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The Impact of Energy Commodity Prices on Selected Clean Energy Metal Prices

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Abstract: The United Nations Framework Convention on Climate Change Paris Agreement has been announced as a crucial step towards combating the global threat of climate change. In the light of ambitious plans for further renewable energy sources development, high demand for nonenergy materials critical for RES is greatly expected. In conclusion, future energy security will be surely based on nonenergy commodities critical for them. As this article directly relates to issues related to new technologies and energy security in new form, the main purpose of this study is to examine the impact of energy commodity prices, namely crude oil, natural gas and coal prices on selected metal prices such as aluminium, chromium, cobalt, copper, lead, nickel, silver, tin, or zinc, both before and over the Paris Agreement period. We are looking for new insights in terms of relationships between traditional fossil fuels and metals used in clean energy technologies potentially established or strengthened shortly after the Paris Agreement was adopted. Currently, the analyses of the impact of institutional conditions such as global agreements (institutional factors) on the emerging or strengthening of relationships between energy and nonenergy resources are very limited. Hence, an autoregressive distributed lag and error correction model are employed.

Keywords: energy security; crude oil; natural gas; coal; clean energy metals; renewable energy sources (RES)

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1. Introduction

Energy security has always been an important element of state policy. It is due to the fact that energy is an important impetus behind the socioeconomic development of society. However, many countries have relatively small deposits of energy resources and are forced to import fuels from third countries. Hence, the most common definitions of energy security still refer to "the uninterrupted availability of energy sources at an affordable price" [1,2] as a core element of this concept. On the other hand, due to serious concerns about climate change and environment pollution (such as CO_2 and greenhouse gas emissions, heavy-metal emissions, water contamination [3], or air pollution [4]), the environmental needs are addressed within the energy security concept as well. Thus, the global shift towards RES is greatly expected in the future.

As energy transitions accelerate globally, clean energy determines the increase in demand for metals and minerals required for wind turbines, solar panels, batteries, and electric networks. Hence, the continued use of RES determines significant growth in demand for such metals as aluminium, chromium, cobalt, copper, lead, nickel, silver, tin, or zinc (clean energy metals), instead of traditional fossil fuels, namely crude oil, natural gas or coal. These metals are especially required in green energy technology such as wind power, solar electricity, fuel cells, electrolysis, hydrogen storage, batteries, electric cars, and energy-efficient lighting [5–11]. Therefore, the prices of clean energy metals are important from the standpoint of energy security and thus, the research for causal relationship between energy and nonenergy commodities seems to be crucial for policymakers.

The global shift from energy commodities towards clean energy metals strongly suggests such a causal supply–demand relationship between them [12]. It should be noted that metal manufacture is highly energy-intensive [13,14]. Therefore, higher production costs, and previously extraction costs, are directly reflected in increasing clean energy metal prices. Furthermore, the crude oil price is directly impacting the metal industry due to the cost of transport as well (influence channel) [15,16]. Therefore, in the current literature, the number of studies on the link between energy commodities, especially crude oil, and the metal markets is still increasing (see, for instance, [12,15,17–20]). However, the relationships in these studies have been investigated from different viewpoints that lead to different conclusions. For example, Baffes [21] assessed the impact of crude oil price on the 35 other primary commodity prices. In his research, he presented evidence that precious metals are strongly affected by the changes in crude oil price. In turn, in their research based on Granger causality tests, Bakhat and Würzburg [22] documented that the adjustments to both positive and negative aberrations from the long-term equilibrium are asymmetric in the case of copper. However, in the case of aluminium and nickel, the adjustments for those metals are symmetric. Moreover, Reboredo and Ugolini [4] assessed the impact of downward/upward oil price changes on metal prices such as aluminium, copper, lead, nickel, tin, and zinc (industrial metals) as well as gold, silver, palladium, and platinum (four precious metals). They indicated that significant oil price changes affected metal prices during both, pre- and postfinancial crisis periods. In turn, Šimáková [23] confirmed links between gold and oil price levels. In her study, she showed evidence of an existing long-term relationship between gold and crude oil markets, and after market fluctuations, both times, the series returned to the long-term equilibrium. Furthermore, Zhang and Wei [24] reported that there was an impact of oil on gold prices but not the opposite. On the other hand, Soytas et al. [25] found evidence that oil prices did not determine the precious metal prices. Additionally, in many other studies, issues such as the spillover effect from the oil market to the stock market were examined using Granger causality approaches (see, e.g., [26]) to provide evidence of the impact of geopolitical events on the energy and nonenergy markets (see, e.g., [27,28]).

Nevertheless, it should be clearly stated that the relationship between changes in fossil fuel prices and metal prices strongly depends on the nature of these metals. The most popular form of classification is the division of metals into two groups relating to their uses: precious metals and base/industry metals. As base/industry metals such as copper, aluminium, lead, zinc, or nickel are widely used in industry and construction, demand for them and their prices are strongly linked with the economic growth and phase of the economic cycle. In contrast, precious metals are mostly used in the jewellery industry. Moreover, gold or silver are seen as safe havens in case of armed conflict or against the risk of market fluctuations (financial crises) or might be treated as hedges against inflationary pressure (see, e.g., [29,30]).

In conclusion, there have been many research publications on oil and both industrial and precious metals. However, the number of publications with other fossil fuels and metals is unexpectedly very limited. Despite oil continuing to play the leading role, coal and gas are also very important. As substitutability of energy sources is increasing (i.e., electricity might be produced by burning coal or gas, but can be generated by wind and solar farms as well), the relationship between coal and gas and clean energy metal prices is also strongly justified.

On the other hand, analyses of the impact of institutional conditions such as global agreements (institutional factors) on the emerging or strengthening of relationships between energy and nonenergy resources are limited as well. This is also a significant gap because the global agreements are currently seen as an extremely important institutional factor in the era of progressing globalization and the dynamics of sustainable development. In this context, the United Nations Framework Convention on Climate Change (UNFCCC) Paris Agreement is perceived as a landmark in the multilateral climate change process, as it provides for a common undertaking of all nations to make ambitious efforts to counteract and adapt to climate change. One key element in this action against climate change is development of renewable energy sources (RES) gradually displacing traditional fossil fuels.

Hence, renewable energy is a crucial component of nationally determined contributions, which are the national pledges submitted under the Paris Agreement [31]. Therefore, RES are currently being rapidly developed by a large number of countries (see, e.g., [32]), and are expected to be developed further in the future [33,34].

In light of the above, the aim of this article is to examine the impact of the prices of fossil fuels, namely crude oil, natural gas and coal, on nine selected clean energy metal prices before and over the Paris Agreement period. Due to the multitude of variables in this research, for the sake of transparency as well as greater clarity in the interpretation of the results, the relationships are examined individually with appropriate econometric models, such as the autoregressive distributed lag (ARDL) or error correction model (ECM). It is expected that any conclusions about causal relationships might be important from the point of view of policymakers in the energy security field (e.g., better prediction of clean energy metal prices).

This paper is divided as follows: Section 2 contains the ARDL bounds test methodology; Section 3 presents the results of the research based on traditional fossil fuel prices and selected clean energy metal prices; finally, Section 4 includes a short discussion and provides prospects for further research.

2. Methodology

The impact of crude oil (Brent Forties and Oseberg Dated FOB North Sea Crude), natural gas (Henry Hub Natural Gas) and coal (Coal FOB Richards Bay) prices on selected clean energy metal prices, of aluminium, chromium, cobalt, copper, lead, nickel, silver, tin, or zinc, was examined with an augmented autoregressive distributed lag (ARDL) bounds test and monthly price time series. To obtain quality statistics, the logarithmic transformation was applied. In order to properly assess the existing causal relationships, the time span from December 2009 to November 2021 (12 years; 144 monthly observations) was split into two 6-year time series: December 2009 to November 2015 (the pre-Paris Agreement period; 72 observations), and December 2015 to November 2021 (the post-Paris Agreement period; also 72 observations). The basic statistics of each variable in both the pre-Paris Agreement and post-Paris Agreement periods are contained in Tables A1 and A2 in Appendix A. It should be noted that during this timeframe, there were also events that could potentially affect the results of the study, e.g., the COVID-19 pandemic. However, despite this limitation of our research, in this study we considered the Paris Agreement as the key event that might influence the relationships between variables.

For the ARDL bounds test methodology, the fossil fuel prices and clean energy metal prices should be stationary at level or at first difference, or variables should have a mixed order of integration such as I(0) or I(1). To assess the stationarity in this research, the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests were applied (ADF [35] and PP [36] tests).

Further, we examined cointegration by applying the ARDL bounds test. We employed the ARDL model developed by Pesaran et al. [37]. Therefore, we constructed a model of the long-run relationship between metal prices and energy commodity prices in the following form:

$$ARDL(k,\ l,\ m,\ n):\ M_t = \beta_0 + \sum_{i=1}^{k} \beta_i M_{t-i} + \sum_{i=0}^{l} \rho_i O_{t-i} + \sum_{i=0}^{m} \lambda_i G_{t-i} + \sum_{i=0}^{n} \delta_i C_{t-i} + \varepsilon_t, \quad (1)$$

where

M_t—selected metal price;
O_t—oil price;
G_t—gas price;
C_t—coal price;
$k,\ l,\ m,\ n$ —number of lags;
$\beta_0, \beta_i,\ \rho_i, \lambda_i, \delta_i$—coefficients;
ε_t—the standard error term.

In accordance with the ARDL bounds test methodology described by Pesaran et al. [38], the ARDL model may have a different number of lag terms (no symmetry of lag lengths). It should be noted that the same number of lag terms is usually assumed to allow the use of OLS while a different number of lags can be addressed for example by using seemingly unrelated regressions. Therefore, we may examine cointegration by applying the ARDL bounds test with the model representation of Equation (1) for testing the long-run causality as follows:

$$\begin{aligned}\Delta M_t = \beta_0 + \sum_{i=1}^{k} \beta_i \Delta M_{t-i} + \sum_{i=0}^{l} \rho_i \Delta O_{t-i} + \sum_{i=0}^{m} \lambda_i \Delta G_{t-i} + \sum_{i=0}^{n} \delta_i \Delta C_{t-i} \\ + \alpha_1 M_{t-1} + \alpha_2 O_{t-1} + \alpha_3 G_{t-1} + \alpha_4 C_{t-1} + \mu_t,\end{aligned} \quad (2)$$

where Δ denotes the difference operator, $\alpha_1,\ \alpha_2,\ \alpha_3,\ \alpha_4$ are the coefficients, μ_t is the serially uncorrelated error term, and the rest of the notations are as in Equation (1).

By estimating the ARDL bounds test (Equation (2)), we computed the F-statistic and the t-statistic for the joint significance of the lagged level variables' coefficients to test the long-run relationship (cointegration) among the variables. The F-statistic and t-statistic examine the null hypothesis of no levels of relationship (cointegration) between energy commodity prices and metal prices. Therefore, the hypothesis tested was H0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = 0$, contrary to the alternative hypothesis, which stated that a long-run relationship (cointegration) existed among the variables: H1: $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq 0$.

Testing for cointegration relies on comparing the F-statistic and t-statistic with the upper and lower critical bounds. The series are cointegrated if both statistics are more extreme than critical values for the I(1) variables (if p-values are less than an appropriate level for the I(1) variables). If both statistics are closer to zero than the critical values for the I(0) variables (if p-values are greater than a desired level for the I(0) variables), it is assumed that the null hypothesis cannot be rejected.

In the case of cointegration among the time series, we also tested the existence of causality between the metal prices and energy commodity prices with an error correction model. This was done within the ECM below:

$$\Delta M_t = \beta_0 + \sum_{i=1}^{k} \beta_i \Delta M_{t-i} + \sum_{i=0}^{l} \rho_i \Delta O_{t-i} + \sum_{i=0}^{m} \lambda_i \Delta G_{t-i} + \sum_{i=0}^{n} \delta_i \Delta C_{t-i} + ECT_{t-1} + \mu_t, \quad (3)$$

where Δ indicates the first-difference operator, ECT_{t-1} the lagged error correction term, and μ denotes the random error term; the rest of the notations are as in Equation (1). Only if the error correction term is negative and highly significant is there a long-run causality between these variables.

Finally, the stability of the models was examined with the cumulative sum of recursive residual test (CUSUM). It tests the assumption that after a time series regression, the coefficients that do not interact with time are constant. This test allowed us to assess the stability of the model. Additionally, we used the cumulative sum of squares of recursive residual test (CUSUMSQ). In both these tests all parameters are assumed to be stable if the plots of CUSUM and CUSUMSQ statistics remain within the critical bounds. Moreover, some other popular diagnostics tests like Breusch–Godfrey serial correlation LM test and ARCH test were also performed to assess the quality of the models.

3. Results

We began our analysis by examining the series stationarity. This is a prerequisite for applying the ARDL bounds testing approach and it allows us to avoid spurious results. As it was noted earlier, the primary assumption is that for ARDL bounds testing, variables should be stationary at level or at first difference, or there should be a mixed order of integration such as I(0) or I(1). Thus, the stationarity was tested with both ADF and PP tests. The results showed that all variables were I(0) or I(1), but not I(2) or higher, based on the 1% level of significance (see Table A3 in Appendix A).

Having established the stationarity, the ARDL bounds testing approach was applied to check the cointegration for individual variables and to determine whether a long-run relationship existed. Importantly, the ARDL bounds test is fragile to lag length. Therefore, we used the AIC and the BIC to determine the appropriate lags. Then, we applied the ARDL bounds test; our findings are presented in Table 1.

Table 1. ARDL bounds test statistics.

Variable	The Pre-Paris Agreement Period				The Post-Paris Agreement Period			
	Decision	Model Selected	Statistics		Decision	Model Selected	Statistics	
aluminium	no levels relationship	ARDL (1 1 1 1)	F t	1.690218 −1.053409	no levels relationship	ARDL (3 3 0 2)	F t	1.6832285 0.441236
tin	no levels relationship	ARDL (1 1 1 1)	F t	2.188668 −2.830941	no levels relationship	ARDL (2 3 3 2)	F t	2.465472 −0.460812
copper	no levels relationship	ARDL (1 1 0 1)	F t	1.467634 −2.328104	no levels relationship	ARDL (1 2 0 0)	F t	3.361894 0.242108
lead	no levels relationship	ARDL (1 1 1 1)	F t	3.208574 −3.104221	no levels relationship	ARDL (1 2 3 3)	F t	3.542931 −2.220967
nickel	no levels relationship	ARDL (1 1 1 1)	F t	3.022256 −1.815346	no levels relationship	ARDL (2 0 1 0)	F t	0.989269 −1.590257
zinc	no levels relationship	ARDL (1 1 1 1)	F t	2.998936 −1.918681	nonsensical cointegration	ARDL (1 3 0 3)	F t	7.082375 −2.347329
silver	no levels relationship	ARDL (1 0 0 0)	F t	3.562224 −3.423077	no levels relationship	ARDL (1 1 0 0)	F t	2.864006 −1.977613
cobalt	no levels relationship	ARDL (1 1 0 0)	F t	3.607244 −3.562367	no levels relationship	ARDL (1 0 0 0)	F t	2.059406 −1.672420
chromium	no levels relationship	ARDL (2 0 0 0)	F t	1.655356 −2.463897	cointegration	ARDL (2 0 3 0)	F t	7.971425 −4.758220

The F-statistic values in the case of all metals as dependent variables in the pre-Paris Agreement period are clearly below the I(0) critical value bound at the 1% level (4.29). Hence, the null hypothesis about no equilibrating relationship cannot be rejected. On the other hand, even if the level of significance is greater, e.g., 10%, the results for lead, nickel, zinc, silver, and cobalt are also inconclusive due to the fact that these values are between the I(0) and I(I) bounds (2.73 and 3.77, respectively). In turn, in the post-Paris Agreement period we find out that for both zinc and chromium, the F-statistics are above I(1), 7.082375 and 7.971425, respectively. However, only in the case of chromium is the absolute value of the t-statistic also significantly above the I(1) bound (4.758220). In the case of zinc, the absolute value (2.347329) is less than the absolute value of either the I(0) or I(1) t-bounds. Accordingly, in the case of zinc based on the t-bounds test we can conclude that the cointegrating relationship is in fact spurious.

Having high statistic values in the case of chromium, the ECM was applied to assess the long-run causality (results in Table 2).

Table 2. Short- and long-run causality in ECM for chromium.

Dependent Variable	Type of Causality					
	Short-Run Causality					Long-Run Causality
	C	D.Chromium(−1)	D.Gas	D.Gas(−1)	D.Gas(−2)	ECT_{t-1}
Chromium	1.557213 (0.0000) (5.789218)	0.207412 (0.0439) (2.058805)	0.018929 (0.4845) (0.703458)	−0.080442 (0.0138) (−2.537097)	−0.070282 (0.0173) (−2.448185)	−0.135295 (0.0000) (−5.786189)

Notes: level of significance in first set of parentheses; t-statistic in second set of parentheses.

The ECT_{t-1} is negative with an estimated coefficient on the level of −0.135295. This implies that about 13.53% of any movements into disequilibrium are corrected for within one period (month). Moreover, considering the high value of the t-statistic, namely −5.786189, we may conclude that the coefficient in this model is highly significant (the *p*-value is 0.0000) and therefore a cointegrating relationship exists. In the case of other clean energy metals, only short-run causality was detected (single lags of oil, gas, or coal are statistically significant in the ARDL models).

Finally, the stability of model parameters was checked with the CUSUM and CUSUMSQ tests for all models. The test results suggested the stability of the parameters, except for three metals: silver, lead, and chromium in the pre-Paris Agreement period (Appendix A, Figure A1). In the post-Paris Agreement period, the results indicated that the models for chromium, silver, cobalt, and tin were not fully stable; however, a significant 5% line crossing was observed only in the case of tin and silver (Appendix A, Figure A2).

Additionally, to check whether the residuals from the model were serially uncorrelated, the Breusch–Godfrey serial correlation LM test was used. The null hypothesis in this test was that the residuals were serially uncorrelated. An F-statistic *p*-value of over 5% for all variables indicated that this null hypothesis could not be rejected and that the residuals were serially uncorrelated.

Moreover, to test for residual homoscedasticity, the ARCH test was applied. The null hypothesis was that the residuals were homoscedastic. An F-statistic *p*-value of over 5% indicated that we should reject this null. Therefore, we may conclude that the residuals are clearly homoscedastic, except for cobalt and nickel (see Appendix A, Tables A4 and A5).

4. Discussion and Prospects for Further Research

Since the Paris Agreement was adopted on 12 December 2015, nearly all countries around the world have agreed to take action with regard to the climate, to reduce the global temperature to well below 2 degrees Celsius (°C) this century compared to preindustrial levels, and to reach a target of 1.5 °C [6]. Importantly, most of them declared in their nationally determined contributions renewables, which include quantified renewable energy targets. If all renewable power targets included in the nationally determined contributions were implemented, an additional 1041 gigawatts of renewables would be added by 2030. Thus, the total installed capacity for the renewable power generation would grow to 3564 gigawatts in 2030 [31]. Therefore, further development of RES determines the demand for nonrenewable resources (see for example [39,40]), such as clean energy metals, gradually excluding traditional fossil fuels.

Therefore, in the era of energy transformation of many developed countries, it is postulated that energy security of the future will require, above all, the stability of strategic supplies of nonenergy resources at affordable prices. Thus, the energy security of the modern economy will mainly rest on nonenergy resources, especially metals used in clean energy technologies. The lack of these in many countries may therefore become an issue for the energy security of these countries still struggling to achieve their own energy independence [41]. Therefore, there is a suggestion that future energy security based on renewable energy sources may require analysts to be more careful in analysing this type of causal relationship, because of the future price prediction of this type of metals. This provides the basis for the analysis of possible causal relationships.

However, despite the assumptions mentioned above and in the introduction, the empirical results obtained from this research does not provide clear evidence that fossil fuel prices affect selected clean energy metal prices, with the exception of chromium in the long-run (chromium is a highly important metal for RES, especially for geothermal energy and solar power installations; chromium is less used in wind and hydro power, nuclear energy, EVs and battery storage [42]).

In total, the number of long-run relationships (cointegration) detected increased from zero in the pre-Paris Agreement period to only one in the post-Paris Agreement period. Hence, we conclude that global agreements such as the Paris Agreement may not strongly affect this type of relationships between energy commodities and metals used in clean energy technologies, or that these relationships are cancelled out by the influence of other significant market factors. For example, the COVID-19 pandemic might potentially have distorted the final results. Therefore, it is postulated that the same research should be carried out in the future, especially with longer time series.

On the other hand, it is postulated that this kind of links might emerge as energy transition are intensified. For example, it is expected that this agreement becomes more stringent, along with the progressive implementation of national goals, which can be expected to ensure the intensification of the existing causal relationships and the emergence of new ones. As institutions determine the effectiveness of individual and collective actions, they can be expected to become more and more visible in changing times. Therefore, a possible prospect for further research on this issue is analysing these relationships in the future. As the decisions of the Paris Agreement are reviewed every five years, the causal dependencies may emerge or intensify in the future (over the next five years). Consequently, there is a broad scope for testing this kind of relationship in the future, especially if it could be important for policymakers, for example concerning energy security [41].

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Appendix A

Table A1. Statistic of time-series in the pre-Paris Agreement period.

Variable	Mean	Median	Minimum	Maximum	Std. Dev.	Ex. Kurtosis.	Jarque–Bera Test	Skewness
ln.tin	9.9470	9.9674	9.5958	10.388	0.18561	−0.28557	0.248604	−0.006760
ln.copper	−8.8865	8.8859	8.4401	9.1970	0.16397	0.31099	3.47635	−0.51142
ln.lead	7.6473	7.6483	7.3877	7.9161	0.11700	−0.20525	0.139175	0.030115
ln.zinc	7.6230	7.6184	7.3278	7.8100	0.10428	−0.23943	1.15375	−0.28372
ln.aluminium	7.5899	7.5884	7.2900	7.8871	0.13792	−0.42377	0.72363	0.12075
ln.nickel	9.7475	9.7628	9.0702	10.249	0.25531	−0.42377	1.73183	−0.37592
ln.chromium	11.067	11.035	10.736	11.374	0.20113	−1.3488	5.51838	0.071092
ln.silver	3.1375	3.0650	2.6440	3.8687	0.31596	−1.1224	4.77565	0.28811
ln.cobalt	10.350	10.334	10.030	10.663	0.13965	−0.55921	1.16531	0.15215
ln.coal	4.5129	4.5340	4.0214	4.9487	0.24726	−0.87494	2.61453	−0.15335
ln.gas	1.2702	1.3110	0.65752	1.7918	0.25290	−0.25843	2.42548	−0.42738
ln.oil	4.4997	4.6417	3.6378	4.8319	0.29458	0.35228	17.4017	−1.1829

Notes: ex. kurtosis is the kurtosis minus 3.

Table A2. Statistic of time-series in the post-Paris Agreement period.

Variable	Mean	Median	Minimum	Maximum	Std. Dev.	Ex. Kurtosis	Jarque–Bera Test	Skewness
ln.tin	9.9224	9.8828	9.5308	10.586	0.23731	1.3604	27.3846	1.3372
ln.copper	8.7536	8.7099	8.4035	9.2286	0.21150	−0.20655	4.61364	0.60707
ln.lead	7.6288	7.6207	7.3890	7.8593	0.12055	−0.90569	2.5033	−0.02612
ln.zinc	7.8485	7.8759	7.3213	8.1718	0.19104	0.19961	6.13558	−0.70309
ln.aluminium	7.5547	7.5349	7.2842	7.9913	0.16339	−0.42377	3.98875	0.57117
ln.nickel	9.4554	9.4496	9.0252	9.9070	0.24136	−0.86986	2.48227	0.12190
ln.chromium	10.973	10.985	10.714	11.264	0.16855	−1.0498	3.9225	0.22667
ln.silver	3.9225	2.8393	2.6273	3.3370	0.19696	−0.47132	8.85672	0.82615
ln.cobalt	10.638	10.515	9.9988	11.451	0.39392	−1.0605	4.18409	0.25987
ln.coal	4.4780	4.5084	3.9393	5.4837	0.34308	0.034746	2.1316	0.41821
ln.gas	1.0106	1.0296	0.48858	1.7066	0.26801	0.35720	2.09939	0.37504
ln.oil	4.0136	4.0782	2.9113	4.4253	0.28177	1.9330	27.7025	−1.1588

Notes: ex. kurtosis is the kurtosis minus 3.

Table A3. Unit root tests.

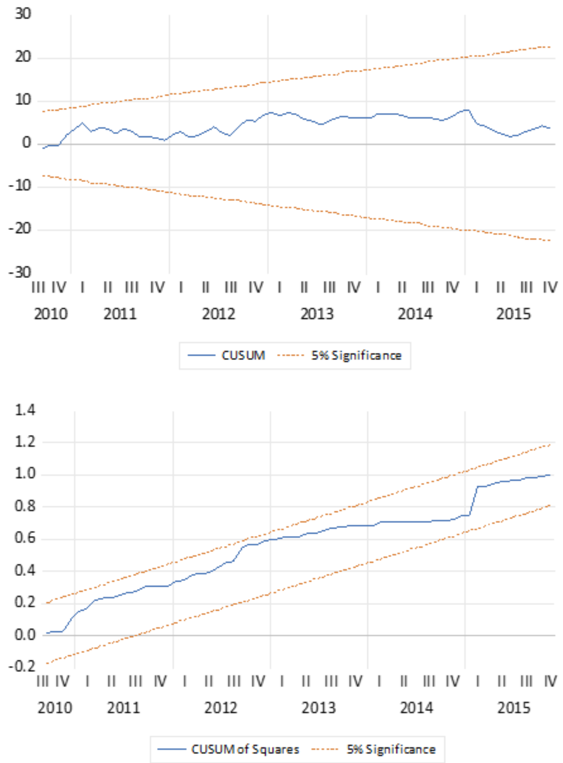
Variable	The Pre-Paris Agreement Period		The Post-Paris Agreement Period	
	Augmented Dickey–Fuller Test	Phillips–Perron Test	Augmented Dickey–Fuller Test	Phillips–Perron Test
ln.tin	−1.975	−1.961	−2.910	−2.546
d.ln.tin	−4.931	−6.569	−4.623	−5.338
ln.copper	−2.759	−2.830	−1.890	−1.452
d.ln.copper	−5.978	−6.502	−5.309	−5.803
ln.lead	−3.119	−2.612	−1.876	−1.573
d.ln.lead	−6.247	−7.582	−6.013	−6.790
ln.zinc	−3.490	−3.263	−0.897	−0.649
d.ln.zinc	−6.395	−7.365	−4.873	−6.061
ln.aluminium	−2.299	−2.104	−1.737	−1.670
d.ln.aluminium	−5.969	−8.214	−5.882	−6.424
ln.nickel	−2.650	−2.752	−1.830	−1.482
d.ln.nickel	−5.720	−6.067	−5.754	−5.719
ln.chromium	−1.455	−1.355	−2.231	−1.917
d.ln.chromium	−4.048	−5.774	−4.436	−5.117
ln.silver	−1.573	−1.608	−1.775	−1.642
d.ln.silver	−6.448	−8.756	−6.233	−8.345
ln.coal	−2.065	−2.005	−3.470	−1.992
d.ln.coal	−4.781	−6.459	−3.951	−7.318
ln.cobalt	−1.462	−1.569	−1.250	−1.277
d.ln.cobalt	−6.659	−10.282	−4.969	−6.728
ln.oil	−2.453	−3.029	−3.205	−2.228
d.ln.oil	−5.605	−6.640	−7.082	−5.924
ln.gas	−2.456	−2.368	−2.605	−2.662
d.ln.gas	−5.455	−6.688	−7.864	−11.911

Table A4. F-statistic of Breusch–Godfrey serial correlation LM and ARCH tests in the pre-Paris Agreement period.

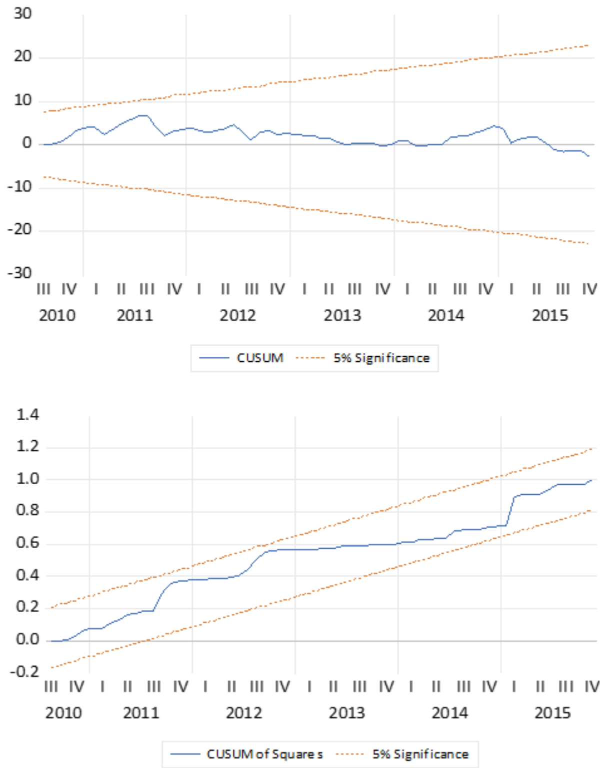
Variable	Breusch–Godfrey Serial Correlation LM Test	ARCH Test
ln.tin	0.2366	0.5291
ln.copper	0.1123	0.2051
ln.lead	0.2288	0.9140
ln.zinc	0.5454	0.6833
ln.aluminium	0.8610	0.3789
ln.nickel	0.3266	0.0211
ln.chromium	0.2332	0.5688
ln.silver	0.9920	0.7200
ln.cobalt	0.4609	0.0263

Table A5. F-statistic of Breusch–Godfrey serial correlation LM and ARCH tests in the post-Paris Agreement period.

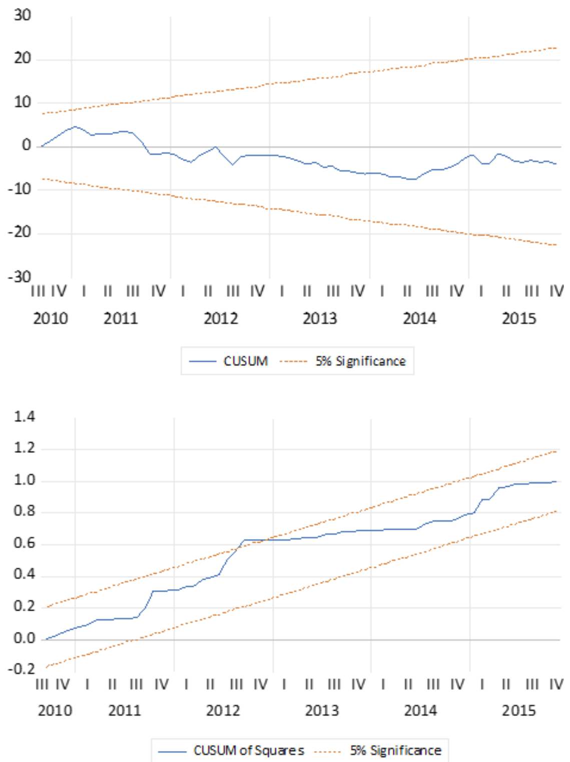
Variable	Breusch–Godfrey Serial Correlation LM Test	ARCH Test
ln.tin	0.2607	0.4595
ln.copper	0.5080	0.7999
ln.lead	0.3130	0.8627
ln.zinc	0.6598	0.3542
ln.aluminium	0.8948	0.4576
ln.nickel	0.4665	0.5193
ln.chromium	0.4621	0.1058
ln.silver	0.1359	0.1067
ln.cobalt	0.1698	0.6081



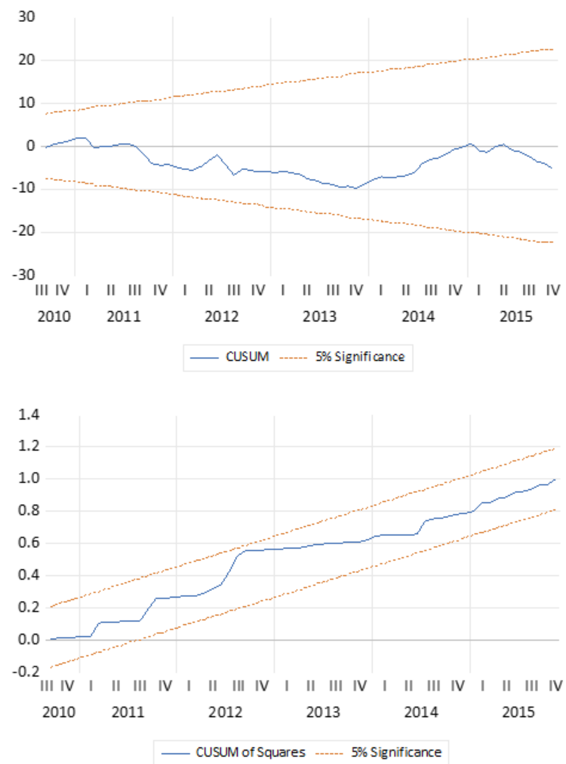
Tin



Copper

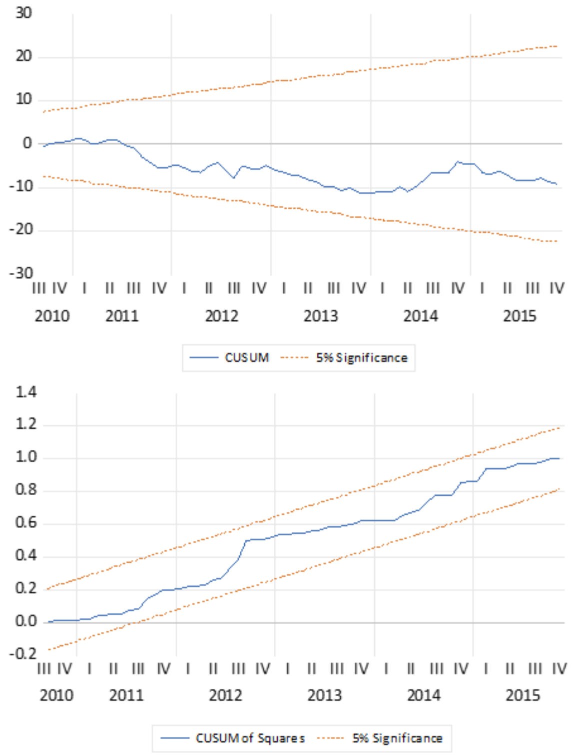


Lead

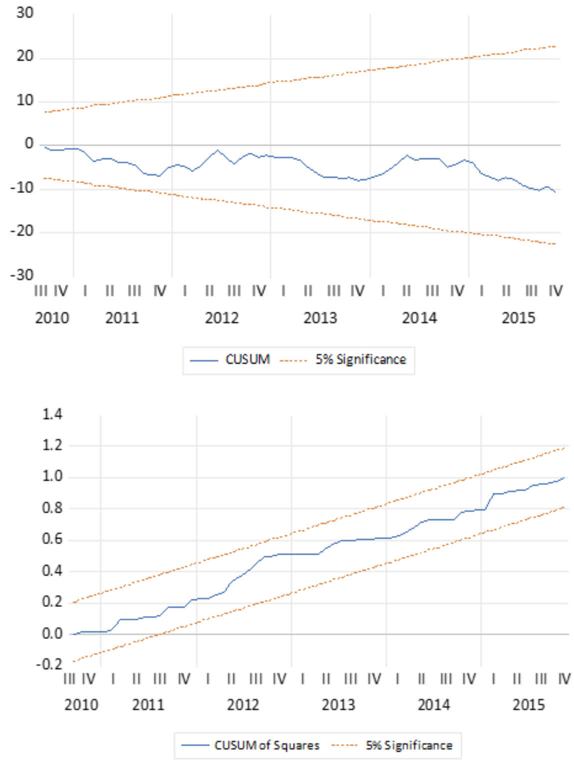


Zinc

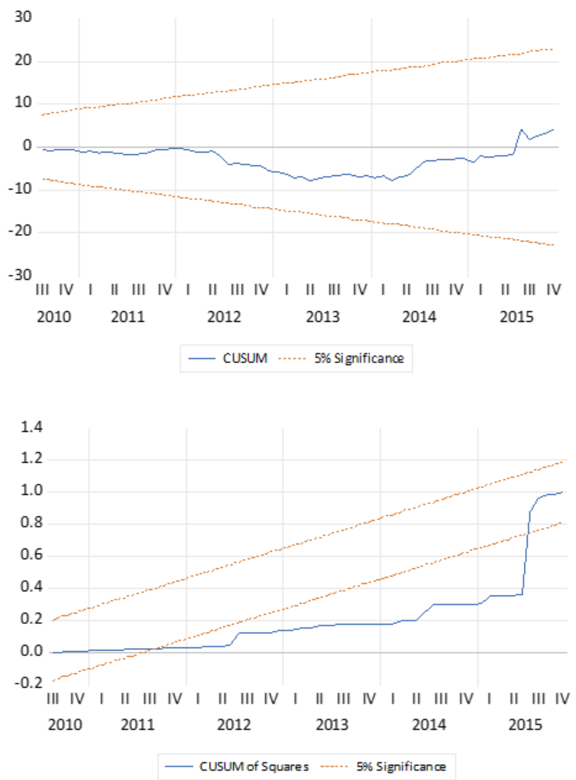
Figure A1. *Cont.*



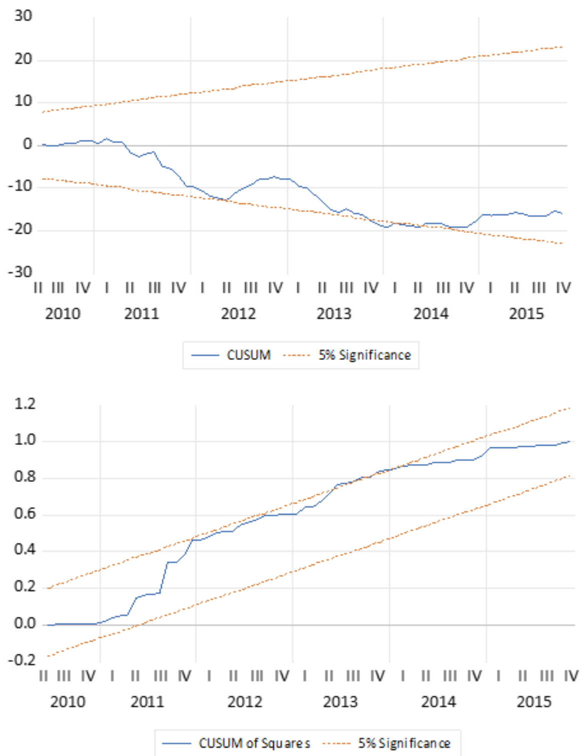
Aluminium



Nickel

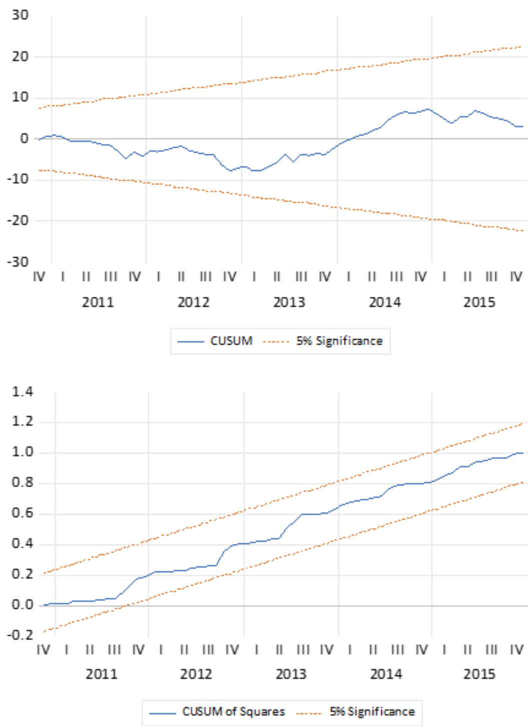


Chromium



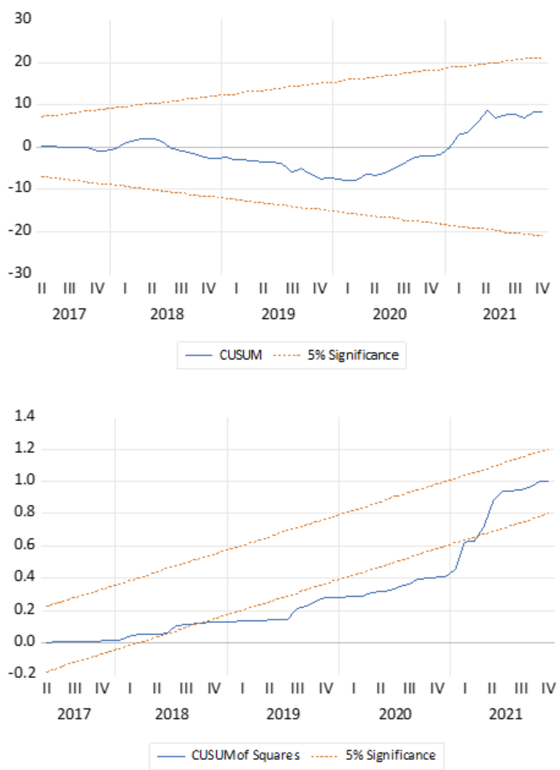
Silver

Figure A1. *Cont.*

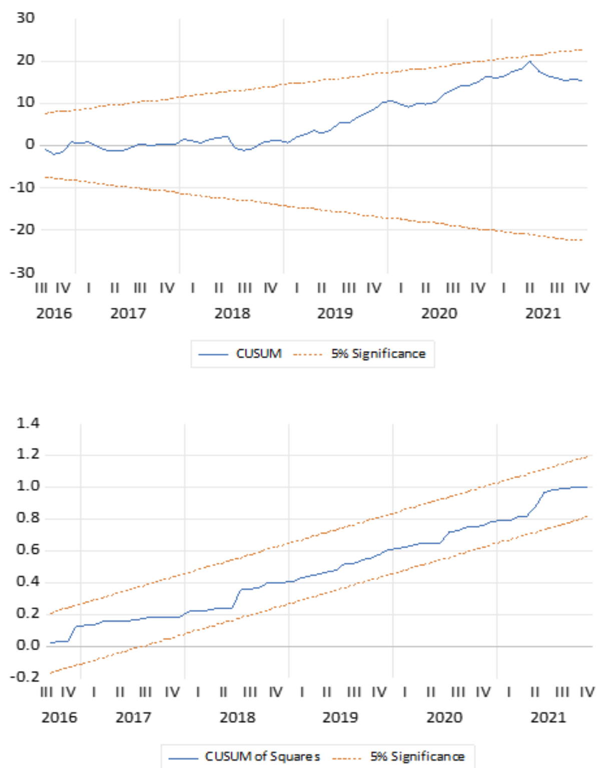


Cobalt

Figure A1. CUSUM and CUSUM of squares tests in the pre-Paris Agreement period.

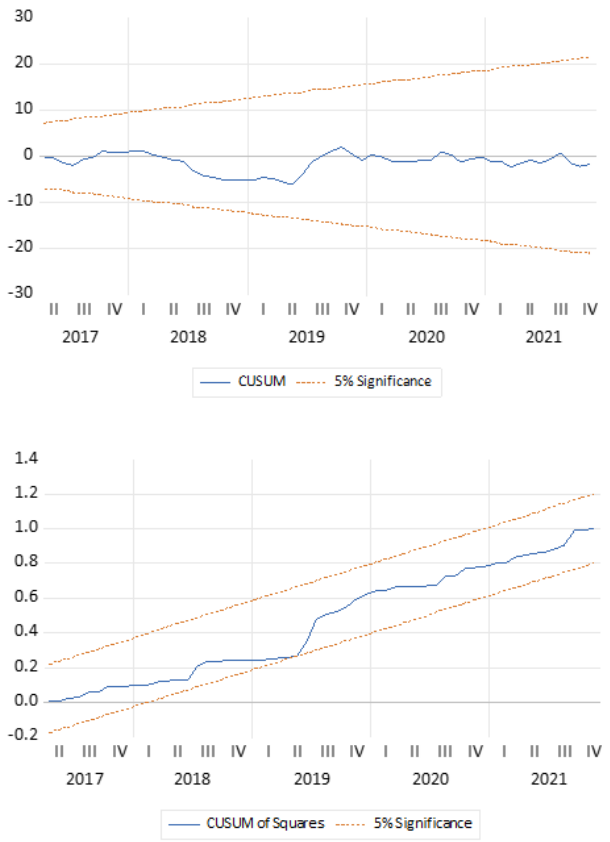


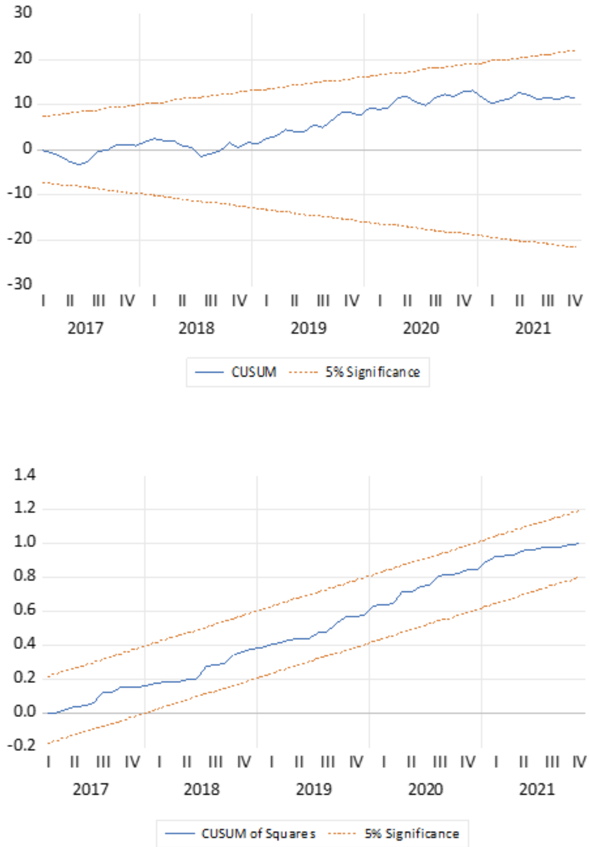
Tin



Copper

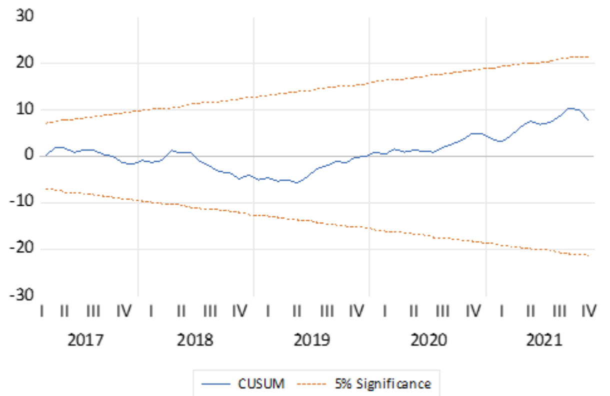
Figure A2. *Cont.*

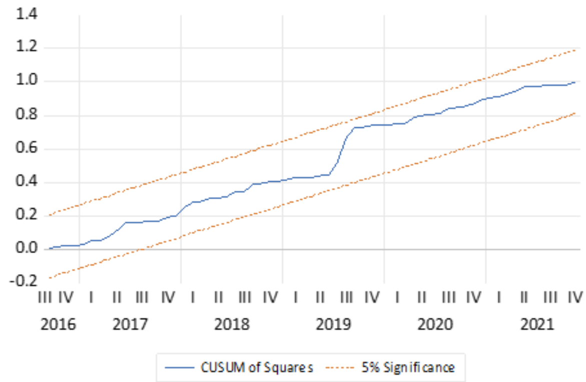




Lead

Zinc

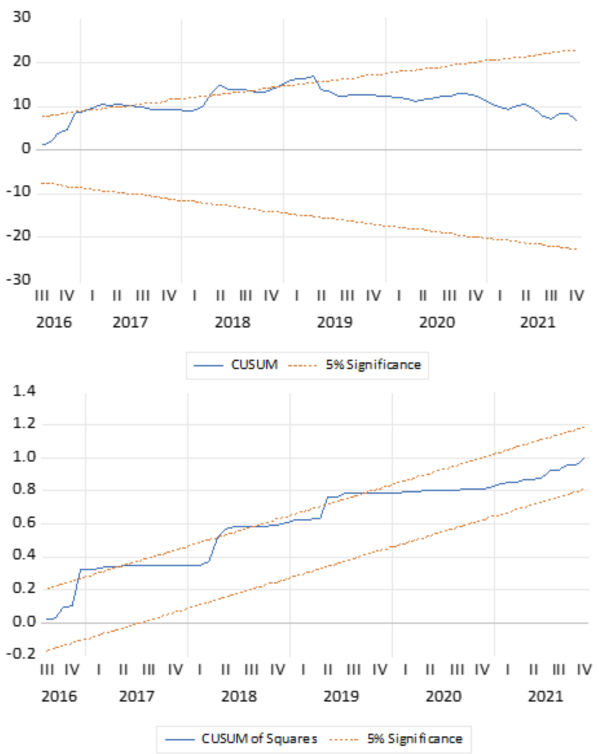




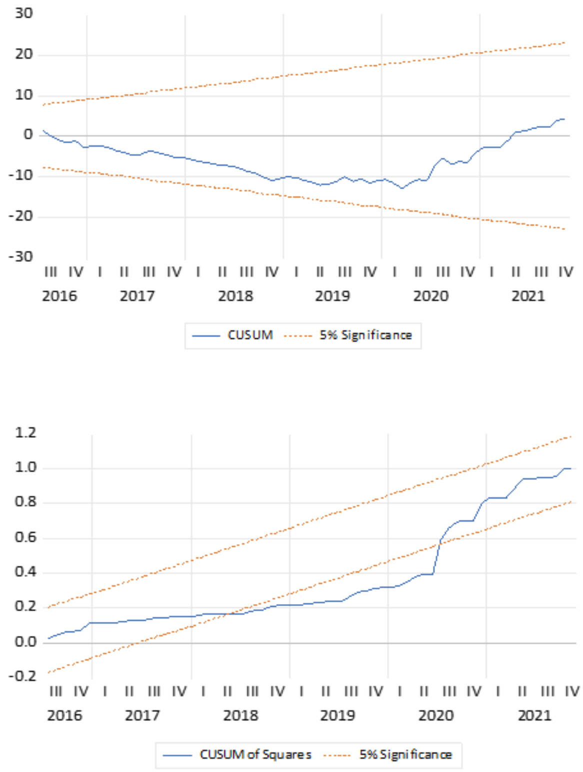
Aluminium

Nickel

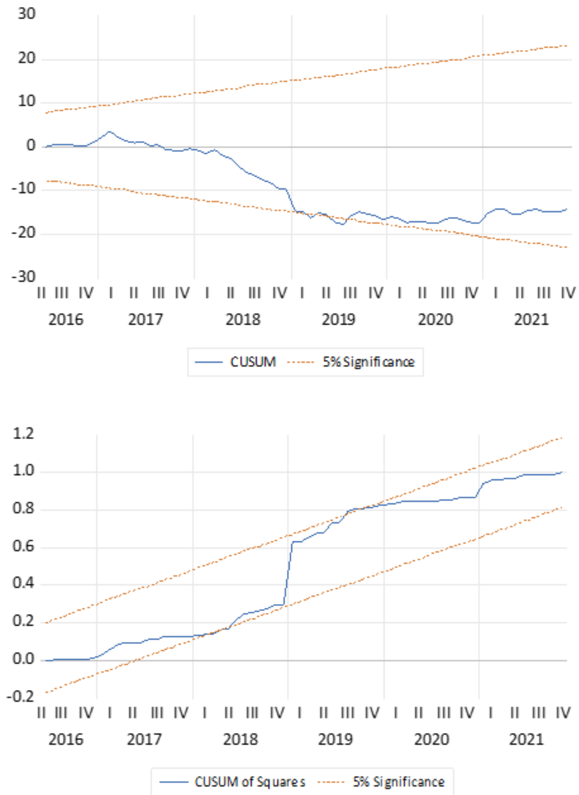
Figure A2. *Cont.*



Chromium



Silver



Cobalt

Figure A2. CUSUM and CUSUM of squares tests in the post-Paris Agreement period.

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