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Spillover Effects between Financial and Physical Copper Markets*

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Abstract

This article investigates the dynamics of information transmission between spot and futures copper markets by extending the Garbade and Silber (1983) model and estimating it within a Vector Logistic Smooth Transition AutoRegressive (VLSTAR) framework. Using copper data—including cyclical prices, returns, conditional volatility, and Value at Risk—we show that the futures market consistently leads information flows, with its dominance intensifying during crisis periods. Financial information is more extensively transmitted across markets than non-financial information, although only the latter exhibits regime-dependent behavior. During crises, market risk tends to remain localized, whereas return uncertainty diffuses more broadly across markets. These findings support the policy recommendation of allowing a moderate and controlled increase in spot prices to stimulate investment and prevent abrupt spikes in futures prices, which could destabilize the real economy and hinder progress in the energy transition.

JEL classification: C32, G13, Q31

Keywords: Copper prices; Spot and futures markets; Price discovery function; Information spillovers; Non-linear modelling

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1 Introduction

As the urge for the energy transition increases, so does the importance of copper as a critical raw material. It is present in all of the most important clean energy technologies due to its electronic conductivity, longevity, ductility, and corrosion resistance. Especially, it is used widely in construction and electricity networks, which account for, respectively, 30% and 15% of the global copper demand in 2023 (IEA, 2024). With the energy transition coming, the IEA (2024) expects the global demand to increase from 26 Mt in 2023 to 40 Mt in the *Net Zero Emission* (NZE) scenario. Seck et al. (2020), on their side, argue that in a +2°C scenario, the cumulative primary demand between 2010 and 2050 could represent between 89.4% and 130.7% of the copper resources known in 2010, depending on the recycling. This surge in demand can be explained by the deployment of renewables and electrical vehicles, which are copper intensive and would represent 50% of the global demand for copper in 2050 in the NZE scenario (IEA, 2024).

However, it is anticipated that the primary supply will not be able to keep up with the rising demand for copper. There are fewer mining projects as a result of the decline in ore quality and the increase in capital and operating costs to about $20,000-$30,000 per tonne of copper (IEA, 2024). Combined with an average of 7 years to make a copper mine operational (Hache and Louvet, 2023), the IEA (2024) predicts a 31% gap between expected primary mine supply and copper demand in 2035. Furthermore, social and environmental issues are becoming more prevalent globally, particularly in Latin America, where local communities are calling for improved living conditions, the redistribution of mining profits, and easier access to water. These considerations can further disturb the production of primary copper.

Given these potential shortages, a spike in the price of copper is likely to occur, with a variety of repercussions. Although a price increase can boost mining and refining projects by increasing investment profitability, it can have disastrous effects on high-end consumers and a significant impact on the actual economy because of copper's widespread use in many industries. Assessing the financial and economic effects of such price increases requires a thorough understanding of price formation as well as information spillovers, which necessitates a detailed analysis of the relationship between the physical and the financial markets. This paper tackles this issue by investigating and quantifying the price and information transfer function of the futures market for financial (cyclical prices and returns) non-financial (volatility and Value at Risk) information.

Specifically, in this paper we aim to examine futures information spillovers to the spot market for the London Metal Exchange (LME) copper market. Although some studies already exist on the topic,[1] we intend to contribute to the literature by investigating different types of information spillovers with the maximal amount of available data. The majority of the studies concentrate on the sole price discovery function, overlooking non-financial observations, and only a few use an extended sample of information.[2] We aim to fill these gaps in the present paper.

From a methodological viewpoint, we extend the Garbade and Silber (1983) model designed to quantify both the price discovery function and the risk transfer function of futures markets. This allows us to determine whether futures markets are the leading market of the information transfer function but also to quantify the strength of this function. Furthermore, we pay particular attention to non-linearity, which enables us to take into consideration various market conditions that could result in significant shifts in the relationships between futures and spot markets.

Our main findings show that futures markets dominate the process of information transmission in normal times, with their leadership intensifying during crisis periods. We also show that a retroactive loop exists between the spot and futures markets. The strength of this loop depends on the interaction between the market state and the type of the transferred information. Financial information tends to be more heavily shared across markets than non-financial information. However, non-financial information transfers are vastly impacted by the state of the market, unlike financial information. Overall, our results may be used to increase our understanding of the relationships between financial and physical markets, which help to improve our ability to model how copper could affect the real economy in the future.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the data and methodology. Section 4 describes the results and provides some policy implications. Finally, Section 5 concludes the paper.

2 The relationship between spot and futures markets: A review of the literature

The price formed in an out-of-market process and the price formed inside a market must be distinguished when discussing raw material prices. The former is used for accountability purposes by intragroup firms and is typically not publicly available. The latter takes place in a market, whether it be financial or physical, where each player is a different entity and is driven by different factors. Physical markets, also referred to as spot or cash markets, are marketplaces where goods are physically

[1] See Garbade and Silber (1983), Beckmann and Czudaj (2013), Ameur et al. (2022), Chen and Tongurai (2023), Zhu et al. (2024).

[2] See Ameur et al. (2022), who use data from 2002 to 2020, or Gulley and Tilton (2014), who use LME copper data from 1994 to 2011.

exchanged with the promise of prompt delivery (within a few days). They usually refer to a reference price in a standardized contract, to which premiums or discounts are added based on the commodity's quality and characteristics, the industry's capacity, and the stocks on the value chain's bottleneck. Financial futures markets, on the other hand, enable participants to purchase or sell the commodity at a predetermined price for a future date known as the maturity date. Compared to physical markets, they facilitate speculative and hedging behavior, which attracts more participants and boosts liquidity.

According to Goss (1981), futures markets have four functions: (i) they facilitate stockholding as the forward premium acts as a mechanism to guide inventory control and can be viewed as a return on a hedged stock; (ii) they perform a risk-transfer role between hedgers and speculators; (iii) futures prices serve as a hub for information gathering and conversion; and in the same idea, (iv) futures markets are believed to provide a price discovery function for the spot market. These last two functions refer to the notion that futures markets can incorporate new information faster than spot markets and then transfer it because of their relatively higher liquidity.

As futures and spot markets seem naturally correlated due to the hedging function of the futures market, a great field of the economics and finance literature has sought to study the link between these two types of markets. Generally, studies aim to assess the pricing efficiency, the information efficiency, or the price discovery function of futures markets. While these notions are very different, in the words of Chen and Zheng (2008), they are often confounded. Pricing efficiency refers to the capacity of the futures market to price the spot market in a way that is compliant with the theory. Information efficiency refers to the concept developed by Fama (1970), stating that if the market is informationally efficient, it is impossible to consistently outperform it by using any information that the market already knows. Finally, the pricing discovery function of the futures market describes the fact that information should first arrive in the futures market before being transferred to the spot market because of liquidity differences.

Theoretically, such a price discovery function should not exist according to Chen and Tsai (2017). In fact, in a perfectly efficient market, there should be no lead-lag relationships between the futures and spot markets. Information would reach the futures and spot markets at the same time, and investors wouldn't have any incentive to establish positions in either market. Many early empirical studies, however, indicate that there appears to be such a price discovery function from the futures markets. We can cite, for example, Booth et al. (1999) for the DAX, Tse (1999) for the DJIA, or Brooks et al. (2001) for the FTSE 100.

These three studies give mainly the same explanation for such results: futures markets are typically characterized by lower transaction costs and the availability of short-selling. The information is then first handled in the futures market since it is more liquid. With few exceptions, a price discovery function is generally found for the futures market. For instance, Chen and Tongurai (2023) note that developing markets or nations, such as Malaysia or India, are more likely to experience a lack of such a price discovery in the futures market. Yang et al. (2012) show a dominance for spot markets in the Chinese stock index, arguing that this is caused by their recent existence.

There are two main theories to explain the apparent correlation between futures and spot prices. The asset pricing theory links the current futures price to the future spot price, while the cost-of-storage theory links the current futures price to the current spot price.

According to Chen and Zheng (2008), because futures prices should represent the price at which market participants agree to transact on a set date in the future, current futures prices should be the prediction of future spot prices in an efficient futures market. Therefore, under the joint assumption of risk neutrality and rationality, Canarella and Pollard (1986) show that the current futures price is an unbiased estimate of the future spot price as in Equation (1).

$$F_{t,\tau} = E_t\left(S_{t+\tau}\right) \tag{1}$$

Where E_t is the conditional expectation given a set of information available in period t; $S_{t+\tau}$ is the spot price in period $t+\tau$; and $F_{t,\tau}$ is the futures price in period t for a delivery in period $t+\tau$. Chen and Zheng (2008) criticize the use of Equation (1) to study the pricing efficiency and the price discovery function of the futures market. They show that this equation can hold only if investors are risk-neutral or if the systematic risk of the asset is zero. Therefore, in most cases, there exists a difference between current futures prices and future spot prices known as the systematic risk premium, as displayed in Equation (2). The existence of such a risk premium leads these authors to argue that in most cases, current futures prices do not have the function of discovering future spot prices, or at least not by the validation of Equation (1).

$$F_{t,\tau} = E_t\left(S_{t+\tau}\right) - \left(R_\tau - r_\tau\right) S_t \tag{2}$$

Where R_τ is the risk-adjusted discount rate and r_τ is the risk-free interest rate to τ periods. The difference between the current futures price and the future spot price is explained by the existence of a risk premium given by $(R_\tau - r_\tau)$. As holding the commodity entails risk, the risk premium is typically positive, and so the current futures price should be lower than the expected future spot price.

The cost of storage theory has been established by Working (1949) and Telser (1958) and states that the current futures price should depend on the current spot price and the net marginal convenience yield. They show that Equation (3) should hold to avoid arbitrage opportunities in the markets. For Chen and Zheng (2008), the pricing efficiency of the futures market can be assessed by testing this theory, as did Watkins and McAleer (2002), using the specification of stock levels proposed by Heaney (1998). Using cointegration and restriction tests, they provide support for the cost of storage theory against the asset pricing theory, which is only supported in one sub-sample.

$$F_{t,\tau} = (1 + r_\tau)\, S_t - (c_{t,\tau} - k_\tau) \tag{3}$$

With $c_{t,\tau}$ being the marginal convenience yield (i.e., the benefits of holding the commodity) and k_τ the per-unit cost of storage. The difference between the marginal convenience yield and the cost of storage $(c_{t,\tau} - k_\tau)$ represents the net marginal convenience yield (i.e., the benefits of holding the commodity net of costs). We can differentiate between two market states, *backwardation* and *contango*, based on the sign of the net marginal convenience yield. A backwardation situation arises when the marginal convenience yield exceeds the cost of storage (and by extension other costs like financial costs), and so the net marginal convenience yield is positive. This situation occurs during periods of unanticipated shortages because firms with greater than normal inventories benefit from holding the commodity to avoid interruptions in their production (Gulley and Tilton, 2014). On the opposite, when the cost of holding the commodity is greater than its benefits, the market is said to be in contango.

The net marginal convenience yield is generally approximated in the literature by measuring the basis. This can simply be done by differencing the nearest futures contract price with the spot price. Jia and Kang (2022) present some other ways for estimating the basis but do not argue for major differences between them. If there is no reliable spot price for the commodity, the spot price can be approximated by the nearest futures contract price. The basis is then the difference between the second nearest futures contract price and the nearest futures contract price. Koijen et al. (2018) explain that most commodities do not have a reliable spot price because futures exchanges do not generally house both futures and spot markets.

Gu et al. (2019) postulate that the net marginal convenience yield can be defined as the sum of a persistent component (financial and transaction costs) and a more transitory component (marginal convenience yield). Using this, they define the *relative basis* as the difference between the basis and a more distant measure of the basis to approximate shocks on the marginal convenience yield. They then define the *residual basis* as the residual of the linear regression between the basis and the relative basis. They postulate that this is an approximation for shocks to financial and storage costs.

Using these different considerations about asset pricing theory and cost of storage theory, Chen and Zheng (2008) define the price discovery process as the information flow mechanism and the lead-lag relationship between the futures and the spot market. This relationship has been largely studied in the literature for most commodities with the use of multiple methodologies. One of the most used tools is the Granger causality test in order to explore if the information of futures (spot) prices increases the explanation of spot (futures) prices. Hernandez and Torero (2010) find that spot prices are typically discovered in the futures market by using both classical and non-parametric Granger tests on agricultural commodities markets. They then demonstrate, using rolling specifications, that shifts in futures prices tend to influence changes in spot prices more frequently than the other way around. As argued by Nicolau and Palomba (2015), while investigating energy products, these dynamical interactions between spot and futures markets are frequently demonstrated to depend greatly on the commodity examined.

Additionally, several research studies with Granger tests have been done using different frequencies, such as Zhu et al. (2024), which use a Complementary Ensemble Empirical Mode Decomposition with Adaptative Noise (CEEDAM) decomposition to break down the price variables of different metals into distinct frequencies. Then, using a Granger causality test, they discovered that futures prices have an impact on spot prices, while the opposite is generally not true. Additionally, they emphasize that the price discovery function's strength varies noticeably depending on the metal and time scale. In the same spirit, Joseph et al. (2014) determine a strong unidirectional association between futures and spot markets by testing Granger causality in the frequency domain on a variety of commodities on the Indian market.

In his review of Granger causality studies, Grosche (2014) lists a few challenges when applying this methodology. Granger tests only reveal the causality's direction. It provides no information regarding the sign or the strength of the relationship. Furthermore, outcomes are highly dependent on the data set and model specification used. Commodity and time sample selection are important factors that can significantly impact outcomes. However, in their analysis of the time-varying problem, Nicolau and Palomba (2015) conclude that, for commodities like gold, gas, and oil, the causal relationship remains largely constant over time. Finally, only lag relationships are considered when using a Granger causality test.

The Error Correction Model (ECM) and cointegration tests are also popular methods for examining whether there is a long-term relationship between spot and futures prices (Booth et al. (1999), Tse (1999), and Brooks et al. (2001)). Furthermore, they can serve as an initial analysis or check before estimating more intricate specifications. This can be found in Beckmann and Czudaj (2013), who find that for a variety of industrial metals, all pairs of spot-futures prices are cointegrated, then use cointegration results to estimate various specifications. This is also the case in Hache and Lantz (2013), who estimate Markov-Switching Vector Error Correction Model (MS-VECM) after having found a long-term relationship between oil WTI futures and spot prices.

While the price discovery function of the futures market is the most studied part of the information transfer function, some studies used Granger tests and cointegration tests to investigate other spillover types between spot and futures markets. To evaluate risk spillovers across Chinese copper markets, Liu et al. (2008) estimate the Value at Risk (VaR) thanks to GARCH-type models. By using Granger tests, they find that there exists a bi-directional causality between the spot and futures markets, but the information and risk spillovers are much stronger from the futures market. Živkov et al. (2022) examine the intra- and between-market volatility spillover on some precious metals with a Markov-Switching (MS)-GARCH model. They find that while there are uncertainty spillovers across the markets, the spillovers within each market are stronger. They also show that the intensity differs from the market that is sending the information. In the same idea, Yang et al. (2012) used an asymmetric ECM-GARCH model and show that there is a strong bidirectional dependence in the intraday volatility of both futures and spot markets for the China stock index.

Such methodology makes it hard to quantify the strength and importance of the price discovery function, especially when bi-causality is found. To overcome this problem, Garbade and Silber (1983) propose an econometric framework based on a theoretical model to quantify both the price discovery function and the risk transfer function of futures markets. Their methodology makes it possible to quantify the rate of convergence between the two prices and determine the proportion of transferred information from futures to spot markets. According to Garbade and Silber (1983), the futures market performs nearly 60% of the price discovery function for a number of agricultural and mineral commodities. The findings for Omaha's hog market and the WTI crude oil market are similar, according to Schroeder and Goodwin (1991) and Moosa (2002), respectively.

Garbade and Silber (1983) initially estimate two AuroRegressive Distributed Lag

(ARDL) specifications by Ordinary Least Squares (OLS) with only one lag for futures and spot prices. In contrast, Moosa (2002) chooses to integrate polynomial trend and time-varying parameters in a Seemingly Unrelated Regression (SUR) framework to get around some econometric issues, like non-stationarity or bi-causality.

Non-linearities have gained attention in this literature on information spillovers and the price discovery process. According to Lin and Liang (2010) and Simioni et al. (2013), non-linearities can be caused by financial market frictions such as high transaction costs or the involvement of noise traders, and they can prevent price shocks from spreading below a certain threshold. Huang et al. (2009) claim that because possible trade gains cannot exceed transaction costs, investors may only react slightly to price changes when the gap between spot and futures prices is not large. Since production lags and finite inventories imply that negative shocks to the future optimal consumption path can be accommodated more quickly than positive shocks, inventory management can also be a source of non-linearities for Borenstein et al. (1997).

Many studies use abrupt transition models to take these non-linearities into account. For example, Ameur et al. (2022) estimate a Non-linear AutoRegressive Distributed Lag (NARDL) model that depends on the short-term and the long-term asymmetry between spot and futures prices. They find a bidirectional relationship between the two markets and a leadership of the futures market. In the same idea, Panagiotou and Naka (2024) estimate a local non-linear regression on different energetical products to test the symmetries in sign and size between spot and futures prices. Contrary to other studies, they do not find evidence of non linearity. Wu et al. (2018) estimate a threshold cointegration model on the corn and soybean markets using the short-term difference between spot and futures prices as a transition variable. They find asymmetry in the spot price adjustment depending on whether the futures price increases or decreases. Chen and Tongurai (2023) take a sample from 2016 to 2019 of the China stock market and find that correlations between spot and futures markets have increased during the trade dispute between China and the USA, emphasizing the role of the state of the economy. This is also supported by Hache and Lantz (2013), who use an MS-VECM model to find two distinct states for the short-term price dynamics: standard and crisis. Schroeder and Goodwin (1991) argue that during large price moves that are not anticipated in the futures market, the spot market discovery dominates or at least gains in importance. As for Živkov et al. (2022), they find that volatility spillovers differ between low and high volatility regimes. During crises, volatility transmission is much stronger within markets than between the markets, indicating that such information tends to stay in the same market during periods of high uncertainties.

Teräsvirta (1996) had criticized these kinds of brutal transition modelings to account for non-linearities, arguing that such a brutal pattern may be insufficient when there are investors with varying expectations and risk assessments on the market. The heterogeneity of participants implies different bands of inaction advocating for a smooth transition framework, as in Beckmann and Czudaj (2014), who find that the predictive power of futures spread is much stronger in a backwardation regime. Beckmann and Czudaj (2013) and Beckmann et al. (2014) used a Logistic Smooth Transition Regression (LSTR) model to find an adjustment of future spot returns to the forward spread when the volatility of the previous spread was low. However, there is minimal indication of a price discovery function when this volatility has been high.

3 Data and methodology

3.1 Data

3.1.1 Prices and returns

We use London Metal Exchange (LME) copper spot and futures price data from the Reuters Refinitiv Eikon database. We take these data from the first available date through January 23, 2025, on a daily basis (see Table 1). Spot prices start in 1987. The first futures contract to be offered was the 15-month in 1991, and the 3- and 27-month contracts followed two years later. The LME has a unique structure by housing both physical and financial markets. The LME copper spot price (suffixed with "CASH") is then a reliable price at which market participants can buy and sell the commodity with an obligation of delivery within three days, while futures prices are settled against this actual spot price. The LME copper market offers futures contracts with the following five maturities: 3-, 15-, 27-, 63-, and 123-month.[3]

Series	Start date	End date
LCPCASH	1987-11-19	2025-01-23
LCP3MTH	1993-07-01	2025-01-23
LCP15MT	1991-04-08	2025-01-23
LCP27MT	1993-07-20	2025-01-23
LCP63MT	2002-09-30	2025-01-23

Note: The beginning date is the day that the Reuters Refinitiv Eikon database begins to provide daily data. Some series, such as the spot series, had their first data removed in order to preserve only the daily data because they were in weekly frequencies.
Source: LME data from Reuters Refinitv Eikon

Table 1: Starting and ending dates for LME copper spot and futures prices

[3]Due to a too weak number of observations, we do not consider the 123-month maturity.

The spot and futures prices for LME copper are shown in Figure 1. From the 1990s to the start of the 2000s, copper prices declined as a result of the two oil shocks, which raised the cost of producing copper while decreasing industrial and construction activity. A significant structural shift in the dynamics of copper prices began in 2001 when China joined the World Trade Organization (WTO). Due to the massive demand for copper in China (whose consumption increased at annual rates of over 15 % between 2003 and 2008) and the constrained mining capacity worldwide,[4] copper prices more than quadrupled, reaching nearly \$9000 per metric tonne prior to the 2008 financial crisis. The price of copper dropped to nearly \$3000 per metric tonne during the subprime crisis, but the market quickly recovered and hit a new high. The global economic contraction of the 2010 decade decreased the demand for copper, thus lowering its price until the end of the COVID-19 crisis and the return to "normal" economic activity, which caused a new surge in prices.

Note: LME spot and futures prices are represented and expressed in dollars per metric tonne.
Source: LME data from Reuters Refinitv Eikon

Figure 1: LME copper spot and futures prices

Price series being characterized by a unit root,[5] we consider their first-log difference, i.e., price returns. As shown in Figure 5 in Appendix 6.2, with the exception of spot returns, which are right-skewed, these series are all left-skewed and exhibit

[4]John Zadeh, "The History of Copper Prices: 175 Years as an Economic Indicator" *Discovery Alert*, 2025-06-27, https://discoveryalert.com.au/news/copper-economic-indicator-2025-predicts-trends

[5]Results are available upon request to the author.

an excess of kurtosis. Additionally, they display clusters of volatility during times of crisis, suggesting that the volatility appears to be serially correlated.

While return series are useful because of their easy computing and interpretation, they cannot obviously be interpreted in the same manner as prices. Specifically, although studying returns information spillovers is important, it is not similar to investigating price information spillovers or the "price discovery function". Thus, to obtain a stationary price series, we use the Hodrick-Prescott (HP) filter developed by Hodrick and Prescott (1997). This is a non-parametric method that allows decomposing a series Y_t into a long-run seasonal component τ_t and a cyclical component $(Y_t - \tau_t)$.[6]

As shown in Figures 6 and 7 in Appendix 6.2, the long-term seasonal component exhibits the same visual characteristics as the original price series: a significant rise in the middle of the 2000s and a sharp decline shortly before 2010 and during the European crisis. Up until the subprime crisis, the cyclical component deviates from the trend by a relatively small amount. Following this episode, there are significantly more departures from the trend, particularly around the years 2010 and 2020. Finally, all cyclical price series appear to follow the same pattern.

3.1.2 Volatility and VaR

We consider the GARCH-type framework to proxy the volatility of our series. To this end, we proceed in three steps. First, we model the conditional mean of returns as an ARMA(p,q) process—with a possibility of adding seasonal orders to have a SARMA(p,q,P,Q) process—and rely on information criteria and oversizing test to select the appropriate lag orders.

Second, we identify the appropriate probability distribution for the innovation among Gaussian and skewed Gaussian distributions, Student and skewed Student distributions, Generalized Error Distributions (skewed or not), normal inverse Gaussian distribution, Generalized Hyperbolic distribution and the Johnson's SU distribution. To this end, we estimate the SARMA(p,q,P,Q)-GARCH(1,1) model for each probability distribution and select the one that minimizes the information criteria.[7]

Third, we select the appropriate GARCH model. Since financial series are known to respond asymmetrically to both positive and negative shocks, we apply the three sign bias tests—a negative sign bias test, a positive sign bias test, and a joint sign bias test—developed by Engle and Ng (1993). If the null hypothesis of no sign bias cannot

[6] Following Weron and Zator (2015), we consider a smoothing parameter equal to 5×10^5, which is the appropriate value when dealing with daily data.

[7] We first tried to process with an out-of-sample methodology to select the best predictive model with the Diebold and Mariano (2002) test. However, we did not find any significant differences across models. We then decided to go with an in-sample methodology.

be rejected by these tests, we retain a standard GARCH specification. If the null is rejected for at least one of these tests, we estimate two additional models—EGARCH and GJR-GARCH—and select the model that minimizes the information criteria.

The specification selected for every return series is summarized in Table 2. A GARCH specification works better for shorter futures maturities, while models with sign effects appear to describe longer maturities more accurately. In order to account for more kurtosis than the Gaussian probability distribution, either the Student, Johnson's SU (JSU) or Generalized Error Distributions (GED) were selected.

Series	Mean model	GARCH model	Distribution	Order
LCPCASH_returns	ARMA(2,2)	GARCH	Student	(1,1)
LCP3MTH_returns	ARMA(0,1)	GARCH	GED	(1,1)
LCP15MT_returns	ARMA(0,1)	GARCH	JSU	(1,1)
LCP27MT_returns	ARMA(0,1)	GJR-GARCH	GED	(1,1)
LCP63MT_returns	ARMA(0,1)	EGARCH	GED	(1,1)

Note: Mean models are chosen from the SARMA(p,q,P,Q) specification that minimizes the AICc criterion and satisfies the oversizing test. The GARCH-type model and the probability distribution of residuals are chosen as the ones that minimize the maximum number of information criteria between the AIC, AICc, BIC, and HQ criteria. The order of the GARCH is always set to (1,1).
Source: Author with LME data from Reuters Refinitiv Eikon

Table 2: ARMA-GARCH specifications for LME copper returns

According to Figure 8 in Appendix 6.2, volatility was relatively low starting in the middle of 1995, but it increased sharply during crises and sustainedly during the subprime crisis.

After estimating the conditional volatility, we use the Value at Risk (VaR) with a time horizon of one day to produce a metric for evaluating market risks (Equation (4)).

$$\mathrm{VaR}_t = -\mu_t + z_\alpha \sqrt{h_t} \tag{4}$$

Where μ_t is the conditional expectation of the market, z_α is the α-quantile of the probability distribution of standardized errors in the GARCH specification,[8] and h_t is the conditional variance of returns.

3.2 Methodology

3.2.1 Granger causality

We first perform a Granger causality test between spot and all futures series separately in accordance with the existing literature. Since this test is sensitive to the specification selected, it is necessary to estimate a suitable system with an accurate

[8] We choose α=0.01 as it is common in the literature (see, e.g., Jorion (1996)).

specification that represents the data-generating process (Grosche, 2014). We estimate a bivariate Vector AutoRegressive (VAR) model between the spot and futures series because we are interested in information spillovers between corresponding markets. Equation (5) describes this VAR, where S_t denotes the spot series and $F_{t,\tau}$ is the futures series with a τ-months maturity.[9]

$$\begin{cases} S_t & = c_1 + \sum_{i=1}^{p} \alpha_i S_{t-i} + \sum_{i=1}^{p} \beta_i F_{t-i,\tau} + \varepsilon_{s,t} \\ F_{t,\tau} & = c_2 + \sum_{i=1}^{p} \gamma_i S_{t-i} + \sum_{i=1}^{p} \delta_i F_{t-i,\tau} + \varepsilon_{f,t} \end{cases} \tag{5}$$

The statistical test associated with the null hypothesis that futures series do not cause spot series is a standard Wald test with H0: $\beta_i = 0$, $\forall i \in 1, \ldots, p$. P-values had been computed using a wild bootstrap computation following Hafner and Herwartz (2009). To test whether the causal relationship is stable over time, we perform the Granger causality test in a recursive way (i.e., adding one observation to the sample at each iteration) and using a rolling window of 1040 days.

3.2.2 Garbade-Silber framework

To analyze the transfer of information between the spot and the futures markets, we partially reuse the methodology developed by Garbade and Silber (1983), named the GS model thereafter. Their framework is based on the model displayed in Equation (6), which links the current values of spot and futures prices to their first past value. They define $\theta = \frac{\beta_s}{\beta_s + \beta_f} \times 100$, which represents the share of transferred new information coming from futures to spot markets. Since the γ coefficients represent the new information coming from the same market and the β coefficients the new information that is transferred between the markets, θ measures the futures market dominance over the spot market. If $\theta = 50$, each market receives and sends the same amount of information to the other market. If $\theta = 100$, all the transferred information comes from the futures market, and the spot market does not send any information to the futures market. It is then a pure satellite of the futures market.

$$\begin{bmatrix} S_t \\ F_{t,\tau} \end{bmatrix} = \begin{bmatrix} \alpha_s \\ \alpha_f \end{bmatrix} + \begin{bmatrix} \gamma_s & \beta_s \\ \beta_f & \gamma_f \end{bmatrix} \begin{bmatrix} S_{t-1} \\ F_{t-1,\tau} \end{bmatrix} + \begin{bmatrix} \varepsilon_s \\ \varepsilon_f \end{bmatrix} \tag{6}$$

Initially, Garbade and Silber (1983) use two ARDL specifications to estimate Equation (6) with price variables. They restrict their coefficients to be strictly positive because of their theoretical model and constraint $\gamma_i + \beta_i = 1$, $\forall i \in \{s, f\}$. This is based on the assumption that the new information can only have a positive effect and

[9] The number of lags is selected using information criteria.

that there is no delay of more than a day in the information integration process. This is reasonable in a perfect market since all new information is immediately integrated. Nonetheless, there is probably a lag in the integration of new information in a real market.

We extend the GS model by adding a number of p lags to our specification in order to address these issues. This enables us to more accurately depict the dynamics of our various series. We can also investigate the transfer function for all the information that the markets receive, not just new information. Equation (7) represents the specification that we obtain.

$$\begin{bmatrix} S_t \\ F_{t,\tau} \end{bmatrix} = \begin{bmatrix} \alpha_s \\ \alpha_f \end{bmatrix} + \begin{bmatrix} \gamma_{1,s} & \beta_{1,s} \\ \beta_{1,f} & \gamma_{1,f} \end{bmatrix} \begin{bmatrix} S_{t-1} \\ F_{t-1,\tau} \end{bmatrix} + \cdots + \begin{bmatrix} \gamma_{p,s} & \beta_{p,s} \\ \beta_{p,f} & \gamma_{p,f} \end{bmatrix} \begin{bmatrix} S_{t-p} \\ F_{t-p,\tau} \end{bmatrix} + \begin{bmatrix} \varepsilon_s \\ \varepsilon_f \end{bmatrix} \quad (7)$$

To compute the θ coefficient, we must first aggregate all the information together. To this end, we define $\gamma_i = \sum_{j=1}^{p} |\gamma_{j,i}|$ and $\beta_i = \sum_{j=1}^{p} |\beta_{j,i}|$, $\forall i \in \{s, f\}$. We choose to take the absolute value of coefficients because we are interested in the amount of information being transferred and not in their sign. This allows us to get rid of the positivity constraints present in the initial model. The share of transferred information imputable to the futures market is then given by $\theta = \frac{\beta_s}{\beta_s+\beta_f} \times 100$.

Because it illustrates the relative importance of the futures market in the information gathering and transfer process, this coefficient is highly interesting. But by itself, it lacks explanatory power because we do not know how much information is transferred from one market to another. To remediate this issue, we calculate $\lambda = \frac{\beta_s+\beta_f}{(\beta_s+\beta_f)+(\gamma_s+\gamma_f)} \times 100$, which represents the share of transferred information in the total amount of information received by both markets. The greater λ is, the more there is a transfer of information between markets, no matter from which market. If $\lambda = 0$, markets are completely partitioned, and all their information comes from their own market. If $\lambda = 1$, the market does not keep any information. They send all their information to the other markets. In other words, each market will be completely determined by the other market. In between 0 and 1, λ indicates how much markets are partitioned from each other.

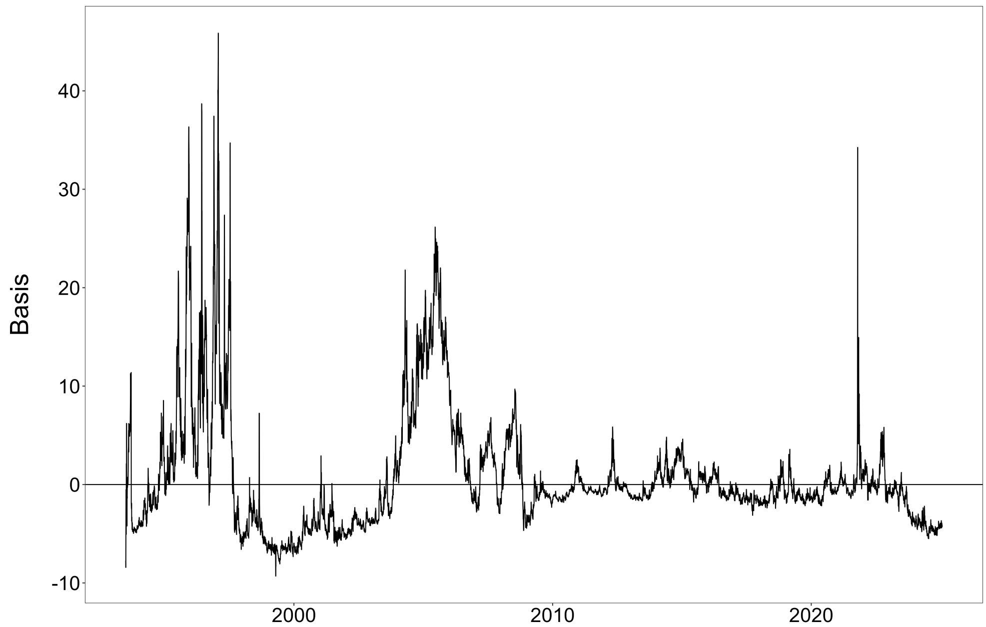
3.2.3 Econometric framework

We estimate Equation (7) with cyclical prices, returns, volatility, and VaR for each maturity—the value of p being selected using information criteria. Each model is a bivariate VAR between the spot and the futures series for a given maturity.

One of our contributions is the non-linear estimation of this model to take into consideration various market conditions that are defined by the sign of the basis given in Equation (8). It is the difference between the spot price and the first nearby contract price (3 months), scaled by the time difference (Gu et al., 2019). Since the basis's values are so tiny, we decide to multiply them by 1000 in order to get clearer results. Figure 2 depicts this series. The market is in backwardation if the basis is positive because the spot price is higher than the futures price. If it is negative, on the other hand, the market is in a state of contango.

$$\text{Basis}_t = \frac{log\,(S_t) - log\,(F_{t,3})}{3} \times 1000 \tag{8}$$

As shown in Figure 2, times of high backwardation occur during crisis periods: in the late 1990s, the 2008 financial crisis, and the COVID-19 pandemic. Furthermore, backwardation situations occur during unexpected shortages, such as sudden crises, as explained by Gulley and Tilton (2014). This is consistent with the fact that only 38.7% of days are in a backwardation situation, indicating that a futures price above the spot price characterizes the "normal" situation. Moreover, if we only take into account a high level of backwardation, this share drops significantly.



Note: The basis has been computed in the following way: $\text{Basis}_t = \frac{log(S_t)-log\left(F_{t,3}\right)}{3} \times 1000$. A positive basis indicates a backwardation situation while a negative basis indicates a contango situation.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 2: Basis of LME copper prices

Given the value of the basis, there are two primary methods for incorporating non-linearities into our specification: a brutal transition and a smooth transition.

The latter assumes that market participants are heterogeneous, resulting in multiple bands of inaction (Teräsvirta, 1996), while the former supposes that investors act approximately in the same way at the same time. We choose to estimate the multivariate Vector Logistic Smooth Transition AuroRegressive (VLSTAR) model introduced by Teräsvirta and Yang (2014), computed by Bucci et al. (2022), and presented in Equation (9) with two regimes.

$$y_t = \mu_0 + \sum_{j=1}^{p} \Phi_{0,j} y_{t-j} + G_t\left(z_t;\gamma;c\right)\left[\mu_1 + \sum_{j=1}^{p} \Phi_{1,j} y_{t-j}\right] + \varepsilon_t \tag{9}$$

Where y_t is an $n \times 1$ vector of dependent time series (namely the spot and futures series); μ_0 and μ_1 are the $n \times 1$ vectors of intercepts; $\Phi_{0,j}$ and $\Phi_{1,j}$ are square $n \times n$ matrices of parameters with lags $j = 1, 2, \ldots, p$ associated with, respectively, the lower and higher extreme regimes; and ε_t is the innovation. $G_t\left(z_t;\gamma;c\right)$ is an $n \times n$ diagonal matrix of transition functions at time t such that:

$$G_t\left(z_t;\gamma;c\right) = \operatorname{diag}\left\{G_{1,t}\left(z_{1,t},\gamma_1;c_1\right), \ldots, G_{n,t}\left(z_{n,t},\gamma_n;c_n\right)\right\} \tag{10}$$

Where γ_i and c_i are the slope and the threshold parameters for the i-th equation for $i = 1, \ldots, n$; and z_t is a stationary transition variable (namely the basis in our case). The function $G()$ is a continuous function so that, given its parameters, $0 \leq G() \leq 1$. As reminded by Dijk et al. (2002) for the univariate case, such a model can have two interpretations. The first is that there are two extreme regimes associated with $G() = 0$ and $G() = 1$ with a continuous transition between them; the second is that there is a continuum of regimes, and the one in place is determined by the particular value of $G()$. Equation (11) shows that such specification can also be interpreted as a VAR with variable coefficients. The coefficient in each period t is given by a weighted mean between extreme coefficients.

$$y_t = \mu_0 + G_t\left(z_t;\gamma;c\right)\mu_1 + \sum_{j=1}^{p}\left[\Phi_{0,j} + G_t\left(z_t;\gamma;c\right)\Phi_{1,j}\right] y_{t-j} + \varepsilon_t \tag{11}$$

The choice of $G()$ is generally made between a logistic and an exponential function. The exponential function is adapted when we are interested in the distance between the transition variable and the threshold and not by its position (superior or inferior). This does not correspond to what we are interested in. In fact, we want to examine whether the information spillover is different between contango and backwardation situations and if changes occur when we approach extreme regimes. For that, a logistic function is more appropriate. This function, described in Equation (12), allows modeling two dynamics, whether the transition variable is above or below the threshold.

$$G_{i,t}\left(z_{i,t};\gamma_i;c_i\right) = \left[1+\exp\left\{-\gamma_i\left(z_{i,t}-c_i\right)\right\}\right]^{-1} \tag{12}$$

When the transition variable is equal to the threshold, the value of the logistic function is $L(z_t;\gamma;c=z_t)=0.5$, and so the time-varying parameter corresponds to the mean between the two extreme coefficients. When the transition variable moves away from the threshold, the ponderation changes and increases the weight of one extreme regime. Eventually, if the transition variable is sufficiently far away from the threshold given a specific value of the slope parameter, only one regime will have an impact on the coefficient.

The speed of transition, and so the speed at which one regime becomes preponderant in the ponderation, is given by the slope parameter γ. The greater γ is, the speedier the transition is. If $\gamma\to\infty$, then $L(z_t>c;\gamma;c)\to 1$ and conversely, $L(z_t<c;\gamma;c)\to 0$ even for small differences between the transition variable and the threshold. In such a case, the transition is almost instantaneous, and the VLSTAR model degenerates into a TVAR model. On the opposite, if $\gamma\to 0$, then $L(z_t;\gamma;c)\to 0.5$. In such cases the time-varying coefficient is almost always the mean between extreme coefficients, and the VLSTAR model degenerates into a linear VAR.

When estimating non-linear models, the choice of starting values is crucial because it is the starting point of the convergence. We need a starting value for the slope and the threshold parameters for each equation of the VLSTAR. For that, we construct a research grid in the following way. We choose the number of different values we want to test for γ and c, denoted n; we choose a maximal possible value for γ and then draw n values of γ evenly spaced from 0 to $\gamma_{\max}$; we draw n values of c evenly spaced between the first decile and the ninth decile of the transition variable (the basis); we then combine all these possibilities together to have $n\times n$ combinations per equation. We estimate one VLSTAR for each combination and take the one that minimizes the sum of the squares of residuals for each equation. After multiple tests, where all starting values of γ were equal to $\gamma_{\max}$, we chose $\gamma_{\max}=10000$ and $n=100$.[10]

There are two primary methods for calculating the θ and λ coefficients in such a framework. The first method consists in calculating these coefficients for every extreme regime. In this manner, two extreme and opposing market conditions are represented by static coefficients. The alternative is to compute θ_t and λ_t after calculating the time-varying coefficients for each date t. In this manner, the futures market's transfer information capacity can be dynamically interpreted.

[10]The starting parameters are available in Table 7 in Appendix 6.1.

4 Results

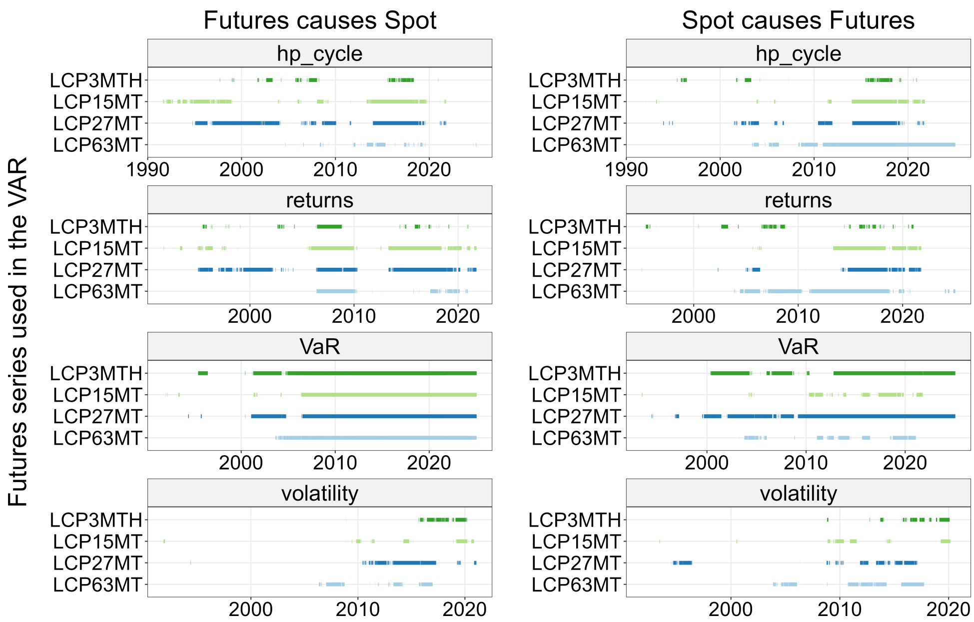
4.1 Granger causality test

We begin by investigating the existence and the mechanism of information spillover causality. To ascertain whether there is an overall causal relationship and whether the sample size has a significant impact on the findings, we employed global and recursive (adding one more observation at each iteration) tests. Using a rolling window of 1040 days, we can identify potential time-varying relationships between spot and futures series.

As predicted by theory and previous studies, a transfer information function is found for the futures market on the entire sample for both risk and returns series, as shown in Figures 10 to 13 in Appendix 6.2. Because spot market transactions depend on the immediate delivery of goods, they are less liquid than those involving the purchase or sale of a financial contract and thus are influenced by the futures market. On the contrary, for the LME copper market's longest maturity of 63-month, futures returns are found to be influenced by spot market returns. Since setting the price for five years in the future is a really long-term action, the 63-month futures market is likely to have less liquidity than the spot market, which explains the inversion of causality. Regarding the market risk information, a bidirectional causality is observed for all maturities. These results are reasonably robust to the sample size when a sufficient number of observations are considered.

Conversely, when examining cyclical prices and volatility, there is no causal relationship between spot and futures markets, except for the 63-month maturity, in which the spot market causes the futures market. We show that the sample's end date may greatly impact the test results for cyclical prices. In particular, we found that a causal relationship is obtained from futures to spot cyclical prices if we cut the sample shortly before 2010.

Figure 3 represents the periods where we find a significant causal relationship between futures and spot series using the rolling window analysis. Contrary to Nicolau and Palomba (2015)'s findings, we show that the relationship is not stable over time. Actually, the late 2000s, the 2008 financial crisis, and the COVID-19 pandemic are the three main periods of significance from futures to spot markets that we can identify. With the volatility series being a bit of an exception, it seems that the causal relationship is stronger during these times for practically all series and maturities. Finding a leading market solely through causality tests is ambitious because this figure also shows that periods of bidirectional causality are fairly common.



Note: The left-side panels represent the periods where the futures series cause the spot series at the 5% significance level. The right-side panels represent the periods where the spot series cause the futures series. Panel names indicate the type of the series studied, while y-axis names indicate the futures series used in the VAR along with the spot series.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 3: Granger causality results on a rolling window of 1040 days

4.2 Linear GS model

We explore the strength of the information transfer function by using the GS specification described earlier. Table 3 presents the estimated θ and λ coefficients for each series and maturity. The futures market is the most important market for information transfer, particularly regarding financial information. With the exception of the 63-month, which is dominated by the spot market, the futures market provides between 50% and 70% of the transferred information. The futures market's price discovery function appears to be fairly large in magnitude and to hold firmly for both returns and cyclical prices. Between 40% and 50% of financial information is transferred between markets. With the decreasing share of transfer price information as the maturity increases, there is a certain disconnection between the spot cyclical price and the longest maturity cyclical price.

The transfer function for the futures market is less important for non-financial information. Only about 20% to 30% of information is transferred between markets, and neither the futures nor the spot markets are systematically in charge of this process. This is unexpected because, in theory, the futures and spot markets are closely related, particularly considering the futures market's role in risk hedging.

Following that, risk information should move between markets; however, it appears that market risks and return uncertainty tend to remain in one market more than prices. As the Granger rolling causality tests indicated, non-linearities in the transfer function could also account for these findings.

Futures series	θ	λ
LCP3MTH_hp_cycle	57.81	43.71
LCP15MT_hp_cycle	61.99	41.18
LCP27MT_hp_cycle	69.91	39.34
LCP63MT_hp_cycle	42.79	31.05
LCP3MTH_returns	62.36	49.95
LCP15MT_returns	70.86	49.15
LCP27MT_returns	73.33	50.46
LCP63MT_returns	36.28	55.24
LCP3MTH_volatility	60.81	34.97
LCP15MT_volatility	48.69	8.09
LCP27MT_volatility	64.33	25.27
LCP63MT_volatility	16.48	15.72
LCP3MTH_VaR	45.54	34.38
LCP15MT_VaR	33.99	16.69
LCP27MT_VaR	52.20	32.14
LCP63MT_VaR	67.35	16.76

Note: Futures series names are futures series used in the VAR along with spot series. θ represents the share of information transferred from the futures to the spot market in the total of transferred information. λ represents the share of transferred information across the market in the total of information given to the two markets.
Source: Author with LME data from Reuters Refinitiv Eikon

Table 3: Estimated θ and λ parameters of the GS model with a VAR specification

4.3 Non-linear GS model

We test the non-linear behavior of our systems using the basis as the transition variable before incorporating non-linearity into our specification. We can differentiate between a contango and a backwardation scenario thanks to the sign of the basis. The contango can be defined as the "normal" market situation since the futures price is higher than the spot price due to the net cost of holding the commodity. The percentage of days in contango is 61%. The backwardation situation can be described as a market crisis since the spot price is higher than the futures prices due to the net positive gains from holding the commodity. This typically happens when stocks are stressed or there is a shortage. Around 40% of days are classified as backwardation, but this share drops sharply to around 20% and lower if we look for a stronger backwardation.

To investigate the existence of non-linearity when using the basis as the transition variable, we apply the joint-LM test proposed by Teräsvirta and Yang (2014) and computed by Bucci et al. (2022). It assesses whether all equations of our system are jointly determined by a linear process or not. We constrain the VLSTAR model to be linear with $\gamma = 0$ and regress the residuals on the endogenous variables and a 3-order Taylor expansion to detect a non-linear process. As shown in Table 4, the null hypothesis of linearity is rejected in all cases.

Futures series	LM	p.value
LCP3MTH_hp_cycle	1671.76	0.00
LCP15MT_hp_cycle	888.24	0.00
LCP27MT_hp_cycle	600.96	0.00
LCP63MT_hp_cycle	149.08	0.00
LCP3MTH_returns	360.73	0.00
LCP15MT_returns	242.45	0.00
LCP27MT_returns	202.43	0.00
LCP63MT_returns	225.71	0.00
LCP3MTH_volatility	1107.17	0.00
LCP15MT_volatility	533.94	0.00
LCP27MT_volatility	288.52	0.00
LCP63MT_volatility	113.41	0.00
LCP3MTH_VaR	900.20	0.00
LCP15MT_VaR	433.51	0.00
LCP27MT_VaR	298.79	0.00
LCP63MT_VaR	115.46	0.00

Note: Futures series are the names of the futures series used in the VLSTAR along with the spot series. LM refers to the Lagrange-multiplier test statistics given by Teräsvirta and Yang (2014). A 3-order Taylor expansion has been chosen for this test. The p.value corresponds to the p-value associated with the test statistics. The basis is used as the transition variable in the model.
Source: Author with LME data from Reuters Refinitiv Eikon

Table 4: Joint-linearity test results

We estimate the GS model using a VLSTAR specification and display the estimated slope and threshold parameter in Table 5. The different thresholds found through non-linear least square estimations are all slightly positive, ranging mainly between 4 and 7. The results show that a contango and a light backwardation situation can be used to describe the market's normal state, whereas a strong backwardation situation can be used to characterize the crisis state. The slope parameters are high—more than 100 and frequently thousands—and show that the transition process is occurring very quickly, almost instantaneously. This may indicate that the LME copper market is somewhat informationally efficient. The basic theory states that when an investor's expected profit is positive, they are motivated to act. If the market is informationally efficient, information is integrated and accessible to all market participants simultaneously. As a result, they all behave the same way and act at the same time, generating an instantaneous transition between the two regimes and leading to an expected profit of zero. On the opposite, this can be the sign of animal spirits among investors (Akerlof and Shiller, 2010). As the backwardation became more prominent, the investor's "confidence" could switch and change their classical behavior into a possibly non-economic rational behavior as postulated by Akerlof and Shiller (2010). They will act at the same time and in the same way, but not through rationality and economic reality, but through instinct. These two hypotheses go against the reasoning developed by Teräsvirta (1996), according to which the heterogeneity of investors implies different bands of inaction and thus a smooth transition process.

Futures series	γ_S	γ_F	c_S	c_F
LCP3MTH_hp_cycle	303.03	202.02	5.68	5.43
LCP15MT_hp_cycle	10000.00	202.02	5.43	5.41
LCP27MT_hp_cycle	606.06	1111.11	5.59	5.46
LCP63MT_hp_cycle	10000.00	10000.00	5.44	1.73
LCP3MTH_returns	1818.18	10000.00	5.42	5.42
LCP15MT_returns	10000.00	202.02	5.42	4.96
LCP27MT_returns	101.01	101.01	5.56	4.67
LCP63MT_returns	1818.18	202.02	5.51	1.70
LCP3MTH_volatility	909.09	1515.15	4.07	4.07
LCP15MT_volatility	7575.76	10000.00	7.51	5.79
LCP27MT_volatility	101.01	101.01	7.50	5.74
LCP63MT_volatility	101.01	3333.33	5.53	1.00
LCP3MTH_VaR	404.04	202.02	5.55	7.51
LCP15MT_VaR	303.03	10000.00	5.55	7.58
LCP27MT_VaR	404.04	101.01	6.64	5.77
LCP63MT_VaR	10000.00	202.02	5.59	1.53

Note: Futures series names indicate the futures series used in the VLSTAR model along with the spot series. γ_S and γ_F are the slope coefficients of the logistic function associated with, respectively, the spot and futures equations of the VLSTAR. c_S and c_F are the thresholds associated with the spot and futures equations of the VLSTAR. The basis is used as the transition variable in the model.
Source: Author with LME data from Reuters Refinitiv Eikon

Table 5: Estimated slope and threshold coefficients of the VLSTAR specification

In the case of such high transition speed, the VLSTAR specification degenerates into a TVAR specification with a brutal transition between the two regimes. Results are displayed in Table 6. The two market states have essentially the same definition when we examine the single threshold for each series. Even though the outcomes are less clear-cut for the VaR, the futures market still seems to be in control of the information transfer process in the standard state, just like in the linear case. The spot market dominates only for the 63-month maturity.

All series and maturities, without exception, see an increase in the futures market's dominance during a market crisis. This can be explained by the relative change in the liquidity between spot and futures markets. Because holding copper has benefits during times of crisis, the futures market's relative liquidity rises. The spot market became less liquid since there are fewer incentives to sell on it. As a result, the futures market incorporates information more quickly and accurately, which explains why its transfer function is reinforced. The spot market's reduced liquidity lowers the "quality" of its information and makes futures information more important. In such a backwardation situation, more than 60-70% of the transferred information comes from the futures market, leaving only a small importance for spot market information.

Futures series	c	θ_{inf}	θ_{sup}	λ_{inf}	λ_{sup}
LCP3MTH_hp_cycle	1.18	52.73	61.05	50.07	44.05
LCP15MT_hp_cycle	1.19	57.58	64.82	45.90	43.59
LCP27MT_hp_cycle	4.78	63.94	69.29	42.19	44.82
LCP63MT_hp_cycle	1.46	32.50	79.41	34.67	37.64
LCP3MTH_returns	6.38	54.28	61.29	50.32	49.59
LCP15MT_returns	6.38	57.85	77.46	49.69	48.53
LCP27MT_returns	4.79	61.71	76.42	49.11	47.68
LCP63MT_returns	1.18	17.83	71.95	54.94	63.51
LCP3MTH_volatility	4.45	59.67	66.08	36.98	41.65
LCP15MT_volatility	7.20	54.76	75.82	27.70	40.82
LCP27MT_volatility	7.26	54.59	81.91	27.78	43.15
LCP63MT_volatility	1.17	12.98	33.98	22.63	6.69
LCP3MTH_VaR	5.48	50.54	51.22	38.26	38.21
LCP15MT_VaR	5.48	15.10	69.24	22.60	21.62
LCP27MT_VaR	5.07	48.92	54.79	37.53	30.12
LCP63MT_VaR	0.86	63.08	65.98	20.80	16.26

Note: Futures series names correspond to the futures series included in the TVAR along with the spot series. c corresponds to the unique threshold of the TVAR. θ represents the share of information transferred from the futures to the spot market in the total of transferred information. λ represents the share of transferred information across the market in the total of information given to the two markets. Indices "inf" indicates that this is the coefficient belonging to the inferior regime, while "sup" indicates that this is the coefficient belonging to the superior regime. The basis is used as the transition variable in the model.
Source: Author with LME data from refinitiv Eikon

Table 6: Estimated θ and λ parameters of the GS model with a TVAR specification

We also find that the strength of the transfer function differs between financial and non-financial information. Financial information exhibits a strong transfer function, with roughly half of the information provided to one market being transferred. Conversely, only about 20% to 30% of the entire amount of information is being transferred for non-financial information. The standard and crisis states of the market do not appear to have systematically different effects for financial information. Information about return uncertainty, however, seems to be more widely shared across markets during crises, rising to over 40%. In a backwardation scenario, information about market risk is less likely to be transferred and is typically more retained in the same market.

As a robustness check, we present in Table 8 in Appendix 6.1 the results for the VLSTAR specification, which appear to be quite consistent with the TVAR one, even if for the VaR and volatility it is less stringent. We also provide in Table 9 in Appendix 6.1 results for a 3-regime TVAR specification. We found that the results are quite the same between the lower and upper regimes, but the middle regime does not appear to exhibit a certain pattern and does not seem to add interesting explanations.

4.4 Economic policy implications

Our findings show that there exist retroactive loops between the financial and physical markets and that the strength of these loops varies depending on (i) which market was the first to incorporate the information, (ii) what kind of information is being transferred, and (iii) market current conditions. This could have a significant impact on how we perceive the interactions between the real and financial markets. Future supply issues for copper, a vital raw material, are anticipated as a result of low investment and potential geological resource shortages. The feedback loop between the futures and physical markets will be larger if this shortage issue is initially integrated in the futures market by a raise in prices or in risk/volatility than if it is first integrated in the physical market.

It may be possible to boost investment profitability and lessen potential future shortages by agreeing to a modest physical price increase in the near future. By doing this, the future price increase might be smaller and have less impact on the actual economy in the long run. Accepting a price increase now could also prevent a price increase during a backwardation scenario, which would strengthen the loop and the impact on the real economy. This theoretical principle, however, may be difficult to implement. The goal behind this proposition is to anchor economic expectations into an increasing price path for the future. Theoretically a perfect market should already integrate climate issues into price anticipations. However, some studies, like Faccini et al. (2023), show that this may not be the case.

Two main, non-exclusive possibilities come to mind for increasing and guiding prices in an incremental and controlled way. The first option is to establish a long-term evolutionary path for copper products and to steer prices along this trajectory through taxation. A more radical approach would be to remove copper elements from the regular market mechanism altogether by setting prices under the supervision of a UN agency. Such mechanisms would make it possible to control prices while avoiding market volatility and inconsistency. Climate risk and urgency would thereby be forcefully integrated into prices, preventing markets from disregarding these constraints. For these processes to be effective, international cooperation would be required—both to define the appropriate price level and to determine the relevant tax base. An impartial procedure and institution could be established for these purposes.

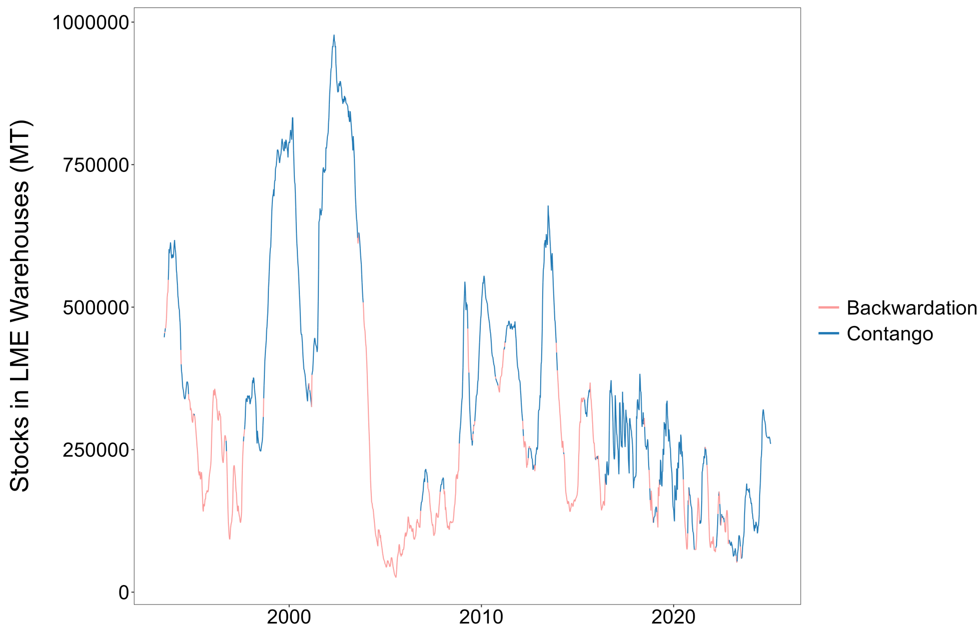
Taxes, like carbon taxes, have been shown to generate positive effects with limited impact on competitiveness provided certain conditions are met (Köppl and Schratzenstaller, 2023). One of the most important is to secure the support of firms and households on the matter in order to avoid the rejection of the tax (Heine and Black (2019), Carattini et al. (2017)), as occured in France with the carbon tax and the yellow jacket protest. Such support is generally acquired by informing the public about the policy's effectiveness and its content. Transparency regarding the use of tax revenues—whether directed toward lowering other taxes or financing climate action—is key to gaining public acceptance (Muhammad et al., 2021). Studies have found that the disruptive effects of climate taxes can be compensated by decreasing labor taxes or social security taxes, thereby yielding for a double dividend.

Another way to guide prices upward, without direct state or UN intervention in price formation, could be through monetary policy. As shown by Frankel (2006), interest rates influence highly volatile commodity prices such as food and minerals. When real interest rates are low, real commodity prices tend to be high. However, such volatile components are often disregarded by central banks, which are focused on the core CPI because monetary policy primarily targets inflation. One option to guide prices upward could therefore be to assign greater weight to these commodities when setting interest rates. It could also be possible to create a new inflation index, and so a new interest rate, focused on transition-related commodities. This would require cooperation among central banks to ensure comparability across countries and to move from a pure inflation-targeting framework toward a more diversified policy approach.

The strength of the feedback loop may also depend on the availability of the commodity itself. Stocks are likely to decline if there is a shortage of copper or if producing companies become more anxious. Such a decrease in inventories makes it more advantageous for firms to hold onto the copper rather than sell it, pushing the market into backwardation and amplifying the impact of the feedback loop originating in the futures market.

Figure 4 represents the evolution of the copper stocks in the LME warehouses. The recent period shows a downward trend, whereas the first part of the sample is marked by an upward trend. In our case, it is not the trend that is of interest but the variations of stocks and their magnitude. In case of shortages or market anxiety, this should manifest as a sharp decrease in the stocks compared to a "normal" level. Although not immediately apparent in this graph, a sharper decline can be observed during periods when backwardation was more significant in magnitude.

For the sake of completness, due to the weekly frequency of LME stocks, we use



Note: This figure displays the copper quantities available in the LME warehouses in metric tonne. The state of the economy is displayed by the color of the line.
Source: LME data from Reuters Refinitiv Eikon

Figure 4: Copper stocks in the LME warehouses

weekly series and present the TVAR results in Table 10 in Appendix 6.1 to compare weekly and daily findings. Overall, the results are robust to the change in frequency, even though the strength of the transfer function for the risk increases during crisis regimes as opposed to daily frequency.

5 Conclusion

Copper is a key material widely used in construction and electricity networks, which also plays a critical role in the energy transition as it is present in the main clean energy technologies. With its demand increasing sharply, the diminishing ore quality, and various possible mining disruptions, the IEA (2024) expects that copper will face a supply shortfall, impeding a price increase and thus possibly impacting mine investment and the real economy. Having a better understanding of the price formation and the relationships between physical and financial markets is thus necessary to better analyze the transition and the challenges we will face.

To this end, we used spot and futures prices of the LME market from 1987 to 2025 in a daily frequency. Starting from the classical idea that futures markets play a price discovery role thanks to their enhanced liquidity, we generalized this analysis to multiple information spillovers. We use two main types of information: financial information with cyclical prices and returns, and non-financial information with volatility and Value at Risk.

We find that the process of information transfer between markets is dominated by futures markets, which means that the majority of transferred information originates from the futures market, with the exception of the longest maturity. The futures market's dominant role is exacerbated during times of market crisis. Since the spot market's relative liquidity is lower than that of the futures market, it is largely unable to transfer accurate and timely information to the futures market.

We also find that financial information is vastly shared across markets, while non-financial information tends to stay more enclosed in its own market. These results show that there exist retroactive loops between the financial and physical markets and that their strength depends on the market receiving the information first and on the type of information. The multiplicative effect of the retroactive loop will be greater if the anticipated incoming shortages are initially reflected in futures prices rather than in the physical market as a result of shortages. Furthermore, we show that the global information transfer function's strength for non-financial information can be altered by market conditions. Return uncertainty spillovers will be higher during crisis states when spot prices are greater than futures prices. On the other hand, market risk spillover will be more contained within its own market, reducing its ability to spread to other markets. Our findings have important policy implications because they advocate for an acceptance of a copper price increase in the near future. This could be done by artificially increasing the copper price by a tax, removing copper and other critical material from the market process, or by creating a new inflation index with only critical materials.

Our results stimulate further research. Since the state of the market is found to be a significant factor in determining the strength of information spillover, considering the relationship between physical stocks and market conditions and how they affect the transfer function may be an interesting investigation. Furthermore, extending our analysis to other metal markets using a panel framework appears as a promising extension. Similarly, combining the different maturities into a single system may be relevant to account for potential redundant information across the various futures markets. It would also be interesting to examine interactions and spillovers from other futures markets, such as the NYMEX or the SHFE, in order to account for the degree of integration among these markets. Finally, our study also advocates for further work on the link between spot prices and their impact on the real economy through the price of clean-tech materials like solar panels or electric vehicle batteries.

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6 Appendix

6.1 Tables

Futures series	γ_S	γ_F	c_S	c_F
LCP3MTH_hp_cycle	303.03	202.02	5.67	5.42
LCP15MT_hp_cycle	10000.00	202.02	5.42	5.42
LCP27MT_hp_cycle	606.06	1111.11	5.59	5.46
LCP63MT_hp_cycle	10000.00	10000.00	5.44	1.73
LCP3MTH_returns	1818.18	10000.00	5.42	5.42
LCP15MT_returns	10000.00	202.02	5.42	4.93
LCP27MT_returns	101.01	101.01	5.55	4.69
LCP63MT_returns	1818.18	202.02	5.51	1.70
LCP3MTH_volatility	909.09	1515.15	4.07	4.07
LCP15MT_volatility	7575.76	10000.00	7.51	5.79
LCP27MT_volatility	101.01	101.01	7.54	5.69
LCP63MT_volatility	101.01	3333.33	5.51	1.00
LCP3MTH_VaR	404.04	202.02	5.54	7.51
LCP15MT_VaR	303.03	10000.00	5.54	7.51
LCP27MT_VaR	404.04	101.01	6.68	5.69
LCP63MT_VaR	10000.00	202.02	5.59	1.01

Note: Futures series names are the futures series included in the VLSTAR along with the spot series. Starting parameters are found using the research grid described in Section 3.2.3. The basis is used as the transition variable in the model.
Source: Author with LME data from Reuters Refinitiv Eikon

Table 7: Starting values used in each VLSTAR

Futures series	θ_{inf}	θ_{sup}	λ_{inf}	λ_{sup}
LCP3MTH_hp_cycle	51.18	67.13	49.35	47.94
LCP15MT_hp_cycle	58.48	68.53	45.78	46.12
LCP27MT_hp_cycle	64.49	69.63	42.38	46.15
LCP63MT_hp_cycle	34.78	86.93	35.74	46.59
LCP3MTH_returns	50.43	63.39	50.18	50.67
LCP15MT_returns	58.46	82.28	49.46	52.49
LCP27MT_returns	60.56	79.46	48.70	47.73
LCP63MT_returns	18.74	75.88	53.47	56.11
LCP3MTH_volatility	60.29	65.76	37.70	41.25
LCP15MT_volatility	54.01	80.41	27.71	41.51
LCP27MT_volatility	52.03	84.84	27.02	40.15
LCP63MT_volatility	13.29	77.58	23.10	14.92
LCP3MTH_VaR	52.06	46.71	39.34	34.65
LCP15MT_VaR	19.53	69.95	19.77	20.78
LCP27MT_VaR	48.18	64.71	38.54	29.61
LCP63MT_VaR	60.72	77.21	19.24	22.34

Note: Futures series names are the futures series included in the VLSTAR along with the spot series. Coefficients are the coefficients associated with extreme regimes. θ represents the share of information transferred from the futures to the spot market in the total of transferred information. λ represents the share of transferred information across markets in the total information given to the two markets. "in" refers to the inferior regime and "su" to the superior regime. The basis is used as the transition variable in the model.
Source: Author with LME data from Reuters Refinitiv Eikon

Table 8: Estimated θ and λ parameters of the GS model with a VLSTAR specification

Futures series	c_1	c_2	θ_{inf}	θ_{mid}	θ_{sup}	λ_{inf}	λ_{mid}	λ_{sup}
LCP3MTH_hp_cycle	1.18	5.81	52.69	53.45	65.56	50.07	47.15	46.43
LCP15MT_hp_cycle	1.52	4.87	57.48	60.40	64.33	45.22	48.49	45.27
LCP27MT_hp_cycle	1.52	4.87	61.88	64.30	68.35	41.48	46.94	42.84
LCP63MT_hp_cycle	1.51	5.02	32.03	63.36	72.39	34.49	40.51	43.22
LCP3MTH_returns	1.46	6.26	53.68	56.51	61.85	50.14	50.09	49.93
LCP15MT_returns	1.57	6.38	59.34	61.37	77.46	49.68	51.16	48.53
LCP27MT_returns	1.18	4.93	63.31	56.59	75.91	49.40	49.79	46.59
LCP63MT_returns	-2.34	1.18	8.51	14.81	71.95	39.98	57.00	63.51
LCP3MTH_volatility	-0.21	4.41	61.40	58.96	65.99	36.46	46.02	41.59
LCP15MT_volatility	-0.54	7.26	59.41	54.19	75.95	30.78	34.09	40.89
LCP27MT_volatility	2.74	7.26	57.68	54.81	81.91	25.73	38.42	43.15
LCP63MT_volatility	-0.74	-0.33	23.00	13.81	24.39	21.44	38.89	9.91
LCP3MTH_VaR	-2.47	5.48	56.01	54.40	51.22	45.67	39.66	38.21
LCP15MT_VaR	-3.33	5.48	52.78	20.77	67.10	31.25	23.93	21.43
LCP27MT_VaR	-2.31	5.07	67.03	48.57	54.79	37.44	39.45	30.12
LCP63MT_VaR	0.85	4.96	62.89	50.37	59.24	20.91	17.02	23.29

Note: Futures series names are the futures series included in the TVAR along with the spot series. Coefficients are the coefficients associated with extreme regimes. θ represents the share of information transferred from the futures to the spot market in the total of transferred information. λ represents the share of transferred information across markets in the total information given to the two markets. "inf" refers to the inferior regime, "sup" to the superior regime, and "mid" to the middle regime. The basis is used as the transition variable in the model.
Source: Author with LME data from Reuters Refinitiv Eikon

Table 9: Estimated θ and λ parameters of the GS model with a 3-regime TVAR specification

Futures series	c	θ_{inf}	θ_{sup}	λ_{inf}	λ_{sup}
LCP3MTH_hp_cycle	-0.64	50.24	55.95	50.62	49.31
LCP15MT_hp_cycle	3.31	54.07	64.56	46.88	48.02
LCP27MT_hp_cycle	3.29	56.94	68.06	38.33	45.51
LCP63MT_hp_cycle	0.29	45.42	70.59	40.27	16.71
LCP3MTH_returns	1.24	51.85	66.42	49.81	50.55
LCP15MT_returns	4.01	60.26	69.96	49.57	51.35
LCP27MT_returns	4.00	58.35	68.67	49.41	48.70
LCP63MT_returns	3.62	53.82	50.28	48.77	62.84
LCP3MTH_volatility	4.12	37.95	78.34	35.44	44.67
LCP15MT_volatility	4.12	46.27	87.11	18.92	39.78
LCP27MT_volatility	5.39	50.30	82.43	18.91	35.72
LCP63MT_volatility	5.30	26.92	43.45	33.75	39.76
LCP3MTH_VaR	4.04	57.70	69.03	47.09	48.07
LCP15MT_VaR	4.12	81.05	78.10	39.08	42.97
LCP27MT_VaR	4.66	56.51	71.81	41.92	38.64
LCP63MT_VaR	-0.99	63.94	68.55	31.12	40.89

Note: Futures series names correspond to the futures series included in the TVAR along with the spot series. c corresponds to the unique threshold of the TVAR. θ represents the share of information transferred from the futures to the spot market in the total of transferred information. λ represents the share of transferred information across the market in the total of information given to the two markets. "inf" refers to the inferior regime and "sup" to the superior regime. The transition variable used is the percentage change in the basis between the spot price and the 3-month futures price. Series are expressed in weekly frequency.
Source: Author with LME data from Reuters Refinitiv Eikon

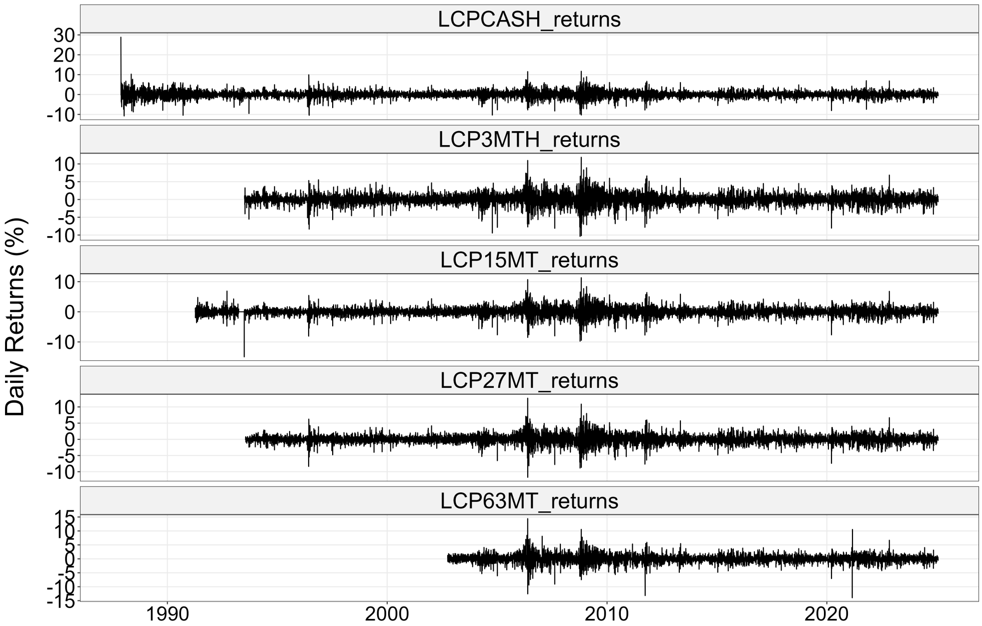
Table 10: Estimated θ and λ parameters of the GS model with a 2-regime TVAR using the basis as the transition variable (weekly frequency)

Futures series	c	θ_{inf}	θ_{sup}	λ_{inf}	λ_{sup}
LCP3MTH_hp_cycle	-0.84	56.45	47.15	50.08	44.33
LCP15MT_hp_cycle	-3.41	58.24	50.52	49.60	44.46
LCP27MT_hp_cycle	-3.41	59.46	58.87	48.46	41.57
LCP63MT_hp_cycle	-4.85	63.67	52.38	45.02	31.76
LCP3MTH_returns	4.54	60.94	51.08	49.97	50.90
LCP15MT_returns	-1.32	63.86	49.28	48.49	53.50
LCP27MT_returns	-0.84	60.43	49.18	48.35	47.67
LCP63MT_returns	-4.85	52.11	60.79	49.17	47.11
LCP3MTH_volatility	5.18	67.71	45.37	30.45	50.00
LCP15MT_volatility	5.18	88.99	40.91	12.54	41.63
LCP27MT_volatility	5.18	67.13	53.75	14.35	36.59
LCP63MT_volatility	5.00	26.44	39.73	34.02	46.26
LCP3MTH_VaR	4.91	64.76	51.31	43.87	50.31
LCP15MT_VaR	2.69	73.87	65.58	37.26	42.25
LCP27MT_VaR	2.68	63.15	48.34	36.07	47.18
LCP63MT_VaR	-1.83	67.26	51.09	38.22	37.06

Note: Futures series names correspond to the futures series included in the TVAR along with the spot series. c corresponds to the unique threshold of the TVAR. θ represents the share of information transferred from the futures to the spot market in the total of transferred information. λ represents the share of transferred information across the market in the total of information given to the two markets. “inf” refers to the inferior regime and “sup” to the superior regime. The transition variable used is the percentage change in the copper stocks available in the LME warehouses.
Source: Author with LME data from Reuters Refinitiv Eikon

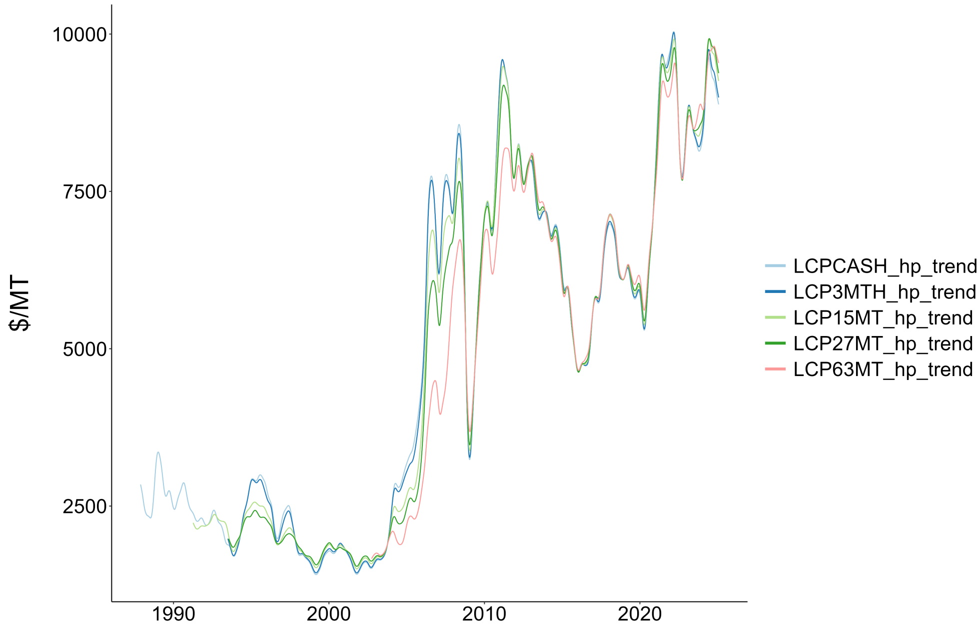
Table 11: Estimated θ and λ parameters of the GS model with a 2-regime TVAR and percentage change in the LME stocks as the transition variable

6.2 Figures



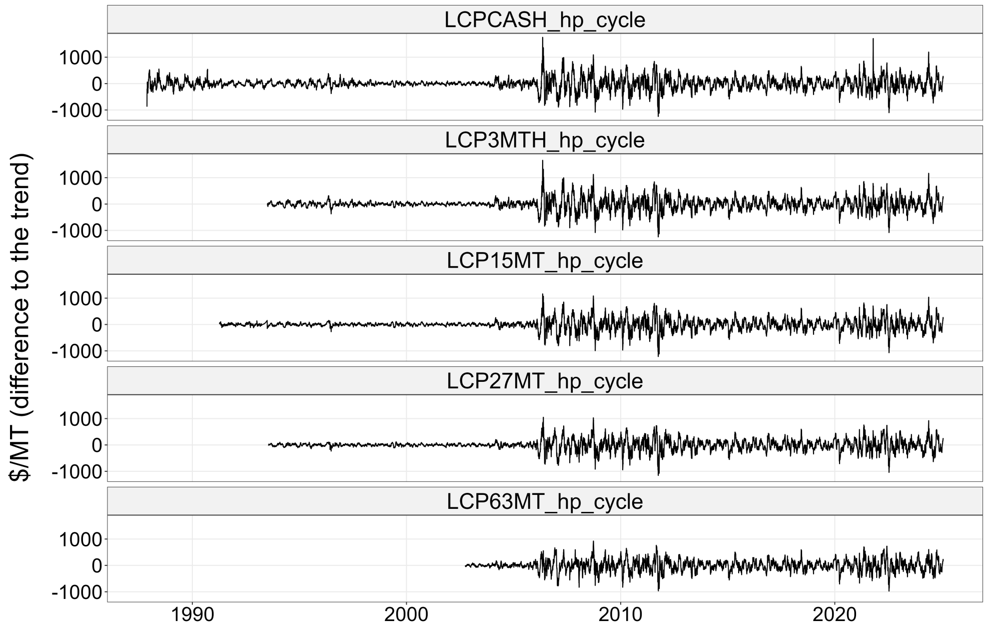
Note: Returns are computed as the log-difference of daily prices, such as:
$\text{Returns}_t = log\,(Y_t) - log\,(Y_{t-1}) \times 100$.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 5: Returns representation of LME copper prices



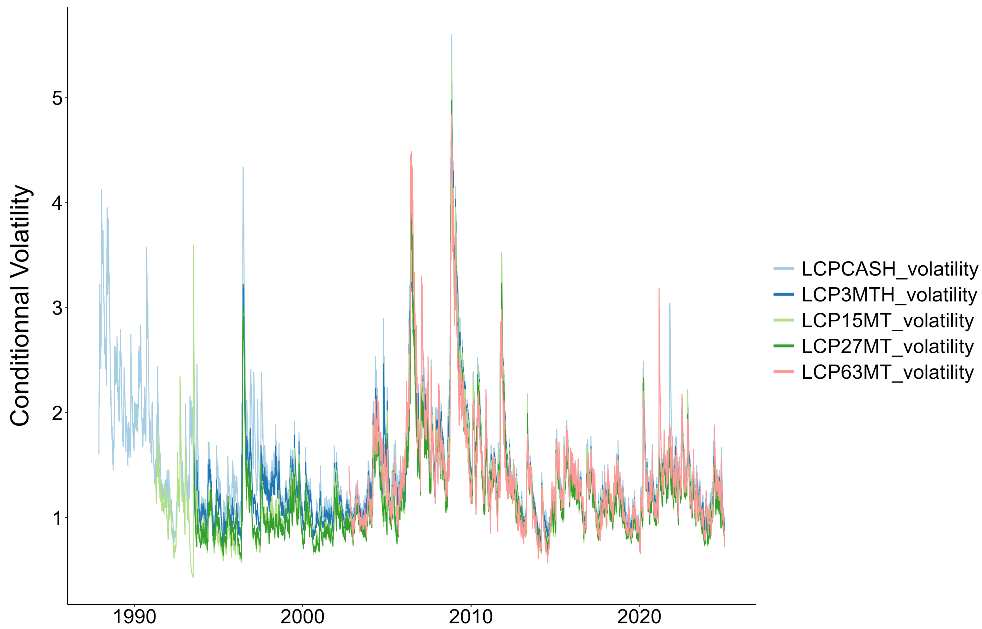
Note: The long-run trend of each price series is defined using the Hodrick-Prescott filter with $\lambda = 5 \times 10^5$.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 6: Long-term seasonal component representation of LME copper prices



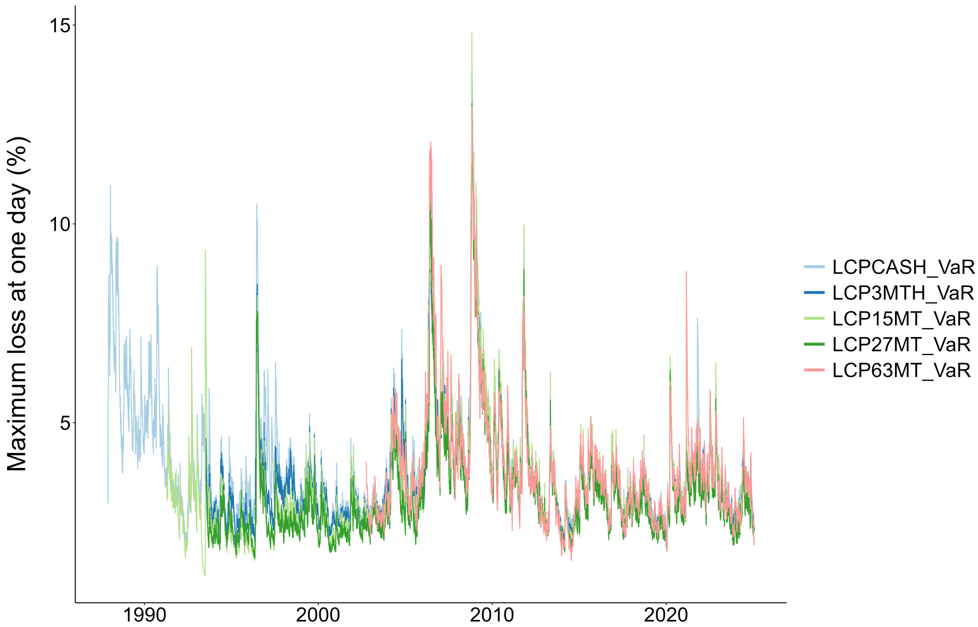
Note: The cyclical component of each price series is defined by using the Hodrick-Prescott filter with $\lambda = 5 \times 10^5$.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 7: Cyclical component representation of LME copper prices



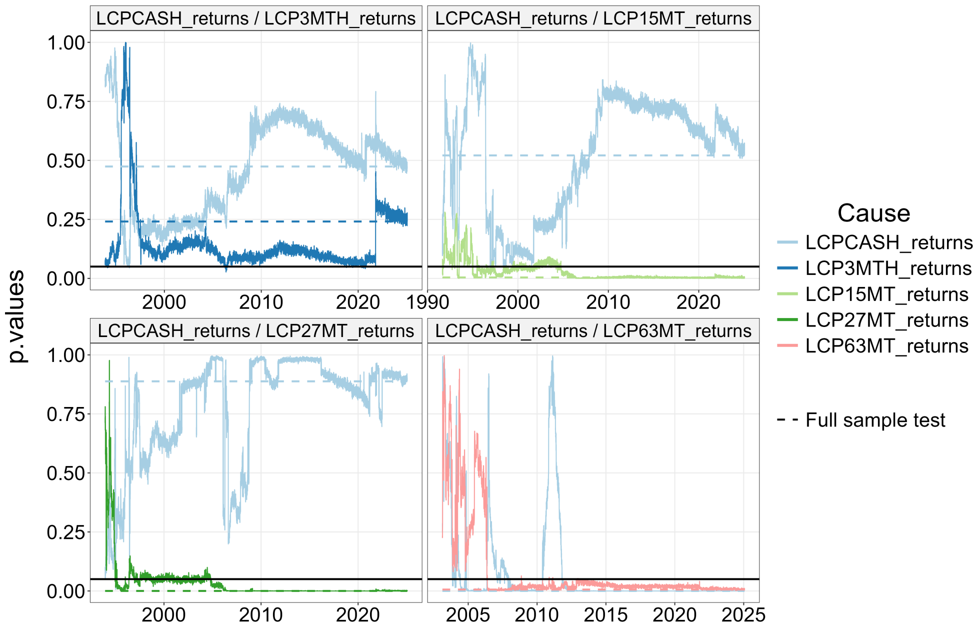
Note: Conditional volatility had been computed using GARCH-type specification from copper returns series. Mean models are chosen from the specification that minimizes the AICc criterion and satisfies the oversizing test. The GARCH model and the probability distribution of residuals are the ones that minimize the maximum number of information criteria between the AIC, AICc, BIC, and HQ criteria. The order of the GARCH is always set to (1,1).
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 8: Conditional volatility representation for LME copper markets



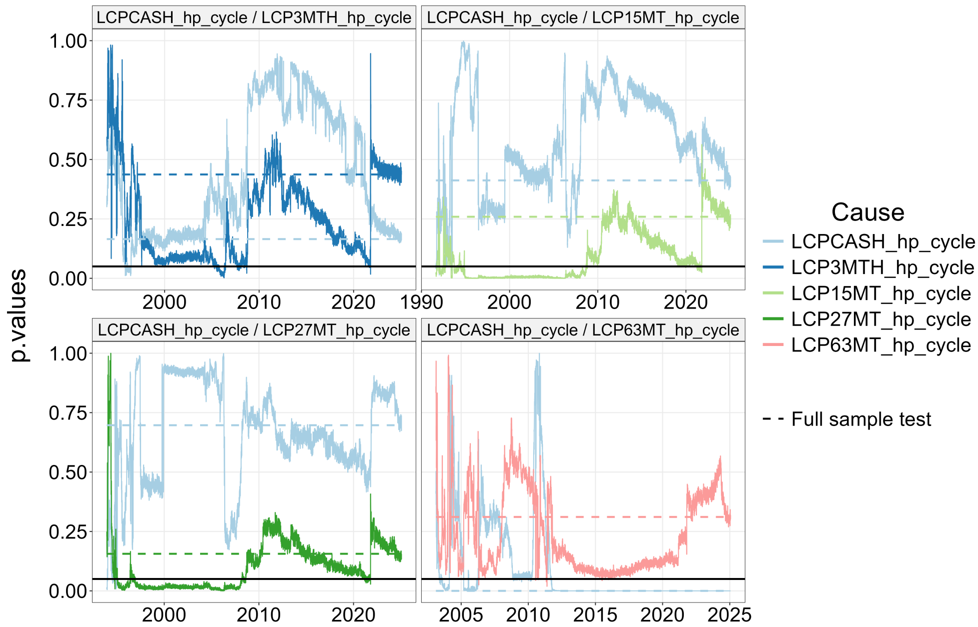
Note: The VaR has been derived using the conditional volatility estimated by GARCH-type specification with a quantile $\alpha = 0.01$ and a time horizon of one day. Mean models are chosen from the specification that minimizes the AICc criterion and satisfies the oversizing test. The GARCH model and the probability distribution of residuals are the ones that minimize the maximum number of information criteria between the AIC, AICc, BIC, and HQ criteria. The order of the GARCH is always set to (1,1).
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 9: Value at Risk representation for LME copper markets



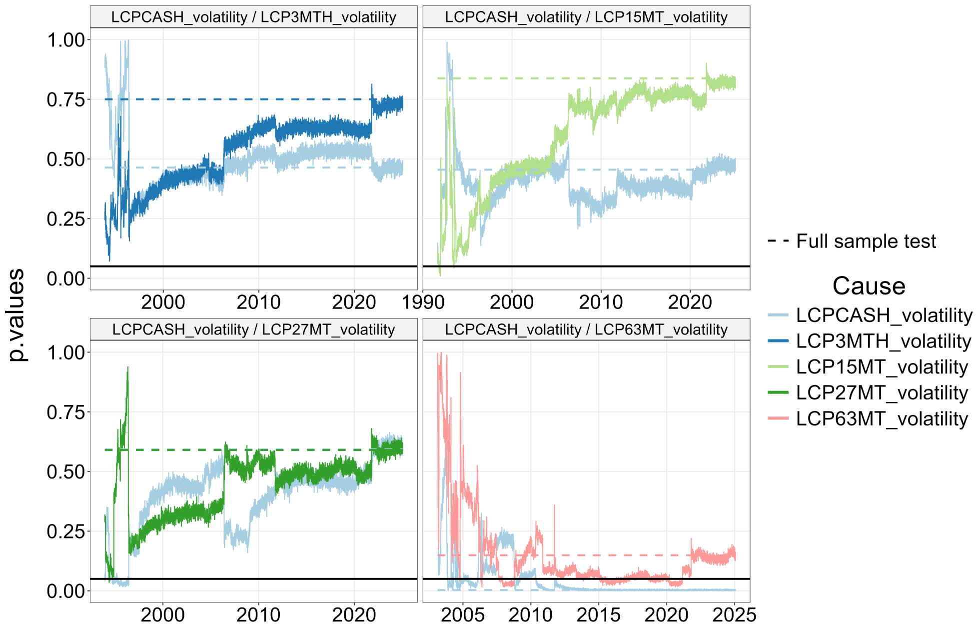
Note: Each panel displays the recursive results of the Granger causality test between spot and future series. The null hypothesis is the absence of Granger causality from the "cause" variable to the other. We choose the optimum number of lags for each iteration by minimizing the AIC criterion. Full lines indicate the p-value associated with the test for a given date, while dashed lines indicate results of the test on the full sample.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 10: Recursive Granger causality test results on returns series



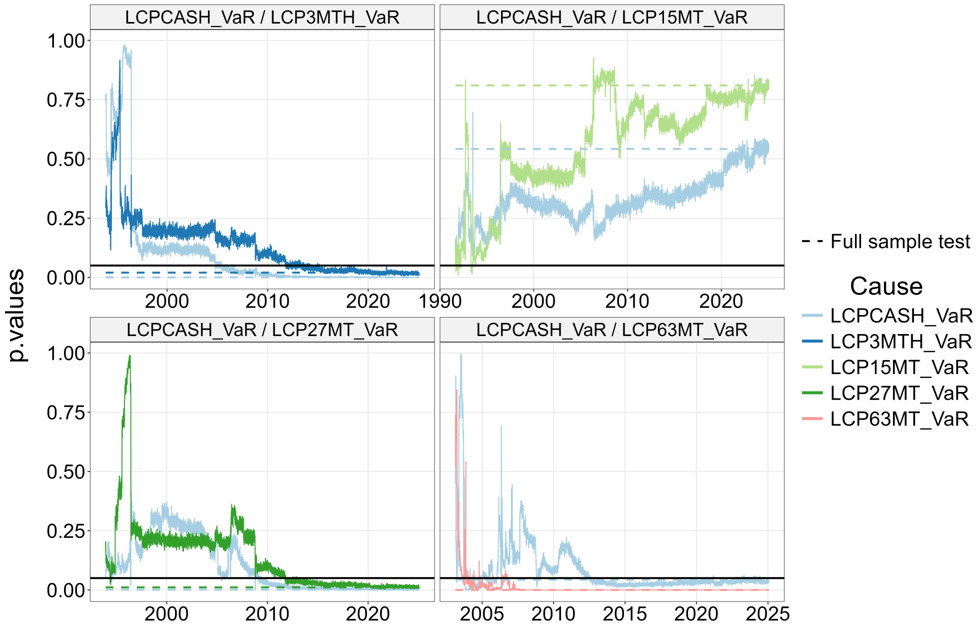
Note: Each panel displays the recursive results of the Granger causality test between spot and future series. The null hypothesis is the absence of Granger causality from the "cause" variable to the other. We choose the optimum number of lags for each iteration by minimizing the AIC criterion. Full lines indicate the p-value associated with the test for a given date, while dashed lines indicate results of the test on the full sample.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 11: Recursive Granger causality test results on cyclical prices series



Note: Each panel displays the recursive results of the Granger causality test between spot and future series. The null hypothesis is the absence of Granger causality from the "cause" variable to the other. We choose the optimum number of lags for each iteration by minimizing the AIC criterion. Full lines indicate the p-value associated with the test for a given date, while dashed lines indicate results of the test on the full sample.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 12: Recursive Granger causality test results on conditional volatility series



Note: Each panel displays the recursive results of the Granger causality test between spot and future series. The null hypothesis is the absence of Granger causality from the "cause" variable to the other. We choose the optimum number of lags for each iteration by minimizing the AIC criterion. Full lines indicate the p-value associated with the test for a given date, while dashed lines indicate results of the test on the full sample.
Source: Author with LME data from Reuters Refinitiv Eikon

Figure 13: Recursive Granger causality test results on VaR series