The Impact of Arbitrage Frictions on Hedging Effectiveness in the CSI 300 Futures Market

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Chapter 1: Introduction

Index futures are a fundamental component of modern financial risk management. As the primary instrument for hedging equity market exposure, they are used by various financial institutions globally to manage the delta risk of structured products (Hull, 2022). The efficiency of these billion-dollar hedging programs, and the precision of the models used to price them, are based on the fundamental assumption that the “Law of One Price” holds (Roll et al., 2005). This assumption implies that the futures-cash basis (the difference between the futures price and its underlying spot price) will remain close to its theoretical cost-of-carry (Hull, 2022). In an efficient market, this price convergence is enforced by the constant, efficient action of arbitrageurs who buy the cheaper asset and sell the more expensive one, ensuring the two markets move in parallel.

However, in practice, this assumption of efficiency is frequently violated, particularly in markets operating under significant regulatory frictions. The Chinese CSI 300 index futures market, one of the world's largest, serves as a case study for this problem. Following extreme market volatility in 2015, Chinese regulators placed severe trading restrictions (Han & Pan, 2016). While these rules have been gradually eased from their 2015 peaks, the 2017-2025 analysis period of this paper remains affected by significant frictions not present in other efficient markets. As of 2025, the China Financial Futures Exchange (CFFEX) still defines “abnormal trading” to include self-trading and frequent opening and closing of positions, which are the very mechanics of arbitrage (Cffex.com, 2024; Cffex.com, 2025b). Non-hedging accounts are also subject to daily open limits of 500 lots (Cffex.com, 2025a). In contrast, the S&P 500 (CME) market has no such daily speculative limits and is designed to handle high-frequency arbitrage (Cmegroup.com, 2025). These remaining Chinese restrictions, while intended to stabilize the market, have a delicate, unintended consequence of crippling the very arbitrage mechanism that guarantees price accuracy. These frictions could create tangible risks for the institutions that rely on this market for hedging.

Numerous pieces of literature have explored this mechanism. Roll et al. (2005) established the foundational two-way feedback loop present in efficient markets. Han & Pan (2016) used the 2015 Chinese regulatory crackdown period as a natural experiment to demonstrate that this relationship breaks down entirely when arbitrage is prohibited.

However, while the existence of this broken mechanism is established, its direct, quantitative impact on hedging performance is less understood. This paper aims to quantify this gap. We argue that these regulatory frictions, by suppressing and delaying arbitrage, create a highly volatile and unpredictable basis. This basis risk, in turn, makes standard hedging strategies less effective, more costly, and far riskier for the financial institutions that deploy them.

This paper provides comparative analysis by benchmarking the restricted CSI 300 market against the highly efficient S&P 500 market. First, we provide evidence that the CSI 300 is less liquid and its basis is significantly more volatile than its US counterpart. Second, we measure the real-world cost to hedgers by calculating a rolling Optimal Hedge Ratio (OHR) and Hedging Effectiveness (HE), revealing significant, persistent instability in the Chinese market, compared to its much more efficient counterpart in the States. Finally, using Granger causality tests, we provide statistical evidence of a broken arbitrage feedback loop in China, where the pricing-to-liquidity relationship found in the S&P 500 are absent. We will then measure this impact using a series of Ordinary Least Squares (OLS) regressions, with Hedging Effectiveness (HE) as the dependent variable. These models will test for asymmetric frictions (similarly to

Han & Pan, 2016) and non-linear threshold effects (similarly to Wu & Zeng, 2019), proving that the market's price-correction mechanism is broken, and is directly undermining the effectiveness of hedging.

The paper will proceed as follows. Chapter 2 reviews the literature on the futures-cash basis, arbitrage, and the institutional context of the Chinese market. Chapter 3 details the data and the econometric methodology. Chapter 4 presents the empirical results from the analyses and discusses the implications of these findings, and Chapter 5 concludes.

Chapter 2: Theory & Institutional Context

This thesis focuses on how market regulations affect the theoretically established properties of the derivatives market, so it is important to review the financial products being discussed. To define the terminology and theory behind these foundational financial instruments, we refer to Hull (2022) and Investopedia.

2.1 The Derivative Market and Its Instruments

A derivative is a type of financial contract, whose price is dependent on the underlying asset, which could be a variety of asset classes, like stocks, bonds, loans or more sophisticated benchmarks. These derivatives are contracts between two or more parties, which can be traded on an exchange, or over the counter (OTC) (Fernando, 2025). A type of derivative can be a forward contract or a credit swap, traded mostly on OTC markets, whereas others, like options and futures, are traded mostly on exchanges. In this paper our focus will be on the exchange-traded futures market, and its distinct characteristics.

A forward contract is an agreement between market participants, such as financial institutions, to buy or sell an asset at a specific future date for an agreed-upon price. These contracts are not standardized and are traded OTC rather than on an exchange. They carry high counterparty risk, meaning both parties are usually fully responsible for fulfilling the contract. Furthermore, forward contracts are typically restricted to large trades and cannot easily be exited before the agreed-upon date (Hull, 2022).

Futures contracts are also agreements to buy or sell an asset at a predetermined price on a specific future date, but they are highly standardized. These contracts are traded on organized exchanges rather than OTC, where the exchanges specify the exact quantity, quality, and delivery terms. The key difference is the mitigation of risk. Exchanges use a clearing house which acts as a counterparty to both the buyer and seller, eliminating counterparty risk. Standardization and exchange trading provides futures contracts with high liquidity and accessibility, allowing contractors to easily exit their positions (Hull, 2022).

2.2 The Margining System

To ensure solvency, futures exchanges use a margining system. To enter a futures contract, a trader is required to provide an initial margin, which acts as collateral against potential losses. Through daily settlement, gains and losses are calculated and settled at the end of each trading day via variation margin payments, ensuring that profits and losses are realized on a daily basis. These funds are processed through the clearing house, the entity responsible for handling these transactions and enforcing margin requirements (Hull, 2022).

Suppose Party A (short) and Party B (long) enter a futures contract for €1 million at a price of $1.15 per Euro, making the total value of the trade $1.15 million. They are both required to post an initial margin (IM), for instance 5% of the contract's value, which would be $57,500 each, held by the clearing house. The exchange also sets a maintenance margin (MM), perhaps $46,000, which is the minimum balance required in the account. As the price changes, the clearing house settles all gains and losses in cash at the end of every single trading day. After one week, the Euro suddenly loses 2% of its value against the Dollar, dropping the market price to $1.1270. This price change creates a loss of $22,700 for Party B (the buyer) and an identical gain for Party A (the seller). The clearing house facilitates this by transferring this amount from

Party B's margin account to Party A's account. Party A's new balance becomes $80,200, while Party B's balance drops to $34,800. Because Party B's account is now below the $46,000 maintenance margin, they receive a margin call from the clearing house. They must deposit funds to restore their account balance all the way back to the initial margin of $57,500, meaning they must add $22,700. If they fail to deposit this amount in time, the clearing house will forcibly liquidate their long position to prevent further losses. It's critical to understand that Party A is completely unaffected by Party B's default. Party A's contract is not with Party B, but with the clearing house. Party A keeps their $80,200 balance and their short position remains open, fully guaranteed by the clearing house, which has now absorbed Party B's default. Party A's position will continue to be evaluated daily, and the clearing house remains responsible for the final settlement when the contract expires.

By eliminating counterparty risk, the clearinghouse framework focuses all market risk onto one single, observable variable: the price of the futures contract itself.

2.3 Hedging

The primary function of these contracts, specifically for institutions, is hedging. Hedging is a risk management strategy to limit your investments' drawdown by taking an opposite stake in a related asset (Catalano, 2022). Building on the example from before, party B is a US based car manufacturer, with a €1m deal finalizing at the end of January with a European client. However, they are worried about the euro taking a fall against the dollar in the next month and the value of their deal taking a significant hit, which would hinder further operations. To hedge against this, they entered into a futures contract where even if the price of euro falls, they are able to exchange their payment into enough dollars to prevent bankruptcy. If the price of euro increases, they miss out on further profits, but retain adequate purchasing power for further business.

The example of the car manufacturer assumes a "perfect" hedge, where the asset, currency, and date align perfectly. In practice, such perfect hedges are rare. Institutional hedgers often rely on cross-hedging, where they use a futures contract on a related, but not identical, asset. For our example, an institution might hold a portfolio of 50 Chinese stocks and use the broader CSI 300 index future to hedge its market risk (Hull, 2022).

This mismatch creates the single most important risk for a hedger: basis risk. Basis risk is the risk that the basis will change unpredictably, causing the hedge to fail.

To manage this, institutions calculate the Minimum Variance / Optimal Hedge Ratio (OHR)**.** The OHR derived from the covariance and variance of the spot and futures returns, that determines the precise number of futures contracts the institutions need to buy to minimize the overall variance (risk) of the hedged position (Hull, 2022).

The success of this strategy is then measured by its Hedging Effectiveness (HE). HE is a metric (usually the R-squared from the regression used to find the OHR) that shows what percentage of the spot position's risk was successfully eliminated by the hedge. A high HE signifies a stable, predictable basis, while a lower HE signifies a volatile, unpredictable basis that makes effective hedging impossible (Hull, 2022).

2.4 Structured Products and the Institutional Motivation

A primary driver of hedging volume comes from banks and financial institutions that issue structured products. These are pre-packaged investment instruments sold to clients, where the return is linked to an underlying asset, index or benchmark, such as the CSI 300 (Hull, 2022).

When an institution sells a structured product, it takes the opposite side of that exposure. Then, they enter the futures market to hedge its own position and manage its risk. This business model is built on the assumption that the futures market is an efficient, reliable, and a cost-effective hedging tool, which assumption is based on a stable basis and a high HE. This paper tests if that assumption holds in the higly regulated Chinese futures market.

2.5 Arbitrage Mechanism and Futures-Cash Basis

According to Hull (2022), in a frictionless market, the theoretical price of a futures contract of an index (F_0) is calculated using the current spot price (S_0), the risk-free interest rate (r), the dividend yield of the index (q), and the time to maturity (T):

$$F_0 = S_0 e^{(r-q)T}$$

The basis is defined as the difference between these two prices ($F_0 - S_0$). If the market price deviates from this theoretical value, it creates a risk-free profit opportunity known as an arbitrage opportunity. Arbitrageurs act as the market's error-correcting mechanism, enforcing the "Law of One Price" in two ways. When the futures price is higher than the spot ($F_0 > S_0$), the basis is positive or in contango. Arbitrageurs sell the expensive asset and buy the cheap one. They will short the futures contract and simultaneously buy the underlying stocks. They hold this position until expiry, profiting the risk-free difference. This selling pressure on the futures drives the price down, closing the basis. This is often referred to as cash-and-carry arbitrage. When the futures price is too low ($F_0 < S_0$), the basis is negative or in backwardation. Arbitrageurs now buy the futures contract and short-sell the underlying stocks. This buying pressure lifts the futures price, and reverting the basis. This is called reverse cash-and-carry arbitrage (Ganti, 2022; Chen, 2022; CME Group, 2025b; Hull, 2022).

The execution of the arbitrage strategies described above requires deep market liquidity. Roll et al. (2005) established that pricing efficiency and liquidity form a dynamic two-way feedback loop. Firstly, high liquidity allows arbitrageurs to enter large positions without moving the price against themselves. If liquidity dries up, the cost of executing arbitrage increases, causing arbitrageurs to withdraw. This causes the basis to stray away. On the other hand, a wide basis represents a profit signal. In a healthy market, a large basis attracts arbitrageurs who flood the market to take profit. This volume deepens liquidity, which subsequently corrects the price.

Therefore, in an efficient market, pricing errors (basis volatility) should be short-lived and should effectively "Granger-cause" an increase in trading volume and conversely, a decrease in trading volume (illiquidity) should "Granger-cause" basis volatility.

2.6 The Chinese Market

While the S&P 500 competently operates under the efficient mechanisms described above, the CSI 300 operates under a unique set of regulatory framework which impedes both directions of arbitrage.

The current structure of the Chinese market is an aftermath of the 2015 stock market crash. Following extreme volatility, index futures were commonly blamed for market decline. In response, the China Financial Futures Exchange (CFFEX) implemented harsh restrictions in an attempt to curb "speculation and arbitrage". These included raising margin requirements to 40% and limiting daily open positions to just 10 lots (Han & Pan, 2016).

Han & Pan (2016) used this period as a natural experiment. They demonstrated that when these restrictions were in place, the feedback loop described by Roll et al. (2005) vanished. With arbitrage activity effectively banned, the spot and futures markets disconnected, leading to a basis that fluctuated based on sentiment rather than causality.

While the extreme restrictions of 2015 have been gradually improved, the market analyzed in this thesis (2017–2025) is not fully liberalized. As of 2025, the CFFEX enforces a daily opening limit of 500 lots for non-hedging accounts. While higher than the 2015 limit, this cap prevents the high-frequency, high-volume trading necessary for modern arbitrage. If an arbitrage opportunity arises that requires 2,000 contracts to correct, a single firm cannot execute it (Cffex.com, 2025a). Another critical friction in China is the settlement mismatch between markets. The futures market operates on T+0 (positions can be opened and closed on the same day), whereas the stock market operates on T+1 (stocks bought today cannot be sold until the next trading day). Furthermore, the exchange actively monitors and penalizes "frequent opening and closing of positions" and "self-trading". These patterns are indistinguishable from algorithmic arbitrage strategies (Cffex.com, 2024; Cffex.com, 2025b; Chizoba Morah, 2023).

Chapter 3: Research Methodology

The analysis was conducted using Python. For full transparency and reproductibility, the complete codebase along with the raw data is available via the public GitHub repository linked in Appendix A.

To quantify the impact of regulatory frictions on hedging performance, this study uses daily trading data from the two markets. The analysis covers the period from January 1, 2017, to October 16, 2025. This timeframe captures the post-crash regulatory environment in China, where trading restrictions have been eased but significant frictions (such as the 500-lot limit) remain.

3.1 Data Construction

The analysis is based on daily trading data sourced from TradingView (2025). The dataset consists of both spot and futures market data for the two indices. CSI 300, representing the Chinese market, and the S&P 500, representing the U.S. market. For the futures, we use a continuous time series of the front-month contracts of the CSI 300 Index Futures (IF) and the E-mini S&P 500 Futures (ES). Contracts were rolled over based on trading volume, transitioning to the next contract when its volume exceeded the volume of the expiring contract. The analysis uses settlement prices rather than close prices to align with exchange clearing standards. Furthermore, both back-adjusted and non-backadjusted futures data was aqcuired to help with specific calculation requirements. Back-adjusted data removed the artificial price gaps caused by contract rollovers, which is important for long-term return analysis, and non-backadjusted data preserved the raw prices necessary for accurate basis calculation. The final dataset for each trading day includes Open, High, Low, and Close prices, along with Volume for both spot and futures markets, with the addition of Open Interest only for the futures contracts.

3.2 Variable Construction

To quantify the impacts of market frictions, we construct the following variables.

We calculate daily logarithmic returns for both spot and futures markets ($\ln(P_t) - \ln(P_{t-1})$). The basis (B_t) is defined as the difference between futures and spot prices ($F_t - S_t$). We also use absolute basis ($|B_t|$), as both positive and negative deviations represent an arbitrage opportunity.

To test the hypothesis that regulatory constraints affect market efficiency asymmetrically (Han & Pan, 2016), we break down the lagged basis into positive and negative variables. The variable $Basis_{t-1}^{+}$ takes the value of the basis when the basis is positive and zero otherwise, representing periods of contango. Conversely, $|Basis_{t-1}^{-}|$ takes the absolute value of the basis when it is negative (backwardation) and zero otherwise.

To investigate threshold effects as suggested by Wu & Zeng (2019), we construct a binary dummy variable (D_{t-1}). This variable equals 1 when the absolute basis is in the highest 75th percentile, and 0 otherwise. This allows us to measure the impact of frictions only during periods of extreme pricing volatility compared to normal market conditions. We use the 75th percentile, since academically this is the most convenient for defining the "high" regimes of distributions while retaining enough data to be statistically significant.

Following Amihud and Noh (2018), we build an illiquidity measure ($ILLIQ_t$) for futures, which is calculated as the return over the currency volume. This metric measures the price impact per unit of trading volume, where a higher value indicates lower liquidity. Ideally, in a frictionless market, large volumes should be traded with minimal price impact.

$$ILLIQ_t = \frac{|R_{f,t}|}{P_{f,t} \cdot Vol_t \cdot M} \times 10^6$$

where $|R_{f,t}|$ is the absolute return of the futures contract, $P_{f,t}$ is the settlement price, Vol_t is the daily trading volume, and M is the contract multiplier (300 for the CSI 300 and 50 for the S&P 500 (CME Group, 2025a; www.cffex.com.cn, 2025)). The measure is scaled by 1 million to ensure the results are readable.

The primary dependent variable, Hedging Effectiveness (HE_t), measures the risk reduction achieved by hedging a long spot position with a short futures position. Following the standard minimum-variance formula (Hull, 2022), we calculate HE_t using a rolling Ordinary Least Squares (OLS) regression with a 60-day window (Bhattacharya, Singh and Alas, 2011). For each trading day t, we estimate the following equation using data from $t - 59$ to t:

$$R_{s,t} = \alpha + \beta R_{f,t} + \epsilon_t$$

where $R_{s,t}$ and $R_{f,t}$ represent the daily logarithmic returns of the spot index and futures contract, respectively. The slope coefficient β represents the Optimal Hedge Ratio (OHR) and the R^2 from this regression is defined as the Hedging Effectiveness (HE_t). A higher HE_t indicates a stronger correlation between spot and futures returns, implying a lower residual variance and a better hedge for the hedged portfolio.

3.3 Econometric Models

To make a comparison between friction variables measured on different scales, all variables in the regression models (hedging effectiveness, amihud illiquidity, and basis measures) were standardized using Z-score normalization before estimation:

$$Z = \frac{X - \mu}{\sigma}$$

Standardization solves the scale disparity between the basis and amihud illiquidity (a ratio often measured in the 10^{-6} range). Consequently, the regression coefficients (β) reported in this study are standardized coefficients. They represent the expected change in Hedging Effectiveness (in standard deviation units) resulting from a one-standard-deviation increase in the independent variable. This allows for a direct ranking of each friction. A coefficient with a larger value indicates a stronger driver of hedging failure.

To quantify the impact of regulatory frictions on hedging performance, we employ a multi-stage econometric approach. First, we establish the existence of causal market mechanisms, then quantify their costs under different conditions.

First, we investigate the relationship between market liquidity and pricing efficiency. According to the efficient market hypothesis and Roll et al. (2005), a feedback loop should exist. Pricing errors (basis) should act as a profit signal that attracts arbitrage trading (liquidity), which in turn, should correct the pricing errors.

To test for this mechanism, we use the Granger Causality (Granger, 1969) test. In the context of this model, "causality" means predictive power. Specifically, we test if past values of the basis (X) provide statistically significant information for predicting the future liquidity (Y) further than what is already included in the history of liquidity itself, and vice versa.

We verify this by comparing two autoregressive models, the Unrestricted Model (URM) and the Restricted Model (RM). The Unrestricted Model (URM) represents the hypothesis, that past values of both the dependent variable (Y) and the independent variable (X) contain information significant enough for accurately forecasting the current value of Y. Mathematically, this is expressed as:

$$Y_t = \alpha + \sum_{i=1}^{k} \beta_i Y_{t-i} + \sum_{i=1}^{k} \gamma_i X_{t-i} + \epsilon_{UR,t}$$

In this equation, Y is the dependent variable at time t (e.g., illiquidity), while X_{t-i} represents the lagged values of the independent variable (e.g., basis) and k represents the maximum lag length. The coefficients β_i capture the autoregressive nature, or "memory" of the dependent variable itself, indicating how strongly past values of the dependent variable influence its current value. The coefficients γ_i measure the predictive contribution of the independent variable. If the sum of the γ coefficients are statistically significant, we can assume that past values of the independent variable are powerful in the prediction of the dependent variable, and provide valuable information that cannot be explained by the dependent variable's history alone. This predictive precedence is what defines "Granger causality" in this context.

The Restricted Model (RM) enforces the null hypothesis ($\gamma_1 = \gamma_2 = \cdots = \gamma_k = 0$), assuming that the history of X has no predictive power for Y_t:

$$Y_t = \alpha + \sum_{i=1}^{k} \beta_i Y_{t-i} + \epsilon_{R,t}$$

To determine if the inclusion of X significantly improves the model's predictive accuracy, we calculate the F-statistic based on the Residual Sum of Squares (RSS) of both models:

$$F = \frac{(RSS_R - RSS_{UR})/k}{RSS_{UR}/(n-k-1)}$$

Where RSS_R is the residual sum of squares of the RM, RSS_{UR} is the residual sum of squares of the URM, k is the number of lags, and n is the number of observations.

If the F-statistic exceeds the critical value and results in a p-value < 0.05, we reject the null hypothesis and conclude that X "Granger-causes" Y. A failure to reject this null in the Chinese market would provide statistical evidence that the arbitrage feedback loop is broken.

To quantify the direct magnitude of market frictions on hedging performance, we use a dynamic regression framework. Because the dependent variable, Hedging Effectiveness (HE_t), is constructed using a 60-day rolling window, consecutive observations share approximately 98% of their underlying data. This property of the variable causes significant serial correlation, where the best predictor of today's HE_t is simply yesterday's value (HE_{t-1}).

To solve this autocorrelation issue and to measure solely the marginal impact of market frictions, we build the model as an Autoregressive Distributed Lag (ADL) model. We regress HE_t against its own lag (HE_{t-1}) and the lagged friction proxies:

$$HE_t = \alpha + \phi HE_{t-1} + \beta_1 Illiq_{t-1} + \beta_2 |Basis_{t-1}| + \epsilon_t$$

The term ϕHE_{t-1} captures the persistence or "memory" of the hedging effectiveness. Following Brooks (2008), including the lagged dependent variable can account for serial correlation, which HE_t inherented from its rolling-window property. Consequently, the coefficients $\beta_1 Illiq_{t-1}$ and $\beta_2 |Basis_{t-1}|$ measure the impact of illiquidity and absolute basis on HE_t.

We hypothesize that $\beta_2 < 0$ and $\beta_2 < 0$. A statistically significant negative coefficient would confirm that an increase in illiquidity or a widening of the basis immediately damages the portfolio's variance reduction capability for the upcoming period.

Building on the work of Han and Pan (2016), we test for asymmetries in the impact of different types of bases. Theory serves, that correcting a positive basis (contango) requires shorting futures, while correcting a negative basis (backwardation) requires buying futures. Given the CFFEX's trading limits and hedger-arbitraguer dynamics, we hypothesize that frictions are more damaging in the positive regime. To test this, we build another ADL model, now using the broken down basis variables.

$$HE_t = \alpha + \phi HE_{t-1} + \beta_1 Illiq_{t-1} + \gamma_{pos} Basis^{+}_{t-1} + \gamma_{neg} |Basis^{-}_{t-1}| + \epsilon_t$$

This model estimates two independent coefficients for bases. We hypothesize that $|\gamma_{pos}| > |\gamma_{neg}|$. A result like this would provide statistical proof that hedging effectiveness is damaged more severely when futures are overpriced.

Finally, we investigate the non-linear dynamics of the basis frictions. Wu and Zeng (2019) argue, that traders ignore small pricing errors within a "no-arbitrage bound" but react more dramatically to larger deviations.

To measure this reaction, we use the binary threshold variable (D_{t-1}) we constructed for high-stress regimes. We set the threshold at the 75th percentile, to measure only periods of significant pricing volatility. We use this dummy variable with our friction proxies to measure their impact during high-stress regimes. This model is specified as:

$$\begin{aligned} HE_t = \alpha + \phi HE_{t-1} + \beta_1 Illiq_{t-1} + \beta_2 |Basis_{t-1}| + \delta_1 (D_{t-1} \cdot Illiq_{t-1}) \\ + \delta_2 (D_{t-1} \cdot |Basis_{t-1}|) + \epsilon_t \end{aligned}$$

The coefficients δ_1 and δ_2 measure the extra stress in the market. Mathematically, the total impact of the basis or illiquidity during a stressed period becomes $(\beta + \delta)$. A statistically significant negative value for δ would confirm that the slope steepens in high-stress regimes, proving that regulatory frictions cause more damage to hedging effectiveness when the market is the most unstable.

Chapter 4: Results and Interpretation

4.1 Introduction to Both Markets

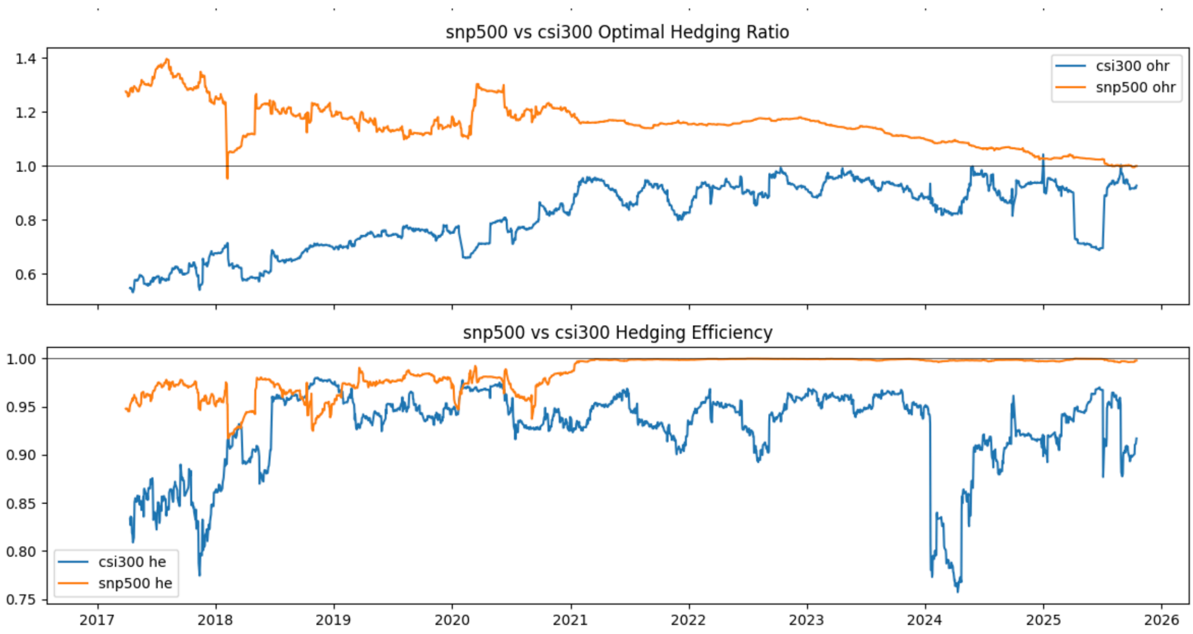

Figure 4.1 Comparison of Hedging Effectiveness and Optimal Hedging Ratio

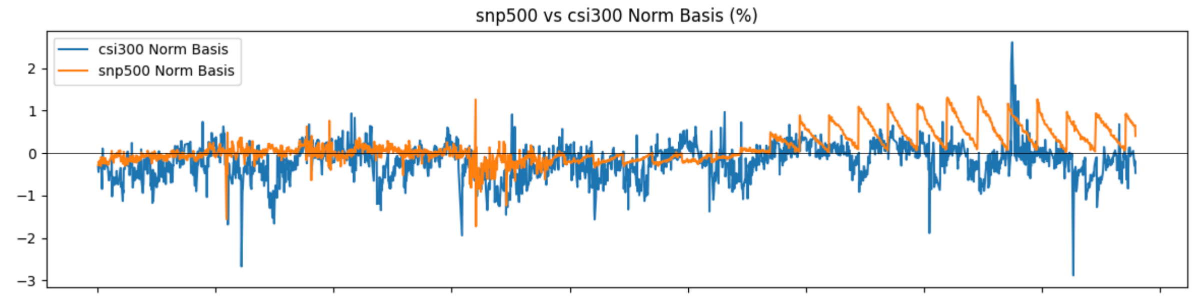

Figure 4.2 Comparison of the Evolution of the Normalized Futures-Cash Basis

As clearly visible in Figure 4.1, the CSI 300 shows significantly higher volatility in hedging effectiveness compared to the S&P 500. While the US market maintains a stable HE near 1.0 (indicating a near-perfect hedge), the Chinese market shows frequent drawdowns where effectiveness drops significantly. This visual evidence helps support the hypothesis that regulatory frictions in China prevent the futures market from consistently tracking the spot index. Correspondingly, Figure 4.2 shows that the CSI 300's basis fluctuates much more than its US counterpart, suggesting that arbitrage is less efficient at reverting prices to their theoretical fair value.

To ensure the validity of our econometric models, we must first address the stationarity of the time series data. Financial asset prices are typically non-stationary, exhibiting random walk behaviour with a stochastic trend. Running regressions on non-stationary data can lead to spurious regressions, where high R-squared values and significant t-statistics incorrectly suggest a relationship between unrelated variables (Granger & Newbold, 1974). We verify stationarity using the Augmented Dickey-Fuller (ADF) test (Wu and Zeng, 2019).

Variable	Market	ADF Statistic	P-value	Stationary ($p < 0.05$)
Abs. Basis	CSI 300	-5.524217	0.000002	Yes
Illiquidity	CSI 300	-3.088041	0.027451	Yes
Hedging Eff.	CSI 300	-3.167527	0.021943	Yes
Abs. Basis	S&P 500	-6.69065	4.117874e-09	Yes
Illiquidity	S&P 500	-7.13693	3.401938e-10	Yes
Hedging Eff.	S&P 500	-2.460238	0.125451	No

Table 4.1 Augmented Dickey-Fuller (ADF) Test Results

As shown in Table 4.1, the friction variables (Basis and Illiquidity) are stationary for both markets. However, a critical discrepancy can be observed with the dependent variables. The CSI 300 HE is stationary, as is shown in the table, but conversely, the S&P 500 HE fails to reject the null hypothesis of a unit root ($p=0.125$). This non-stationarity stems from the S&P 500's efficiency. Since its HE remains near-constant at 0.99 with miniscule variance (as it can be seen in Figure 4.1), it behaves more similarly to a random walk than to a mean-reverting variable. Consequently, the regression results for the S&P 500 HE would likely be spurious and unreliable. Therefore, the subsequent regression analysis focuses exclusively on the CSI 300.

4.2 Results of Granger Causality

To understand the source of the instability, we test the feedback loop (Roll et. al 2005) between pricing errors and liquidity. Since both the Basis and Illiquidity variables were confirmed stationary for both markets in Table 4.1, Granger Causality tests are valid for both.

CSI 300	Illiquidity GC Basis	S&P 500	Illiquidity GC Basis
Lag	P-value	Lag	P-value
1	0.350953	1	0.795079
2	0.540441	2	0.022660
3	0.598243	3	0.056689
4	0.767210	4	0.078446
5	0.479161	5	0.073076
CSI 300	Basis GC Illiquidity	S&P 500	Basis GC Illiquidity
1	0.333121	1	0.006032
2	0.304260	2	0.061883
3	0.304153	3	0.219187
4	0.084004	4	0.560715
5	0.062384	5	0.738518
6	0.045756	-	-
7	0.047581	-	-

Table 4.2 Results of the Granger Causality Test

The S&P 500 demonstrates a healthy feedback loop in both directions ($p<0.05$). Pricing errors immediately trigger liquidity reactions, which in turn corrects the prices. The CSI 300, however, shows a broken mechanism. While pricing errors eventually affect liquidity, the reaction is significantly delayed (statistically significant only at Lag 6-7), and crucially, liquidity does not Granger-cause pricing corrections (p=0.351). This confirms that arbitrage in China is not a consistent, self-correcting mechanism, leaving hedgers exposed to basis risks.

4.3 Results of the Regressions

Now, focusing only on the stationary CSI 300 dataset, we quantify the direct impact of frictions on hedging performance using the Baseline Autoregressive Distributed Lag (ADL) model.

Variable	Coefficient (β_{std})	P-value
Lagged Illiquidity	-0.0068	0.042
Lagged Basis	-0.0103	0.002

Table 4.3 Results of the Baseline Regression

The standardized coefficients in Table 4.3 reveal that pricing errors cause a significant influence on hedging effectiveness. While both frictions are statistically significant, the impact of absolute basis (β = -0.0103) is approximately 50% larger than that of illiquidity (β = -0.0068). This suggests that for a hedger in the chinese market, the main risk is not the inability to trade (illiquidity), but price inconsistency (basis risk) which cannot be diversified away.

We next test if different positive and negative basis create asymmetric risks for hedgers using the Asymmetric ADL.

Variable	Coefficient (β_{std})	P-value
Lagged Positive Basis	-0.0171	0.000
Lagged Negative Basis	-0.0091	0.009

Table 4.4 Results of the Asymmetric Regression

There is a significantly larger negative impact of a positive basis on hedging effectiveness compared to a negative basis. While both bases are statistically significant, a ratio of approximately 2:1 in our regression results provides evidence of a clear asymmetry in the Chinese market. This phenomenon stems from a fundamental mismatch between the behaviours and needs of market participants and the specific regulatory constraints they face. When the basis is positive, arbitrageurs must short futures to profit off the pricing error, however, they are competing for a limited number of buyers with hedgers who are structurally mostly long in the spot market and thus must also sell futures to hedge their portfolios. This effect is heightened by the CFFEX's strict daily lot limit on non-hedging positions, which effectively caps the ability of arbitrageurs to supply the liquidity necessary once the limit is reached, leaving the basis high and forcing hedgers to buy at unfavorable prices. On the other hand, in a backwardation market, the interests of the two groups align. Hedgers continue to sell futures, while arbitrageurs step in to buy futures (opening long positions) to capture the spread. It is also important to note that opening long positions is not subject to the same restrictive limits as shorting, and the futures part of the trade avoids the severe costs and T+1 settlement delays associated with shorting the spot market. This natural behavioural alignment helps arbitrageurs to absorb selling pressure during a negative basis period, hurting hedging effectiveness less, compared to a positive basis period.

Finally, we investigate the non-linear dynamics of market frictions, using the Threshold model.

Variable	Coefficient (β_{std} or δ_{std})	P-value
Illiquidity (Normal Regime)	-0.0014	0.732

Basis (Normal Regime)	0.0039	0.663
$(D \times Illiq)$ Illiquidity (Stressed Regime)	-0.0135	0.048
$(D \times \text{Basis})$ Basis (Stressed Regime)	-0.0273	0.017

Table 4.5 Results of the Threshold Regression

The results from the threshold regression provide statistical support for our hypothesis, showing that the market's sensitivity to frictions is not linear but rather, entirely state dependent. In normal market conditions (periods where the absolute basis and illiquidity remain below the 75th percentile), neither pricing errors (β = 0.0039) or illiquidity (β = -0.0014) show a statistically significant impact on hedging effectiveness (p>0.6). From this, we could imply that the market is strong enough to absorb minor inefficiencies, not hurting hedging effectiveness. However, if the market enters the high-stress regime, a significant change occurs. The interaction coefficient for the basis becomes negative and significant (δ = -0.0273, p=0.017), indicating that large pricing deviations cause a strong degradation in hedging performance that is almost triple the magnitude of the baseline relationship (as seen in Table 4.3). Furthermore, the impact of illiquidity also shifts from insignificant to significant in this regime (δ = -0.0135, p=0.048). This contrast between the normal regime and the stress regime proves that the regulatory structure creates a non-linear risk environment where the hedging mechanism functions adequately under low pressure but fractures during periods of high uncertainty, validating our theory that constraints on arbitrage further heighten basis risk in a self-reinforcing spiral.

Chapter 5: Conclusion

This thesis aimed to quantify the impact of regulatory frictions on hedging effectiveness in the CSI 300 futures market. By benchmarking it against the efficient S&P 500, we identified structural weaknesses that fundamentally change how hedging strategies perform.

Our empirical results point to a clear hierarchy of risks. Compared to the theoretical expectations for efficient markets (where liquidity constraints are typically the primary driver of hedging failure) our regression analyses reveal that basis deviations are the more dominant friction in the chinese market. In the baseline model, the standardized impact of basis deviations on hedging effectiveness was approximately 50% larger than the illiquidity's impact, and in the threshold model it is also clear that the impact of the basis interaction variable is double that of the illiquidity's. This inversion of the expected relationship would suggest that in the CSI 300, the main risk to hedgers is not the inability to execute trades (illiquidity in the market), but the price disconnects that arbitrageurs fail to correct.

This finding is reinforced by the Granger Causality results, which demonstrate a broken feedback loop in the CSI 300. While the S&P 500 showed an immediate, bidirectional reaction between liquidity and pricing efficiency, the CSI 300 showed no significant causal link from illiquidity to basis. This statistical disconnect confirms that the market is missing the self-correcting mechanism found in efficient financial markets.

Furthermore, the threshold regression also confirmed that these risks are non-linear. A structural break is observed when the basis exceeds the 75th percentile, and it indicates that the market fractures under stress. In this high-volatility regime, the negative impact of pricing errors triple, validating our hypothesis and proving that regulatory constraints are a fragility multiplier especially during high-stress periods.

5.1 Limitations of the Study

While this study provides evidence of market frictions, certain limitations must be acknowledged. The primary limitation lies in the construction of the threshold. We defined this regime using the 75th percentile of the absolute basis distribution. While it was effective in identifying periods of relative dislocation, this fixed threshold serves as an approximation, rather than a precise economic bound.

In reality, the no-arbitrage bound is dynamic, fluctuating even daily with changes in transaction costs, interest rates, and securities lending fees. A basis of x might be an arbitrage opportunity on one day but fall within the transaction-costs on another. Our model does not account for these changes in costs, potentially misclassifying some trading days. Additionally, the use of daily settlement data (while it is standard for longer term studies) averages out intraday price movements. It is entirely possible that high-frequency arbitrageurs might attempt to profit on minute-by-minute timescales that our daily data is averaging out.

5.2 Suggestions for Future Research

This study highlights the need for a better understanding of the no-arbitrage band in restricted markets. An interesting take for future research would be to replace the statistical proxy of the 75th percentile with a more profound structural model. Calculating the cost of carry by incorporating risk-free rates, dividend yields, and transaction taxes future studies could pinpoint the precise threshold at which arbitrage becomes profitable. By mapping this boundary against actual trading data, it would allow researchers to estimate exactly how much profit arbitrageurs failed to capitalize on due to regulatory constraints. Additionally, as CFFEX (and other) regulations continue to change and evolve, repeating this analysis after future policy changes and possible relaxations, it would provide a valuable insight of how markets respond to regulatory liberalization.

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Appendix A: Python Source Code

Repository Link: https://github.com/horvathsebi/AWP