Common Volatility of Precious, Industrial and Transition Metals: Estimating Metal-Specific COVOL and Analysing Its Response to Global Shocks

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Abstract

This dissertation examines the dynamics of common volatility of three different metal categories (Precious, Industrial and Transition) by applying the Global Common Volatility (COVOL) framework of Engle and Campos-Martins (2023). The analysis is structured around two central aims: estimating the common volatility factor for each metal category and assessing the extent to which macro-financial and global uncertainty indicators explain the dynamics of these metal-specific indices. Exchange-Traded Funds (ETFs) representing each metal category are individually modelled through GARCH(1,1) specifications to obtain their conditional variance dynamics. The resulting standardized volatility shocks are then used to extract a metal-specific common volatility factor, which is subsequently aggregated to a monthly frequency. These metal (M)COVOL indices are then analysed and incorporated into a set of regression models that include macroeconomic variables, financial risk indicators, global uncertainty measures and event dummies. The empirical findings indicate strong comovement patterns across all metal groups, with pronounced spikes during geopolitical, financial and macroeconomic shocks such as the global financial crisis, trade tensions and the COVID-19 pandemic. Industrial and transition metals display the highest sensitivity to common shocks, consistent with their exposure to economic cycles and energy transition dynamics. The regression analysis shows that MCOVOL is significantly shaped by macroeconomic and global risk factors, confirming its sensitivity to systemic conditions. Altogether, the results highlight MCOVOL's usefulness as a complementary risk monitoring indicator, being capable of capturing systemic pressures beyond traditional uncertainty measures and reflecting how global shocks spread to metal markets.

Keywords: Metal-specific Common Volatility (MCOVOL); Geopolitical Risks and Global/Systemic shocks; Metal Volatility Comovements and Dynamics.

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Resumo

Esta dissertação analisa a volatilidade comum em três categorias de metais (Preciosos, Industriais e de Transição) aplicando o modelo de volatilidade global comum (COVOL) proposto por Engle e Campos-Martins (2023). A investigação segue dois objetivos centrais: estimar o fator de volatilidade comum de cada categoria e avaliar até que ponto variáveis macroeconómicas, financeiras e de incerteza global explicam a dinâmica dos índices específicos por metal. Os fundos (ETFs) que representam cada categoria são modelizados individualmente com especificações GARCH(1,1), permitindo obter as respetivas variâncias condicionais. Os choques de volatilidade padrão são então utilizados para extrair um fator comum. Estes índices MCOVOL são integrados em regressões que incluem variáveis macroeconómicas, indicadores de risco financeiro, medidas de incerteza global e dummies de eventos como variáveis explicativas. Os resultados empíricos evidenciam padrões claros de movimento conjunto entre os grupos de metais, com picos durante choques geopolíticos, financeiros e macroeconómicos como a crise financeira global ou a pandemia de COVID-19. Os metais industriais e de transição revelam maior sensibilidade a choques comuns, refletindo a sua exposição aos ciclos económicos e às dinâmicas associadas à transição energética. Os resultados das regressões indicam que o MCOVOL é significativamente explicado por indicadores macroeconómicos e de risco global, confirmando a sensibilidade da volatilidade comum dos metais. Concluindo, os resultados realçam a utilidade do MCOVOL como indicador complementar de monitorização de risco, sendo este capaz de captar pressões sistémicas além das medidas tradicionais de incerteza e de explicar a forma como os choques globais se propagam aos mercados de metais.

Palavras-chave: Volatilidade Global Comum Específica por Metal (MCOVOL); Riscos Geopolíticos e Choques Globais/Sistémicos; Comovimentos e Dinâmicas da Volatilidade dos Metais.

Título: Volatilidade Comum dos Metais Preciosos, Industriais e de Transição: Estimação do COVOL específico de cada grupo de metais e Análise da Sua Resposta a Choques Globais

Autor: Pedro José Lente Ferreira

Preface

Quando me perguntam quem é o meu Herói, tenho a enorme sorte de puder dizer que não tenho só um, mas sim dois, a minha Mãe e o meu Pai, a Teresa e o Jorge. São eles, que todos os dias não me deixam desistir dos meus sonhos, que por vezes são bem altos, e me apoiam sempre com tudo o que têm e o que não têm. Não foi uma caminhada fácil, exigindo muito deles a vários níveis que só nós sabemos. Por isso, com esta Dissertação completamos esta conquista que é tão minha quanto deles, pois não teria chegado ao final deste percurso sem os meus Heróis.

Agradecer ainda à minha namorada, Bárbara, por estares ao meu lado em todos os momentos difíceis, em que pensava que não iria conseguir, sendo a minha casa e a minha força, acreditando em mim mesmo quando eu não conseguia fazê-lo. Obrigado por me dares tanto amor e por me relembrares do quanto mereço e sou capaz. Obrigado por me permitires amar-te e construir este caminho ao teu lado. Esta conquista também é tua.

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

ACF1 – First Order Autocorrelation Function

CBOE – Chicago Board Options Exchange

COVOL – Global Common Volatility

DXY – U.S. Dollar Index

EPU – Economic Policy Uncertainty Index

ETFs – Exchange-Traded Funds

GEPU – Global Economic Policy Uncertainty Index

GPR – Geopolitical Risk Index

HAC - Heteroskedasticity and Autocorrelation Consistent

i.i.d. – Independent and Identically Distributed

Max – Maximum

MCOVOL – Metal-specific Common Volatility

Min – Minimum

N – Number of Observations

OLS – Ordinary Least Squares

P25 – 25th Percentile

P75 – 75th Percentile

Std Dev – Standard Deviation

UI – Uncertainty Index

VIX – CBOE Volatility Index

1. Introduction

Market participants face an overwhelming variety of risks. Therefore, they must constantly evaluate both their potential impacts and the strategies needed to manage them. The World Economic Forum (2025) analyses these uncertainties for their likelihood and impact, capturing insights from over 900 experts worldwide. According to the Global Risks Report 2025, we face an increasingly fractured global landscape where escalating geopolitical, environmental, societal and technological challenges threaten stability and progress. The top risks highlighted in 2025 are state-based armed conflicts, extreme weather events, geoeconomic confrontation and misinformation/disinformation.

The twenty first century has witnessed a succession of such shocks, that have demonstrated the global nature of risk. Within all the events, the terrorist attacks of September 11, 2001, the Global Financial Crisis of 2008, the Brexit referendum of 2016, the COVID-19 pandemic and the Russia-Ukraine war are just a few examples of simultaneously increased market volatility across asset classes and countries. Accordingly, understanding and measuring the magnitude of such events has become a central goal.

In line with this common objective and the increasing relevance of the topic, different methods of measurement have arisen. Traditional measures of risk and uncertainty, such as the Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2016) or the Geopolitical Risk (GPR) index of Caldara and Iacoviello (2022), have relied heavily on text-based methodologies or expert assessments. However, while these indicators provide useful insights into the perception of risk, they may not fully capture the materiality of events, which is their actual impact on financial markets. Text-based indices are sensitive to the tone, language, availability of media coverage and may lag in detecting abrupt changes in risk conditions. In contrast, empirical measures based on financial data tend to respond immediately to realized shocks and therefore offer a more direct representation of how markets perceive and price global uncertainty, such as the framework described next.

Building upon this foundation, Engle and Campos-Martins (2023) introduce the concept of Global Common Volatility (COVOL) as a new empirical measure of broad financial and geopolitical risk. COVOL is defined as the magnitude of shocks to volatility that are common across assets, sectors and countries. Essentially, it measures the extent to which volatilities move together in response to global events. This novel method bridges the gap between qualitative assessments of geopolitical uncertainty and quantitative modeling of market dynamics, by relying solely on observable financial data and robust econometric techniques. Thus, the COVOL framework provides an immediate, objective and comprehensive measure of global risk.

This thesis seeks to build on the COVOL framework, by analyzing volatility comovements within the metals markets. Firstly, it estimates metal-specific MCOVOL measures for three main groups: precious, industrial and transition. MCOVOL thus captures global common volatility shocks within each metal category. Secondly, it examines whether macroeconomic, financial and global uncertainty indicators explain the dynamics of MCOVOL. This approach evaluates the sensitivity of metal-specific COVOL indices to global risk conditions, controlling for additional factors. By doing so, this dissertation contributes to understanding how systemic shocks propagate into these commodity markets and how the volatility dynamics relate to broader financial stability.

This thesis aims to shorten this research gap by applying the COVOL methodology, originally developed for equities, to the metals market. In doing so, it provides new empirical evidence that volatility comovements and global risk factors are not limited to financial assets but are also a defining feature of real assets, such as metals. This extension broadens the applicability of the COVOL concept and reinforces its relevance as a comprehensive and flexible tool for analyzing systemic risk across asset classes.

The empirical analysis provides evidence of a common volatility component across metal markets, which intensifies during periods of heightened financial, geopolitical and macroeconomic uncertainty. This common volatility differs across precious, industrial and transition metals, reflecting their distinct economic roles. Overall, the results suggest that metal-specific common volatility is closely linked to global uncertainty and financial conditions, supporting its relevance for assessing systemic risk in metal markets.

This dissertation is organized as follows. In the next section the existing literature is presented and analyzed. Section 3 presents the two main hypotheses, followed by a detailed description of the data in Section 4. The data section describes the sample selection and the variables considered. Section 5 explains the methodology applied to the two hypotheses. The resulting empirical evidence is discussed along with some robustness tests in Section 6. Subsequently, the main findings are summarized in Section 7, as well as the study's limitations and avenues for future research. Finally, Section 8 presents the conclusion of the thesis.

2. Literature Review

This section reviews the existing literature on volatility comovements, global uncertainty transmission and the behavior of metal and commodity markets under systemic shocks. Consequently, it provides the conceptual and empirical foundation for examining the existence of global common volatility patterns across metal markets and for analyzing how macroeconomic, financial and uncertainty indicators relate to the behavior of the resulting MCOVOL indices.

2.1. Global Common Volatility and Systemic Risk

The notion that volatility comoves globally has gained substantial empirical support. Engle and Campos-Martins (2023) introduce the Global Common Volatility model, showing that international markets are driven by a pervasive volatility factor that spikes during systemic events such as the Global Financial Crisis, the Brexit and the COVID-19 pandemic. This configuration demonstrates that COVOL captures material risk more effectively than news-based uncertainty or risk indices, offering a structured approach to quantifying volatility dynamics shared by many assets. The procedure is extended in this dissertation to metal markets through the construction of metal (M)COVOL indices.

Subsequent research applies the COVOL framework to specific sectors. Such as, Campos-Martins and Hendry (2024) by analyzing a global panel of oil and gas equities and finding strong common volatility that intensifies during major crises, including the Black Monday, the Dot-Com crash, 9/11, the Global Financial Crisis and the COVID-19 pandemic. Importantly, they show that negative news related to climate and transition themes significantly amplify global volatility. These results illustrate how sector volatility is shaped by systemic forces and provide methodological alignment with this dissertation's use of COVOL to identify the events driving global common volatility of metals.

Additional evidence on systemic risk transmission is provided by Xu, Hu, Corbet, and Goodell (2023), who study the connectedness between COVOL and major volatility indices such as the VIX. They show that COVOL predominantly acts as a receiver of shocks, with VIX emerging as the main global transmitter, which implies that connectedness intensifies during episodes such as the Global Financial Crisis, the European sovereign debt crisis and the COVID-19 pandemic. These findings reinforce the central premise that volatility is globally interconnected and validate the inclusion of global macro-financial variables in the regression analysis.

2.2. Volatility Comovement and Connectedness in Commodity Markets

The literature on commodity volatility highlights significant interconnectedness and the amplification of comovements during global shocks. Lang, Hu, Goodell, and Hou (2024) analyze the dynamic connectedness between COVOL, dirty energy (oil and fossil fuels) and clean energy markets. Their study shows that dirty energy markets are the predominant transmitters of volatility to COVOL and that comovement increases substantially during major geopolitical and macroeconomic events, including COVID-19 and the Russia-Ukraine conflict. On the other hand, clean energy markets display weaker transmission. This pattern supports the idea that systemic shocks propagate through commodity markets in complex ways, an argument central to the rationale for modelling global common volatility within metals.

Similarly, Pham, Pham, Do, Bissoondoyal-Bheenick, and Brooks (2025) apply the COVOL approach to clean energy equities and find a strong common volatility factor driven by global shocks and macro-financial uncertainty, showing significant sensitivity to indices such as the VIX and news-based uncertainty measures. The methodological proximity of their framework to this dissertation further supports the application of global common volatility models to commodity markets.

2.3. Volatility in Metal Markets: Drivers, Asymmetries and Spillovers

Metal markets display heterogeneous responses to macroeconomic and financial shocks. Umar, Jareño, and Escribano (2021) show that demand and risk driven oil shocks generate strong spillovers across metals, with industrial metals, particularly copper and zinc, acting as dominant transmitters, whereas gold behaves largely as a safe-haven asset.

Repeatedly, spillover intensity rises sharply during systemic crises such as the Global Financial Crisis, the 2014-2015 oil collapse and the COVID-19 pandemic, highlighting sensitivities that motivate the construction of separate MCOVOL indices.

Batten, Ciner, and Lucey (2010) provide further evidence of heterogeneity within precious metals, demonstrating that gold volatility is mainly driven by monetary conditions, while platinum and palladium react to broader financial and economic factors. However, silver exhibits weaker direct macroeconomic sensitivity and is influenced primarily through spillovers from other metals. These findings reinforce that precious metals do not form a uniform asset class, supporting the analysis of global common volatility within granular metal groups.

2.4. Volatility Forecasting and Global Uncertainty

A substantial part of the literature examines the explanatory power of uncertainty and macro-financial variables for commodity volatility. Salisu, Gupta, Bouri, and Ji (2020) combine daily return data with monthly global economic conditions through a GARCH-MIDAS model and show that global macro indicators significantly explain gold volatility, also highlighting strong heterogeneity among precious metals, which aligns with the differentiated behavior captured by MCOVOL.

Moreover, Gupta and Pierdzioch (2022) study whether climate risk indicators improve the explainability of realized volatility of gold, silver, copper, platinum and palladium. They find that climate risk significantly enhances forecast accuracy and that metals respond meaningfully to broad global shocks, particularly at monthly horizons. This parallels the central idea of this dissertation, namely that metals share exposures to global volatility drivers and that a common factor such as MCOVOL should therefore reflect these systemic influences.

Finally, Wang, Ma, Wang, and Wu (2023) examine the contribution of economic uncertainty for international stock market volatility, showing that a comprehensive uncertainty index has strong in-sample and out-of-sample explanatory power, outperforming traditional metrics such as VIX and economic policy uncertainty. These findings strengthen the argument that global uncertainty metrics should be considered in regression models, as done in this dissertation.

Generally, the existing literature shows that volatility comoves globally and is strongly influenced by global systemic shocks. Commodity and metal markets display heterogeneous but interconnected volatility dynamics, where global macroeconomic and uncertainty indicators hold significant explanatory power. Despite the advances in COVOL modelling, no study has applied this framework to such a variety of metal markets or examined its implications across different metal categories. This dissertation fills this gap by constructing metal-specific common volatility indices for precious, industrial and transition metals, analyzing their behavior during major global shocks and evaluating the extent to which macroeconomic, financial and uncertainty indicators explain their dynamics.

3. Research Hypothesis

This study applies the global common volatility framework of Engle and Campos-Martins (2023) to metal markets, aiming to identify and quantify volatility patterns across different metal categories. While the original COVOL model was developed for equity markets as a measure of broad financial and geopolitical risk, its application to commodities allows for assessing whether similar global common volatility patterns exist among real assets that play key roles in the global economy.

Beyond identifying global common volatility patterns, the study examines how macroeconomic, financial and global risk indicators influence the dynamics of the metal-specific COVOL indices. This analysis evaluates the sensitivity of common metal volatility to broad sources of systemic risk or sectoral stress. Together, these two hypotheses aim to broaden the empirical understanding of COVOL and its relevance beyond equity markets, providing new insights into how global risk propagates through commodity markets.

Hypothesis 1 states the existence and behavior of MCOVOL. Under this hypothesis, volatility comovements, within each group, are extracted and studied to test whether certain metals are more exposed to global common shocks. Hypothesis 2 is stated to evaluate how macroeconomic, financial and uncertainty variables relate to fluctuations in MCOVOL while identifying the key global drivers of common volatility across precious, industrial and transition metals.

To test Hypothesis 1, an empirical approach is employed to estimate and analyze the MCOVOL measures and their behavior across different metal groups. To test Hypothesis 2, a regression analysis is conducted to evaluate the explanatory power of macro-financial indicators for MCOVOL. Both methods are explained with more detail in Section 5.

Hypothesis 1: "Metals exhibit distinct global common volatility structures, with the magnitude and persistence of MCOVOL differing across metal groups (precious, industrial and transition). These differences reflect the heterogeneous nature of global shocks and sectoral sensitivities."

Hypothesis 2: "Macroeconomic, financial and global uncertainty indicators significantly move with MCOVOL, indicating that global common volatility in metal markets is systematically associated with broad systemic risk conditions."

4. Data

This section presents an overview of the datasets used in this study, detailing the sample selection process, the definition of the variables and their key statistical characteristics. Overall, it provides the foundation for the methodological framework and subsequent empirical analysis. Subsection 4.1 describes the data used to test Hypothesis 1, which focuses on estimating and analyzing the behavior of the MCOVOL factors, while Subsection 4.2 details the data employed to test Hypothesis 2, which is done through the regression analysis.

4.1. MCOVOL estimation data

In the context of this research, to estimate MCOVOL and analyze volatility comovements within each metal category, the analysis employs Exchange-Traded Funds (ETFs) as investable proxies for the different groups of metals. Moreover, the use of ETFs ensures market exposure, high liquidity and data consistency across assets. All selected ETFs are listed in the United States, trade daily and cover a sufficiently long time period to allow for reliable volatility estimation. This dataset includes nine ETFs, grouped into three metal categories (precious, industrial and transition) all taken from Refinitiv (Workspace) on October 31, 2025.

Notably, the chosen ETFs offer several advantages that make them suitable for this analysis. Collectively, the three metal groups provide a broad coverage of the metal spectrum, by capturing diverse economic roles and market sensitivities. Additionally, most ETFs have more than a decade of historical data, enabling robust volatility modeling. Moreover, although some ETFs represent sector portfolios rather than single commodities, this approach enhances the financial relevance of the analysis by capturing the actual market exposure to global metal risk. Hence, this is consistent with the objective of the COVOL framework, which is to identify common volatility patterns that are meaningful for market participants. Finally, the ETF's practical relevance lies in reflecting real and tradable exposures available to investors.

Along this analysis, to ensure temporal consistency and comparability within each metal group, the time span of the analysis is restricted to the period covered by the ETF with the shortest availability in each metal group. This alignment guarantees that all assets within each category share the same number of observations and synchronized time series, the latter being required for the estimation of COVOL. Specifically, the precious metals group covers the period from January 2010 to October 2025, the industrial metals group from January 2015 to October 2025, and the transition metals group from April 2010 to October 2025. These time frames ensure data completeness by capturing multiple global macroeconomic and geopolitical events, providing sufficient variability in market conditions to identify and analyze global common volatility patterns. Table 1 presents some characteristics of the used ETFs by metal group.

Table 1 - Selected Exchange-Traded Funds (ETFs) used to represent each metal, alongside their corresponding metal classification, ticker and name.

Metal	Metal group	ETF ticker	ETF name
Gold	Precious	GLD	SPDR Gold Shares
Silver	Precious	SLV	iShares Silver Trust
Platinum	Precious	PPLT	Aberdeen Physical Platinum Shares
Palladium	Precious	PALL	Aberdeen Physical Palladium Shares
Iron / Aluminium / Copper	Industrial	PICK	iShares MSCI Global Metals & Mining Producers
Aluminum / Copper / Zinc	Industrial	DBB	Invesco DB Base Metals Fund
Steel	Industrial	SLX	VanEck Steel
Lithium & Batery tech	Transition	LIT	Global X Lithium & Battery Tech
Copper	Transition	COPX	Global X Copper Miners
Rare Earth	Transition	REMX	VanEck Rare Earth and Strategic Metals

Sourced from Refinitiv on October 31, 2025.

Appendix 1 presents the descriptive statistics of the daily log returns of the metal ETFs used to estimate metal-specific MCOVOL, indexed by metal group. The reported measures include the mean, standard deviation, minimum, maximum, skewness and kurtosis. It is worth noting that the standard deviations reveal clear differences in volatility levels across metal categories. For instance, transition metals have the highest dispersion in returns, reflecting their stronger exposure to global shocks. In addition, industrial metals show moderate volatility consistent with the cyclical economic activity of this group, while precious metals present comparatively lower volatility, which is in line with their safe-haven nature. Furthermore, skewness is negative across all ETFs, implying a higher probability of large negative returns, which is a common feature of commodity markets. Finally, kurtosis indicates leptokurtic distributions, suggesting that extreme movements occur more frequently than under a normal distribution.

4.1.1. Precious Metals

The precious metals category comprises physically backed ETFs, which directly hold the underlying metals and provides highly accurate tracking of spot prices. Notably, GLD and SLV are among the most liquid and longest established commodity ETFs. PPLT and PALL extend the coverage by including platinum and palladium, that are also industrially significant metals with strong demand in the automotive and manufacturing sectors. Together, these funds capture the safe-haven and monetary role of precious metals, typically associated with global uncertainty and store of value behavior.

4.1.2. Industrial Metals

The industrial metals group includes ETFs that have a representative exposure to base and heavy industrial metals, which are crucial to manufacturing, construction and infrastructure development. In fact, PICK provides diversified exposure to large global mining companies that produce iron ore, aluminum and copper. Furthermore, DBB is a fund based in futures that tracks an equal-weighted basket of aluminum, copper and zinc, serving as a clean proxy for industrial metals price movements. On the other hand, SLX focuses on steel producers, reflecting activity in cyclical sectors such as construction and heavy industry. Collectively, this group mirrors the behavior of traditional industrial cycles, offering an effective setting for assessing volatility comovements linked to global economic growth and demand.

4.1.3. Transition Metals

The transition metals category comprises ETFs whose underlying metals are critical to the energy transition and development of green technologies. On one hand, LIT invests in companies involved in lithium extraction and battery production, providing a proxy for lithium exposure. On the other hand, COPX grants access to copper miners, which is a core component in renewable infrastructure and electrification, while REMX encompasses firms producing rare earths and strategic metals, such as cobalt and nickel. Together, these ETFs capture the structural shift toward cleaner technologies, linking volatility in commodity markets to environmental and technological transformation.

4.2. Regression Analysis Data

Having estimated MCOVOL, the next step is to examine which global uncertainty factors explain the behavior of the different MCOVOL measures. Accordingly, this section describes the variables employed in the regression analysis designed to test Hypothesis 2, which evaluates the extent to which global risk conditions drive fluctuations in MCOVOL indices.

4.2.1. Dependent Variables

Following the analysis presented above, the dependent variable in the regression models is the metal-specific COVOL (MCOVOL). The original MCOVOL estimates obtained at a daily frequency are subsequently aggregated into monthly averages to smooth out short-term noise and capture broader trends in volatility dynamics. This monthly transformation also aligns the data with the lower frequency of the independent variables. A more detailed description of the previously estimated MCOVOL characteristics and behavior is presented in Section 6.1 when testing Hypothesis 1. This variable will have the acronym ($MCOVOL_g$), where g represents each metal group and so P refers to precious, I to industrial and T to transition.

4.2.2. Independent Variables

A set of global and financial indicators are considered as explanatory variables of MCOVOL. These independent variables are proxies for macroeconomic uncertainty, risk appetite and external shocks, potentially driving volatility comovements across metal markets. Together, these controls assess how broader sources of global risk can influence the dynamics of MCOVOL. Table 2 presents all independent variables used in the regression analysis, including their name, acronym and data source. The data on all independent variables was also collected on October 31, 2025, at a monthly frequency. For more details, Appendix 2 presents the descriptive statistics of these explanatory variables.

Table 2 - Selected independent variables, alongside their corresponding name, acronym and source.

Name	Acronym	Source
Global Economic Policy Uncertainty Index	GEPU	Baker, Bloom and Davis Website
Global Common Volatility	GCV	V-Lab
CBOE Volatility Index	VIX	Refinitiv (Workspace)
Climate Policy Uncertainty Index	CLIMATE_UI	Baker, Bloom and Davis Website
Oil Uncertainty Index	OIL_UI	Baker, Bloom and Davis Website
Sustainability Uncertainty Index	SUSTAIN_UI	Baker, Bloom and Davis Website
U.S. Dollar Index	DXY	Federal Reserve Bank of St. Louis Website
U.S. Credit Spread	CREDIT_SPREAD	Federal Reserve Bank of St. Louis Website
China Purchasing Managers' Index	CHINA_PMI	Refinitiv (Workspace)
Dummy for Conference of the Parties Meetings (Decembers when it applies)	DUMMY_COP	-
Dummy for the COVID-19 Period (March 2020–December 2021)	DUMMY_COVID	-

Table 3 - Correlation matrix (of the explanatory variables).

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GEPU (1)	1.000								
GCV (2)	-0.014	1.000							
VIX (3)	0.112	0.559	1.000						
CLIMATE_UI (4)	-0.293	0.117	0.177	1.000					
OIL_UI (5)	0.051	0.171	0.216	0.088	1.000				
SUSTAIN_UI (6)	0.494	-0.054	-0.063	-0.111	-0.070	1.000			
DXY (7)	0.763	-0.086	-0.052	-0.404	-0.093	0.556	1.000		
CREDIT_SPREAD (8)	-0.167	0.359	0.797	0.196	0.110	-0.300	-0.308	1.000	
CHINA_PMI (9)	-0.449	-0.150	-0.230	0.315	-0.164	-0.094	-0.396	-0.133	1.000

Table 3 displays the correlation matrix for the explanatory variables, which reveals that the correlations are generally low to moderately high, indicating that the variables capture different aspects of global and sectoral risk. The highest correlations are observed between VIX and CREDIT_SPREAD (0.797) and between GEPU and DXY (0.763), reflecting the close relationship shared by market volatility and financial stress as well as global uncertainty and dollar strength, respectively. Overall, these larger correlations are economically intuitive and not indicative of a multicollinearity issue.

4.2.2.1. Financial Risk Variables

The set of financial risk indicators includes VIX and CREDIT_SPREAD. VIX measures the implied volatility of the S&P 500 index, serving as a proxy for global risk aversion and overall market uncertainty. CREDIT_SPREAD is defined as the difference between BAA and AAA U.S. corporate bond yields, reflecting financial stress and perceived credit risk in the economy. Together, these variables control for changes in global financial conditions that may affect volatility comovements across metals.

4.2.2.2. Macroeconomic Indicators

The series of macroeconomic indicators includes DXY and CHINA_PMI. DXY represents the strength of the U.S. dollar relative to a basket of major currencies, being included to account for currency driven effects on metal prices, given that most commodities are dollar denominated. CHINA_PMI measures business activity in China's manufacturing sector, serving as a proxy for global industrial demand, as China is the world's largest producer and consumer of metals. Overall, these indicators help capture the influence of macroeconomic factors and global demand on metal volatility dynamics.

4.2.2.3. Global and Sectoral Uncertainty Indices

The lot of uncertainty indices includes GCV, GEPU, CLIMATE_UI, SUSTAIN_UI and OIL_UI. GCV is a market price-based index of worldwide volatility shocks, capturing global risk conditions. This is measured by Engle and Campos-Martins (2023) using their model of global common volatility. GEPU is rather a text-based index, capturing policy related uncertainty in the global economy, being provided by Baker et al. (2016). CLIMATE_UI accounts for news related to energy and the green transition, taking into consideration both physical (from the exposure to e.g., floods and droughts) and transition (e.g., a carbon tax) risk. SUSTAIN_UI summarizes uncertainty related to news around climate policy and broader sustainability themes. Finally, OIL_UI captures expected volatility in crude oil prices, providing information on shocks to the energy market that can influence commodity dynamics in a broader way. Together, these measures capture information that originates outside pure market pricing but can affect metals through policy, energy and transition channels.

4.2.2.4. Event Dummies

Two time-dummy variables are introduced to isolate the effect of specific global events. These are the DUMMY_COVID and the DUMMY_COP. DUMMY_COVID equals one during the COVID-19 pandemic period (March 2020 to December 2021) and zero otherwise, capturing the unprecedented market disruption and global uncertainty caused by this health crisis. DUMMY_COP equals one during months in which the United Nations Climate Change Conferences occurred and zero otherwise, reflecting the influence of major climate policy discussions and announcements on markets, particularly the ones linked to the energy transition.

5. Methodology

This section describes the methodology used to test the hypotheses stated in Section 3. Subsection 5.1. describes the methods used for testing Hypothesis 1, which focuses on estimating and analyzing the behavior of MCOVOL, while Subsection 5.2. explains the approach employed for the testing of Hypothesis 2, which is based on a regression analysis of the MCOVOL indices on the independent variables presented in Section 4.2. These analyses are carried out using the *R* statistical software.

5.1. MCOVOL Estimation Method

To construct the metal-specific common volatility indices, this study adapts the methodology proposed by Engle and Campos-Martins (2023) to commodities. The objective is to isolate unexpected volatility shocks at the asset level and to identify the common volatility component shared across metals within each group.

For each metal-based ETF described in Section 4.1, the daily log returns ($r_{i,t}$) were modeled assuming GARCH(1,1) type of errors to capture the conditional variance dynamics of each asset:

$$r_{i,t} = \mu_i + \varepsilon_{i,t} \quad \mathbf{(1)},$$

$$\varepsilon_{i,t} \mid \mathcal{F}_{t-1} \sim (0, h_{i,t}) \quad \mathbf{(2)},$$

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \quad \mathbf{(3)}.$$

Where $h_{i,t}$ denotes the conditional variance of ETF i at time t. For each specification, volatility standardized residuals can be obtained as:

$$e_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}} \quad \mathbf{(4)},$$

which represent volatility shocks normalized by their expected variance. Notably, under correct model specification $E[e_{i,t}^2] = 1$. Following Engle and Campos-Martins (2023), unexpected volatility innovations are therefore defined by recentering the squared standardized residuals:

$$z_{i,t} = e_{i,t}^2 - 1 \quad \textbf{(5).}$$

Thus, centering the squared standardized residuals in this way ensures that the analysis captures deviations from expected volatility rather than differences in mean volatility across assets. The resulting $z_{i,t}$ series are then used to identify the global common volatility component within each metal group.

Following Engle and Campos-Martins (2023), common volatility is modeled using a multiplicative structure. Specifically, standardized residuals are scaled by a latent common volatility factor:

$$e_{i,t} = \sqrt{g(s_i, x_t)} \,.\, u_{i,t} \quad \textbf{(6)}.$$

Where x_t denotes the latent common volatility factor, s_i captures the exposure of asset i to the common volatility component and $u_{i,t}$ represents an i.i.d. component, distributed with mean zero and unit variance. This specification implies that movements in the common factor generate coordinated changes in volatility across assets within the same metal group.

The latent factor x_t and the exposure parameters s_i are estimated iteratively using the maximization-maximization (MM) algorithm of Engle and Campos-Martins (2023), available in *R* software, which iterates the log-likelihood maximization of a cross-section and a time-series regression to get the optimal estimates of the two sets of unknowns. The estimation is conducted for each metal group using synchronized sample periods to ensure temporal consistency. Further details on the underlying model and estimation procedure are provided in Engle and Campos-Martins (2023).

Before and after factor extraction, the presence of a common volatility component is assessed using the test proposed by Engle and Campos-Martins (2023) to check for cross-sectional dependence in the standardized residuals. Notably, under the null hypothesis of no common volatility, the statistic follows a standard normal distribution.

As reported in Table 4, the $\xi - statistic$ is highly significant prior to factor extraction, indicating strong cross-sectional dependence in volatility innovations. After extracting the common factor, the statistic becomes insignificant, confirming that the estimated MCOVOL factor successfully captures the shared volatility component across metals. The post-estimation statistic serves solely as a diagnostic check. The number of observations used for each metal group is also reported in Table 4.

Table 4 reports the $\xi - test$ statistics proposed by Engle and Campos-Martins (2023). Under the null hypothesis of no common volatility component, the ξ statistic follows a standard normal distribution. The highly significant values observed before factoring indicate strong cross-sectional dependence in volatility innovations within each metal group. Further, after extracting the common factor, the ξ statistic becomes statistically insignificant, confirming that the estimated MCOVOL factor successfully captures the shared volatility component. The post-factoring ξ statistic serves solely as a post-estimation diagnostic check. N denotes the number of observations in each metal group.

Table 4 - ξ_{-test} statistics.

Metal Group	ξ Before	ξ After	N
Precious	63.8***	-7.4	3954
Industrial	31.1***	-5.2	2050
Transition	49.4***	-11.4	3751

*** p<0.01, ** p<0.05, * p<0.1

Having obtained the daily MCOVOL series, these are then aggregated monthly to align with the frequency of the explanatory variables used in the regression analysis described in the next section.

5.2. Regression Analysis Method

This section is devoted to examining how global and sector-specific sources of uncertainty, financial conditions and macroeconomic factors influence global common volatility within each metal group. Overall, the idea is to test whether the MCOVOL indices, representing the magnitude of volatility comovements across metals, respond systematically to global risk indicators and external shocks. To address this, several linear models are estimated where the dependent variable is the monthly average of $MCOVOL_g$. The explanatory variables comprise the financial risk variables, the macroeconomic indicators, the global and sectoral uncertainty indices and the event dummies. These are all described in Section 4.2.2.

5.2.1. Regression Specifications

Different model specifications are considered in this dissertation to progressively assess the contribution of each set of variables. The first regressions include only uncertainty measures, while subsequent models additively incorporate financial/macroeconomic variables and finally the event dummies, to isolate the effect of specific global shocks. Hence, this layered structure reveals how the MCOVOL indices are influenced as additional sources of global and sectoral risk are introduced.

All regressions are estimated using Ordinary Least Squares (OLS) with Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors to account for potential serial correlation in the monthly data. Recall that all variables have been converted to the monthly frequency, and standardized to have zero mean and unit variance as follows:

$$x_t^* = \frac{x_t - \bar{x}}{\sigma_x}, \qquad \textbf{(7)}$$

where $\bar{x}$ represents the variable sample mean and σ_x corresponds to the sample standard deviation of the variable. This standardization eases the comparability of the coefficients across variables with different measurement scales. The coefficients can thus be interpreted as the marginal effect of each variable on the degree of volatility comovement across metals. Finally, given that global common volatility exhibits strong persistence, autoregressive terms up to order two are included in Equation (9) to control for serial dependence in $MCOVOL_g$.

Each of the following regression models (R1 to R7 and RB1 to RB8) is estimated individually for each metal type *g*. Note that, to simplify notation, coefficients remain the same across regressions.

$$\boldsymbol{R1}\text{: } MCOVOL_{g,t} = \beta_0 + \beta_1 GEPU_t + \beta_2 GCV_t + \epsilon_{g,t} \qquad \textbf{(8)},$$

$$\boldsymbol{R2}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{R1} + \beta_3 MCOVOL_{t-1} + \beta_4 MCOVOL_{t-2} + \epsilon_{g,t} \qquad \textbf{(9)},$$

where **(R1)** includes the explanatory variables only presented in Equation (8). This notation will apply to all the following equations.

$$\boldsymbol{R3}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{R1} + \beta_3 VIX_t + \epsilon_{g,t} \qquad \mathbf{(10),}$$

$$\boldsymbol{R4}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{R3} + \beta_4 CLIMATE\_UI_t + \beta_5 OIL\_UI_t + \beta_6 SUSTAIN\_UI_t + \epsilon_{g,t} \qquad \mathbf{(11),}$$

$$\boldsymbol{R5}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{R4} + \beta_7 DXY_t + \beta_8 CREDIT\_SPREAD_t + \beta_9 CHINA\_PMI_t + \epsilon_{g,t} \qquad \mathbf{(12),}$$

$$\boldsymbol{R6}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{R5} + \beta_{10} DUMMY\_COP_t + \epsilon_{g,t} \qquad \mathbf{(13),}$$

$$\boldsymbol{R7}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{R5} + \beta_{10} DUMMY\_COVID_t + \epsilon_{g,t} \qquad \mathbf{(14).}$$

5.2.2. Robustness and Alternative Specifications

The country equity based global common volatility index captures a broad measure of global volatility that is correlated with several of the other explanatory variables, as is outlined further in Section 6. Consequently, when GCV is included, it tends to dominate the regressions and partially cancel the individual contribution of the remaining variables. For this reason, and to ensure the robustness of the results, an alternative set of regressions is estimated excluding GCV. These alternative regressions allow for the assessment of the explanatory power of the other variables. By estimating regressions both including and excluding GCV, the analysis assesses the robustness of the results, examining whether the explanatory power of the other variables persists once the overarching global common volatility factor is removed. Regression models (RB1) to (RB8), presented in Equations (15) to (22), are the basis for this second, slightly different analysis:

$$\boldsymbol{RB1}\text{: } MCOVOL_{g,t} = \beta_0 + \beta_1 CLIMATE\_UI_t + \beta_2 OIL\_UI_t + \beta_3 SUSTAIN\_UI_t + \epsilon_{g,t} \qquad \mathbf{(15),}$$

$$\boldsymbol{RB2}\text{: } MCOVOL_{g,t} = \beta_0 + \beta_1 DXY_t + \beta_2 CREDIT\_SPREAD_t + \beta_3 CHINA\_PMI_t + \epsilon_{g,t} \qquad \mathbf{(16),}$$

$$\boldsymbol{RB3}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{RB1} + \boldsymbol{RB2} + \epsilon_{g,t} \qquad \mathbf{(17),}$$

where **(RB1)** and **(RB2)** include the explanatory variables only presented in Equation (15) and (16), respectively. This notation will apply to all the following equations.

$$\boldsymbol{RB4}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{RB3} + \beta_7 VIX_t + \epsilon_{g,t} \qquad \textbf{(18)},$$

$$\boldsymbol{RB5}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{RB3} + \beta_7 DUMMY\_COP_t + \epsilon_{g,t} \qquad \textbf{(19)},$$

$$\boldsymbol{RB6}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{RB3} + \beta_7 DUMMY\_COVID_t + \epsilon_{g,t} \qquad \textbf{(20)},$$

$$\boldsymbol{RB7}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{RB4} + \beta_8 GEPU_t + \beta_9 DUMMY\_COP_t + \epsilon_{g,t} \qquad \textbf{(21)},$$

$$\boldsymbol{RB8}\text{: } MCOVOL_{g,t} = \beta_0 + \boldsymbol{RB4} + \beta_8 GEPU_t + \beta_9 DUMMY\_COVID_t + \epsilon_{g,t} \qquad \textbf{(22)}.$$

The subsequent section presents the empirical results derived from the above MCOVOL regression models, offering insights into the patterns observed.

6. Results

This section presents the empirical results derived from applying the methodological framework outlined in Section 5 and using the data described in Section 4. Subsection 6.1 addresses Hypothesis 1, focusing on the empirical behavior of the metal-specific common volatility indices. Subsection 6.2 examines the testing of Hypothesis 2 through a regression assessment. All computations and statistical analyses are performed using *R* software.

6.1. MCOVOL Results

The analysis of the MCOVOL behavior focuses on three complementary aspects: the joint dynamics of each MCOVOL index relative to global volatility benchmarks, the factor loadings that quantify the contribution of each ETF to its group-level volatility factor and a set of descriptive statistics summarizing the distributional properties of the resulting MCOVOL series.

6.1.1. Dynamics of MCOVOL and Comparison with Global Volatility Measures

Figures 1 to 3 plot the monthly MCOVOL indices for precious, industrial and transition metals, respectively, against two global volatility indicators: the global common volatility (GCV) index and the U.S. implied volatility index (VIX). All series are normalized to have mean zero and unit variance, allowing for direct comparison of comovement patterns.

Figure 1 - Standardized monthly MCOVOL for the precious metals group (black) shown together with the GCV (red) and the VIX (green). The figure illustrates the extent to which the precious MCOVOL comoves with global risk indicators.

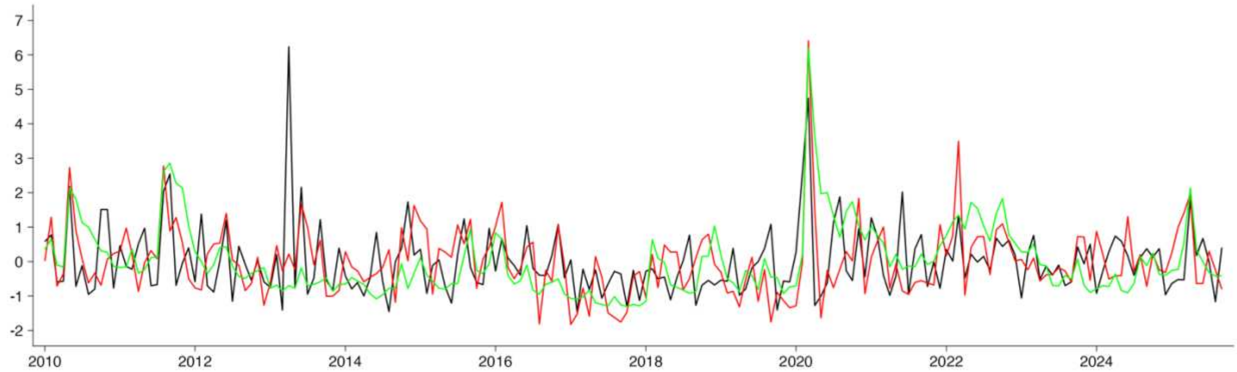


Figure 2 - Standardized monthly MCOVOL for the industrial metals group (black) shown together with the GCV (red) and the VIX (green). The figure illustrates the extent to which the industrial MCOVOL comoves with global risk indicators.

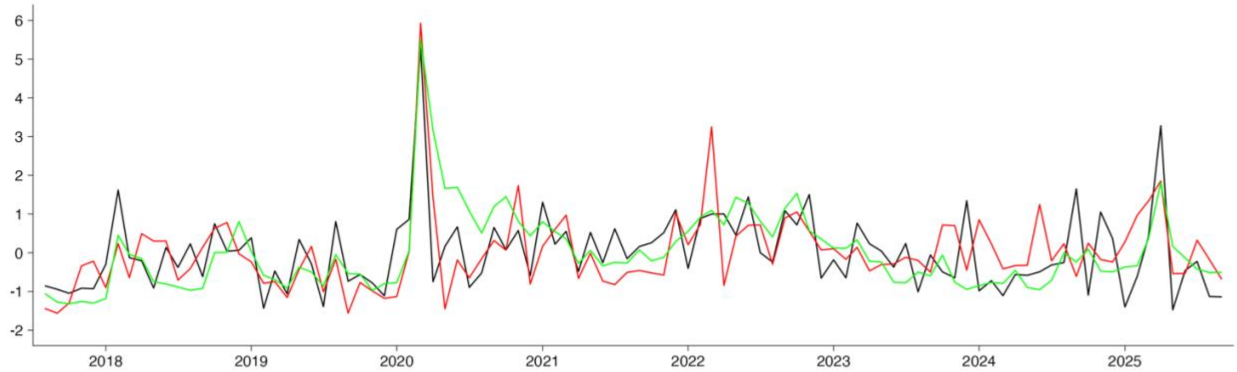
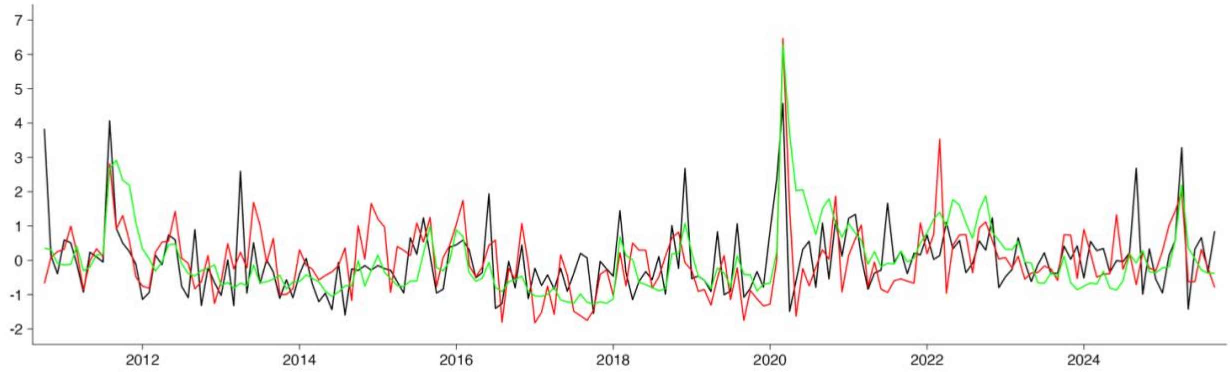


Figure 3 - Standardized monthly MCOVOL for the transition metals group (black) shown together with the GCV (red) and the VIX (green). The figure illustrates the extent to which the transition MCOVOL comoves with global risk indicators.



Across all metal categories, MCOVOL exhibits a clear cyclical behavior, punctuated by short-lived spikes associated with major global events as outlined in Table 5. These spikes align closely with increases in the VIX and with movements in GCV, confirming that MCOVOL reacts strongly to U.S. and global risk conditions. For instance, all three MCOVOL indices display pronounced peaks during the onset of the COVID-19 pandemic in March 2020, mirroring the sharp surge in the two benchmarks. This synchronicity illustrates the sensitivity of metal volatility to broad episodes of market turbulence and stress.

MCOVOL shows distinct cross-sectional behavior. Precious metals present comparatively smoother dynamics, reflecting their safe-haven characteristics. On the contrary, industrial and transition metals show more frequent and sharper fluctuations, consistent with their dependence on global industrial demand, supply chain disruptions and technological cycle shocks. Overall, these distinctions suggest that, while global risk is a key driver of volatility comovements, sector-specific forces also play a significant role in shaping the magnitude of each group's global common volatility component.

To complement the graphical analysis, Table 5 identifies the largest MCOVOL spikes within each metal group and links them with the global or sector-specific events, occurring at the time of each surge. The examination of these peak episodes provides a clearer understanding of the type of shocks that generate the strongest global common volatility responses and validates MCOVOL's ability to capture meaningful global risk conditions.

Table 5 - Major MCOVOL spikes for each metal group, paired with the calendar dates and the descriptions of the corresponding global events.

Metal Group	Date	MCOVOL	Event
Precious	15-Apr-2013	55.93	Boston Marathon bombings
Precious	17-Jun-2021	36.20	Biden-Putin Summit & China launches Shenzhou-12
Precious	12-Mar-2020	34.03	**Global COVID-19 Pandemic outbreak**
Precious	11-Aug-2020	25.18	George Floyd case breakthrough & U.S. Presidential pick (Joe Biden chose Kamala Harris) & U.S. Election Campaign big event by Trump
Industrial	9-Mar-2020	37.43	**Global COVID-19 Pandemic outbreak**
Industrial	3-Apr-2025	23.45	Trump announced near-universal tariffs what lead to a market crash & Strong Israel strikes in Syria
Industrial	15-Mar-2023	20.39	Russian warplane hits American drone over Black Sea
Industrial	11-Jun-2020	18.67	Fed leaves rates unchanged and projects years of high unemployment
Transition	4-Aug-2011	30.21	Stock markets in Europe experienced their worst single-day drop since 2009
Transition	15-Apr-2013	29.30	Boston Marathon bombings
Transition	20-Dec-2018	27.31	Trump orders troop withdrawal from Syria, declaring ISIS defeated & Fed raises interest rates, showing confidence in health of economy
Transition	9-Mar-2020	24.20	**Global COVID-19 Pandemic outbreak**

The event analysis from Table 5 confirms that, for all three metal groups, one of the highest recorded MCOVOL values occur during the onset of the COVID-19 pandemic in March 2020, consistent with the extreme levels of global risk documented in the GCV and in the VIX. Precious metals show strong spikes during politically charged events such as the Boston Marathon bombings (2013) and the Biden-Putin Summit (2021), reflecting their role as safe-haven assets. On the contrary, industrial metals peak primarily during macro-financial shocks, like trade tensions, interest rate announcements and energy related geopolitical events. Transition metals exhibit a mixed pattern, reacting both to global political events, like the Syria troop withdrawal and to market wide stress episodes. Overall, these results provide evidence that MCOVOL captures economically meaningful shocks that are aligned with global uncertainty surges.

6.1.2. Factor Loadings and Contribution of Individual Metals

Table 6 reports the estimated factor loadings (λ_i), which capture the sensitivity of each metal ETF to its group-level MCOVOL factor. These coefficients are informative for understanding how strongly each metal is impacted by common volatility dynamics.

Table 6 - Factor loadings for each metal.

Metal ETF ticker	Metal Group	Loading (λ_i)
GLD	Precious	0.56
SLV	Precious	0.61
PPLT	Precious	0.41
PALL	Precious	0.38
PICK	Industrial	0.62
DBB	Industrial	0.38
SLX	Industrial	0.68
LIT	Transition	0.58
COPX	Transition	0.55
REMX	Transition	0.60

Within the precious metals group, SLV and GLD display the highest loadings (0.61 and 0.56, respectively), indicating that silver and gold are the main carriers of volatility comovement in this segment. On the other hand, PPLT and PALL exhibit lower contributions, consistent with their smaller markets and greater exposure to idiosyncratic supply shocks.

In the industrial metals group, SLX (steel producers) and PICK (global miners) show the strongest sensitivity to the common factor, reflecting their high cyclical exposure. DBB (also global miners) presents a lower loading (0.38), consistent with being a basket ETF based in future expectations and having a more diversified behavior.

For the transition metals, all three display relatively similar loadings, ranging from 0.55 to 0.60. Evidently, this reflects the pervasive influence of energy transition themes across lithium, copper and rare earths markets, suggesting that volatility comovement is relatively homogeneous in this segment.

Overall, the loading structure confirms that the MCOVOL estimation successfully extracts a meaningful group-level factor and that the contributions of the individual metals align with economic intuition.

6.1.3. Descriptive Statistics of each MCOVOL Index

Table 7 summarizes the main statistical properties of the monthly MCOVOL series for each metal group. Despite being standardized, the indices display meaningful differences in dispersion and tail behavior.

Table 7 – Descriptive statistics for each monthly MCOVOL index.

Metal Group	Mean	Std Dev	Min	Max	Skewness	Kurtosis	Volatility Persistence (ACF1)
Precious	1.00	0.49	0.28	3.59	1.89	10.22	0.02
Industrial	1.00	0.56	0.18	4.51	2.23	12.34	-0.04
Transition	1.01	0.50	0.22	3.30	1.69	7.54	0.01

As expected, the standard deviation is highest for industrial metals (0.56), suggesting a more volatile common component than other metals, due to their cyclicality and global integration. Transition metals also exhibit elevated dispersion (0.50), consistent with their sensitivity to technological cycles and energy transition shocks. Conversely, precious metals show the lowest variability (0.49), in line with their safe-haven characteristics.

The skewness and kurtosis values indicate that all MCOVOL series are characterized by asymmetric distributions and heavy tails, with occasional large volatility shocks. Kurtosis is particularly high for industrial metals (12.34), reflecting their sharp tail events. These features are consistent with the role of MCOVOL in capturing unexpected, large volatility movements.

Finally, the first order autocorrelation (ACF1) is close to zero for all groups, implying minimal persistence in the MCOVOL series. This is by construction as MCOVOL isolates unexpected volatility shocks rather than long-memory volatility dynamics (which are absorbed by the GARCH filtering step). Consequently, the resulting series behave like high frequency innovations rather than persistent volatility levels.

Taken together, the above results reveal that the estimated MCOVOL indices successfully capture economically meaningful volatility shocks across metal markets. These findings raise the question of whether such shocks can be systematically linked to broader risk factors, uncertainty indices or macro-financial conditions. This will be discussed in the next section.

6.2. Regression Analysis Results

Building on the characterization of MCOVOL dynamics presented in the previous subsection, the regression analysis in this section investigates whether the common volatility of each metal group responds systematically to global, financial and sector-specific factors. This approach examines the determinants of MCOVOL through two layers of investigation. First, the progressive baseline regressions evaluate the influence of all explanatory variables. Second, comparable specifications exclude the GCV to assess whether independent effects emerge once global common volatility is removed. Taken together, these results provide a detailed understanding of the forces that shape metal-specific common volatility across precious, industrial and transition metal markets.

6.2.1. Regression Results (R1 to R7)

Table 8 reports the regression results for precious MCOVOL as dependent variable centered around its mean. The models progressively incorporate global uncertainty indices, autoregressive terms, financial variables, macroeconomic indicators and event dummies.

Table 8 – Regression results for the precious metals group (R1 to R7). This table includes the coefficients for the independent variables and their significance levels.

	R1	R2	R3	R4	R5	R6	R7
(Intercept)	0.000	0.000	0.000	0.000	0.000	-0.004	-0.081
GEPU	0.072	0.071	-0.010	0.060	0.100	0.098	0.073
GCV	0.524***	0.505***	0.406***	0.390***	0.395***	0.396***	0.400***
MCOVOLt-1		0.154**					
MCOVOLt-2		-0.135**					
VIX			0.210**	0.191*	0.174	0.177	0.113
CLIMATE_UI				-0.053	-0.056	-0.057	-0.057
OIL_UI				0.060	0.062	0.061	0.056
SUSTAIN_UI				-0.081	-0.061	-0.060	-0.043
DXY					-0.069	-0.067	-0.115
CREDIT_SPREAD					0.002	-0.001	0.056
CHINA_PMI					-0.017	-0.016	-0.019
DUMMY_COP						0.091	
DUMMY_COVID							0.264
AdjR2	0.278	0.303	0.296	0.293	0.281	0.277	0.283

Robust standard errors were calculated but not presented
*** p<0.01, ** p<0.05, * p<0.1

The results for precious metals reinforce the central role of global uncertainty in driving volatility comovement. The coefficient attached to GCV is strongly significant and positive in all models, indicating that precious MCOVOL responds sharply to broad volatility shocks of global nature. This behavior appears intuitive because of the safe-haven nature of the assets in this metal group.

Autoregressive components are added in regression (R2). Results show that $MCOVOL_{t-1}$ has a positive coefficient and $MCOVOL_{t-2}$ has a negative one. This pattern reflects some anticipation before the event, with precious MCOVOL increasing even before an important event happens.

VIX appears to be significant in explaining precious MCOVOL. This suggests that U.S. equity market stress influences precious metals, but global risk conditions as measured by the

GCV index remain the dominant source of volatility comovement in precious metals. Moreover, when DXY, CREDIT_SPREAD and CHINA_PMI are included, the VIX loses its significance, indicating that these variables cancel the VIX effect, despite not being significant themselves.

The remaining financial, macroeconomic and sectoral variables do not exhibit any significance, implying that macroeconomic cycles and sector-specific dynamics play a limited role in shaping joint volatility in this segment. Event dummies are also insignificant, indicating that global volatility indicators already account for these key shocks.

Overall, precious MCOVOL is primarily driven by global volatility conditions, with little incremental contribution from other indicators. Volatility shocks to this group of commodities tend to be abrupt but short-lived, consistent with the safe-haven property of this asset class.

Table 9 presents the regression estimates using industrial MCOVOL as dependent variable. The sequence of models evaluates the contribution of global volatility, financial conditions and macroeconomic activity to industrial MCOVOL, controlling for major global events.

Table 9 – Regression results for the industrial metals group (R1 to R7). This table includes the coefficients for the independent variables and significance levels.

	R1	**R2**	**R3**	**R4**	**R5**	**R6**	**R7**
(Intercept)	0.000	0.000	0.000	0.000	0.000	-0.001	0.046
GEPU	0.196***	0.130	-0.041	-0.044	0.059	0.058	0.061
GCV	0.719***	0.711***	0.460***	0.458***	0.453***	0.454***	0.447***
MCOVOLt-1		0.120					
MCOVOLt-2		0.049					
VIX			0.502***	0.474***	0.584***	0.585***	0.613***
CLIMATE_UI				0.092	0.079	0.078	0.074
OIL_UI				0.013	-0.009	-0.009	-0.009
SUSTAIN_UI				-0.004	0.024	0.023	0.017
DXY					-0.106	-0.106	-0.082
CREDIT_SPREAD					-0.155	-0.154	-0.180
CHINA_PMI					-0.064	-0.064	-0.061
DUMMY_COP						0.031	
DUMMY_COVID							-0.070
AdjR2	0.621	0.629	0.716	0.713	0.722	0.719	0.719

Robust standard errors were calculated but not presented
*** p<0.01, ** p<0.05, * p<0.1

Industrial metals also exhibit strong sensitivity to global volatility indicators, as both GCV and the VIX are consistently significant across specifications. GEPU is significant in the baseline model (R1), but once broader volatility indicators are included, its effect disappears indicating that its explanatory power is largely absorbed by the other global risk measures.

In contrast, the remaining financial, macroeconomic and sectoral variables do not display any systematic significance. Their lack of explanatory power suggests that once global volatility conditions are accounted for, additional macro-financial factors contribute little to the understanding of joint volatility behavior in industrial metals. Event dummies are too insignificant, indicating that global shocks captured by GCV and the VIX likely capture the key sources of volatility affecting this market segment.

Taken together, these results show that industrial MCOVOL is predominantly shaped by global volatility forces, with limited incremental influence from sector-specific or macroeconomic indicators. This pattern aligns with the strong exposure of industrial metals to broad global uncertainty and financial market stress, consistent with the cyclical and globally integrated nature of this sector.

Table 10 reports the regression results for the transition metals group. The models assess the sensitivity of transition MCOVOL to global uncertainty, financial stress and sector-specific factors.

Table 10 – Regression results for the transition metals group (R1 to R7). This table includes the coefficients for the independent variables and their significance levels.

	R1	R2	R3	R4	R5	R6	R7
(Intercept)	0.000	0.000	0.000	0.000	0.000	-0.010	0.071
GEPU	0.268***	0.266***	0.129*	0.024	0.004	0.001	0.028
GCV	0.582***	0.576***	0.412***	0.421***	0.413***	0.417***	0.411***
MCOVOLt-1		0.057					
MCOVOLt-2		-0.049					
VIX			0.309***	0.354***	0.398***	0.404***	0.448***
CLIMATE_UI				0.043	0.037	0.032	0.036
OIL_UI				-0.057	-0.064	-0.068	-0.059
SUSTAIN_UI				0.112	0.077	0.075	0.060
DXY					0.018	0.021	0.055
CREDIT_SPREAD					-0.050	-0.058	-0.094
CHINA_PMI					-0.048	-0.045	-0.049
DUMMY_COP						0.227	
DUMMY_COVID							-0.027
AdjR2	0.436	0.434	0.476	0.477	0.470	0.469	0.471

Robust standard errors were calculated but not presented
*** p<0.01, ** p<0.05, * p<0.1

Transition metals also display clear sensitivity to global volatility conditions. In the first models (R1 to R2), both GEPU and GCV are highly significant, indicating that broad global uncertainty and aggregate volatility shocks influence common volatility in this metal segment. However, once additional volatility indicators are introduced, GEPU progressively loses significance, suggesting that its informational content is largely absorbed by broader measures of global risk. In the extended specifications (R3 to R7), when introduced, the VIX reveals to be strongly significant and consistently positive, confirming that U.S. financial stress and global risk sentiment are also drivers of volatility comovements for transition metals.

In contrast, the sector-specific indicators (CLIMATE_UI, OIL_UI and SUSTAIN_UI) do not show systematic significance across all models. This outcome is somewhat unexpected, given that transition metals are closely linked to decarbonization policies, energy related uncertainty and long-term technological investment cycles. Their lack of explanatory power suggests that once broad global volatility measures are included, additional transition related uncertainties provide limited incremental information to explain MCOVOL in this category.

Similarly to the other metals, macro-financial variables do not contribute meaningfully to the regressions and event dummies remain consistently insignificant as well. This indicates that the major global shocks influencing transition metals are already captured through the global volatility indices rather than through event-specific or sector-specific channels.

All in all, transition MCOVOL is primarily shaped by global volatility forces, mirroring the behavior observed for the other two metal groups, while sector-specific risks associated with the energy transition do not appear to materially influence the common volatility dynamics for transition metals.

6.2.1.1. Conclusion of the Baseline Analysis

Across all metal groups, the baseline regressions reveal three main findings. Firstly, GCV emerges as the primary explanatory factor for MCOVOL, confirming that broad global risk and uncertainty are the main sources of synchronized volatility within metal markets. Secondly, the VIX provides explanatory power consistently across all metal groups, particularly for industrial and transition (higher significance and magnitude), reflecting the contribution of financial market stress to volatility comovement. Thirdly, macro-financial variables, sector-specific uncertainty indices and event dummies offer very limited to no additional explanatory power. Taken together, these results indicate that GCV and, to a lower extent, the VIX, absorb a substantial portion of the common volatility of the analyzed metal categories.

These findings and intuition set the stage for the robustness analysis in Section 6.2.2, where GCV is excluded from the regressions. The goals are to evaluate whether the remaining regressors have any explanatory power and to assess whether the conclusions from the baseline specifications still hold. Generally, the evidence from (R1) to (R7) supports Hypothesis 2, demonstrating that metal-specific volatility comovement is systematically linked to global sources of risk and broader macro financial conditions.

6.2.2. Robustness Regression Results (RB1 to RB8)

Table 11 reports the robustness regression results with precious MCOVOL as dependent variable, estimated without including the GCV index, to isolate the incremental contribution of the remaining uncertainty, financial, macroeconomic and event variables.

Table 11 – Robustness regression results for the precious metals group (RB1 to RB8). This table includes the coefficients for the independent variables and their significance levels.

	RB1	RB2	RB3	RB4	RB5	RB6	RB7	RB8
(Intercept)	0.000	0.000	0.000	0.000	0.000	0.000	-0.004	-0.076
GEPU							0.078	0.057
VIX				0.196**			0.195**	0.168
CLIMATE_UI	0.006		-0.013	-0.037	-0.015	-0.039	-0.038	-0.043
OIL_UI	0.109***		0.084***	0.051*	0.084***	0.068**	0.051*	0.050
SUSTAIN_UI	-0.031		0.002	-0.024	0.002	0.009	-0.024	-0.018
DXY		0.029	0.018	-0.030	0.017	-0.078	-0.031	-0.058
CREDIT_SPREAD		0.142**	0.120*	-0.004	0.122*	0.135**	-0.003	0.019
CHINA_PMI		-0.018	0.000	-0.014	-0.001	-0.007	-0.014	-0.014
DUMMY_COP					-0.066		-0.026	
DUMMY_COVID						0.305***		0.110
AdjR2	0.050	0.075	0.092	0.200	0.088	0.147	0.195	0.201

Robust standard errors were calculated but not presented
*** p<0.01, ** p<0.05, * p<0.1

Once GCV is excluded from the regressions, several variables that were previously insignificant gain statistical relevance for precious metals. Notably, OIL_UI becomes significant in multiple specifications, indicating that uncertainty related to energy contributes to explaining volatility comovement in precious metals when the global common volatility factor is removed. This is economically intuitive, as oil market disruptions often coincide with geopolitical tensions, inflationary episodes and broader macroeconomic uncertainty, reinforcing precious metals as safe-haven investments.

The variable DUMMY_COVID also becomes significant in model (RB6), reflecting that the extraordinary shock during the COVID-19 pandemic in March 2020 had a direct influence on precious metal volatility. This is only noticeable when GCV is not included, since previously GCV already absorbed this shock. However, the DUMMY_COVID loses significance in (RB8), suggesting that the inclusion of the GEPU and the VIX, which are absent in (RB6), absorbs the volatility related to the pandemic, even though neither variable is itself statistically significant.

CREDIT_SPREAD appears significant in several robustness specifications, suggesting that tighter financial conditions and funding stress are associated with higher volatility comovement. VIX is significant in (RB4) and (RB7), indicating that high frequency financial stress also retains explanatory power when not overshadowed by the broader global common volatility factor.

On the whole, the robustness regressions show that, once GCV is excluded, uncertainty related to oil, credit conditions, financial stress and the COVID shock all contribute to explaining global common volatility in precious metals. This confirms that the global common volatility factor absorbs much of the shared dynamics in the baseline models and that other risk channels become notable when this dominant component is not included.

Table 12 presents the robustness regression results for the industrial metals group, excluding the GCV index and revealing the independent influence of financial, macroeconomic, sector-specific and dummy variables on industrial MCOVOL.

Table 12 – Robustness regression results for the industrial metals group (RB1 to RB8). This table includes the coefficients for the independent variables and their significance levels.

	RB1	RB2	RB3	RB4	RB5	RB6	RB7	RB8
(Intercept)	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.050
GEPU							0.028	0.035
VIX				0.372***			0.371***	0.402***
CLIMATE_UI	-0.064		0.010	0.007	0.006	0.001	0.006	0.011
OIL_UI	0.165***		0.126**	-0.017	0.126**	0.102**	-0.016	-0.017
SUSTAIN_UI	-0.033		-0.041	0.020	-0.036	0.000	0.021	0.005
DXY		-0.051	-0.081	-0.008	-0.083	-0.266	-0.008	0.090
CREDIT_SPREAD		0.252**	0.232***	-0.172	0.231***	0.243***	-0.172	-0.211
CHINA_PMI		-0.014	-0.002	-0.022	-0.001	-0.014	-0.022	-0.017
DUMMY_COP					-0.085		-0.023	
DUMMY_COVID						0.221*		-0.110
AdjR2	0.119	0.198	0.253	0.627	0.245	0.289	0.622	0.631

Robust standard errors were calculated but not presented
*** p<0.01, ** p<0.05, * p<0.1

For industrial metals, several variables gain statistical significance too, indicating effects that were previously absorbed by the dominant global common volatility factor. For instance, CREDIT_SPREAD becomes significant in several models, suggesting that tighter financial conditions and heightened funding stress contribute to stronger volatility comovement for industrial metals. This aligns with the cyclical nature of this metal segment, whose demand is closely tied to global investment cycles and the cost of capital.

OIL_UI also becomes significant in multiple specifications, reflecting the sector's exposure to energy intensive production processes and sensitivity to fluctuations in global commodity input costs. These effects appeared muted in the baseline regressions due to the informational dominance of GCV.

Whenever included, the VIX exhibits strong statistical significance across all models, indicating that high frequency financial stress continues to shape the volatility dynamics of industrial metals when broader global common volatility patterns are left out. The variable DUMMY_COVID also gains significance in (RB6), confirming that disruptions related to the COVID-19 pandemic had a direct and measurable impact in this group once the global shock component is removed. Nevertheless, the DUMMY_COVID is also no longer significant in

(RB8) following the inclusion of the GEPU and VIX, mirroring the findings for precious metals.

Altogether, the robustness regressions for industrial metals also reveal a broader set of contributing factors such as the credit stress, oil uncertainty and financial market volatility once GCV is excluded. These results demonstrate that, while global volatility is the primary driver in the baseline models, several macro-financial and sector-specific channels can also play a meaningful role when considered independently.

Table 13 displays the robustness regression estimates for the transition metals group after removing the GCV index, testing whether the explanatory variables retain relevant content for explaining MCOVOL, in the absence of the global common volatility factor.

Table 13 – Robustness regression results for the transition metals group (RB1 to RB8). This table includes the coefficients for the independent variables and their significance levels.

	RB1	RB2	RB3	RB4	RB5	RB6	RB7	RB8
(Intercept)	0.000	0.000	0.000	0.000	0.000	0.000	-0.019	0.072
GEPU							0.007	0.010
VIX				0.246***			0.246***	0.273***
CLIMATE_UI	0.025		0.024	-0.005	0.023	0.004	-0.004	0.002
OIL_UI	0.079***		0.045*	0.002	0.045*	0.034	0.002	0.003
SUSTAIN_UI	0.045		0.048	0.013	0.048	0.054	0.013	0.006
DXY		0.088*	0.056	-0.004	0.056	-0.012	-0.004	0.022
CREDIT_SPREAD		0.131**	0.124**	-0.029	0.125**	0.135***	-0.030	-0.050
CHINA_PMI		-0.019	-0.004	-0.026	-0.004	-0.009	-0.026	-0.026
DUMMY_COP					-0.021		0.026	
DUMMY_COVID						0.216*		-0.103
AdjR2	0.047	0.109	0.119	0.365	0.114	0.157	0.361	0.368

Robust standard errors were calculated but not presented
*** p<0.01, ** p<0.05, * p<0.1

For transition metals, removing the GCV index also reveals several variables that gain statistical significance, unveiling effects that were previously absorbed by the dominant global common volatility factor. OIL_UI appears significant in various models, confirming that uncertainty related to energy influences volatility comovement in this metal group. However, the magnitude of the sector-specific coefficient is noticeably lower than for the precious and industrial groups. This outcome was initially not expected given the strong link between transition metals and global energy transformation dynamics.

Additionally, CLIMATE_UI and SUSTAIN_UI remain insignificant across all robustness specifications, consistent with the baseline regressions. This outcome is also quite unexpected, given that transition metals, which are central to decarbonization, electrification and sustainable technologies, should in principle be particularly sensitive to uncertainty related to climate and sustainability.

CREDIT_SPREAD also becomes significant in several models, indicating that financial conditions can play a relevant role. This aligns with the capital-intensive nature of transition metals, which depend heavily on financing conditions for renewable energy infrastructure, battery production and technological development. DXY becomes marginally significant in (RB2), reflecting the group's exposure to USD denominated pricing and global trade flows.

When included, the VIX remains highly significant throughout all models, showing that high frequency financial stress continues to be an important driver of volatility comovement when broader volatility pressures are not accounted for already. The DUMMY_COVID also becomes significant in (RB6), indicating that the pandemic introduced meaningful disruptions to this segment as well, although with a lower magnitude. Nonetheless, the DUMMY_COVID likewise becomes insignificant following the introduction of the GEPU and VIX in (RB8), paralleling the findings for the other metal segments.

All in all, the robustness regressions reveal that transition metal comovement is shaped by a versatile interaction between uncertainty related to energy, financial conditions, exchange rate pressures and shocks related to global crisis such as the COVID-19 pandemic. Moreover, despite the exclusion of GCV, the expected sensitivity to climate and sustainability uncertainty does not appear to materialize for the volatility dynamics in the current setting and the influence of oil uncertainty is weaker than anticipated.

6.2.2.1. Conclusion of the Robustness Analysis

The robustness regressions confirm that removing GCV substantially reshapes the explanatory landscape of MCOVOL. Across all three metal categories, excluding GCV reveals a set of meaningful economic effects that would have been otherwise overshadowed. Most notably, OIL_UI, CREDIT_SPREAD, DXY and the DUMMY_COVID appear significant only when GCV is not included, demonstrating that volatility comovement in metal markets is not driven exclusively by a single global factor but instead reflects an interaction of macro-financial, sector-specific and event driven forces.

Altogether, these findings reinforce that GCV, while highly informative, aggregates multiple dimensions of global uncertainty and can therefore overshadow the explanatory content of less dominant variables. Finally, by uncovering these hidden relations, the robustness analysis strengthens the support for Hypothesis 2, revealing that MCOVOL responds systematically to global and macro-financial conditions even when the overarching global common volatility variable is excluded.

7. Key Findings, Limitations and Future Research

This section provides an integrated interpretation of the evidence, connecting the behavior of the MCOVOL indices with the results of the regression models, while situating the study within the larger context of volatility modelling and commodity market dynamics. It also outlines the limitations of the analysis and suggest ideas and avenues for future studies.

7.1. Key Findings and Discussion

The estimated MCOVOL factors exhibit sharp reactions to global events and limited serial dependence, which is consistent with the design of the COVOL methodology of Engle and Campos-Martins (2023). These features provide a natural motivation for the regression analysis, which tests whether these shocks can be systematically linked to global and macro-financial drivers. The findings from the regressions (R1) to (R7) and (RB1) to (RB8) reinforce the conclusions from the MCOVOL dynamics, showing consistent patterns between both stages of the analysis.

The analysis across the three metal groups reveals that global common volatility conditions are the dominant force driving comovement in metal markets. The MCOVOL indices react strongly to global uncertainty shocks, with pronounced spikes during periods of financial stress, such as the COVID-19 outbreak, also showing smoother behavior outside crisis episodes. Moreover, precious metals exhibit the mildest volatility comovement and sharper but short-lived reactions, reflecting their safe-haven role. Industrial and transition metals display stronger and more frequent fluctuations, driven by economic activity, market stress and cyclical demand factors.

The regression analysis confirms that global risk as measured by global common volatility is the main driver of MCOVOL, with the GCV index consistently emerging as the most powerful explanatory variable across all metal groups, when included. This finding demonstrates that a substantial source of metal volatility comovement is tied to broad global shocks, consistent with the nature of the COVOL methodology. The VIX also contributes significantly, especially for industrial and transition metals, which is an indication that high frequency financial stress plays a key role in shaping volatility comovement in these commodity segments.

Finally, macro-financial indicators, such as the CREDIT_SPREAD and DXY, can play meaningful roles too. Furthermore, OIL_UI is the only sector specific uncertainty index that displays occasional significance, being consistent with the distinct economic drivers influencing each metal group. The DUMMY_COVID also becomes significant when GCV is excluded, revealing that disruptions related to the pandemic contributed to metal-based volatility comovement. Overall, the empirical results reveal a multidimensional structure of joint volatility dynamics, where global risks and uncertainty interact with macro-financial and sectoral forces in economically meaningful ways.

7.2. Limitations

Although the results provide consistent and economically meaningful insights, there are some limitations to the analysis. First, the data relies on proxies based on ETFs for metal prices, which offer tradable and liquid instruments but may not reflect market dynamics. The ETFs capture broader sector exposure rather than single metal fundamentals, potentially diluting or amplifying certain relationships. Although these instruments are commonly employed in empirical research due to their availability and liquidity, alternative ETF compositions or other asset selections could be explored in future work to better characterize each group. Further, also increasing the number of assets in each group, could potentially improve the estimation of the metal-based volatility factors and factor loadings.

Second, the estimation of MCOVOL uses daily returns aggregated into monthly indices for the regression framework. While this approach aligns the volatility measure with the monthly frequency of the independent variables, it inevitably smooths high frequency volatility dynamics and may understate short-lived effects.

Third, the heavy informational content of GCV introduces a potential confounding effect due to the presence of other uncertainty and macro-financial variables, making it difficult to interpret results from the baseline models. Therefore, this complicates the interpretation of individual coefficients and may suppress the significance of otherwise relevant variables.

Fourth, the scope of the explanatory variables, while being broad, does not capture all possible drivers of metal markets. Hence, factors such as global supply disruptions, shipping and logistic bottlenecks, futures positioning or liquidity in metal exchanges were not included due to time and feasibility constraints. These avenues could certainly be addressed in the future, possibly revealing additional volatility patterns driven by variables not accounted for in the current regressions. Additionally, due to time constraints, it was not possible to introduce lagged versions of the explanatory variables, as market adjustments to macro-financial and sector-specific shocks may not be instantaneous and some effects may materialize with a delay.

Finally, the empirical analysis relies on linear regression specifications to explain variations in MCOVOL, which may not fully capture nonlinear dynamics, structural breaks or regime dependent responses to uncertainty. These are features that often characterize volatility behavior during periods of severe stress. Consequently, extending the analysis to nonlinear or time varying modelling approaches could provide a more flexible framework for better understanding MCOVOL dynamics.

7.3. Future Research Proposals

Several avenues for future research emerge from this thesis, offering opportunities to extend and deepen the analysis. First, given the reliance on proxies based on ETFs for underlying metal markets, future studies could incorporate direct spot or futures prices for metals where reliable time series exist. This would allow researchers to test whether MCOVOL dynamics differ when using instruments that are more closely related to physical market fundamentals, or when employing more targeted ETF structures as new financial products become available.

Second, the aggregation of daily MCOVOL into monthly indices implies a loss of high frequency information. A natural extension would therefore involve estimating regressions at weekly or daily frequencies, enabling a closer examination of short-lived volatility responses and improving the alignment between metal market adjustments and the timing of global shocks.

Third, the strong absorption effect of GCV in the baseline regressions suggests that overlapping sources of uncertainty are difficult to interpret within a linear framework. Future work could explore modelling strategies that explicitly separate global, regional and sector-specific sources of volatility.

Fourth, expanding the set of explanatory variables would help capture drivers of volatility that were excluded due to time and feasibility constraints. Hence, incorporating indicators of supply chain stress, mining output constraints, futures positioning, financial market liquidity or shipping costs could reveal additional channels through which volatility comovement arises in metal markets. Also, introducing lagged versions of the explanatory variables could also reveal delayed adjustments in how macro-financial and sector-specific shocks propagate through common volatility.

Finally, since linear specifications may not capture nonlinear or regime dependent dynamics, future studies could evaluate whether MCOVOL responds asymmetrically to uncertainty.

8. Conclusion

This dissertation investigates the dynamics of common volatility across metal markets by constructing metal-specific common volatility indices for precious, industrial and transition metals. This is done using the COVOL framework of Engle and Campos-Martins (2023). The results show clear and economically meaningful volatility comovements within each metal group, with pronounced spikes during periods of geopolitical, financial and macroeconomic turbulence, supporting Hypothesis 1. These patterns confirm that global shocks represent a key source of volatility transmission to metal markets and that MCOVOL effectively captures the shared component of these shocks.

This study also examines the extent to which global variables help explain fluctuations in MCOVOL. Across categories, the GCV index displays the strongest overall explanatory power, while the VIX provides significant additional insight into high frequency financial stress, particularly for the industrial and transition groups. When GCV is not included in the robustness checks, variables such as OIL_UI, CREDIT_SPREAD, DXY and DUMMY_COVID become relevant, indicating that MCOVOL reflects a broader set of economic forces than what otherwise appears in the baseline models. Overall, the results demonstrate that MCOVOL captures unexpected and economically significant volatility shocks and responds systematically to global uncertainty and macro-financial conditions, validating Hypothesis 2.

By applying the COVOL methodology to several metal markets, this dissertation broadens the empirical scope of common volatility modelling and provides new insights into how systemic shocks spread across commodities that are central to global production chains and energy transition subjects. Furthermore, the evidence highlights the potential usefulness of MCOVOL as a complementary risk monitoring indicator for investors, policymakers and market participants seeking to better understand global volatility.

Future research can extend this analysis in several complementary directions. First, expanding the dataset to include futures prices or more granular ETF structures could improve the precision of MCOVOL estimation and address current data limitations. Second, incorporating lagged effects or alternative model specifications could help assess whether the impact of global common volatility materializes over longer horizons. Third, extending the framework to additional commodities or sectoral indices would allow for cross-market comparisons and a deeper assessment of global risk transmission. Moreover, future studies can also broaden the set of explanatory variables to capture additional sources of volatility not covered in the current framework. Finally, exploring causal relationships or employing more advanced econometric approaches could further clarify the mechanisms through which global common volatility disseminates across metal markets.

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10. Appendix

Appendix 1 - Descriptive Statistics of Daily Log Returns of the ETFs (Aligned by Group Common Time Span)

ETF ticker	Metal Group	Average	Std dev	Min	Max	Skewness	Kurtosis
GLD	Precious	0.0003	0.01	-0.09	0.05	-0.46	4.51
SLV	Precious	0.0002	0.02	-0.15	0.09	-0.68	6.63
PPLT	Precious	0.0000	0.01	-0.14	0.10	-0.41	5.04
PALL	Precious	0.0002	0.02	-0.22	0.19	-0.45	7.11
PICK	Industrial	0.0002	0.02	-0.14	0.13	-0.50	6.91
DBB	Industrial	0.0001	0.01	-0.09	0.06	-0.35	2.92
SLX	Industrial	0.0003	0.02	-0.16	0.12	-0.59	6.91
LIT	Transition	0.0001	0.02	-0.15	0.14	-0.17	5.22
COPX	Transition	0.0000	0.02	-0.19	0.14	-0.31	4.30
REMX	Transition	-0.0003	0.02	-0.17	0.14	-0.17	3.89

Appendix 2 – Descriptive Statistics of Explanatory Variables (Monthly)

Variable	P25	Median	P75	Mean	Std Dev	Min	Max
GEPU	0.45	0.56	0.72	0.61	0.25	0.12	2.01
GCV	49.88	50.75	52.03	51.12	2.60	35.70	59.20
VIX	-0.01	0.00	0.00	0.00	0.01	-0.02	0.02
CLIMATE_UI	3.65	4.63	6.42	5.39	2.60	2.57	20.31
OIL_UI	93.67	108.36	116.12	105.91	12.33	86.32	129.04
SUSTAIN_UI	81.50	120.48	205.11	152.39	91.32	51.14	628.48
DXY	37.85	77.47	127.66	96.00	75.41	3.62	470.70
CREDIT_SPREAD	23.35	26.92	31.32	28.28	7.76	16.73	75.50
CHINA_PMI	14.08	17.66	23.08	19.47	7.44	10.13	62.67