

Robust Regression Analysis of International Metal Futures: Outliers, Return Relationships and Gold Market Linkages

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Abstract—The study investigates the behavior of price, return, dependence, stationarity, outliers and robust regression of nine international metal futures (Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc) in the period 2021-2025. The analysis employs descriptive statistics, Pearson's correlation coefficients, Augmented Dickey-Fuller (ADF), DF-GLS, Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests and various outlier detection methods. The results show that the metals have significantly different return behavior and volatility. Correlation analysis shows that most metal futures move in the same direction. The stationarity tests indicate that monthly returns should be employed in econometric modeling. However, the results of the outlier detection differ in the Tukey, the Mean / Standard Deviation, Autoregressive Moving Average (ARMA) and the Wavelet methods, which shows the importance of the use of proper diagnostic techniques to detect extreme market observations.

In this study, we also use M-estimation, S-estimation, and MM-estimation, which are robust regression methods, and Huber Type-I, Type-II, and Type-III standard errors and covariance specifications to check the relationships between the returns of Gold and the returns of the other metals. For the main robust regression specifications, the results are positive associations for gold returns with Copper and Silver returns and a negative association for gold returns with Lead returns. Given the strength of the statistical significance to alternative covariance specifications, we recommend MM-estimation with Huber Type-I covariance estimates as the preferred specification with Andrews M-estimation providing a useful robustness check. Finally, the results add to the knowledge of risk features and linkages of international metal futures markets, and have implications for portfolio diversification and commodity risk management.

Index Terms—International Metal Futures, Gold, Robust Regression, M-Estimation, S-Estimation, MM-Estimation.

I. INTRODUCTION

International metal markets are an integral part of the world economy supporting industrial growth, technological development, infrastructure investment and international trade. The behavior of metals prices is one of the key topics in financial and economic research. This is because metals have different economic functions, supply conditions, demand conditions and investment characteristics. Aluminium is a metal, used extensively in transportation, construction, packaging and electrical applications. Copper is essential to power generation, electrical wiring, renewable energy, and industrial manufacturing. Lead is used in industry and the manufacture of batteries. Tin is important in solder, electronics and specialized manufacture. Zinc is frequently used to galvanize steel, shielding structures from rust. Changes in industrial production, energy prices, mining production and the rate of global economic growth can affect demand and prices for these base metals, creating uncertainty for producers, consumers and investors.

In addition, their industrial applications and investment significance also position precious metals in a unique manner in the international commodity markets. Gold is a store of value and potential safe-haven asset during times of financial turmoil, inflationary pressure and geopolitical uncertainty. Silver is a dual investment/industrial commodity, with industry accounting for 60% of silver demand in 2014. Palladium and platinum are employed in catalytic

converters in automobiles, chemical processing and other special industrial activities. Prices may change due to changes in industrial demand, technology, supply of mined commodities, environmental regulations and investor sentiment. The market forces that drive all of these metals are the same, but the supply characteristics and the uses of the metals can be different, resulting in different price trends. For one to understand commodity market risk, investment diversification and the economic relationships between industrial and precious metals it is important to understand the behavior of Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc. The global economy was affected by changes in inflation, interest rates, geopolitical tensions, supply-chain disruptions and industrial activity in 2021-2025, which created a lot of uncertainty in the international metal futures markets. These developments served to emphasize how sensitive metal prices are to the global economic environment and to metal-specific factors. Futures markets are a vehicle for price discovery, and give producers, manufacturers and investors a way to hedge against price volatility of commodities. The financial characteristics of metal futures are however quite different and the returns can show abrupt price changes, very large gains or losses and observations that are inconsistent with the usual statistical assumptions. These patterns are particularly relevant in relation to linkages between gold and other metals where common economic drivers may induce positive correlations, while differences in industrial and investment demand may lead to divergent return behavior. A better understanding of these relationships can lead to improved commodity risk management and a better interpretation of metal market behavior.

A major problem in modeling returns to metal futures is that extreme observations can have an undue influence on the standard regression estimates. Commodities markets are volatile, with sharp swings in prices driven by shortages, unexpected policy changes, geopolitical developments and sudden shifts in market sentiment. Such extreme movements may be true economic information and not data errors, so that the automatic removal of outliers does not seem appropriate in many cases. Another approach is to use robust regression methods which downplay the influence of atypical observations but retain potentially useful information in the data. Huber proposed the foundation of robust estimation and

introduced M-estimation to decrease the impact of large residuals (Huber, 1964). The importance of influence curves in measuring how sensitive statistical estimators are to individual observations has also been stressed (Hampel, 1974). These developments provided a theoretical basis for the analysis of financial relationships with outliers or deviations from idealized statistical assumptions on the data.

Recent work on robust regression has developed estimation procedures that combine robustness to outliers with efficiency of the parameter estimates. S-estimation is robust against contaminated data because it minimizes a robust measure of the scale of the residuals (Rousseeuw and Yohai, 1984). The MM-estimation approach is preceded by a robust estimator with a high-breakdown property with an additional estimation step, which aims to achieve high statistical efficiency under appropriate circumstances (Yohai, 1987). Also, M-estimation is robust to the choice of alternative weighting functions like Andrews, Bisquare, Cauchy, Huber, Huber-Bisquare, Logistic, Talworth and Welsch. They differ in the way the influence of observations with large residuals is downweighed. It may affect the estimated relationships and the statistical significance. The alternative robust estimators' question is of particular relevance to commodity research, because a strong relationship perceived by one estimation procedure may be weaker with another. This enables a comparison of their results, which potentially can help to detect relatively stable associations and associations sensitive to extreme observations or choice of estimator.

Gold is of particular relevance because its investment function differs from the much more industrial function of many other metals, whereas Silver, Palladium and Platinum are a mix of investment and industrial functions. Looking at these metals and how they relate to Aluminium, Copper, Lead, Tin and Zinc we can measure how much they are moving together and if these correlations hold when we look at unexpected market movements. Metals return correlations do not necessarily mean a direct economic impact as many commodities may be affected by the same macro-economic conditions. Robust regression can help provide a more reliable estimate of conditional relationships by down-weighting the effect of aberrant observations, but does not establish causality per se. Therefore, the stability of the

estimated coefficients across alternative robust procedures is an important issue in interpreting the relationships between gold returns and other metal futures.

The present study contributes to the understanding of international metal futures by examining the return relationships of Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc, with special emphasis on the returns of Gold and the relationship of gold returns with the returns of other metals. The main motivation is that extreme price movements in commodity markets can affect traditional statistical estimates, and robust estimation techniques can offer an alternative basis for investigating these relationships. The comparison of M-, S- and MM-estimation gives a more general view on the consistency of the estimated associations under various approaches to the outlier resistance and statistical efficiency. The results can be useful for identifying which relationships are relatively robust to estimation methods and which should be treated with a higher degree of caution. This study contributes to the empirical literature on interdependence in commodity markets by combining the economic importance of the nine metals with the nature of robust regression. It also provides useful information for investors, commodity traders and researchers interested in the behavior and risk aspects of international metal futures.

II. LITERATURE

Ordinary least squares (OLS) regression is a common method researchers use to study relationships among variables. The results from the estimation of OLS regression can be quite sensitive to the extreme values and outliers. Robust regression methods overcome this difficulty by diminishing the influence of outliers on the estimated parameters, but still providing valid statistical inference. Huber (1964) suggested robust estimation procedures to reduce the influence of outliers and give a compromise between efficiency and robustness. Later he extended the theoretical foundation of robust estimation by showing that other loss functions can be used when the classical statistical assumptions are not fully satisfied (Huber, 1973).

In the area of robust statistics, certain criteria have been developed for judging the reliability of estimators under different data conditions. Hampel et al. (1986)

have proposed a general scheme for robustness analysis of statistical estimators which consists of influence functions, breakdown points and sensitivity analysis. For a detailed discussion of the theory and practice of robust estimation when the data are contaminated and the usual assumptions are violated, see Huber and Ronchetti (2009). Maronna et al. (2006) described robust statistical methods to obtain reliable estimates in the presence of influential observations in the data for regression and multivariate analysis.

Additional analyzes used robust regression methods to minimize the influence of outliers on the estimated coefficients. Robust procedures Least median of squares (LMS) and least trimmed squares (LTS) of Rousseeuw and Leroy (1987) use different criteria to estimate the regression parameters and thereby reduce the effect of extreme observations. Zaman et al. (2001) studied the robust regression methods and statistical properties and gained an insight of behavior of various estimators under various data conditions. Hubert and Debruyne (2010) reviewed least-squares regression and robust alternatives. They said that odd observations might affect the standard regression and proper estimators should be used.

Other work in robust estimation has considered the trade-off between robustness to outliers and statistical efficiency. If the accuracy and precise estimation are required, MM-estimation is good. It combines the robustness of the first high breakdown estimator with the efficiency of the subsequent estimation procedure. Comparative studies have been done on robust estimators comparing the performance of the estimators at different levels of contaminations and distributions of data. Yao and Wang (2016) further extended this work by exploring other robust estimation methods and understanding how robust estimators function within regression analysis. The paper was a contribution to the discussion of methodology concerning the choice of estimators and their reliability.

Robust regression has been extended to nonparametric models when a specific functional form is not a satisfactory representation of the relationship. The nonparametric methods do not take into account the linear relationship between the dependent and explanatory variables as in the case of the usual linear regression. But this relation is fixed in a flexible data driven way. Čížek and Sadıkoğlu (2020) discussed robust nonparametric regression methods and pointed

out the advantage of flexible functional modeling with robustness to outliers. Such developments are empirically important because relations can be non-linear and observations can be extreme, which can affect the reliability of the estimated results. Marisetty (2025) used OLS, heteroskedasticity and serial correlation consistent estimation, GARCH and VAR models to examine the predictive relationships and international spillover effects between NSE NIFTY and other major global stock indices. Asian and emerging markets had a major influence on NSE NIFTY whereas a number of European indices had weak or mixed predictive relations. The study underlined the importance of combining strong estimation, volatility modeling and dynamic econometric frameworks to improve market forecasting and to understand international financial integration.

During the last years, robust regression methods have been extended to the high dimensional data and modern statistical learning setting. We study robust regression with maximum mean discrepancy (MMD) proposed by Alquier and Gerber (2024). Robustness is an alternative to estimation under the failure of the usual distributional assumptions. Robust regression is difficult to estimate in a high dimensional setting where the number of explanatory variables in a model is large (Vilucchio, 2024). Marchese et al. (2024) examined high-dimensional interpretable models for annual stock returns. They have improved interpretability of the analysis of complex financial relationships. These developments highlight the continuing need for powerful methods of analyzing large and complex data sets including many variables and possibly influential observations.

Recent work has included detection, assessment and correction for outlier induced coefficient distortion and estimation under heavy tailed distributions. Adomaityte et al. (2024) studied robust regression in the high dimensional setting with heavy tailed data. They showed that the usual estimators are invalid when the errors are not normal. The coefficient-distortion test was introduced by Jiao et al. (2024) for assessing the impact of outliers on regression estimates. Heng and Lange (2025) proposed a bootstrap method to estimate the percentage of outliers, and thus the contamination of statistical data sets. The robust Kibria estimators have been proposed by Naz et al. (2025) for the improvement of regression

estimation in the tough data sets. The contributions insist on the necessity to identify influential observations and to select estimation methods that might yield stable coefficients.

Robust estimation has also been generalized to other regression settings and statistical objectives. Robust regression with heteroscedasticity, i.e. the variance of the error term is not constant across the observations, was considered by Amado et al. (2025). Olaluwoye et al. (2025) studied robust beta regression for bounded response variables. Alshangiti et al. (2025) considered robust gamma regression for positive and possibly skewed data. Mohammad et al. (2025) developed robust Poisson regression for count data. Kumar et al. (2026) investigated the robust estimation of population means and Amado et al. (2026) extended robust semiparametric and nonparametric methods, using this methodological development. The results of these studies indicate the relevance of robust statistical procedures to a wide range of data distributions, model specifications, and estimation needs.

Robust regression methods are proposed in the literature as useful alternatives to the classical OLS in data sets with outliers, extreme observations, heavy tailed distributions or other violations of the classical assumptions. However, even with the methodological improvements, the choice of the estimator is conditional on the data characteristics and the research purpose. This is especially relevant for international metal markets where prices can be subject to volatile swings due to geopolitical conflicts, supply chain disruptions, changing industrial demand, trade restrictions, and uncertainty in the global commodity markets. Large price changes can distort the OLS estimated relationships between international metals. Hence, in addition to OLS, robust regression can be used to test the robustness of the links between international metal prices and extreme market movements and geopolitical uncertainty.

III. METHODOLOGY

This study uses a quantitative research design to study the price movements, monthly returns, statistical characteristics, interrelationships and robust regression relationships of nine international metal futures namely: Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc. The metals have been chosen for their significance in international

commodity markets, industrial production, investment activity and risk management. Aluminium, Copper, Lead, Tin and Zinc are key base metals used extensively in manufacturing, construction, electrical equipment and infrastructure development. Gold and Silver are precious metals. They are used as investment assets and can offer diversification benefits during times of economic uncertainty. Palladium and platinum are precious and industrial metals used in automotive manufacturing, catalytic converters, and other industrial processes. The inclusion of these nine metals provides a broad view of the behavior of the industrial and precious metals futures markets and allows for an assessment of the relationships between gold returns and returns of other metals.

The study period is 2021 to 2025, which is the market development over five years. This period is important because international commodity markets experienced changing economic conditions, inflationary pressures, changes in interest rates, geopolitical uncertainty and changes in industrial demand and supply. These factors can influence metal prices, and lead to large divergences in returns and volatility across commodities. Consistent time series for all nine metals were constructed using international metal futures price data. To measure the percentage change in metal futures prices over time, monthly returns were calculated from successive monthly prices. Monthly returns are used to make it easier to compare different metals which may have different price levels and units of measurement. It provides good basis to correlation analysis, stationarity testing, outliers detection and robust regression modeling. Consistent periods of observation and definitions of the data are necessary for the comparability and reliability of the empirical results.

Descriptive statistics were used to analyze the measures of central tendency, dispersion and distributional characteristics of monthly returns of Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc. The measures of typical return performance were the mean and median, while the minimum and maximum were used to identify the observed extremes in monthly returns. The standard deviation was used to assess the volatility of returns and the coefficient of variation was used to assess the relative variability relative to the mean (caution when mean returns are close to zero). Skewness was used to characterize the asymmetry of the return distributions

while kurtosis was used to describe the concentration of observations and the presence of heavy or light tails relative to a normal distribution. The null hypothesis of normality was tested using the Jarque–Bera test. These statistics provide a first insight into differences in return performance, risk and distributional behavior and help to identify the potential need for estimation methods that are less sensitive to extreme observations.

The direction and strength of linear relationships between the monthly returns of the nine metal futures were investigated by using the Pearson's correlation coefficient. The correlation matrix tells us if the returns of two metals are likely to move in the same direction or in the opposite direction and how strongly their movements are associated. Positive correlations mean two metals tend to show similar movements in returns while negative correlations mean they tend to show opposite movements. Correlation analysis is particularly valuable when considering the potential diversification benefits of combining different metal futures in an investment portfolio. It also provides preliminary evidence of relationships among explanatory variables included in the gold return regression models. Reported correlation coefficients were tested for statistical significance at the five per cent significance level. Correlation coefficients measure the degree of association, not causality, and do not say whether movements in one metal directly influence the returns of another.

To check the stationarity of the monthly returns, four complementary tests were used: the Augmented Dickey-Fuller (ADF) test, the DF-GLS test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The ADF test tests for a unit root, allowing for serial correlation by adding in extra lagged difference terms. The DF-GLS test first applies generalized least-squares detrending and then tests for a unit root, whereas the PP test uses a non-parametric correction to account for serial correlation and heteroskedasticity. The KPSS test, in contrast, assumes stationarity as the null hypothesis and therefore provides a complementary view to the unit-root tests. The ADF, DF-GLS and PP results were interpreted under their null hypothesis of a unit root, while the KPSS results were interpreted under the null hypothesis of level or trend stationarity, as appropriate for the specification. The tests were evaluated at five per cent level of significance. Stationarity is important

as non-stationary series might lead to misleading statistical relationships. The combined use of these tests gives a more detailed evaluation of the adequacy of monthly returns to further econometric analysis.

Four methods were employed to investigate potential outliers in the monthly return, these are: Tukey's method, Mean/Standard Deviation method, Autoregressive Moving Average (ARMA) method, and Wavelet method. Tukey's method flags observations that are outside of a given interquartile-range boundary, while the Mean/Standard Deviation method flags observations that are far away from the sample mean, relative to the standard deviation. The ARMA-based procedure checks for unusual observations in relation to the fitted time-series structure. In contrast, Wavelet analysis can identify local irregularities and sudden changes at different time scales. These approaches capture different kinds of extreme behavior and therefore their results are not expected to be the same. Outlier detection is important since extreme returns may unduly influence the conventional least-squares regression estimates and their associated statistical tests. But very extreme observations in financial and commodity markets may be real economic events, not mistakes. Thus, instead of being automatically removed or modified, the observations were evaluated using different diagnostic methods. The possible presence of outliers justified the use of robust regression methods, which are designed to minimize the effect of extreme observations.

Robust regression was used to explore relationships between Gold monthly returns (dependent variable) and monthly returns of Aluminium, Copper, Lead, Palladium, Platinum, Silver, Tin and Zinc (independent variables). Three procedures, namely M-estimation, S-estimation and MM-estimation, were considered. M-estimation uses a suitable objective function and weighting procedure to reduce the impact of large residuals. The analysis compared eight weighting functions namely Andrews, Bisquare, Cauchy, Huber, Huber-Bisquare, Logistic, Talworth and Welsch. This comparison provides an assessment of the consistency of the estimated relationships in the case of different treatments of extreme residuals. S-estimation was used in this study as a robust method. It aims at obtaining parameter estimates by minimizing a robust measure of residual scale, resistant to unusual observations. MM-estimation combines a high breakdown initial estimator with a

subsequent M-estimation step to achieve a compromise between outlier resistance and statistical efficiency. The three approaches were compared in terms of coefficient signs, coefficient magnitudes, statistical significance, adjusted R-squared, adjusted robust R-squared where available, overall test statistics, information criteria where comparable, deviance and scale. We also examined Huber Type-I, Type-II and Type-III standard errors and covariance specifications to test the sensitivity of statistical inference to alternative covariance calculations. The robustness of the empirical findings was assessed based on the stability of the coefficients and the patterns of significance across these specifications.

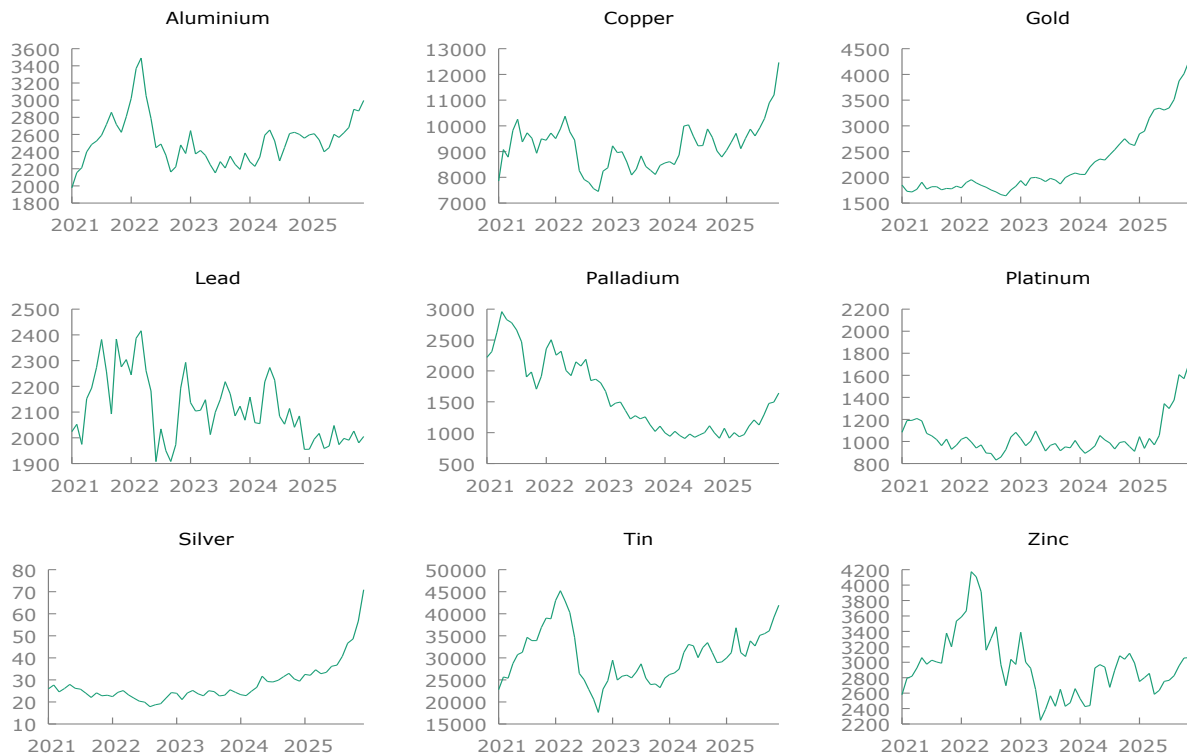
The estimated models of robust regression were checked by significance of the coefficient tests, significance of the overall model statistics, adjusted R squared, adjusted robust R squared where available, Akaike Information Criterion (AIC), Schwarz Criterion (SC), deviance and scale. These measures provide complementary information on explanatory performance, model complexity, residual dispersion and statistical significance. Generally, lower AIC and SC values indicate a better model among a set of models fitted on a similar basis, and using compatible likelihood or objective function definitions. However, information criteria and deviance values obtained from different robust estimation procedures should not be mechanically compared when the underlying calculations are not equivalent. The model was chosen based on the stability of the coefficients, the significance of the explanatory variables, the overall performance of the model and its resistance to extreme observations and not on one statistic. Sensitivity of results to Huber Type-I, Type-II and Type-III covariance specifications were also examined. Alternative specifications were used as robustness checks. All statistical analyses were performed using EViews software to conduct descriptive statistical analysis, correlation analysis, stationarity tests, outlier procedures and robust regression estimations. The final model was chosen based on the total empirical evidence and the consistency of the main relationships across different estimators and covariance specifications.

IV. RESULTS DISCUSSION

The analysis considers the price and returns behavior of nine international metal futures markets for the period 2021-2025: Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc. Descriptive statistics are used to test the distribution and variability of returns, while Pearson's correlation coefficients test the degree of association among the metal futures. The Augmented Dickey-Fuller (ADF), DF-GLS, Phillips-Perron (PP) and KPSS tests are used to check the stationarity properties of the data. Additionally, we use a variety of outlier detection techniques such as Tukey, Mean/Standard Deviation, Autoregressive Moving Average (ARMA) and Wavelet to identify extreme observations and analyze variations in their detection across different methods.

Then the robust regression techniques are applied to explore the relationships between the gold returns and the returns of the other 8 metal futures. We assess the stability of estimated relationships in the presence of extreme observations by comparing M-estimation, S-estimation and MM-estimation. We also consider alternative weighting functions and Huber Type-I, Type-II and Type-III covariance specifications to investigate robustness of coefficient estimates and their statistical significance. The combined analytical framework provides a systematic basis for understanding return relationships across international metal futures markets and for assessing the sensitivity of empirical results to outliers and alternative estimation procedures.

Chart 1: Price (USD) movement of international metal future indexes during 2021 – 2025



(Source: Author's Computations)

The chart 1 presents the price developments of nine popular international metal futures from 2021 to 2025 including Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc. Aluminium and Copper were very volatile during this period going down at

some points in 2022-2023 before bouncing back to around 2025. Gold price showed rather powerful upward trends especially since 2023 and reached the maximum at the end of the period. Moves like this show the effect of global economic conditions,

industrial demand, inflationary pressures and changing investor sentiment on international metal prices.

In the period under review the prices of lead, palladium and platinum have moved in different directions. Lead prices are expected to remain relatively flat through 2025 following wild swings between 2021 and 2023. Palladium fell sharply from its 2021 peak to lower levels in 2023-2024, before climbing back to the end of 2025. Platinum also fell sharply from its relatively high levels in 2021, but steadied during 2023-2024 and then rose again toward the end of 2025. These are trends that reflect changes taking place in the industrial and precious metals markets, including automotive demand, industrial uses, supply conditions and investment activity.

During the period (2021-2025) of observation great variations in Silver, Tin and Zinc were noted. Silver fluctuated in 2021-2023 and then began a slow upward trend with a very sharp rise in 2025. Tin soared in 2021-2022, then fell off a cliff and came back to finish 2025 at a relatively high level. Zinc was volatile with a sharp price rise in 2022, a large fall during 2023 and then fluctuating prices, followed by a moderate recovery toward the end of 2025. The chart, in general, shows that the international metal futures did not move in the same direction. Gold and Silver were strong in the later period with Aluminium, Copper, Tin and Zinc all recovering to varying degrees. These differences underscore the influence of specific supply-demand factors and the overall health of the economy on the direction of metal prices.

Chart 2: Monthly returns (%) of international metal future indexes during 2021 – 2025



(Source: Author's Computations)

Chart 2 shows Monthly returns (%) for nine international metal futures indexes: Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc, 2021-2025. Monthly Aluminium and Copper returns were evenly distributed around 0. The pattern during this period was positive and negative

movements each month. Gold also experienced a lot of short-term volatility but its monthly returns were generally in a much narrower band than some of the other metals. Lead had some ups and downs with some big jumps and drops at times. Such trends point to considerable near-term uncertainties in the metal

futures markets, caused by evolving global demand, supply disruptions, inflation and geopolitical events. Palladium, Platinum and Silver prices were very volatile 2021 – 2025. The monthly return of the Palladium market was very volatile as it had many large ups and downs. “Platinum was also very volatile with some big negative years and some big positive years, and finished in 2025. Silver had alternating positive and negative monthly returns and then a sharp increase at the end of the observation period. Tin was very volatile with huge gains and losses every month. Zinc was sharply up and down several times. Such differences suggest that metals have responded in different ways to shifts in industrial demand,

production costs, supply conditions and investor expectations.

Monthly returns of Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc show international metals futures are characterized by high short-term volatility and not stable monthly gains. To summarize, Aluminium, Copper, Gold, Lead and Silver had also alternated positive and negative returns. Palladium, platinum, tin and zinc were especially volatile at various points in the period. Several metals had strong positive monthly returns into 2025, but not uniformly across all indices.

Table 1: Descriptive Statistics of Monthly returns (%) of international metal futures

Variable	Aluminium	Copper	Gold	Lead	Palladium	Platinum	Silver	Tin	Zinc
Mean	0.871	0.940	1.477	0.121	-0.188	1.350	1.966	1.654	0.497
Median	1.660	0.535	1.640	0.805	-0.270	0.625	1.480	1.760	1.480
Minimum	-12.560	-12.590	-7.020	-12.580	-23.020	-10.140	-11.950	-23.710	-19.330
Maximum	11.500	15.540	10.280	13.930	23.220	27.310	25.010	30.000	19.970
Std. Dev.	6.009	5.546	4.076	4.784	9.898	7.760	8.179	9.468	7.591
C.V.	6.897	5.901	2.759	39.431	52.650	5.749	4.162	5.726	15.284
Skewness	-0.209	0.359	0.102	0.244	0.109	0.855	0.450	-0.002	-0.105
Kurtosis	-0.573	0.088	-0.740	0.564	-0.683	0.824	-0.324	0.664	0.223
Normality JB Test	1.2570 (0.5334)	1.3103 (0.5193)	1.4755 (0.4782)	1.3923 (0.4985)	1.2835 (0.5264)	9.0004 (0.0112) *	2.2914 (0.3178)	1.1035 (0.5759)	0.2348 (0.8892)

(Source: Authors computations) (* significant @ 5%)

Table 1 shows descriptive statistics for the monthly returns of nine metal futures on international markets Aluminium, copper, gold, lead, palladium, platinum, silver, tin and zinc. Except Palladium (-0.188%), all other metals had positive mean monthly returns. Silver had the highest mean return of 1.966% followed by Tin (1.654%), Gold (1.477%), Platinum (1.350%), Copper (0.940%), Aluminium (0.871%), Zinc (0.497%) and Lead (0.121%). Palladium had a negative median of -0.270%. Eight metals also had a positive median return. Silver and Tin had relatively high average monthly returns. Lead had the lowest positive average return. The minimum and maximum values vary considerably over the course of the metal futures markets. The highest maximum return was for Tin (30.000%) followed by Platinum (27.310%) and Silver (25.010%) and the highest minimum return was for Tin (-23.710%) and Palladium (-23.020%). The results show that the metals varied greatly in their average

performance and exposure to extreme monthly price movements during the study period.

The standard deviation and the coefficient of variation (C.V.) are calculated to provide further information on the volatility and the relative risk of the metal futures returns. Gold had the least standard deviation (4.076%) followed by Lead (4.784%) and Copper (5.546%) indicating relatively lower absolute variability in monthly returns. In contrast, Palladium showed the highest standard deviation (9.898%), followed by Tin (9.468%), Silver (8.179%), Platinum (7.760%), and Zinc (7.591%) indicating a higher instability in prices. The lowest value of reported coefficients of variation was for Gold (2.759), followed by Silver (4.162), Tin (5.726), Platinum (5.749), Copper (5.901), Aluminium (6.897), Zinc (15.284), Lead (39.431) and Palladium (52.650). Hence, Gold showed the best combination of positive average returns and relatively low volatility, whereas

Palladium displayed a negative mean return and the greatest relative variability. However, the coefficient of variation should be interpreted with caution for returns as it becomes unstable when the mean is close to zero or negative, especially in the case of Lead and Palladium.

The skewness and kurtosis statistics are measures of the distributional characteristics of the monthly returns. Aluminium (-0.209), Tin (-0.002) and Zinc (-0.105) had slightly negative skewness which indicates a relatively mild asymmetry toward negative returns. The skewness values for Copper, Gold, Lead, Palladium, Platinum and Silver were (0.359), (0.102), (0.244), (0.109), (0.855) and (0.450) respectively and were positively skewed with Platinum having the highest right skewed distribution. Copper, Lead,

Platinum, Tin and Zinc had positive kurtosis indicating relatively heavier tails than a normal distribution under the conventional excess-kurtosis interpretation, whereas Aluminium, Gold, Palladium and Silver had negative excess kurtosis. The Jarque–Bera normality test indicated that only the Platinum index departed significantly from the normal at the 5% significance level ($JB = 9.0004$, $p = 0.0112$). The p-values for Aluminium, Copper, Gold, Lead, Palladium, Silver, Tin and Zinc were greater than 0.05 and therefore we could not reject the null hypothesis of normality. Overall, the results find differences in return performance, volatility and distributional behavior with gold exhibiting relatively low variability and Platinum exhibiting statistically significant non-normal returns.

Table 2: Pearson's correlation coefficient of Monthly returns (%) of international metal futures

Particulars	Aluminium	Copper	Gold	Lead	Palladium	Platinum	Silver	Tin	Zinc
Aluminium	1.0000	0.634*	0.295*	0.379*	0.338*	0.344*	0.347*	0.624*	0.684*
Copper	0.634*	1.0000	0.427*	0.561*	0.2270	0.465*	0.614*	0.708*	0.685*
Gold	0.296*	0.427*	1.0000	0.1626	0.271*	0.375*	0.634*	0.392*	0.2350
Lead	0.379*	0.561*	0.1626	1.0000	0.1816	0.366*	0.463*	0.474*	0.488*
Palladium	0.338*	0.2270	0.270*	0.1816	1.0000	0.513*	0.344*	0.2529	0.2359
Platinum	0.344*	0.465*	0.374*	0.365*	0.513*	1.0000	0.719*	0.378*	0.1911
Silver	0.348*	0.614*	0.634*	0.463*	0.344*	0.719*	1.0000	0.471*	0.271*
Tin	0.624*	0.708*	0.392*	0.474*	0.2529	0.378*	0.471*	1.0000	0.584*
Zinc	0.686*	0.685*	0.2350	0.488*	0.2359	0.1911	0.271*	0.584*	1.0000

(Source: Authors computations) (* significant @ 5%)

Table 2 depicts the Pearson's Correlation coefficients of the nine international metal futures monthly returns Aluminium Copper Gold Lead Palladium Platinum Silver Tin Zinc. The results show that all the pairwise correlation coefficients are positive in the range of 0.1626-0.719. This means that the returns of the metals move in the same direction to a certain degree or another. The highest association was observed between Platinum and Silver (0.719), Copper and Tin (0.708), Aluminium and Zinc (0.684), Copper and Zinc (0.685) and Aluminium and Copper (0.634). The relatively high positive correlation coefficients indicate that there are some metal futures influenced by the common market factors such as global industrial requirements, economy and commodity market trends. In contrast, the correlation between Gold and Lead (0.1626), Palladium and Lead (0.1816)

and Platinum and Zinc (0.1911) is lower and the linear co-movement is less.

Copper had strong positive relationships with several metals such as Tin (0.708), Zinc (0.685), Aluminium (0.634), Silver (0.614) and Lead (0.561). The relationships indicate that copper returns are likely to be correlated with other industrial metals, possibly because they are sensitive to similar cycles in manufacturing activity and the world economy. Aluminium was also positively correlated with Tin (0.624), Zinc (0.684 as shown in respective row) and Copper (0.634) signifying interdependence of industrial metal markets. The highest correlation was seen between Platinum and Silver (0.719) followed by Gold and Silver (0.634) which also had a relatively strong positive relationship. The correlation of Palladium and Platinum prices was found to be 0.513

which implies moderate co-movement. However, Gold's relationships to Lead (0.1626) and Zinc (0.2350) were weaker and Gold's monthly returns may respond differently to market conditions than some industrial metals.

The t-tests showed that the majority of the pairwise correlations were significant at the 5% level. However, some of the relationships such as Copper –Palladium, Gold –Lead, Lead –Palladium, Palladium –Tin, Palladium –Zinc, Platinum –Zinc and Gold –Zinc was not significant. Thus, although positive co-movement was the rule, the magnitude and statistical significance

of the relationships varied across metal pairs. The results overall indicate that there is interconnection between international metal future markets especially between Aluminium, Copper, Tin and Zinc and Platinum and Silver. These correlations may have implications on portfolio diversification. Metals with a higher positive correlation may be less diversified when mixed together. But correlation does not imply causation, nor does it guaranty future relationships, and each metal's diversification potential should be weighed along with volatility and expected returns.

Table 3: Stationarity check of Monthly returns (%) of international metal futures

Particulars	ADF Test	DF GLS Test	PP Test	KPSS Test
Aluminium	-6.8508 (0.0000) *	-6.8948 (0.0000) *	-6.8088 (0.0000) *	1.1232 (0.2659)
Copper	-7.0896 (0.0000) *	-7.0463 (0.0000) *	-7.0885 (0.0000) *	1.3128 (0.1943)
Gold	-6.8677 (0.0000) *	-5.8439 (0.0000) *	-6.8569 (0.0000) *	0.1129 (0.9105) #
Lead	-4.4871 (0.0006) *	-8.8360 (0.0000) *	-10.4537 (0.0000) *	0.1964 (0.8449)
Palladium	-7.9676 (0.0000) *	-6.7693 (0.0000) *	-7.9627 (0.0000) *	-0.1471 (0.8835)
Platinum	-7.4400 (0.0000) *	-7.4673 (0.0000) *	-7.4594 (0.0000) *	1.3474 (0.1830)
Silver	-6.2703 (0.0000) *	-6.2598 (0.0000) *	-6.2361 (0.0000) *	1.8614 (0.0677)
Tin	-6.7961 (0.0000) *	-5.3509 (0.0000) *	-6.7849 (0.0000) *	1.3527 (0.1813)
Zinc	-8.5731 (0.0000) *	-7.2046 (0.0000) *	-8.7343 (0.0000) *	0.5067 (0.6142)

(Source: Authors computations) (* significant @ 5%) (# Difference at Level 1)

The Augmented Dickey–Fuller (ADF), Dickey–Fuller Generalized Least Squares (DF-GLS), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are used to examine the stationarity of the monthly returns of nine international metal futures, namely Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin, and Zinc, and the results are presented in Table 3. The ADF, DF-GLS and PP tests show statistically significant results at the 5% level for all nine metals with p-values less than 0.05. So, the null hypothesis of unit root is rejected. This means the monthly return series of all nine metals are stationary. The results indicate that the returns fluctuate around fairly stable statistical characteristics during the study period and can be used in the subsequent time series and econometric analyses that require stationary data. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test is a complement to the unit-root tests in that it tests the null hypothesis that a time series is stationary, either around a constant level or around a deterministic trend, based on the parameters of the test. Unlike the ADF, DF-GLS, and PP tests, a non-significant KPSS test indicates that the available evidence is not sufficient to

reject the stationarity hypothesis. In Table 3, the KPSS p-value for Aluminium (0.2659), Copper (0.1943), Gold (0.9105), Lead (0.8449), Palladium (0.8835), Platinum (0.1830), Silver (0.0677), Tin (0.1813) and Zinc (0.6142) are greater than 5%. Hence, the stationarity null hypothesis cannot be rejected for all the nine metals. Gold shows very strong support for stationarity with a high p-value whereas Silver has a relatively low p-value of 0.0677 close to the 5% level. However, Silver's KPSS result is not statistically significant at 5% level.

To summarize, the results of the four tests unanimously suggest the stationarity of monthly returns of Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc during the period 2021–2025. The ADF, DF-GLS and PP tests reject the null hypothesis of existence of a unit root, whereas the KPSS test does not reject the null hypothesis of stationarity. The agreement of these tests reinforces the robustness of the conclusion that the monthly return series is stationary. This is an important prerequisite for many subsequent econometric techniques including regression analysis, vector autoregression

and other time series models. However, stationarity does not imply that there is no volatility clustering, extreme observations or structural breaks in returns;

these features may have to be examined separately in further empirical analysis.

Table 4: Outliers check of Monthly returns (%) of international metal futures

Particulars	Tukey	Mean/Stdev	ARMA	Wavelet
Aluminium	10	10	0	1
Copper	10	8	0	0
Gold	10	8	0	3
Lead	13	6	0	1
Palladium	6	4	0	2
Platinum	7	4	0	2
Silver	9	8	0	1
Tin	13	8	0	2
Zinc	19	9	0	1

(Source: Authors computations)

The results for outlier detection in the monthly returns of nine international metal futures – Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc – using four methods – Tukey, Mean/Standard Deviation, Autoregressive Moving Average (ARMA) and Wavelet – are shown in Table 4. The number of outliers identified with all the nine metals by Tukey method varied with Zinc having the highest number (19) followed by Lead and Tin (13), Aluminium and Copper (10), Gold (10), Silver (9), Platinum (7) and Palladium (6). The results show that extreme monthly returns were found for all metal futures, but the occurrence of them was very different. The relatively high number of outliers in Zinc, Lead and Tin indicates that these metals had more observations outside the expected range defined by the Tukey method during the study period.

The Mean/Standard Deviation method also detected outliers for all nine metals although the number detected was generally lower than under the Tukey method. Aluminium had 10 outliers followed by Zinc (9), Copper, Gold, Silver, Tin (8 each), Lead (6) and Palladium, Platinum (4 each). These differences between Tukey and Mean/Standard Deviation results

suggest that outliers' identification depends on the statistical criteria used. These observations may reflect actual market events and not data errors, as returns on metal futures can be very volatile and experience extreme price moves.

The ARMA approach did not find any outliers for all nine metal futures, so the Wavelet approach found relatively few outliers in the data, with the largest number (3) being found in Gold. Palladium, Platinum and Tin each had two outliers, Aluminium, Lead and Silver each had one; Copper and Zinc had none. To summarize, the results reveal significant differences in outlier detection between methods and emphasize the significance of applying multiple diagnostic procedures in the analysis of international metal futures returns. Since there are possible extreme observations, in the following analysis we make use of robust regression techniques to determine whether the estimated relationships among metal futures returns are robust to the influence of outliers. This extra analysis helps to evaluate the robustness of the empirical results without automatically discarding the extreme observations that could be true market movements.

Table 5: Robust Regression Analysis of International metal futures monthly futures by M-Estimation and Huber Type-I Standard errors and Covariance type on gold returns

Particulars	Function - Weight							
	Andrews	Bisquare	Cauchy	Huber	Huber-B	Logistic	Talworth	Welsch
Constant	0.8701 (0.0084)*	0.8742 (0.0078)*	0.8222 (0.5439)	0.7752 (0.0238)*	0.8327 (0.6970)	0.7956 (0.0201)*	0.8076 (0.0097)*	0.8616 (0.0000)*

Aluminium	0.0130 (0.8737)	0.0131 (0.8719)	0.0375 (0.9108)	0.0421 (0.6198)	0.0212 (0.9681)	0.0465 (0.5826)	0.0029 (0.9701)	0.0213 (0.0241)*
Copper	0.3468 (0.0018)*	0.3471 (0.0016)*	0.2484 (0.5847)	0.2096 (0.0686)	0.3415 (0.6342)	0.1913 (0.0960)	0.3565 (0.0007)*	0.3054 (0.0000)*
Lead	-0.3197 (0.0002)*	-0.3194 (0.0001)*	-0.2706 (0.4346)	-0.2514 (0.0041)*	-0.3112 (0.5694)	-0.2478 (0.0046)*	-0.3361 (0.0000)*	-0.2938 (0.0000)*
Palladium	0.0581 (0.1370)	0.0582 (0.1339)	0.0534 (0.7386)	0.0516 (0.2026)	0.0586 (0.8166)	0.0496 (0.2195)	0.0504 (0.1719)	0.0543 (0.0000)*
Platinum	-0.0425 (0.5168)	-0.0428 (0.5117)	-0.0737 (0.7840)	-0.0934 (0.1705)	-0.0543 (0.8982)	-0.0897 (0.1873)	-0.0554 (0.3719)	-0.0687 (0.0000)*
Silver	0.3539 (0.0000)*	0.3541 (0.0000)*	0.3534 (0.1833)	0.3641 (0.0000)*	0.3565 (0.3952)	0.3579 (0.0000)*	0.3531 (0.0000)*	0.3474 (0.0000)*
Tin	0.0268 (0.5963)	0.0263 (0.6010)	0.0322 (0.8770)	0.0347 (0.5103)	0.0236 (0.9428)	0.0377 (0.4726)	0.0384 (0.4234)	0.0292 (0.0000)*
Zinc	-0.0314 (0.6530)	-0.0318 (0.6464)	-0.0151 (0.9579)	-0.0134 (0.8535)	-0.0297 (0.9476)	-0.0041 (0.9553)	-0.0245 (0.7110)	-0.0267 (0.0009)*
Adj R-squared	0.4772	0.4757	0.4187	0.4137	0.1666	0.4038	0.5056	0.4552
Adj Rw-squared	0.7730	0.7723	0.7076	0.6661	0.9352	0.6736	0.7328	0.7005
Rn-squared stat	144.1461 (0.0000) *	145.8293 (0.0000) *	6.9459 (0.5424)	100.6650 (0.0000)*	3.3705 (0.9090)	98.0796 (0.0000)*	159.4721 (0.0000)*	9276.228 (0.0000)*
AIC	84.8818	85.3922	84.6135	115.004	27.4551	98.0974	93.7439	87.6112
SC	107.8988	108.4019	120.5471	133.8518	57.4978	119.6598	113.7232	122.1274
Deviance	296.2404	297.4023	302.8485	358.3123	73.9903	305.9462	345.8609	281.1998
Scale	2.0421	2.0387	1.9022	1.9219	1.8929	1.9221	2.1211	1.8158

(Source: Authors computations) (* significant @ 5%)

The results of the robust regression with the Gold monthly returns as the dependent variable and Aluminium, Copper, Lead, Palladium, Platinum, Silver, Tin and Zinc monthly returns as explanatory variables are presented in Table 5. We estimate the models using M-estimation with eight weighting functions (Andrews, Bisquare, Cauchy, Huber, Huber-Bisquare, Logistic, Talworth and Welsch) and with Huber Type-I standard errors and covariance estimates. The aim of the analysis is to study whether the relationships between Gold and other metal futures returns are robust to the reduction of the effect of extreme observations. The findings suggest that the size and the statistical significance of the coefficient estimates are sensitive to the selection of the weighting functions and emphasize the significance of testing the robustness of the estimated relationships to alternative specifications.

The constant term is positive in all eight specifications and ranges from 0.7752 with Huber weighting to 0.8742 with Bisquare weighting. It is statistically significant at the 5% level for Andrews, Bisquare, Huber, Logistic, Talworth and Welsch weighting but not for Cauchy and Huber-Bisquare weighting. The

coefficient for copper is positive in all eight models, ranging from 0.1913 (Logistic weighting) to 0.3565 (Talworth weighting). Its coefficient is statistically significant for Andrews, Bisquare, Talworth and Welsch weighting with p-values of 0.0018, 0.0016, 0.0007 and 0.0000 respectively. But it is negligible for the Cauchy, Huber, Huber-Bisquare and Logistic weights. All the specifications have positive coefficients for aluminium, varying from 0.0029 to 0.0465, but it is statistically significant only with Welsch weighting. The results reveal that returns of Copper and Gold are generally positively related with each other while the evidence for Aluminium is relatively weak.

Lead has a negative coefficient in all of the 8 models ranging from -0.2478 in Logistic weighting to -0.3361 in Talworth weighting. The coefficient of the model is statistically significant under Bisquare, Huber, Logistic, Talworth and Welsch weighting of the model but it is not statistically significant under Cauchy and Huber-Bisquare weighting of the model. This provides fairly consistent evidence that Lead and Gold returns are negatively related. Silver, in contrast, has a positive coefficient between 0.3474 and 0.3641, which is

statistically significant under Andrews, Bisquare, Huber, Logistic, Talworth and Welsch weighting. The coefficient estimates are fairly stable and statistically significant consistently pointing to a relatively strong positive relationship between silver and gold returns. The coefficients of the Palladium and Tin positives are significant in all specifications, those of Platinum and Zinc are significant in all specifications. However, under most weighting functions, these four metals are statistically insignificant, implying that their independent relations with gold returns are less robust to the choice of the estimator.

Additional details on the performance of the eight specifications are given by the model-fit statistics. Talworth has the highest adjusted R-squared at 0.5056, followed by Andrews at 0.4772 and Bisquare at 0.4757. The R-squared statistic for the Andrews model is 144.1461 ($p = 0.0000$) and for the Talworth model is 159.4721 ($p = 0.0000$), both statistically significant. Both models find Copper, Lead and Silver as statistically significant explanatory variables and offer comparable estimates of coefficients, which suggests consistency in the direction and magnitude of the main relationships. Importantly, Andrews has AIC of 84.8818 and SC of 107.8988 as against Talworth AIC and SC of 93.7439 and 113.7232 respectively. Thus, Andrews's values of AIC and SC being lower than Talworth indicate a more favourable trade-off between fit of the model and complexity for those criteria. This is assuming the information criteria are calculated on a comparable basis across the robust estimators.

The Huber-Bisquare model exhibits the lowest AIC (27.4551), SC (57.4978) and deviance (73.9903) but it

has an adjusted R-squared value of only 0.1666 and the Rn-squared statistic is not statistically significant ($p = 0.9090$). The conflicting results obtained make it necessary to check the output of the Huber-Bisquare estimate before using its information criteria for the selection of the preferred model. Similarly, the overall Rn-squared statistic for the Cauchy model is insignificant ($p=0.5424$). However, Andrews, Bisquare, Huber, Logistic, Talworth and Welsch have statistically significant overall statistics. Therefore, the choice of model should not be made only on a single fit statistic but also on overall significance, stability of coefficients, explanatory power and comparability of information criteria. Andrews and Talworth are both competitive specifications here. Andrews has lower AIC and SC and Talworth has higher adjusted R-square.

To put it simply, the results show that Copper and Silver returns are positively related to gold returns and Lead returns are negatively related to gold returns. The three relationships are statistically significant under both the Andrews and Talworth weighting as well as the Bisquare specification, which gives us more confidence that they are robust to different robust estimators. Andrews provides a specification that is particularly defensible as it produces similar substantive results to Talworth but with smaller AIC and SC values. Therefore, we can select Andrews as the preferred method of robust regression after verifying that the information criteria are comparable across the models, and keep Talworth as a robustness check.

Table 6: Robust Regression Analysis of International metal futures monthly futures by M-Estimation and Huber Type-II Standard errors and Covariance type on gold returns

Particulars	Function - Weight							
	Andrews	Bisquare	Cauchy	Huber	Huber-B	Logistic	Talworth	Welsch
Constant	0.8701 (0.0084)*	0.8742 (0.0061)*	0.8222 (0.9664)	0.7752 (0.0208)*	0.8327 (0.8501)	0.7956 (0.0162)*	0.8076 (0.0090)*	0.8616 (0.0000)*
Aluminium	0.0130 (0.8625)	0.0131 (0.8610)	0.0375 (NA)	0.0421 (0.6052)	0.0212 (0.9986)	0.0465 (0.5653)	0.0029 (0.9692)	0.0213 (0.0167)*
Copper	0.3468 (0.0031)*	0.3471 (0.0030)*	0.2484 (0.9994)	0.2096 (0.1147)	0.3415 (0.9668)	0.1913 (0.1365)	0.3565 (0.0019)*	0.3054 (0.0000)*
Lead	-0.3197 (0.0000)*	-0.3194 (0.0000)*	-0.2706 (0.9996)	-0.2514 (0.0035)*	-0.3112 (NA)	-0.2478 (0.0036)*	-0.3361 (0.0000)*	-0.2938 (0.0000)*
Palladium	0.0581 (0.1125)	0.0582 (0.1111)	0.0534 (1.0000)	0.0516 (0.1857)	0.0586 (0.9995)	0.0496 (0.1983)	0.0504 (0.1595)	0.0543 (0.0000)*
Platinum	-0.0425 (0.5770)	-0.0428 (0.5746)	-0.0737 (1.0000)	-0.0934 (0.2473)	-0.0543 (0.9991)	-0.0897 (0.2250)	-0.0554 (0.3627)	-0.0687 (0.0000)*

Silver	0.3539 (0.0000)*	0.3541 (0.0000)*	0.3534 (0.9999)	0.3641 (0.0000)*	0.3565 (0.9908)	0.3579 (0.0000)*	0.3531 (0.0000)*	0.3474 (0.0000)*
Tin	0.0268 (0.5884)	0.0263 (0.5933)	0.0322 (1.0000)	0.0347 (0.5074)	0.0236 (0.9998)	0.0377 (0.4659)	0.0384 (0.4220)	0.0292 (0.0000)*
Zinc	-0.0314 (0.6346)	-0.0318 (0.6286)	-0.0151 (NA)	-0.0134 (0.8458)	-0.0297 (0.9998)	-0.0041 (0.9523)	-0.0245 (0.7071)	-0.0267 (0.0006)*
Adj R-squared	0.4772	0.4757	0.4187	0.4137	0.1666	0.4038	0.5055	0.4552
Adj Rw-squared	0.7730	0.7723	0.7076	0.6661	0.9352	0.6736	0.7328	0.7005
Rn-squared stat	125.8983 (0.0000)*	127.2047 (0.0000)*	0.0000 (1.0000)	90.3016 (0.0000)*	-0.0028 (NA)	86.4343 (0.0000)*	131.8164 (0.0000)*	7072.919 (0.0000)*
AIC	84.8818	85.3922	84.6135	115.0040	27.4551	98.0974	93.7439	87.6112
SC	107.8988	108.4019	120.5471	133.8518	57.4978	119.6598	113.7232	122.1274
Deviance	296.2404	297.4023	302.8485	358.3123	73.9903	305.9462	345.8609	281.1998
Scale	2.0419	2.0387	1.9022	1.9219	1.8929	1.9221	2.1211	1.8158

(Source: Authors computations) (* significant @ 5%)

Table 6 shows the results of the robust regression for Gold monthly returns as dependent variable with Aluminium, Copper, Lead, Palladium, Platinum, Silver, Tin and Zinc monthly returns as explanatory variables. The models are estimated using M-estimation with 8 weighting functions, Andrews, Bisquare, Cauchy, Huber, Huber-Bisquare, Logistic, Talworth and Welsch with Huber type-II standard errors and covariance estimates. This is an analysis to test if the relationships between gold returns and other metal futures return hold under an alternative standard error and covariance specification. The coefficient estimates are the same as those reported in Table 5, but some p-values and overall test statistics differ. Thus, the estimated relationships are unchanged, but the statistical significance of some of the coefficients does depend on the covariance estimation procedure.

The constant term is positive for all eight specifications, varying from 0.7752 for Huber weighting to 0.8742 for Bisquare weighting. Weighting methods Andrews, Bisquare, Huber, Logistic, Talworth and Welsch are statistically significant at the 5% level, however Cauchy and Huber-Bisquare weighting is insignificant. The coefficient for copper is positive in all models, ranging from 0.1913 under Logistic weighting to 0.3565 under Talworth weighting. It is statistically significant for Andrews (0.3468; $p = 0.0031$), Bisquare (0.3471; $p = 0.0030$), Talworth (0.3565; $p = 0.0019$) and Welsch (0.3054; $p = 0.0000$). But it is negligible in Cauchy, Huber, Huber-Bisquare and Logistic weighting. Aluminium also has positive coefficients for all specifications but significance only under Welsch weighting (0.0213; $p = 0.0167$). The results suggest

that Copper and Gold returns are generally positively associated, while the evidence for Aluminium is comparatively weak.

Lead has a consistently negative coefficient across all eight models, ranging from -0.2478 under Logistic weighting to -0.3361 under Talworth weighting. It is statistically significant under Andrews, Bisquare, Huber, Logistic, Talworth and Welsch weighting. The Cauchy is insignificant and the Huber-Bisquare p-value is unavailable. Silver has a positive and statistically significant coefficient (0.3474 to 0.3641) across Andrews, Bisquare, Huber, Logistic, Talworth, and Welsch weighting. These results give relatively strong evidence of a negative association between Lead returns and gold returns and a positive association between silver returns and gold returns. The coefficients of Palladium and Tin are positive and those of Platinum and Zinc are negative. These variables are usually insignificant under Andrews, Bisquare, Huber, Logistic and Talworth weighting. Welsch finds statistically significant coefficients for all four. The lack of consistent significance across weighting functions suggests that the evidence for these relationships is sensitive to the choice of robust estimator and covariance specification.

The fit of the model statistics offers additional insights into the performance of the eight specifications. Talworth has the highest adjusted R-squared of 0.5055 and Andrews and Bisquare are 0.4772 and 0.4757 respectively. The overall Rn-squared statistics are significant under Andrews (125.8983; $p = 0.0000$), Bisquare (127.2047; $p = 0.0000$), Huber (90.3016; $p = 0.0000$), Logistic (86.4343; $p = 0.0000$), Talworth (131.8164; $p = 0.0000$), and Welsch (7072.919; $p =$

0.0000). Conversely, the global statistic with Cauchy is negligible and the Huber-Bisquare result is not available. The Andrews AIC is 84.8818 and the Andrews SC is 107.8988 which is less than the Talworth AIC which is 93.7439 and the Talworth SC which is 113.7232. There is no overall test for Huber-Bisquare but it has the lowest AIC (27.4551), SC (57.4978) and deviance (73.9903) with an adjusted R-squared of 0.1666. These inconsistencies should be checked before applying its information criteria for selecting the preferred model.

The overall results suggest a positive association of Copper and Silver returns with gold returns, while Lead returns are negatively associated with gold

returns. The findings are robust to both Andrews and Talworth weighting, providing support for the stability of the main findings across these specifications. Andrews is a defensible preferred model because it produces similar substantive results as Talworth and has lower AIC and SC values, assuming that these criteria are comparable across robust estimators. As a robustness check, Talworth can be kept as it has the highest adjusted R-squared and a statistically significant overall test. The results in Table 6 are mostly in line with the conclusions in Table 5, but some p-values shift under the Type-II covariance specification.

Table 7: Robust Regression Analysis of International metal futures monthly futures by M-Estimation and Huber Type-III Standard errors and Covariance type on gold returns

Particulars	Function - Weight							
	Andrews	Bisquare	Cauchy	Huber	Huber-B	Logistic	Talworth	Welsch
Constant	0.8709 (0.0057)*	0.8742 (0.0055)*	0.8222 (1.0000)	0.7752 (0.0219)*	0.8327 (0.9990)	0.7956 (0.0146)*	0.8076 (0.0082)*	0.8616 (0.0000)*
Aluminium	0.0130 (0.8500)	0.0131 (0.8491)	0.0375 (1.0000)	0.0421 (0.6090)	0.0212 (1.0000)	0.0465 (0.5545)	0.0029 (0.9682)	0.0213 (0.0112)*
Copper	0.3468 (0.0044)*	0.3471 (0.0045)*	0.2484 (1.0000)	0.2096 (0.1823)	0.3415 (0.9998)	0.1913 (0.1884)	0.3565 (0.0052)*	0.3054 (0.0000)*
Lead	-0.3197 (0.0000)*	-0.3194 (0.0000)*	-0.2706 (1.0000)	-0.2514 (0.0072)*	-0.3112 (1.0000)	-0.2478 (0.0052)*	-0.3361 (0.0000)*	-0.2938 (0.0000)*
Palladium	0.0581 (0.0847)	0.0582 (0.0851)	0.0534 (1.0000)	0.0516 (0.1695)	0.0586 (1.0000)	0.0496 (0.1764)	0.0504 (0.1460)	0.0543 (0.0000)*
Platinum	-0.0425 (0.6399)	-0.0428 (0.6402)	-0.0737 (1.0000)	-0.0934 (0.3747)	-0.0543 (1.0000)	-0.0897 (0.2881)	-0.0554 (0.3537)	-0.0687 (0.0000)*
Silver	0.3539 (0.0000)*	0.3541 (0.0000)*	0.3534 (1.0000)	0.3641 (0.0000)*	0.3565 (1.0000)	0.3579 (0.0000)*	0.3531 (0.0000)*	0.3474 (0.0000)*
Tin	0.0268 (0.5796)	0.0263 (0.5851)	0.0322 (1.0000)	0.0347 (0.5020)	0.0236 (1.0000)	0.0377 (0.4575)	0.0384 (0.4213)	0.0292 (0.0000)*
Zinc	-0.0314 (0.6132)	-0.0318 (0.6082)	-0.0151 (1.0000)	-0.0134 (0.8379)	-0.0297 (1.0000)	-0.0041 (0.9491)	-0.0245 (0.7033)	-0.0267 (0.0004)*
Adj R-squared	0.4772	0.4757	0.4187	0.4137	0.1666	0.4038	0.5055	0.4552
Adj Rw-squared	0.7730	0.7723	0.7076	0.6661	0.9352	0.6736	0.7328	0.7005
Rn-squared stat	122.0000 (0.0000)*	122.7257 (0.0000)*	0.0000 (1.0000)	97.4471 (0.0000)*	-0.0021 (1.0000)	88.9343 (0.0000)*	112.4252 (0.0000)*	6190.013 (0.0000)*
AIC	84.8818	85.3922	84.6135	115.0040	27.4551	98.0974	93.7439	87.6112
SC	107.8988	108.4019	120.5471	133.8518	57.4978	119.6598	113.7232	122.1274
Deviance	296.2404	297.4023	302.8485	358.3123	73.9903	305.9462	345.8609	281.1998
Scale	2.0419	2.0387	1.9022	1.9219	1.8929	1.9221	2.1211	1.8158

(Source: Authors computations) (* significant @ 5%)

Table 7 presents the robust regression results where the dependent variable is the monthly returns of Gold and the explanatory variables are the monthly returns of Aluminium, Copper, Lead, Palladium, Platinum,

Silver, Tin and Zinc. The models are estimated using M-estimation with eight weighting functions: Andrews, Bisquare, Cauchy, Huber, Huber-Bisquare, Logistic, Talworth and Welsch. The standard errors

and covariance estimates are Huber Type-III. The analysis tests the robustness of the relations between gold returns and the other international metal futures returns using an alternative covariance specification. The estimated coefficients are quite robust across Huber Type-I, Type-II, and Type-III covariance specifications, as shown in Tables 5, 6, and 7. The main differences are in terms of changes in p-values and small changes in the Rn-squared statistics, which indicates that the broad interpretation of the regression results is broadly consistent across the three specifications.

The constant term is positive for all the eight weighting functions and varies from 0.7752 for the Huber weighting to 0.8742 for the Bisquare weighting. It is statistically significant at the 5% level under Andrews, Bisquare, Huber, Logistic, Talworth and Welsch weighting, but insignificant under Cauchy and Huber-Bisquare weighting. Copper has positive coefficients under all specifications, from 0.1913 under Logistic weighting to 0.3565 under Talworth weighting. The coefficient is statistically significant for Andrews (0.3468; $p = 0.0044$), Bisquare (0.3471; $p = 0.0045$), Talworth (0.3565; $p = 0.0052$) and Welsch (0.3054; $p = 0.0000$). However, it is negligible for Cauchy, Huber, Huber-Bisquare and Logistic weighting. Aluminium has positive coefficients for all eight models but is only statistically significant under Welsch weighting (0.0213; $p = 0.0112$). These results suggest a generally positive relationship between Copper and Gold returns, while the evidence for Aluminium is relatively weak across the robust specifications.

In all eight models, a consistently negative coefficient for lead is found, from -0.2478 in the Logistic weighting to -0.3361 in the Talworth weighting. Its coefficient is significant in Andrews, Bisquare, Huber, Logistic, Talworth and Welsch weighting but insignificant in Cauchy and Huber-Bisquare results. Silver shows a consistent positive coefficient (0.3474 to 0.3641) and is statistically significant when Andrews, Bisquare, Huber, Logistic, Talworth and Welsch weighting are used. The similarity of these coefficients across the three covariance specifications provides relatively strong evidence that Lead returns are negatively associated with gold returns, and that silver returns are positively associated with gold returns. The coefficients are positive for Palladium and Tin and negative for Platinum and Zinc. These four

variables are generally insignificant under Andrews, Bisquare, Huber, Logistic, and Talworth weighting; only Welsch reports statistically significant coefficients for all four. Their estimated relations, thus, seem more sensitive to the choice of weighting function than those of Copper, Lead and Silver.

The model-fit statistics give further information on the performance of the eight robust regression specifications. Adjusted R-squared is highest for Talworth at 0.5055, followed by Andrews at 0.4772 and Bisquare at 0.4757. The overall Rn-squared statistics are statistically significant at Andrews (122.0000; $p=0.0000$), Bisquare (122.7257; $p=0.0000$), Huber (97.4471; $p=0.0000$), Logistic (88.9343; $p=0.0000$), Talworth (112.4252; $p=0.0000$), and Welsch (6190.013; $p=0.0000$). In contrast, the overall statistics of the Cauchy and Huber-Bisquare are not statistically significant. The AIC for Andrews is 84.8818 and SC is 107.8988 which are lower than the Talworth values of 93.7439 and 113.7232 respectively. Huber-Bisquare has the smallest AIC (27.4551), SC (57.4978) and deviance (73.9903), but its adjusted R-squared is only 0.1666 and its overall test is not significant. The conflicting results should be checked before using the Huber-Bisquare information criteria to choose the preferred model.

As can be seen by comparing Tables 5, 6 and 7, the Huber Type-I, Type-II and Type-III covariance specifications produce largely similar regression results. The coefficient estimates are the same or almost the same, the p-values change a little, and the Rn-squared statistics change relatively little across the three specifications for most weighting functions. Under Andrews, Bisquare and Talworth weighting the positive association of Copper and Silver returns with gold returns and the negative association of Lead returns with gold returns are still evident. These similarities suggest that the main results are not substantially affected by the choice of the three covariance specifications. Thus, Huber Type-I standard errors and covariance estimates can be maintained for the main analysis, whereas Type-II and Type-III can be used in supplementary robustness checks. However, the very large Welsch Rn-squared statistics and the inconsistent Huber-Bisquare fit measures should be scrutinized against the original estimation output.

Overall, Andrews is a defensible choice for the preferred robust regression specification because it

produces statistically significant relationships for Copper, Lead and Silver, a statistically significant overall test, and lower AIC and SC values than Talworth. Talworth has the highest adjusted R-squared. Andrews however is a good compromise between explanatory fit, model parsimony and coefficient stability. Thus, Andrew's weighting can be used as the preferred estimation method and Huber

Type-I as the covariance specification for reporting the principal results, if the underlying estimation diagnostics support such a choice. We can retain Talworth as a robustness check, and report the Type-II and Type-III results as evidence that the primary findings are broadly robust to covariance specifications.

Table 8: Robust Regression Analysis of International metal futures monthly futures by S-Estimation and Huber Type-I, II & III Standard errors and Covariance type on gold returns

Particulars	Huber Type - I	Huber Type - II	Huber Type - III
Constant	0.9188 (0.0003) *	0.9188 (0.0001) *	0.9188 (0.0000) *
Aluminium	0.1461 (0.0212) *	0.1461 (0.0240) *	0.1461 (0.1852)
Copper	0.0908 (0.2906)	0.0908 (0.5883)	0.0908 (0.8136)
Lead	-0.2018 (0.0021) *	-0.2018 (0.0014) *	-0.2018 (0.0015) *
Palladium	0.0415 (0.1704)	0.0415 (0.4519)	0.0415 (0.7361)
Platinum	-0.0554 (0.2764)	-0.0554 (0.2971)	-0.0554 (0.3118)
Silver	0.3145 (0.0000) *	0.3145 (0.0000) *	0.3145 (0.0000) *
Tin	0.0489 (0.2130)	0.0489 (0.2180)	0.0489 (0.4135)
Zinc	0.0129 (0.8107)	0.0129 (0.8394)	0.0129 (0.9166)
Adj R-squared	0.5159	0.5159	0.5159
Adj Rw-squared	----	----	----
Rn-squared stat	167.9146 (0.0000) *	207.9929 (0.0000) *	463.1304 (0.0000) *
AIC	----	----	----
SC	----	----	----
Deviance	4.9541	4.9541	4.9541
Scale	2.2258	2.2258	2.2258

(Source: Authors computations) (* significant @ 5%)

Table 8 shows the robust regression results using S-estimation to investigate the relationship between the monthly returns of Gold and the monthly returns of Aluminium, Copper, Lead, Palladium, Platinum, Silver, Tin, and Zinc. The analysis compares three covariance specifications: Huber Type-I, Huber Type-II and Huber Type-III standard errors and covariance estimates. The constant term is positive and statistically significant in all the three specifications (coefficient = 0.9188; p-values = 0.0003, 0.0001 and 0.0000, respectively). The adjusted R-squared is 0.5159 for all three models. The coefficient estimates, adjusted R-squared, deviance (4.9541) and scale (2.2258) are the same across the three specifications, suggesting that the underlying regression estimates are identical, but the estimated standard errors and associated p-values differ.

Aluminium has positive coefficient of 0.1461 in all the three specifications. It is significant under Huber

Type-I ($p = 0.0212$) and Type-II ($p = 0.0240$) but insignificant under Type-III ($p = 0.1852$). This means that the evidence of a positive association between Aluminium and Gold returns is sensitive to the covariance specification. The coefficient for copper is positive at 0.0908 but not statistically significant in any of the three specifications. Lead has a negative coefficient of -0.2018 and is statistically significant at 1% for Type-I, Type-II and Type-III with p-values of 0.0021, 0.0014 and 0.0015 respectively. This provides consistent evidence of a negative association between Lead returns and gold returns. Palladium has a positive coefficient (0.0415), whereas Platinum has a negative coefficient (-0.0554). None of them are statistically significant under any of the three specifications. These results suggest that the evidence for relationships between Copper, Palladium and Platinum is relatively weak in the estimated model.

Silver has a positive coefficient of 0.3145 and is statistically significant for all three covariance specifications with p-values of 0.0000 for each. This demonstrates that the positive correlation between silver returns and gold returns is robust. Tin has a positive coefficient of 0.0489 and Zinc has a positive coefficient of 0.0129; however, both variables are statistically insignificant across all three specifications. The reported test shows overall Rn-squared statistics, in which Huber Type-I (167.9146; $p = 0.0000$), Type-II (207.9929; $p = 0.0000$) and Type-

III (463.1304; $p = 0.0000$) are statistically significant, meaning overall statistical significance. Since the estimated coefficients and the adjusted R-squared are the same, the differences in the Rn-squared statistics and p-values mainly reflect changes in the reported inferential statistics rather than in the estimated relationships. Overall Lead and Silver seem to be the most consistent statistically significant explanatory variables. Aluminium is significant only under Type-I and Type-II.

Table 9: Robust Regression Analysis of International metal futures monthly futures by MM-Estimation and Huber Type-I, II & III Standard errors and Covariance type on gold returns.

Particulars	Huber Type - I	Huber Type - II	Huber Type - III
Constant	0.8816 (0.0071)*	0.8816 (0.0056)*	0.8816 (0.0047)*
Aluminium	0.0133 (0.8702)	0.0133 (0.8604)	0.0133 (0.8491)
Copper	0.3498 (0.0015)*	0.3498 (0.0029)*	0.3498 (0.0047)*
Lead	-0.3193 (0.0001)*	-0.3193 (0.0000)*	-0.3193 (0.0000)*
Palladium	0.0571 (0.1409)	0.0571 (0.1193)	0.0571 (0.0947)
Platinum	-0.0493 (0.4490)	-0.0493 (0.4935)	-0.0493 (0.5421)
Silver	0.3555 (0.0000)*	0.3555 (0.0000)*	0.3555 (0.0000)*
Tin	0.0243 (0.6289)	0.0243 (0.6227)	0.0243 (0.6142)
Zinc	-0.0333 (0.6310)	-0.0333 (0.6153)	-0.0333 (0.5978)
Adj R-squared	0.4733	0.4733	0.4733
Adj Rw-squared	0.7573	0.7573	0.7573
Rn-squared stat	144.1548 (0.0000)*	124.5138 (0.0000)*	116.4225 (0.0000)*
AIC	76.5402	76.5402	76.5402
SC	101.0540	101.0540	101.0540
Deviance	318.0765	318.0765	318.0765
Scale	2.2258	2.2258	2.2258

(Source: Authors computations) (* significant @ 5%)

The results of the robust regression using MM-estimation to study the relationship between the Gold monthly returns and the monthly returns of the Aluminium, Copper, Lead, Palladium, Platinum, Silver, Tin and Zinc are shown in table 9. The analysis tests the consistency of estimated relationships by comparing the Huber Type-I, Type-II and Type-III standard error and covariance specifications. The constant term is positive and statistically significant for all the three specifications with coefficient 0.8816 and p-values 0.0071, 0.0056 and 0.0047 respectively. All the three models have 0.4733 as adjusted R-squared. This means the model explains 47.33% of the variation in gold returns based on this measure. The adjusted robust R-squared is also the same at 0.7573. The AIC (76.5402), Schwarz Criterion (101.0540),

deviance (318.0765) and scale (2.2258) are the same across the specifications. These findings suggest that the estimated coefficients and model-fit measures are stable, although the reported p-values and overall Rn-squared statistics differ.

Copper has a positive coefficient of 0.3498 and is statistically significant in all three covariance specifications with p-values of 0.0015, 0.0029 and 0.0047 for Huber Type-I, Type-II and Type-III respectively. This provides strong evidence of positive relationship between copper returns and gold returns. Lead is statistically significant in all three specifications with p-values of 0.0001, 0.0000 and 0.0000 and has a negative coefficient of -0.3193 implying a consistent negative association with gold returns. Silver also has a positive coefficient of 0.3555

and is statistically significant in all the three specifications with p-values of 0.0000. The signs, magnitudes of coefficients and statistical significance of Copper, Lead and Silver are consistent, implying that these relationships are robust to the choice of covariance specification.

In the case of Aluminium, the coefficient is positive (0.0133) but statistically insignificant across all three specifications. Palladium has a positive coefficient, 0.0571, while Platinum has a negative coefficient, -0.0493. Huber Type-I Both Type-II and Type-III are statistically insignificant. The positive and negative coefficients of 0.0243 and -0.0333 are insignificant for Tin and Zinc respectively in none of the three specifications. The overall Rn-squared statistics are statistically significant for all the models with values of 144.1548, 124.5138 and 116.4225 for Huber Type-I, Type-II and Type-III respectively all with reported p-values of 0.0000. Overall, the MM estimation results quite consistently suggest that Copper and Silver are positively related to gold returns and Lead negatively related to gold returns. Given the lack of differences in coefficient estimates and model-fit statistics across the three covariance specifications, there is no reason to not take Huber Type-I as the main specification and Types-II and III as robustness checks. These are associations, not causation, and that's an important thing to remember.

The three robust estimation methods, M-estimation, S-estimation and MM-estimation were compared to find the most appropriate method to analyze the relationship between Gold monthly returns and the returns of Aluminium, Copper, Lead, Palladium, Platinum, Silver, Tin and Zinc during 2021-2025. The M-estimation using Andrew's weighting records the adjusted R-squared of 0.4772 and the adjusted robust R-squared of 0.7730. The S-estimation gives the highest adjusted R-squared of 0.5159. The MM-estimation gives the adjusted R-squared of 0.4733 and the adjusted robust R-squared of 0.7573. Although S-estimation has the highest explanatory power in terms of the adjusted R-squared, the best method selection should also consider the stability of coefficient estimates, statistical significance, and robustness to extreme observations.

The results suggest that M-estimation with Andrews weighting consistently identifies Copper and Silver as positively related with gold returns and Lead as negatively related with gold returns. The MM-

estimation also produces similar results with Copper, Lead and Silver statistically significant under Huber Type-I, Type-II and Type-III covariance specification. The consistency of these relationships adds confidence in their robustness. Conversely, S-estimation detects Aluminium, Lead and Silver as statistically significant under Huber Type-I, whereas Copper is not. In addition, Aluminium is statistically insignificant when using Huber Type-III covariance estimation. The MM-estimation has a slightly lower adjusted R-squared than Andrews M-estimation. The coefficient estimates and the significance patterns of the coefficients are consistent across the three covariance specifications. The Andrews M-estimation also shows higher AIC (84.8818) and SC (107.8988) than MM-estimation (76.5402 and 101.0540, respectively). These comparisons are only valid if the criteria are computed comparably across methods.

The preferred method for the main analysis is MM-estimation with Huber Type-I standard errors and covariance estimates. Andrews M-estimation can be used as a robustness check and S-estimation as a supplementary comparison. This recommendation is based on the consistent statistical significance of Copper, Lead and Silver across the three covariance specifications of MM-estimation and the stability of the estimated coefficients. Although S-estimation has the highest adjusted R-squared, explanatory power alone cannot be used to establish the superiority of an estimator. The final choice should also consider reliability of the test statistics, robustness to outliers and proper model diagnostics. Before using the reported AIC and SC values for ranking the estimation methods, their comparability should be checked.

V. CONCLUSION

The study concludes that, significant differences in price changes, monthly returns and volatility in the international metal futures markets over the study period. Aluminium, Copper, Gold, Lead, Palladium, Platinum, Silver, Tin and Zinc showed different return patterns, reflecting their different market characteristics. Palladium had a negative average return, while silver and tin had relatively high average returns. The different distributions of volatility and returns suggest that the investors in the different metal futures markets are exposed to different risk. This finding indicates the need to consider both expected

return and risk in investment and portfolio allocation decisions.

Correlation analysis showed positive co-movements of most metal futures indicating interrelatedness of price changes in these markets. Some metals are highly correlated and tend to move in the same direction in their returns when faced with common market shocks. But the strength of these bonds varies from one pair of metals to another. The stationarity analysis indicated that the general tendency is to use monthly returns for econometric modeling. However, the results for Tukey, Mean/Standard Deviation, ARMA and Wavelet outlier detection methods were quite different. The variation suggests that extreme observations depend on the detection technique and that they may be attributed to real market shocks rather than data errors. Thus, it is important to detect and treat outliers so that you can obtain reliable empirical results.

In the robust regression analysis, Copper and Silver were positively related to gold returns, and Lead was negatively related to gold returns. Andrews and Talworth M-estimation specifications and alternative covariance specifications used in MM-estimation, the relationship was relatively stable. The relationships with Aluminium, Palladium, Platinum, Tin and Zinc showed less consistent statistical significance. The comparison of Huber Type-I, Type-II and Type-III covariance specifications implied that the coefficient estimates were generally stable but there were changes of p-values and test statistics. S-estimation showed quite strong explanatory power. MM-estimation showed robust evidence of the relationships of Copper, Lead and Silver with Gold return.

The specification of choice is MM-estimation with Huber Type-I standard errors and covariance estimation. As a robustness check we use Andrews M-estimation and as a further check we use S-estimation. This recommendation is consistent with the stability of the main relationships and the statistical significance that is robust to alternative covariance specifications. The results offer insight into the behavior and interrelationships of international metal futures markets and can help investors to evaluate diversification opportunities and manage risks of commodities. However, the results are statistical associations, not causal links, and the interpretation of the results should take into account the limitations of the estimation methods, the effect of extreme

observations, and the sensitivity of statistical inference to different model specifications.

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