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Modeling Volatility and Persistent Shocks in Metal Prices: A Markov Regime-Switching DGARCH Approach Applied to the London Metal Exchange

Modélisation de la volatilité et des chocs persistants sur les prix des métaux : une approche DGARCH à changement de régime de Markov appliquée à la Bourse des métaux de Londres

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Abstract

This study focuses on the volatility of major base metals traded on the London Metal Exchange, using a DGARCH model with Markov regime switching. The objective was to better understand price dynamics and identify the phases of stability and turbulence specific to each market. The methodology relies on the analysis of daily logarithmic returns for aluminum, copper, lead, nickel, tin, and zinc, based on long historical series from Investing.com. The results show that aluminum and copper alternate between moderate and high volatility regimes, reflecting their strong sensitivity to global industrial cycles. Lead appears structurally more stable, dominated by a low-volatility regime, while tin is characterized by chronic instability with frequent regime shifts. Nickel and zinc, however, display convergence issues, suggesting more complex price dynamics, strongly linked to speculation and structural changes such as the energy transition.

Keywords: volatility; metals; DGARCH; Markov regimes; London Exchange.

Résumé

Cette étude s'est intéressée à la volatilité des principaux métaux de base cotés à la Bourse des métaux de Londres, en mobilisant un modèle DGARCH à changement de régime de Markov. L'objectif était de mieux comprendre les dynamiques de prix et d'identifier les phases de stabilité et de turbulence propres à chaque marché. La méthodologie repose sur l'analyse des rendements logarithmiques quotidiens de l'aluminium, du cuivre, du plomb, du nickel, de l'étain et du zinc sur des séries longues issues d'Investing.com. Les résultats montrent que l'aluminium et le cuivre alternent entre des régimes de volatilité modérée et élevée, reflétant leur forte sensibilité aux cycles industriels mondiaux. Le plomb apparaît plus stable, dominé par un régime de faible volatilité, tandis que l'étain se distingue par une instabilité chronique. Enfin, le nickel et le zinc révèlent des difficultés de convergence, signe de dynamiques plus complexes, liées notamment à la transition énergétique et à la spéculation.

Mots clés : volatilité ; métaux ; DGARCH ; régimes de Markov ; Bourse de Londres.

Introduction

Metals play a vital role in today's global economy. Their importance goes far beyond their status as raw materials: they have become both indicators of economic health and strategic levers for key sectors such as energy, construction, and advanced technologies. This central role, however, comes with pronounced price instability. Copper, aluminum, zinc, and precious metals all react almost immediately to economic and political disruptions, from geopolitical tensions to health crises and energy transitions. In this context, the London Metal Exchange (LME) stands out as the leading marketplace where these fluctuations are most clearly expressed and where the global balance of metal markets is shaped (J. Park & Lim, 2018).

This instability is far from random. Recent research shows that metal prices evolve through distinct regimes, alternating between phases of expansion, stability, and contraction. Copper provides a striking illustration of this dynamic: its rising demand, driven by technological and energy transitions, is amplified by speculative activity, resulting in asymmetric behaviors and persistent regime shifts (Su et al., 2023). Precious metals such as gold and silver follow a similar pattern. Although they are widely perceived as safe-haven assets, their volatility is also shaped by alternating regimes that determine their effectiveness as risk-hedging instruments (Naeem et al., 2019).

Traditional econometric models, however, quickly show their limits when confronted with these complex dynamics. Linear models fail to properly account for the persistence of shocks and the structural breaks that characterize price series. To overcome these shortcomings, more advanced approaches have been developed, such as the Double GARCH (DGARCH) model combined with Markov regime switching. These models prove effective in capturing transitions between volatility regimes and provide more accurate forecasts and risk assessments, offering a richer understanding of market behavior (Ahmed & Sarkodie, 2021; Bildirici & Ersin, 2022).

In light of these considerations, this study aims to answer the following research question: **To what extent do the prices of strategic metals traded on the LME follow identifiable volatility regimes that can be effectively modeled through a DGARCH approach with Markov regime switching?** This question places this study within a positivist epistemological framework, which assumes that economic and financial phenomena can be objectively observed and measured through empirical data. The research adopts a hypothetico-deductive posture, drawing on theoretical insights from the literature to formulate hypotheses about the existence of distinct volatility regimes and the persistence of shocks, and then testing these empirically with econometric tools (Y. S. Park et al., 2020). The reasoning underpinning the analysis rests on the assumption that fluctuations are not purely random but follow patterns that can be modeled and explained.

Within this framework, the aim of the research is to analyze the volatility and persistence of shocks affecting the prices of metals traded on the LME using a DGARCH approach with Markov regime switching (Segnon et al., 2024). Beyond identifying asymmetric behaviors across different market regimes, the study also seeks to shed light on how risks are transmitted among major strategic metals. To achieve this, the article follows a logical progression: it begins with a literature review highlighting previous contributions and their limitations, then presents the methodological framework and dataset, before moving on to the empirical results and their discussion. Finally, the conclusion reflects on the main findings and outlines potential avenues for future research.

1. Literature Review

The study of volatility modeling has long been a central theme in financial and economic research. Early work was largely built on GARCH models, which provided useful insights into market dynamics. However, these traditional approaches showed clear limits, particularly in their ability to capture the persistence of shocks and sudden breaks in price series(Efimova & Serletis, 2014). To address these shortcomings, Markov regime-switching models were introduced, offering a more flexible framework to describe markets that alternate between low- and high-volatility phases (Salhi et al., 2016).

Building on this foundation, researchers have extended and refined these models across different contexts. In energy markets, for instance, evidence shows that Markov-Switching GARCH models outperform traditional approaches in forecasting oil price volatility by accounting for structural breaks and persistent shocks (Günay, 2015). Similarly, Blazsek & Haddad (2023) demonstrate that more advanced specifications, such as multi-regime MS-EGARCH models, enhance predictive performance in G20 financial markets. These models are especially effective at capturing asymmetric effects and identifying transitions between volatility regimes. Together, these findings highlight the value of regime-switching approaches for markets that are highly sensitive to external shocks.

Despite these advances, the literature is not without debate. Some authors argue that the increasing complexity of multi-regime models does not always translate into greater explanatory power. Caldara et al., (2021), apply a regime-switching framework to Growth-at-Risk and show that it improves the anticipation of extreme scenarios. Yet this comes at the cost of greater methodological complexity, which limits the model's usability in real-time contexts. This tension between precision and practicality remains a recurring issue in the literature.

Another observation is that most applications of regime-switching models focus on financial markets, oil, or precious metals. By contrast, industrial metals which are central to the London Metal Exchange (LME) have received far less attention. Yet these metals are directly linked to the ongoing energy transition and technological change, making their price dynamics particularly important to understand. This lack of attention represents a significant gap in the literature (Han et al., 2022; Mensi et al., 2022)

More recently, studies have also extended these approaches to less traditional markets. De la Torre-Torres et al., (2024), for instance, apply an MS-EGARCH model to the futures market for timber. Their findings show that regime-switching models not only improve the description of volatility patterns but also help design trading strategies that outperform passive approaches. This suggests that the relevance of these methods extends beyond traditional financial assets.

Taken together, the literature highlights the strengths of regime-switching models in capturing the unstable nature of prices and providing more reliable forecasts than conventional models. At the same time, several limitations remain. The balance between sophistication and practical usability is still debated, and the relative lack of research on industrial metals traded at the LME leaves an important gap. Moreover, few studies have explored how shocks are transmitted across different metals, despite their interconnected roles in the global economy. It is within this context that the present study positions itself, aiming to address these gaps by applying a DGARCH model with Markov regime switching to industrial metals and shedding light on both asymmetries and shock transmission mechanisms (Panopoulou & Pantelidis, 2012; Shu et al., 2024).

2. Methodological Framework

This study applies a Double GARCH (DGARCH) model with Markov regime switching (MRS) to capture the complex dynamics of metal price volatility. While traditional GARCH models account for conditional heteroskedasticity, they often fail to capture structural breaks and differences in the persistence of shocks across market phases. Incorporating regime switching allows parameters to vary across states of volatility, providing a more flexible and realistic framework for markets characterized by abrupt transitions and external shocks (Liu et al., 2021).

2.1. Model specification

Let r_t denote the return of a given metal at time t. The mean equation is:

$$r_t = \mu_{s_t} + \epsilon_t, \epsilon_t \sim N(0, h_t) \tag{1}$$

where s_t is the unobserved state of the market (e.g., low or high volatility), evolving according to a firstorder Markov chain with K regimes.

The conditional variance follows a regime-dependent DGARCH process:

$$h_t = \omega_{s_t} + \alpha_{s_t}\epsilon_{t-1}^2 + \beta_{s_t}h_{t-1} \tag{2}$$

This structure not only models volatility clustering but also allows each regime to have its own dynamics, capturing the heterogeneity of calm and turbulent market conditions.

2.2. Properties and estimation

A key strength of the DGARCH-MRS model lies in its ability to capture different levels of shock persistence across regimes. For example, during turbulent phases, shocks may last longer and propagate more strongly compared to stable periods. This feature is particularly relevant for metals, where price dynamics are often driven by external shocks such as geopolitical tensions, energy transitions, or global crises (Shi, 2023).

Estimation is generally carried out using Maximum Likelihood Estimation (MLE), sometimes complemented by Bayesian approaches such as Markov Chain Monte Carlo (MCMC) to estimate regime probabilities more precisely. Simulation-based methods, including the EM algorithm and particle filters, are also used to handle the nonlinear nature of regime-switching GARCH models (Bao et al., 2012).

2.3. Model validation and testing

Several diagnostic and validation procedures are essential:

- Regime existence tests: Likelihood Ratio (LR) tests and procedures developed by Cho & White, later refined by Bostwick & Steigerwald (2014), are used to determine whether regime switching significantly improves model fit.
- Stationarity conditions: For each regime, parameters must satisfy $\alpha_{s_t} + \beta_{s_t} < 1$, ensuring finite variance and mean-reverting volatility.
- Model selection: Information criteria such as AIC and BIC help identify the optimal number of regimes.
- Forecast evaluation: Out-of-sample tests, including Value-at-Risk (VaR) backtesting, assess whether the DGARCH-MRS provides superior predictive power compared to alternative models like EGARCH or APARCH (Lauenstein & Walther, 2016).

2.4. Justification of the chosen methodology

The decision to use a DGARCH-MRS model is grounded in several considerations. First, it effectively captures the nonlinear and heterogeneous nature of volatility in metal prices, distinguishing clearly between calm and turbulent phases. Second, it is particularly suited to markets affected by external and persistent shocks, a defining characteristic of metals that respond to global supply-demand imbalances, geopolitical tensions, and macroeconomic uncertainty (Ahmed & Sarkodie, 2021). Third, empirical evidence shows that regime-switching GARCH variants consistently outperform traditional approaches in forecasting and risk assessment (Carpinteyro et al., 2021).

3. Data and Variables

To structure the empirical analysis, we rely on historical daily price series for the main base metals traded on the London Metal Exchange (LME). The data were collected from Investing.com and cover copper, aluminum, lead, nickel, tin, and zinc. Each dataset corresponds to a specific metal and spans a distinct time period, ensuring that the dynamics specific to each market are adequately captured. Table 1 summarizes the sample coverage and number of observations for each series.

Table 1:Summary of metals analyzed and observation periods

Metal	Period covered	Number of observations
Copper	04/06/2010 – 14/08/2025	3,885
Aluminum	16/06/2014 – 14/08/2025	2,824
Lead	04/06/2010 – 14/08/2025	3,885
Nickel	04/06/2010 – 14/08/2025	3,793
Tin	04/06/2010 – 14/08/2025	3,885
Zinc	04/06/2010 – 14/08/2025	3,887

Source: Investing.com

From the raw price data, we compute daily logarithmic returns, defined as:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{3}$$

where p_t denotes the daily closing price at time t. This transformation is standard in financial econometrics as it stabilizes variance, allows for better comparability across series, and ensures additivity of returns over time (Tsay, 2005).

Table 2 presents descriptive statistics of the daily returns for each metal. Overall, the mean daily returns for all six metals are very close to zero, which is consistent with the random-walk nature of financial time series. Tin records the highest average return (0.000168), while lead and nickel exhibit slightly negative averages. The standard deviation values highlight substantial differences in volatility. Nickel clearly stands out with the highest volatility (0.025092), reflecting larger price swings, whereas aluminum and copper display relatively lower volatility, indicating more stable price behavior. Extreme values confirm the presence of occasional but significant shocks. Nickel shows the most dramatic fluctuations, with a minimum of –77.99% and a maximum of +53.01%, pointing to episodes of severe instability. Other metals also experienced pronounced shocks, such as copper (–10.59% to +7.53%) and tin (–13.48% to +9.63%). Finally, quartile analysis (Q1, median, Q3) reveals that most daily variations remain within a narrow range around zero. This suggests that extreme events are rare but impactful, consistent with the leptokurtic distribution often observed in financial return series.

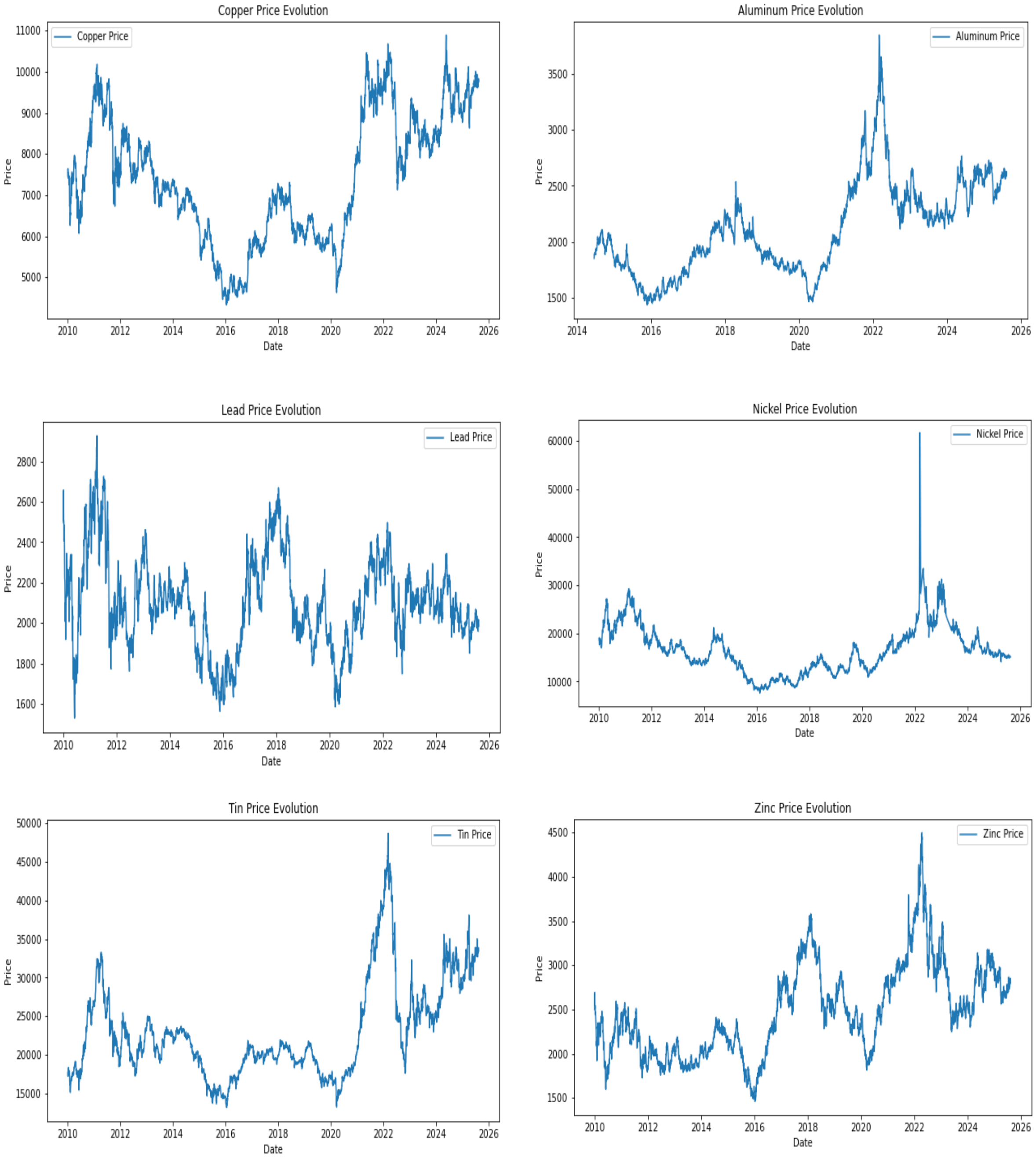
Table 2:Descriptive statistics of daily log returns

Metal	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Copper	3,885	0.000069	0.013381	-0.10594	-0.006856	0.00029	0.007477	0.075309
Aluminum	2,824	0.000123	0.012421	-0.07440	-0.007492	-0.00027	0.007629	0.060432
Lead	3,885	-0.000058	0.015583	-0.10128	-0.009118	0.000107	0.008879	0.093236
Nickel	3,793	-0.000060	0.025092	-0.77997	-0.010827	0.000271	0.011068	0.530083
Tin	3,885	0.000168	0.015907	-0.13478	-0.006685	0.000668	0.008012	0.096359
Zinc	3,887	0.000024	0.016201	-0.08767	-0.009565	0.000351	0.009934	0.097666

Source: Author’s calculations

The figures below showing the evolution of metal prices provide a clear picture of how each market has behaved over time. Aluminum illustrates a market that has gone through several distinct phases: a decline between 2014 and 2016, followed by a gradual recovery until 2018, before falling again in 2019–2020. The Covid-19 pandemic shock is evident, but the most striking feature is the sharp surge in 2021–2022, when prices climbed above 3,800 USD per ton, driven by supply chain tensions and post-pandemic demand. Since then, prices have settled into a more stable range between 2,500 and 2,700 USD, showing moderate but persistent volatility. Copper, observed over a longer horizon from 2010, shows a more pronounced cyclical behavior. After peaking above 10,000 USD in 2011, prices steadily declined until 2016, reflecting weaker demand from China. In recent years, however, copper has surged again, nearly reaching 10,000 USD in 2021–2022. These swings highlight its dual role as both a strategic material for the energy transition and a barometer of speculative movements, making copper one of the clearest indicators of global economic trends. Lead presents a more stable pattern compared to the other metals. Prices generally fluctuate between 1,600 and 2,600 USD from 2010 to 2025, with smaller upward and downward cycles. While some temporary spikes reveal moments of heightened volatility, the lead market overall appears less exposed to structural shocks, its behavior largely tied to demand from the battery industry.

Fig. 1 :Evolution of Base Metal Prices on the London Metal Exchange (2010–2025)



Source: Author's calculations

Nickel, in contrast, is the clearest example of extreme volatility. Prices generally moved between 10,000 and 20,000 USD for much of the period, but in 2022 they spiked dramatically above 60,000 USD per ton. This unprecedented surge was directly linked to the war in Ukraine and uncertainty over Russian supplies, since Russia is one of the world's largest nickel producers. Even after the correction, prices remain unstable and above their historical average, confirming the highly speculative nature of this market. Tin shows a steadier path until 2019, moving between 15,000 and 25,000 USD. Like other metals, however, it experienced a dramatic surge in 2021–2022, climbing above 45,000 USD per ton. This spike reflected both its growing importance in the electronics industry and global supply disruptions. While prices later corrected, they remain at historically high levels, signaling strong structural demand. Zinc occupies an intermediate position, with fluctuations ranging from 1,500 to 4,500 USD. The 2022 peak, similar to aluminum and tin, reflects post-pandemic recovery and supply pressures. Since 2023, prices have moved in a narrower band around 2,500 to 3,000 USD, maintaining notable volatility but without the extreme swings observed in nickel or tin.

4. Result and discussion

Before estimating the volatility models, it is essential to verify some fundamental statistical properties of the series under study. Preliminary tests are needed to confirm the stationarity of returns (ADF test), to assess the normality of their distribution (Jarque-Bera test), and to detect the presence of conditional heteroskedasticity (ARCH LM test). These steps are crucial in the present study, as they determine the validity of applying GARCH and DGARCH models to capture the volatility dynamics of metal prices on the London Metal Exchange (LME). The results for all six metals are reported in Table 3.

Table 3:Preliminary test results on logarithmic returns

Metal	**Observations**	**ADF p-value**	**Jarque-Bera Stat.**	**JB p-value**	**ARCH LM Stat.**	**ARCH LM p-value**
Copper	3,885	0.0	2,311.55	0.0	309.88	1.26e-60
Aluminum	2,824	0.0	581.71	4.83e-127	277.57	8.47e-54
Lead	3,885	9.87e-30	2,410.46	0.0	291.35	1.05e-56
Nickel	3,793	0.0	14,241,608.73	0.0	669.14	2.63e-137
Tin	3,885	0.0	5,988.28	0.0	295.73	1.24e-57
Zinc	3,887	3.95e-23	526.27	5.26e-115	186.26	1.17e-34

Source: Author’s calculations

The results highlight several important features of the daily return series for the metals under review. The extremely small p-values of the ADF test, often below 0.01%, robustly confirm the stationarity of all series. This is a fundamental property, as volatility modeling with GARCH-type approaches assumes that returns follow a stationary process. Stationarity means that past shocks have a stable influence over time, making the forecasting of volatility more reliable.

The Jarque-Bera statistics, such as 2,311 for copper and an extraordinary 14 million for nickel, combined with p-values equal to zero, provide strong evidence against normality. This non-normality is reflected in asymmetry and particularly in excess kurtosis, with fat tails relative to the normal distribution, pointing to a higher probability of extreme price changes. Such findings are consistent with commodity markets, where prices are often affected by geopolitical shocks, supply disruptions, or sudden shifts in demand.

The ARCH LM test results also confirm strong conditional heteroskedasticity. With statistics such as 309.88 for copper and 669.14 for nickel, and p-values close to zero, the evidence suggests that return variance is not constant over time but instead depends on past shocks. This creates alternating periods of high and low volatility, a phenomenon known as volatility clustering. Such persistence is typical of both financial markets and commodity markets, and it fully justifies the use of GARCH and DGARCH models.

Taken together, these preliminary tests lead us to reject the null hypotheses of non-stationarity, normality, and homoscedasticity simultaneously. This triple rejection strongly supports the choice of advanced econometric frameworks, particularly DGARCH models combined with Markov regime switching, as they are specifically designed to capture structural breaks, persistence, and regime-dependent dynamics in volatility.

Looking at the six volatility plots reinforces these statistical findings. Metals such as aluminum and zinc show relatively stable volatility over time, with fluctuations concentrated around a constant mean level and few extreme peaks. Others, such as copper, lead, and tin, display more pronounced volatility spikes, often linked to market-specific events or broader macroeconomic shocks.

Nickel stands out with an exceptionally high volatility episode in 2022, which far exceeds the levels observed for the other metals and signals the impact of an extreme market shock. This behavior reflects the particular sensitivity of nickel to supply or demand disruptions, in this case largely tied to geopolitical tensions.

Across all metals, volatility tends to revert to a long-term mean after each peak, consistent with the properties captured by GARCH models. However, the magnitude and frequency of these peaks vary substantially across metals, highlighting heterogeneous risk profiles. Such differences are critical for portfolio management and hedging strategies, further reinforcing the relevance of adopting a DGARCH approach with regime switching in order to capture these nuances in the dynamics of LME-traded metals.

Table 4:Synthetic Table of Markov Switching Results – Metals

Metal	**Regime 0 (const, σ^2)**	**Regime 1 (const, σ^2)**	**p [0→0]**	**p [1→0]**
Aluminum	const = 2.52; $\sigma^2 = 0.37$	const = 1.90; $\sigma^2 = 0.01$	0.58	0.21
Copper	const = 4.14; $\sigma^2 = 0.33$	const = 3.66; $\sigma^2 = 0.002$	0.45	0.30
Lead	const = 1.78; $\sigma^2 = 0.17$	const = 1.25; $\sigma^2 = 0.014$	0.97	0.01

Tin	const = 6.38; $\sigma^2 = 0.84$	const = 5.54; $\sigma^2 = 0.015$	0.38	0.16
Nickel	const = 0.005; $\sigma^2 = 0.96$	const = 8.25; $\sigma^2 = 0.0004$	0.999	0.999
Zinc	const = 4.39; $\sigma^2 = 0.17$	const = 0.30; $\sigma^2 = 0.0004$	1.000	0.992

Source: Author's calculations

The results obtained from the estimation of Markov regime-switching models applied to the different metals provide several insights into the dynamics of their volatility. Overall, base metals such as aluminum, copper, lead, and tin yield coherent results that highlight the existence of two distinct regimes. These regimes can be interpreted as phases of high volatility and phases of more moderate volatility. The marked gap between the conditional variances across regimes confirms that these metal markets alternate between stability and turbulence.

Aluminum and copper illustrate this logic particularly well. In both cases, the estimated parameters show a clear differentiation between regimes, indicating that the market alternates between periods of heightened volatility and calmer phases. The persistence probabilities of each regime remain moderate, suggesting that these markets do not remain indefinitely locked in a single state, but instead transition relatively regularly from one regime to another. This reflects a more flexible dynamic, likely linked to cyclical factors such as fluctuations in industrial demand or global economic cycles.

Lead stands out with a different result. Here, the low-volatility regime overwhelmingly dominates. The estimated probability of remaining in this regime is extremely high, implying that the lead market is structurally more stable and less exposed to sudden shocks. This characteristic may be explained by market-specific determinants, such as more regular demand or a relatively better-controlled supply. Tin, on the other hand, presents the opposite situation: while its two regimes are well identified, the persistence of each is weak. This suggests that the tin market experiences frequent regime shifts, making it unstable and more difficult to forecast in the long term. The results for nickel and zinc call for greater caution. In both cases, the estimations reveal convergence issues that strongly undermine the reliability of the obtained parameters. Transition probabilities appear anomalous, and the variance-covariance matrix suffers from singularity.

From an economic perspective, the analysis of the results shows that metals such as aluminum and copper often lie at the intersection of these dynamics. Their volatility is characterized by clearly differentiated regimes that reflect the sensitivity of these markets to global industrial cycles. During periods of economic expansion, demand driven in particular by the construction, electronics, and infrastructure sectors pushes prices upward and sustains higher volatility. Conversely, during economic slowdowns or financial crises, these markets shift into a lower-volatility regime, reflecting a more stable but downward-oriented demand. The DGARCH-MS model captures this alternation well, demonstrating that the prices of these metals respond directly to global macroeconomic fluctuations.

Lead and tin present contrasting dynamics. The lead market appears structurally more stable, with a high probability of remaining in a low-volatility regime. This can be interpreted as the result of a less cyclical demand, more closely tied to long-term industrial uses such as batteries or certain niche industries, where consumption remains relatively steady. Tin, by contrast, is marked by chronic instability, with frequent regime shifts. This instability may be explained by supply conditions that are geographically concentrated, dependence on specific producer countries, and a more fragmented global demand. In this case, the regime-switching DGARCH model highlights endemic volatility, reflecting the market’s weak resilience to supply shocks or trade tensions.

The results for nickel and zinc underline the limitations of the exercise but also open up avenues for economic interpretation. The fact that the model fails to converge or that the variance-covariance matrices are unstable may reveal a more complex price dynamic, driven by episodes of speculation or by structural influences related to the energy transition. Nickel, for example, is central to the battery and green technology industries, which increases uncertainty and generates fluctuations that the standard model struggles to capture. Zinc, often used in galvanization and thus directly linked to construction and infrastructure, may also be subject to highly heterogeneous shocks depending on public investment policies.

Table 5:Estimated Transition Matrices

Metal	**Estimated Transition Matrix**	**Expected Average Duration Regime 1**	**Expected Average Duration Regime 2**
Aluminum	[[0.36944954, 0.63055046] [0.9885705, 0.0114295]]	1.59 periods	1.01 periods
Copper	[[0.32945052, 0.67054948] [0.99764732, 0.00235268]]	1.49 periods	1.00 periods
Lead	[[0.17053953, 0.82946047] [0.98598432, 0.01401568]]	1.21 periods	1.01 periods
Tin	[[0.83984526, 0.16015474] [0.98532281, 0.01467719]]	6.24 periods	1.01 periods
Nickel (1)	[[1.96973997, -0.96973997] [-0.0803158, 1.0803158]]	-1.03 periods	-12.45 periods
Nickel (2)	[[9.99053344e-01,9.46655859e-04] [9.99605155e-01, 3.94844775e-04]]	1056.35 periods	1.00 periods

Source: Author’s calculations

The table above highlights the dynamics of persistence and transitions between different volatility regimes for the metals under study. What stands out first is that aluminum and copper show relatively balanced transition matrices, with probabilities of remaining in a given regime that are not excessively high. This indicates that these two markets regularly alternate between periods of high volatility and calmer phases. The estimated average duration in regime 1, around one and a half periods, reflects this moderate instability: the markets do not remain locked in a single state for long, which corresponds well to the sensitivity of these metals to global industrial and cyclical fluctuations.

Lead, on the other hand, is characterized by a strong tendency to stay in regime 0. The associated probability is very high, which explains the near-permanent average duration in this state. In other words, the lead market displays structural stability, with transitions to the other regime occurring much more rarely. This likely illustrates a market less reactive to external shocks, where demand driven by specific uses such as batteries evolves more regularly.

Tin presents an opposite dynamic. The probability of remaining in regime 0 is particularly strong, which translates into an average duration of more than six periods in this regime. However, transitions to the other state remain possible and occur relatively frequently. This alternation paints the picture of an unstable market, subject to rapid fluctuations, possibly reflecting frequent tensions in supply or demand conditions.

Nickel is a very special case. The two available estimations reveal inconsistent or extreme results. In the first, average durations are negative, signaling a convergence issue and rendering the results unusable. In the second, regime 1 appears extremely persistent with a theoretical average duration of more than a thousand periods, which is unrealistic and indicates an anomaly in the adjustment. These results confirm that, for this metal, the classical methodology struggles to capture a more complex price dynamic, likely driven by structural factors such as the energy transition and speculation.

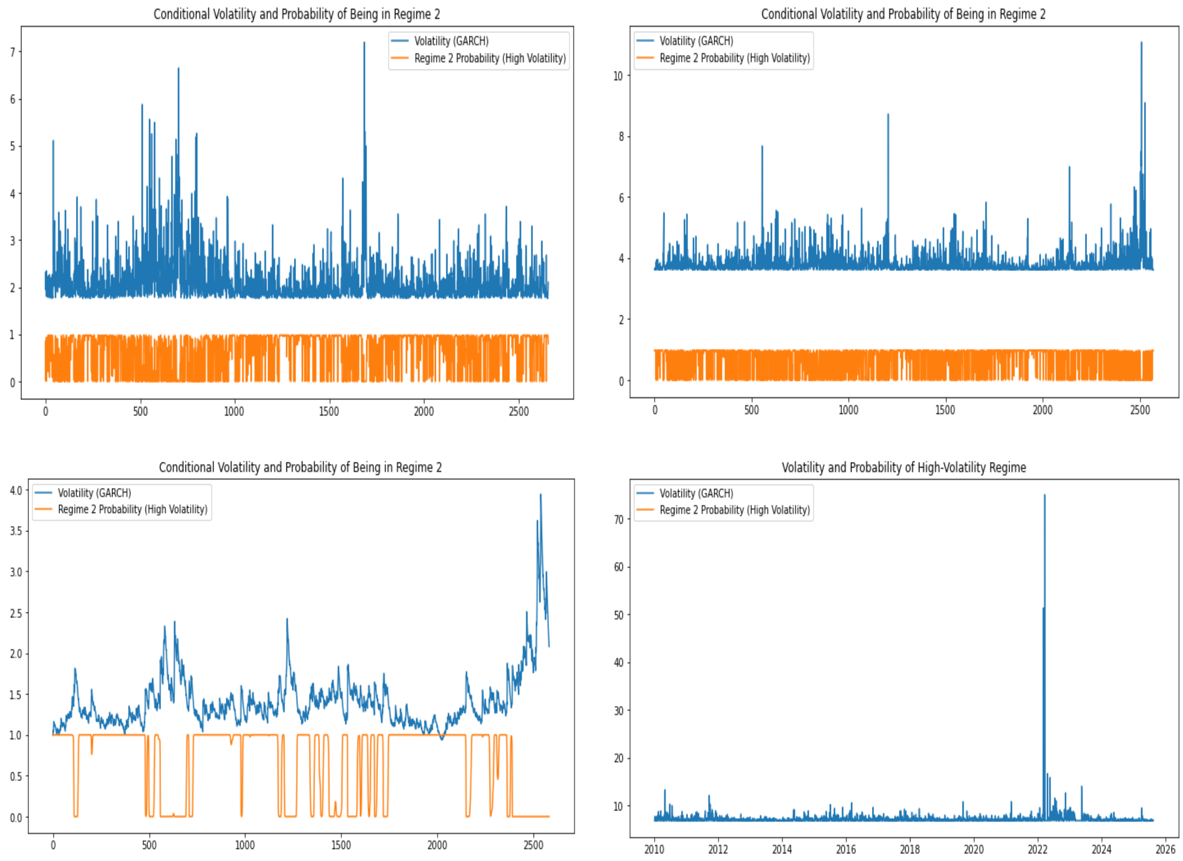
The examination of the graphs derived from the DGARCH model with Markov regime switching applied to major base metals highlights contrasting dynamics of volatility. These results shed light on how each market reacts to cyclical and structural shocks.

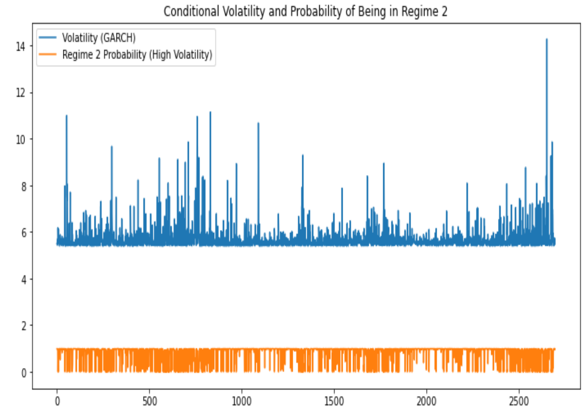
For aluminum and copper, the graphs reveal a relatively regular alternation between periods of moderate volatility and episodes of higher volatility. The transition probabilities suggest that these markets frequently switch from one regime to another, reflecting their sensitivity to industrial demand fluctuations and global economic cycles. This flexible dynamic indicates that aluminum and copper act as cyclical barometers, strongly correlated with the evolution of global growth.

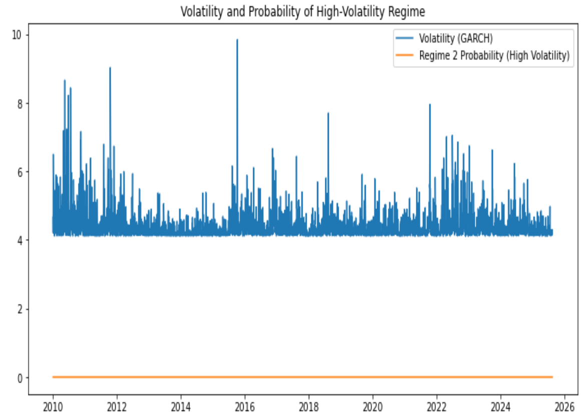
Lead, by contrast, displays a very different profile. Volatility remains overall contained, and the probability of switching to a high-volatility regime is very low. This confirms that the lead market is structurally more stable, likely due to a more consistent demand tied to specific industrial uses (batteries, niche industries), which are less subject to cyclical fluctuations. The graph therefore illustrates a market dominated by persistent stability.

Tin shows a much more unstable dynamic. Transition probabilities between regimes are frequent, reflecting recurring shifts from one state to another. This chronic instability can be explained by a geographically concentrated supply and dependence on specific producing countries, which weaken the resilience of this market against supply shocks. Tin therefore appears as one of the most unpredictable metals in the long run.

Fig. 2:Conditional Volatility and Probabilities of High-Volatility Regimes in Base Metals







Source: Author's calculations

Nickel, on the other hand, exhibits extreme behaviors with pronounced volatility spikes and a tendency to remain in high-volatility regimes. However, some results also suggest convergence issues with the model, making interpretation more complex. Given its strategic role in the battery industry and green technologies, the uncertainty surrounding this market reflects high exposure to speculation and structural tensions linked to the energy transition.

Finally, zinc shows a paradoxical dynamic. Conditional volatility displays significant fluctuations, but the probability of switching to a high-volatility regime often appears biased or unstable due to covariance issues in estimation. This suggests that while the zinc market is exposed to strong shocks, the model struggles to fully capture the complexity of its dynamics. As zinc is strongly tied to construction and infrastructure, its behavior directly reflects public and private investment cycles.

Conclusion

This article has highlighted the dynamics of base metal prices traded in London and their sensitivity to both economic cycles and external shocks. Aluminum and copper emerged as true barometers of the global economy: they alternate between phases of high volatility during industrial expansion and calmer phases during slowdowns. This alternation reflects the central role of these two metals in construction, electronics, and infrastructure, sectors directly tied to global growth. Lead presents a different profile, characterized by structural stability that reflects a steady and less cyclical demand, particularly for batteries. In contrast, tin stands out for its chronic instability and frequent regime shifts, signaling a fragile market that depends on geographically concentrated producers and more fragmented global demand. Nickel and zinc highlight the limitations encountered in modeling but also open avenues for economic interpretation. Nickel, central to the energy transition and the battery industry, remains highly exposed to speculation and geopolitical tensions. Zinc, on the other hand, is closely linked to investment cycles in infrastructure and construction. Their complex volatility confirms that these markets respond not only to cyclical dynamics but also to structural factors that are more difficult to capture. From an economic perspective, several insights emerge. Metals such as aluminum and copper confirm their role as leading indicators of global industrial activity. Lead illustrates the possibility of more resilient markets, less exposed to crises. Finally, the instability of tin and the challenges linked to nickel and zinc remind us that an energy transition based on these resources will require deeper reflection on supply security and market regulation.

A natural extension of this approach would be to broaden the analysis by directly incorporating macroeconomic and geopolitical factors into the model. While the DGARCH regime-switching method effectively captures the internal dynamics of price series, it remains limited when it comes to explaining the origins of observed shocks. Combining this modeling with explanatory variables such as interest rates, the evolution of the US dollar, Chinese demand cycles, or geopolitical tensions would make it possible to more clearly link metal price volatility to the major drivers of the global economy. Another promising extension would be to apply this method in a multivariate framework to study interdependencies between metals, for instance the strategic role of copper and nickel in the energy transition. Such an approach would provide a deeper understanding of systemic risks and allow for the design of more effective hedging strategies for both investors and industrial users.

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