var  -0.016889   S.D. dependent var   5.253568
Sum squared resid    3103.515   S.E. of regression   5.240681
R-squared            0.013629   Adjusted R-squared   0.004900
F(1, 113)            1.561368   P-value(F)           0.214047
Log-likelihood      -352.6610   Akaike criterion     709.3221
Schwarz criterion    714.8119   Hannan-Quinn         711.5504
rho                  0.532378   Durbin-Watson        0.936395
```

```
Model 6: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Alum

             coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------
  const      -0.0614302    0.766018    -0.08019   0.9362
  W2          8.36916      4.74272      1.765     0.0803   *

Mean dependent var   0.156896   S.D. dependent var   8.181593
Sum squared resid    7426.339   S.E. of regression   8.106776
R-squared            0.026818   Adjusted R-squared   0.018206
F(1, 113)            3.113932   P-value(F)           0.080327
Log-likelihood      -402.8297   Akaike criterion     809.6593
Schwarz criterion    815.1492   Hannan-Quinn         811.8876
rho                  0.551034   Durbin-Watson        0.902290
```

```
Model 7: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Iron

             coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------
  const      -0.0509786    0.660556    -0.07718   0.9386
  W2          1.10443      4.08976      0.2700    0.7876

Mean dependent var  -0.022167   S.D. dependent var   6.962189
Sum squared resid    5522.253   S.E. of regression   6.990672
R-squared            0.000645   Adjusted R-squared  -0.008199
F(1, 113)            0.072925   P-value(F)           0.787617
Log-likelihood      -385.7954   Akaike criterion     775.5909
Schwarz criterion    781.0808   Hannan-Quinn         777.8192
rho                  0.431188   Durbin-Watson        1.134309
```

```
Model 8: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Co

             coefficient   std. error   t-ratio   p-value
  -------------------------------------------------------
  const       0.430250     0.661544     0.6504   0.5168
  W2         -6.67113      4.09588     -1.629    0.1062

Mean dependent var   0.256221   S.D. dependent var   7.051688
Sum squared resid    5538.770   S.E. of regression   7.001119
R-squared            0.022938   Adjusted R-squared   0.014291
F(1, 113)            2.652806   P-value(F)           0.106152
Log-likelihood      -385.9672   Akaike criterion     775.9344
Schwarz criterion    781.4242   Hannan-Quinn         778.1627
rho                  0.199708   Durbin-Watson        1.592559
```

```
Model 9: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Alum

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const        0.530447     1.03901      0.5105   0.6107
  W2          -7.17264      6.43290     -1.115    0.2672

Mean dependent var   0.343334   S.D. dependent var   11.00754
Sum squared resid    13662.59   S.E. of regression   10.99581
R-squared            0.010882   Adjusted R-squared   0.002129
F(1, 113)            1.243212   P-value(F)           0.267219
Log-likelihood      -437.8833   Akaike criterion     879.7666
Schwarz criterion    885.2565   Hannan-Quinn         881.9949
rho                  0.262882   Durbin-Watson        1.409277
```

```
Model 10: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Iron

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const        0.878886     2.33494      0.3764   0.7073
  W2         -14.8661      14.4565      -1.028    0.3060

Mean dependent var   0.491076   S.D. dependent var   24.71692
Sum squared resid    68999.90   S.E. of regression   24.71070
R-squared            0.009271   Adjusted R-squared   0.000504
F(1, 113)            1.057458   P-value(F)           0.305992
Log-likelihood      -531.0013   Akaike criterion     1066.003
Schwarz criterion    1071.492   Hannan-Quinn         1068.231
rho                  0.362591   Durbin-Watson        1.246537
```

```
Model 11: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Co

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       -0.182981     0.465680    -0.3929   0.6951
  W2           7.68821      2.88321      2.667    0.0088   ***

Mean dependent var   0.017581   S.D. dependent var   5.058646
Sum squared resid    2744.549   S.E. of regression   4.928290
R-squared            0.059200   Adjusted R-squared   0.050874
F(1, 113)            7.110486   P-value(F)           0.008788
Log-likelihood      -345.5932   Akaike criterion     695.1865
Schwarz criterion    700.6763   Hannan-Quinn         697.4148
rho                  0.191292   Durbin-Watson        1.583548
```

```
Model 12: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Alum

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       -0.287891     1.04743     -0.2749   0.7839
  W2           8.35390      6.48502      1.288    0.2003

Mean dependent var  -0.069963   S.D. dependent var   11.11693
Sum squared resid    13884.91   S.E. of regression   11.08491
R-squared            0.014473   Adjusted R-squared   0.005751
F(1, 113)            1.659417   P-value(F)           0.200314
Log-likelihood      -438.8114   Akaike criterion     881.6228
Schwarz criterion    887.1127   Hannan-Quinn         883.8511
rho                  0.385090   Durbin-Watson        1.203499
```

```
Model 13: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Iron

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       -0.335271     1.14267     -0.2934   0.7697
  W2           6.63632      7.07470      0.9380   0.3502

Mean dependent var  -0.162150   S.D. dependent var   12.08648
Sum squared resid    16524.79   S.E. of regression   12.09285
R-squared            0.007727   Adjusted R-squared  -0.001055
F(1, 113)            0.879910   P-value(F)           0.350227
Log-likelihood      -448.8198   Akaike criterion     901.6396
Schwarz criterion    907.1295   Hannan-Quinn         903.8679
rho                  0.195216   Durbin-Watson        1.590229
```

```
Model 14: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Co

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const        0.454751     0.716244     0.6349   0.5268
  W2          -9.85901      4.43455     -2.223    0.0282   **

Mean dependent var   0.197559   S.D. dependent var   7.709977
Sum squared resid    6492.593   S.E. of regression   7.580012
R-squared            0.041908   Adjusted R-squared   0.033429
F(1, 113)            4.942746   P-value(F)           0.028190
Log-likelihood      -395.1033   Akaike criterion     794.2067
Schwarz criterion    799.6965   Hannan-Quinn         796.4350
rho                  0.067149   Durbin-Watson        1.839531
```

ANNEX 4

Regression $\hat{y}_t = a_0 + a_2 \cdot Wt + \varepsilon_t$

```
Model 15: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Alum

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       -0.338486    0.629285     -0.5379   0.5917
  W1_t         0.144648    0.0350995     4.121    7.22e-05 ***

Mean dependent var   0.080364   S.D. dependent var   7.111283
Sum squared resid    5011.773   S.E. of regression   6.659727
R-squared            0.130658   Adjusted R-squared   0.122965
F(1, 113)            16.98338   P-value(F)           0.000072
Log-likelihood      -380.2182   Akaike criterion     764.4363
Schwarz criterion    769.9262   Hannan-Quinn         766.6646
rho                  0.524111   Durbin-Watson        0.948815
```

```
Model 16: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Iron

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       0.201822     1.15070      0.1754    0.8611
  W1_t        0.0424436    0.0641824    0.6613    0.5098

Mean dependent var   0.324724   S.D. dependent var   12.14779
Sum squared resid    16757.99   S.E. of regression   12.17788
R-squared            0.003855   Adjusted R-squared  -0.004960
F(1, 113)            0.437312   P-value(F)           0.509769
Log-likelihood      -449.6256   Akaike criterion     903.2512
Schwarz criterion    908.7411   Hannan-Quinn         905.4795
rho                  0.672367   Durbin-Watson        0.652494
```

Model 17: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Co

	coefficient	std. error	t-ratio	p-value	
const	-0.117493	0.495152	-0.2373	0.8129	
W1_t	0.0347431	0.0276180	1.258	0.2110	

Mean dependent var	-0.016889	S.D. dependent var	5.253568
Sum squared resid	3102.941	S.E. of regression	5.240196
R-squared	0.013811	Adjusted R-squared	0.005084
F(1, 113)	1.582539	P-value(F)	0.210989
Log-likelihood	-352.6504	Akaike criterion	709.3008
Schwarz criterion	714.7907	Hannan-Quinn	711.5291
rho	0.532379	Durbin-Watson	0.936393

Model 18: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Alum

	coefficient	std. error	t-ratio	p-value	
const	-0.0637208	0.765795	-0.08321	0.9338	
W2_t	0.0755086	0.0423322	1.784	0.0772	*

Mean dependent var	0.156896	S.D. dependent var	8.181593
Sum squared resid	7422.011	S.E. of regression	8.104413
R-squared	0.027385	Adjusted R-squared	0.018778
F(1, 113)	3.181642	P-value(F)	0.077154
Log-likelihood	-402.7961	Akaike criterion	809.5923
Schwarz criterion	815.0821	Hannan-Quinn	811.8206
rho	0.551061	Durbin-Watson	0.902241

Model 19: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Iron

	coefficient	std. error	t-ratio	p-value
const	-0.0526468	0.660531	-0.07970	0.9366
W2_t	0.0104319	0.0365133	0.2857	0.7756

Mean dependent var	-0.022167	S.D. dependent var	6.962189
Sum squared resid	5521.828	S.E. of regression	6.990403
R-squared	0.000722	Adjusted R-squared	-0.008121
F(1, 113)	0.081625	P-value(F)	0.775630
Log-likelihood	-385.7910	Akaike criterion	775.5821
Schwarz criterion	781.0719	Hannan-Quinn	777.8104
rho	0.431038	Durbin-Watson	1.134602

Model 20: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Co

	coefficient	std. error	t-ratio	p-value
const	0.429386	0.661620	0.6490	0.5177
W2_t	-0.0592679	0.0365735	-1.621	0.1079

Mean dependent var	0.256221	S.D. dependent var	7.051688
Sum squared resid	5540.051	S.E. of regression	7.001928
R-squared	0.022712	Adjusted R-squared	0.014063
F(1, 113)	2.626065	P-value(F)	0.107909
Log-likelihood	-385.9805	Akaike criterion	775.9610
Schwarz criterion	781.4508	Hannan-Quinn	778.1893
rho	0.199662	Durbin-Watson	1.592648

Model 21: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Alum

	coefficient	std. error	t-ratio	p-value
const	0.527481	1.03919	0.5076	0.6127
W2_t	-0.0630265	0.0574449	-1.097	0.2749

Mean dependent var	0.343334	S.D. dependent var	11.00754
Sum squared resid	13667.31	S.E. of regression	10.99771
R-squared	0.010541	Adjusted R-squared	0.001784
F(1, 113)	1.203768	P-value(F)	0.274902
Log-likelihood	-437.9032	Akaike criterion	879.8063
Schwarz criterion	885.2962	Hannan-Quinn	882.0346
rho	0.262612	Durbin-Watson	1.409774

Model 22: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Iron

	coefficient	std. error	t-ratio	p-value
const	0.879321	2.33491	0.3766	0.7072
W2_t	-0.132881	0.129071	-1.030	0.3054

Mean dependent var	0.491076	S.D. dependent var	24.71692
Sum squared resid	68998.42	S.E. of regression	24.71043
R-squared	0.009293	Adjusted R-squared	0.000525
F(1, 113)	1.059909	P-value(F)	0.305434
Log-likelihood	-531.0001	Akaike criterion	1066.000
Schwarz criterion	1071.490	Hannan-Quinn	1068.228
rho	0.362599	Durbin-Watson	1.246522

```
Model 23: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Co

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const      -0.181837     0.465845     -0.3903   0.6970
  W2_t        0.0682532    0.0257514     2.650    0.0092   ***

Mean dependent var   0.017581   S.D. dependent var   5.058646
Sum squared resid    2746.504   S.E. of regression   4.930045
R-squared            0.058529   Adjusted R-squared   0.050198
F(1, 113)            7.024992   P-value(F)           0.009191
Log-likelihood      -345.6342   Akaike criterion     695.2683
Schwarz criterion    700.7582   Hannan-Quinn         697.4966
rho                  0.191278   Durbin-Watson        1.583595
```

```
Model 24: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Alum

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const      -0.287450     1.04746      -0.2744   0.7843
  W2_t        0.0744375    0.0579021     1.286    0.2012

Mean dependent var  -0.069963   S.D. dependent var   11.11693
Sum squared resid    13885.72   S.E. of regression   11.08524
R-squared            0.014415   Adjusted R-squared   0.005693
F(1, 113)            1.652701   P-value(F)           0.201220
Log-likelihood      -438.8148   Akaike criterion     881.6295
Schwarz criterion    887.1194   Hannan-Quinn         883.8578
rho                  0.384884   Durbin-Watson        1.203890
```

```
Model 25: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Iron

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const      -0.336693     1.14259      -0.2947   0.7688
  W2_t        0.0597396    0.0631612     0.9458   0.3463

Mean dependent var  -0.162150   S.D. dependent var   12.08648
Sum squared resid    16522.66   S.E. of regression   12.09207
R-squared            0.007855   Adjusted R-squared  -0.000926
F(1, 113)            0.894590   P-value(F)           0.346255
Log-likelihood      -448.8124   Akaike criterion     901.6248
Schwarz criterion    907.1147   Hannan-Quinn         903.8531
rho                  0.195241   Durbin-Watson        1.590176
```

```
Model 26: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Co

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const       0.453500     0.716394      0.6330   0.5280
  W2_t       -0.0875988    0.0396014    -2.212    0.0290   **

Mean dependent var   0.197559   S.D. dependent var   7.709977
Sum squared resid    6495.333   S.E. of regression   7.581611
R-squared            0.041504   Adjusted R-squared   0.033021
F(1, 113)            4.892995   P-value(F)           0.028978
Log-likelihood      -395.1276   Akaike criterion     794.2552
Schwarz criterion    799.7450   Hannan-Quinn         796.4835
rho                  0.067177   Durbin-Watson        1.839484
```

ANNEX 5

Regression $\hat{y}_t = a_0 + a_1 \cdot W + a_2 \cdot Wt + \varepsilon_t$

```
Model 27: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Alum

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const        -0.337257     0.624686   -0.5399   0.5903
  W1         -847.909      518.908      -1.634    0.1051
  W1_t          7.78305      4.67472     1.665    0.0987   *

Mean dependent var   0.080364   S.D. dependent var   7.111283
Sum squared resid    4895.076   S.E. of regression   6.611054
R-squared            0.150900   Adjusted R-squared   0.135738
F(2, 112)            9.952209   P-value(F)           0.000105
Log-likelihood      -378.8635   Akaike criterion     763.7269
Schwarz criterion    771.9617   Hannan-Quinn         767.0694
rho                  0.524680   Durbin-Watson        0.947610
```

```
Model 28: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Iron

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const         0.202294     1.15523     0.1751   0.8613
  W1         -325.722      959.619      -0.3394   0.7349
  W1_t          2.97672      8.64497     0.3443   0.7312

Mean dependent var   0.324724   S.D. dependent var   12.14779
Sum squared resid    16740.77   S.E. of regression   12.22584
R-squared            0.004879   Adjusted R-squared  -0.012891
F(2, 112)            0.274550   P-value(F)           0.760424
Log-likelihood      -449.5665   Akaike criterion     905.1330
Schwarz criterion    913.3678   Hannan-Quinn         908.4754
rho                  0.670680   Durbin-Watson        0.655866
```

```
Model 29: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_G_Co

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const       -0.116830     0.494626    -0.2362   0.8137
  W1        -457.618      410.871       -1.114    0.2678
  W1_t         4.15720      3.70144      1.123    0.2638

Mean dependent var  -0.016889   S.D. dependent var   5.253568
Sum squared resid    3068.950   S.E. of regression   5.234629
R-squared            0.024615   Adjusted R-squared   0.007197
F(2, 112)            1.413200   P-value(F)           0.247669
Log-likelihood      -352.0171   Akaike criterion     710.0341
Schwarz criterion    718.2689   Hannan-Quinn         713.3766
rho                  0.533553   Durbin-Watson        0.934104
```

```
Model 30: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Alum

             coefficient    std. error   t-ratio    p-value
  ----------------------------------------------------------
  const       -0.0614302     0.747508    -0.08218   0.9347
  W2        -1609.14       626.527       -2.568     0.0115  **
  W2_t         14.4420       5.59384      2.582     0.0111  **

Mean dependent var   0.156896   S.D. dependent var   8.181593
Sum squared resid    7009.195   S.E. of regression   7.910885
R-squared            0.081482   Adjusted R-squared   0.065080
F(2, 112)            4.967802   P-value(F)           0.008568
Log-likelihood      -399.5056   Akaike criterion     805.0112
Schwarz criterion    813.2459   Hannan-Quinn         808.3536
rho                  0.487871   Durbin-Watson        1.022912
```

```
Model 31: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Iron

             coefficient    std. error   t-ratio    p-value
  ----------------------------------------------------------
  const       -0.0509786     0.650186    -0.07841   0.9376
  W2        -1171.92       544.956       -2.150     0.0337  **
  W2_t         10.4735       4.86554      2.153     0.0335  **

Mean dependent var  -0.022167   S.D. dependent var   6.962189
Sum squared resid    5302.866   S.E. of regression   6.880917
R-squared            0.040347   Adjusted R-squared   0.023210
F(2, 112)            2.354428   P-value(F)           0.099631
Log-likelihood      -383.4645   Akaike criterion     772.9290
Schwarz criterion    781.1638   Hannan-Quinn         776.2714
rho                  0.447328   Durbin-Watson        1.102402
```

```
Model 32: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Exp_Co

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const         0.430250     0.661035    0.6509   0.5165
  W2         -606.995      554.049      -1.096    0.2756
  W2_t          5.36004      4.94673     1.084    0.2809

Mean dependent var   0.256221   S.D. dependent var   7.051688
Sum squared resid    5481.310   S.E. of regression   6.995732
R-squared            0.033074   Adjusted R-squared   0.015807
F(2, 112)            1.915489   P-value(F)           0.152063
Log-likelihood      -385.3676   Akaike criterion     776.7351
Schwarz criterion    784.9699   Hannan-Quinn         780.0776
rho                  0.213617   Durbin-Watson        1.565031
```

```
Model 33: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Alum

             coefficient    std. error   t-ratio   p-value
  ---------------------------------------------------------
  const          0.530447     1.01705     0.5216   0.6030
  W2         -2083.25       852.445      -2.444    0.0161   **
  W2_t          18.5364       7.61091     2.436    0.0164   **

Mean dependent var   0.343334   S.D. dependent var   11.00754
Sum squared resid    12975.40   S.E. of regression   10.76345
R-squared            0.060633   Adjusted R-squared   0.043858
F(2, 112)            3.614582   P-value(F)           0.030115
Log-likelihood      -434.9159   Akaike criterion     875.8318
Schwarz criterion    884.0666   Hannan-Quinn         879.1743
rho                  0.280034   Durbin-Watson        1.374935
```

```
Model 34: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Iron

             coefficient   std. error   t-ratio   p-value
  --------------------------------------------------------
  const        0.878886       2.34506    0.3748   0.7085
  W2         305.172       1965.53       0.1553   0.8769
  W2_t        -2.85748       17.5489    -0.1628   0.8709

Mean dependent var   0.491076   S.D. dependent var   24.71692
Sum squared resid    68983.57   S.E. of regression   24.81783
R-squared            0.009506   Adjusted R-squared  -0.008182
F(2, 112)            0.537431   P-value(F)           0.585746
Log-likelihood      -530.9877   Akaike criterion     1067.975
Schwarz criterion    1076.210   Hannan-Quinn         1071.318
rho                  0.362561   Durbin-Watson        1.246585
```

```
Model 35: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_Imp_Co

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const       -0.182981     0.459067    -0.3986   0.6910
  W2         803.558      384.769        2.088    0.0390   **
  W2_t        -7.10598      3.43535     -2.068    0.0409   **

Mean dependent var    0.017581   S.D. dependent var   5.058646
Sum squared resid     2643.559   S.E. of regression   4.858313
R-squared             0.093818   Adjusted R-squared   0.077636
F(2, 112)             5.797722   P-value(F)           0.004019
Log-likelihood       -343.4375   Akaike criterion     692.8750
Schwarz criterion     701.1098   Hannan-Quinn         696.2175
rho                   0.210006   Durbin-Watson        1.546805
```

```
Model 36: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Alum

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const       -0.287891     1.05154     -0.2738   0.7848
  W2         309.823      881.354        0.3515   0.7259
  W2_t        -2.69169      7.86902     -0.3421   0.7329

Mean dependent var   -0.069963   S.D. dependent var   11.11693
Sum squared resid     13870.42   S.E. of regression   11.12848
R-squared             0.015501   Adjusted R-squared  -0.002079
F(2, 112)             0.881728   P-value(F)           0.416921
Log-likelihood       -438.7514   Akaike criterion     883.5027
Schwarz criterion     891.7375   Hannan-Quinn         886.8452
rho                   0.391135   Durbin-Watson        1.191974
```

```
Model 37: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Iron

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const       -0.335271     1.14214     -0.2935   0.7696
  W2        -999.108      957.291       -1.044    0.2989
  W2_t         8.97986      8.54701      1.051    0.2957

Mean dependent var   -0.162150   S.D. dependent var   12.08648
Sum squared resid     16363.51   S.E. of regression   12.08730
R-squared             0.017411   Adjusted R-squared  -0.000135
F(2, 112)             0.992285   P-value(F)           0.373964
Log-likelihood       -448.2559   Akaike criterion     902.5117
Schwarz criterion     910.7465   Hannan-Quinn         905.8542
rho                   0.195981   Durbin-Watson        1.588537
```

Model 38: OLS, using observations 2013:07-2023:01 (T = 115)
Dependent variable: mc_TT_Co

	coefficient	std. error	t-ratio	p-value
const	0.454751	0.712737	0.6380	0.5248
W2	−878.570	597.383	−1.471	0.1442
W2_t	7.75635	5.33363	1.454	0.1487

Mean dependent var	0.197559	S.D. dependent var	7.709977
Sum squared resid	6372.271	S.E. of regression	7.542896
R-squared	0.059664	Adjusted R-squared	0.042872
F(2, 112)	3.553153	P-value(F)	0.031905
Log-likelihood	−394.0277	Akaike criterion	794.0555
Schwarz criterion	802.2903	Hannan-Quinn	797.3979
rho	0.080164	Durbin-Watson	1.813784