Global Arbitrage under Settlement Cycle Mismatch

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PRELIMINARY DRAFT

Abstract

I provide the first causal evidence that settlement cycle mismatches across jurisdictions disrupt arbitrage mechanisms. Using the US transition to T+1 settlement as a quasi-natural experiment, I find that arbitrage activity significantly declines for US ETFs tracking foreign assets. This decline increases tracking error and reduces liquidity for these ETFs. The effects spill over, impacting other ETFs that share the same arbitrageurs and reducing liquidity in the underlying foreign assets. These findings underscore the economic costs of uncoordinated settlement cycles.

JEL Classification: G14, G15, G23

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1 Introduction

How does a mismatch in the settlement cycle affect arbitrage? Figure A1 presents a simplified example. Consider an initial scenario (Panel A) involving two assets, A and B, both tracking the same fundamental value and settling on a T+1 cycle. Suppose an exogenous demand shock inflates the price of asset B at time T, while the price of asset A remains unchanged. An arbitrageur intervenes, buying low (asset A) and selling high (asset B) to exploit the price discrepancy with an expectation that the price of asset A and asset B will converge. This trade executes seamlessly: both legs settle concurrently at T+1, enabling the arbitrageur to capture the price differential as profit. Such arbitrage enhances market efficiency by supplying liquidity to asset A—thereby countering directional demand pressure—and facilitating price discovery by realigning the prices of A and B.

Consider a second scenario (Panel B) where asset A settles at $T+2$ and asset B at $T+1$. After a demand shock at time T, the arbitrageur executes the trade—buying asset A and selling asset B. At $T+1$, however, the position cannot be fully settled: asset B's sale settles, but asset A, purchased to offset the trade, is not delivered until $T+2$.[1] To close the position at $T+1$, the arbitrageur could either borrow asset A (as shown in Panel A of Figure A2), incurring costs and risks, or acquire asset A in advance (as shown in Panel B of Figure A2), facing inventory risk. These frictions, arising from the settlement cycle mismatch, erode arbitrage profitability, discourage participation, and impair the liquidity provision and price discovery seen in the first scenario.

In this paper, I provide causal evidence that a mismatch in the settlement cycle impedes cross-border arbitrage. Using exchange-traded funds (ETFs) as a laboratory, I employ a difference-in-differences (DID) framework to examine the effects of a settlement cycle mismatch on arbitrage activities after the United States shortened its settlement cycle from T+2 to T+1 on 27 May 2024 (the T+1 Rule).[2] The Rule leads to a mismatch

[1]Two exceptions allow selling asset A before $T+2$ settlement: (1) Same-day (intraday) trading, where asset A is bought and sold on Monday, clearing the position before T settlement; (2) A margin account, though we assume a cash account here.

[2]The settlement cycle change in the US, effective May 28, 2024, refers to the transition from a T+2 (trade date plus two business days) to a T+1 (trade date plus one business day) settlement cycle. This change applies specifically to financial assets traded in the US markets and settled through the Depository Trust & Clearing Corporation (DTCC) system. Financial instruments subject to the settlement cycle

between the United States, the largest financial market, and other major jurisdictions, such as the European Union, the United Kingdom, and Japan. I conduct a global study and compare ETFs tracking the same index, where one group is exposed to a settlement cycle mismatch and the other is not. Specifically, I examine the arbitrage activities of US ETFs tracking a basket of non-US assets in a different settlement cycle to non-U.S. ETFs tracking the same basket of non-US assets but in the same settlement cycle. The US ETFs are subject to settlement cycle mismatch because the US ETF shares settle in T+1 while the non-US underlying assets that the US ETFs track settle in T+2. Under a DID framework, I can identify the effect attributed to variation in the exposure to the settlement cycle mismatch rather than other factors related to the underlying assets. My findings suggest that a settlement cycle mismatch significantly reduces the arbitrage activities of the ETFs exposed to the settlement cycle mismatch problem.

This reduction in arbitrage activity leads to diminished price discovery and liquidity for the affected ETFs. In the context of ETFs, price discovery refers to how closely the price of an ETF tracks its benchmark, a metric which is naturally measured by the tracking error of the ETF. Meanwhile, liquidity provision refers to the liquidity measure of the ETFs shares. I regress tracking error (σ_t^{TE}), as a measure of price discovery, and Roll (1984) impact ratio (Roll), as a proxy for liquidity, on the interaction of an exposure indicator $\mathbf{1}(T1ETF_f)$ and a post-change indicator $\mathbf{1}(CycleChange_t)$. The difference-in-differences results show that exposed ETFs experience an increase in tracking error of 10 basis points, equivalent to 25% of the annual expense ratio and 10% of the return volatility. It also leads to an increase in effective spread of 10.3 basis points, representing a 47% rise from the pre-change effective bid-ask spread of 22 basis points.

I move on to examine the spillover effect of the settlement cycle mismatch. First, I document a horizontal spillover effect where ETFs unexposed to the settlement cycle

change include: 1. Equity instruments (common stocks, preferred stocks, and other equity securities listed on US exchanges, American depositary receipts (ADRs) and equity warrants and rights); 2. Fixed income instruments (corporate bonds and municipal bonds); 3. Fund instruments (ETFs, closed-ended funds, UITs, REITs and some mutual funds cleared through the DTCC); 4. Derivatives instruments (asset-backed securities (ABS) and options). Instruments, such as foreign exchange (FX), money market instruments and government securities are not subject settlement cycle change because they do not settle through DTCC.

mismatch also exhibit a reduction in arbitrage activities. I attribute this to a spillover effect from shared authorized participants (APs) acting as arbitrageurs across both exposed and unexposed ETFs, driven by a highly intermediated and concentrated AP market. To illustrate, the number of APs actively trading with the largest 10 equity ETFs is 24. This figure rises to 27 when considering the largest 50 equity ETFs, an increase of just 3 APs. Given the concentrated nature of the primary market arbitrage space, where a small subset of APs handles a large share of ETF trading, I constructed a continuous variable to capture the indirect exposure of unexposed ETFs to the settlement cycle mismatch via APs in two steps. First, I assess each AP's exposure to cross-border ETFs by aggregating their trading activities with these ETFs in the year prior to the U.S. settlement cycle shock. The APs are then classified as "exposed" or "non-exposed" based on whether they engaged in such trades during that period. Next, I calculate the percentage of a local ETF's total trading activity conducted with these exposed APs, creating a proxy for indirect exposure. In the subsample of ETFs traded in the United States, I interact this variable with the post-change indicator ($\mathbf{1}(CycleChange_t)$) and find that reductions in primary market arbitrage is more pronounced for unexposed ETFs with greater trading exposure to APs heavily involved in the arbitrage of exposed ETFs.

I further explore the dynamics of arbitrageur competition in response to this settlement cycle shock. Focusing on ETFs traded in the United States, I find that other market participants, particularly high-frequency trading (HFT) firms, increase their presence in the secondary market for ETFs. Three proxies for HFT activity - the cancel-to-trade ratio (CTR), trade-to-order ratio (TOR), and odd-lot ratio (ODD) - each indicate a rise in HFT participation in the ETF market (Hendershott et al., 2011; Hasbrouck and Saar, 2013; O'Hara et al., 2014; Weller, 2017). This increased HFT activity enhances the liquidity provision of the U.S. ETFs, partially offsetting the reduction caused by diminished primary market arbitrage. However, it also introduces higher latency risk and adverse selection for market makers (described by Foucault et al. (2016) as "toxic arbitrage"). Consequently, I observe that the quoted bid-ask spread increases with greater HFT involvement. For example, a 1% decrease in the TOR (indicating an increase in HFT activities) after the

settlement cycle change is associated with a 14 basis points widening of the quoted bid-ask spread, reflecting the trade-off between improved liquidity and increased market-making costs.

Finally, I document a vertical spillover effect on underlying assets tracked by the U.S. ETFs. More specifically, I investigate how reduced arbitrage activities in U.S. ETFs — key purchasers of foreign assets — affect the underlying foreign securities. Given that settlement cycle mismatches impede ETF creation and redemption, I assess their impact on the liquidity provision and price informativeness of these underlying assets, employing measures such as the Roll (1984) impact ratio, the Lesmond et al. (1999) Zero ratio, and Roll (1988)'s $1 - R^2$ metric over a 22-day rolling window. My findings reveal that when foreign securities predominantly held by U.S. ETFs encounter settlement cycle mismatches, their liquidity provision declines significantly. However, no effect is observed in the price informativeness measure, suggesting that the reduction in arbitrage activities is not driven by informational factors.

Related Literature This paper contributes to the extensive literature on the limits to arbitrage,[3] which attributes these limits to various risks and constraints, including noise trader risk (De Long et al., 1990), short-sale constraints (Harrison and Kreps, 1978), equity capital constraints (Shleifer and Vishny, 1997), funding constraints (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2008), and balance sheet constraints (Pan and Zeng, 2016). While prior research has primarily examined single-market dynamics, this study extends the literature by exploring arbitrage across markets with differing settlement cycles. I identify a novel source of friction: settlement cycle mismatch and show that this misalignment represents a previously unrecognized limit to arbitrage. This paper provides the first empirical evidence that cross-jurisdictional differences in settlement cycles hinder arbitrage activities, which impedes the price discovery and liquidity provision of assets affected by these mismatches.

This paper also contributes to both the intermediary asset pricing literature (He and

[3]Limits to arbitrage refer to obstacles that prevent arbitrageurs from fully correcting market price discrepancies.

Krishnamurthy, 2013; Adrian et al., 2014; He et al., 2017) and the growing literature on ETFs by examining the asset pricing implications of financial intermediary constraints, with a particular focus on authorized participants (APs) in ETF markets (Pan and Zeng, 2016; Shim and Todorov, 2021; Dannhauser and Hoseinzade, 2021; Reilly, 2022). I document a novel spillover effect: APs, constrained by capital-intensive arbitrage and balance sheet limitations, reduce their arbitrage activities not just for ETFs exposed to the settlement cycle shock, but also for unexposed ETFs that share a common pool of arbitrageurs. Unlike Gorbatikov and Sikorskaya (2021), which explores how AP network characteristics (e.g., number, concentration, and diversity) affect ETF mispricing in the primary market, my work pinpoints settlement cycle mismatch as a specific constraint and quantifies its broader implications. Similarly, while Hong et al. (2022) study comovement in ETF premia linked to a common lead market maker, I distinguish my contribution by tracing the effects of a precise shock—settlement cycle mismatch—on AP-conducted arbitrage across both exposed and unexposed assets.

Lastly, my paper documents fierce competition in arbitrage, particularly from high-frequency trading (HFT) firms, as documented by Brogaard et al. (2014); Budish et al. (2015). While intermediary constraints reduce arbitrage on unexposed assets, I find that HFT activities increase, partially offsetting the decline in liquidity provision. However, consistent with Foucault et al. (2016), this liquidity is "toxic," as market makers face heightened latency risk and adverse selection, prompting them to widen quoted bid-ask spreads.

2 Institutional Background

2.1 Settlement cycle mismatch under interconnected financial markets

I begin by providing a brief overview of the settlement cycle changes in major jurisdictions. A shorter settlement cycle is considered effective in reducing counterparty risk and has been at the top of regulators' agendas. However, the settlement cycle regulations

are tailored to the specific needs and structures of local financial markets, resulting in regulatory fragmentation. For example, as illustrated in Figure 1, the two largest financial jurisdictions, the United States and the European Union, had a period of consistent settlement cycles prior to 2013. Since then, they have had changes in their settlement cycles in different paces. In fact, following the rule, the US now settles in a T+1 regime while other large financial regimes such as the European Union, Japan, and the United Kingdom still settle at T+2, as shown in Figure 2. Although some jurisdictions, such as the European Union and the United Kingdom, are exploring a shift to T+1, these mismatches are likely to endure absent coordinated global reform.[4] More importantly, these mismatches become even more problematic as settlement cycles get shorter: the difference between T+3 and T+2 is 33%, between T+2 and T+1 is 50%, and between T+1 and T+0 is 100%. When major jurisdictions potentially move to T+0 in the future, the problem of mismatches will continue to intensify until all jurisdictions move to a T+0 settlement cycle, which could be challenging to achieve in the foreseeable future.

Settlement cycle mismatch affects the trading of cross-border assets, defined as assets traded in foreign markets. Due to the increasing interconnectedness of asset markets around the world, cross-border assets are growing rapidly. As of the end of 2024, the $100 trillion equity market in the U.S. is comprised of $90 trillion in common equity and $10 trillion in ETFs. One-third of the equity market capitalization is attributed to non-U.S. companies through American depositary receipts (ADRs), and one-fifth of ETF market capitalization is attributed to ETFs tracking non-U.S. indexes. As a result, arbitrage activities in different jurisdictions subject to different settlement cycles become increasingly important, as arbitrage is a key mechanism for an efficient capital market due to its role in price discovery and liquidity provision (Rösch, 2021).[5]

[4]Additional information on settlement cycle transitions in major jurisdictions is provided in Table A1.

[5]In addition to the settlement cycle mismatch among jurisdictions, a second layer of mismatch could emerge across asset classes within a single jurisdiction, driven by further regulatory segmentation. In the U.S., for instance, futures contracts, overseen by the Commodity Futures Trading Commission (CFTC), effectively settle on a T+0 basis due to daily mark-to-market mechanisms. In contrast, stocks and ETFs, regulated by the SEC, adhere to the T+1 cycle under the new rule. This disparity creates settlement cycle mismatches for arbitrageurs who engage in trades across these asset classes, introducing frictions that might limit arbitrage activities. These types of future-ETF arbitrage trades are popular in the U.S. market, as summarized in Table A2. As a result, the problem of settlement cycle mismatch is likely to persist unless all assets under all jurisdictions settle in the same cycle.

2.2 ETF Arbitrage under Settlement Cycle Mismatch

To investigate the effect of settlement cycles on arbitrage activities, it is essential to identify arbitrage opportunities within asset markets. This task poses significant challenges, as these activities occur "faster than the blink of an eye" (Budish et al., 2015). Moreover, the vast number of potential arbitrage pairs among correlated assets complicates detection, as these pairs are often neither obvious nor well-defined. As a result, I focus on ETFs as a laboratory to explore the impact of settlement cycle mismatch. First, ETFs have a well-defined benchmark, namely the underlying assets in the index they track. More importantly, the arbitrage activities in the primary market of ETFs are observable and trackable. To start with, arbitrage activities in ETFs can be categorized into two types: primary market arbitrage and secondary market arbitrage [6].

Primary Market Arbitrage The primary market for ETFs involves transactions between authorized participants (APs)—a group of institutional investors granted exclusive rights to engage in in-kind or cash transactions with the ETF issuer—and the ETF manager or issuer. APs are normally also market maker or official liquidity provider (OLP) who provide liquidity to market through arbitrage. The defining feature of primary market arbitrage is its reliance on the creation and redemption of ETF shares. When the *price* exceeds the *NAV*, APs can create new shares by delivering the underlying assets (or cash equivalent) to the ETF issuer, subsequently selling these shares at the higher market price. The arbitrage moves the prices of ETF shares and underlying assets together and eliminates the price discrepancy. Conversely, when the *NAV* surpasses the *price*, APs can redeem shares for the underlying assets and profit from the discrepancy. These activities are directly observable through changes in the total number of outstanding ETF shares.

Secondary Market Arbitrage The secondary market arbitrage of ETF involves transaction between all other market participants. In this context, arbitrageurs operate

[6] Unlike other asset classes, ETFs possess two distinct value indicators: the market price (*price*) and the net asset value (*NAV*). The *price* represents the prevailing market price that a buyer pays or a seller receives for an ETF share, while the *NAV* reflects the per-share value of the underlying assets managed by the ETF. A critical mechanism aligning the *price* with the *NAV* is arbitrage, whereby arbitrageurs exploit deviations between these two values to generate profit, thereby restoring price alignment.

solely within the open market, buying ETF shares when the *price* falls below the *NAV* and selling when it exceeds the *NAV*, without change the number of ETF oustanding share. Unlike their primary market counterparts, secondary market arbitrageurs lack the "option" to convert underlying asset baskets into ETF shares or vice versa. Consequently, they face higher costs—such as equity borrowing fees—and elevated risks, including exposure to noise trader behavior or market volatility, compared to primary market arbitrageurs. Their profitability hinges on the eventual convergence of *price* and *NAV*, a process that lacks the structural certainty of share creation or redemption. Holding all else constant, primary market arbitrageurs, with their direct access to the ETF issuer, are likely to dominate arbitrage opportunities. As a result, secondary market arbitrage is typically undertaken by specialized investors, such as high-frequency trading (HFT) firms, which leverage superior speed and informational advantages to exploit fleeting price discrepancies Budish et al. (2015).

The distinct mechanisms of primary and secondary market arbitrage facilitate the observation and analysis of arbitrage activities. When authorized participants (APs) engage in primary market arbitrage, their typically uninformative (i.e., non-toxic) actions lead to observable changes in the total number of outstanding ETF shares. In contrast, secondary market arbitrage—whether informative or uninformative—does not affect the share count. This distinction offers a valuable framework for examining the heterogeneous responses of different arbitrage types, especially when they face settlement cycle mismatches. [7] In the following sections, I will concentrate my analysis on primary market arbitrage to assess the impact of settlement cycle mismatches on these trackable activities. In Section 4.3, I will also explore how secondary market arbitrageurs respond to changes in primary market arbitrageurs' behavior.

[7]Although APs could participate in secondary market activities, they are unlikely to do so. In primary market arbitrage, APs are entitled to an "option" to convert baskets into shares and vice versa, an advantage absent in secondary market arbitrage. Consequently, primary market arbitrage does not rely on price convergence for profit realization; the conversion "option" functions as a call option in the creation process (APs can call ETF shares at the cost of NAV) and a put option in the redemption process (APs can put ETF shares at the cost of NAV).

3 Data and Methodology

3.1 Data Description

Exchange-Traded Funds This study examines the year 2024, during which the Rule took effect on May 28. Given its mid-year implementation, the analysis divides the calendar year into two equal halves to compare pre- and post-implementation periods. Data on ETFs is obtained from several widely recognized sources. First, I construct the ETF universe using the Morningstar dataset, which includes both listed and delisted ETFs to avoid survivorship bias. To focus on vanilla passive ETFs, I exclude leveraged ETFs and actively managed ETFs, and restrict the sample to ETFs employing physical replication strategies. To isolate the impact of the Rule change in the United States, I exclude ETFs primarily trading in or tracking assets from Mexico and Canada, which follow the U.S. transition to a T+1 settlement cycle but have smaller markets. Additionally, I exclude ETFs from China and India, where some assets already operate under T+1 or T+0 settlement cycles.[8] I focus on ETFs tracking equity securities, including those tied to larger benchmarks (with total AUM tracking the benchmark exceeding $100 million), because arbitrage activities are more prominent in these ETFs and their underlying assets. The Morningstar data is supplemented with the CRSP Mutual Fund dataset and ETF Global, both widely used in academic research and accessible via the WRDS platform.

For simplicity and coherence, I denote U.S. (non-U.S.) ETFs as T1 (T2) ETFs, as they follow a T+1 (T+2) settlement cycle. Similarly, I denote local (foreign) benchmarks as T1 (T2) benchmarks, as all (some) of their underlying assets follow a T+1 (T+2) settlement cycle. The final dataset comprises 2,064 U.S. and non-U.S. ETFs, with 714 U.S. T1 ETFs, 516 U.S. T2 ETFs, 279 non-U.S. T1 ETFs, and 555 non-U.S. T2 ETFs. Restricting to ETFs tracking the same benchmark, the DID dataset comprises 255 U.S. and non-U.S. ETFs, with 53 U.S. T1 ETFs, 38 U.S. T2 ETFs, 83 non-U.S. T1 ETFs, and 81 non-U.S. T2 ETFs. Table 1 provde the summary statistics of ETFs prior to the U.S. T+1 settlement

[8] China's A-shares follow a T+0 settlement cycle, while B-shares use T+3. In India, the standard settlement cycle is T+1, though an optional T+0 cycle has been available for select stocks since March 2024, enabling same-day settlement for those who opt in.

cycle change in 27 May 2024.

Authorized Participants The information on authorized participants (APs) is available through the NCEN reporting framework mandated by the SEC as part of its Investment Company Reporting Modernization initiative[9]. All registered investment funds, including ETFs, must disclose details about related counterparties, including the APs for ETFs. Specifically, they are required to report each "registered" AP's name, identifier, and annual creation and redemption volumes even if the AP is has not engaged in creation or redemption during the year. Thus, this dataset enables us to measure each ETF's connection to the exhaustive list of registered APs and to analyze the APs' creation and redemption networks with ETFs. It is crucial for my analysis to study how the AP could spill over the inefficiency of arbitrage activities from exposed ETF to unexposed ETF in the result session.[10]

My dataset comprises 39 authorized participants (APs), as detailed in Table A3. The majority are subsidiaries of globally systemically important banks (G-SIBs), with a growing presence of non-bank intermediaries, such as high-frequency trading firms, in the sector. I manually identify the parent companies of these APs and obtain their regulatory and balance sheet data from Capital IQ. The primary focus is on Basel III regulatory ratios, including the Common Equity Tier 1 (CET1) ratio, Total Capital Ratio, and Total Loss-Absorbing Capacity (TLAC) ratio, which serve as proxies for the balance sheet capacity of these APs. A detailed description of these Basel III ratios is provided in Section 4.

Secondary Market Activities In addition to primary market arbitrage, examining the dynamics of secondary market participants in response to primary market activities is essential for understanding the full impact of settlement cycle mismatches on arbitrage activities. Specifically, I focus on high-frequency trading (HFT) firms, which are prominent

[9]On October 13, 2016, the SEC adopted new rules, forms, and amendments to modernize reporting requirements and enhance transparency for registered investment companies. See https://www.sec.gov/resources-small-businesses/small-business-compliance-guides/investment-company-reporting-modernization-rules for details.

[10]A growing number of studies leverage this informative reporting to examine intermediation of ETF (Gorbatikov and Sikorskaya, 2021).

arbitrageurs in the secondary market. Although I lack access to minute-by-minute high-frequency complete order books to directly identify HFT arbitrage, I use daily secondary market summaries from MIDAS as a proxy for the presence and activity of HFT firms (Hendershott et al., 2011; Hasbrouck and Saar, 2013; O'Hara et al., 2014; Weller, 2017). MIDAS collects and processes data from consolidated tapes and individual proprietary feeds provided by each equity exchange. These exchange-specific feeds are typically utilized by sophisticated market participants, such as market makers and high-frequency traders, making them well-suited to my goal of capturing HFT activities exclusively, rather than quantifying each distinct arbitrage activity as in Budish et al. (2015).

3.2 Methodology

To isolate the effect of settlement cycle mismatch, I employ a difference-in-differences approach, comparing an ETF exposed to the mismatch with another ETF not exposed to it, both tracking the same benchmark index under the following specification:

$$Y_{f,b,t} = \beta_{DID} \times \mathbf{1}(T1ETF_f) \times \mathbf{1}(CycleChange_t) + \alpha_b + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

, where I regress the independent variable $Y_{f,b,t}$ on the interaction of indicator variables $\mathbf{1}(T1ETF_f)$, which equals 1 if the ETF is a U.S. ETF, $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change. λ_f is The benchmark or fund fixed effect to account for unobservable heterogeneity among benchmarks or ETFs, α_t is the time fixed effect to account for time-specific effects or trends and $\sum_{n=1}^{N} x_{f,t-1}\beta_n$ are the lagged control variables which include $\ln(FundTNA)$, the log of total net assets, $\ln(FundAge)$, the log of fund age in years, *Return*, raw returns, *Flow*, fund flows, *Roll*, Roll's (1984) impact ratio as a proxy for ETF illiquidity and $Mispricing$, the deviation of ETF price from its nav.

I use ETFs that are traded in the US but track foreign indices as the treatment group. They are subject to settlement cycle mismatch, arising from cross-jurisdictional differences in settlement timelines of ETF shares (settle in T+1) and underlying securities (settle in T+2). The control group comprises foreign ETFs that track the same foreign

indices. They do not subject to settlement cycle mismatch because both the ETF and the underlying securities are settled in the same settlement cycle. By holding the benchmark index constant across both groups, I ensure that differences in arbitrage activities, price discovery, or liquidity provision can be attributed to the settlement cycle mismatch rather than variations in the underlying assets. This quasi-experimental design leverages the natural variation in settlement rules across markets, allowing meremo to estimate the causal impact of the mismatch on arbitrage efficiency and market quality.

4 Results

4.1 Reduced primary market arbitrage

I first examine whether the mismatch affect the authorized participant's arbitrage activities in the ETF context. To capture the change of responsiveness of primary market arbitrage activities to mispricing, I use change of share outstanding in the ETF as a proxy for AP arbitrage activities given the fact that creation and redemption will necessarily change the share of outstanding of the ETF. I use $Mispricing$: $\frac{price-nav}{nav}$, the percentage deviation between price and nav of the ETF as the main proxy for the level of mispricing. I also construct two other proxies to disentangle the positive and negative mispricing: 1) $Mispricing^{+}$: $\max\left\{\text{Mispricing}_t^{+} \mid t \in [T-5, T]\right\}$, the maximum positive mispricing (i.e. premium) for the last 5 days and 2) Min($Mispricing^{-}$) : $\min\left\{Mispricing_t^{-} \mid t \in [T-5, T]\right\}$, the minimum negative mispricing (i.e. discount) for the past 5 days, respectively. Column (1) in Table 2 confirms the reduced activities in the U.S. ETFs tracking foreign benchmark after the settlement cycle change relative to non-U.S. ETFs. The economic magnitude of the change is large. After the settlement mismatch shock, the sensitivity of arbitrage to mispricing for T1 ETFs decrease by 0.061 / 0.068 = 89%, relative to the T2 ETFs tracking the same T2 benchmark. Column (2) and (3) in Table 2 shows that the magnitude is larger in the positive mispricing compared to the negative mispricing, suggesting that APs are more constrained in the creation process than the redemption process. Column (4) - (6) repeats the regression but include fund

fixed effect rather than benchmark fixed effect.

An important component in cross-border transactions is the foreign exchange rate (FX). Given that FX rate fluctuations are a critical factor in cross-border ETF transactions, as these ETFs are exposed to FX risk, but absent in domestic ETFs, my result could be confounded with FX fluctuation co-occurs during the settlement cycle shock. However, I argue that FX fluctuations are unlikely to be the primary driver of my results. First, the settlement cycle mismatch does not directly affect FX settlement, as it pertains to instruments cleared through the Depository Trust & Clearing Corporation (DTCC) system, whereas FX transactions are settled via the Continuous Linked Settlement (CLS) system or bilateral arrangements.

Second, while direct FX impacts are minimal, indirect effects from settlement cycle changes could arise. To address this, I analyze a subsample of U.S. ETFs tracking foreign assets that explicitly hedge currency risk, as reported in Table A4. A subsample test confirms that the effect persists, though statistical significance is reduced due to the smaller sample size. These findings suggest that settlement cycle mismatches, rather than FX fluctuations, primarily drive the observed spillover effects on ETF arbitrage activities.

4.2 Direct Effects of Reduced Arbitrage Activities

How do reduced arbitrage activities directly affect ETF markets in general? As discussed in the previous section, arbitrage plays a pivotal role in price discovery and liquidity provision. Here, I use ETFs as a testing ground to gain insights into these effects. In this context, the efficiency of price discovery corresponds to how closely an ETF tracks its benchmark. Thus, tracking error - defined as the persistent deviation between an ETF's price, its net asset value (NAV), and its benchmark - quantifies the extent to which reduced arbitrage, due to settlement cycle mismatch, impairs the price discovery function. Additionally, I examine the impact on liquidity provision by assessing the liquidity of ETF shares under the same mismatch, offering broader insights into its effects on other assets.

4.2.1 Price Discovery

Prolonged disruptions in price discovery can lead to significant financial market dislocations, where markets fail to accurately price assets on absolute and relative bases (Pasquariello, 2014). These recurring dislocations, such as the 1990s Mexico "Tequila Crisis", Asian Financial Crisis, and LTCM collapse; the 2000s "Dot-com" crash and Argentine Crisis; and recent events like the 2010 "Flash Crash", 2020 COVID-19 market turmoil, and 2022 UK Gilt Crisis, highlight the important role for effective arbitrage and price discovery, particularly under stressed market conditions (Hubrich and Tetlow, 2015; Alessandri and Mumtaz, 2019).

In this section, I examine how settlement cycle mismatches impair the price discovery. More specifically, I focus on relative arbitrage parity, where arbitrage ensures that nearly identical assets adhere to the law of one price, preventing unlimited risk-free profits. I quantify this "relative mispricing" in ETFs by calculating the tracking error, defined as the volatility of deviations between an ETF's returns and those of its benchmark index. It is formally defined as the standard deviation of the difference between these returns, calculated over a rolling window of $N = 22$ days:

$$\sigma_t^{TE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_{p,t-i} - R_{b,t-i})^2},$$

, where $R_{p,t-i}$ and $R_{b,t-i}$ denote the daily returns of the ETF portfolio and its benchmark, respectively. This metric quantifies the additional risk or volatility beyond that of the benchmark—risk that a mean-variance investor typically seeks to minimize. My analysis indicates that, following a regulatory change in settlement cycles, U.S. ETFs tracking foreign benchmarks experience a notable increase in tracking error. As shown in Column (1) - (2) of Table 3, the tracking error of U.S. ETFs rises by 8.6 to 10 basis points more than that of non-U.S. ETFs tracking the same benchmarks.

How to interpret the economic magnitude of the increase? First, the increase is significant, particularly given that the average tracking error differential before the settlement cycle change was -10 basis points, suggesting that the prior comparative

advantage of U.S. cross-border ETFs in minimizing tracking error disappears post-shock. Second, the 10-basis-point rise represents approximately 25% of the annual expense ratio of these U.S. cross-border ETFs, underscoring its relevance to cost-conscious ETF investors. Third, when viewed relative to return volatility, the increase is substantial: with an average benchmark return standard deviation of 86 basis points over the same 22-day window, the 10-basis-point increase in tracking error equates to more than a 10% rise in return volatility.[11]

4.2.2 Liquidity Provision

Alongside their role in price discovery, arbitrage activities are pivotal to liquidity provision in financial markets. The impact of arbitrage activities is twofold. On one hand, Foucault et al. (2016) provides empirical and theoretical evidence that "toxic" arbitrage, arising from informational advantages, reduces liquidity provision due to increased adverse selection risk faced by liquidity providers. On the other hand, the theoretical review by Gromb and Vayanos (2010) and empirical evidence from Rösch (2021) show that arbitrage, arising from price pressure, enhances liquidity provision. My setting of primary market arbitrage in ETFs aligns more closely with the latter, where authorized participants (APs) operationally conduct arbitrage between ETF prices and their net asset values (NAVs) to capture price deviations from fundamentals due to temporary price pressure. While "toxic" arbitrage may also occur in ETFs, it is more prevalent in the secondary market, as documented by Comerton-Forde and Marta (2025). Thus, in this section, I focus on the impact of settlement cycle mismatches on primary market arbitrage in ETFs, while Section 4.3 elaborates on secondary market arbitrage dynamics.

To assess the impact of reduced primary market activity on ETF liquidity following the settlement cycle shock, I employ the Roll impact ratio (*Roll*) as a proxy for ETF illiquidity, defined as:

$$\text{Roll} = 2 \times \sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})}$$

where ΔP_t and ΔP_{t-1} represent the price changes at times t and $t-1$, respectively. When

[11] Parallel trend assumption is examined in Figure A4.

the sample serial covariance is positive, the formula is undefined, so I substitute a default value of zero, following (Goyenko et al., 2009). Thus, I use a modified Roll estimator:

$$\text{Roll} = \begin{cases} 2\sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})} & \text{when } \text{Cov}(\Delta P_t, \Delta P_{t-1}) < 0, \\ 0 & \text{when } \text{Cov}(\Delta P_t, \Delta P_{t-1}) \geq 0. \end{cases}$$

Columns (3)–(4) of Table 3 indicate that U.S. ETFs experience a significant decline in liquidity post-settlement cycle change. The illiquidity measure *Roll* increase by 0.1% for U.S. ETF relative to non-U.S. ETF after the settlement cycle change. This result is consistent with prior studies that arbitrage activity significantly enhances asset liquidity and reduced arbitrage activity distorts liquidity provision.

4.3 Horizontal Spillover to Unexposed ETFs

In this section, I investigate whether settlement cycle mismatches in the ETF primary market generate spillover effects on ETFs not directly exposed to such mismatches, given the highly intermediated and concentrated nature of this market. First, ETF primary market is hevaily intermediated because only APs —typically large financial institutions like banks, broker-dealers and high-frequency trading firms — can interact directly with the ETF issuer in the creation and redemption by design. Second, I document that ETF primary market is heavily concentrated. Panel A of Figure 4 illustrates the network of APs for the 10 largest ETFs in my sample, which collectively involve 24 APs in creation and redemption activities. Expanding the sample to the 50 largest ETFs increases the number of APs only marginally to 27, indicating a highly concentrated AP market where individual APs conduct creation and redemption activities for numerous ETFs, including both cross-border and domestic ETFs. [12]

I hypothesize that settlement cycle mismatches impose additional balance sheet constraints on APs, who need to pre-acquire or borrow securities to facilitate arbitrage in

[12] I also find that there are heterogeneous preference in APs: Bank-affiliated APs, whose parent companies engage in deposit-taking activities, tend to participate more in cross-border transactions, likely due to greater balance sheet capacity while non-bank-affiliated APs, such as high-frequency trading firms or dedicated market makers, participate more in local transactions.

cross-border ETFs under settlement cycle mismatch. This increased demand on balance sheet capacity may limit APs' ability to engage in arbitrage activities for domestic ETFs, which are not directly affected by settlement cycle mismatches. To test this hypothesis, I exploit variations in APs' exposure to settlement cycle mismatches. For instance, Figure 5 compares two major APs in the ETF market: UBS, which allocates 20% of its creation and redemption activities to cross-border ETFs, and Barclays, which has no exposure to cross-border ETFs (0%). This variation enables us to assess how APs' exposure to cross-border ETFs influences their arbitrage activities in domestic ETFs. The concentrated nature of the AP market and the varying degrees of AP involvement in cross-border versus domestic ETFs create a channel through which settlement cycle mismatches may indirectly impact the arbitrage efficiency of domestic ETFs, despite their insulation from direct settlement issues.

To measure a local ETF's indirect exposure to settlement cycle mismatches through its authorized participant (AP) network, I construct a continuous variable, $IndExp_{f,t}$. The construction proceeds as follows: First, I evaluate each AP's exposure to cross-border ETFs by aggregating their creation and redemption activities with these ETFs over the year preceding the U.S. settlement cycle shock. An AP is classified as "exposed" if its trading volume with cross-border ETFs exceeds the median across all APs. Next, for each local ETF, I calculate the proportion of its total trading volume conducted with these exposed APs. This proportion serves as a proxy for indirect exposure, defined as:

$$IndExp_{f,t} = \sum_{a} \frac{TradeVol_{f,a,t} \cdot \mathbf{1}(AP_a^{\text{Exposed}})}{TradeVol_{f,t}},$$

where $TradeVol_{f,a,t}$ represents the primary market trading volume of ETF f with "exposed AP" at time t, $\mathbf{1}(AP_a^{\text{Exposed}})$ is an indicator equal to 1 if AP a is classified as "exposed", and $TradeVol_{f,t}$ is the total primary market trading volume of ETF f at time t. This metric captures the extent to which a local ETF's trading activity relies on APs with significant exposure to cross-border ETFs, thereby quantifying its indirect exposure to settlement cycle mismatches.

The results, presented in Table 4, show that higher exposure to settlement cycle

mismatch risk via the AP network reduces AP responsiveness to local ETF mispricing. Shown in column (1), for local ETFs with zero indirect exposure to settlement cycle mismatch, one standard deviation increase in positive (negative) mispricing leads to 0.166% inflow (outflow) after the settlement cycle change. However, A 1% increase in the indirect exposure (*IndExp*), measured as the fraction of trade volume conducted by exposed AP prior to settlement cycle change, will leads to 0.27% lower flow for 1 standard deviation of mispricing. [13] This pattern of declining sensitivity of arbitrage activity to mispricing exist for both extreme postivie and negative mispricing as shown in Column (2) and (3).

4.3.1 Spillover Effects and Authorized Participant Balance Sheet

To identify the channel of balance sheet constraints for authorized participants (APs), I collect data from financial and regulatory reports by linking APs to their parent companies. I focus on the following measures from the Basel III regulatory framework and balance sheet metrics:

Common Equity Tier 1 (CET1) ratio, defined as

$$\text{CET1 Ratio} = \frac{\text{Common Equity Tier 1 Capital}}{\text{Risk-Weighted Assets}},$$

measures the core equity capital (common shares, retained earnings, and reserves) relative to risk-weighted assets (RWAs). It captures balance sheet capacity by indicating the highest-quality capital available to absorb losses. A higher CET1 ratio allows APs to allocate more balance sheet resources to ETF creation/redemption, particularly for cross-border ETFs requiring pre-funding or borrowing of risk assets due to settlement mismatches. A lower ratio limits this flexibility, as APs must conserve capital to meet

[13] Several factors may drive this spillover effect. Industry reports suggest that the spillover may stem from increased collateral requirements in the arbitrage process, driven by heightened counterparty risks during ETF creation. An industry report highlights one key reason: APs must post additional collateral for creation activities with ETFs due to heightened counterparty risk, as the settlement cycle mismatch increases the chance that APs cannot settle newly created ETF shares. Specifically, since Authorized Participants (APs) may not receive foreign assets in time to deliver to the ETF during the creation process, ETF issuers require APs to post additional collateral to mitigate these elevated risks. This tightens APs' financial constraints, limiting their capacity to conduct primary market arbitrage in local ETFs.

regulatory thresholds.[14]

Total Capital Ratio, defined as

$$\text{Capital Ratio} = \frac{\text{Total Capital (Tier 1 + Tier 2)}}{\text{Risk-Weighted Assets}},$$

includes Tier 1 (CET1 and Additional Tier 1) and Tier 2 (subordinated debt, reserves) capital. It reflects the additional capital buffer for loss absorption.

The Liquidity Coverage Ratio (LCR), defined as

$$\text{LCR} = \frac{\text{High-Quality Liquid Assets}}{\text{Total Net Cash Outflows over 30 Days}},$$

ensures that financial institutions hold sufficient high-quality liquid assets (HQLA), such as cash or government bonds, to cover net cash outflows during a 30-day stress scenario. The LCR captures balance sheet capacity by measuring liquidity available for activities like ETF creation/redemption. A high LCR supports resilience but ties up capital in low-yielding assets, while a low LCR limits funding for arbitrage, particularly in cross-border ETFs with settlement mismatches.

Total Loss-Absorbing Capacity (TLAC) ratio, defined as

$$\text{TLAC Ratio} = \frac{\text{TLAC-Eligible Instruments}}{\text{Risk-Weighted Assets or Leverage Exposure}},$$

ensure the financial institution have sufficient loss-absorbing capacity for resolution scenarios. TLAC-eligible instruments include CET1, additional Tier 1, tier 2 capital, and bail-in-able debt.

For each of the above balance sheet capacity measures, I construct a fund level continuous measure with the following steps: First, I define an AP as “Robust" if it has larger balance sheet capacity if the proxies (*CET1 ratio*, *Capital ratio*, *LCR* & *TLAR*)

[14]Under Basel III, banks must maintain a minimum CET1 ratio of 4.5%, plus a 2.5% capital conservation buffer, totaling 7%, with additional buffers (e.g., systemic risk) often raising the effective requirement to 8–10% for globally systemically important banks (G-SIBs). Similarly, banks much maintain a minimum total capital ratio of 8%, plus a 2.5% buffer, totaling 10.5%, a minimum LCR of 100%, and a minimum TLAC of 16% of RWAs and 6% of leverage exposure.

for capacity above the median of all APs. Second, I measure the trading activities of unexposed US ETFs with AP with larger balance sheet capacity, defined as:

$$Capacity_{f,t} = \sum_{a} \frac{TradeVol_{f,a,t} \cdot \mathbf{1}(AP_a^{\text{Robust}})}{TradeVol_{f,t}},$$

where $TradeVol_{f,a,t}$ represents the primary market trading volume of ETF f with AP a at time t, $\mathbf{1}(AP_a^{\text{Robust}})$ is an indicator equal to 1 if AP a is classified as "robust", and $TradeVol_{f,t}$ is the total primary market trading volume of ETF f at time t. This metric captures the extent to which a local ETF's trading activity relies on APs with significant balnce sheet capacity. Table 5 presents the results. I add the interaction term $Capacity_{f,t}$ to the specification in Table 4. The interpretation is that keeping the indirect exposure constant, trading with a more "robust" AP mitigate the reduction in the sensitivity to mispricing. In column (1), a 1% increase in the trading activities with "robust" AP (*Capacity*), measured as the fraction of trade volume conducted by "robust" AP prior to settlement cycle change, will leads to 0.485% higher flow for 1 standard deviation of mispricing.

4.3.2 Effect of Reduced Arbitrage Activities for U.S. local ETFs

The effects on U.S. local ETFs are twofold. First, as reported in Column (1) and (2) of Table 6, the tracking error of U.S. local ETFs increases relative to non-U.S. ETFs tracking the same index, suggesting a deterioration in price discovery efficiency. This confirms a spillover effect tied to primary market disruptions. The magnitude of increase in σ_{Total} (11 basis points) accounts erase 20% of the pre-change advantage of 52 basis points in tracking error. This magnitude is lower than the 100% reduction in the direct effect as shown in Table 3 for US cross-border ETFs but is still economically significant when compared to their lower annual expense ratio of 29 basis points. Second, and unexpectedly, Column (3) and (4) of Table 6 reveals no decline in liquidity provision for U.S. local ETFs, despite evidence of reduced arbitrage activity in the primary market. These findings convey two key insights. First, they validate the interdependence of primary market activity and price discovery as the shock's impact propagates through AP exposure. Second, the absence

of a liquidity decline in U.S. local ETFs suggests that other market participants may be compensating for diminished AP activity. Notably, these substitute participants influence liquidity but not tracking error, implying they operate in the secondary market rather than engaging in creation and redemption processes. A plausible candidate for these secondary market arbitrageurs is high-frequency trading (HFT) firms, whose active role in ETF arbitrage is well-documented (e.g., Budish et al. (2015)).

To test this hypothesis, I construct three secondary market measures to capture HFT activity. First, I examine the cancel-to-trade ratio (CTR). A recognized HFT technique, known as "sniping" involves submitting a large volume of orders to the exchange to exploit stale quotes or orders, followed by rapid cancellation of unexecuted orders. An increase in the cancel-to-trade ratio thus suggests greater HFT involvement in the secondary market (Hasbrouck and Saar, 2013; Weller, 2017). Second, I consider the trade-to-order ratio (TOR). Regulatory efforts, such as the SEC's proposed order-to-trade tax (Aggarwal et al., 2022), aim to curb excessive HFT activity, highlighting its prominence in this space (Hendershott et al., 2011). Third, I analyze the odd lot ratio (ODD), a measure widely documented by O'Hara et al. (2014) as indicative of HFT-driven trading, given their tendency to execute small, fragmented trades. Table 7 reports the first differences in these HFT activity measures following the settlement cycle change, shedding light on the extent to which HFT firms may offset the liquidity decline in ETFs. The HFT activities, as proxied by the three variables, for US T1 ETFs increase significantly after the settlement cycle shock while such pattern absent in the US T2 ETFs.

Unfortunately, although high-frequency trading (HFT) firms supplement liquidity provision through secondary market arbitrage, such activities are often deemed "toxic" as argued by Foucault et al. (2016). This toxicity stems from arbitrage strategies that prioritize sniping stale orders over enhancing liquidity, thereby elevating latency risk and adverse selection risk for market makers. Consistent with this view, Table 8 reveals that, while the liquidity provision of U.S. local ETFs remains intact as measured by the Roll impact ratio, their quoted bid-ask spreads widen significantly post-settlement cycle shock. This widening reflects the increased risks induced by HFT-driven arbitrage. This

finding raises a potential contradiction between the quoted bid-ask spread and the Roll impact ratio (Roll, 1984), as both are proxies for asset liquidity. The distinction lies in their definitions: the Roll impact ratio, Roll $= 2 \times \sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})}$, estimates the effective bid-ask spread based on price dynamics, whereas the quoted bid-ask spread reflects prevailing market conditions. Thus, the stable Roll measure alongside a wider quoted spread suggests that 1) HFT provide liquidity within the quoted spread and 2) HFT activity may sustain effective liquidity while simultaneously amplifying perceived trading costs and risks in the secondary market.

4.4 Vertical Spillover to Underlying Assets

In the final section, I look at how the reduced arbitrage activities could propagate to the underlying assets. U.S. ETF is major buyers of foreign assets thus reduced creation and redemption could reduce the trading activities in the underlying assets. In Table 9 I examine the whether the reduced arbitrage activities have an impact on the liquidity provision and information informativeness of the underlying assets. Similar to the previous session, I use Roll impact ratio as a proxy for illiquidity, as well as the Lesmond et al. (1999) Zero, ratio of the number of zero-return days to the total number of trading days. I use Roll (1988)'s R^2 measure to proxy for price informativeness or price nonsynchronicity which measured as 1 - R^2 obtained from the regression: $r_{i,j,t} = \beta_{i,0} + \beta_{i,m} r_{m,t} + \beta_{j,m} r_{j,t} + \epsilon_{i,t}$ where $r_{i,j,t}$ is the return of stock i in industry j at day t. For all the measure I use a 22-days rolling window. Results show that when the foreign securities largely held by the U.S. ETF has a settlement cycle mismatch with the ETF, the liquidity provision is reduced. For one percentage increase in the US ETF holding on the foreign stock prior to the settlement cycle change, the effective spread will increase by $1 dollar, after controlling for the market capitalization and the price level of the stock, as shown in column 1. Similarly, for one percentage increase in the US ETF holding on the foreign stock prior to the settlement cycle change, the days with zero return increase by 56% for the last 22-days. There is no result in the price informativeness measure, indicating that the holding of foreign asset in the passive U.S. ETF is not informational.

In the final section, I examine how reduced arbitrage activity in U.S. ETFs can propagate to their underlying assets. U.S.-listed ETFs are major buyers of foreign securities; therefore, a decline in creation and redemption activity may reduce trading in these underlying markets. In Table 9, I investigate whether such reductions in arbitrage activity affect the liquidity provision and price informativeness of the underlying assets. Similar to the previous session, I use Roll (1984) impact ratio as a proxy for illiquidity, as well as the Lesmond et al. (1999) Zero, ratio of the number of zero-return days to the total number of trading days. I use Roll (1988)'s R^2 measure to proxy for price informativeness or price nonsynchronicity which measured as 1 - R^2 obtained from the regression: $r_{i,j,t} = \beta_{i,0} + \beta_{i,m} r_{m,t} + \beta_{j,m} r_{j,t} + \epsilon_{i,t}$ where $r_{i,j,t}$ is the return of stock i in industry j at day t. For all the measure I use a 22-days rolling window. The results indicate that when foreign securities heavily held by U.S. ETFs are subject to a settlement cycle mismatch with the ETF shares, liquidity provision declines. Specifically, as shown in column (1) of Table 9, a one-percentage-point increase in the U.S. ETF's pre-policy holding of a foreign stock is associated with a $1 increase in the stock's effective spread, after controlling for market capitalization and price level. Similarly, column (2) shows that the number of zero-return days increases by 56% over the prior 22 days. In contrast, column (3) shows no statistically significant effect on price informativeness, suggesting that passive U.S. ETFs holding do not convey or change the information content in the prices of the foreign assets.

5 Robustness Checks

Settlement Cycle Mismatch Effects on American Depository Receipt In the main analysis, I use ETFs as a laboratory to study the effect of settlement cycle mismatches on arbitrage activities because these activities are trackable and the arbitrageurs are identifiable. To test the generalizability of my findings, I examine ADRs as a robustness out-of-sample test because ADRs are subject to similar cross-border settlement dynamics.[15]

[15]An American Depository Receipt (ADR) is a financial instrument representing shares in a foreign company, allowing U.S. investors to invest in non-U.S. companies without trading on foreign stock exchanges. ADRs are issued by U.S. depository banks (e.g., JPMorgan Chase or Bank of New York

Two motivations drive this test: First, the total market capitalization of ADRs exceeds $30 trillion, accountinf for one-third of the equity trade on U.S. stock market. Like ETFs, ADRs have well-defined fundamentals tied to their underlying home shares, and arbitrage activities between ADRs and home shares are well-documented (Gagnon and Andrew Karolyi, 2010). Thus, ADRs provide an testing ground to assess whether the impact of settlement cycle mismatches generalizes to a broader asset class. Second, I take advantage of country-level heterogeneity in exposure to U.S. settlement cycle shocks to examine the effect and provide additional evidence to rule out alternative explanations.

In this section, I plan to examine whether ADRs exhibit comparable reductions in arbitrage efficiency following the U.S. transition to a T+1 settlement cycle on May 27, 2024 under a first difference framework where I compare the price deviation between US ADR and its home share pair around the settlement cycle mismatch shock. My main specification is as below:

$$P_{i,t}^{ADR} = \beta_1 P_{i,t}^{Home} \times \mathbf{1}(CycleChange_t) + \beta_2 P_{i,t-1}^{Home} \times \mathbf{1}(CycleChange_t) + \beta_3 P_{i,t}^{Home} + \beta_4 P_{i,t-1}^{Home} + \alpha_t + \epsilon_{i,t}$$

, where $P_{i,t}^{ADR}$ is the price of ADR of stock i at day t; $P_{i,t}^{Home}$ is the price of home share of stock i at day t, adjusted for ADR ratio [16] and exchange rate. I also include the lagged price of home share to account for short-term momentum. I run this specification on 13 countries with the at least 10 ADR firms listed on the US and divide these countries two groups: (1) those with a settlement mismatch with the US after the US moved to T+1 on 29 May 2024 (Europe, Japan, Hong Kong, Australia, Brazil, South Africa, Singapore, Argentina, Israel, and South Korea), and (2) those without a mismatch because they either adopted T+1 alongside the US (Canada and Mexico) or already had a T+1 or shorter settlement cycle (China and India). Column (1) - (10) in Table A5 show that the correlation between ADR price and home price decrease in stocks in countries with settlement cycle mismatch with the US after the T+1 change. This observation is largely

Mellon), which hold the underlying foreign shares in custody. Each ADR corresponds to a specific number of shares (or a fraction thereof) of the foreign company's stock and is traded on U.S. exchanges, such as the NYSE or NASDAQ, in U.S. dollars.

[16] ADR ratio refers to the number of foreign company shares represented by a single ADR share traded on a U.S. exchange.

absent in countries which follow US's T+1 moves or had moved to T+1 settlement cycle.

Another observation is that currency risk does not seems to be the main drive of the price deviation. Column (3) show the deviation between ADR price and home price with 124 firm co-listed in the US and the Hong Kong stock exchanges. Given the Linked Exchange Rate System (LER)[17] in Hong Kong, Hong Kong Monetary Authority (HKMA) ensures the Hong Kong dollar fluctuates within a narrow band of HK$7.75- $7.85 to one US dollar. LER system largely mitigates the currency risk involved in the cross-border ADR transactions yet I still observe a deviation between the ADR price and home price of stock.

Decomposition of Total Tracking Error The observed increase in tracking error shown in Section 4 could stem from persistent deviations between (1) the ETF's price and its net asset value (NAV), (2) the NAV and the benchmark, or a combination of both. To pinpoint the sources of this increase and assess whether it reflects reduced arbitrage activity, I decompose the variance of the tracking error into its constituent components as follows:

$$\begin{aligned}\sigma^2(R^{\text{Price}} - R^{\text{Benchmark}}) = \sigma^2(R^{\text{Price}} - R^{\text{NAV}}) \\ + \sigma^2(R^{\text{NAV}} - R^{\text{Benchmark}}) \\ + 2\,\text{Cov}(R^{\text{Price}} - R^{\text{NAV}}, R^{\text{NAV}} - R^{\text{Benchmark}})\end{aligned}$$

, where R^{Price} is the ETF's market price return, R^{NAV} is the return of the ETF's net asset value (NAV), and $R^{\text{Benchmark}}$ is the benchmark return. The first term, $\sigma^2(R^{\text{Price}} - R^{\text{NAV}})$, measures the variance of the deviation between the ETF's market price and its NAV over time. A high variance suggests that the market price frequently diverges from the NAV, likely due to diminished arbitrage activity, which fails to keep these two values aligned. The second term, $\sigma^2(R^{\text{NAV}} - R^{\text{Benchmark}})$, quantifies the variance of the deviation between the ETF's NAV and the benchmark return. A large value indicates that the NAV

[17]For more operational details of LER, please refer to https://www.hkma.gov.hk/eng/key-functions/money/linked-exchange-rate-system/how-does-the-lers-work/.

consistently fails to track the benchmark, potentially reflecting inefficient replication of the benchmark's performance. The final term, $2\,\mathrm{Cov}(R^{\text{Price}} - R^{\text{NAV}}, R^{\text{NAV}} - R^{\text{Benchmark}})$, is the covariance between the price-NAV deviation (premium or discount) and the NAV-benchmark deviation. These components are generally assumed to lack systematic correlation.

Empirical results, presented in Table A6, confirm that the primary driver of the increased tracking error stems from reduced arbitrage activity in ETFs with settlement cycle mismatches, which hinders the alignment of market prices with NAVs. This finding aligns with Bae and Kim (2020), which highlights that price-NAV deviations account for a significant portion of tracking error variance. Interestingly, I also observe a decline in replication efficiency in the cross-border ETF, a phenomenon I will explore further in subsequent sections.

6 Concluding Remarks

In conclusion, this paper demonstrates that settlement cycle mismatches, triggered by the U.S. transition to a T+1 settlement cycle on May 27, 2024, introduce significant frictions in financial markets by constraining arbitrage activities of intermediaries. Employing ETFs in a quasi-natural experiment within a difference-in-differences framework, I find that ETFs exposed to these mismatches suffer substantial reductions in arbitrage activity, resulting in a 10 basis point increase in tracking error—equivalent to 25% of the annual expense ratio—and diminished liquidity provision. Interestingly, I uncover a novel spillover effect wherein unexposed ETFs, linked through shared APs, experience comparable declines in price discovery and liquidity, with effects amplified for those with greater indirect exposure to affected APs. This interconnectedness, driven by a concentrated AP market, underscores the systemic reach of settlement cycle disparities. Additionally, I find an increasing participation of other market participants, especially high-frequency trading (HFT) firms in the secondary market of ETF, partially offset liquidity losses from primary market arbitrage. However, the increased HFT activities elevate latency risks and quoted

bid-ask spreads, reflecting a complex trade-off. Finally, I show that these disruptions propagate to underlying foreign securities, significantly reducing their liquidity provision without altering price informativeness, highlighting the non-informational nature of the shock. Collectively, these findings reveal the unintended consequences of settlement cycle regulation on arbitrage efficiency, market quality, and cross-border asset dynamics, suggesting policymakers and market participants to address settlement cycle harmonization to mitigate such frictions in an increasingly globalized financial system.

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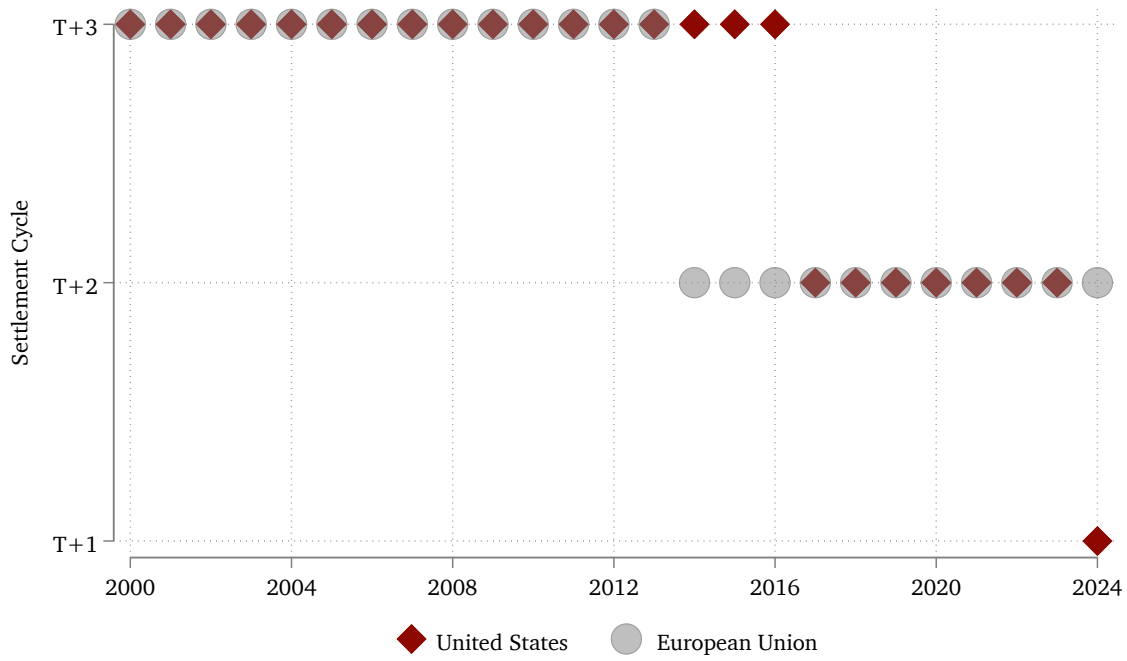


Figure 1: Settlement Cycle Changes in Major Jurisdiction

This figure illustrates the evolution of settlement cycles for exchange-traded products in the two largest financial jurisdictions, the United States (diamond) and the European Union (circle), from 2000 to 2024. Settlement cycles ranged from T+3 to T+1 indicate the binding period required for trade settlement following execution in these jurisdictions. Financial product subject to the United States settlement cycle change in 2024 include: 1) Equity instruments (common stocks, preferred stocks, and other equity securities listed on US exchanges, American depositary receipts (ADRs) and equity warrants and rights); 2) Fixed income instruments (corporate bonds and municipal bonds); 3) Fund instruments (ETFs, closed-ended funds, UITs, REITs and some mutual funds cleared through the DTCC); and 4) Derivatives instruments (asset-backed securities (ABS) and options).

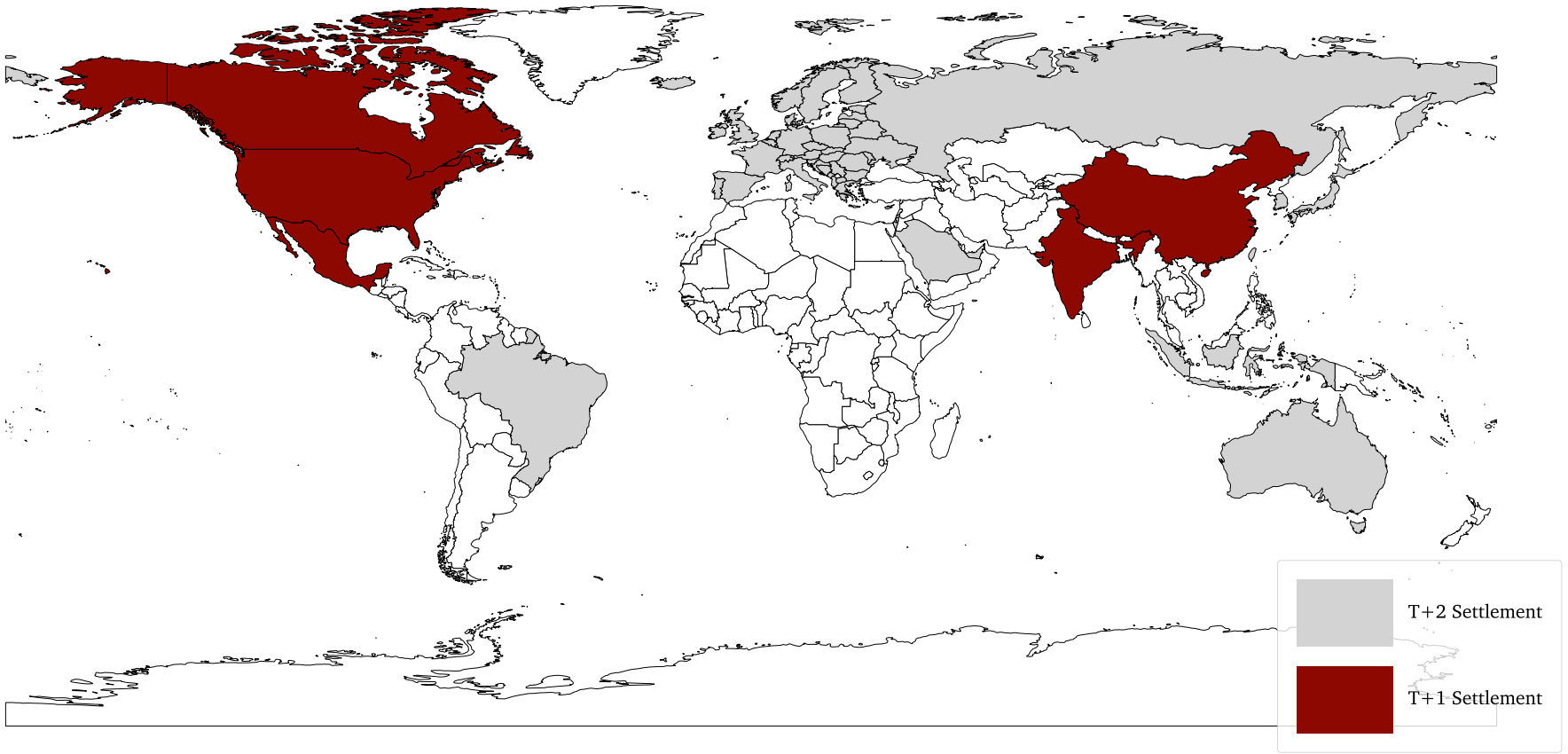


Figure 2: Settlement Cycle of Major Jurisdictions as of December 2024

This figure presents the effective settlement cycle of exchange-traded securities in major jurisdictions as of December 2024. Countries under T+1 settlement cycle regime include: United States, Canada, Mexico, India and China. Countries or regions under T+2 settlement cycle regime include: European Union, Japan, United Kingdom, Saudi Arabia, Switzerland, Taiwan, Australia, South Korea, United Arab Emirates, Hong Kong, Brazil, Singapore, Russia, Israel and Indonesia.

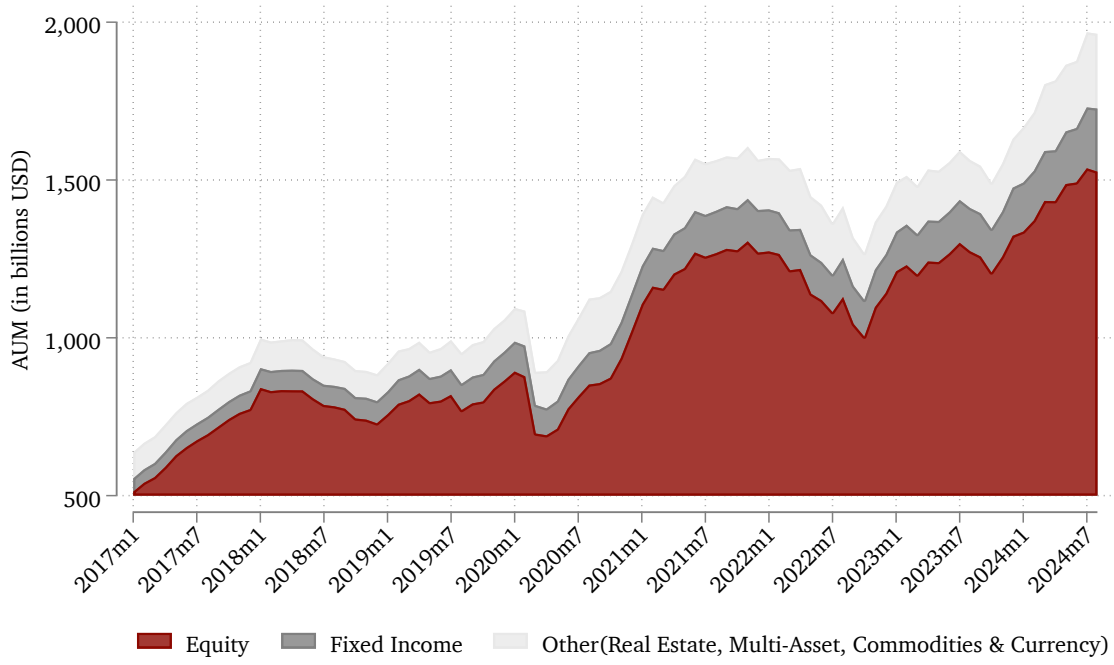
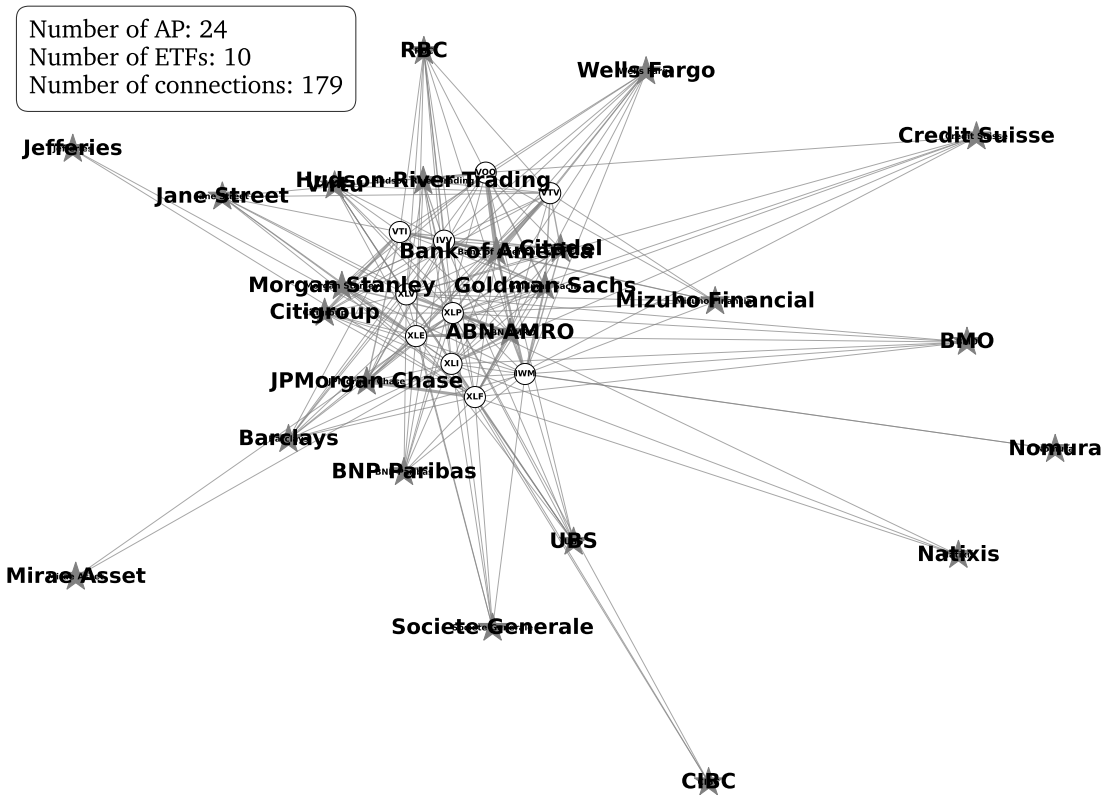
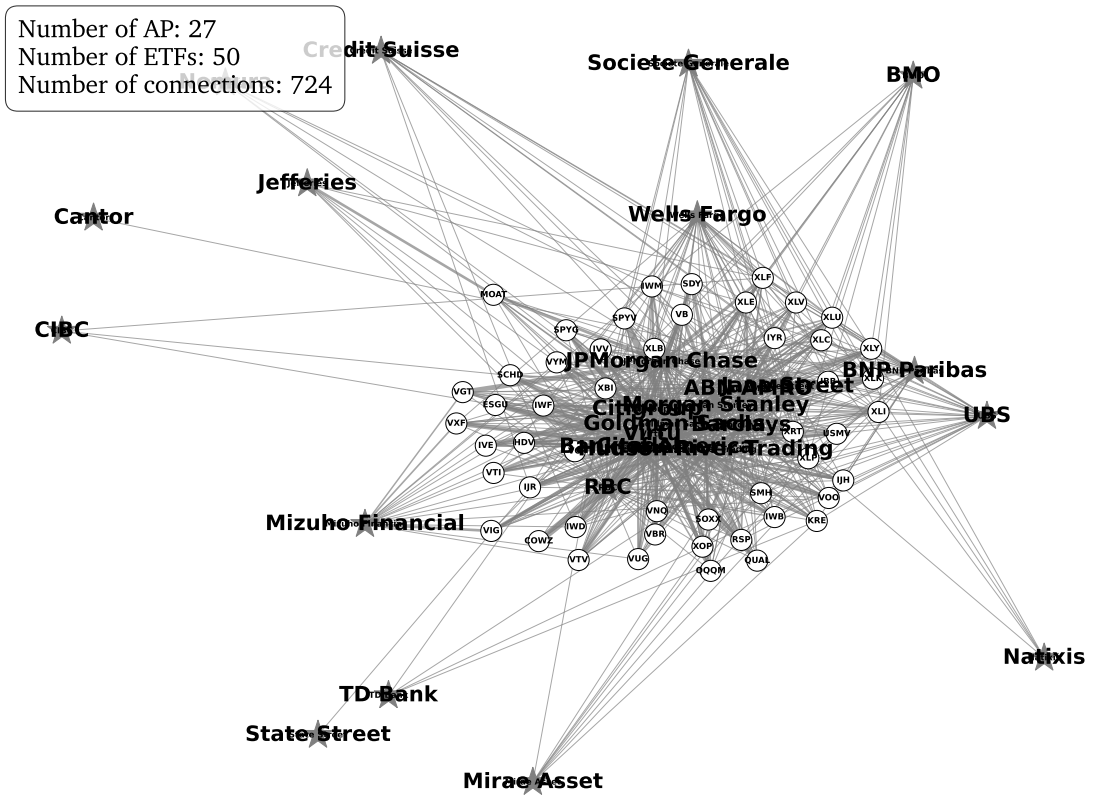


Figure 3: Growth in the US ETF tracking foreign assets

This figure illustrates the growth in assets under management (AUM) of ETFs tracking foreign assets traded in the U.S. from January 2017 to August 2024. Assets are grouped into three major categories: 1) Equity, 2) Fixed Income, 3) Other (includes Multi Asset, Currency, Commodities and Real Estate).



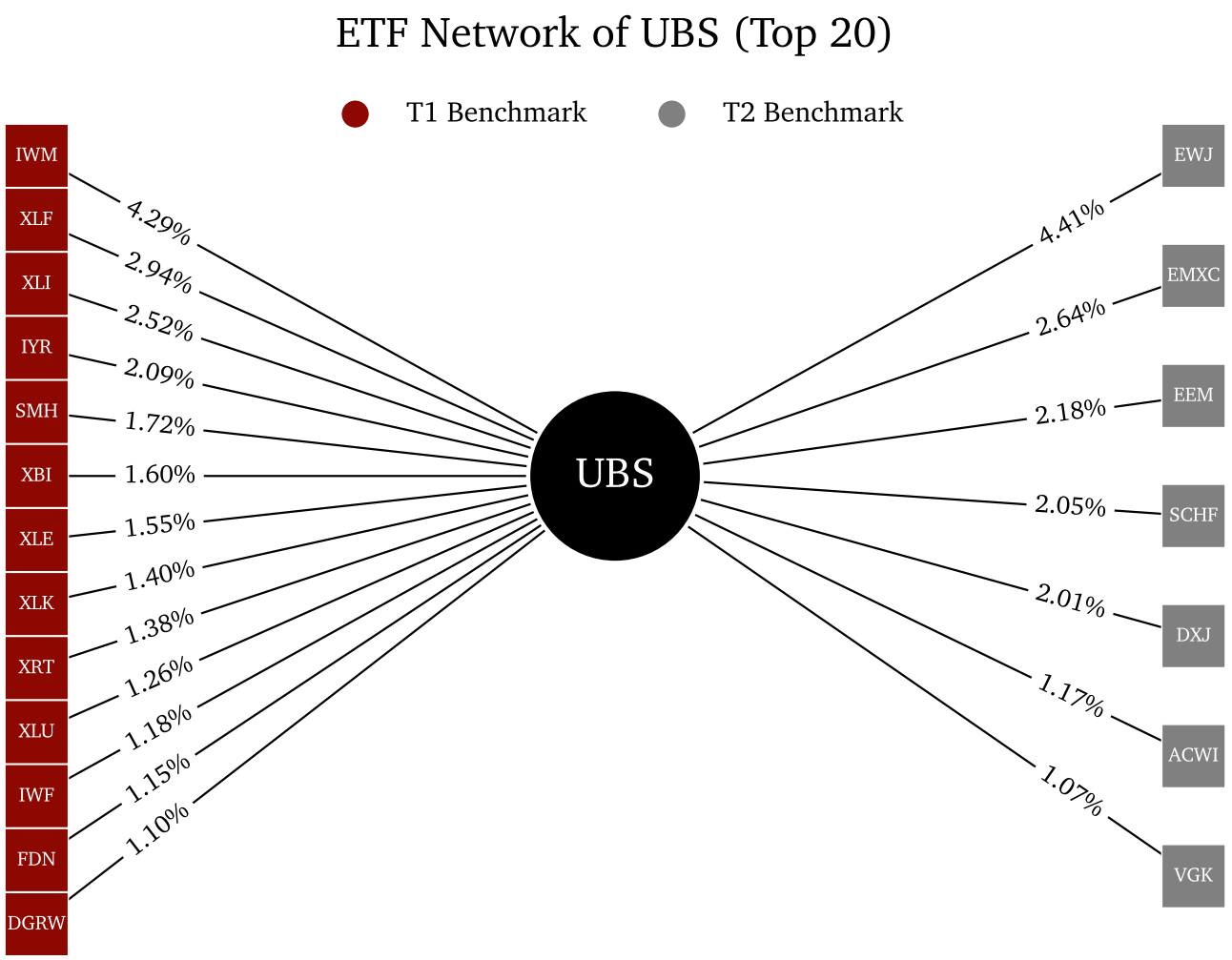
(a) Panel A: AP network of 10 largest ETFs



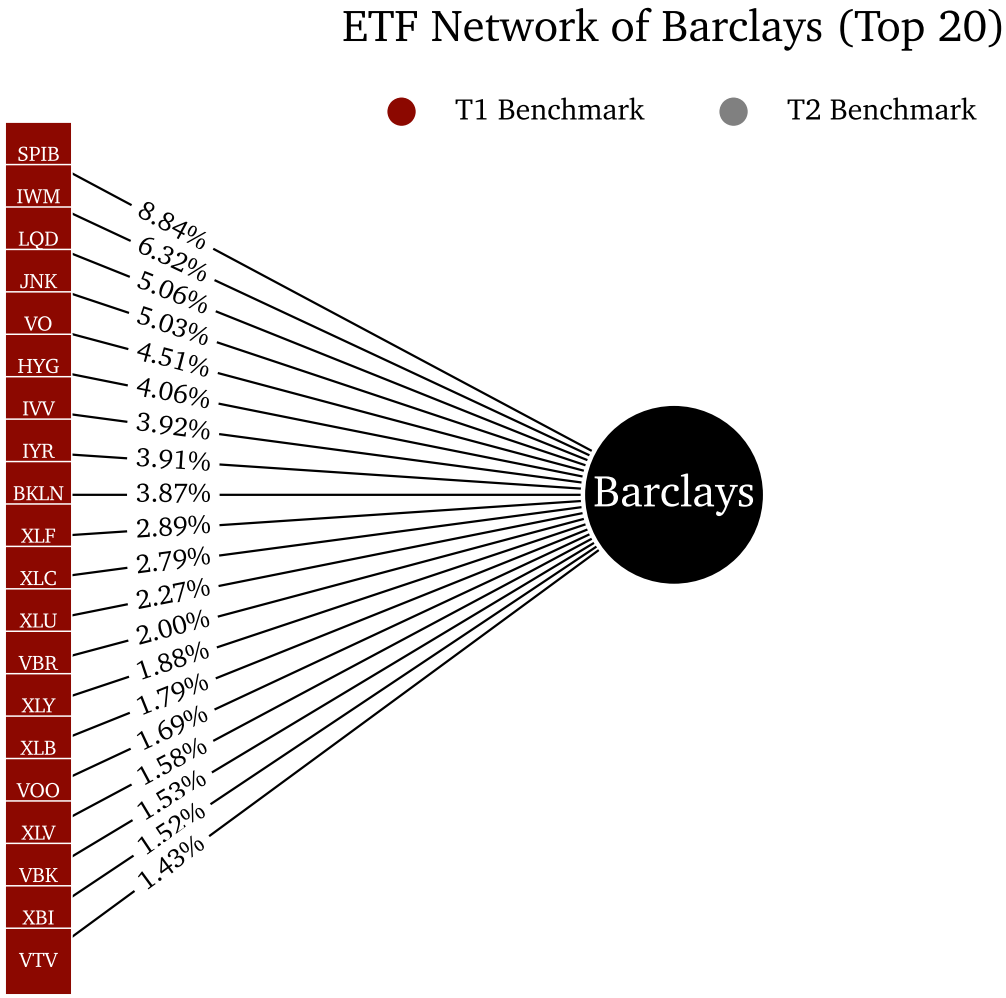
(b) Panel B: AP network of 50 largest ETFs

Figure 4: Primary Market Network of Authorized Participants and ETFs

This figure illustrates the primary market trading activities between authorized participants (APs) and ETFs in 2023, one year prior to the Rule change. Panel A (Panel B) presents the complete list of APs actively trading with the 10 (50) largest equity ETFs in my sample. Each connecting line represents trading activity, defined as whether an AP has traded with a given ETF.



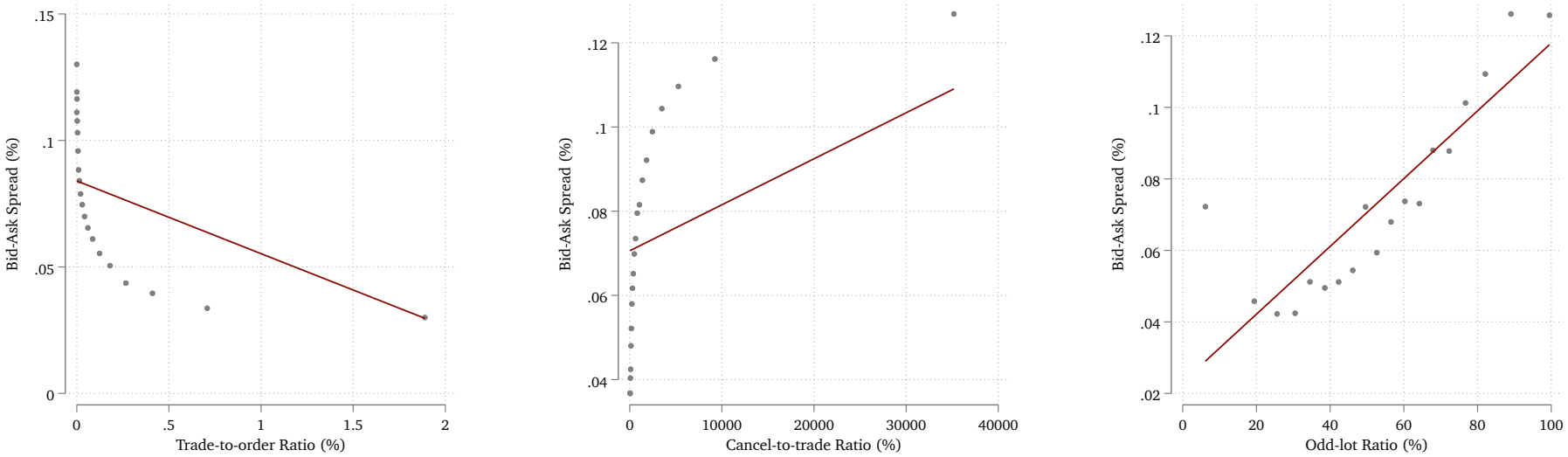
(a) Panel A: Trading activities of ETFs (UBS)



(b) Panel B: Trading activities of ETFs (Barclays)

Figure 5: An Illustrative Example of Primary Market Network

This figure illustrates the top 20 ETFs with which selected authorized participants engage in primary market trading activities in 2023, one year prior to the Rule change. Panel A (Panel B) describes the trading relationship of UBS (Barclays). Red (gray) boxes denote U.S. ETFs tracking the T1 (T2) benchmark. The share of trading activity for each ETF by the respective authorized participant is also reported.



(a) Panel A: Bid-ask spread and the Total-to-order ratio

(b) Panel B: Bid-ask spread and the Cancel-to-order ratio

(c) Panel C: Bid-ask spread and the Odd-lot ratio

Figure 6: High-Frequency Trading Activities and Quoted Bid-Ask Spread

This figure presents a scatter plot of proxies for high-frequency trading (HFT) activity in the ETF secondary market and the quoted bid-ask spread of the ETFs. The proxies include the 1) trade-to-order ratio (TOR), 2) cancel-to-trade ratio (CTR), and 3) odd-lot ratio (ODD).

Table 1: Descriptive Statistics of ETFs Tracking T1 and T2 Benchmarks prior to United States T+1 Settlement Cycle Change

This table presents summary statistics for exchange-traded funds tracking U.S. local (T1) and U.S. foreign (T2) benchmarks, separately for US and non-US domiciled funds in the year of 2024 prior to the United States T+1 Settlement Cycle Change. Panel A includes all ETFs, while Panel B a subsample of ETFs tracking the same benchmarks. *TNA* is total net assets in billions. *Fund Age* is years since inception. *Expense Ratio* is the annual management fee percentage. *Fund Flow* is the daily percentage net flow into the fund, which is the result of creation and redemption of authorized participants. *Raw Return* is the fund's daily reported return. *Mispricing* measures daily price-nav deviation in basis points. *Tracking Error* is the standard deviation of return difference between fund and the benchmark for the past 22 days. *Roll* is the Roll (1984) impact ratio that measures the effective spread (i.e. liquidity) of ETFs. Statistics include mean, standard deviation (SD), and median (P50) values.

Panel A: Summary Statistics of All ETFs Tracking T1 and T2 Benchmarks

	A. T1 Benchmark						B. T2 Benchmark					
	i. US Exchange Traded Funds			ii. Non-US Exchange Traded Funds			i. US Exchange Traded Funds			ii. Non-US Exchange Traded Funds		
	Mean	SD	P50	Mean	SD	P50	Mean	SD	P50	Mean	SD	P50
TNA (Billions)	10	43	1	1.8	6.7	0.36	3.7	12	0.57	1.3	4.6	0.33
Fund Age (Years)	12	6.9	11	6.1	4.3	5.6	12	6.3	11	7	4.8	5.5
Expense Ratio	0.29	0.19	0.25	0.2	0.12	0.2	0.4	0.19	0.41	0.34	0.16	0.3
Fund Flow (%)	0.03	0.62	0	0.05	0.62	0	0.011	0.52	0	0.063	0.61	0
Raw Return (%)	0.068	0.92	0.1	0.08	0.88	0.086	0.061	0.88	0.098	0.066	0.84	0.1
Mispricing (bps)	0.5	8.3	0.36	-0.9	55	-2.3	0.66	34	0.38	-1.9	61	0.87
Tracking Error (%)	0.12	0.18	0.07	0.47	0.25	0.47	0.75	0.26	0.72	0.56	0.23	0.54
Roll (%)	0.6	0.6	0.4	0.38	0.93	0.16	0.34	0.3	0.27	0.23	0.3	0.14
Number of Funds	714			279			516			555		

Panel B: Summary Statistics of ETFs Tracking the Same T1 and T2 Benchmarks

	A. T1 Benchmark						B. T2 Benchmark					
	i. US Exchange Traded Funds			ii. Non-US Exchange Traded Funds			i. US Exchange Traded Funds			ii. Non-US Exchange Traded Funds		
	Mean	SD	P50	Mean	SD	P50	Mean	SD	P50	Mean	SD	P50
TNA (Billions)	45	113	4.5	3.1	10	0.44	4.7	13	0.74	2.6	8.7	0.29
Fund Age (Years)	14	8	14	6.7	4.7	5.9	12	6.7	12	8.5	5.4	9
Expense Ratio	0.21	0.17	0.15	0.21	0.12	0.2	0.44	0.24	0.45	0.36	0.19	0.2
Fund Flow (%)	0.028	0.56	0	0.058	0.57	0	-0.014	0.48	0	0.067	0.56	0
Raw Return (%)	0.069	0.92	0.097	0.078	0.87	0.095	0.052	0.91	0.12	0.063	0.84	0.13
Mispricing (bps)	-0.23	9.2	0	-1.5	57	-3.2	-1.4	37	-2.7	1.5	53	0.76
Tracking Error (%)	0.12	0.17	0.064	0.77	0.27	0.74	0.5	0.24	0.5	0.59	0.24	0.56
Roll (%)	0.82	0.9	0.43	0.56	1.3	0.21	0.34	0.25	0.27	0.25	0.29	0.16
Number of Funds	255			38			53			83		

Table 2: Reduced Primary Market Arbitrage Activities in ETFs

This table reports OLS regression results examining the change in primary market arbitrageurs' sensitivity to mispricing before and after the Rule change under a difference-in-differences framework. US ETFs are compared to non-US ETFs tracking the same benchmark index. Following the US settlement cycle reduction from T+2 to T+1 on May 29, 2024, US ETFs tracking T+2 benchmarks, i.e., non-US indices, experience a settlement cycle mismatch, while their non-US counterparts do not. This regression evaluates the reduction in primary market arbitrage activities for exposed US ETFs relative to unexposed non-US ETFs using the specification:

$$\Delta\%ShareOut_{f,b,t} = \mathbf{1}(T1ETF_f) \times \mathbf{1}(CycleChange_t) \times Mispricing_{f,t} + \alpha_b + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

where the percentage change in shares outstanding is regressed on the interaction of indicator variables $\mathbf{1}(T1ETF_f)$, which equals 1 if the ETF is a US ETF, $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change, and $Mispricing_{f,t}$, proxied by one of three measures: 1) Mispricing = Price/NAV − 1, 2) Max($Mispricing^+$) = max{Mispricing$_t^+$ | $t \in [T-5, T]$}, or 3) Min($Mispricing^-$) = min{Mispricing$_t^-$ | $t \in [T-5, T]$}. Control variables include ln(*FundTNA*), the log of total net assets, ln(*FundAge*), the log of fund age in years, *Return*, the raw returns, *Flow*, the daily percentage net flow into the fund, and *Roll*, Roll (1984) impact ratio as a proxy for ETF illiquidity. Benchmark (or Fund) and day fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Mispricing (1)	Mispricing$^+$ (2)	Mispricing$^-$ (3)	Mispricing (4)	Mispricing$^+$ (5)	Mispricing$^-$ (6)
$\mathbf{1}(T1ETF) \times \mathbf{1}(CycleChange) \times Mispricing$	-0.061***	-0.070**	0.092***	-0.057***	-0.067**	0.087**
	(0.019)	(0.028)	(0.033)	(0.019)	(0.028)	(0.034)
$\mathbf{1}(T1ETF) \times \times Mispricing$	0.068***	0.068***	-0.111***	0.068***	0.079***	-0.120***
	(0.018)	(0.025)	(0.035)	(0.018)	(0.026)	(0.036)
$\mathbf{1}(T1ETF) \times \mathbf{1}(CycleChange)$	-0.029	-0.028	-0.029	0.018*	0.039***	-0.017
	(0.021)	(0.022)	(0.022)	(0.011)	(0.015)	(0.014)
$\mathbf{1}(CycleChange) \times Mispricing$	0.016	0.035**	-0.014	-0.030	-0.026	-0.029
	(0.011)	(0.015)	(0.014)	(0.021)	(0.022)	(0.022)
$\mathbf{1}(T1ETF)$	-0.046**	-0.031	-0.048**			
	(0.019)	(0.020)	(0.020)			
ln(FundTNA)	0.015**	0.015**	0.014**	-0.040	-0.035	-0.040
	(0.007)	(0.007)	(0.007)	(0.038)	(0.037)	(0.037)
ln(FundAge)	-0.074***	-0.073***	-0.072***	0.066	0.052	0.087
	(0.019)	(0.019)	(0.019)	(0.130)	(0.125)	(0.130)
Return	0.011	0.009	0.009	0.010	0.009	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Flow	0.027	0.026	0.026	0.017	0.015	0.016
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Roll	-0.009	-0.004	0.001	-0.014	-0.012	0.011
	(0.011)	(0.014)	(0.012)	(0.011)	(0.014)	(0.014)
Mispricing	0.022	0.021	0.022	0.020	0.021	0.020
	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)
Observations	20,433	20,467	20,467	20,433	20,467	20,467
R-squared	0.043	0.045	0.044	0.053	0.055	0.054
Benchmark FE	Yes	Yes	Yes			
Fund FE				Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: The Effects on Price Discovery and Liquidity Provision of Reduced Arbitrage Activities U.S. cross-border ETFs

This table reports OLS regression results examining the changes in price discovery and liquidity of ETFs before and after the U.S. settlement cycle change from T+2 to T+1 on May 29, 2024 under a difference-in-differences framework. US ETFs are compared to non-US ETFs tracking the same non-US benchmark index. Price discovery is measured by the standard deviation of tracking error over a 22-day rolling window: $\sigma_t^{TE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_{p,t-i} - R_{b,t-i})^2}$, where $R_{p,t-i}$ and $R_{b,t-i}$ are daily ETF and benchmark returns, respectively. Liquidity is proxied by Roll's (1984) impact ratio: $\text{Roll} = 2\sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})}$. Columns (1)–(4) assess effects on U.S. ETFs with T1 and T2 benchmarks using:

$$Y_{f,b,t} = \mathbf{1}(T1ETF_f) \times \mathbf{1}(CycleChange_t) + \alpha_b + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

where tracking error and liquidity measure are regressed on the interaction of indicator variables $\mathbf{1}(T1ETF_f)$, which equals 1 if the ETF is a US ETF, $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change. Control variables include ln(*FundTNA*), the log of total net assets, ln(*FundAge*), the log of fund age in years, *Return*, the raw returns, *Flow*, the daily percentage net flow into the fund, and *Roll*, Roll (1984) impact ratio as a proxy for ETF illiquidity. Benchmark (or Fund) and day fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	σ_{Total}		Roll	
	(1)	(2)	(3)	(4)
$T1ETF \times \mathbf{1}(CycleChange)$	0.099***	0.086***	0.103***	0.091**
	(0.035)	(0.032)	(0.039)	(0.040)
T1ETF	-0.100*		0.030	
	(0.053)		(0.045)	
Mispricing	0.004	0.026	0.004	-0.001
	(0.013)	(0.022)	(0.004)	(0.004)
ln(FundTNA)	-0.041	-0.158	-0.038	-0.062
	(0.030)	(0.179)	(0.025)	(0.037)
ln(FundAge)	0.001	0.000	0.171**	0.024
	(0.004)	(0.005)	(0.075)	(0.232)
Return	0.005	0.004	-0.007*	-0.008**
	(0.004)	(0.003)	(0.004)	(0.004)
Flow	-0.002	-0.000	0.009	0.009*
	(0.005)	(0.004)	(0.006)	(0.005)
Roll	0.078***	0.066***		
	(0.022)	(0.024)		
Observations	9,201	18,979	14,760	14,758
R-squared	0.544	0.295	0.302	0.449
Benchmark FE	Yes		Yes	
Fund FE		Yes		Yes
Day FE	Yes	Yes	Yes	Yes

Table 4: Spillover from exposed US ETF to unexpoesed ETF via reduced primary arbitrage activities

This table reports OLS regression results examining how primary market arbitrageurs' sensitivity to mispricing changes around the settlement cycle shock for US ETFs not directly exposed to the settlement cycle mismatch. We capture this indirect exposure in following steps: Step 1 is to classify whether an AP is exposed to the settlement cycle change through cross-border ETFs. We define an AP is exposed to settlement cycle shock if its trading activities with cross-border ETF above the median of all APs in the same year. Step 2 is to measure the trading activities of unexposed US ETFs with these exposed exposed APs, i.e. $IndExp_{f,t} = \sum \frac{TradeVol_{f,a,t}(\mathbf{1}(AP_a^{Exposed}))}{TradeVol_{f,t}}$. The regression evaluates the reduction in primary market arbitrage activities for unexposed US ETFs using the following specification:

$$\Delta\%ShareOut_{f,b,t} = IndExp_{f,t} \times \mathbf{1}(CycleChange_t) \times Mispricing_{f,t} + \alpha_f + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,t}$$

where the percentage change in shares outstanding is regressed on the interaction of variables $IndExp_{f,t}$, the indirect exposure of unexposed US ETF proxied by the percentage of ETF trading volume with exposed APs, the indicator variable $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change, and $Mispricing_{f,t}$, the level of mispricing measured by one of three ways: 1) Mispricing = Price/(NAV − 1), 2) Max($Mispricing^+$) = max{Mispricing$_t^+$ | $t \in [T-5, T]$}, or 3) Min($Mispricing^-$) = min{Mispricing$_t^-$ | $t \in [T-5, T]$}. Control variables include ln(*FundTNA*), the log of total net assets, ln(*FundAge*), the log of fund age in years, *Return*, the raw returns, *Flow*, the daily percentage net flow into the fund, and *Roll*, Roll (1984) impact ratio as a proxy for ETF illiquidity. Fund and day fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Mispricing (1)	Mispricing$^+$ (2)	Mispricing$^-$ (3)
$\mathbf{1}(CycleChange) \times Mispricing \times IndExp$	-0.271***	-0.213**	0.398**
	(0.085)	(0.104)	(0.187)
$\mathbf{1}(CycleChange) \times IndExp$	0.006	-0.024	0.021
	(0.032)	(0.045)	(0.035)
$\mathbf{1}(CycleChange) \times Mispricing$	0.166**	0.096	-0.298**
	(0.068)	(0.081)	(0.150)
$Mispricing \times IndExp$	-0.008	-0.034	-0.023
	(0.082)	(0.101)	(0.166)
Mispricing	-0.177***	-0.167**	-0.179***
	(0.067)	(0.067)	(0.068)
ln(FundTNA)	-0.280	-0.258	-0.288
	(0.189)	(0.194)	(0.192)
ln(FundAge)	0.063***	0.063***	0.063***
	(0.012)	(0.012)	(0.012)
Return	-0.011	-0.011	-0.010
	(0.021)	(0.021)	(0.021)
Flow	0.106	0.151*	-0.098
	(0.069)	(0.080)	(0.122)
Roll	0.016*	0.016*	0.015*
	(0.008)	(0.008)	(0.008)
Observations	59,092	59,090	59,090
R-squared	0.059	0.059	0.058
Day FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes

Table 5: Spillover from exposed US ETF to unexpoesed ETF via reduced primary arbitrage activities, interact with arbitraguers's balance sheet capacity

This table reports OLS regression results examining how primary market arbitrageurs' sensitivity to mispricing changes around a settlement cycle shock for US ETFs not directly exposed to the settlement cycle mismatch, interact with the balance sheet capacity of the authorized participants (AP). Indirect exposure ($IndExp$) is measured as in Table 4. To capture the balance sheet capacity ($Capacity$), we follow similar steps. First, we define an AP has larger balance sheet capacity if the proxies for capacity, including tier 1 common equity ratio ($CET1Ratio$), capital ratio ($CapitalRatio$), liquidity coverage ratio (LCT) and total loss absorption ratio ($TLAR$), above the median of all APs in the same year. Second, we measure the trading activities of unexposed US ETFs with AP with larger balance sheet capacity, i.e. $Capacity_{f,t} = \sum \frac{TradeVol_{f,a,t}(\mathbf{1}(AP_a^{Robust}))}{TradeVol_{f,t}}$. The regression evaluates the reduction in primary market arbitrage activities for unexposed US ETFs using the following specification:

$$\Delta\%ShareOut_{f,b,t} = IndExp_{f,t} \times \mathbf{1}(CycleChange_t) \times Mispricing_{f,t} \times Capacity + \alpha_f + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,t}$$

where the percentage change in shares outstanding is regressed on the interaction of variables $IndExp_{f,t}$, the indirect exposure of unexposed US ETF proxied by the percentage of ETF trading volume with exposed APs, the indicator variable $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change, and $Mispricing_{f,t}$, the level of mispricing measured by Price/(NAV − 1). Control variables include ln($FundTNA$), the log of total net assets, ln($FundAge$), the log of fund age in years, $Return$, the raw returns, $Flow$, the daily percentage net flow into the fund, and $Roll$, Roll (1984) impact ratio as a proxy for ETF illiquidity. Fund and day fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	CET1 Ratio (1)	Capital Ratio (2)	LCR (3)	TLAC (4)
$\mathbf{1}CycleChange \times Capacity \times Mispricing \times IndExp$	0.485***	0.470**	0.322*	0.485***
	(0.176)	(0.191)	(0.192)	(0.176)
$\mathbf{1}CycleChange \times Capacity \times Mispricing$	-0.436***	-0.427**	-0.278	-0.436***
	(0.156)	(0.166)	(0.177)	(0.156)
$\mathbf{1}CycleChange \times Mispricing \times IndExp$	-0.286**	-0.310***	-0.245**	-0.286**
	(0.115)	(0.110)	(0.112)	(0.115)
$\mathbf{1}CycleChange \times Capacity \times IndExp$	-0.001	0.018	-0.117	-0.001
	(0.053)	(0.049)	(0.095)	(0.053)
$Capacity \times Mispricing \times IndExp$	-0.491**	-0.449**	-0.437	-0.491**
	(0.199)	(0.196)	(0.436)	(0.199)
$\mathbf{1}CycleChange \times Mispricing$	0.176*	0.198**	0.147*	0.176*
	(0.090)	(0.088)	(0.088)	(0.090)
$\mathbf{1}CycleChange \times Capacity$	0.011	-0.001	0.088	0.011
	(0.039)	(0.035)	(0.084)	(0.039)
$\mathbf{1}CycleChange \times IndExp$	-0.038	-0.040	-0.040	-0.038
	(0.051)	(0.051)	(0.050)	(0.051)
$Capacity \times Mispricing$	0.499***	0.464***	0.433	0.499***
	(0.181)	(0.175)	(0.418)	(0.181)
$Mispricing \times IndExp$	-0.063	-0.034	-0.093	-0.063
	(0.119)	(0.110)	(0.139)	(0.119)
Mispricing	0.153	0.126	0.181	0.153
	(0.095)	(0.090)	(0.122)	(0.095)
Observations	53,536	53,536	53,536	53,536
R-squared	0.061	0.061	0.061	0.061
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Table 6: The Effects on Price Discovery and Liquidity Provision of Reduced Arbitrage Activities for U.S. local ETFs

This table replicates Table 3 and reports OLS regression results examining the changes in price discovery and liquidity of ETFs before and after the U.S. settlement cycle change from T+2 to T+1 on May 29, 2024 under a difference-in-differences framework. US ETFs are compared to non-US ETFs tracking the same non-US benchmark index. Price discovery is measured by the standard deviation of tracking error over a 22-day rolling window: $\sigma_t^{TE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_{p,t-i} - R_{b,t-i})^2}$, where $R_{p,t-i}$ and $R_{b,t-i}$ are daily ETF and benchmark returns, respectively. Liquidity is proxied by Roll's (1984) impact ratio: $\text{Roll} = 2\sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})}$. Columns (1)–(4) assess effects on U.S. ETFs with T1 and T2 benchmarks using:

$$Y_{f,b,t} = \mathbf{1}(T1ETF_f) \times \mathbf{1}(CycleChange_t) + \alpha_b + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

where tracking error and liquidity measure are regressed on the interaction of indicator variables $\mathbf{1}(T1ETF_f)$, which equals 1 if the ETF is a US ETF, $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change. Control variables include $\ln(FundTNA)$, the log of total net assets, $\ln(FundAge)$, the log of fund age in years, *Return*, the raw returns, *Flow*, the daily percentage net flow into the fund, and *Roll*, Roll (1984) impact ratio as a proxy for ETF illiquidity. Benchmark (or Fund) and day fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	σ_{Total}		Roll	
	(1)	(2)	(3)	(4)
$T1ETF \times \mathbf{1}(CycleChange)$	0.110***	0.119***	0.024	0.086
	(0.032)	(0.032)	(0.071)	(0.057)
T1ETF	-0.515***		-0.226	
	(0.053)		(0.182)	
Mispricing	-0.010	-0.039**	0.070**	-0.038
	(0.012)	(0.019)	(0.028)	(0.032)
ln(FundTNA)	-0.018	0.209	0.233**	0.559**
	(0.041)	(0.218)	(0.105)	(0.241)
ln(FundAge)	0.002	0.001	-0.003	-0.006
	(0.003)	(0.003)	(0.016)	(0.014)
Return	0.001	-0.002	-0.014**	-0.012**
	(0.004)	(0.003)	(0.006)	(0.005)
Flow	0.005	0.006	0.021	0.006
	(0.010)	(0.009)	(0.018)	(0.007)
Roll	0.003	0.010**		
	(0.007)	(0.005)		
Observations	23,091	23,091	30,602	30,602
R-squared	0.672	0.818	0.212	0.483
Benchmark FE	Yes		Yes	
Fund FE		Yes		Yes
Day FE	Yes	Yes	Yes	Yes

Table 7: High-frequency Trading Activities Before and After the Settlement Cycle Change

This table reports OLS regression results examining the change in high-frequency trading activities in the secondary market of US ETFs before and after the U.S. settlement cycle change from T+2 to T+1 on May 29, 2024 in the following specification:

$$\sigma^{y}_{f,b,t} = \mathbf{1}(CycleChange_t) + \alpha_f + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

, where the proxies of high-frequency trading activities are regressed on the indicator variables $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change. Proxies include *CTR*, the cancel-to-trade ratio suggested by Hasbrouck and Saar (2013) and Weller (2017); *TOR*, the trade-to-order ratio suggested by Hendershott et al. (2011); and *ODD*, odd-lot ratio suggested by O'Hara et al. (2014). Control variables include ln(*FundTNA*), the log of total net assets, ln(*FundAge*), the log of fund age in years, *Return*, the raw returns, *Flow*, the daily percentage net flow into the fund, and *Roll*, Roll (1984) impact ratio as a proxy for ETF illiquidity. Fund fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	T2 Benchmark			T1 Benchmark		
	TOR	CTR	ODD	TOR	CTR	ODD
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}(CycleChange)$	-0.00607	-367.2**	2.558***	-0.0551***	422.3**	4.996***
	(0.00832)	(150.6)	(0.535)	(0.0121)	(210.3)	(0.447)
Mispricing	0.972*	-503.6	63.64**	7.406**	-35,423	112.3
	(0.557)	(7,905)	(32.17)	(3.425)	(29,204)	(85.69)
ln(FundTNA)	0.0182	-708.7**	1.953	0.0105	-1,391***	-0.540
	(0.0170)	(273.1)	(1.384)	(0.0348)	(532.1)	(1.175)
ln(FundAge)	-0.0314	4,087**	10.09	0.181***	-93.23	1.064
	(0.0637)	(1,802)	(6.517)	(0.0667)	(1,469)	(3.979)
Return	0.00233	-75.48*	0.165	0.00270**	-267.0**	-0.0261
	(0.00163)	(40.68)	(0.118)	(0.00130)	(109.2)	(0.158)
Flow	0.00481	20.09	-0.161	0.0110	63.30	-0.221**
	(0.00349)	(23.58)	(0.169)	(0.00778)	(53.75)	(0.0976)
Roll	0.00429***	2.228	0.0194	0.00128	-7.399	-0.231**
	(0.000617)	(23.54)	(0.0888)	(0.00104)	(54.37)	(0.0937)
Observations	68,285	61,950	63,899	94,155	87,755	89,073
R-squared	0.509	0.381	0.322	0.503	0.385	0.427
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Quoted bid-ask spread and High-frequency Trading Activities Before and After the Settlement Cycle Change

This table reports OLS regression results examining the level change in quoted bid-ask spread in the secondary market of US ETFs before and after the U.S. settlement cycle change from T+2 to T+1 on May 29, 2024 in the following specification:

$$Spread_{f,b,t}^{Quote} = \mathbf{1}(CycleChange_t) + \alpha_f + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

, where the quoted bid-ask spread $Spread^{Quote}$ is regressed on the indicator variables $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change. In Column (2) - (4) and (6) - (8) we also interact with the proxies of high-frequency trading activities. Proxies include *CTR*, the cancel-to-trade ratio suggested by Hasbrouck and Saar (2013) and Weller (2017); *TOR*, the trade-to-order ratio suggested by Hendershott et al. (2011); and *ODD*, odd-lot ratio suggested by O'Hara et al. (2014). Control variables include ln(*FundTNA*), the log of total net assets, ln(*FundAge*), the log of fund age in years, *Return*, the raw returns, *Flow*, the daily percentage net flow into the fund, and *Roll*, Roll (1984) impact ratio as a proxy for ETF illiquidity. Fund fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	T2 Benchmark				T1 Benchmark			
	Quoted Bid-Ask Spread				Quoted Bid-Ask Spread			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbf{1}(CycleChange)$	0.626*	0.579	0.719	0.502	0.590***	0.714***	0.734***	0.728***
	(0.335)	(0.442)	(0.563)	(0.521)	(0.137)	(0.167)	(0.157)	(0.163)
$\mathbf{1}(CycleChange) \times TOR$		-0.420***				-0.144***		
		(0.106)				(0.0476)		
$\mathbf{1}(CycleChange) \times CTR$			1.574				0.104	
			(1.059)				(0.0974)	
$\mathbf{1}(CycleChange) \times ODD$				0.358*				0.233**
				(0.195)				(0.109)
TOR		0.0805				0.0852***		
		(0.0788)				(0.0208)		
CTR			-0.0482				0.0143	
			(0.125)				(0.0550)	
ODD				-0.135				-0.0761
				(0.0883)				(0.0700)
Mispricing	-2.080	1.794	4.272	3.926	44.31**	36.90	27.44	23.73
	(24.49)	(14.89)	(17.42)	(15.46)	(19.22)	(27.08)	(22.86)	(23.06)
ln(FundTNA)	0.0868	-0.771	-0.930	-1.018	-1.098**	-1.685**	-1.496**	-1.444**
	(0.687)	(0.870)	(1.026)	(0.990)	(0.455)	(0.664)	(0.575)	(0.591)
ln(FundAge)	6.959	11.41	12.91	14.40	-2.953**	-4.406**	-3.585**	-4.047**
	(6.452)	(10.87)	(13.74)	(13.29)	(1.428)	(1.956)	(1.677)	(1.854)
Return	0.0734	-0.0163	-0.0145	-0.0181	-0.0535	-0.0778	-0.0872	-0.0865
	(0.0541)	(0.0570)	(0.0572)	(0.0581)	(0.0510)	(0.0618)	(0.0596)	(0.0618)
Flow	-0.0617	-0.0916**	-0.0964**	-0.0860*	-2.44e-05	-0.00194	-8.43e-05	0.000114
	(0.0401)	(0.0461)	(0.0467)	(0.0451)	(0.0237)	(0.0299)	(0.0300)	(0.0295)
Roll	1.813***	2.299**	2.175**	2.258**	0.236	0.403	0.391	0.381
	(0.624)	(0.884)	(0.877)	(0.916)	(0.154)	(0.247)	(0.248)	(0.248)
Observations	94,241	68,031	61,703	63,650	125,257	93,783	87,393	88,710
R-squared	0.695	0.689	0.675	0.684	0.566	0.551	0.565	0.563
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Spillover Effect to the Foreign Underlying Assets

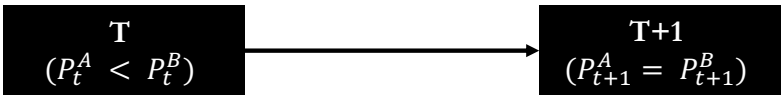
This table reports the OLS regression examining the change of liquidity and price informativeness of underlying assets tracked by the US ETFs exposed to settlement cycle mismatch in the following specification:

$$Y_{i,t} = \mathbf{1}(CycleChange_t) \times pct_{t-1}^{USETF} + pct_{t-1}^{non-USETF} + \alpha_i + \alpha_t + \sum_{n=1}^{N} x_{i,t-1}\beta_n + \epsilon_{i,t}$$

, where $Y_{i,t}$, the proxy for illiquidity and price informativeness, is regressed on the indicator variables $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change and pct_{t-1}^{T2ETF} the aggregated percentage of outstanding shares held by the exposed ETFs. Proxies of illiquidity include *Roll*, the Roll (1984) impact ratio and *Zero*, the Lesmond et al. (1999) zero ratio. The proxy of price informativeness is R^2 measure from Roll (1988). Control variables include $pct^{non-USETF}$, the aggregated percentage of outstanding shares held by the unexposed ETFs, *ln(MarketCap)*, the log of market capitalization and *1/Price*, the inverse of the price of the stocks. Stock and day fixed effects are included, with heteroskedasticity-robust standard errors clustered at the stock and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)
	Illiquidity		Price Informativeness
	I	Zeros	R^2
$pct^{USETF} \times \mathbf{1}(CycleChange)$	1.088***	0.555***	-0.0228
	(0.336)	(0.134)	(0.467)
pct^{USETF}	-1.444***	-0.462**	0.407
	(0.418)	(0.194)	(0.785)
$pct^{non-USETF}$	2.094	0.614	-0.140
	(3.122)	(0.569)	(3.375)
ln(MarketCap)	-0.149	-0.000272	-0.1000***
	(2.395)	(0.00339)	(0.0146)
1 / Price	-0.0343**	3.52e-06	-0.00622
	(0.0150)	(3.57e-05)	(0.00804)
Observations	330,963	352,859	346,084
R-squared	0.458	0.819	0.588
Stock FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

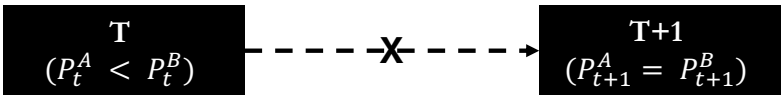
7 Appendix



Initiate arbitrage trades:
- Buy A at P_t^A (settle T+1)
- Borrow and sell B at P_t^B (settle T+1)

Close by reversal:
- Receive A, sell at P_{t+1}^A
- Buy B at P_{t+1}^B and return B

(a) Panel A: Arbitrage under the same settlement cycle



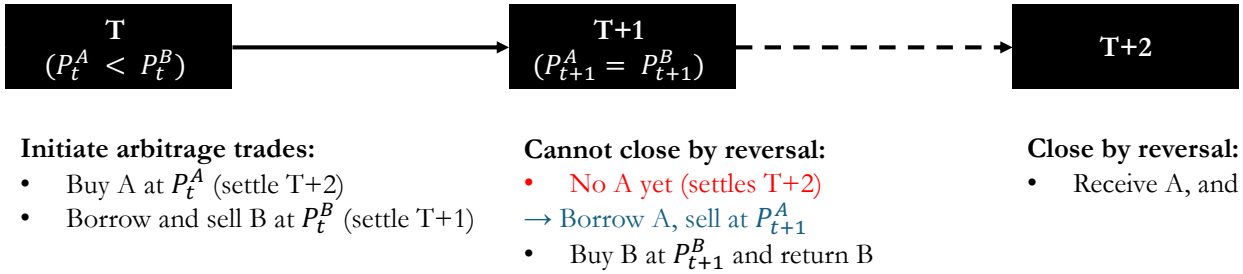
Initiate arbitrage trades:
- Buy A at P_t^A (settle T+2)
- Borrow and sell B at P_t^B (settle T+1)

Cannot close by reversal:
- No A yet (settles T+2)
- Buy B at P_{t+1}^B and return B

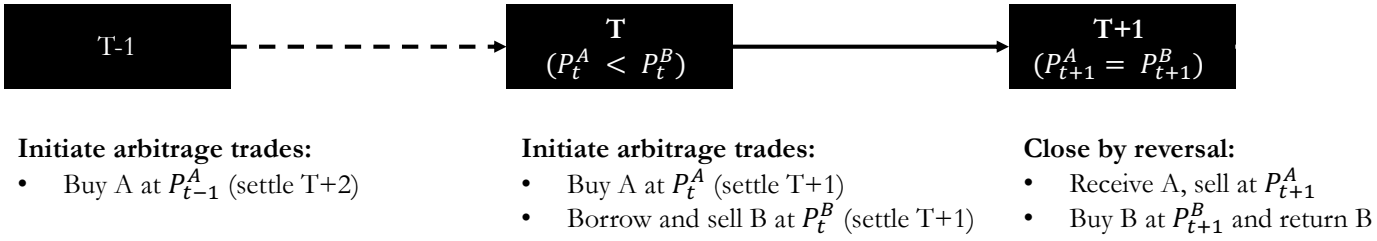
(b) Panel B: Arbitrage under the different settlement cycle

Figure A1: Arbitrage under Settlement Cycle Mismatch

This figure illustrates a simple arbitrage example comparing two scenarios: same settlement cycles (T+1 for both assets) and different settlement cycles (T+2 for Asset A, T+1 for Asset B). It demonstrates how a trader exploits a price discrepancy ($P_t^A < P_t^B$) at time T, assuming prices converge ($P_{t+1}^A = P_{t+1}^B$) by T+1. The mismatch in settlement cycles introduces additional complexity, requiring the trader to borrow Asset A at T+1 in the T+2 & T+1 case, incurring extra costs or market risk that reduce the net profit compared to the T+1 & T+1 case.



(a) Panel A: Arbitrage under different settlement cycle



(b) Panel B: Arbitrage under different settlement cycle

Figure A2: Arbitrage under Settlement Cycle Mismatch

This figure illustrates trader's solution to overcome the problem of different settlement cycles (T+2 for Asset A, T+1 for Asset B). It demonstrates how a trader exploits a price discrepancy ($P_t^A < P_t^B$) at time T, assuming prices converge ($P_{t+1}^A = P_{t+1}^B$) by T+1 when two assets are settled at settlement cycle mismatch of 1 day. Panel A shows a trader can borrow Asset A at T+1 in the T+2 & T+1 case, incurring extra costs. Panel B shows that a trader can pre-require the assets, incurrinig additional market risk.

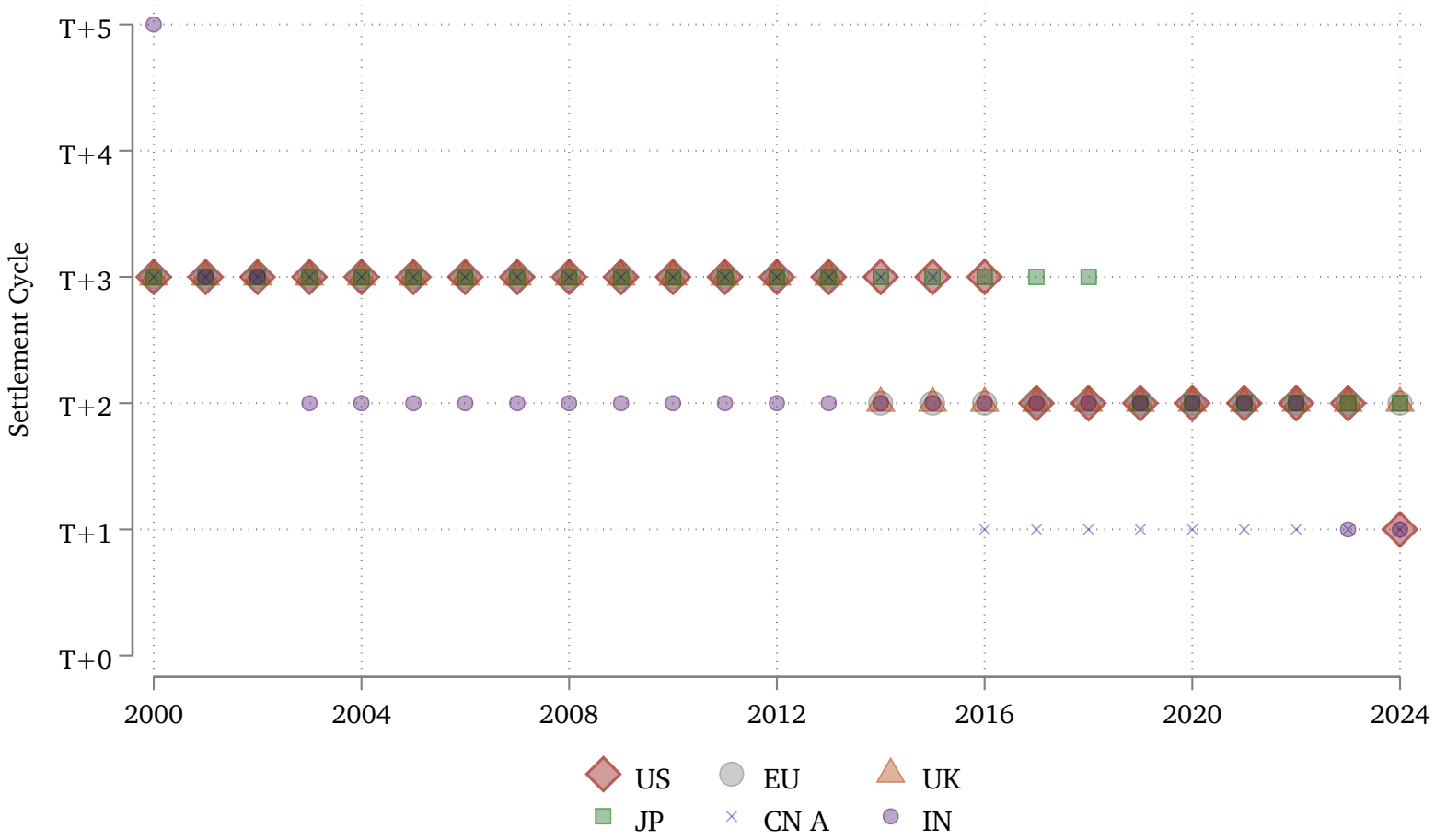
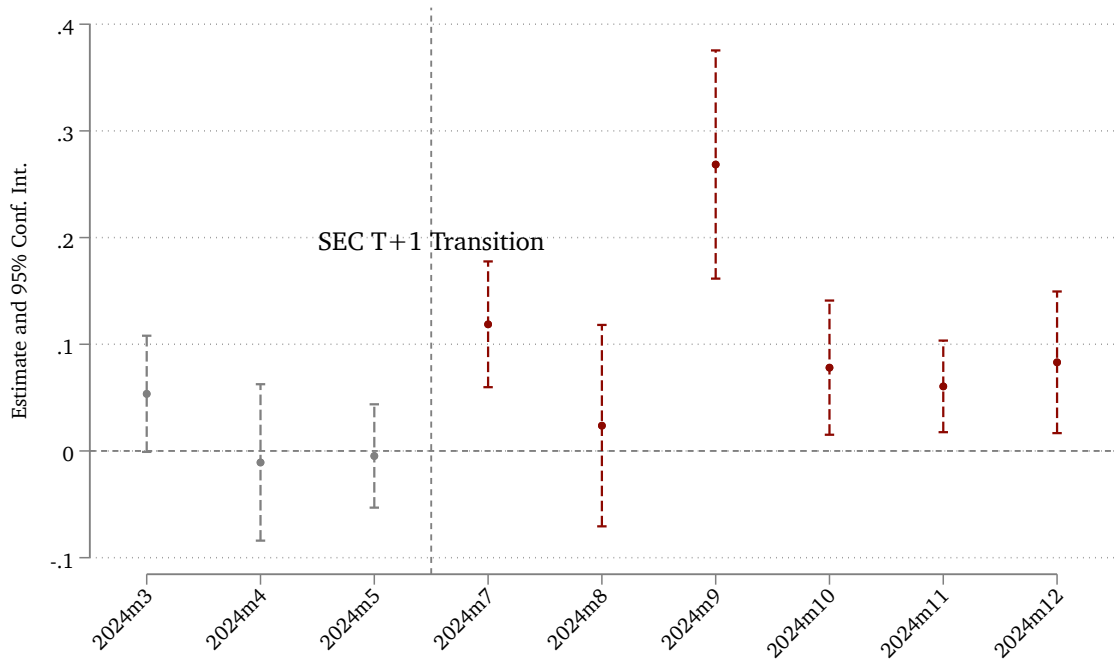
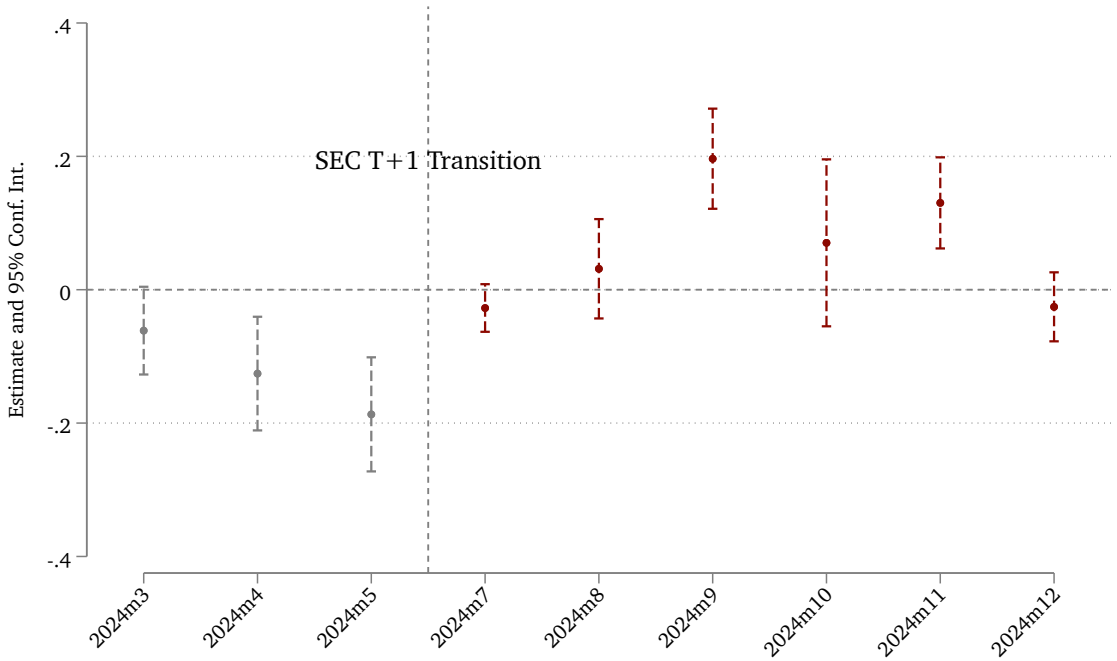


Figure A3: Settlement Cycle Changes in Major Jurisdiction

This figure illustrates the evolution of settlement cycles for exchange-traded products across the major jurisdictions from 2000 to 2024. Jurisdictions are represented by distinct shapes: US (diamond), EU (large circle), UK (triangle), Japan (square), China A-share (cross), and China B-share (small circle). Settlement cycles, ranging from T+5 to T+1, indicate the binding period required for trade settlement following execution in these jurisdictions.



(a) Panel A: Coefficient plot of tracking error



(b) Panel B: Coefficient plot of liquidity measures

Figure A4: Coefficient Plot of Tracking Error and Liquidity Measure

This figure plots the coefficient estimates from the OLS regression results examining the changes in price discovery and liquidity of ETFs before and after the U.S. settlement cycle change from T+2 to T+1 on May 29, 2024, using a difference-in-differences framework. US ETFs are compared to non-US ETFs tracking the same non-US benchmark index. Price discovery is measured by the standard deviation of tracking error over a 22-day rolling window: $\sigma_t^{TE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_{p,t-i} - R_{b,t-i})^2}$, where $R_{p,t-i}$ and $R_{b,t-i}$ are daily ETF and benchmark returns, respectively. Liquidity is proxied by Roll's (1984) impact ratio: $\text{Roll} = 2\sqrt{-\text{Cov}(\Delta P_t, \Delta P_{t-1})}$. The regression specification is:

$$Y_{f,b,t} = \mathbf{1}(T1ETF_f) \times \mathbf{1}(CycleChange_t) + \alpha_b + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

, where $\mathbf{1}(T1ETF_f) = 1$ for U.S. ETFs and $\mathbf{1}(CycleChange_t) = 1$ post-change. Control variables include $\ln(FundTNA)$, the log of total net assets, $\ln(FundAge)$, the log of fund age in years, *Return*, raw returns, Flow, fund flows, and *Roll*, Roll's (1984) impact ratio as a proxy for ETF illiquidity. Benchmark and day fixed effects are included with heteroskedasticity-robust standard errors clustered at the fund and day level. Panel A and B plot the coefficient estimates for tracking error and Roll's impact ratio, respectively, along with their 95% confidence intervals.

Table A1: Settlement Cycles Across Major Jurisdictions

This table presents the settlement cycles as of December 31, 2024, and the effective dates of these cycles for the top 20 equity markets by market capitalization.

Rank	Jurisdiction	Market Cap (USD Trillions)	Settlement Cycle	Effective Date of Current Rule
1	United States	61.743	T+1	28-May-24
2	European Union	16.904	T+2	October 6, 2014 (CSDR implementation)
3	China	7.68	A: T+1, B: T+3	April 15, 2016 (A shares to T+1)
4	Japan	5.215	T+2	16-Jul-19
5	India	3.931	T+1, T+0	January 27, 2023 (full transition)
6	United Kingdom	3.686	T+2	6-Oct-14
7	Canada	2.967	T+1	27-May-24
8	Saudi Arabia	2.713	T+2	23-Apr-17
9	Switzerland	2.488	T+2	Long-standing (pre-2014)
10	Taiwan	1.914	T+2	Long-standing (pre-2017)
11	Australia	1.676	T+2	March 2016 (ASX transition)
12	South Korea	1.082	T+2	Long-standing (pre-2017)
13	United Arab Emirates	1.028	T+2	Long-standing (pre-2017)
14	Hong Kong	0.929	T+2	Long-standing (pre-2017)
15	Brazil	0.716	T+2	26-Aug-13
16	Singapore	0.558	T+2	9-Dec-13
17	Mexico	0.482	T+1	28-May-24
18	Russia	0.424	T+2	2-Sep-13
19	Israel	0.388	T+2	Long-standing (pre-2017)
20	Indonesia	0.357	T+2	26-Nov-18

Table A2: Popular Arbitrage Pairs Across Asset Classes

This table lists popular arbitrage pairs across asset classes based on estimated daily trading volume in the US. These pairs typically involve futures and ETFs, with ETFs tracking the price movements of the corresponding futures. The settlement cycle of the arbitrage instruments are also reported.

Arbitrage Pair	**Instrument A (Future)**	**Instrument B (ETF)**	**Settlement Cycle A**	**Settlement Cycle B**
S&P 500 mini future & SPY	S&P 500 mini future (ES)	SPY	T+0 (Daily mark-to-market)	T+1
NASDAQ 100 future & QQQ	NASDAQ 100 future (NQ)	QQQ		
Russell 2000 future & IWM	Russell 2000 future (RTY)	IWM		
Dow Jones future & DIA	Dow Jones future (YM)	DIA		
Crude oil future & USO	Crude oil future (CL)	USO		
Gold future & GLD	Gold future (GC)	GLD		
Treasury bond future & TLT	Treasury bond future (ZB)	TLT		
Treasury note future & GOVT	Treasury note future (ZN)	GOVT		
Euro FX future & FXE	Euro FX future (EC)	FXE		
Japanese Yen future & FXY	Japanese Yen future (JY)	FXY		
British Pound future & FXB	British Pound future (BP)	FXB		
Canadian Dollar future & FXC	Canadian Dollar future (CD)	FXC		
Soybean future & SOYB	Soybean future (S)	SOYB		
Corn future & CORN	Corn future (C)	CORN		
Wheat future & WEAT	Wheat future (W)	WEAT		
Natural gas future & UNG	Natural gas future (NG)	UNG		
Bitcoin future & GBTC	Bitcoin future (BTC)	GBTC		
VIX future & VXX	VIX future	VIX		
MSCI EAFE future & EFA	MSCI EAFE future	EFA		
MSCI Emerging Markets future & EEM	MSCI Emerging Markets future	EEM		

Table A3: List of Authorized Participants

This table lists authorized participants (APs) engaged in primary market trading of ETFs, detailing their institution type, total trade value, and settlement cycle distribution. Trade value is reported in millions of USD. The T+1 ETF Share and T+2 ETF Share columns represent the percentage of ETF trades settled on T+1 and T+2, respectively, based on the APs' activity from 2018 to 2024.

Authorized Participant	**Institution Type**	**Trade Value (USD Mn)**	**T+1 ETF Share (%)**	**T+2 ETF Share (%)**
Bank of America	Bank	4,346,648.00	89%	11%
JPMorgan Chase	Bank	2,803,391.00	90%	10%
Goldman Sachs	Bank	2,553,707.00	94%	6%
Citadel	Non-Bank	1,218,997.00	98%	2%
Morgan Stanley	Bank	1,125,009.00	94%	6%
ABN AMRO	Bank	963,199.10	97%	3%
Virtus	Non-Bank	742,328.90	93%	7%
Hudson River Trading	Non-Bank	724,919.70	94%	6%
Citigroup	Bank	670,455.50	98%	2%
RBC	Bank	557,725.40	96%	4%
Jane Street	Non-Bank	445,116.40	78%	22%
BNP Paribas	Bank	346,403.70	96%	4%
Barclays	Bank	288,668.30	98%	2%
Jefferies	Non-Bank	201,305.60	100%	0%
Credit Suisse	Bank	352,340.20	45%	55%
Societe Generale	Bank	122,729.60	98%	2%
UBS	Bank	291,347.80	38%	62%
Wells Fargo	Bank	112,555.50	98%	2%
Mizuho Financial	Bank	96,985.54	99%	1%
Deutsche Bank	Bank	49,048.77	98%	2%
BNY Mellon	Bank	26,663.21	100%	0%
TD Bank	Bank	16,937.12	100%	0%
BMO	Bank	15,205.53	100%	0%
CIBC	Bank	6,744.07	100%	0%
Natixis	Non-Bank	7,264.07	92%	8%
Nomura	Non-Bank	6,341.50	100%	0%
Cantor	Non-Bank	6,885.45	91%	9%
HSBC	Bank	5,559.01	100%	0%
Cowen	Non-Bank	5,854.06	94%	6%
Macquarie	Non-Bank	4,167.79	73%	27%
Mirae Asset	Non-Bank	2,792.97	88%	12%
Wedbush	Non-Bank	2,107.82	100%	0%
State Street	Bank	1,404.70	100%	0%
Fidelity	Non-Bank	409.63	100%	0%
Knight Capital	Non-Bank	307.74	81%	19%
Interactive Brokers	Non-Bank	269.41	81%	19%
DTCC	Non-Bank	90.03	52%	48%
Robert W. Baird	Non-Bank	22.20	100%	0%
Clear Street	Non-Bank	4.51	100%	0%

Table A4: Reduced Primary Market Arbitrage Activities in a subsample of hedged ETFs

This table replicates Table 2 and reports OLS regression results examining the change in primary market arbitrageurs' sensitivity to mispricing around a settlement cycle shock under a difference-in-differences framework in a subsample of US ETFs hedged for currency exposure and their non-US counterparts. We rely on Morningstar dataset to identify whether a ETF is hedged to its base currency. US ETFs are compared to non-US ETFs tracking the same benchmark index. Following the US settlement cycle reduction from T+2 to T+1 on May 29, 2024, US ETFs tracking T+2 benchmarks, i.e., non-US indices, experience a settlement cycle mismatch, unlike their non-US counterparts. This regression evaluates the reduction in primary market arbitrage activities for exposed US ETFs relative to unexposed non-US ETFs using the specification:

$$\Delta\%ShareOut_{f,b,t} = \mathbf{1}(T1ETF_f) \times \mathbf{1}(CycleChange_t) \times Mispricing_{f,t} + \alpha_b + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

where the percentage change in shares outstanding is regressed on the interaction of indicator variables $\mathbf{1}(T1ETF_f)$, which equals 1 if the ETF is a US ETF, $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change, and $Mispricing_{f,t}$, proxied by one of three measures: 1) Mispricing = Price/NAV − 1, 2) Max($Mispricing^+$) = max{Mispricing$_t^+$ | $t \in [T-5, T]$}, or 3) Min($Mispricing^-$) = min{Mispricing$_t^-$ | $t \in [T-5, T]$}. Control variables include ln(*FundTNA*), the log of total net assets, ln(*FundAge*), the log of fund age in years, *Return*, the raw returns, *Flow*, the daily percentage net flow into the fund, and *Roll*, Roll (1984) impact ratio as a proxy for ETF illiquidity. Benchmark (or Fund) and day fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Mispricing (1)	Mispricing$^+$ (2)	Mispricing$^-$ (3)	Mispricing (4)	Mispricing$^+$ (5)	Mispricing$^-$ (6)
$\mathbf{1}(T1ETF) \times \mathbf{1}(CycleChange) \times Mispricing$	-0.145	-0.511**	0.724**	-0.145	-0.526**	0.729***
	(0.139)	(0.211)	(0.237)	(0.140)	(0.215)	(0.233)
$\mathbf{1}(T1ETF) \times \times Mispricing$	-0.020	0.028	0.441**	-0.018	0.032	0.442**
	(0.088)	(0.067)	(0.176)	(0.096)	(0.071)	(0.177)
$\mathbf{1}(T1ETF) \times \mathbf{1}(CycleChange)$	-0.286***	-0.626***	-0.189***	0.112	0.400*	-0.763***
	(0.069)	(0.176)	(0.057)	(0.132)	(0.214)	(0.214)
$\mathbf{1}(CycleChange) \times Mispricing$	0.110	0.398*	-0.751***	-0.300***	-0.649***	-0.188**
	(0.131)	(0.205)	(0.214)	(0.073)	(0.193)	(0.076)
$\mathbf{1}(T1ETF)$	0.200***	0.485**	0.105*			
	(0.061)	(0.191)	(0.053)			
ln(FundTNA)	-0.045**	-0.046**	-0.049***	-0.187***	-0.221***	-0.237**
	(0.015)	(0.015)	(0.015)	(0.055)	(0.052)	(0.083)
ln(FundAge)	-0.299***	-0.300***	-0.310***	-0.175	-0.082	0.108
	(0.042)	(0.040)	(0.043)	(0.246)	(0.200)	(0.283)
Return	0.044	0.045	0.041	0.044	0.045	0.041
	(0.036)	(0.035)	(0.033)	(0.046)	(0.049)	(0.034)
Flow	0.005	0.006	0.005	0.006	0.007	0.006
	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)
Roll	-0.022	-0.010	-0.049	-0.034	-0.024	-0.057
	(0.208)	(0.210)	(0.209)	(0.216)	(0.230)	(0.207)
Mispricing	0.076	0.004	-0.421**	0.074	-0.000	-0.423**
	(0.062)	(0.039)	(0.172)	(0.066)	(0.047)	(0.171)
Observations	1,984	1,984	1,984	1,984	1,984	1,984
R-squared	0.154	0.153	0.158	0.155	0.153	0.158
Benchmark FE	Yes	Yes	Yes			
Fund FE				Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A5: Price Deviation between ADR and Homd Price around United States T+1 Settlement Cycle Change

This table reports OLS regression results examining the deviation between the price of American Depository Receipts (p^{ADR}) and the price of home shares (p^{Home}) for shares co-listed in the US and their home (non-US) stock exchanges, before and after a settlement cycle shock. The regression follows the specification:

$$P_{s,t}^{ADR} = \mathbf{1}(CycleChange_t) \times P_{s,t}^{Home} + P_{s,t}^{Home} + \mathbf{1}(CycleChange_t) \times P_{s,t-1}^{Home} + P_{s,t-1}^{Home} + \alpha_t + \epsilon_{s,t}$$

where $P_{s,t}^{ADR}$ is the opening price of the ADR, and $P_{s,t}^{Home}$ is the closing price of the home shares for stock s. The indicator variable $\mathbf{1}(CycleChange_t)$ equals 1 after the US settlement cycle change. We group countries or regions into two categories: (1) those with a settlement mismatch with the US after the US moved to T+1 on 29 May 2024 (Europe, Japan, Hong Kong, Australia, Brazil, South Africa, Singapore, Argentina, Israel, and South Korea), and (2) those without a mismatch because they either adopted T+1 alongside the US (Canada and Mexico) or already had a T+1 or shorter settlement cycle (China and India). We use the closing price of home shares and the opening price of ADRs because the US stock market opens later than most markets in our sample. Lagged home prices are included as controls to account for potential short-term momentum. The regression includes day fixed effects, and standard errors are heteroskedasticity-robust and clustered at the stock and day levels. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	Countries with T+2 Settlement Cycle										Countries with T+1 Settlement Cycle (Placebo)		
	Europe	Japan	HongKong	Australia	Brazil	SouthAfrica	Singapore	Argentina	Israel	SouthKorea	Mexico	China	India
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$P^{Home} \times \mathbf{1}(CycleChange)$	0.018**	-0.045***	0.013***	-0.117***	-0.110*	0.049**	0.009*	-0.309*	0.073***	-0.012***	0.019	-0.015	0.096
	(0.009)	(0.015)	(0.002)	(0.023)	(0.059)	(0.018)	(0.005)	(0.159)	(0.023)	(0.002)	(0.074)	(0.012)	(0.100)
$L.P^{Home} \times \mathbf{1}(CycleChange)$	-0.018**	0.046***	-0.013***	0.116***	0.112*	-0.049**	-0.009*	0.401**	-0.074***	0.011***	-0.016	0.031***	-0.096
	(0.008)	(0.015)	(0.002)	(0.023)	(0.060)	(0.018)	(0.005)	(0.142)	(0.022)	(0.003)	(0.075)	(0.010)	(0.101)
P^{Home}	0.851***	1.007***	0.985***	0.547**	0.615***	0.931***	0.994***	0.449***	0.649***	1.005***	0.287***	0.625***	0.898***
	(0.066)	(0.008)	(0.001)	(0.246)	(0.088)	(0.034)	(0.002)	(0.081)	(0.011)	(0.001)	(0.067)	(0.065)	(0.084)
$L.P^{Home}$	0.149**	-0.007	0.015***	0.453*	0.382***	0.068*	0.006***	0.300***	0.351***	-0.005***	0.711***	0.101	0.103
	(0.066)	(0.008)	(0.001)	(0.246)	(0.087)	(0.033)	(0.002)	(0.087)	(0.011)	(0.002)	(0.068)	(0.095)	(0.086)
Number of Firms	469	172	124	60	44	27	19	14	14	12	16	19	13
Observations	85,872	32,192	19,876	10,185	7,611	4,783	3,623	2,024	2,627	2,136	2,907	1,738	2,292
R-squared	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.987	1.000	1.000	1.000	0.987	0.999
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Decomposition of Total Tracking Error

This table reports OLS regression results examining the change in decomposed component of tracking errors of ETFs before and after the U.S. settlement cycle change from T+2 to T+1 on May 29, 2024, using a difference-in-differences framework. US ETFs are compared to non-US ETFs tracking the same benchmark index under the following specification:

$$\sigma^{y}_{f,b,t} = \mathbf{1}(T1ETF_f) \times \mathbf{1}(CycleChange_t) \times Mispricing_{f,t} + \alpha_b + \alpha_t + \sum_{n=1}^{N} x_{f,t-1}\beta_n + \epsilon_{f,b,t}$$

where the components of tracking erros are regressed on the interaction of indicator variables $\mathbf{1}(T1ETF_f)$, which equals 1 if the ETF is a US ETF and $\mathbf{1}(CycleChange_t)$, which equals 1 after the settlement cycle change. Total tracking error is decomposed into the following components: $\sigma^2(R^{\text{Price}} - R^{\text{Benchmark}}) = \sigma^2(R^{\text{Price}} - R^{\text{NAV}}) + \sigma^2(R^{\text{NAV}} - R^{\text{Benchmark}}) + 2\text{Cov}(R^{\text{Price}} - R^{\text{NAV}}, R^{\text{NAV}} - R^{\text{Benchmark}})$, where R^{Price} is the ETF's market price return, R^{NAV} is the return of the ETF's net asset value (NAV), and $R^{\text{Benchmark}}$ is the benchmark return. Control variables include ln(*FundTNA*), the log of total net assets, ln(*FundAge*), the log of fund age in years, *Return*, raw returns, Flow, fund flows, and *Roll*, Roll's (1984) impact ratio as a proxy for ETF illiquidity. Benchmark and day fixed effects are included, with heteroskedasticity-robust standard errors clustered at the fund and day level. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

	T2 Benchmark				T1 Benchmark			
	σ^2_{Total}	$\sigma^2_{price-nav}$	$\sigma^2_{nav-benchmark}$	cov	σ^2_{Total}	$\sigma^2_{price-nav}$	$\sigma^2_{nav-benchmark}$	cov
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$T1ETF \times \mathbf{1}(CycleChange)$	0.157***	0.135**	0.035***	-0.033**	0.267***	0.258***	0.001	0.002
	(0.053)	(0.053)	(0.011)	(0.015)	(0.091)	(0.083)	(0.002)	(0.005)
T1ETF	-0.104	-0.246***	0.105***	0.054***	-0.642***	-0.654***	0.000	-0.000
	(0.062)	(0.058)	(0.036)	(0.019)	(0.077)	(0.076)	(0.002)	(0.008)
Mispricing	-0.003	0.001	-0.007*	0.007*	-0.007	-0.007	-0.001	-0.000
	(0.008)	(0.009)	(0.004)	(0.004)	(0.022)	(0.021)	(0.001)	(0.002)
ln(FundTNA)	0.005	-0.004	0.002	0.012*	-0.009	-0.004	-0.003*	0.000
	(0.013)	(0.018)	(0.012)	(0.007)	(0.026)	(0.022)	(0.002)	(0.002)
ln(FundAge)	-0.045	-0.016	-0.007	-0.036**	0.011	-0.002	0.011	-0.002
	(0.039)	(0.048)	(0.025)	(0.016)	(0.094)	(0.081)	(0.006)	(0.005)
Return	0.011	0.004	0.007	-0.001	-0.001	0.000	0.001***	-0.003
	(0.010)	(0.007)	(0.004)	(0.002)	(0.010)	(0.010)	(0.000)	(0.003)
Flow	0.008	0.001	0.004	0.003	0.015	0.012	-0.000	-0.003
	(0.005)	(0.006)	(0.003)	(0.004)	(0.012)	(0.011)	(0.000)	(0.002)
Roll	0.077*	0.080**	-0.028	0.033*	-0.017	-0.013	-0.002	0.001*
	(0.045)	(0.039)	(0.041)	(0.018)	(0.021)	(0.018)	(0.002)	(0.001)
Observations	9,201	9,187	9,201	9,061	9,790	9,771	9,839	9,808
R-squared	0.449	0.447	0.443	0.232	0.502	0.510	0.173	0.074
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes