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Liquidity Commonality and the Risk Premium in the Chinese Metal Futures Market

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Abstract

Our study finds strong liquidity commonality across China's metal futures contracts, as about 47% of liquidity changes in individual contracts can be explained by a market-wide factor during 2019-2025. Liquidity fluctuations also show mean-reverting behavior, meaning they tend to return to normal levels after short-term shocks. Moreover, this co-movement in liquidity remains statistically significant both before and after China’s Zero-COVID policy shift.

The analysis also reveals a statistically significant liquidity risk premium in this market. Less liquid contracts earn higher average returns, indicating that investors demand extra compensation for illiquidity. This result is robust when using the raw Amihud illiquidity measure, but the effect becomes much weaker and loses significance when the liquidity measure is log-transformed. These findings emphasize that liquidity risk is priced in Chinese metal futures while highlighting how the choice of liquidity metric can influence the observed premium.

Keywords: Liquidity Commonality, Risk Premium, Amihud Illiquidity, Chinese Futures Market, Panel Regression

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Content

1 Introduction

1.1 Research Background

In modern financial markets, liquidity is widely regarded as a core indicator of market efficiency and stability. It affects how easily assets can be traded without causing major price swings, and supports essential market functions such as price formation, resource distribution, and risk transfer. In futures markets, its role is even more pronounced, as it supports risk control and hedging activities while also reflecting the market's level of development and operational quality.

In China, the futures market has grown rapidly in recent years, with a wider range of products and steady upgrades in trading systems. Among these, metal futures have gained importance as tools that connect different stages of the industrial value chain. They now contribute significantly to price setting, risk mitigation, and investment flows. Still, this expansion has brought challenges like uneven liquidity, higher volatility, and increased systemic risk.

At the macro level, the global economic landscape has become increasingly uncertain in recent years. Sharp fluctuations in international commodity prices, divergence in regional monetary policies, and the resurgence of trade protectionism have exerted ongoing pressure on financial markets, including those in China. In this context, liquidity risk is no longer confined to specific assets or markets; instead, it increasingly exhibits cross-asset interconnectedness and systemic contagion. Existing studies have found that liquidity in the stock and bond markets often declines simultaneously, a phenomenon known as liquidity commonality. Whether this phenomenon also exists in the futures market, particularly in metal futures, remains an open empirical question.

From a microstructure perspective, trading behaviors in the futures market have grown increasingly complex. The rise of algorithmic and high-frequency trading, the coexistence of institutional and retail investors, and differences in trading intensity and leverage levels all contribute to greater heterogeneity and time-varying characteristics in market liquidity. Although different contracts may exhibit varying levels of liquidity at any given time, it remains unclear whether there are underlying common factors driving co-movements in liquidity across contracts. Moreover, such co-movements may be amplified during extreme events, posing a potential threat to market stability.

Therefore, an in-depth investigation into the dynamics of liquidity in China's metal futures market—particularly the existence of liquidity commonality and its role in risk pricing—represents a highly relevant and meaningful research direction.

1.2 Research Content

This paper examines two key topics in China's metal futures market: Liquidity Commonality and the Liquidity Risk Premium. To address these issues, the study applies concepts from market microstructure theory, draws on models related to liquidity and asset pricing (e.g., Pastor & Stambaugh, 2003; Acharya & Pedersen, 2005), and considers unique features of the Chinese futures market to build empirical frameworks and carry out comprehensive analyses.

First, to examine liquidity commonality, this study adopts Amihud's (2002) illiquidity measure as a proxy for liquidity. The dataset includes eight major metal futures contracts listed on China's three main futures exchanges, covering the period from January 2019 to March 2025. Principal Component Analysis (PCA) is applied to capture the common liquidity factor across contracts. A panel regression approach—incorporating both static and dynamic panel models—is used to determine whether individual contract liquidity is driven by overall market liquidity. Control variables include trading volume growth, return volatility, SHIBOR rates, the Producer Price Index (PPI), and open interest, reflecting both micro and macro aspects of liquidity behavior. To test robustness, the sample is divided into two phases—before and after the implementation of China's "Zero-COVID" policy—to assess how major policy changes may have influenced the market's liquidity dynamics.

Second, to investigate the liquidity risk premium, this study employs the two-step Fama–MacBeth (1973) regression approach to examine whether liquidity is a priced risk component. Key factors influencing returns—such as volatility, open interest, and contract maturity—are included as controls in the cross-sectional analysis. To improve estimation quality and maintain sample consistency, contracts with extremely high or low liquidity (e.g., iron ore and lead futures) are excluded, focusing instead on six contracts with more stable liquidity. The dataset is monthly, and all independent variables are lagged by one period to reduce the risk of forward-looking bias. The analysis also tests the robustness of results under different liquidity measures, including raw and log-transformed forms. Additionally, the Newey–West adjustment is used to address issues of autocorrelation and heteroskedasticity in the coefficient estimates.

Overall, this study constructs two integrated empirical frameworks to investigate liquidity from the perspectives of commonality and pricing. It offers empirical evidence and policy implications for understanding the systemic characteristics and pricing mechanisms of liquidity in China's metal futures market, contributing to a better understanding of liquidity dynamics in emerging derivatives markets.

1.3 Research Hypotheses

Based on the literature review and the specific characteristics of China's metal futures market, this thesis proposes the following hypotheses:

Hypothesis 1 (Liquidity Commonality): Liquidity in China's metal futures market exhibits significant commonality, meaning liquidity conditions of individual contracts co-move systematically.

Hypothesis 2 (Liquidity Risk Premium): In China’s metal futures market, contracts with lower liquidity yield higher expected returns, indicating priced liquidity risk.

2 Literature Review

2.1 Liquidity Concepts and Measures

Liquidity is a fundamental feature of financial assets, reflecting how easily they can be traded across various markets and time periods. As early as 1968, Demsetz introduced the bid-ask spread as a practical measure of transaction costs, sparking widespread interest in liquidity research.

Advances in electronic trading and the rise of high-frequency data have significantly shaped liquidity measurement methods. One widely adopted metric is the illiquidity ratio developed by Amihud (2002), which captures the price impact per unit of trading volume. This approach is widely used in equity, bond, and commodity markets due to its clarity and reliability. It has also been widely adopted in emerging markets such as China (Zhang & Ding, 2021). To further improve the accuracy of liquidity measurement, Goyenko et al. (2009) compared various liquidity indicators, including the Roll measure and the zero-return frequency. Their findings suggest that Amihud's method performs well under a range of market conditions.

In contrast, measuring liquidity in futures and commodity markets is more challenging due to features such as margin requirements, physical delivery mechanisms, and market-specific rules. Marshall et al. (2012) demonstrated that even in the absence of high-frequency data, the Amihud measure remains effective in futures markets. Fong et al. (2017) further validated the robustness of mainstream liquidity measures—including Amihud, Pastor-Stambaugh, and Roll—across international commodity markets.

2.2 Liquidity Commonality: Theory and Evidence

Liquidity commonality refers to the phenomenon in which the liquidity conditions of different assets move in tandem, suggesting that a set of underlying market-wide factors may simultaneously affect the liquidity of multiple instruments. This concept was first systematically introduced by Chordia et al. (2000), who observed significant co-movements in the liquidity measures of U.S. equities.

Brockman et al. (2009) conducted a comprehensive study across 37 countries and found evidence of liquidity commonality globally. They also noted that the strength of commonality tends to intensify during periods of financial distress, such as the global financial crisis. Karolyi et al. (2012) extended this perspective by proposing the concept of global liquidity commonality, attributing its formation to the growing integration of financial markets, cross-border fund flows, and coordinated monetary policy actions. Research in emerging markets has also documented the presence of liquidity commonality, even under less developed institutional environments.

Subsequent research has sought to uncover the sources of this commonality. Hasbrouck and Seppi (2001) approached the issue from the perspective of trading behavior, suggesting that order flows exhibit synchronization across stocks, partly due to institutional investors rebalancing across similar holdings. Huberman and Halka (2001) further emphasized that stocks with large market capitalizations tend to show stronger liquidity comovements, as they attract concentrated attention from institutional investors and passive funds, amplifying shared liquidity patterns.

From a methodological perspective, principal component analysis (PCA) has emerged as a powerful tool for identifying latent liquidity factors. Sadka (2006) applied PCA to construct tradable liquidity risk factors and demonstrated that non-traded liquidity components also command risk premiums in asset pricing. This line of research laid the groundwork for integrating liquidity commonality into broader pricing frameworks. Building on this, Korajczyk and Sadka (2008) showed that although various liquidity proxies (such as zero-return days, quoted spreads, or Amihud ratios) may differ in form, they often produce consistent principal components—reinforcing the robustness of the liquidity commonality phenomenon across proxies.

In the Chinese commodity futures market, Zhang and Ding (2021) applied Amihud's illiquidity measure along with PCA to detect liquidity co-movements across major metal futures including copper, aluminum, and gold. Their results revealed heightened liquidity synchronization during periods of macroeconomic uncertainty. Notably, the identified common liquidity factor closely mirrored the co-movement of futures prices, suggesting a potential causal link between liquidity shocks and market-wide price dynamics.

2.3 Liquidity Risk as a Priced Factor in Asset Markets

Liquidity risk is commonly understood as a type of systematic risk for which investors require extra compensation. It relates to the difficulty or cost of trading an asset without causing significant price changes. When it is harder to buy or sell an asset, or when overall market liquidity changes sharply, investors often expect greater returns in exchange. This suggests that liquidity risk may lead to a return premium. This section summarizes key research that supports this idea, focusing on how these studies are connected and what they contribute.

Early studies have found that assets with lower liquidity tend to deliver stronger returns, compensating investors for the difficulty in trading them. In a well-known paper, Amihud (2002) shows that stocks with greater price sensitivity—indicating lower liquidity—often produce higher future returns. This suggests that investors demand additional returns for holding illiquid stocks. Using the two-stage regression method developed by Fama and MacBeth (1973), Amihud identified a clear illiquidity premium, which remained significant even after adjusting for other risk variables. These findings laid the groundwork for recognizing liquidity as a key factor in asset pricing.

Later studies moved from focusing only on individual asset illiquidity to examining systematic liquidity risk, which reflects market-wide liquidity changes and how they influence asset pricing. Pastor and Stambaugh (2003) proposed a broad market liquidity factor and demonstrated that stocks more responsive to these liquidity changes—those with high liquidity beta—tend to generate higher returns. In their analysis, the return difference between portfolios with strong and weak exposure to liquidity shocks was approximately 7% per year, suggesting that markets reward exposure to aggregate liquidity shifts. Building on this, Acharya and Pedersen (2005) developed a liquidity-based version of the CAPM. Their model splits liquidity risk into multiple sources, including a stock's own illiquidity and its correlation with market-wide liquidity and return movements. They showed that investors price all these components. Their empirical work confirmed that firms more affected by negative liquidity conditions tend to earn higher expected returns. These findings strongly support the view that liquidity risk is a crucial element in explaining asset returns.

Many studies have shown that the liquidity premium exists across different proxies and time periods. For instance, Liu (2006) introduced a new liquidity measure that combines multiple aspects such as trading consistency and volume. His findings suggest that a model including this liquidity factor explains stock performance more effectively than the traditional CAPM or even the Fama–French framework. He also found that the liquidity premium remains significant after adjusting for size, value, and market-related variables. This highlights that liquidity should be considered a separate risk dimension. Numerous works using Fama–MacBeth regression techniques confirm that liquidity risk carries a positive price across different samples and market environments. Overall, the evidence suggests that markets reward assets that are harder to trade or more vulnerable to liquidity shocks with higher returns.

The importance of liquidity risk is not confined to U.S. equities; it extends across asset classes and geographies. Bekaert, Harvey, and Lundblad (2007) examine emerging equity markets and find that liquidity is an important driver of expected returns there as well. They show that in less developed markets, periods of low aggregate liquidity predict higher future stock returns, consistent with a global liquidity risk premium. Beyond equity markets, liquidity effects have been observed in other domains: Sadka (2010) finds that hedge fund returns reflect exposure to liquidity risk, indicating that funds with higher sensitivity to liquidity conditions earn higher returns on average. In commodity futures markets, recent work by Zhang and Ding (2021) shows that liquidity significantly influences price co-movements and return dynamics of futures contracts.

Their results suggest that even in commodities, contracts with lower liquidity or higher covariance with market liquidity tend to command higher expected returns.

In conclusion, a large body of research has shown that liquidity risk plays a key role in asset pricing. Assets with low liquidity or those that perform poorly during liquidity shortages need to deliver higher returns to remain attractive to investors. From Amihud's early work to Pastor and Stambaugh's factor model and Acharya–Pedersen's theoretical framework, the literature agrees that liquidity represents a meaningful and systematic risk. Investors are therefore compensated for taking on liquidity risk, making it a central element in both theoretical and empirical approaches to asset pricing.

2.4 Liquidity Risk in Commodity Futures Markets

Compared with equity markets, commodity and futures markets present unique structural and trading features that introduce greater complexity to liquidity research. Key distinctions include the use of high leverage, the presence of margin requirements, and the obligation of physical delivery in some contracts. These characteristics, along with significant heterogeneity across contract types, create challenges for consistent liquidity measurement. Moreover, the dominance of institutional investors and speculative traders in these markets contributes to higher volatility and more irregular liquidity conditions. Differences in trading rules, holding patterns, and macroeconomic sensitivities across contracts further complicate the dynamics of liquidity.

Marshall et al. (2012) examined transaction costs and liquidity across 13 major commodity futures contracts. Despite variations in trading intensity, they found that the Amihud illiquidity measure remained effective in capturing liquidity behavior, especially in contexts with limited high-frequency data. Their findings support the extension of liquidity metrics from equity markets to commodity markets, showing practical relevance under real-world data constraints.

Recent studies have also explored the role of liquidity in pricing futures contracts. Acharya et al. (2005) argued that when liquidity dries up, transaction costs increase and price discovery becomes less efficient, resulting in greater return volatility. Supporting evidence from Menkhoff et al. (2012) showed that during periods of global financial instability, liquidity conditions deteriorated across commodities, foreign exchange, and equity index futures—highlighting a phenomenon known as "liquidity contagion."

A growing body of empirical research has confirmed the existence of a liquidity risk premium in commodity futures. Bessembinder et al. (1996), for instance, found that open interest and trader positioning significantly influence liquidity in energy and precious metal markets, which then impacts long-term returns. Other studies argue that liquidity risk is time-varying, and that advanced models such as GARCH-M and stochastic volatility frameworks can better capture its pricing effects (Tang & Xiong, 2012).

2.5 Research Progress and Gaps in the Chinese Market

China's financial landscape is shaped by unique institutional features, including a dominant presence of retail investors, frequent policy-driven interventions, and evolving market infrastructure. These characteristics introduce additional complexity and context dependence in the analysis of liquidity commonality and liquidity-related risk, warranting tailored methodological approaches.

Initial investigations in the Chinese context concentrated primarily on the equity market, with a focus on selecting appropriate liquidity proxies and constructing factor-based explanatory models. In a parallel effort, Liu and Hu (2005) examined trading data from the Dalian and Zhengzhou Commodity Exchanges, observing that during periods of intensified market activity, agricultural futures contracts tended to experience synchronous improvements in liquidity—an indication of potential cross-contract commonality.

More recent research has shifted toward identifying common liquidity factors and exploring their pricing implications. A growing number of studies have employed classical liquidity measures—such as the Amihud illiquidity ratio, Roll's spread, and the Pastor-Stambaugh factor—combined with dimensionality reduction techniques like principal component analysis (PCA) to derive composite liquidity indices. A notable example is Zhang and Ding (2021), who applied this methodological framework to China's metal futures market, demonstrating that the principal components extracted from various liquidity proxies significantly account for fluctuations in returns during volatile market phases. Similarly, Wu and Zhang (2020) constructed a liquidity index based on CSI 300 constituents, revealing stronger explanatory power for mid- and small-cap stocks, which are typically more sensitive to liquidity shocks.

Within the broader futures market literature in China, empirical efforts have been largely concentrated on agricultural commodities—such as soybean meal, cotton, and palm oil—or energy-related contracts like crude oil and purified terephthalic acid (PTA). For example, Xu (2020) investigated the role of liquidity changes in signaling shifts in price discovery leadership across agricultural futures. Their findings suggest that liquidity not only captures transactional frictions but also reflects the dynamic reallocation of informational efficiency within the market. By contrast, research focusing on industrial metal futures—including copper, aluminum, and zinc—remains relatively limited. This gap is particularly noteworthy considering that these commodities are closely tied to global economic cycles and industrial output, rendering their liquidity patterns especially sensitive to macroeconomic indicators such as GDP growth and manufacturing activity (e.g., PMI indices). Furthermore, trading in these contracts is typically dominated by institutional and commercial hedgers, resulting in higher capital concentration and episodic liquidity clustering or deterioration, which may have important implications for market stability and systemic risk transmission.

Another limitation in existing research is that most studies remain at the level of descriptive statistics or single-indicator analysis. Only a few papers apply more advanced empirical strategies, such as Fama-MacBeth regressions, to evaluate whether liquidity factors earn measurable risk premiums. Even fewer integrate PCA and FMB jointly to construct and test liquidity-based pricing frameworks. As a result, the literature remains fragmented and lacks a comprehensive approach to capturing the structural properties and pricing implications of liquidity commonality in China's futures markets.

From a theoretical perspective, most Chinese studies continue to rely heavily on classical frameworks developed in the West, such as those proposed by Amihud (2002), Chordia et al. (2000), and Pastor and Stambaugh (2003). There is limited evidence of efforts to adapt or localize more advanced models, such as Acharya and Pedersen's (2005) liquidity-adjusted CAPM (LCAPM), for the unique institutional and behavioral conditions present in China.

Data availability also presents a barrier. Although exchanges such as the China Financial Futures Exchange (CFFEX) and the Dalian Commodity Exchange (DCE) provide some contract-level data, standardized high-frequency order flow data remains largely inaccessible. This limits the applicability of more sophisticated microstructure models, such as Hasbrouck's (2009) effective spread estimation. Moreover, frequent changes in regulatory policy—ranging from margin adjustments to position limits—introduce exogenous shocks that complicate the modeling of stable liquidity patterns.

In conclusion, substantial gaps remain in the literature on China's metal futures market, particularly concerning the construction of cross-sectional and time-series liquidity factors, the measurement of systemic liquidity risk, and the empirical testing of liquidity risk premiums. Future research should prioritize the development of integrated frameworks that combine factor extraction techniques (e.g., PCA) with robust pricing tests (e.g., Fama-MacBeth regression), while also considering the distinct regulatory and behavioral dynamics of China's financial system.

2.6 Summary and Research Positioning

A review of domestic and international literature reveals that liquidity, once considered a secondary market feature, is now recognized as a central factor in shaping market efficiency, asset valuation, and systemic resilience. In equity markets, the concepts of liquidity commonality and liquidity risk premia have matured significantly. Though research on commodity and futures markets started later, it is rapidly catching up, with growing empirical support and methodological sophistication.

However, China’s futures markets—particularly the metal segment—still lack comprehensive studies on cross-sectional liquidity structures and the dynamics of liquidity risk pricing. Much of the existing literature remains confined to single-contract analyses or descriptive statistics, falling short of integrating cross-sectional and time-series dimensions into a unified analytical framework.

This thesis aims to address that gap by focusing on the Chinese metal futures market. Utilizing the Amihud illiquidity measure, principal component analysis (PCA), and Fama-MacBeth two-stage regression techniques, the study will identify common liquidity factors and examine whether they are systematically priced. By pursuing this empirical strategy, the research seeks not only to fill an important academic void but also to offer practical guidance for market participants and regulatory authorities.

3 Methodology and Empirical Design

This chapter presents the data sources and key variables used in the empirical analyses. The specific empirical strategies and model estimations will be discussed in Chapters 4 and 5, respectively

3.1 Data Sources and Sample Selection

We utilize daily data for major Chinese metal futures contracts obtained from the Wind database, covering the period from Jan 2019 through Mar 2025. Our sample focuses on actively traded base metal futures listed on the major Chinese commodity exchanges. Specifically, metals such as CU, AL, ZN, PB, and NI are selected from the Shanghai Futures Exchange (SHFE); iron ore (I) is sourced from the Dalian Commodity Exchange (DCE); and contracts like SF and SM are obtained from the Zhengzhou Commodity Exchange (CZCE). These contracts are selected due to their high trading volumes, continuous listing status, and importance in China’s industrial economy. They represent key commodities with active participation from hedgers and speculators, making them ideal for analyzing liquidity dynamics in the Chinese futures market.

Each of these contracts is represented by its continuous near-month series (denoted with the “00” suffix in Wind) to ensure a continuous price and liquidity time series despite contract expiration and rollover. Using continuous series allows us to capture the primary liquidity and price dynamics of each metal over time without breaks.

Note that the analyses of liquidity commonality and liquidity premium use slightly different contract samples. For the commonality analysis, we retain all eight major metal futures contracts (including iron ore and lead) to capture a broad, market-wide view of liquidity co-movements. This inclusive approach is consistent with the objective of identifying systemic liquidity dynamics across diverse instruments.

In contrast, the liquidity premium analysis focuses on isolating pricing effects and requires a more homogeneous sample to avoid biases from contracts with extreme or atypical characteristics. Therefore, we exclude I.DCE (iron ore) and PB00.SHF (lead) from this part of the analysis due to their highly disproportionate liquidity profiles (see Section 4.1 for further detail). The refined sample for premium includes six base metal futures, ensuring comparability across contracts and a cleaner identification of return–liquidity relationships. Price and trading data (settlement prices, trading volume, open interest, date to maturity etc.) for each futures contract are from Wind database. Macroeconomic series are incorporated from other Chinese financial databases – for instance, the Shanghai Interbank Offered Rate (SHIBOR)), which serves as a proxy for short-term funding rates, and the Producer Price Index (PPI) from the National Bureau of Statistics. All series are aligned at a daily frequency. For the liquidity risk premium analysis, which is conducted at a monthly frequency, we aggregate or sample the daily data into monthly observations (e.g. end-of-month prices to compute one-month returns, monthly averages for liquidity measures, etc.). The sample period (2019–2025) covers a recent regime in China's commodity markets, including calm and volatile subperiods (such as the COVID-19 shock), providing a robust test for liquidity effects in different market conditions.

3.2 Key Variables

For each futures contract i and day or month t, we choose the following key variables:

Individual Contract Liquidity ($\mathbf{LIQ_{i,t}}$): This is the dependent variable in liquidity commonality analysis and an independent variable in liquidity premium analysis, also serving as inputs for PCA to extract the market-wide liquidity factor. For each contract, liquidity is proxied by the Amihud illiquidity ratio, a benchmark metric that quantifies the sensitivity of prices to trading volumes. Specifically, for daily data we compute:

$$Amihud_{i,t} = \frac{|R_{i,t}|}{V_{i,t}} \tag{3.1}$$

Where $R_{i,t}$ denotes the raw return (price change as a fraction of price, typically using the log return for continuity) of contract i on day t, and $V_{i,t}$ represents the transaction volume in monetary units, calculated as:

$$\text{Trading Value}_{i,t} = \text{Price}_{i,t} \times \text{Volumei}_{i,t} \times \text{Contract Multiplier}_{i,t},$$

where $\text{Price}_{i,t}$ is the settlement price of contract i at time t, and the contract multiplier of a futures contract specifies the unit quantity of the underlying asset for commodity futures.

$Amihud_{i,t}$ quantifies the price response relative to the amount of trading activity. A larger ratio indicates that small trades move the price substantially, implying lower liquidity. We take absolute return in the numerator because liquidity is related to the magnitude of price movement regardless of direction. In constructing this measure, we follow the original specification proposed by Amihud (2002), who shows its effectiveness in capturing illiquidity effects in stock markets. Subsequent studies have confirmed its validity in various asset classes, including global equities and commodity futures, making it a standard liquidity proxy in empirical finance.

Market-Wide Liquidity Factor ($\mathbf{LIQ_{m,t}}$): $\text{LIQ}_{m,t}$ serves as the key independent variable in our analysis of liquidity commonality, representing the single latent factor that drives co-movements in individual contract illiquidity. On each trading day t, we collect the cross-section of Amihud illiquidity ratios ($\text{LIQ}_{i,t}$) for all eight selected metal futures contracts and extract the shared factor structure through principal component analysis (PCA). The first principal component—being the linear combination of $\text{LIQ}_{i,t}$ values that captures the largest share of total variance—constitutes $\text{LIQ}_{m,t}$. By construction, PCA guarantees that $\text{LIQ}_{m,t}$ is orthogonal to all higher-order components. We then normalize the series to have a mean of 0 and a standard deviation of 1, facilitating interpretation of regression coefficients and ensuring time-series comparability. A positive shock in $\text{LIQ}_{m,t}$ corresponds to simultaneous increases in individual illiquidity (i.e. a market-wide liquidity contraction), whereas negative values indicate a broad easing of trading frictions. This approach follows Chordia et al. (2000) and allows us to quantify systemic liquidity fluctuations in a concise, statistically robust manner.

Return variable $\boldsymbol{R_{i,t}}$: $R_{i,t}$ is the dependent variable in our Fama–MacBeth liquidity premium regressions, capturing the realized return on futures contract i at time t. We compute $R_{(i,t)}$ as the log change in settlement prices:

$$R_{i,t} = \ln\frac{P_{i,t}}{P_{i,t-1}} \tag{3.2}$$

where $P_{i,t}$ refers to the settlement price recorded at the close of trading on day t. Logarithmic returns are preferred for their time additivity and desirable statistical properties—specifically, they facilitate aggregation across days and stabilize variance. In the monthly cross-sectional analysis, we sum daily log returns within each month and then convert the cumulative log into a simple return to preserve the additive framework. We use raw log returns rather than excess returns because prevailing short-term interest rates in China over 2019–2025 remain negligible, rendering the difference immaterial.

Volume Growth ($\boldsymbol{volumegrowth_{i,t}}$) is employed as a control variable to capture day-to-day shifts in trading intensity that may affect contract-level liquidity. We obtain measures of trading activity—reflected by the number of executed contracts—through the Wind Financial Terminal. To focus on short-term fluctuations and mitigate scale heterogeneity across contracts, we define:

$$Volumegrowth_{i,t} = Volume_{i,t} - Volume_{i,t-1} \tag{3.3}$$

where $Volume_{i,t}$ denotes the daily total volume for contract i. We use the first difference of volume, denoted as $volumegrowth_{i,t}$, to capture short-term fluctuations in trading activity and reduce the impact of extreme cross-sectional heterogeneity in scale across contracts. This first-difference transformation aligns with the differencing applied to our dependent variable $\Delta\log(LIQ_{i,t})$, thereby enhancing consistency in a dynamic panel framework. Prior studies document that increased trading activity generally improves market depth and tightens bid-ask spreads (Chordia et al., 2000; Fong et al., 2017). Including $volumegrowth_{i,t}$ allows us to account for contract-specific trading surges, so that we can more precisely estimate how market-wide liquidity shocks affect each contract's illiquidity.

Volatility ($\boldsymbol{\sigma_{i,t}}$) enters our panel regressions as a control variable. $\sigma_{i,t}$ measures the return uncertainty of each futures contract. We compute daily volatility using the Exponentially Weighted Moving Average (EWMA) method, following the RiskMetrics framework (J.P. Morgan, 1996). The formula is:

$$\sigma_{i,t}^2 = \lambda\sigma_{i,t-1}^2 + (1 - \lambda)R_{i,t-1}^2 \tag{3.4}$$

where λ=0.94, and $R_{i,t-1}$ is the log return on day t-1. EWMA captures volatility clustering by assigning higher weights to recent shocks. This approach has been widely adopted in commodity and futures research (e.g., Bali and Cakici, 2004; Tang and Xiong, 2012). To isolate short-term shifts in risk, we also include the first difference, $\Delta\sigma_{i,t}$, which aligns with our dynamic panel framework and helps distinguish idiosyncratic volatility shocks from market-wide liquidity movements.

Interest Rate (SHIBOR): The 1-week Shanghai Interbank Offered Rate (SHIBOR) is introduced as a control variable to reflect variations in near-term funding pressures within China's financial markets. SHIBOR reflects the average cost rate at which banks extend unsecured funds credit to one another, serving as China's equivalent of LIBOR. Prior studies (see Acharya and Pedersen, 2005; Brunnermeier and Pedersen, 2009) suggest that tighter funding conditions impair market-making and reduce liquidity. Accordingly, we include the first difference of SHIBOR ($\Delta SHIBOR_t$) in daily regressions to capture short-term shifts in monetary stance, and end-of-month values in monthly models.

Producer Price Index (PPI) is included as a macro-level control to capture industrial cost pressures in liquidity commonality analysis. The PPI reflects upstream price pressures by measuring producer-level price changes across industrial sectors, making it particularly relevant for commodity markets. We obtain commodity-specific PPI series and match each futures contract to its corresponding category: non-ferrous metals (e.g., copper, aluminum, zinc) use the PPI for non-ferrous smelting; ferrous metals (e.g., rebar, hot-rolled coil) use the ferrous smelting PPI; and iron ore uses the PPI for mining and dressing. Since PPI is released monthly, we forward-fill its value into the daily panel. In regressions, we use the first difference of PPI (monthly percentage change) to capture shifts in industrial pricing conditions. For monthly specifications, the year-over-year inflation rate is used. The use of PPI as macro control is consistent with prior studies linking producer-level inflation to commodity return dynamics and liquidity (e.g., Goyenko and Ukhov, 2009).

Open Interest (OI) is incorporated as a control variable to account for variation in market participation and depth. It reflects the number of open futures contracts that have not yet been closed or delivered, and is widely used as a proxy for trading engagement. Higher OI typically signals stronger investor involvement and greater market liquidity, while lower OI may indicate reduced participation and thinner markets. Prior literature (e.g., Bessembinder and Seguin, 1993) documents a positive relationship between OI and market depth. In our panel regressions, we use the first difference of OI (ΔOI_t) to capture short-term shifts in participation intensity.

Time to Maturity (DTM) is incorporated as a control factor in liquidity premium analysis. It denotes the number of days left before contract expiry, thereby serving as an indicator of the investment horizon and the sensitivity of prices to time-related risk. It reflects the temporal distance to contract expiration. Shorter time to maturity often implies higher price volatility due to rapid convergence toward spot prices, while longer horizons allow for more speculative trading and gradual price adjustment. Prior studies (e.g., Bessembinder et al., 1996) have shown that futures contracts exhibit distinct volatility profiles depending on their maturity structure, particularly for agricultural and energy commodities where volatility tends to increase as contract expiration approaches (the "Samuelson hypothesis"). In our regression framework, we compute DTM on the last trading day of each month, ensuring comparability across contracts with varying delivery cycles.

4 Liquidity Commonality

4.1 Empirical Methodology

Liquidity commonality captures the degree to which liquidity movements are synchronized across a variety of financial assets. To empirically examine the liquidity commonality in China's metal futures market, we employ a panel data regression approach based on the methodology established by Chordia et al. (2000) and later utilized in commodity markets by Marshall et al. (2012). Specifically, we examine how individual contract liquidity ($LIQ_{i,t}$) relates to the overall market liquidity ($LIQ_{m,t}$).

We estimate the following panel regression model:

$$\Delta\log(LIQ_{i,t}) = \alpha + \beta_1\Delta\log(LIQ_{m,t}) + \beta_2 Controls_{i,t} + \eta_i + \varepsilon_{i,t} \tag{4.1}$$

where $\Delta\log(LIQ_{i,t})$ denotes the daily change in log individual-contract Amihud illiquidity, and $\Delta\log(LIQ_{m,t})$ represents the first principal component derived from all contracts' liquidity measures, serving as the market-wide illiquidity proxy. To address skewness and improve comparability, log transformations are applied to liquidity measures. Control variables include volume growth, changes in volatility, PPI, SHIBOR (1-week), and open interest (OI), all in first-difference form to ensure stationarity. To account for unobserved heterogeneity specific to each contract, we incorporate contract-level fixed effects (η_i). Additionally, standard errors are clustered at the contract level to address potential autocorrelation and cross-sectional dependence.

4.2 Data Processing

Prior to empirical analysis, we performed some data processing steps to ensure the validity and robustness of results. Continuous contract data obtained from Wind Database ensures the seamless integration of contracts across expiry dates and preserves data continuity, which is crucial for long-term liquidity analysis.

Given the highly skewed distribution and the presence of extreme values across futures contracts, we apply a log-transformation to the liquidity variables $LIQ_{i,t}$ and $LIQ_{m,t}$. Specifically, we use the transformation log(x + 1) to ensure that the function is defined even when the original Amihud measure equals zero—a common occurrence in highly liquid contracts with minimal price movement. This approach reduces the impact of extreme outliers, stabilizes variance across contracts, and improves comparability. Furthermore, we take first differences of the log-transformed series to emphasize short-term fluctuations in liquidity and to eliminate potential non-stationarity or persistent trends that may bias the estimation.

For control variables, we calculate volume growth as percentage change, compute volatility differences using first differences, and apply first differences to both PPI variations and SHIBOR one-week rate changes.

4.3 Model Estimation and Selection

We estimate two panel specifications to examine the drivers of contract-level illiquidity. The baseline model is a static first-difference regression that relates individual illiquidity to market-wide liquidity and other control variables. To capture the persistence in illiquidity, we extend this framework by including a lagged dependent variable, yielding a dynamic panel model. This extension allows us to account for temporal dependencies in liquidity, which may arise from order splitting, inventory effects, or gradual adjustment processes (e.g., Hasbrouck, 2007).

Baseline First-Difference Model is as follows:

$$\begin{aligned}\Delta \log\left(LIQ_{i,t}\right) = \alpha + \beta_1 \Delta \log\left(LIQ_{m,t}\right) + \beta_2 volumegrowth_{i,t} + \beta_3 \Delta\sigma_{i,t} \\ + \beta_4 \Delta PPI_t + \beta_5 \Delta SHIBOR_t + \beta_6 \Delta OI_t + \varepsilon_{i,t}\end{aligned} \quad (4.2)$$

Dynamic Panel Model is as follows:

$$\Delta \log\left(LIQ_{i,t}\right) = \alpha + \gamma \Delta \log\left(LIQ_{i,t-1}\right) + \beta_1 \Delta \log\left(LIQ_{m,t}\right) + \beta_2 volumegrowth_{i,t} + \beta_3 \Delta\sigma_{i,t} + \beta_4 \Delta PPI_t + \beta_5 \Delta SHIBOR_t + \beta_6 \Delta OI_t + \varepsilon_{i,t} \quad (4.3)$$

We employ contract-level fixed effects to control individual contract heterogeneity and utilize clustered standard errors to address cross-sectional dependence and heteroscedasticity (Pedersen, 2009).

4.4 Empirical Results

4.4.1 Descriptive Statistics

Before proceeding to regression estimation, we examine the statistical properties of the variables used in our panel models. Table 1 summarizes the core statistics of major variables after log-transformation and differencing. As expected, the original illiquidity measures (e.g.,$LIQ_{i,t}$) exhibit extreme skewness and kurtosis, indicating heavy tails and the presence of outliers. Log-transformed and differenced series - particularly for $\Delta log(LIQ_{i,t})$ - show reduced skewness and more symmetric distributions, though moderate leptokurtosis remains. These adjustments enhance the distributional properties for panel regression analysis. Among the control variables, volume growth displays extremely high standard deviation and kurtosis, which motivates our exclusion of outliers in robustness checks. The macro variables such as $\Delta SHIBOR1W_t$ and ΔPPI_t appear to be relatively well-behaved and approximately symmetric.

Table 1: Descriptive Statistics for Liquidity Commonality

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Individual Illiquidity (Raw)	52.9544	597.4285	0.0000	34783.5927	31.6400	1386.0430
Individual Illiquidity (Log)	1.4114	1.5290	0.0000	10.4569	1.7765	3.2651
Individual Illiquidity(Log-Diff)	-0.0002	1.1298	-9.9738	6.4003	-1.2802	9.0293
Market Illiquidity (Raw)	0.0003	1.3671	-0.9443	16.2803	4.3975	29.1423
Market Illiquidity (Log)	-0.4867	0.9210	-2.8870	2.8496	0.5274	0.0904
Market Illiquidity (Log-Diff)	-0.0002	0.8854	-4.0324	2.7439	-1.0549	2.9157
Volume Growth	21.5658	822.2249	-0.9967	83258.5000	89.3919	8823.7968
Volatility Diff	0.0000	0.0009	-0.0018	0.0224	9.7834	173.4496
PPI Diff	-0.0063	0.4901	-8.3000	9.7000	-1.8792	91.8525
SHIBOR Diff	-0.0004	0.0985	-0.9530	0.4320	-0.8827	8.6401
Open Interest Diff	-18.3521	25413.6480	-567057.0	386504.000	2.9479	50.1044

Note: Sample consists of 12,016 observations across 8 metal futures contracts.

Table 2 displays the pairwise correlation among the first-differenced variables. Notably, the computed correlation between individual and market liquidity changes is 0.46, suggesting moderate evidence of liquidity commonality. Changes in individual liquidity exhibit negative correlations with volume growth (-0.17) and volatility (-0.21), consistent with the view that increased trading activity and heightened market volatility tend to enhance liquidity conditions. Meanwhile, correlations between individual liquidity and macroeconomic indicators such as PPI (0.00), SHIBOR 1W (-0.04), and open interest (-0.24) are relatively weak in magnitude. These findings imply that The effects of macro variables on liquidity may be indirect or lagged, rather than immediate.

Table 2: Correlation Matrix of Key Variables for Liquidity Commonality Analysis

	Individual Illiq. (Log-Diff)	Market Illiq. (Log-Diff)	Volume Growth	Volatility Diff	PPI Diff	SHIBOR Diff	Open Interest Diff
Individual Illiq. (Log-Diff)	1.00	0.46	-0.17	-0.21	0.00	-0.04	-0.24
Market Illiq. (Log-Diff)	0.46	1.00	-0.09	-0.12	0.00	-0.07	-0.29
Volume Growth	-0.17	-0.09	1.00	0.00	0.00	0.00	0.09
Volatility Diff	-0.21	-0.12	0.00	1.00	-0.02	-0.01	-0.01
PPI Diff	0.00	0.00	0.00	-0.02	1.00	0.05	0.02
SHIBOR Diff	-0.04	-0.07	0.00	-0.01	0.05	1.00	0.01
Open Interest Diff	-0.24	-0.29	0.09	-0.01	0.02	0.01	1.00

4.4.2 Regression Results

The regression findings presented in Table 3 provide robust support for the existence of liquidity commonality within Chinese metal futures market. Both the baseline first-difference model and the dynamic panel model reveal that market-wide liquidity changes $\Delta \log(LIQ_{m,t})$ significantly influence individual contract liquidity, with results significant at the 1% level. Specifically, the dynamic panel model yields an estimated coefficient close to 0.473, implying that a 1% rise in overall market illiquidity corresponds to an approximate 0.473% uptick in individual contract illiquidity.

Table 3: Regression Results from Panel Estimation Models

	Baseline Model		Dynamic Panel Model	
	Estimate	t-Stat.	Estimate	t-Stat.
Constant	0.003***	5.400	0.003***	5.450
Lagged Individual Illiquidity	-	-	-0.256***	-10.010
Market Illiquidity Factor	0.498***	4.930	0.473***	4.680
Volume Growth	0.000***	-5.150	0.000***	-5.240
Volatility Change	-215.030***	-3.040	-153.450***	-2.760
PPI Change	-0.001	-0.140	0.005	0.550
SHIBOR Change	-0.185**	-2.120	-0.231**	-2.310
Open Interest Change	0.000**	-2.240	0.000**	-2.260
R^2	0.264		0.326	

*Note: *p<0.1, **p<0.05, ***p<0.01*

Moreover, the dynamic panel model identifies a significantly negative estimate for the lagged liquidity term (−0.256), suggesting that individual illiquidity tends to revert toward its mean over time. This suggests that liquidity shocks are temporary and tend to be corrected in subsequent periods, reflecting the self-adjusting nature of liquidity in futures markets. Such negative autocorrelation implies that when liquidity deteriorates due to short-term imbalances or shocks, it typically improves over time as market participants adjust their trading behavior and liquidity provision.

Among control variables, increased trading volume growth significantly reduces illiquidity, indicating that higher market participation enhances liquidity conditions. Volatility changes exhibit a significant negative relationship with liquidity, suggesting that heightened market uncertainty tends to deteriorate liquidity conditions. Additionally, the short-term interest rate (1W SHIBOR) negatively and significantly impacts liquidity, implying that tighter short-term monetary conditions are associated with reduced liquidity. Conversely, changes in the Producer Price Index (PPI) do not display a significant relationship with liquidity in either model, suggesting limited direct contemporaneous effects of price-level changes on futures market liquidity.

Finally, the explanatory power of the dynamic panel model ($R^2 = 0.326$) exceeds that of the baseline model ($R^2 = 0.264$), highlighting the importance of incorporating past liquidity conditions when modeling liquidity dynamics in commodity futures markets.

4.4.3 Robustness Analysis

To examine whether liquidity commonality remains stable under different macroeconomic regimes, we conduct a split-sample analysis based on the timeline of China's COVID-19 containment policies. Specifically, we define the Zero-COVID period as spanning from January 2020 to December 2022, during which China implemented stringent virus control measures including mass testing, regional lockdowns, mobility restrictions, and community-level risk classification systems.

The formal end of this policy regime occurred on December 7, 2022, marked by the Chinese authorities' announcement of the "Ten New Measures." This signaled a nationwide transition toward reopening and coexisting with the virus. This policy shift had substantial macroeconomic and financial consequences. According to Gong et al. (2023), China's GDP declined by 3.9% in 2022, driven primarily by reductions in mobility, factory activity, and energy consumption. Declines in satellite-based night light intensity and PM2.5 concentrations further corroborate the contraction in economic activity during periods of strict lockdown. In contrast, Cook and Matschke (2023) find that the post-COVID reopening period witnessed a rebound in domestic consumption and service-sector activity, with retail sales returning to positive year-over-year growth and the services Purchasing Managers Index exceeding pre-pandemic averages. Financial markets reacted as well. Using an event study on 18 sectoral indices of the Shenzhen Stock Exchange, Sharma and Kumar (2023) show that the announcement of Zero-COVID withdrawal triggered significant positive abnormal returns in sectors such as hospitality, real estate, consumer staples, and finance. This reflects a sharp reversal in investor sentiment, suggesting that markets anticipated improved business conditions and reduced policy uncertainty following the reopening.

Given this structural shift, we partition the sample into two distinct phases: (i) the Zero-COVID phase (January 2020 to December 2022), and (ii) the Post-Reopening phase

(January 2023 – March 2025).

We then re-estimate the panel regressions separately for each sub-sample to assess whether the strength of liquidity commonality changes across policy regimes. This design helps assess evaluate the robustness of our main findings in the context of a significant exogenous policy event.

Table 4 presents the regression results of liquidity commonality estimated separately for the two policy phases: (i) the Zero-COVID phase (January 2020 to December 2022), and (ii) the Post-Reopening phase (January 2023 to March 2025).

Table 4: Regression Results for Sub-Sample Periods

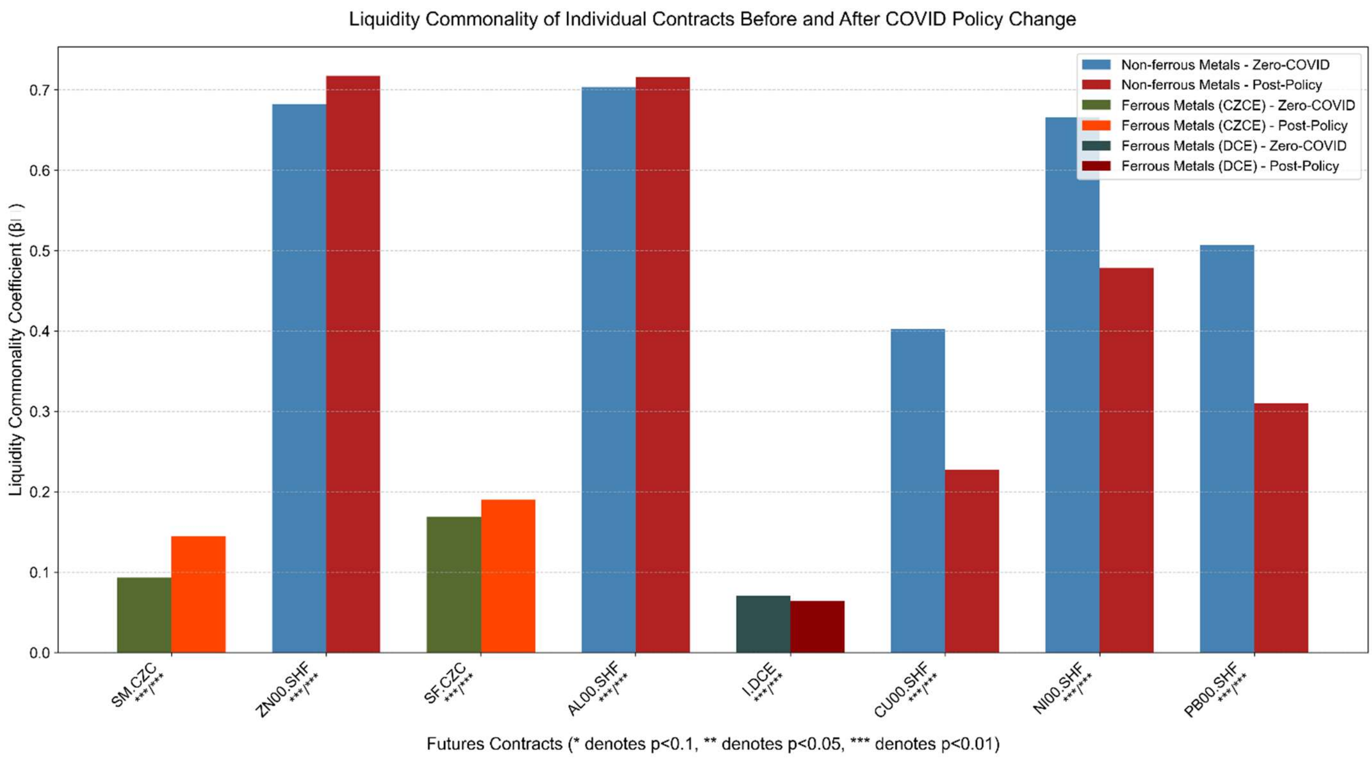
	Zero-COVID Period		Post-Reopening Period	
	Estimate	t-Stat.	Estimate	t-Stat.
Constant	0.004***	5.418	0.019***	3.795
Market Illiquidity Factor	0.500***	4.600	0.439***	4.544
Volume Growth	-0.000***	-8.483	0.002***	-4.718
Volatility Change	-202.985***	-4.220	-274.366**	-2.267
PPI Change	0.034**	1.972	0.028	1.018
SHIBOR Change	-0.271***	-2.625	-0.073	-0.798
Open Interest Change	-0.000**	-2.376	0.000**	-2.379
R-squared	0.293		0.312	
Observations	5800		4328	

*Note: *p<0.1, **p<0.05, ***p<0.01*

The results of Table 5 demonstrate that the commonality coefficient remains significantly positive across both sub-periods, indicating persistent co-movement between individual and market illiquidity. Specifically, during the Zero-COVID period (January 2020 – December 2022), the coefficient on market illiquidity (β1) is 0.500 (t = 4.60, $p < 0.01$). In the Post-Policy Adjustment period (January 2023 – March 2025), the coefficient slightly declines to 0.439 (t = 4.54, $p < 0.01$). This suggests that while liquidity commonality remains statistically significant after the policy shift, its magnitude weakens modestly.

To further explore heterogeneity across contracts, we repeat the regression for each individual futures contract. When grouped by commodity type, a clear contrast emerges. Non-ferrous metal futures (e.g., ZN, CU, NI, PB) display an average decline in commonality of 0.102, whereas ferrous metal futures (e.g., SF, SM, I) experience a slight increase averaging 0.022. This heterogeneity indicates that the sensitivity of liquidity commonality to macro-policy regime shifts may be linked to market structure, contract liquidity, or industrial relevance.

Figure 1: Comparison of Liquidity Commonality Across Contracts Before and After COVID-19 Policy Adjustment



Overall, the robustness checks confirm the persistence of liquidity commonality in China's metal futures market, with moderate shifts in magnitude around structural changes in policy. These results highlight that structural policy environments play a critical role in shaping market-wide liquidity co-movements and should be explicitly accounted for in empirical analysis.

5 Liquidity Risk Premium

5.1 Sample Selection and Contract Exclusions

While our commonality analysis intentionally includes all available contracts to capture broad market-wide liquidity dynamics, the liquidity premium analysis focuses on the pricing of liquidity risk, which necessitates a more homogeneous sample. Using contracts with similar trading intensity and liquidity levels helps ensure that differences in returns are attributable to liquidity risk itself, rather than being driven by extreme outliers. This distinction in sample selection reflects the differing empirical goals of the two analyses. Therefore, we exclude contracts with extremely high or low trading volume or illiquidity to improve sample consistency.

For the liquidity premium analysis, we exclude the I.DCE (iron ore) and PB00.SHF (lead) contracts to reduce sample heterogeneity and avoid distortion from outliers. These two contracts exhibit trading behavior and liquidity levels that are substantially different from other metal futures. For example, the iron ore contract shows extremely high trading intensity, with an average daily volume of 824,731 contracts—846% higher than the sample average—and open interest 734% above the mean. Conversely, the lead contract demonstrates much lower liquidity, with an Amihud illiquidity measure of 114.46 (123% above the sample average of 51.41) and an average daily volume of just 12,998 contracts—85% below the sample average.

These extremes suggest that the two contracts reflect different market dynamics and may not share the same risk pricing mechanisms as the other metal futures. Including them could introduce bias and reduce the internal validity of our estimates. Therefore, we focus on a more homogeneous sample of six core metal contracts, yielding 444 monthly observations and providing a consistent and controlled environment for evaluating liquidity risk premiums.

5.2 Empirical Methodology

To assess whether a liquidity risk premium exists in the market, we employ the Fama-MacBeth two-step regression framework. This approach estimates both the magnitude and statistical relevance of the premium, while controlling for standard risk factors. This methodology aligns with the established approach in liquidity premium literature (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005).

Following Amihud (2002) and Acharya and Pedersen (2005), we test whether futures contracts with higher illiquidity measures command higher expected returns. The corresponding empirical specification is presented below:

$$R_{i,t} = \gamma_0 + \gamma_1 LIQ_{i,t-1} + \gamma_2 Controls_{i,t-1} + \varepsilon_{i,t} \tag{5.1}$$

For control variables, we include volatility, open interest (in logarithmic form), and time to maturity (DTM), which have been shown to influence commodity futures returns (Marshall et al., 2012). To avoid look-ahead bias, we lag all explanatory variables by one period, ensuring that only information available before the return period is used for prediction. This is standard practice in empirical finance. For example, Irani and Kim (2019) mitigate look-ahead bias by lagging investor and firm characteristics by one quarter in their regression analyses of institutional inertia. Jia et al. (2025) follows a standard empirical design in commodity futures research by regressing next-week futures returns on lagged predictors, such as profit margin growth and control variables, ensuring signals come from an earlier period. By using lagged predictors, we ensure that all explanatory variables are known prior to the return period. This prevents look-ahead bias and preserves the correct timing relationship between market conditions and realized returns, consistent with empirical asset pricing conventions.

In line with prior asset pricing research, we employ a monthly data frequency rather than daily or weekly. Using monthly observations helps reduce high-frequency noise and microstructure biases that can distort results. Daily returns often reflect frictions like bid–ask bounce and non-synchronous trading, which introduce measurement errors and spurious short-term autocorrelations (Blume and Stambaugh 1983; Lo and MacKinlay 1988). Aggregating to monthly intervals smooths out transitory fluctuations, yielding more stable relationships and far less serial correlation in the time series. Many influential analyses of asset returns and commodity futures rely on monthly data for consistency and robustness. For example, Fama and French (1987) examine commodity futures premiums using monthly observations, and Gorton and Rouwenhorst (2006) develop commodity indices from monthly futures returns.

5.3 Data Processing and Variable Construction

We construct monthly observations from our daily dataset to explore how liquidity affects expected returns. Such a frequency is common in asset pricing studies and helps reduce noise in return measurements while allowing sufficient variation in liquidity conditions. Following Acharya and Pedersen (2005), we adopt monthly frequency to balance data granularity and return stability in the context of liquidity risk pricing.

For each futures contract i and month t, we compute the following:

Monthly returns $\boldsymbol{R_{i,t}}$: We compute monthly returns by first summing daily log returns within each month and then converting the cumulative log return into a simple return using the formula:

$$R_{i,t} = e^{\sum log(Ri,t)} - 1 \tag{5.2}$$

This approach preserves the time-additive property of log returns while facilitating interpretation in simple return terms.

Lagged Individual Contract Liquidity $\boldsymbol{LIQ_{i,t-1}}$: We measure individual contract illiquidity using the Amihud ratio from the previous month. To ensure consistency with our liquidity commonality analysis, we examine both the original Amihud ratio and its logarithmic transformation $log(LIQ_{i,t-1} + 1)$.

Control variables (Lagged at t−1): To address potential reverse causality and ensure proper temporal ordering, we use one-period lagged values (t−1) for all three control variables. First, volatility ($\sigma_{i,t-1}$) is calculated as the standard deviation of daily returns over the previous month. Second, open interest ($log(OI_{i,t-1})$) is proxied by the natural log of the contract's open interest on the final trading day of the preceding month. Third, time to maturity ($DTM_{i,t-1}$) captures the number of calendar days remaining until contract expiry. Employing lagged values for these variables aligns with established practices in asset pricing literature, where such an approach helps reduce simultaneity bias and enhances the robustness of regression estimates. Prior studies, such as Hong and Yogo (2012) utilize lagged open interest to capture its predictive power regarding macroeconomic activity and asset prices, while Boons et al. (2014) adopt similar methodologies to control for market dynamics in their analysis of commodity risk premiums.

5.4 Fama-MacBeth Regression Analysis

We implement the two-stage regression procedure of Fama-MacBeth (1973), which involves monthly cross-sectional regressions of excess returns on lagged illiquidity and other predetermined variables:

$$\mathrm{R_{i,t}} = \gamma_{0,t} + \gamma_{1,t}\mathrm{LIQ_{i,t-1}} + \gamma_{2,t}\sigma_{i,t-1} + \gamma_{3,t}\log\mathrm{O\,I_{i,t-1}} + \gamma_{4,t}\mathrm{DTM_{i,t-1}} + \varepsilon_{i,t} \quad (5.3)$$

We derive the final estimates by averaging the coefficients obtained from each cross-sectional regression over time:

$$\widehat{\gamma_J} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\gamma_{J,t}} \quad (5.4)$$

To correct for serial correlation and heteroskedasticity in the estimated coefficients, we use the HAC standard error estimator proposed by Newey-West (1987), with 4 lags. Additionally, to mitigate the influence of extreme observations, We apply a 1st and 99th percentile winsorization to the Amihud illiquidity ratio in each cross-sectional month. The coefficient associated with illiquidity is found to be positive and statistically significant in initial estimations (see Section 4.5.2 for details).

5.5 Empirical Results

5.5.1 Descriptive Statistics

Summary statistics of the main variables in the monthly sample are reported in Table 6. The average monthly return is 0.49%, with substantial cross-sectional variation (standard deviation of 7.12%). The individual contract liquidity measure shows considerable right skewness (mean of 9.97 with maximum value reaching 3000.47), which is significantly reduced through logarithmic transformation. This confirms the appropriateness of our log transformation approach.

Table 6 Descriptive Statistics of Monthly Variables

Variable	Mean	Std. Dev.	Min	Median	Max
Monthly return	0.0049	0.0712	-0.3101	0.0013	0.5422
Individual Illiquidity (Raw)	9.9704	142.3551	0.0000	1.4485	3000.4700
Individual Illiquidity (Log)	1.0523	0.8567	0.0000	0.8955	8.0069
Volatility	0.0116	0.0066	0.0034	0.0101	0.0605
Open Interest (Log)	10.6745	1.1598	3.8712	10.8134	13.2683
Days to Maturity	29.3063	25.3503	9.0000	15.0000	116.0000

Table 7 presents the correlation matrix for the key variables used in the liquidity risk premium analysis. It includes correlations between monthly returns, individual contract illiquidity (raw and log-transformed), volatility, open interest, and days to maturity. This preliminary analysis helps identify potential relationship among explanatory variables.

Table 7 Correlation Matrix – Liquidity Risk Premium

	Monthly return	LIQi	LIQi (Log)	Volatility	Open Interest (Log)	DTM
Monthly return	1.00	0.04	0.02	-0.15	-0.02	0.00
Individual Illiquidity (Raw)	0.04	1.00	0.42	-0.02	-0.30	-0.04
Individual Illiquidity (Log)	0.02	0.42	1.00	0.16	-0.51	-0.13
Volatility	-0.15	-0.02	0.16	1.00	-0.14	0.16
Open Interest (Log)	-0.02	-0.30	-0.51	-0.14	1.00	0.61
Days to Maturity	0.00	-0.04	-0.13	0.16	0.61	1.00

The matrix shows a modestly positive association between returns and individual contract illiquidity (0.04 for raw illiquidity and 0.02 for log-transformed illiquidity), suggesting a potential positive liquidity premium. However, the effect appears limited. Returns exhibit a stronger negative correlation with volatility (-0.15), indicating that higher volatility tends to precede lower returns. Additionally, the strong negative correlation between logarithmic illiquidity and open interest (-0.51) reflects the intuitive relationship that more actively traded contracts tend to be more liquid.

5.5.2 Fama-MacBeth Regression Results

HAC standard errors (Newey–West, 1987) with four lags are employed to account for autocorrelation and heteroskedasticity. The results in Table 8 are based on these adjusted estimates. The key finding is that the Amihud illiquidity variable carries a positive and statistically meaningful coefficient (0.0034, $t = 2.19$, $p = 0.03$), providing strong evidence that less liquid contracts earn higher expected returns, consistent with the liquidity premium hypothesis. Other control variables including volatility and time to maturity do not exhibit statistically significant effect. Taken together, the evidence suggests the notion that liquidity risk is priced in the Chinese metal futures market.

Table 8. Fama-MacBeth Regression Results with HAC (Newey-West) Standard Errors (Lag = 4)

Variable	Estimate	t-Statistic
Constant	0.0195	1.4691
LIQi	0.0034**	2.1939
Volatility	-1.7005	-1.4322
Days to Maturity	-0.0002	-0.6347

*Notes: HAC standard errors are calculated using the Newey–West (1987) method with 4 lags. *p<0.1, **p<0.05, ***p<0.01*

Table 9 presents the results from Fama-MacBeth regressions using both the original and logarithmically transformed Amihud illiquidity measures to examine the sensitivity of liquidity pricing estimates to variable specification.

Table 9 Fama-MacBeth Regression Results

Variable	Amihud Illiquidity Specification		Log Amihud Illiquidity Specification	
	Estimate	t-Statistic	Estimate	t-Statistic
Market Illiquidity Factor	0.00685***	2.69	0.0039	0.33
Volatility	-2.1685	-1.56	-0.3756	-0.26
Log(Open Interest)	0.0088	0.93	-0.0021	-0.18
Days to Maturity	-0.0005	-1.16	0.0005	0.6
Constant	-0.0711	-0.64	0.0225	0.17

*Note: Newey-West adjusted standard errors with 4 lags in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

The analysis reveals that the raw Amihud illiquidity measure yields a coefficient that is both statistically significant and positively signed (0.00685, t = 2.69), indicating that each one-unit rise in illiquidity corresponds to an increase of 0.685% in expected monthly returns. This finding supports the liquidity premium hypothesis and is consistent with prior evidence in both equity markets (Amihud, 2002) and international commodity futures (Marshall et al., 2012). However, when the log-adjusted form of the Amihud indicator is used, the coefficient becomes smaller (0.00388) and statistically insignificant (t = 0.33). Although the positive direction persists, the effect disappears after transformation, indicating some sensitivity to variable specification.

This difference likely arises for several reasons. First, the log transformation reduces the spread of high illiquidity values and shrinks extreme outliers, which may carry important information about trading frictions. Second, the log-transformed illiquidity measure exhibits substantial multicollinearity with open interest (correlation coefficient of -0.51, as documented in Table 6). Third, with only six contracts each month, compressing the variation in liquidity further limits the model's ability to identify a return premium. These results are consistent with earlier studies, suggesting that the specific specification of liquidity metrics can substantially affect empirical results (Goyenko et al., 2009), particularly in markets with small cross-sections and distinctive liquidity dynamics.

6 Conclusion

This thesis investigates two main questions in China's metal futures market: (1) whether liquidity co-moves across different contracts (liquidity commonality), and (2) whether liquidity risk is priced (liquidity risk premium). Through empirical analyses, our findings provide strong support for the existence and economic significance of both phenomena.

Firstly, our study confirms significant liquidity commonality across metal futures contracts in China. Using panel regression analyses for the period between 2019 and 2025, we find that approximately 47% of the variability in contract-level liquidity is attributable to market-wide liquidity factors. The dynamic panel regression model yields an R-squared of approximately 32.6%, demonstrating the strong explanatory capacity. This result highlights the importance of considering market-wide liquidity shocks, which simultaneously influence multiple contracts.

Moreover, liquidity conditions demonstrate notable mean-reverting behavior, as indicated by the significant negative coefficient on the lagged liquidity variable (-0.256). This implies that liquidity disruptions tend to be temporary, gradually correcting as market participants adjust their trading strategies. This finding has important implications for risk management practices and suggests that liquidity provision in metal futures markets is relatively resilient over the medium term.

Our robustness tests further strengthen these conclusions. To enhance the robustness of our findings, the analysis segments the sample into two distinct phases demarcated by the termination of China's Zero-COVID policy, thereby enabling an evaluation of the policy regime's macroeconomic implications. Results reveal that liquidity commonality persists throughout both periods. Although the magnitude of commonality slightly declines from 0.504 during the Zero-COVID period to 0.439 in the subsequent reopening phase, the overall relationship remains robust and statistically significant. Additionally, we observe variations in liquidity commonality by commodity type, where non-ferrous metals exhibit a notable reduction in commonality, whereas ferrous metals experience a slight increase post-policy shift. This differentiation emphasizes the role of market structure and contract characteristics in influencing liquidity dynamics.

Secondly, our analysis addresses whether liquidity risk is priced in the metal futures market. Employing the Fama-MacBeth regression methodology, we identify a statistically significant liquidity premium. Specifically, contracts characterized by lower liquidity consistently deliver higher average returns, providing compensation for the risks associated with illiquidity. The raw Amihud illiquidity measure yields a significant positive coefficient (0.00685), indicating that investors demand higher returns for bearing greater liquidity risk.

However, our findings demonstrate sensitivity to the measurement approach of liquidity. When using a log-transformed version of the Amihud measure, the liquidity premium weakens and loses statistical significance. This suggests that while liquidity is indeed priced, capturing this premium accurately depends critically on the liquidity metric used. Therefore, market participants and researchers should carefully select and interpret liquidity measures, particularly in markets characterized by limited contract diversity and pronounced liquidity variation.

Despite the robust findings, this study faces several limitations. Primarily, our sample includes only eight contracts over a relatively short period of six years, with the liquidity premium analysis further narrowed to six contracts. The limited breadth may affect the generalizability of our findings across broader asset classes or different market environments. Additionally, our reliance on a single liquidity metric—Amihud's illiquidity measure—may not fully capture all dimensions of trading frictions.

Future research could address these constraints by incorporating a broader range of contracts and examining alternative liquidity indicators. Extending the analysis to other commodity classes or employing high-frequency transaction data could also provide deeper insights into liquidity dynamics and risk pricing mechanisms. Furthermore, given the observed sensitivity of the liquidity premium to measurement specification, developing multi-dimensional liquidity measures or composite indices may offer enhanced robustness and reliability.

From a practical standpoint, our findings hold valuable implications for market participants and regulatory bodies. The presence of systemic liquidity risk underscores the importance of monitoring aggregate market liquidity conditions. Policymakers and exchange authorities could consider strategies such as incentivizing market-making activities or refining trading regulations to ensure sustained liquidity, especially during market stress periods. By enhancing liquidity management practices, the overall market stability and efficiency in the metal futures sector can be substantially improved.

In summary, this thesis presents robust empirical findings supporting the presence of co-movement in liquidity across contracts, as well as a discernible liquidity-related return premium within China's metal derivatives market. These results not only advance the academic understanding of liquidity dynamics but also offer actionable insights for market practitioners and regulators aiming to manage liquidity-related risks effectively.

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