

Bitcoin Arbitrage: The Role of a Single Exchange

Ethan Flowerday*

Neil Gandal†

Hanna Halaburda‡

Eric Olson§

Gabriela Ardel¶

University of Tulsa, Tel Aviv University, New York University

Abstract

This paper examines arbitrage in Bitcoin markets and the role of a single exchange, Bitfinex, in shaping market inefficiencies. Using tick-level data from four major centralized exchanges between 2017-2020, we find that nearly 80% of arbitrage opportunities were concentrated on Bitfinex, where Bitcoin traded at a sustained premium. Removing Bitfinex from the system cuts the frequency and size of spreads, lowers the volatility–arbitrage correlation from 0.86 to 0.59, and shortens median lifetime from 11 to 4 minutes. Event studies trace the mispricing to fiat liquidity constraints and regulatory frictions specific to Bitfinex. The findings extend limits of arbitrage theory to digital assets, showing how venue level constraints propagate system-wide inefficiency and suggest that secure fiat routes, rather than faster trading speed alone, are crucial for cryptocurrency price convergence. This challenges the assumption that arbitrage alone is sufficient to eliminate price discrepancies in digital asset markets.

*University of Tulsa, ethan-flowerday@utulsa.edu

†University of Tulsa and Tel Aviv University, gandal@tauex.tau.ac.il

‡New York University, hh66@stern.nyu.edu

§University of Tulsa, eric-olson@utulsa.edu

¶Tel Aviv University, gabryu@gmail.com

Highlights

- 80% of Bitcoin arbitrage (2017-2020) involved one centralized exchange (Bitfinex)
- The high arbitrage and volatility correlation greatly reduces when excluding Bitfinex
- Removing Bitfinex reduces arbitrage magnitudes and shortens lifetimes
- Event studies link fiat and regulatory shocks to mispricing
- This case study shows how institution-specific frictions drive market inefficiency

Keywords: Arbitrage, Bitcoin, Cryptocurrency Markets, Institutions, Market Microstructure, Price Efficiency

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Declaration of Interest Statement

The authors have no relevant financial interests in the manuscript and no other potential conflicts of interest to disclose.

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Data Statement

The data analyzed in this study were supplied by Coin Metrics (<https://www.coinmetrics.io>); researchers can obtain identical data by contacting the provider.

Declaration of generative AI and AI-assisted technologies in the writing process

Generative AI and AI-assisted technologies were not used in this investigation or during manuscript preparation.

Author Contributions

E.F. Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review and editing.

N.G. Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – review and editing.

H.H. Conceptualization, Investigation, Writing – review and editing.

E.O. Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – review and editing.

G.A. Data curation.

1 Introduction

Arbitrage is fundamental to financial market efficiency, ensuring that identical assets trade at the same price across different venues (Fama 1970). In traditional markets, arbitrage opportunities tend to be short-lived, as competitive forces and liquidity provision mechanisms drive price convergence (Budish et al. 2015). However, the cryptocurrency market exhibits persistent arbitrage opportunities, raising important questions about the underlying structural barriers that prevent price equalization.

Bitcoin (BTC), the largest cryptocurrency by market capitalization, is traded 24/7 across a variety of centralized (CEX) and decentralized (DEX) exchanges. In principle, arbitrageurs should eliminate price discrepancies between these platforms. Yet, empirical evidence suggests that significant and prolonged arbitrage opportunities exist in Bitcoin markets (Makarov and Schoar 2020). Unlike traditional markets, where price disparities are quickly corrected, cryptocurrency exchanges operate under varying regulatory environments, liquidity constraints, and technological limitations that create persistent inefficiencies. Furthermore, inconsistent regulatory oversight allows room for market distortions, enabling sustained arbitrage opportunities.

While arbitrage is expected to reduce price discrepancies across markets, its persistence in certain settings suggests structural barriers to immediate correction. Traditional financial theories highlight two key mechanisms that can sustain arbitrage opportunities. First, inventory risk models suggest that when volatility increases, market makers demand greater compensation for holding risky assets, leading to wider bid-ask spreads and more persistent price differences. Second, asymmetric information models indicate that volatile markets attract informed traders, which can temporarily amplify price misalignments before arbitrage forces act. However, in cryptocurrency markets, additional frictions – such as liquidity constraints, fiat withdrawal restrictions, and regulatory uncertainty – can significantly delay arbitrage corrections, making the link between arbitrage and volatility more persistent than in traditional markets. Understanding these structural barriers is critical to evaluating market efficiency in Bitcoin trading. Thus, a gap is presented requesting evidence of how a single cryptocurrency venue’s institutional friction affect arbitrage in the broader market.

This paper asks whether persistent cross-exchange spreads in Bitcoin arise from aggregate market conditions - volatility, volume, order-book depth, price impact - or from venue-specific

frictions that hinder capital mobility. Focusing on four major centralized exchanges, it is found that 80% of arbitrage opportunities between 2017 and 2020 were concentrated on a single exchange, Bitfinex, where Bitcoin traded at a sustained premium. To isolate the cause of that premium, we triangulate evidence from cross-sectional spread regressions, Kaplan-Meier and Cox models, and an event-study of Bitfinex-specific banking and regulatory shocks. It is shown that once Bitfinex is removed from the system, both the frequency and magnitude of arbitrage opportunities decline, weakening the correlation between arbitrage and volatility and reducing mean arbitrage durations. These results suggest that market inefficiencies were not driven solely by volatility but were largely shaped by institutional frictions at Bitfinex, including fiat withdrawal restrictions and regulatory uncertainty. Our findings highlight the importance of considering exchange-specific conditions when analyzing arbitrage efficiency in cryptocurrency markets.

Bitfinex’s liquidity constraints and regulatory uncertainty followed a major hack in August 2016, in which 120,000 BTC were stolen. At the time, the stolen Bitcoin was worth approximately \$72 million. In response to the hack, Bitfinex imposed restrictions on fiat withdrawals, limiting traders’ ability to transfer funds efficiently between exchanges. This liquidity bottleneck created structural barriers that slowed arbitrage corrections, allowing BTC to trade at a sustained premium on Bitfinex. Additionally, the exchange increasingly relied on Tether (USDT) as a workaround for fiat transaction limitations, further distorting price dynamics. Given concerns over USDT’s stability and occasional deviations from its \$1 peg, arbitrageurs faced additional uncertainty when executing trades across platforms. As regulatory scrutiny over Bitfinex and Tether intensified, institutional traders grew wary of engaging with the exchange, reducing competitive arbitrage activity. These market frictions illustrate how exchange-specific constraints can shape arbitrage behavior and sustain price disparities beyond what would be expected in an efficient market. The findings emphasize that understanding arbitrage efficiency in cryptocurrency markets requires not only analyzing price and volatility data but also examining the underlying market microstructure, including liquidity access, regulatory pressures, and exchange-level constraints.

This study contributes to the broader understanding of market inefficiencies in cryptocurrency trading, illustrating how frictions on a dominant exchange can result in system-wide effects. While previous research, such as Gandal et al. (2018) and Chen et al. (2019), documented explicit price manipulation on Mt.Gox, this paper examines a different mechanism:

how institutional constraints at a single exchange can drive persistent arbitrage. By demonstrating that structural barriers - rather than aggregated risk - explain arbitrage persistence, our findings provide valuable insights for traders, market participants, and regulators seeking to improve the efficiency and stability of digital asset markets.

The remainder of the paper proceeds as follows: section 2 provides a literature review of past work, section 3 presents characteristics of and events influencing the Bitfinex exchange, section 4 explains the data and variables used for analysis, section 5 presents the empirical findings, and section 6 concludes. The findings include an exploration of descriptive statistics, an analysis of arbitrage durations by means of survival analysis, and an investigation of events contributing to arbitrage in the system.

2 Previous Research

The cryptocurrency market continues to gain prominence, with the total market capitalization reaching approximately \$3.55 trillion in January 2025. Among the myriads of digital assets in the ever-evolving landscape, Bitcoin still maintains its prominence, drawing attention from investors and researchers. Given that many business entities offer the sale of Bitcoin, one particularly intriguing aspect of the Bitcoin market is arbitrage, which involves capitalizing on price discrepancies across different exchanges. As market dynamics evolve, understanding the mechanisms behind Bitcoin arbitrage becomes increasingly valuable for those seeking profit. This paper seeks to explore the intricacies of Bitcoin arbitrage, examining its origins, the role exchanges play in its creation, and implications for market efficiency.

Classical finance cites arbitrage as the benchmark mechanism that enforces the law of one price. The simplest form of arbitrage is the practice of exploiting price discrepancies by buying an asset at a low price in one market and selling it for a higher price in another market. This results in a profit which incurs little to no risk. This practice relies on the efficient market hypothesis (Fama 1970), which suggests that market prices should reflect all available information, thereby minimizing the opportunity for arbitrage. Thus, as prices diverge, arbitrageurs swiftly act to correct these inefficiencies, thereby contributing to the overall stability of the market.

Arbitrage has been extensively studied in traditional financial markets. A foundational work by Harrison and Kreps (1979) established essential principles surrounding arbitrage

in multi-period securities markets, emphasizing the role of martingales in understanding market behavior. Renshaw (1977) and Varian (1987) examined the principles of short selling and financial arbitrage, emphasizing the importance of arbitrage in achieving market equilibrium. Chan and Chung (1993) found that index arbitrage is influenced by liquidity and trading volume, highlighting the dynamic interactions affecting arbitrage opportunities in the market. Furthermore, their research suggests that arbitrage leads volatility, which contrasts with the idea that volatility creates arbitrage opportunities.

Bodie et al. (2009) emphasize that while arbitrage opportunities play a crucial role in aligning prices across different financial instruments, these opportunities are often constrained by transaction costs, market frictions, and the time required to exploit discrepancies, ultimately affecting the efficiency of market pricing. The limits of arbitrage were further investigated by Gromb & Vayanos (2010), who indicated that factors of risk, margin constraints, and capital constraints each play a role when determining effective arbitrage strategies. More recently, Jialu et al. (2024) have shown that arbitrage strategies still hold value for determining market inefficiencies as markets respond differently to recent events. Together, these studies underscore the evolving landscape of arbitrage, revealing both its foundational role in market efficiency and the complexities that influence its effectiveness across different contexts.

Traditional financial markets exhibit strong arbitrage forces that drive price convergence (Fama 1970). However, Shleifer & Vishny (1997) argue that arbitrage is not always self-correcting due to constraints such as regulatory barriers, liquidity issues, and institutional frictions. In the context of high-frequency trading, Budish et al. (2015) highlight that while arbitrageurs compete to exploit inefficiencies, structural barriers can still create persistent price disparities. Budish et al (2015) show that between 2005-2011, the duration of arbitrage opportunities between two specific indexes declined from a median of 97 milliseconds to 7 milliseconds. Furthermore, Aquilina et al. (2022) suggest that while there is an obvious arms race in speed, it does not affect the size of the arbitrage price but raises the bar to how quickly one should act to have a chance at capturing the opportunity. Applying this framework to cryptocurrency markets, our findings suggest that Bitfinex’s market dominance and withdrawal restrictions acted as constraints on arbitrage, sustaining long-run price discrepancies not observed in traditional asset classes.

In the paper that is probably the most similar to this work, Gandal et al (2018) show that

there was Bitcoin price manipulation on the Mt.Gox exchange during a ten-month period in 2013. An earlier hack of the Mt.Gox exchange was the driving force behind the high Bitcoin price on Mt.Gox (relative to other exchanges) during this period. Mt.Gox kept its Bitcoin price higher than other exchanges in large part to attract sellers of Bitcoin. This generated trading fees which, in theory, could have covered some of the loss from the hack. A similar factor (increased trading fees associated with high volume) likely played a significant role in why Bitfinex kept its Bitcoin price above that of other exchanges. Herein, however, we look for sources of sustained arbitrage opportunities beyond manipulation.

Cryptocurrency markets are relatively new and are characterized by high volatility and varying levels of liquidity across different trading platforms and geographic locations. These traits can lead to price discrepancies between exchanges, creating opportunities for successful arbitrage trades. Publications discussing Bitcoin arbitrage emerged shortly after the technology’s inception (Petrov & Schufla 2013). Research indicates that high volatility is often associated with an increase in arbitrage opportunities, as prices can diverge at different rates over short time frames (Hattori & Ishida 2021). Additionally, varying liquidity levels across trading platforms can exacerbate these price differences, with low liquidity potentially leading to larger price swings and slower responses to market information (Kabašinskas & Šutienė 2021).

It has been shown that arbitrageurs play a crucial role in cryptocurrency markets by swiftly exploiting these inefficiencies, contributing to price convergence across exchanges (Makarov & Schoar 2020). Kroeger & Sarkar (2017) emphasize the importance of the “Law of One Price” in the Bitcoin market, which suggests that price discrepancies should ideally be quickly eliminated through arbitrage activity.

However, Krückeberg & Scholz (2020) note that the decentralized nature of cryptocurrency markets can both facilitate and complicate arbitrage, influencing the efficiency of price adjustments. While the presence of multiple platforms creates greater opportunities for price discrepancies, the slower dissemination of information and varied trading conditions among fragmented market segments can hinder arbitrageurs’ ability to act quickly and effectively, potentially reducing the profitability of their trades. Shynkevich (2021) reinforces this idea, observing that arbitrage opportunities are often short-lived as market conditions continuously evolve.

Shynkevich (2021) used hourly data from Jan 2016 to Dec 2019 and stated, “Profitable

arbitrage opportunities have become scarce since 2018”. Crépellière et al. (2023) suggest that a decrease in cryptocurrency arbitrage opportunities is a result of traders becoming better informed. Prior work establishes that price discrepancies persist in crypto markets, even as informed trading is on the rise. It is open whether a single venue’s idiosyncratic frictions can systematically widen and prolong those gaps. The next section details why Bitfinex provides an ideal case study.

3 The Role of Bitfinex

This investigation of exchange couples revealed that selling Bitcoin on Bitfinex accounted for the majority of arbitrage opportunities (Figure 1). Between 2017 and 2019, Bitfinex consistently maintained higher BTC/USD prices compared to other exchanges. Excluding Bitfinex data from our analysis resulted in a dramatic 80% reduction in available arbitrage opportunities. Figure 2 illustrates this pattern over time, demonstrating that Bitfinex’s elevated BTC/USD price was responsible for most arbitrage occurrences after 2018. Several factors contributed to Bitfinex’s consistently higher prices: regulatory challenges, banking restrictions that limited fiat deposits and withdrawals, and unique trading liquidity conditions.

Prior literature predicts that pronounced cross-exchange arbitrage should arise on venues that combine high volatility with thin trading volume. Contrary to this expectation, Bitfinex maintained the second lowest volatility among the four exchanges studied, closely behind Coinbase. Moreover, as shown in Figure 3, Bitfinex commanded the highest trading volume from early 2017 through late 2018. Bitfinex’s margin constraints, leverage options, and fee structures were largely comparable to other exchanges. The coexistence of deep liquidity and persistent price premia indicates that the drivers of mispricing on Bitfinex lie in market frictions rather than in an absence of trading activity.

One of those frictions originates with the August 2016 security breach, during which 120,000 Bitcoin were stolen from the exchange causing a significant decrease in capital reserves. A more decisive constraint affecting fiat liquidity was a sequence of banking-related disruptions which began in 2017. In April 2017 Wells Fargo ceased processing USD wire transactions, abruptly halting customer fiat deposits and withdrawals. This disruption pushed Bitfinex and traders to increase reliance on USD-denominated stable-coin USDT.

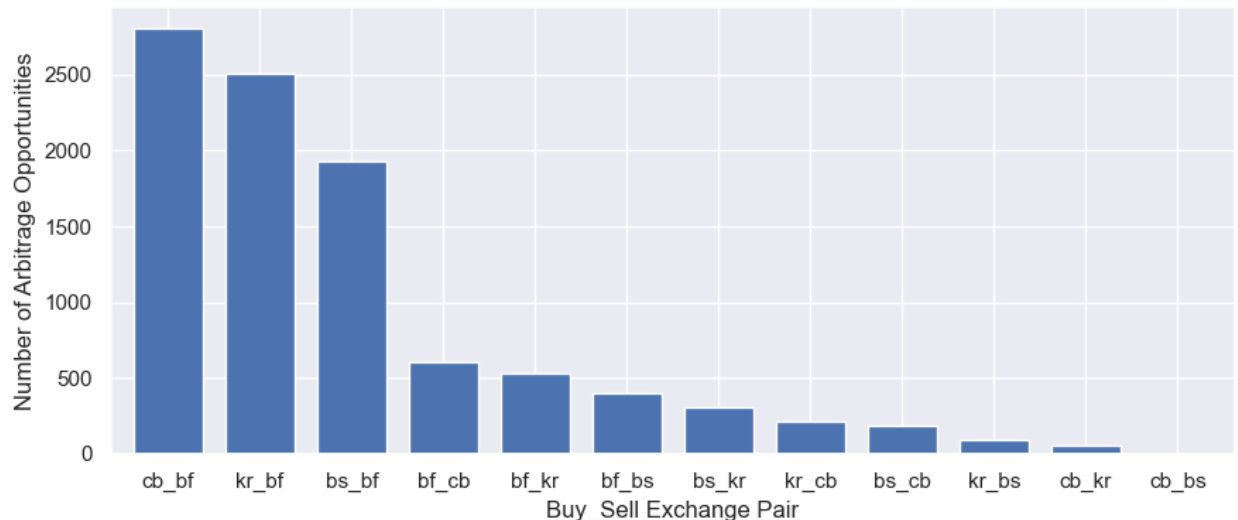


Figure 1: Optimal exchange flows to capture occurrences of arbitrage. The x-axis denotes the buy exchange (left) and sell exchange (right). The y-axis is the count of observations within a bar. cb=Coinbase, bf=Bitfinex, kr=Kraken, bs=Bitstamp.

Without banking partners to process fiat transactions, Bitfinex struggled to maintain adequate fiat liquidity – a common challenge as traditional financial institutions increasingly avoided cryptocurrency exchanges amid growing regulatory concerns (Castor 2018).

Bitfinex restored dollar clearing during mid-2017 by opening accounts at Puerto-Rico-based Noble Bank, only to end that relationship in October 2018. During the same month Bitfinex began routing fiat deposits through HSBC via a shell entity (Global Trading Solutions). However, shortly after the partnership HSBC closed the account prompting a week-long Bitfinex fiat freeze affecting USD, EUR, JPY, and GBP. Unable to secure a conventional banking partner, the exchange channeled substantial balances to the payment processor Crypto Capital Corp. Authorities quietly seized Crypto Capital accounts during 2018, a fact that became public in April 2019, making \$850 million of Bitfinex funds inaccessible. Furthermore, during October USDT struggled to consistently hold its dollar pegged value, reaching as low as \$0.88. Fiat access stabilized only after 1 November 2018, when Bitfinex announced a new banking partnership with Deltec Bank & Trust in the Bahamas, restoring USD deposit and withdrawal capability. By early 2020 these Deltec rails had matured into a reliable, though slower, fiat channel.

Bitfinex’s extensive use of USDT introduced additional complexity to its price dynam-

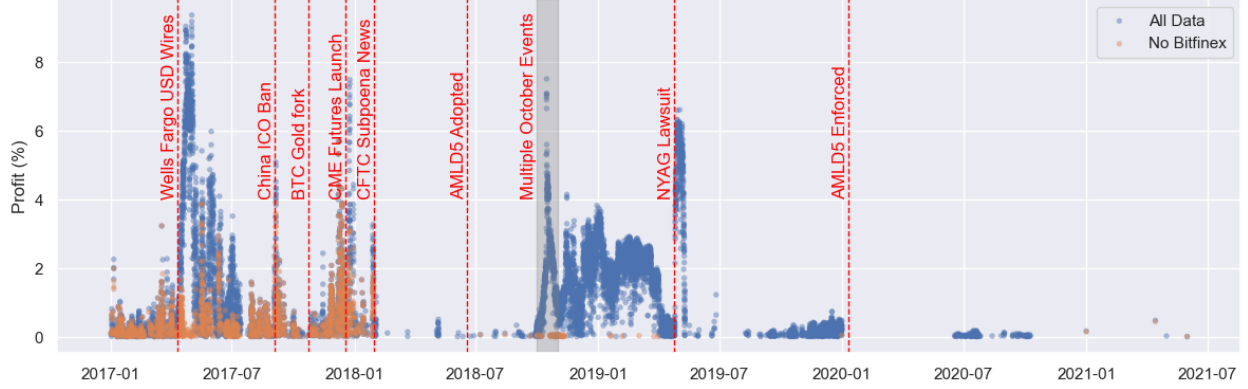


Figure 2: Comparison between arbitrage occurrences with and without Bitfinex in the system. Dates of events impacting Bitfinex have been included as red vertical lines. October 2018 events include: Noble Bank relationship ends, HSBC account freeze, USDT de-peg, Deltec Partnership announcement.

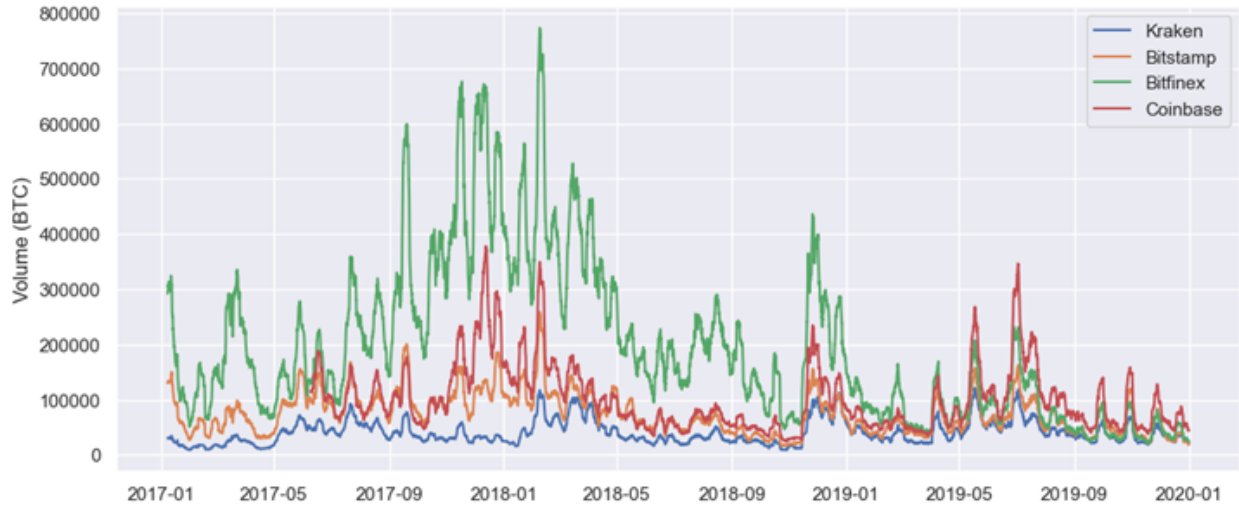


Figure 3: Weekly rolling average of daily exchange volumes over time per exchange.

ics. USDT enabled traders to conduct transactions using USD equivalents without relying on traditional banking channels, effectively circumventing the exchange’s fiat withdrawal constraints (Castor, 2018). However, this reliance on USDT created its own price discrepancies, particularly due to early stability issues that caused Tether to occasionally deviate from its intended \$1 peg (Morin et al. 2022; CNBC 2018; Bloomberg 2018). Traders also developed alternative methods to navigate fiat restrictions, including peer-to-peer (p2p) and over-the-counter (OTC) cryptocurrency transactions. These workarounds allowed trading to continue without adding or removing fiat currency from the system. Importantly, the difficulty of transferring capital back to the traditional banking system created a trapped liquidity effect, incentivizing traders to keep their funds active within the exchange ecosystem.

During this period, Chinese traders emerged as a critical factor driving Bitcoin demand on Bitfinex. From 2017 to 2019, the Chinese government progressively intensified restrictions on cryptocurrency trading and capital outflows (WSJ 2017; WSJ 2024b). A pivotal moment came in September 2017 when China’s central bank prohibited Initial Coin Offerings (ICOs) and forced domestic cryptocurrency exchanges to close, compelling Chinese traders to seek international alternatives. Concurrently, the government strengthened capital flight controls during 2017-2018, implementing stricter limitations on citizens’ ability to transfer substantial funds abroad — part of a broader strategy to maintain control over capital markets and reduce yuan outflows. In response, Chinese investors increasingly utilized platforms like Bitfinex that operated beyond the reach of domestic regulations and provided a mechanism to access Bitcoin while circumventing the country’s capital controls (WSJ 2024a; WSJ 2025). This influx of Chinese capital may have contributed to Bitfinex’s price premium.

Between 2018 and 2019, Bitfinex and Tether faced mounting regulatory scrutiny, particularly in the United States. Regulatory attention sharpened on 30 January 2018, when it became public that the U.S. Commodity Futures Trading Commission (CFTC) had subpoenaed both Bitfinex and Tether (subpoenas issued 6 December 2017) to obtain documentation on USDT’s dollar reserves and on potential price-manipulation links between the two entities. A watershed moment occurred when the New York Attorney General (NYAG) filed a lawsuit in 2019, alleging that Bitfinex had misappropriated Tether’s reserves to cover an \$850 million shortfall linked to asset seizures held at Crypto Capital Corp, a shadow banking partner. This legal action triggered additional regulatory investigations and heightened con-

cerns about the platform’s operational transparency (New York Attorney General’s Office 2019). Trust issues were further exacerbated when over a billion USDT was minted in early 2018, raising serious questions about the stablecoin’s backing.

These developments precipitated a significant erosion of institutional confidence in Bitfinex. Simultaneously, evolving global regulations — such as the EU’s 5th Anti-Money Laundering Directive (AMLD5) — alongside the emergence of more compliant exchanges like Coinbase and Binance redirected traders toward platforms offering greater transparency and regulatory certainty (European Union, 2018). Both institutional and retail investors increasingly prioritized regulatory compliance and risk reduction in their trading strategies. As a result, arbitrage opportunities between Bitfinex and competing exchanges gradually diminished, contributing to the narrowing of Bitfinex’s price premium by 2020.

By early 2020, Bitfinex had experienced a substantial decline in market dominance. Institutional investors and major traders increasingly favored exchanges like Coinbase that offered superior regulatory clarity and more robust Know Your Customer (KYC) and Anti-Money Laundering (AML) protocols. This migration of significant trading volume progressively narrowed the liquidity gap between Bitfinex and its competitors. This market transition produced two important effects: it eliminated Bitfinex’s persistent price premium and facilitated the correction of cross-exchange price discrepancies as arbitrage opportunities became less profitable. The overall efficiency of the Bitcoin market improved as a result. The convergence of prices across exchanges aligned with fundamental principles of arbitrage pricing theory and market microstructure, which predict that as market frictions decrease, price discrepancies naturally diminish. This case study thus provides empirical support for theoretical models of how cryptocurrency markets mature toward greater efficiency.

4 Data and Empirical Methodology

4.1 *Raw Data and Variables*

The collected data consists of the BTC/USD trading pair data from four major cryptocurrency exchanges: Bitfinex, Bitstamp, Coinbase, and Kraken. These exchanges were chosen due to their prominence during the period of investigation and due to their differing location based regulatory regimes. Kraken and Coinbase are hosted in the United States,

Bitstamp was founded in Luxembourg and is EU regulated, and Bitfinex historically focused on servicing the Asian market, with significant historic operating presence in Hong Kong and Singapore. However, Bitfinex is registered in the British Virgin Islands, where the regulatory regime remains less imposing.

The raw data consists of executed transactions from the order-book (including timestamp, trade price, BTC volume, and exchange) and covers the period from 2017-01-01 to 2021-06-01. From this data, variables used for analysis were calculated for hourly discrete time intervals. $Volume_t$ is the total USD value of BTC transacted during period t . This USD volume was chosen over the volume of BTC traded due to the exponential valuation of the asset during the data period. That is, the same USD value of trade would be approximately 40x more BTC volume at early periods of the data than at the end of the data.

The measure of arbitrage is defined as the highest minimum price among the four exchanges during the discrete time interval, divided by the lowest maximum price among the exchanges, as described in equations (1)-(3).

$$MaxMinP_t = \max \left(\min_{1 \leq j \leq 4} p_t(j) \right) \quad (1)$$

$$MinMaxP_t = \min \left(\max_{1 \leq j \leq 4} p_t(j) \right) \quad (2)$$

$$A_t = \frac{MaxMinP_t}{MinMaxP_t} \quad (3)$$

Where p_t represents the transaction prices during hourly interval time $t \in [1, \dots, N]$, with N being the number of observations, $j \in [1, 2, 3, 4]$ indicates the exchange, and A_t is the arbitrage value at time t . Values of $A_t > 1$ indicate potentially profitable arbitrage opportunities, not accounting for fees and other frictions, with higher values of A_t indicating more attractive opportunities. Note that even if $A_t < 1$, there may still exist arbitrage opportunities within the complete ecosystem of cryptocurrency exchanges.

Since order-book bid-ask data were not available, this method is employed as a proxy measure for the bid-ask spread. Furthermore, because exchange trading fees are calculated as a percentage of USD volume transacted, which is the largest contributor to costs for all but small transactions, this method makes it easy to set a threshold for profitable arbitrage, compared to a USD spread value. That is, $(A_t - 1) * 100$ returns a conservative estimate

for the percentage of profit attained from an arbitrage trade during period t , excluding fees. Thus, setting a threshold greater than the percentage of exchange fees ensures a profitable trade. For the sake of simplicity, fees were not considered during this study.

Prior to defining volatility measures, volume-weighted average price ($vwap_t$) and returns (r_t) were calculated as per equations (4) and (5), respectively.

$$vwap_t = \frac{\sum_{i=1}^n (p_i * v_i)}{\sum_{i=1}^n v_i} \quad (4)$$

$$r_t = \frac{vwap_t - vwap_{t-1}}{vwap_{t-1}} \quad (5)$$

Where p_i is the average execution price of a trade, v_i is the volume of BTC transacted, and n is the number of transactions during period t .

Using the returns, five volatility measures were calculated for comparison, including: absolute hourly returns, squared hourly returns, standard deviation of tick-by-tick returns during an hour, standard deviation of 5-minute returns within an hour, and hourly realized volatility of 5-minute returns. Each of these measures have previously been used in literature and captured volatility effects from fine granularity (transaction-by-transaction level), medium granularity (5-minute intervals), and larger trends (hourly). The standard deviation of 5-minute returns was seen to hold the highest correlation magnitude with arbitrage, closely followed by realized 5-minute returns, hence, this was the volatility measure chosen for any further analysis. It is noteworthy that standard deviation of returns and realized volatility are very highly correlated when calculated from 5-minute returns, with a Pearson correlation coefficient of 0.999. These findings are consistent with Liu et al. (2015) who determined that 5-minute realized volatility was generally the best performing measure of market volatility.

Proxies for order-book depth (VWAP premium) and price impact (Amihud illiquidity (Amihud 2002)) were included in the analysis to rule out conventional market microstructure explanations for arbitrage. The VWAP premium and Amihud illiquidity were calculated as per equations (6) and (7), respectively. The premium was first calculated per exchange and then volume weighted to determine the market-wide measure.

$$Premium_{j,t} = (vwap_{j,t} - vwap_{market,t}) / vwap_{market,t} \quad (6)$$

$$Amihud\ Illiquidity = |r_t|/v_t \quad (7)$$

4.2 Data Exploration

The distribution of A_t is illustrated in Table 1 and Figure 4. When observing the whole dataset (with Bitfinex included), the observations are seen to cluster tightly below 1 with a mean of 0.997 and a standard deviation of 0.016. A kurtosis value of 11.062 indicates a heavy leptokurtic distribution, as seen by the sharp peak and fat tails. Furthermore, the data is positively skewed, seen by the significant cluster of points greater than 1, indicating a prevalence of arbitrage opportunities in the data. It is noteworthy that 25% of the observations present arbitrage opportunities, with 5% of the observations holding an arbitrage profit of greater than 2.5%.

Table 1: Summary Statistics for A_t

Statistic	Count	Skewness	Kurtosis	Mean	Std Dev	Min	5%
All Data	38504	0.383	11.062	0.997	0.016	0.721	0.976
No Bitfinex	38504	-3.806	42.012	0.991	0.011	0.721	0.974

Statistic	10%	25%	50%	75%	90%	95%	Max
All Data	0.983	0.990	0.996	1.000	1.018	1.025	1.094
No Bitfinex	0.980	0.988	0.994	0.997	0.999	1.000	1.057

When Bitfinex is excluded from the data, there is a clear change in the distribution of A_t , particularly when looking at $A_t > 1$. The mean and standard deviation both decrease, indicating a lower likelihood to observe arbitrage opportunities within the data. This is further enforced by the skewness changing from positive to greatly negative. Now only 5% of observations present positive arbitrage opportunities, with the maximum profit decreasing from 9.4% to 5.7%. Thus, not only is a decrease in the number of arbitrage opportunities seen, but the magnitude of opportunities is also seen to dampen. This implies that Bitfinex introduces dynamics not observed in the broader market.

Figure 5 shows a scatter plot illustrating the relationship between volatility and arbitrage (A_t). When considering the full dataset, there is a clear positive linear trend. Hence, the

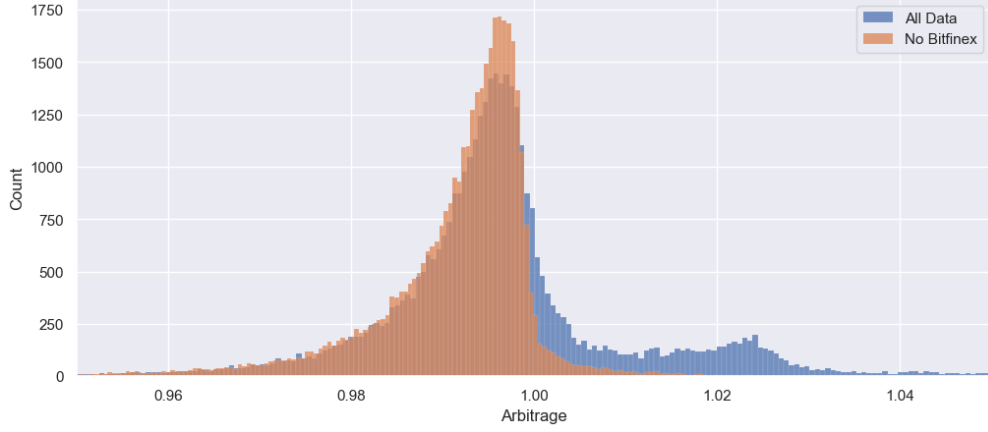


Figure 4: Arbitrage variable distribution, where the x-axis is the value of A_t and the y-axis is the number of observations within a histogram bar.

greater the arbitrage opportunity, the higher the expected volatility and vice versa. However, when Bitfinex is excluded from the data, the gradient is flattened.



Figure 5: Scatter plot describing the relationship between A_t and volatility.

Table 2 shows that when $A_t > 1$ the correlation between arbitrage and volatility is positive. Interestingly, the magnitude of the relationship is much weaker when Bitfinex is excluded from the data, decreasing from 0.862 for the full dataset to 0.592, confirming what was seen in Figure 5. This indicates that some unique characteristics of Bitfinex strongly influence the relationship between arbitrage and volatility. Volume's correlation with arbitrage and volatility increases once Bitfinex is excluded, suggesting that the exchange

may experience some idiosyncratic behavior affecting these relationships. It is noted that the vwap premium and Amihud illiquidity variables hold very low correlation values.

Table 2: Correlation Matrix for $A_t > 1$

Variable	Arbitrage		Volume		Volatility		VWAP Prem.	
	All	No BF	All	No BF	All	No BF	All	No BF
Volume	-0.023	0.385						
Volatility	0.862	0.592	0.094	0.338				
VWAP Prem.	-0.009	0.008	0.012	-0.015	-0.009	-0.003		
Amihud Illiq.	0.275	-0.041	-0.155	-0.210	0.271	0.079	0.005	-0.003

No BF is an abbreviation for Bitfinex excluded.

5 Results

We proceed in three steps that move from descriptive associations to progressively tighter causal identification. First, we estimate baseline OLS specifications that relate cross-exchange arbitrage magnitudes and market characteristics (volatility, depth, liquidity) in the full sample and in a counterfactual sample with Bitfinex removed. This establishes the conditional correlations that motivate our main hypothesis. Second, we turn to Cox proportional-hazard models of arbitrage duration to test whether the same covariates explain how long profitable spreads persist - an efficiency metric that captures frictions beyond price levels. Finally, we exploit a series of plausibly exogenous shocks in an event-study framework, investigating event impacts on abnormal arbitrage. The road-map demonstrates how Bitfinex’s presence amplifies arbitrage magnitudes, slows the arbitrage closure rate, and how institution-specific shocks magnify these effects, thereby offering a narrative from correlation to causal mechanism.

5.1 Regression Analysis

Regression analysis was performed for $A_t > 1$ on the two data groups, including and excluding Bitfinex. This threshold value was informed by the fact that values of $A_t > 1$ ensure profitable arbitrage, excluding frictions. Regressions were run with arbitrage and volatil-

ity as the dependent variable.¹ Heteroskedasticity-consistent robust standard errors were implemented.

Table 3: OLS Regression Estimates ($A_t > 1$)

Dependent Variable	Independent Variables	Coefficient	SE
Arbitrage (AD) Obs. = 9 632 $R^2 = 0.754$	Volatility	2.733***	0.030
	Volume	-10^{-6} ***	10^{-7}
	VWAP Prem.	10^{-12} ***	10^{-12}
	Amihud Illiq.	45.794***	11.387
Arbitrage (NB) Obs. = 1 875 $R^2 = 0.390$	Volatility	1.258***	0.086
	Volume	10^{-6} ***	10^{-7}
	VWAP Prem.	10^{-12} ***	10^{-13}
	Amihud Illiq.	-14.340 ***	4.976
Volatility (AD) Obs. = 9 632 $R^2 = 0.758$	Arbitrage	0.268***	0.005
	Volume	10^{-7} ***	10^{-8}
	VWAP Prem.	10^{-12}	10^{-12}
	Amihud Illiq.	30.484	23.767
Volatility (NB) Obs. = 1 875 $R^2 = 0.382$	Arbitrage	0.225***	0.015
	Volume	10^{-6} ***	10^{-7}
	VWAP Prem.	10^{-12} ***	10^{-13}
	Amihud Illiq.	19.685***	4.517

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results, displayed in Table 3, present substantial differences between variable relationships when the two datasets are compared. Regardless of whether arbitrage or volatility is the dependent variable, the R^2 decreases significantly from the “All Data” model to the “No Bitfinex” model, with magnitudes falling from 0.75 to less than 0.4. Once again, this indicates that Bitfinex plays a key role in strengthening the relationship between arbitrage and volatility within the Bitcoin market.

Though coefficients are significant, excluding volume, VWAP premium, and Amihud illiquidity from the models decreases arbitrage R^2 from 0.754 to 0.742 for “All Data” and from

¹These regressions are not viewed as implying causal relationships between arbitrage and volatility. The key point of the paper is that once Bitfinex is removed, there is a much weaker relationship between arbitrage and volatility.

0.390 to 0.350 for “No Bitfinex”. This indicates that the key relationship for these models is that existing between volatility and arbitrage. Furthermore, we see a large reduction in R^2 when the “All Data” result is compared to the “No Bitfinex” model. This suggests that Bitfinex plays a key role in the creation of arbitrage for the system, while conventional explanations like order-book depth, price impact, and volume have minuscule effects.

5.2 *Survival Analysis*

Survival analysis was performed to investigate how the presence of Bitfinex and the explanatory variables impact the duration of arbitrage events. The findings suggest that when Bitfinex is included in the data arbitrage durations increase on average, as noted by the mean survival times for the Kaplan-Meier models. Cox proportional-hazards estimates show that a one-standard-deviation rise in volatility lowers the hazard of closure by approximately 20% while the inclusion of Bitfinex lifts model concordance from 0.587 to 0.656, confirming its presence adds explanatory power. These results reinforce the idea that Bitfinex related frictions slow the process of price returning to equilibrium across the exchange.

To construct the dataset for the analysis, the variables were sampled to one-minute intervals. An arbitrage episode was said to begin at an instance when the value of A_t moved from a value of less than one to have a value greater than one. This event continued until the arbitrage value moved back below one. This provides a duration measure of the event in minutes, and each contiguous measure is counted as a single event. Thus, the dependent variable for this section of modeling is duration of arbitrage, measured in length of time. The covariates were averaged for each event, except volatility which was calculated as per equation (8), where sigma is volatility and n is the number of 1 minute observations in an event. No censoring was present and events did not overlap.

$$\sigma_{event} = \sqrt{\frac{1}{n} \sum_{i=1}^n \sigma_i^2} \quad (8)$$

Kaplan-Meier survival curves were calculated from the “All Data” and “No Bitfinex” event data, displayed in Figure 6. A log-rank test was used to determine if the two survival curves were significantly different. With a p-value of <0.001 the null hypothesis can be rejected; thus, the two groups are not from the same survival distribution. The median

survival time for both models is 2 minutes, however, when Bitfinex is included in the data we see an increase in survival probability, from a restricted mean survival time of 3.64 to 11.11 minutes. This indicates that the inclusion of the Bitfinex exchange plays a role in lengthening arbitrage events. This is an expected result as the unique characteristics and frictions related to the exchange are assumed to decrease efficiency, as discussed previously.

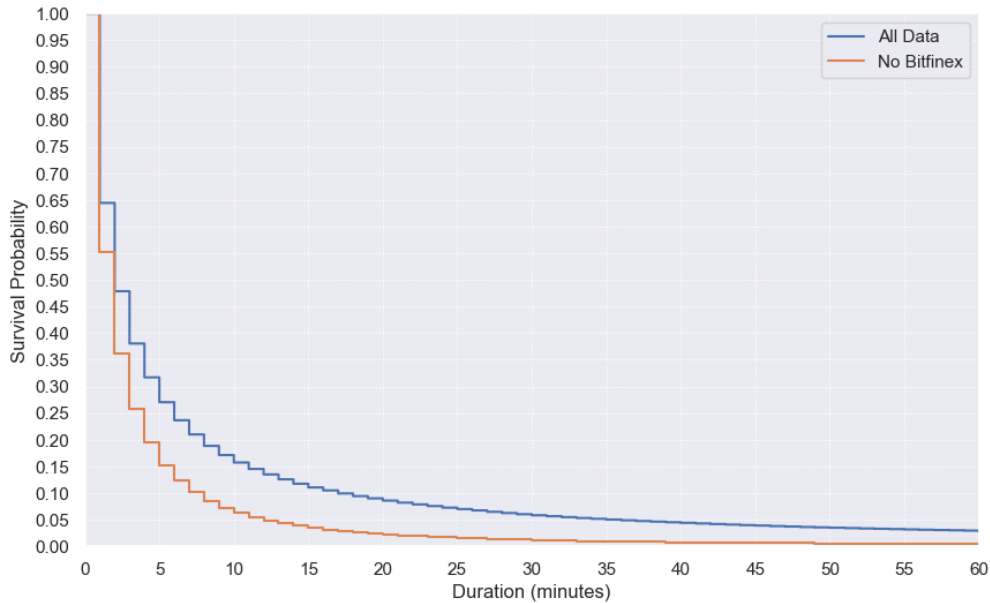


Figure 6: Kaplan-Meier estimates for arbitrage duration.

Cox proportional hazard models were estimated to evaluate the determinants of arbitrage duration, Table 4. For baseline hazard estimation, the Breslow method was used, and the Efron method was applied to handle tied event times. Data was scaled using the standard scaler prior to model fitting. Thus, the results suggest that a one standard deviation change in the variable results in a coefficient percentage change to baseline proportional hazard.

The “All Data” model has a concordance of 0.660, while “No Bitfinex” yields a concordance of 0.586. It is noted that the “All Data” model has the fewer observations of the two, while we previously showed that this dataset has more arbitrage. This occurs as the observations are longer on average than the “No Bitfinex” dataset, for example, if there is a single event for “All Data” which lasts 20 minutes this represents one observation, however during the same 20-minute period the “No Bitfinex” data may have 3 events each lasting

Table 4: Cox Proportional Hazards Model Results

Model	Variable	coef	exp(coef)	se(coef)	p-value
All Data	Volatility	-0.236	0.790	0.004	<0.001
Obs = 159,847	Volume	0.018	1.018	0.003	<0.001
Conc = 0.656	Amihud Illiq.	0.026	1.026	0.001	<0.001
	VWAP Premium	0.004	1.004	0.004	0.369
No Bitfinex	Volatility	-0.208	0.812	0.003	<0.001
Obs = 298,358	Volume	0.016	1.017	0.002	<0.001
Conc = 0.587	Amihud Illiq.	0.014	1.014	0.001	<0.001
	VWAP Premium	0.001	1.001	0.003	0.574

2 minutes each. Thus, there is a longer duration of arbitrage for “All Data” but there is a lower number of events in total.

Volatility is significant for both models, with a negative coefficient. This suggests that increased volatility reduces proportional hazard, thus increasing arbitrage survival times. Furthermore, volatility is the greatest contributor to changes in baseline event duration. One standard deviation change in volatility decreases proportional hazard by approximately 20%, which is an approximate duration increase of 25%.

Volume and Amihud illiquidity are significant to both models and hold positive coefficients indicating an increase in proportional hazard. This indicates that increases in these variables are consistent with decreases in arbitrage durations; however, their effects are very small, as noted by the $\exp(\text{coef})$ values being close to one. It is noted that VWAP premium is not significant to either model. These results appear consistent with the previous descriptive statistics.

5.3 Event Studies

To investigate the causal impact of previously mentioned friction-related events on arbitrage creation, event studies were conducted. Again, the analysis was run on the two hourly datasets, the full dataset with Bitfinex included and the dataset with Bitfinex excluded from the system. A list of the events investigated can be viewed in the first column of Table 5.

The events fall into three broad groups, Bitfinex-related events, China-related events, and Bitcoin-related events. The parliamentary adoption of the EU AMLD5 and the deadline for member-state transposition were both investigated; however, no arbitrage was observed surrounding these events, thus they do not appear in the analysis.

To conduct the event study analysis, the values of A_t were transformed using the function $\max(0, A_t - 1)$. This allows the study to determine significant changes to actionable post-event arbitrage in percentage terms. The day (UTC) of the event was excluded from the data and a pre-event window comprising the 24 hours of the previous calendar day was used to determine 'normal' arbitrage prior to the event taking place. This was done by taking the mean of observations during this pre-event period. This arbitrage baseline value was subtracted from the post-event window observations, 24 hours of the calendar day following the event, and a two-sided T -test was used to determine if the result was statistically significant from zero. Thus, small p -values indicate significant changes to arbitrage due to the event's occurrence. The resulting T -test p -values are displayed in Table 5. Empty values indicate that there were no arbitrage observations during the observation period.

The event study isolates thirteen dated shocks and compares their impact on actionable cross-exchange arbitrage in the full sample and in a counterfactual dataset that excludes Bitfinex. Seven of those shocks are tied to Bitfinex's own banking or regulatory frictions - namely the Wells Fargo wire freeze, CFTC subpoena news announcement, Noble Bank exit, HSBC deposit freeze, USDT de-peg, the Deltec banking partnership announcement, and the NYAG lawsuit filing. Each of the seven produces a significant rise in post-event arbitrage when Bitfinex is present yet becomes statistically insignificant once Bitfinex is removed. This pattern strongly supports the core hypothesis that Bitfinex-specific frictions are the source of the observed price spreads.

Policy shocks originating in China affect the whole market, as shown by the significant p -values in both datasets, yet their economic impact is clearly larger when Bitfinex is included. After the ICO ban, mean abnormal-arbitrage widens by 1.54% in the full sample but by only 0.97% once Bitfinex is excluded. For the exchange-shutdown notice the spread increase falls from 0.30% to 0.26%, and for the closure deadline from 0.21% to 0.13%. These smaller magnitudes in the exclusionary sample indicate that Bitfinex may amplify, rather than generate, the shock transmitted by Chinese regulation.

Bitcoin market-wide events were included as placebo, notably the CME futures launch

Table 5: Event Study p -values and Mean Deltas.

Event	Date	P-values		Magnitude ($\Delta\%$)	
		All Data	No BF	All Data	No BF
Bitfinex–Linked Events					
Wells Fargo Cuts USD Wires	2017-04-11	<0.001***	0.473	0.243	0.010
CFTC Bitfinex Subpoena News	2018-01-30	<0.001***	No Arb.	-1.021	-
Noble Bank Ends Relationship	2018-10-01	0.002***	0.519	0.140	0.002
HSBC Deposit Freeze	2018-10-11	<0.001***	No Arb.	0.476	-
Tether Depeg	2018-10-15	<0.001***	No Arb.	2.254	-
Deltec Partnership Announced	2018-11-01	0.054*	No Arb.	0.071	-
NYAG Lawsuit	2019-04-25	<0.001***	No Arb.	3.454	-
China-Specific Events					
China ICO Ban	2017-09-04	<0.001***	0.002***	1.536	0.966
China CEX Shutdown Notice	2017-09-15	0.003***	0.005***	0.301	0.263
China CEX Closure Deadline	2017-09-30	<0.001***	<0.001***	0.206	0.131
Bitcoin-Related Events					
Bitcoin Gold Hard Fork	2017-10-24	0.086*	No Arb.	0.007	-
Bitcoin Diamond Hard Fork	2017-11-24	<0.001***	<0.001***	0.367	0.367
CME Futures Launch	2017-12-18	<0.001***	<0.001***	-0.673	-0.670

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

and Bitcoin forks. These events show near identical p -values and magnitudes in both datasets, as expected. ²

This event study complements the earlier regression analysis, survival results, and narrative developed in Section 3. Exchange-specific shocks related to Bitfinex’s fiat-rail or regulatory status consistently widen post-event spreads in the full dataset yet vanish once Bitfinex is removed, mirroring the sharp fall in regression R^2 and drop in mean arbitrage duration earlier reported. Market-wide policy shocks, such as China’s September 2017 measures, remain detectable without Bitfinex but with muted economic impact. Placebo dates show little material difference between the two samples, reinforcing the conclusion that the Bitfinex-tied frictions are the causal drivers of the price discrepancies. Together these patterns confirm the paper’s central theme that fiat frictions on a single CEX venue can both create and amplify cross-exchange mispricing.

²Other events were explored - for example the EU AMLD5 milestones, Bitcoin Cash hard fork, or ETF announcements - but showed no abnormal arbitrage surrounding the event dates, thus were omitted.

6 Conclusion

From 2017 to the end of 2019, Bitfinex consistently had a BTC/USD price premium over other major centralized exchanges. Multiple factors unique to Bitfinex contributed to this phenomenon, most notably venue-specific liquidity restrictions resulting from holds on fiat deposits and withdrawals. These higher prices presented as arbitrage opportunities in the data and accounted for 80% of the arbitrage occurrences. To determine whether the premium reflected market-wide factors or frictions unique to Bitfinex, we estimated cross-sectional regressions, Cox duration models, and event studies on the full and counterfactual datasets for comparison.

Volatility consistently is the largest contributor to arbitrage in the models, with changes to volatility greatly impacting Cox model survival times and explaining 74% of cross-sectional variance when Bitfinex is present. Furthermore, by removing this exchange with artificially inflated Bitcoin values, the relationship between volatility and arbitrage was observed to be weaker in reality.

Volume, Amihud illiquidity, and VWAP premium were seen to contribute little to the models, indicating little explanatory influence for conventional market microstructure explanations. This is somewhat surprising, though recent research has indicated the presence of wash-trading at major Bitcoin venues, which may impact these results (Aloosh & Li 2024; Cong et al. 2023). Bitfinex significantly increases the occurrence of arbitrage, magnitude of arbitrage, and duration of arbitrage. This seems to stem from Bitfinex-specific frictional-events which indicate that arbitrage originates on Bitfinex. Furthermore, Bitfinex appears to magnify some market-wide arbitrage-affecting events, shown by when “Full Data” and “No Bitfinex” resulting significance and magnitudes are compared.

As noted, the dynamics surrounding Bitfinex’s sustained BTC/USD price premium share notable similarities with other instances of manipulation and disruption in the cryptocurrency market, such as the case of Mt.Gox (Gandal et al. 2018). Following serious hacks in which the exchanges lost significant amounts of Bitcoins, both exchanges offered higher than market Bitcoin prices (in terms of USD), likely to generate a large volume of trade and accompanying fees from those who sold Bitcoin on their exchanges. It is noteworthy that Bitfinex received a tangential benefit in that Tether was successful at garnering adoption among the broader cryptocurrency market during this time.

A key comparison between the two exchanges lies in liquidity constraints. Mt.Gox’s eventual collapse in 2014 was due, in part, to its inability to meet withdrawal demands, a liquidity crisis exacerbated by security breaches. Similarly, Bitfinex struggled with fiat withdrawals. This situation paralleled the behavior of traditional bank runs, where concerns over solvency can trigger a self-fulfilling cycle of withdrawal requests, ultimately exacerbating the exchange’s liquidity problems. Bitfinex’s withdrawal restriction prevented a bank run effect from occurring immediately around periods of uncertainty. However, once resolution followed regulatory scrutiny - including greater market transparency and shifts toward higher regulatory standards - many traders appeared to seek alternative platforms, diminishing Bitfinex’s market dominance, much like the collapse of Mt.Gox. As Bitfinex worked to improve its security infrastructure and as competition from other exchanges increased, the previously significant arbitrage opportunities that had fueled the price premium gradually dissipated.

The case of Bitfinex underscores the interplay between liquidity, market sentiment, and regulation in the cryptocurrency market. Just as Mt.Gox’s collapse demonstrated the dangers of poor liquidity management and security, Bitfinex’s experience highlights how regulatory intervention and shifting market dynamics can correct artificial price inefficiencies over time. Both cases emphasize the vulnerability of exchanges that hold a dominant market position and the potential for market manipulation when transparency and regulatory oversight are lacking.

More broadly, these findings highlight that arbitrage opportunities do not always vanish quickly, even in competitive markets. Structural constraints — such as liquidity frictions, withdrawal limitations, and regulatory uncertainty — can sustain price discrepancies for extended periods. While traditional financial markets exhibit strong arbitrage forces that drive price convergence, the cryptocurrency market remains fragmented, with exchange-specific conditions influencing the efficiency of price adjustments. The case of Bitfinex underscores how institutional and regulatory barriers can shape market dynamics, limiting the speed at which arbitrageurs can act and prolonging inefficiencies that might otherwise disappear rapidly. These insights suggest that understanding market microstructure is crucial for assessing price formation and efficiency in digital asset markets. Ultimately, the parallels between Bitfinex and Mt.Gox reveal the fragility of cryptocurrency exchanges and the importance of improving market safeguards to prevent manipulation and ensure long-term

stability in the digital asset ecosystem.

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