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The effect of liquidity and arbitrage on the price efficiency of Chinese ETFs

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Abstract

We study the potential factors that determine the large and persistent price deviations in Chinese equity exchange-traded funds (ETFs). Our results suggest that ETF liquidity and arbitrage activity are positively correlated with ETF price efficiency, and the relation is more pronounced with higher institutional ownership. We also evaluate the effect of two exogenous shocks in the Chinese market. Using a policy change that added market makers to ETFs on the Shenzhen Stock Exchange (SZSE) and Shanghai Stock Exchange (SSE), we find that market makers improve price efficiency and that the impact is stronger for ETFs with lower liquidity. We also exploit a change in trading rules on the SZSE and show that the relaxation of arbitrage restrictions improves price efficiency. Altogether, these findings provide evidence that lack of liquidity, due to the unique market structure and regulations of the Chinese market, contributes to price inefficiency of Chinese ETFs.

JEL CLASSIFICATION
G12, G14

1 | INTRODUCTION

The importance of financial innovation is widely recognized.[1] Exchange-traded funds (ETFs), one of the most important financial innovations in recent decades, have transformed the asset management industry by providing investors with not only a more liquid and lower cost alternative to mutual funds but also access to previously

[1]Many leading scholars, including Miller (1986) and Merton (1992), highlight the importance of new products and services in the financial market and suggest that the addition of a new type of security (e.g., futures and options) can complete the financial market (Duffie & Rahi, 1995), lead to more risk sharing (Allen & Gale, 1994), and promote more hedging and informed trading (Dow, 1998), but also create complexity to exploit the users (Allen, 2012).

unavailable asset classes. The total assets under management (AUM) of ETFs in the United States has grown six-fold since 2009 to over $6 trillion in 2021, exceeding the size of the hedge fund industry.[2] The Chinese ETF market has experienced similar rapid growth, with AUM growing from 150 billion yuan in 2013 to 1.2 trillion yuan (approximately $200 billion) in June 2021.[3] The popularity of ETFs has attracted increasing attention from academic researchers, market participants, and regulators to better understand ETFs as a financial innovation.

Although several studies have evaluated the market impact of ETFs,[4] the price efficiency of ETFs, particularly in emerging markets, has received limited attention. In a well-functioning market, ETF prices are kept in line with the prices of their underlying assets, or net asset value (NAV), through arbitrage between primary and secondary markets. However, ETFs are not always priced efficiently (Engle & Sarkar, 2006). Inefficient ETF prices can distort market signals and disperse risk into the underlying assets through creation and redemption activities that drive prices away from the fundamental value, increase volatility, and even promote market instability. Previous studies have linked the efficiency of ETF prices to trading costs and limits to arbitrage, such as holding illiquid assets, market stress, or stale NAV prices (Madhavan, 2012; Petajisto, 2017). Although price deviations are generally small for equity ETFs in the United States, this may not be the case in emerging or other markets because of differences in market design and arbitrage restrictions. Broman (2020) indicates that mispricing in the European ETF market is several times higher compared to that in the US market because of the structure of multiple cross-listings and higher arbitrage costs imposed through settlement systems.[5] Given the paucity of studies on the price efficiency of ETFs in emerging markets such as China, we first document distinct characteristics of the Chinese ETF market and then analyze the potential factors that determine price inefficiencies of Chinese equity ETFs, including liquidity and relative liquidity, arbitrage environment and activity, and ownership structure.

Substantial variations in trading processes and market structures exist between the Chinese and US markets. Importantly, restrictions on short selling and *T*+1 trading make the well-functioning arbitrage mechanism that ties prices and NAVs closely together for US ETFs not directly applicable for Chinese ETFs. Accordingly, we identify two important differences between the Chinese ETF market and more developed markets such as the US market. First, we provide evidence that price deviations of Chinese ETFs are substantially larger and more persistent than those for US ETFs. The equal-weighted (value-weighted) mean value of the deviation is 0.586% (0.204%), as opposed to around 0.022% (0.037%) for US equity ETFs (Jain et al., 2021; Petajisto, 2017). Deviations can also persist on average for 5.53 days in China, approximately 10 times longer than in the US. Second, the liquidity of Chinese equity ETFs is mostly lower than the liquidity of their underlying portfolios, suggesting that relative liquidity is negative. One of the most well-established advantages of ETFs in the United States and other developed markets is increased liquidity, or positive relative liquidity.[6] We find that this advantage does not exist in the Chinese ETF market and is actually reversed. These differences prompt us to investigate the causes of the significant and persistent price deviations in Chinese ETFs: whether the unique restrictions on the Chinese market are to blame and how the interplay of the liquidity of Chinese ETFs and that of their underlying portfolio affect the price efficiency of Chinese ETFs.

[2]Data are collected and compiled from the ETF database (www.etfdb.com).

[3]Data are collected and compiled from the Wind database.

[4]Some believe that ETFs can improve the price discovery of the underlying assets (Ernst, 2020; Hasbrouck, 2003), the short-term information efficiency of underlying assets (Glosten et al., 2021), and the liquidity of underlying assets (Holden & Nam, 2017; Sağlam et al., 2020), and expand the market's ability to hedge (Huang et al., 2021). In contrast, others have highlighted risks and concerns of ETFs, including more rapid transmission of liquidity shocks, higher return correlations among stocks held by the same ETFs (Da & Shive, 2018), higher return volatility (Ben-David et al., 2018; Broman & Shum, 2018), higher comovement in liquidity of the underlying assets (Agarwal et al., 2019), and elevated market instability (Bhattacharya & O'Hara, 2018).

[5]Costs in the European ETF market on arbitrageurs include creation and redemption fees, depending on the rules in the exchanges on which ETFs are listed (Kaminska, 2011), operational costs in each jurisdiction, and increased risk of settlement failure that arises because the broker's back-office system cannot transfer ETFs across central securities depositories (CSDs) in time (Lijnse & Scholtes, 2010).

[6]The sample makes a big difference in the direction of relative liquidity. Even in the US ETF market, relative liquidity can be negative when including a broader sample of ETFs (Box et al., 2021). European ETFs are generally also much more illiquid and less price efficient compared to their US counterparts (Broman, 2020).

We first explore how liquidity and relative liquidity affect ETF price efficiency in the Chinese market. The liquidity of ETFs is essential in keeping prices aligned with fundamental value and minimizing price deviations from the NAV. Several papers have studied the impact of liquidity on price efficiency in the context of US equity ETFs and demonstrated that lack of ETF liquidity (Cespa & Foucault, 2014; Madhavan & Sobczyk, 2016; Petajisto, 2017) or a large liquidity mismatch between the ETF and its underlying portfolio (Pan & Zeng, 2019) discourages arbitrage and leads to more persistent mispricing. Bae and Kim (2020) highlight the impact of liquidity on price efficiency, showing that ETFs have large tracking errors[7] when underlying assets are less liquid. However, it is unclear whether these findings translate to the Chinese ETF market, with its unique trading process and market structure and ETFs that are less liquid than their underlying portfolios. Thus, the impact of liquidity on the price efficiency of Chinese equity ETFs may differ from that of developed markets and needs to be empirically analyzed.

To study the relations among ETF liquidity, relative liquidity, and price efficiency, we use daily absolute deviation and premium (discount) persistence to measure the size and duration of price inefficiency and four measures of ETF liquidity: relative quoted spread, relative effective spread, market depth, and Amihud illiquidity. Our findings reveal a strong negative correlation between ETF liquidity and both the magnitude and persistence of price deviations after controlling ETF and day fixed effects in regressions. Consistent with the literature (Pan & Zeng, 2019), we also find that a greater liquidity mismatch between the ETF and its underlying portfolio leads to higher and more persistent mispricing. Broman and Shum (2018) demonstrate that for US equity ETFs, relative liquidity, as opposed to the liquidity of the ETF itself, is significantly more important for short-term versus long-term investors. However, Chinese equity ETFs have not shown sufficient liquidity advantages to attract short-term traders. In the Chinese market, we find that the impact of ETF liquidity on price efficiency remains statistically significant after controlling for liquidity mismatch.

ETF prices and NAVs must be up-to-date for the deviation to be interpreted as an accurate gauge of price dislocation. Otherwise, the price deviation is artificial and biased when the ETF closing prices, NAVs, or both are stale. This issue is well recognized (Broman, 2020; Petajisto, 2017). We use ETF closing midquote prices instead of closing prices to address the concern of stale ETF closing prices. To resolve the issue of stale NAVs, we adopt the peer-group approach proposed in Petajisto (2017). We compute the percentage deviation of the ETF closing midquote prices from adjusted NAVs, which are estimated from the prices of ETFs that track the identical benchmark indices. Our results remain consistent after purging the effect of stale prices from our deviation measures. We also use transaction-cost-adjusted deviations to confirm that the documented inefficiency cannot be explained away after considering arbitrage costs.

Although our ordinary least squares (OLS) regressions control for observable ETF characteristics and include ETF and day fixed effects, ETF liquidity may be endogenous. A higher ETF price efficiency may attract more active trades, thereby resulting in better liquidity. To address this concern, we rely on the quasi-natural experiments provided by changes in the relevant rules of the Shenzhen Stock Exchange (SZSE) and Shanghai Stock Exchange (SSE), specifically, the addition of liquidity service providers.[8] According to the new regulations, liquidity service providers provide market-making services for some ETFs, which improve ETF liquidity. Our empirical results reveal that the addition of liquidity service providers does indeed improve price efficiency of ETFs, consistent with a causal interpretation between liquidity and price efficiency.

Next, we analyze how arbitrage restrictions influence price efficiency. Arbitrage between primary and secondary markets keeps ETF prices aligned with their NAV. However, there are significant differences between China and the United States in market regulations and rules. The T+1 trading rule in China, different creation/redemption rules, and inactive short selling on stocks and ETFs in China all pose direct and serious restrictions on

[7]Bae and Kim (2020) define tracking errors as the return differences between ETF price and NAV, NAV and index, and ETF price and index. Deviations between NAV and index and between ETF price and index are mainly due to fees and expenses or representative sampling of the ETF product structure and thus may be less reflective of actual price inefficiency.

[8]The SZSE and SSE introduced liquidity service providers to provide market-making services for Harvest CSI 300 ETF and Huatai Berry CSI 300 ETF in May 2012. Since then, an increasing number of fund management companies have added securities firms as liquidity services providers for their ETFs. The exchanges rate their market-making services on a quarterly basis and provide incentives for outstanding market makers, including reductions in commission fees and refunds of transaction fees. See Section 2.1 for more details.

arbitrage. Although the literature has highlighted the importance of secondary market trading on price efficiency (Jain et al., 2021), prevailing intraday liquidity and liquidity risk when arbitrage opportunities are observed (Marshall et al., 2013), and the role of the AP network on mispricing (Gorbatikov & Sikorsekaya, 2021), less evidence has been presented on how changes to the arbitrage restrictions affect ETF price efficiency. Although both investors' capital restrictions and illiquidity of the underlying assets can contribute to the lack of sufficient arbitrages, we believe that insufficient arbitrage is mainly due to restrictions on arbitrage in China. Thus, we perform several tests to understand whether insufficient arbitrage activity is indeed an important reason for ETF price inefficiency in China.

Using quarterly creation and redemption data to proxy for arbitrage activity, we show that greater arbitrage activity is significantly related to lower and less persistent price deviations. An increase in market demand may lead to an increase in absolute flow, resulting in more active trading of ETFs and higher price efficiency. To further show that arbitrage activities instead of market demand change contribute to a lower deviation, we employ a pooled regression in a difference-in-difference (DiD) design using a new policy implemented on the SZSE on October 21, 2019, which changed the creation and redemption mechanism of cross-market ETFs to allow for settlement of cross-market ETF shares or stocks on day *T* instead of on day *T*+1. This facilitates arbitrage of cross-market ETFs on the SZSE but has no direct influence on single-market ETFs and market demand, creating an ideal setting to study the price efficiency of cross-market ETFs before and after implementation of the new policy (more details are provided in Sections 2.2 and 2.3). We find that the new policy significantly promoted arbitrage and improved the price efficiency of cross-market ETFs on the SZSE. We also find that the improvement of the arbitrage environment has a more significant impact on the price efficiency of ETFs with lower liquidity, further supporting the conjecture that increased ETF liquidity and arbitrage activity have a significant positive effect on price efficiency.

In addition, the short-selling restriction is an important part of arbitrage restrictions. Although arbitrage appears possible without short selling under current trading mechanisms in China, there are several potential constraints and risks. The arbitrage strategy without short selling when ETFs trade at a discount takes three steps: buying underlying assets, creating ETF shares, and selling ETF shares (more details are provided in Section 2.3). The major uncertainty is that arbitrageurs cannot move onto the next step until the current step is finished, and delays in any step may reduce or eliminate potential profits. However, ETFs with short selling permitted can be arbitraged similar to how US ETFs are arbitraged when trading at a discount: short selling the ETF while buying the underlying assets, and then creating ETF shares to cover the short position. Arbitrage through short selling allows for more cost control, which may increase arbitrage transactions. Furthermore, any new buying or selling that comes into a market adds liquidity. Short selling does that by adding more volume above normal levels. Therefore, we investigate the influence of short selling on price efficiency and liquidity. To determine whether an ETF can be shorted on a given trading day, we collect the lists of securities lending published by the exchanges daily. We find that ETFs with short selling permitted have significantly higher liquidity and price efficiency than ETFs with short selling restrictions. Furthermore, the negative impact of lower liquidity on price efficiency is lessened for ETFs with short-selling restrictions relaxed, supporting the conjecture that lifting the short-selling restriction has a significant positive effect on price efficiency.

Last, we consider the influence of institutional ownership on ETF price efficiency. Despite numerous studies on mutual fund ownership, the role of institutional ownership in the ETF space—and its impact on price efficiency—has not been studied. Institutional investors are better positioned than individual investors to take advantage of mispricing in ETFs through arbitrage given that institutions generally have higher liquidity and lower transaction costs (Edmans et al., 2013). We hypothesize that institutional ownership is positively correlated with the price efficiency of ETFs and that the impact is larger for ETFs with higher liquidity and larger AUM. Our results are consistent with the prediction.[9]

Our study makes several important contributions. First, it builds on the growing literature on ETFs as a financial innovation and provides new perspectives on the price efficiency of ETFs. To the best of our knowledge, we are the

[9]Alternatively, it is plausible that longer term institutions may prefer to invest in ETFs with higher price efficiency as these institutional investors do not actively “correct” mispricing. We thank an anonymous referee for pointing out that the relation between institutional ownership and ETF price efficiency may be endogenous.

first to evaluate the price efficiency of ETFs within the context of the Chinese market, and we find that in contrast to the US and other developed markets, ETF price deviations are significantly larger and more persistent. As argued by Roll et al. (2007), the law of one price is a fundamental building block of modern financial theory, and finance scholars have long recognized that deviations from no-arbitrage relations are related to the frictions associated with transacting and, in particular, liquidity. We demonstrate that in China, different trading rules and market structures, not practiced in developed markets where ETFs have been more well characterized, create market frictions and reduce the liquidity of ETFs, lowering ETF price efficiency.

Second, we provide empirical findings on the forces that determine the price efficiency of ETFs. Many studies have explored the broader market impact of ETFs, showing that ETFs improve asset price discovery and short-term information efficiency (Ernst, 2020; Glosten et al., 2021; Hasbrouck, 2003) but may also increase return volatility of underlying assets, comovement in the liquidity of the underlying assets, and market instability (Ben-David et al., 2018; Bhattacharya & O'Hara, 2018; Broman & Shum, 2018; Da & Shive, 2018). The price efficiency of ETFs continues to be a major concern for investors and financial regulators, yet the literature on the market impact and determinants of ETF price efficiency is limited, particularly in emerging markets. We find that ETF liquidity and factors that influence liquidity, such as arbitrage and ownership structure, are strongly related to price efficiency, complementing findings for the US market (Bae & Kim, 2020). To address endogeneity concerns that could confound findings, we employ two exogenous shocks unique to the Chinese market: (1) the introduction of liquidity service providers as market makers to provide liquidity and new creation and (2) redemption rules on the SZSE that relaxed cross-market arbitrage restrictions. We also consider how the short-selling eligibility of ETFs improves liquidity and price efficiency. Earlier works, such as Pontiff (2006), highlight the importance of idiosyncratic risk (a holding risk) for arbitrageurs. Regulations in Chinese markets that state that newly created ETFs must held until 1 day after settlement (T+1) and positions that often cannot be hedged because of short-sale restrictions illustrate the unique arbitrage risk in Chinese ETFs. The policy changes on October 21, 2019 that eliminated this arbitrage risk make it an interesting quasi-natural experiment to establish causality. Our findings thus make a marginal contribution to our understanding of how removing frictions improves arbitrage and price efficiency.

Finally, our article expands on the literature that explores the unique institutional features of the Chinese capital market and the implications of policies that differ from developed markets. We show that the large and persistent price deviations in Chinese ETFs may be explained by unique differences in market structure and trading rules. Trading constraints originally introduced in the name of protecting investors, such as the T+1 trading rule, may actually increase market inefficiency. Our research also demonstrates that steady progress in recent market reforms and regulations that promote arbitrage and liquidity have increased ETF price efficiency and may support further growth of the Chinese ETF market. Therefore, although some of our results may not generalize to more developed markets, the findings do have broad implications for other markets undergoing changes in regulations and rules.

2 | INSTITUTIONAL DETAILS OF CHINESE ETFS

ETFs are listed on exchanges and traded throughout a trading day. In China, the largest ETF (at the end of 2020) is Huaxia SSE 50 with AUM of 56.57 billion yuan, which is significantly smaller than the largest US ETF. Besides the difference in the sheer size of the two markets, there are also notable differences in institutional settings such as restrictions on short selling and the T+1 trading rule. Given that short selling is a crucial part of the arbitrage between primary and secondary markets in the United States, it is interesting to explore how Chinese ETF prices are kept in line with their NAVs while facing short-selling restrictions (even after short selling is permitted on some ETFs, the overall short volume is very low).

In addition, regulators have introduced several new policies to further grow the Chinese ETF market over the years, including the introduction of liquidity service providers, changes in the creation and redemption rules on the SZSE, and ETF short selling. These changes in the institutional environment are unique, and they are ideal for us to construct our tests on the causal relations between our main variables of interests such as price efficiency, liquidity and arbitrage. Therefore, we briefly discuss these changes and outline the arbitrage mechanisms in Chinese ETFs.

2.1 | ETF liquidity service providers

Liquidity service providers, the same as market makers in the United States, are financial institutions that quote both a buy and a sell price in a tradable asset and provide the market with liquidity and depth while profiting from the difference in the bid–ask spread. Although ETFs have grown in number and size, most ETFs other than the top funds suffer from low liquidity and trading volume. Because of the high level of homogeneity in ETF products, liquidity is a crucial factor in attracting investors. Thus, more ETF issuers are adding liquidity service providers.

In 2010, only three equity ETFs had liquidity service providers. At the end of 2020, the number of ETFs with liquidity service providers increased to 194, thereby accounting for 71.06% of all equity ETFs, with an average of 2.83 liquidity service providers per ETF. The fund with the largest number of liquidity service providers is Huaxia 300, which has 18. HS300, CSI 500, and STAR 50[10] each has 13 liquidity service providers. Moreover, almost 70% of ETFs have 2 to 5 liquidity service providers. The top three liquidity service providers are CITIC Securities, Founder Securities, and China Merchants Securities, which provide market-making services for 123, 108, and 87 ETFs, respectively.

2.2 | Creation and redemption rules

Unlike trades in the United States, which are settled in one depository system (Depository Trust Company, a CSD), the transactions of different exchanges in China are settled in different depository systems. The structure of multiple cross-settlements, similar to the situation in Europe (Broman, 2020), raises the risk of settlement failure; that is, the broker's back-office system cannot transfer ETF shares or underlying assets between CSDs in time. Specifically, if the underlying assets and ETFs are traded on different exchanges, they are settled in separate depository systems. This has no effect on transactions on the secondary market, but it does affect the creation and redemption in the primary market because of the difficulties in the confirmation and transfer between the underlying assets and ETF shares.

Therefore, to mitigate settlement failure and facilitate arbitrage between the primary and secondary markets of ETFs in the presence of short-selling restrictions, exchanges implement distinct creation and redemption rules for cross-market ETFs with underlying securities, including both SSE- and SZSE-listed stocks. In contrast, single-market ETFs, with underlying assets and ETFs traded on the same exchange, have the identical creation and redemption rules for either SSE or SZSE ETFs.

When creating single-market ETF shares, investors need to prepare a basket of stocks (or a portion of cash) in accordance with the portfolio composition file (PCF) announced by the ETF issuer on day *T* and swap that basket for ETF shares. The transfer is confirmed immediately, and the ETF shares can be sold on the same day. Similarly, ETF shares that are bought on the secondary market on day *T* can be redeemed and swapped for a basket of stocks immediately on the same day. Figures 1 and 2 illustrate the creation and redemption processes for a single-market ETF, respectively.

For cross-market ETFs on the SSE, investors are required to prepare SSE stocks and cash equivalent to the market value of SZSE stocks in accordance with the PCF announced by the ETF issuer on day *T* to create ETF shares.[11] The newly acquired ETF shares can be immediately sold in the secondary market on day *T*. Similarly, ETF shares that are bought on the secondary market on day *T* can be redeemed on the same day and immediately swapped for SSE stocks and cash equivalent of the market value of SZSE stocks.

For cross-market ETFs on the SZSE, the rules of creation and redemption changed on October 21, 2019. Specifically, before October 21, 2019, investors needed to prepare SSE stocks and SZSE stocks in accordance with

[10]STAR 50 ETF is listed on the SSE and tracks the Science and Technology Innovation Board 50 Index with tick number 588000.

[11]Cash can be used to buy SZSE stocks on the next trading day (*T*+1). Here is an example. On May 6, 2021, according to the PCF of the Huatai CSI 300 ETF, 2300 shares of Ping An Bank are required to create one ETF share. Because Ping An Bank is listed on the SZSE, the 2300 shares of Ping An Bank shares must be replaced by 53,567 yuan in cash (23.29 yuan is the closing price of the previous trading day). Cash is used by the fund manager to purchase 2300 shares of Ping An Bank on the next trading day. If the purchase price is higher than 23.29 yuan, investors are required to add cash to the account, and if the purchase price is lower than 23.29 yuan, the fund manager returns the remaining cash to the account.

FIGURE 1 Creation process for a single-market exchange-traded fund (ETF). [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE 2 Redemption process for a single-market exchange-traded fund (ETF). [Color figure can be viewed at wileyonlinelibrary.com]

the PCF announced by the ETF issuer on day *T* and swap those for ETF shares, but ETF shares were confirmed on day *T*+1 because of cross-settlement. The inability to confirm and sell newly created ETF shares on day *T* created significant uncertainty as arbitrageurs could not lock in the arbitrage profit or complete the arbitrage transaction on day *T* when there was a deviation between ETF price and its NAV.

Under the new trading rules launched by the SZSE on October 21, 2019, the settlement of shares or stocks can be completed on day *T*, similar to the rule on the SSE. This new mechanism improves the efficiency of creating and redeeming cross-market ETFs on the SZSE and provides us with a plausible natural experiment to study the impact of the improvement of the arbitrage environment on the price efficiency of ETFs.

2.3 | Arbitrage mechanisms

In general, the unique structure of ETFs provides arbitrage opportunities to investors when there is a deviation between ETF price and NAV. When ETF prices and underlying security prices diverge, arbitrageurs typically buy the less expensive asset (ETF shares or a basket of the underlying securities) and exchange it for a more expensive asset, thereby leading to the creation or redemption of ETF shares.[12]

However, because of the unique trading rules and mechanism in China, the ETF arbitrage process in China is significantly different from that in the United States. First, designated brokers or authorized participants (APs) have a unique right to create and redeem ETF shares to perform arbitrage in the United States. However, there are no designated APs in China and any qualified investor can play the role of AP. ETF issuers designate primary dealers

[12] Petajisto (2017) provides additional details on the arbitrage mechanism.

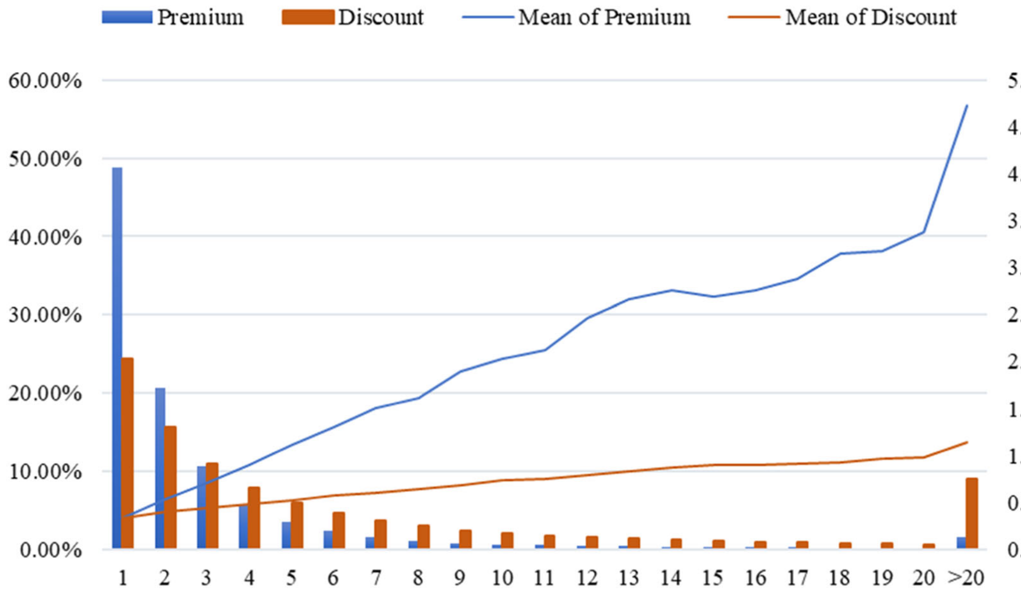

FIGURE 3 Persistence of *Premium* (*Discount*) to net asset value (NAV), 2010–2019. [Color figure can be viewed at wileyonlinelibrary.com]

(PDs) only for creation and redemption. In fact, any investor with sufficient cash or stock positions can become an AP in the Chinese ETF market. However, because the minimum creation (redemption) unit of an ETF is generally several million yuan and arbitrage opportunities may disappear quickly, investors who act as APs in China are generally institutional investors who specialize in algorithmic trading.

Second, the process of arbitrage trading is different from that in the United States, where creating and redeeming ETFs occurs after trading hours, investors can short sell the more expensive assets, and they can reverse out of the short position after trading hours.[13] However, because of the short-selling restrictions and *T*+1 trading rules in China, selling more expensive assets and buying less expensive assets cannot be done at the same time. Investors need to buy less expensive assets first and swap them immediately for more expensive assets, and then sell the more expensive assets to complete the arbitrage. Generally, completion of an arbitrage in Chinese ETFs involves a time lag, and inefficiency in any link may cause the failure of an otherwise profitable arbitrage.

2.4 | ETF short selling

On December 5, 2011, the list of securities lending was initiated in China and several ETFs were added to the list for the first time. After several expansions of the securities lending list, short selling was permitted for 117 ETFs in 2020. During our sample period (2010–2020), the proportion of ETFs that can be short sold is about 50%. Exchanges publish the list of securities lending daily, which provides us the possibility to track the short feasibility of ETFs on a daily basis.

Although it is possible to arbitrage without short selling under the existing trading mechanism in China, ETFs with short selling have an added advantage in performing arbitrage. When an ETF is traded at a discount, investors can simultaneously short the ETF and underlying assets, and then create ETF shares to cover the short position.

[13]Although short selling is permitted for a selected group of stocks and ETFs in China, it accounts for a small percentage of daily trading activities and is often restricted. Thus, arbitrage through direct short selling of ETFs or stocks is generally difficult to implement in the Chinese market.

This way of arbitrage is almost the same as the arbitrage of ETFs traded at a discount in the United States and allow for more cost control, which may increase arbitrage activities.

3 | DATA AND DESCRIPTIVE STATISTICS

3.1 | ETF sample

The Chinese ETF market mainly includes equity ETFs, bond ETFs, commodity ETFs, currency ETFs, and cross-border ETFs. We focus on equity ETFs for the following reasons. First, there are 365 listed ETFs with total assets of about 1077 billion yuan by the end of 2020, with a compound annual growth rate of 21% over 5 years. There are 290 listed equity ETFs with total assets of 743.1 billion yuan, accounting for 69% of the entire ETF market and 91% of the ETF market excluding currency ETFs. Equity ETFs are the most active type in terms of issuance and trading, and have the greatest market demand, which makes understanding price efficiency particularly important. Second, commodity ETFs, bond ETFs, and cross-border ETFs have unique trading rules and creation/redemption procedures, as well as liquidity provisions. For example, bond ETFs and cross-border ETFs can be bought and sold on the same trading day; the underlying bonds of fixed-income ETFs are highly illiquid, which may raise concerns about more serious measurement errors due to stale prices. These characteristics, which are vastly different from those of equity ETFs, make tests on price efficiency more difficult to carry out.

Focusing on equity ETFs, our initial sample comprises all Chinese equity ETFs from the SSE and SZSE from January 2010 to December 2020. From the Wind database, we retrieve daily data on ETF share prices, NAVs, shares outstanding, turnover, and trading volumes. Following Petajisto (2017), we exclude ETF days with an ETF deviation above 20%. To calculate liquidity measures, we retrieve intraday data including opening price, closing price, high price, low price, bid price and volume, ask price and volume, and transaction price in 5-min intervals for ETFs and underlying stocks from the Resset database. We retrieve ETF characteristics from China Stock Market & Accounting Research (CSMAR) and include ETF listing date, fees, tracking index, and stock information on the daily PCF. We winsorize all variables at the 1st and 99th percentiles. Our final sample has 273 unique Chinese ETFs and 228,895 ETF-day observations.

We classify the market type of ETFs into single-market versus cross-market ETFs. If the underlying securities of the tracked index include both SSE- and SZSE-listed stocks, the ETF is cross-market; otherwise, the ETF is single-market. In total, we have 77 single-market ETFs and 196 cross-market ETFs.

We manually collect information regarding the time and number of new liquidity service providers added for each ETF from the announcements on the SSE and SZSE. Overall, we have 194 announcements made by fund sponsors for adding new liquidity service providers in our final sample.

3.2 | ETF price efficiency measure

To examine the effect of ETF liquidity on price efficiency, we calculate daily price deviation and deviation persistence. Deviation is defined as the absolute difference between the ETF closing price and NAV, divided by NAV and multiplied by 100:

$$Deviation_{i,t} = \text{abs}\left(\frac{P_{i,t}^{ETF} - P_{i,t}^{NAV}}{P_{i,t}^{NAV}}\right) \times 100, \tag{1}$$

where $P_{i,t}^{ETF}$ is the closed price of ETF at the end of day, and $P_{i,t}^{NAV}$ is the net asset price of the ETF at the end of day.

We also decompose deviation into premiums and discounts. The ETF premium (discount) is the absolute difference between an ETF's price and its NAV as a percentage of the NAV, when the ETF price is greater (smaller) than its NAV:

$$Premium_{i,t} = \text{abs}\left|\max\left(\frac{P^{ETF}_{i,t} - P^{NAV}_{i,t}}{P^{NAV}_{i,t}} \times 100, 0\right)\right|, \tag{1a}$$

$$Discount_{i,t} = \text{abs}\left|\min\left(\frac{P^{ETF}_{i,t} - P^{NAV}_{i,t}}{P^{NAV}_{i,t}} \times 100, 0\right)\right|, \tag{1b}$$

where *Persistence* (*Discount*) is defined as the number of days in each run of premium (discount) between an ETF's NAV and price (deviation in the same direction).

We recognize that NAVs may be stale, where the price deviation can be artificial and does not reflect inefficiency (Broman, 2020; Petajisto, 2017). Following Petajisto (2017), we sidestep the issue of stale NAVs by using a peer-group strategy.[14] In particular, instead of comparing ETF prices with NAVs (which can be stale), we measure them relative to the average market price of a peer group of similar funds. To solve the problem that the prices of different ETFs are incomparable, we calculate the equal-weighted change in daily prices for ETFs in the same group and simulate the estimated price, which is a proxy for the NAV of an ETF using the equal-weighted change in daily prices. Then, we calculate adjusted deviation as the difference between ETF midquote closing prices and the estimated price (NAV).

In addition, a significant factor in determining whether arbitrage occurs is round-trip transaction costs. If deviation, which is the potential profit for the arbitrager, is smaller than transaction costs, there is no incentive for arbitragers. Hence, we modify deviation (our price efficiency measure) to be the difference between the ETF price and the NAV of its underlying securities minus the trading costs of a round-trip arbitrage strategy (Section 6.2 provides additional details).

3.3 | Liquidity measures

The daily ETF liquidity is measured by relative quoted spread, relative effective spread, market depth, and Amihud illiquidity. To ensure comparability and ease of interpretation, we multiply by −100 the usual measures of relative quoted spread (*QSpread*), relative effective spread (*ESpread*), and Amihud illiquidity (*Amihud*). Then, all liquidity variables have the same sign, such that higher value indicate greater liquidity.

The relative quoted spread is defined as the average time-weighted relative quote spread, multiplied by −100, which is the bid–ask spread divided by the quote midpoint:

$$QSpread_{i,t} = -100 \times \frac{1}{48}\sum_{j=1}^{J}\frac{\left(P^{Ask}_{i,t} - P^{Bid}_{i,t}\right)}{0.5\left(P^{Ask}_{i,t} + P^{Bid}_{i,t}\right)}, \tag{2}$$

where $P^{Ask}_{i,t}$ is the ask price at the end of every 5 min and $P^{Bid}_{i,t}$ is the bid price at the end of every 5 min.[15]

The effective spread is the absolute difference between the trade price and the quote midpoint of the associated price. The daily relative effective spread is defined as the average trade-weighted ratio of the effective spread to the quote midpoint of the associated price, multiplied by −100:

$$ESpread_{i,t} = -100 \times \sum_{j=1}^{J} tradeweight_j \times \frac{\left|P_{i,t} - 0.5\left(P^{Ask}_{i,t} + P^{Bid}_{i,t}\right)\right|}{0.5\left(P^{Ask}_{i,t} + P^{Bid}_{i,t}\right)}, \tag{3}$$

where *tradeweight*$_j$ is the trading volume weight and $P_{i,t}$ is the transaction price at the end of every 5 min.

[14]Petajisto (2017, p. 26) states, *"Most importantly, I devised a novel approach to addressing the stale-pricing issue: I sorted funds into groups with nearly identical underlying portfolios, using the average market price of the group as a real-time proxy for the true underlying value of the funds."*
[15]The daily trading hours of the exchange are 9:30–11:30 and 13:00–15:00, a total of 4 hr, or 48 five-min intervals.

Daily depth is defined as the logarithm of the sum of bid price multiplied by volume and ask price multiplied by volume:

$$Depth_{i,t} = \ln\left(P_{i,t}^{Bid} \times Vol_{i,t}^{Bid} + P_{i,t}^{Ask} \times Vol_{i,t}^{Ask}\right), \tag{4}$$

where $Vol_{i,t}^{Bid}$ is the trading volume of the bid price at the end of every 5 min and $Vol_{i,t}^{Ask}$ is the trading volume of the ask price at the end of every 5 min.

Daily Amihud illiquidity is defined as the ratio of the daily absolute return (in percentage) to the trading volume (in million yuan), multiplied by −1:

$$Amihud_{i,t} = -\frac{|R_{i,t}|}{Vol_{i,t}}, \tag{5}$$

where $|R_{i,t}|$ is the daily absolute return (in percentage) and $Vol_{i,t}$ is trading volume (in million yuan).

We also compute the weighted liquidity of underlying portfolio and relative liquidity. The weighted liquidity of underlying portfolio is measured as:

$$WLiq_{i,t} = \sum_{k=1}^{K} w_{i,k,t} \times Liq_{i,k,t}, \tag{6}$$

where $w_{i,k,t}$ is the weight that each security k has in the underlying basket held by ETF i on day t. $Liq_{i,k,t}$ represents the three liquidity measures of stock k in ETF i on day t, including *QSpread*, *ESpread*, and *Amihud*.[16]

Relative liquidity is defined following Broman and Shum (2018):

$$Rel\,(Liq)_{i,t} = \log(WLiq_{i,t}/Liq_{i,t}), \tag{7}$$

where $WLiq_{i,t}$ is the weighted liquidity of the underlying portfolio and $Liq_{i,t}$ is the liquidity of ETF i on day t. *Rel(Liq)* variables are constructed in a way so that positive values indicate the ETF has higher liquidity than underlying assets, and negative values indicate the ETF has lower liquidity than underlying assets.

In regressions, we are more interested in the influence of the liquidity mismatch between ETFs and underlying assets on price efficiency, so we use the absolute value of relative liquidity to measure the liquidity mismatch between ETFs and underlying assets. We define *Liq_Mismatch* as:

$$Liq\_Mismatch_{i,t} = \text{abs}(\log(WLiq_{i,t}/Liq_{i,t})). \tag{7a}$$

3.4 | Measure of arbitrage activities

To measure how active arbitrages are in ETFs, we would ideally add daily creations and redemptions. However, because the data are not available to us in that format and ETF quarterly reports do include information on creations and redemptions separately, we calculate quarterly absolute flow instead. *Absolute Flow* represents how active creation and redemption activities are, which is defined as the sum of creation and redemption shares in a given quarter divided by the average of the total outstanding shares at the beginning and end of the quarter.[17] This is expressed as:

$$Absolute\ Flow_{i,t} = \frac{(Creation_{i,t} + Redemption_{i,t})}{(Shareoutstanding_{i,t-1} + Shareoutstanding_{i,t})/2} \times 100. \tag{8}$$

[16]The data on the daily depth of stocks are not available to us. Thus, we have only three measures of relative liquidity.

[17]Net flows are employed as a proxy for market demand in the literature. Broman and Shum (2018) recognize ETF net flows as the proxy of aggregate demand, both short and long term. Brown et al. (2020) find that ETF flows occur when there is net excess demand in either the ETF shares or ETF underlying assets, and ETF net flow can be a proxy for net excess demand. Therefore, we also use net flow as a proxy of arbitrage to ensure that our results are robust to alternative measures (results untabulated for brevity).

Finally, we control for several fund level characteristics that may influence the price efficiency of ETFs. *AUM* is the natural logarithm of the ETF closing price multiplied by the shares outstanding. *Volume* is the natural logarithm of the number of shares traded on a daily basis. *Volatility* is the standard deviation of ETF prices at 5-min intervals on a given day. Because the age and fees of an ETF remains the same throughout the year, they are not included in the regression, as we control for ETF and day fixed effects. Controlling for ETF and day fixed effects is important because the overall liquidity of the market (probably) increases over time, and ETF individual fixed effects can control for many unobserved characteristics, such as ETFs with "hot" investment styles that may have more noise trader demand.

3.5 | Summary statistics

Table 1 provides means, medians, and standard deviations of ETF fund characteristics from the inception date to the end of the sample period. The variables are defined in Appendix A. For each day, we take value-weighted and equal-weighted means across ETFs to calculate daily averages. We also calculate the daily standard deviation across ETFs and report the time-series averages for our sample.

Panel A of Table 1 reports the mean, minimum, maximum, and standard deviation of ETF price efficiency. Approximately 31.75% of ETF days are traded at a premium and 65.98% of ETF days are traded at a discount. The equal-weighted (value-weighted) mean value of the deviation is 0.586% (0.204%). The equal-weighted (value-weighted) mean value of the premium is 0.656% (0.183%), and the equal-weighted (value-weighted) mean value of the discount is 0.549% (0.222%). On average, a run of deviation in the same direction (discount or premium) persists for 5.530 days on an equal-weighted basis and 4.362 days on a value-weighted basis.[18] The value-weighted mean for deviations is much smaller than the equal-weighted mean, which indicates that the price efficiency of larger ETFs is better than that of smaller ETFs. These results are different from those of the US market, which mostly trades at a premium, and the magnitude of the deviation is approximately one-tenth that of the ETFs in China.

Panel B of Table 1 presents the summary statistics of ETF liquidity, underlying portfolio liquidity, and relative liquidity. For ETF liquidity, the mean value of the daily relative quoted spread (relative effective spread) is −0.706% (−0.598%). The mean of the market depth is 11.820 and the mean of the Amihud illiquidity measure is −6.412. In addition, for underlying portfolio liquidity and relative liquidity, we find that relative liquidity (logarithm of difference between liquidity of value-weighted underlying portfolio and that of the ETF) remains consistently negative, indicating that underlying portfolio liquidity is significantly better than that of ETFs. This is contrary to the findings in the US market, as Broman and Shum (2018) report that US ETFs have higher relative liquidity. Specifically, there is improvement in quoted spreads, higher turnover, and less price impact (Amihud illiquidity) relative to the underlying basket. This is an aspect worth noting, as one of the most significant advantages documented for ETFs is better liquidity, which is not the case for Chinese ETFs. Panel C provides the statistics for measures of arbitrage activities. The mean of *Absolute Flow* is 57.566%. Panel D presents the statistics for ETF ownership. Institutional ownership ranges from 0.06% to 99.7% with a mean of 52.48%.

Table 2 presents data on how liquidity and the relative liquidity of ETFs and the underlying portfolio vary over time and across various AUM and deviation distributions. We report the equal-weighted and value-weighted mean of deviation, measures of ETF liquidity, weighted underlying portfolio liquidity, and relative liquidity. Panel A reports the data by year. We expect deviation to decrease and liquidity to increase over time along with the rapid development of ETFs and financial markets in China. Deviations from NAV generally decrease since 2016, thereby indicating increased

[18]We also conduct a detailed examination of the persistence of premiums and discounts separately. We count the number of days in each run of premium (discount) between the ETF's NAV and price. Figure 3 illustrates the percentage of ETF-days of various durations for which the deviation from NAV lasted one run.

TABLE 1 Descriptive statistics.

Variable	Obs.	Mean: Equal weighted	Mean: Value weighted	*SD*	Min.	Max.
Panel A: Descriptive statistics of ETF price efficiency						
Deviation	228,895	0.586	0.204	0.883	0.000	5.360
Premium	72,676	0.656	0.183	1.408	0.007	5.360
Discount	151,019	0.549	0.222	0.723	0.010	5.360
Persistence	228,895	5.530	4.362	9.605	0.000	28.000
Panel B: Descriptive statistics of liquidity						
ETF Liquidity	129,939	−0.706	−0.080	1.006	−0.022	−5.387
QSpread						
ESpread	130,029	−0.598	−0.074	0.948	0.000	−5.335
Depth	129,939	11.820	14.318	1.976	7.251	16.310
Amihud	225,670	−6.412	−0.642	12.710	−0.003	−39.62
Portfolio Liquidity						
WQSpread	129,939	−0.102	−0.102	0.030	−0.032	−0.183
WESpread	130,029	−0.115	−0.115	0.031	−0.038	−0.199
WAmihud	225,670	−0.008	−0.007	0.008	−0.001	−0.050
Rel(QSpread)	129,939	−1.280	−0.811	1.255	−3.887	1.264
Rel(ESpread)	130,029	−0.995	−0.609	1.217	−3.757	1.387
Rel(Amihud)	225,670	−4.359	−1.054	3.096	−11.18	2.943

Variable	Obs.	Mean	*SD*	Min.	Max.
Panel C: Descriptive statistics of arbitrage activities					
Absolute Flow	3139	57.566	120.810	0.216	490.429
Panel D: Descriptive statistics of ETF ownership					
Institutional Ownership	3272	52.48	36.03	0.06	99.7
Panel E: Descriptive statistics of control and other variables					
AUM	228,895	19.885	1.835	15.939	24.148
Volatility	228,895	0.019	0.009	0.001	0.074
Volume	228,895	13.999	3.213	5.704	20.611
Turn	228,895	1.862	3.324	0.000	19.413
Age	228,895	7.042	3.795	0.730	16.190
Fee	228,895	0.467	0.103	0.150	0.600
Price	228,895	1.921	1.498	0.163	16.147

Note: This table presents summary statistics for liquidity, price efficiency, and control variables for January 2010 to December 2020. Panel A presents descriptive statistics for exchange-traded fund (ETF) price efficiency for the ETF-day sample, measured by *Deviation*, *Premium*, *Discount*, and *Persistence*. Panel B presents descriptive statistics for *ETF Liquidity*. High-frequency liquidity measures such as *Rel(QSpread)*, *Rel(ESpread)*, and *Depth* are calculated for January 2015 to December 2019. Panel C presents descriptive statistics for arbitrage activities. Panel D presents descriptive statistics for ETF ownership. Panel E presents descriptive statistics for the control and other related variables. Appendix A provides variable definitions.

price efficiency. ETF liquidity also generally increases since 2016. To our surprise, relative liquidity is always negative over time, indicating that ETFs are always less liquid than the underlying assets.

Panel B of Table 2 presents the variables across various AUM. We divide the sample into deciles to create ranks based on daily AUM. Deviations are smaller and the ETF liquidity is higher when AUM is larger, which is consistent with our expectation. We also present the distribution of institutional ownership and ETF size. We can see that institutional investors' holdings account for more than 65% for the top 20% ETFs by AUM, and institutional holdings decline to only about 30% for the bottom 40% ETFs based on AUM. In addition, although relative liquidity remains mostly negative, it turns positive for ETFs in the two deciles with the largest AUM. Panel C presents these variables for various deviation levels. We sort ETF-trading days by deviation to create deciles and find results similar to those reported in Panel B; ETF liquidity is higher in funds with smaller deviations. Overall, these descriptive statistics provide us an intuitive picture of the relation between the price efficiency and liquidity of ETFs.

4 | EFFECT OF ETF LIQUIDITY ON PRICE EFFICIENCY

4.1 | ETF price deviation and ETF liquidity: OLS regressions

In a frictionless market, ETF prices equal their NAV, as ETFs and their underlying assets share the same fundamental values. However, there is often a gap between the ETF price and its NAV. The lack of liquidity in ETFs and in the underlying portfolios can lead to an increase in the cost of arbitrage and prevent investors from actively participating in the ETF market even when ETF prices deviate from their NAVs. Given the creation/redemption mechanism in the Chinese ETF market, any investor with sufficient cash or stock positions can act as an AP and arbitrage to profit from the deviation. Therefore, Chinese ETFs may have higher price efficiency because of the potentially more intense competition among arbitrageurs to take advantage of arbitrage opportunities. However, the price deviation of Chinese equity ETFs is large and persistent—approximately 10 times that of the United States. It is natural to ask why the price deviation remains large and persistent. In this section, we investigate whether ETF liquidity and relative liquidity lead to better ETF price efficiency in Chinese equity ETF markets.

We begin by running OLS regressions of daily price efficiency on ETF liquidity and absolute value of relative liquidity. We follow two approaches to address the problem of potentially omitted variables. First, we include ETF and day fixed effects. Second, we control for a set of variables that include trading volume (*Volume*), assets under management (*AUM*), and the standard deviation of 5-min prices during the day (*Volatility*) (see, e.g., Ben-David et al., 2018; Chordia et al., 2008). The regression models are:

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \tag{9}$$

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} + \beta_2 Liq\_Mismatch_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}. \tag{10}$$

Table 3 reports the results from the pooled panel regressions. For ease of interpretation, we standardize all variables by subtracting the sample mean and dividing by the sample standard deviation so that the means of dependent and independent variables equal 0 and the variances equal 1.[19]

In Columns 1–4 of Panel A of Table 3, we use relative quoted spread, relative effective spread, market depth, and Amihud illiquidity measure as proxies for ETF liquidity, respectively. We find that the relation between the measures of liquidity and deviation is negative and statistically significant. Economically, a 1 *SD* increase in ETF *QSpread* (*ESpread*, *Depth*, *Amihud*) is associated with a 44.6% (36.0%, 24.6%, 12.9%) decrease in ETF deviation relative to the mean. Next, we examine the role of ETF liquidity along with liquidity mismatch on deviations. Columns 5–7 include variables of liquidity

[19]All the following analyses are based on standardized regressions.

TABLE 2 Summary statistics by year, AUM, and deviation deciles.

			Liq			*WLiq*			*Rel(Liq)*		
Year	**No. of ETFs**	***Deviation***	***QSpread***	***ESpread***	***Amihud***	***WQSpread***	***WESpread***	***WAmihud***	***Rel(QSpread)***	***Rel(ESpread)***	***Rel(Amihud)***
Panel A: Descriptive statistics by year											
2011	33	0.21			−1.47			−0.02			−0.96
2012	38	0.40			−7.66			−0.02			−3.20
2013	56	0.59			−7.20			−0.02			−3.43
2014	64	0.71			−6.47			−0.01			−3.86
2015	80	1.37	−1.08	−0.94	−6.99	−0.09	−0.11	−0.01	−1.79	−1.48	−4.93
2016	89	0.97	−1.13	−0.91	−12.03	−0.11	−0.12	−0.01	−1.70	−1.35	−5.68
2017	101	0.88	−0.79	−0.65	−10.01	−0.10	−0.11	−0.01	−1.43	−1.10	−5.29
2018	127	0.83	−0.82	−0.68	−9.80	−0.11	−0.13	−0.01	−1.25	−0.98	−4.70
2019	179	0.40	−0.47	−0.43	−5.45	−0.11	−0.12	−0.01	−0.81	−0.60	−3.97
2020	273	0.28			−2.99			−0.01			−3.66

			Liq			*WLiq*			*Rel(Liq)*		
Decile	***Deviation***	***InstitutionalOwnership***	***QSpread***	***ESpread***	***Amihud***	***WQSpread***	***WESpread***	***WAmihud***	***Rel(QSpread)***	***Rel(ESpread)***	***Rel(Amihud)***
Panel B: Descriptive statistics by AUM deciles											
Bottom decile	1.10	33	−1.46	−1.18	−14.60	−0.10	−0.12	−0.01	−2.32	−1.96	−6.82
	1.14	43	−1.38	−1.14	−14.12	−0.11	−0.12	−0.01	−2.12	−1.78	−6.55
	0.93	33	−1.18	−0.99	−10.87	−0.11	−0.12	−0.01	−1.87	−1.53	−5.88
	0.78	31	−1.06	−0.91	−9.47	−0.10	−0.12	−0.01	−1.80	−1.50	−5.72
	0.56	51	−0.70	−0.60	−7.40	−0.11	−0.12	−0.01	−1.32	−1.04	−5.08
	0.59	43	−0.76	−0.66	−7.16	−0.10	−0.11	−0.01	−1.45	−1.16	−4.73
	0.43	51	−0.45	−0.40	−3.43	−0.10	−0.12	−0.01	−0.92	−0.68	−3.62

(Continues)

TABLE 2 (Continued)

Decile	Deviation	InstitutionalOwnership	*Liq* QSpread	ESpread	Amihud	*WLiq* WQSpread	WESpread	WAmihud	*Rel(Liq)* Rel(QSpread)	Rel(ESpread)	Rel(Amihud)
	0.34	48	−0.25	−0.24	−1.67	−0.10	−0.11	−0.01	−0.55	−0.37	−2.97
	0.21	65	−0.12	−0.12	−0.89	−0.10	−0.11	−0.01	0.00	0.13	−1.75
Top decile	0.17	67	−0.09	−0.09	−0.13	−0.09	−0.11	−0.01	0.42	0.55	−0.77
Panel C: Descriptive statistics by deviation deciles											
Bottom decile	0.02		−0.27	−0.25	−2.28	−0.10	−0.11	−0.01	−0.37	−0.19	−2.96
	0.06		−0.25	−0.24	−1.99	−0.10	−0.11	−0.01	−0.35	−0.18	−2.91
	0.10		−0.29	−0.26	−2.39	−0.10	−0.11	−0.01	−0.44	−0.24	−3.02
	0.14		−0.31	−0.28	−2.62	−0.10	−0.11	−0.01	−0.51	−0.31	−3.12
	0.20		−0.38	−0.34	−3.38	−0.10	−0.11	−0.01	−0.69	−0.48	−3.47
	0.29		−0.47	−0.42	−4.67	−0.10	−0.12	−0.01	−0.96	−0.72	−4.04
	0.44		−0.69	−0.61	−7.72	−0.10	−0.12	−0.01	−1.42	−1.15	−5.05
	0.73		−0.96	−0.82	−10.95	−0.10	−0.12	−0.01	−1.83	−1.52	−5.94
	1.28		−1.24	−1.02	−14.59	−0.11	−0.12	−0.01	−2.15	−1.79	−6.48
Top decile	3.00		−2.00	−1.62	−19.43	−0.11	−0.12	−0.01	−2.62	−2.21	−6.87

Note: This table reports the summary statistics of exchange-traded fund (ETF) liquidity, value-weighted liquidity of the underlying portfolio, relative liquidity, and price efficiency by year, assets under management (AUM), and deviation deciles. Panel A presents ETF liquidity, value-weighted liquidity of the portfolio, relative liquidity, and price efficiency by year. Panel B presents ETF liquidity, value-weighted liquidity of the portfolio, relative liquidity, institutional ownership, and price efficiency by AUM deciles. Panel C presents ETF liquidity, value-weighted liquidity of portfolio, relative liquidity, and price efficiency by deviation deciles. Appendix A provides variable definitions.

TABLE 3 Effect of ETF liquidity on price efficiency.

Variable	*QSpread* (1)	*ESpread* (2)	*Depth* (3)	*Amihud* (4)	*Rel(QSpread)* (5)	*Rel(ESpread)* (6)	*Rel(Amihud)* (7)
Panel A: Effect of ETF liquidity on deviation, full sample							
Liq	−0.446***	−0.360***	−0.246***	−0.129***	−0.409***	−0.305***	−0.103***
	(−113.430)	(−88.401)	(−37.722)	(−35.251)	(−63.425)	(−52.733)	(−33.677)
Liq_Mismatch					0.067***	0.011***	0.046***
					(8.193)	(4.630)	(9.028)
AUM	−0.020***	−0.020***	−0.006	−0.029***	−0.033***	−0.046***	−0.056***
	(−3.414)	(−3.420)	(−0.494)	(−7.513)	(−6.041)	(−8.483)	(−14.346)
Volatility	0.013***	0.018***	0.026***	0.013***	0.001	0.004***	0.004***
	(7.060)	(9.145)	(13.125)	(11.390)	(0.920)	(2.620)	(3.920)
Volume	−0.045***	−0.066***	−0.058***	−0.044***	−0.028***	−0.047***	−0.038***
	(−9.579)	(−8.302)	(−9.740)	(−9.662)	(−13.436)	(−22.359)	(−18.443)
Constant	0.555***	1.126***	0.672***	1.013***	1.355***	1.862***	1.875***
	(3.603)	(7.108)	(4.003)	(7.179)	(6.836)	(9.226)	(10.046)
ETF fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	129,939	130,029	129,939	225,670	129,939	130,029	225,670
Adj. R^2	0.486	0.466	0.431	0.407	0.485	0.462	0.429
Panel B: Effect of ETF liquidity on persistence, full sample							
Liq	−0.004***	−0.003***	−0.066***	−0.017***	−0.002***	−0.002***	−0.014***
	(−3.618)	(−3.524)	(−8.159)	(−3.727)	(−8.103)	(−5.374)	(−5.839)
Liq_Mismatch					0.002***	0.001*	0.009***
					(5.396)	(1.745)	(3.230)
AUM	−0.019***	−0.020***	−0.011	−0.028***	−0.035***	−0.037***	−0.040***
	(−2.859)	(−2.681)	(−1.571)	(−5.871)	(−5.397)	(−5.867)	(−8.695)
Volatility	0.012***	0.004***	0.001***	0.001***	0.015***	0.015***	0.009***
	(8.151)	(7.881)	(9.545)	(3.464)	(8.371)	(8.475)	(6.937)
Volume	−0.054***	−0.054***	−0.045***	−0.037***	−0.041***	−0.042***	−0.042***
	(−8.662)	(−8.596)	(−4.767)	(−4.759)	(−16.591)	(−17.254)	(−17.717)
Constant	2.024***	2.033***	1.711***	1.005***	1.940***	2.006***	1.191***
	(10.552)	(10.457)	(8.775)	(6.940)	(8.214)	(8.511)	(5.513)
ETF fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 3 (Continued)

Variable	*QSpread* (1)	*ESpread* (2)	*Depth* (3)	*Amihud* (4)	*Rel(QSpread)* (5)	*Rel(ESpread)* (6)	*Rel(Amihud)* (7)
Obs.	129,939	130,029	129,939	225,670	129,939	130,029	225,670
Adj. R^2	0.272	0.272	0.272	0.261	0.237	0.237	0.237

Note: This table reports estimates from ordinary least squares regressions of daily price efficiency on exchange-traded fund (ETF) liquidity, ETF relative liquidity, and controls. The following are the associated regression models:

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \quad (9)$$

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} + \beta_2 Liq\_Mismatch_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \quad (10)$$

where *Price Efficiency* denotes two dependent variables: *Deviation* and *Persistence*. *Liq* denotes four explanatory variables: relative quote spread (*QSpread*, in Columns 1 and 5), relative effective spread (*ESpread*, in Columns 2 and 6), market depth (*Depth*, in Column 3), and Amihud illiquidity (*Amihud*, in Columns 4 and 7). *Liq_Mismatch* denotes three variables: absolute relative *QSpread* (*Rel(QSpread)*, in Column (5)), absolute relative *ESpread* (*Rel(ESpread)*, in Column 6), and absolute relative *Amihud* (*Rel(Amihud)*, in Column 7). *QSpread*, *ESpread*, *Depth*, and *Liq_Mismatch* are measured from January 2015 to December 2019. *Amihud* is measured from January 2010 to December 2020. In Panels A and B, the dependent variables are *Deviation* and *Persistence*, respectively. The dependent variables and liquidity variables are standardized by subtracting the mean and dividing by the standard deviation. All regression specifications include ETF and day fixed effects. The standard errors are double-clustered at the ETF and day levels; *t*-statistics are given in parentheses. Appendix A provides variable definitions.

*$p < 0.10$; ***$p < 0.01$.

mismatch, which are measured as the absolute log difference between value-weighted underlying portfolio liquidity and ETF liquidity. The coefficients on ETF liquidity are negative and significant, and the coefficients on liquidity mismatch are positive and significant. However, the point estimates on the measures of liquidity mismatch are smaller in magnitude than the coefficient on ETF liquidity. Although ETF liquidity is clearly the main driver of ETF mispricing, the significant effect of relative liquidity is in line with Pan and Zeng (2019), who argue that the liquidity mismatch may result in persistent mispricing.

In Columns 1–4 of Panel B of Table 3, we replicate the analysis with *Persistence* as the dependent variable. We find similar results that the relation between the measures of liquidity and persistence is negative and statistically significant. Economically, a 1 *SD* increase in ETF liquidity is associated with a 0.4% (0.3%, 6.6%, 1.7%) decrease in *Premium* (*Discount*) persistence relative to the mean. Columns 5–7 include relative quoted spread, relative effective spread, and relative Amihud between ETFs and underlying portfolios. The coefficients on ETF liquidity remain negative and significant, and the coefficients on liquidity mismatch are positive and significant. However, the point estimates on the measures of relative liquidity are significantly smaller in magnitude than those for ETF liquidity. Thus, ETF liquidity appears to have a stronger impact on the persistence of deviations.

Next, we report results for premium and discount subsamples in the Internet Appendix. In Table I1, we replicate the analysis with *Premium* (*Discount*) as the dependent variable. The coefficients of both *Premium* and *Discount* are negative and significant, but the effect of ETF liquidity on *Premium* is weaker than on *Discount*. This could be because of the difference in transaction costs for arbitrages based on premium versus discount. Arbitrage profit is deviation minus the transaction costs of buying or selling ETFs and the underlying portfolio. Therefore, transaction costs and any other limits to arbitrage may deter arbitrageurs from attempting to profit from a mispricing. The transaction costs in a round-trip arbitrage trading are presented in Appendix B. The arbitrage costs of ETFs traded at a discount is 0.14%, which is much larger than 0.04% for arbitrage based on premium. Arbitrage based on discount involves buying ETFs, redeeming for shares of underlying stocks, and selling the shares in the secondary market. The stamp tax is 0.10% for selling stocks. In contrast, arbitrage based on premium requires buying the underlying stocks (stamp tax is 0 on purchases), creating ETFs, and selling

ETFs. The costs of buying and selling ETFs are similar at 0.01% of the transaction values. Creation and redemption fees are very small relative to the value of the transactions in millions of yuan. This suggests that investors require a larger deviation to perform arbitrage on ETFs traded at a discount and are more sensitive to liquidity. This also explains the higher sensitivity of price efficiency to ETF liquidity in the discount sample, as liquidity is more important for arbitrage activities associated with higher transaction costs. In addition, we conduct the analysis separately for the 2010–2014, 2015–2016, and 2017–2020 subsamples (not reported for brevity) to confirm that the relation is robust across different sample periods. Overall, the significant positive link between ETF liquidity and price efficiency provides initial evidence in support of our conjectures.

Following Piccotti (2018) and Jain et al. (2021), we also include control variables such as trading volume, AUM, and intraday price volatility. Higher intraday volatility (trading volume) is associated with larger (smaller) price deviations. The negative coefficients on AUM indicate that absolute deviation from NAV is smaller for large ETFs, which are tracked and traded more actively. Moreover, the expense ratio and ETF age are not included in the regression, as we include fixed effects (ETF and day).

4.2 | Identification using a quasi-natural experiment

Although our research designs control for well-known characteristics related to ETF price efficiency, liquidity may be endogenous. ETFs with higher liquidity may have higher price efficiency, whereas ETFs with higher price efficiency are also more attractive to investors and have better liquidity. To alleviate this concern, we rely on a quasi-natural experiment provided by the addition of liquidity service providers for ETFs and conduct a DiD analysis.

Panel A of Table 4 presents descriptive statistics for ETF market makers by year, and Panel B presents evidence for the difference between ETF days with market makers and ETF days with no market makers in terms of liquidity and price efficiency. For all measures of liquidity and price efficiency, the average of ETF trading days with market makers is much more efficient and more liquid. For example, the deviation of the ETF-days with market makers is 0.300%, which is lower than the deviation of ETF-days without market makers at 0.872%. Overall, the evidence suggests that market makers provide more liquidity and make ETFs more price efficient.

Next, we perform DiD analysis based on the addition of market makers to ETFs. First, we collect the time of the first announcement of the addition of market makers for all ETFs in our sample. Then, we assign ETFs into the treatment and control groups based on whether the ETF has at least one market maker during our sample period. Furthermore, if the trading day is after the addition of market makers to the ETF, *Post1* equals 1. We conduct a pooled DiD regression to empirically test and quantify the effect of an exogenous liquidity increase on price efficiency. Our regression specification controls for characteristics that may affect price efficiency of ETFs. The regression model is:

$$\mathit{Price\ Efficiency}_{i,t} = \beta_0 + \beta_1 \mathrm{Treat1}_i \times \mathrm{Post1}_{i,t} + \gamma' X_{i,t} + \eta \mathit{ETF}_i + \lambda \mathit{Day}_t + \varepsilon_{i,t}. \tag{11}$$

Table 5 presents our main results using DiD regressions, and the variable of interest is the interaction variable, $Treat_i \times Post1_{i,t}$. The coefficient β_1, which captures the DiD effect, shows the difference in price efficiency between the treated and control ETFs after the addition of market makers. The results in Columns 1 and 2 are consistent with our hypothesis, providing evidence that the addition of market makers increases price efficiency measured by deviation and persistence. As shown in Column 1, the deviation of ETFs with market makers is, on average, 0.037 percentage points less than ETFs with no market makers. These results reveal that having market makers has a positive and significant effect on ETF price efficiency.

The key identifying assumption in the DiD analysis is the parallel trend assumption, which requires that the treatment group has a similar trend as the control group in the absence of treatment (the addition of market

TABLE 4 Descriptive statistics of ETF market makers.

Panel A: Descriptive statistics of ETF market makers

Year	Avg. No. market makers in ETF	No. of ETFs with market makers	% of ETFs with market makers
2010	0.05	3	15.00%
2011	0.09	6	18.18%
2012	0.16	9	23.68%
2013	0.33	17	30.36%
2014	0.39	21	32.81%
2015	0.52	28	35.00%
2016	0.61	34	38.20%
2017	0.72	40	39.60%
2018	0.89	51	40.16%
2019	1.71	113	63.13%
2020	2.83	194	71.06%

Panel B: Summary statistics of price efficiency, liquidity, and market makers by groups

	With no market makers			With market makers		
Variable	Obs.	Mean	*SD*	Obs.	Mean	*SD*
Deviation	162,833	0.872	1.093	142,170	0.300	0.575
Premium	102,939	1.158	1.896	98,677	0.328	0.828
Discount	134,795	0.808	0.845	118,363	0.300	0.492
Persistence	162,833	6.767	8.035	142,170	4.294	5.632
QSpread	138,856	1.034	1.156	114,443	0.378	0.691
ESpread	138,881	0.861	1.112	114,451	0.334	0.634
Depth	138,856	10.961	1.956	114,443	12.679	1.693
Amihud	160,358	10.361	14.556	141,910	2.462	7.886
No. of market makers	162,833	0.000	0.000	142,170	5.080	2.972

Note: This table presents descriptive statistics for exchange-traded fund (ETF) market makers. Panel A presents the average number of market makers in an ETF, number of ETFs with market makers, and percentage of ETFs with market makers by year. Panel B presents summary statistics for price efficiency, liquidity, and number of market makers for two subgroups; ETF-days with no market makers and ETF-days with at least one market maker. Appendix A provides variable definitions.

makers). That is, ETFs should have similar price efficiency before the addition of market makers. To investigate the identifying assumption, we estimate the treatment effects at different periods as follows:

$$Price\ Efficiency_{i,t} = \beta_0 + \sum_{j\in[-3,1]} \beta_j \times \text{Treat1}_i \times \text{Post1}_{t+j} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \quad (12)$$

where $Post1_{t+j}$ are pre- and posttreatment indicators for within j years before or after the addition of market makers to treatments. The coefficients of the interaction terms capture the difference in price efficiency between treatment and control groups in the pre- or postinception period.

As shown in Table 6, in each year before the addition of market makers, price efficiency is not significantly different for ETFs with and without market makers. More important, ETFs with market makers experience higher price efficiency

TABLE 5 Difference-in-difference analysis based on the inclusion of market makers.

Variable	*Deviation* (1)	*Persistence* (2)
Treat1 × Post1	−0.037***	−0.102***
	(−6.882)	(−3.822)
AUM	−0.056***	−0.071***
	(−22.231)	(−8.629)
Volatility	0.030***	0.039***
	(15.882)	(9.599)
Volume	−0.250***	−0.150***
	(−93.377)	(−20.823)
Constant	−0.139***	−0.071
	(−6.098)	(−1.008)
ETF fixed effects	Yes	Yes
Day fixed effects	Yes	Yes
Obs.	225,670	225,670

Note: This table reports estimates from a quasi-natural experiment that is based on the addition of market makers to exchange-traded funds (ETFs). The following is the associated regression model:

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Treat1_i \times Post1_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \quad (11)$$

where *Price Efficiency* denotes two dependent variables: *Deviation* and *Persistence*. $Treat1_i \times Post1_{i,t}$ is the interaction term between *Post1* and *Treat1*. $Post1_{i,t}$ is a dummy variable that equals 1 if the trading day is after the addition of market makers to the ETF, and 0 otherwise. $Treat1_i$ is a dummy variable that equals 1 if ETF *i* has at least one market maker, and 0 otherwise. We present the results where the dependent variables are *Deviation* and *Persistence* in Columns 1 and 2, respectively. Variables are standardized by subtracting the mean and dividing by the standard deviation. All regression specifications include ETF and day fixed effects. The standard errors are double-clustered at the ETF and day levels; *t*-statistics are given in parentheses. Appendix A provides variable definitions.

***$p < 0.01$.

than those with no market makers in the postaddition period. This evidence suggests that the price efficiency increase observed in the DiD analysis comes from the addition of market makers rather than the time trend.

Overall, our results show that the addition of market makers can improve price efficiency, and these tests lend further support to the causal relation between ETF liquidity and price efficiency.

5 | EFFECT OF ARBITRAGE ACTIVITIES ON PRICING EFFICIENCY

5.1 | ETF absolute flow and pricing efficiency

In this section, we directly examine the impact of arbitrage activities on the price efficiency of ETFs. This is empirically challenging, as arbitrage is not directly observable and the motive behind transactions cannot be observed. We use *Absolute Flow*, the ratio of the sum of creation and redemption shares on share outstanding, as the proxy for arbitrage activeness.

TABLE 6 Difference-in-difference analysis based on the inclusion of market makers: Parallel trend.

Variable	*Deviation* (1)	*Persistence* (2)
$Treat1 \times Post1_{-3}$	0.000	0.172
	(0.009)	(0.055)
$Treat1 \times Post1_{-2}$	−0.125	0.018
	(−0.251)	(0.634)
$Treat1 \times Post1_{-1}$	0.018	−0.174
	(1.535)	(−0.264)
$Treat1 \times Post1$	−0.100***	−0.056**
	(−8.505)	(−2.024)
$Treat1 \times Post1_{+1}$	−0.073***	−0.096***
	(−6.456)	(−3.602)
AUM	−0.058***	−0.363***
	(−12.998)	(−3.564)
Volatility	0.014***	0.279***
	(7.235)	(3.749)
Volume	−0.107***	−0.296***
	(−29.884)	(−4.064)
Constant	−0.339***	0.203
	(−5.444)	(0.359)
ETF fixed effects	Yes	Yes
Day fixed effects	Yes	Yes
Obs.	213,947	213,947

Note: We examine the parallel trend to identify whether there is any significant difference between the control group and treatment group before the addition of market makers. The following is the associated regression model:

$$Price\ Efficiency_{i,t} = \beta_0 + \sum_{j\in[-3,1]} \beta_j \times Treat1_i \times Post1_{t+j} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \tag{12}$$

where *Price Efficiency* includes two measures: *Deviation* and *Persistence*. $Post1_{t+j}$ are pre- and posttreatment indicators for j years before or after the addition of market makers. The coefficients of the interaction terms capture the difference in the price efficiency between treatment and control groups in the pre- or postinception period. Variables are standardized by subtracting the mean and dividing by the standard deviation. All regression specifications include exchange-traded fund (ETF) and day fixed effects. The standard errors are double-clustered at the ETF and day levels; t-statistics are given in parentheses. Appendix A provides variable definitions.

$^{**}p < 0.05$; $^{***}p < 0.01$.

Because of the limited availability of daily data for creation and redemption shares,[20] we use quarterly data of total creation and redemption shares to proxy for how active arbitrage activity is during the quarter. The associated regression model is:

[20]We can infer the daily net flow through the difference between shares outstanding on days T and $T-1$, but daily creation and redemption shares separately are not available.

TABLE 7 Effect of absolute flow on ETF price efficiency.

	Deviation			Persistence		
	QSpread	*ESpread*	*Amihud*	*QSpread*	*ESpread*	*Amihud*
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Absolute Flow	−0.020***	−0.001***	−0.012***	−0.135***	−0.003***	−0.080**
	(−3.671)	(−3.835)	(−2.282)	(−3.237)	(−3.254)	(−2.542)
Liq	−0.511***	−0.554***	−0.405***	−0.689***	−0.255***	−0.101***
	(−14.850)	(−14.465)	(−12.838)	(−2.159)	(−4.928)	(−8.139)
Liq_Mismatch	0.133***	0.116***	0.019***	0.381***	0.213***	0.071***
	(3.231)	(4.065)	(3.057)	(4.476)	(5.097)	(4.801)
AUM	−0.056**	−0.006	−0.026	−0.087	−0.191	−0.036
	(−2.349)	(−0.361)	(−1.537)	(−0.448)	(−1.347)	(−0.259)
Volatility	1.935***	1.845***	1.798***	1.461***	1.614***	1.137***
	(4.912)	(5.150)	(5.366)	(4.788)	(3.390)	(3.095)
Volume	−0.024*	−0.079***	−0.060***	−0.243**	−0.465***	−0.356***
	(−1.722)	(−6.752)	(−5.877)	(−2.245)	(−5.749)	(−4.534)
Constant	1.630***	1.293***	1.100***	1.669***	2.724***	9.008***
	(3.434)	(3.408)	(2.737)	(4.278)	(4.433)	(2.296)
ETF fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3139	3139	3139	3139	3139	3139
Adj. R^2	0.791	0.767	0.766	0.498	0.494	0.491

Note: This table reports estimates of regressions of exchange-traded fund (ETF) price efficiency on ETF quarterly *Absolute Flow*. The regression model is:

$$Price\ Efficiency_{i,q} = \beta_0 + \beta_1 Absolute\ Flow_{i,q} + \beta_2 Liq_{i,q} + \beta_3 Liq\_Mismatch_{i,q} + \gamma' X_{i,q} + \eta ETF_i + \lambda Quarter_q + \varepsilon_{i,q}, \quad (13)$$

where *Price Efficiency* denotes two dependent variables with daily measures averaged over a quarter: *Deviation* and *Persistence*. *Absolute Flow* is the ratio of total creation and redemption shares in quarter *q* to the average share outstanding at the beginning and end of quarter *q*. *Liq* denotes three variables with daily measures averaged over a quarter: relative quote spread (*QSpread*, in Columns 1 and 4), relative effective spread (*ESpread*, in Columns 2 and 5), Amihud illiquidity (*Amihud*, in columns 3 and 6). *Liq_Mismatch* denotes three variables: absolute relative *QSpread* (*Rel(QSpread)*), absolute relative *ESpread* (*Rel(ESpread)*), and absolute relative *Amihud* (*Rel(Amihud)*). The dependent variables are *Deviation* in Columns 1–3 and *Persistence* in Columns 4–6. All variables are standardized by subtracting the mean and dividing by the standard deviation. All control variables are estimated at quarter *q* as the average of daily measures over a quarter, and all regression specifications include ETF and quarter fixed effects. The standard errors are double-clustered at the ETF and quarter levels; *t*-statistics are given in parentheses. Appendix A provides variable definitions.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Absolute\ Flow_{i,q} + \beta_2 Liq_{i,q} + \beta_3 Liq\_Mismatch_{i,q} + \gamma' X_{i,q} + \eta ETF_i + \lambda Quarter_q + \varepsilon_{i,q}. \quad (13)$$

Columns 1–3 of Table 7 present the coefficients of *Absolute Flow* on deviation while controlling for liquidity and liquidity mismatch. We also include the same set of controls—ETF and quarter fixed effects—in the regressions. Based on the results of the standardized regression, we find that the relation between *Absolute Flow* and *Deviation* is negative and statistically significant. Columns 4–6 show that the coefficients of *Absolute Flow* on *Persistence* are negative and statistically significant.

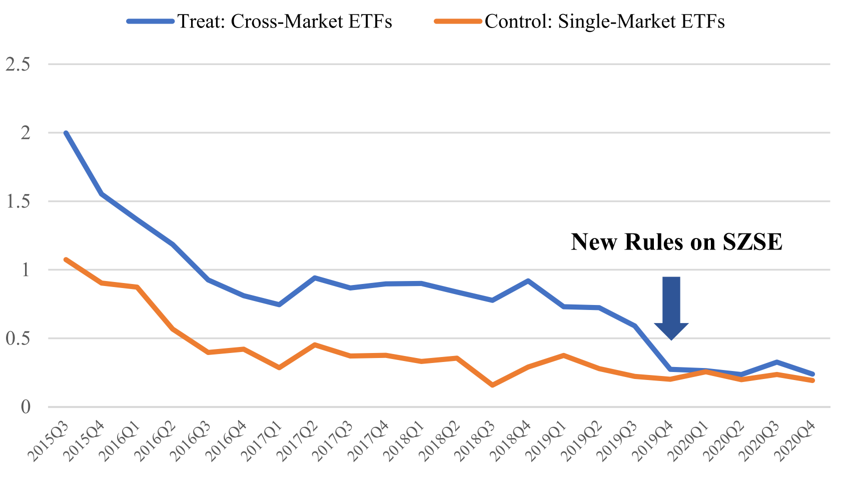

FIGURE 4 Mean of deviations (single-market exchange-traded funds [ETFs] vs. cross-market ETFs) on the Shenzhen Stock Exchange (SZSE). [Color figure can be viewed at wileyonlinelibrary.com]

Taken together, these findings indicate that greater arbitrage activity is significantly related to lower price deviations and shorter premium (discount) persistence. Therefore, persistent deviations may be caused by insufficient arbitrage activity.[21]

5.2 | Multivariate analysis with DiD

Absolute Flow (quarterly share creation and redemption) may not be entirely due to arbitrage activity, as *Absolute Flow* includes transactions caused by changes in market demand. The increase in market demand may lead to an increase in flow, and ETFs with more market demand may be more popular and liquid, resulting in lower deviation and higher ETF price efficiency. Although we control for the effect of liquidity in our analysis, we cannot rule out the influence of market demand changes.

To address this concern, we use the changes in the trading rules on the SZSE as an exogenous shock. On October 21, 2019, the SZSE introduced new rules that improved the cross-market ETF creation and redemption process. Because the changes in the trading rules on the SZSE relaxed the arbitrage restrictions of cross-market ETFs without directly affecting market demand and single-market ETFs, we employ a pooled regression in a DiD design using this new policy implemented on the SZSE. We divide ETFs listed on the SZSE into control and treatment groups by market type. Single-market ETFs are in the control group, and cross-market ETFs are in the treatment group. *Post2* equals 1 for all observations after October 21, 2019, and 0 otherwise.

First, we conduct a simple parallel trend test to confirm that the parallel trends assumption required for DiD analysis is satisfied. We compute the mean of the deviation over time. As illustrated in Figure 4, before the implementation of the new trading mechanism, cross-market ETFs have larger mean deviations than single-market ETFs, and the differences remain stable over time. We also regress price deviation on *Post2* using only single-market ETFs and do not find evidence that deviations of single-market ETFs have statistically significant changes after the new trading mechanism is

[21]We also use net creation as in Brown et al. (2020) to proxy arbitrage activities and run the regression model of Equation (13). The results (unreported for brevity) are similar.

implemented. The convergence of the differences in deviations (between single-market and cross-market ETFs) primarily stems from the lower deviations of cross-market ETFs after the new rule.

Then, we perform DiD analysis to study the relation between the cross-market ETFs' arbitrage flows and price efficiency on the SZSE before and after the implementation of the new policy. The following are the associated regression models:

$$Absolute\ Flow_{i,q} = \beta_0 + \beta_1 \text{Post2}_{i,q} \times \text{Treat2}_{i,q} + \beta_2 \text{Post2}_{i,q} + \beta_3 \text{Treat2}_{i,q} + \gamma' X_{i,q} + \eta ETF_i + \lambda Quarter_q + \varepsilon_{i,q}, \tag{14}$$

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 \text{Post2}_{i,t} \times \text{Treat2}_{i,q} + \beta_2 \text{Post2}_{i,t} + \beta_3 \text{Treat2}_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}. \tag{15}$$

Table 8 reports the results of these regressions. Our coefficient of interest is the loading of the interaction variable, *Post2* × *Treat2*, which captures the relative increase in arbitrage activities and price efficiency on cross-market ETFs due to the new policy. In Column 1, we find that cross-market ETFs show an increase in arbitrage activities relative to single-market ETFs. In Columns 2–3, we observe that there is a relative decrease for cross-market ETFs in deviation and persistence. These results indicate that cross-market ETFs on the SZSE have significantly more arbitrage activities and improved price efficiency after the implementation of the new policy, and they support our conjecture that the imperfect arbitrage environment leads to restricted arbitrage activities and lower price efficiency.

There may also be a concern that *Absolute Flow*, our proxy for arbitrage activities, may capture activities unrelated to price deviation. Because of the specific trading restrictions in Chinese equity markets, the ETF creation/redemption mechanism provides a channel for investors to realize $T+0$ trading or to speculate when stocks are suspended.[22] However, there is limited evidence that creations and redemptions are primarily driven by private information when stocks are suspended.[23] Furthermore, as there are many stocks within an ETF, investors may trade in different directions on different stocks based on their private information. The impacts on price efficiency may offset each other. Finally, the results of DiD analysis can also alleviate the concern. If the current price inefficiency is mainly caused by insufficient arbitrage based on mispricing, price efficiency is expected to improve after arbitrage restrictions are relaxed. If the current price inefficiency is associated with excessive creation and redemption activities based on private information, price efficiency is expected to decline after the rule change. Our empirical results are consistent with higher ETF price efficiency caused by more arbitrage activities.

The improvement in the arbitrage environment not only increases arbitrage activity but also enhances the liquidity of cross-market ETFs. Therefore, we expect the impact of weakened arbitrage restrictions to be stronger for ETFs with lower liquidity and higher transaction costs. To test these conjectures, we run regressions of ETF price efficiency on ETF liquidity, a dummy variable of the new policy, and an interaction term between the two. Because of a lack of high-frequency data (used to calculate spread and depth) for 2020, we rely on the Amihud

[22]Investors can trade based on private information through the unique structure of ETFs to circumvent the $T+1$ trading rule or to gain exposure to halted stocks. Specifically, $T+0$ trading can be completed by buying stocks on the secondary market, then creating ETF shares using the stocks in the basket according to the PCF and selling ETF shares on the same day. In addition, trading can be realized through ETFs when a stock is suspended from trading and investors foresee a substantial rise (fall) in the stock after trading is resumed. For example, if investors believe that the price of stock A will rise sharply after trading resumes, they can buy suspended stocks by buying ETF shares on the secondary market and immediately redeeming them on the primary market to obtain a portfolio basket. Then, they can sell other stocks at market value while retaining the suspended stocks. This process can be replicated several times in a trading day, thereby enabling investors to purchase vast quantities of suspended stocks. Similarly, if investors expect that stock A will decline rapidly after trading resumes, trading through ETFs can short sell the suspended stocks (to circumvent the short-selling restriction on a suspended stock) in the following manner: Buy all other stocks in the ETF on the secondary market, use the “allowed cash substitution” provision to substitute the suspended stocks with cash, use the combination of stocks and cash to create ETF shares, and sell the ETF shares on the secondary market.

[23]There were 104 trading suspensions in 2020, with an average halt duration of 7.36 trading days. For the sample of 712 stocks that experienced a positive return (based on the price after the halt was lifted relative to the price when the halt occurred), the average of net flows shows redemptions at 2.45%, which is consistent with trading using ETFs based on private information. However, for the remaining 641 halts on stocks that experienced negative returns, net flows are still negative, suggesting that there were no creations as expected from ETFs trading on negative news.

TABLE 8 Difference-in-difference analysis for the new policy on the SZSE.

Variable	*Absolute Flow* (1)	*Deviation* (2)	*Persistence* (3)
Post2 × *Treat2*	0.969***	−0.240***	−4.143***
	(4.321)	(−27.430)	(−32.664)
Post2	0.347	−0.748	−9.244
	(0.674)	(−1.252)	(−1.061)
Treat2	−1.321	0.319***	5.840***
	(0.254)	(62.021)	(78.173)
AUM	−5.564***	−0.001	−0.009
	(−5.780)	(−0.541)	(−0.441)
Volatility	3.665***	0.097***	0.124***
	(2.684)	(97.854)	(8.621)
Volume	4.501***	−0.017***	−0.043***
	(6.710)	(−32.383)	(−5.791)
Constant	2.967	0.971	−0.814
	(1.160)	(1.638)	(−0.090)
ETF fixed effects	Yes	Yes	Yes
Quarter fixed effects	Yes	No	No
Day fixed effects	No	Yes	Yes
Obs.	1274	110,044	110,044
Adj. R^2	0.481	0.376	0.178

Note: This table reports coefficient estimates of difference-in-difference (DID) regressions of exchange-traded fund (ETF) *Absolute Flow* and *Price Efficiency*. The regression models are:

$$Absolute\ Flow_{i,q} = \beta_0 + \beta_1 \mathrm{Post2}_{i,q} \times \mathrm{Treat2}_{i,q} + \beta_2 \mathrm{Post2}_{i,q} + \beta_3 \mathrm{Treat2}_{i,q} + \gamma' X_{i,q} + \eta ETF_i + \lambda Quarter_q + \varepsilon_{i,q}, \tag{14}$$

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 \mathrm{Post2}_{i,t} \times \mathrm{Treat2}_{i,q} + \beta_2 \mathrm{Post2}_{i,t} + \beta_3 \mathrm{Treat2}_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \tag{15}$$

where *Absolute Flow* is the ratio of total creation and redemption shares in quarter q to the average share outstanding at the beginning and end of quarter q. *Price Efficiency* denotes two dependent variables; *Deviation* and *Persistence*. *Post2* × *Treat2* is the interaction term between *Post2* and *Treat2*. *Post2* is a dummy variable that equals 1 if the trading day is after October 21, 2019, the day on which the Shenzhen Stock Exchange (SZSE) implemented new creation and redemption rules, and 0 otherwise. *Treat2* is a dummy variable that equals 1 if the type of ETF is cross-market, in which the tracked index of the ETF includes both Shanghai Stock Exchange (SSE-) and SZSE-listed stocks, otherwise 0. All control variables are estimated at day t in Equation (15) and estimated as the average of daily measures over quarter q in Equation (14). All regression specifications include day fixed effects or quarter fixed effects. The standard errors are double-clustered at the ETF and day levels; t-statistics are given in parentheses. Appendix A provides variable definitions.

***$p < 0.01$.

illiquidity measure here. We also include liquidity mismatch, the same set of controls, ETFs, and day fixed effects in the regressions. The regression model is:

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} \times Post2_{i,t} + \beta_2 Post2_{i,t} + \beta_3 Liq_{i,t} + \beta_4 Liq\_Mismatch_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}. \tag{16}$$

TABLE 9 Effect of the new policy on the SZSE on ETF Price Efficiency.

Variable	*Deviation* (1)	*Persistence* (2)
Liq × *Post2*	−0.038***	−0.050***
	(−6.323)	(−5.012)
Post2	−0.015***	−0.065**
	(−6.793)	(−2.114)
Liq	−0.045***	−0.043***
	(−8.764)	(−5.109)
Liq_Mismatch	0.025***	0.020***
	(3.286)	(4.385)
AUM	−0.048***	−0.027
	(−4.544)	(−1.557)
Volatility	0.255***	0.361***
	(27.108)	(23.688)
Volume	−0.152***	−0.211***
	(−10.663)	(−8.869)
Constant	1.319***	2.637***
	(3.838)	(4.707)
ETF fixed effects	Yes	Yes
Day fixed effects	Yes	Yes
Obs.	73,422	73,422
Adj. R^2	0.412	0.233

Note: This table reports coefficients estimates of daily regressions of exchange-traded fund (ETF) price efficiency on ETF liquidity, the new policy dummy, and an interaction term between the two. In this analysis, we include only the cross-market ETFs in the sample. The regression model is:

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} \times \mathrm{Post2}_{i,t} + \beta_2 Post_{i,t} + \beta_3 Liq_{i,t} + \beta_4 Liq\_Mismatch_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \tag{16}$$

where *Price Efficiency* denotes two dependent variables: *Deviation* and *Persistence*. *Liq* × *Post2* denotes the interaction effect between *Liq* and *Post2*. *Post2* is a dummy variable that equals 1 if the trading day is after October 21, 2019, the day on which the Shenzhen Stock Exchange (SZSE) implemented new creation and redemption rules, and 0 otherwise. *Liq* denotes Amihud illiquidity (*Amihud*) (because most of the ETFs in the sample added liquidity service providers in 2019, and we do not have intraday data on spreads and depth in 2020). *Liq_Mismatch* denotes absolute relative Amihud (*Rel(Amihud)*). The dependent variables are *Deviation* and *Persistence* in Columns 1 and 2, respectively. All regression specifications include ETF and day fixed effects. The standard errors are double-clustered at the ETF and day levels; *t*-statistics are given in parentheses. Appendix A provides variable definitions.

**$p < 0.05$; ***$p < 0.01$.

Table 9 reports the results of these regressions. The coefficient of interest is the loading on the interaction variable, *Liq* × *Post2*, which measures the implication of liquidity on price efficiency after the introduction of the new policy. We find that the coefficients are positive and significant for all measures of price efficiency, indicating that the new policy has a stronger impact on price efficiency in less liquid ETFs.

TABLE 10 Descriptive statistics of ETF short-selling restrictions.

Panel A: Number of ETF without short-selling restrictions			
Year	No. of ETFs with no short selling allowed	No. of ETFs with short selling permitted	% of ETFs with short selling allowed
2010	6	8	57%
2011	20	13	39%
2012	23	15	39%
2013	31	25	45%
2014	39	25	39%
2015	45	35	44%
2016	46	43	48%
2017	51	50	50%
2018	70	57	45%
2019	88	91	51%
2020	156	117	43%

Panel B: Comparison before and after the implementation of securities lending for ETFs eligible for short selling					
	After		Before		
	Obs.	Mean	Obs.	Mean	Differences
Deviation	52,583	0.231	159,048	0.646	−0.415***
Premium	19,455	0.004	53,060	0.015	−0.011***
Discount	34,638	0.006	109,426	0.016	−0.010***
Persistence	52,474	3.271	158,219	6.328	−3.057***
QSpread	52,583	0.001	159,048	0.003	−0.002***
ESpread	52,583	0.001	159,048	0.003	−0.002***
Depth	49,910	13.311	108,004	11.944	1.367***
Amihud	52,567	0.008	156,445	0.189	−0.181***

Note: This table presents descriptive statistics of exchange-traded funds (ETFs) with and without short- selling restrictions. Panel A presents the number of ETFs without short selling restrictions, number of ETFs, and percentage of ETFs without short selling restrictions in the sample by year. Panel B presents a comparison of price efficiency and liquidity before and after the implementation of securities lending for ETFs. Appendix A provides variable definitions.

***$p < 0.01$.

5.3 | ETF short selling and pricing efficiency

In this section, we examine how changes in short-selling restrictions affect the relation between liquidity and price efficiency of ETFs. We investigate whether the relaxation of short-selling restrictions improves price efficiency as short-selling restrictions are an important part of market frictions to arbitrage.

Panel A of Table 10 presents the number and proportion of ETFs in which short selling is allowed by year, and Panel B presents the comparison of price efficiency and liquidity before and after the implementation of short selling for ETFs on the short-selling list. The average of all measures of liquidity and price efficiency is significantly higher after the implementation of short selling.

We further investigate the impact of short-selling restrictions and liquidity on price efficiency. The easing of the short-selling restriction is expected to improve price efficiency and weaken the effect of liquidity on price efficiency. To examine this conjecture, we run regressions of ETF price efficiency on *Liq* (ETF liquidity), *Short*, and an interaction term between the two. *Short* is a dummy variable that equals 1 when the ETF is on the list of securities lending announced by exchanges on a given day, and 0 otherwise. Our regression specification controls for characteristics that may affect ETF price efficiency. The regression model is:

$$\begin{aligned} \textit{Price Efficiency}_{i,t} = {} & \beta_0 + \beta_1 \textit{Liq}_{i,t} \times \textit{Short}_{i,t} + \beta_2 \textit{Short}_{i,t} + \beta_3 \textit{Liq}_{i,t} + \beta_4 \textit{Liq\_Mismatch}_{i,t} + \gamma' X_{i,t} + \eta \textit{ETF}_i \\ & + \lambda \textit{Day}_t + \varepsilon_{i,t}. \end{aligned} \tag{17}$$

Panel A of Table 11 presents our main results. The coefficient of interest is the loading on the interaction term, *Liq* × *Short*, which measures the impact of liquidity on price efficiency after the implementation of securities lending. We find that the coefficients are positive and significant for deviation and persistence, indicating that liquidity has a weaker effect on price efficiency after the implementation of securities lending. We also find that the coefficient for *Short* is negative and significant, indicating the positive effect of easing short-selling restrictions on price efficiency.

Overall, ETFs that investors can short have significantly higher liquidity and price efficiency than ETFs with short-selling restrictions. The impact of liquidity on price efficiency for ETFs that have lifted short-selling restrictions is weaker, further supporting the conjecture that easing short-selling restrictions has a significant positive effect on price efficiency.

6 | ADDITIONAL TESTS

6.1 | ETF institutional ownership, ETF size, liquidity, and price efficiency

In this section, we consider the role of ETF institutional ownership, ETF size, and liquidity on price efficiency. Consistent with international experience, the top 25% ETFs in China account for almost 80% of the AUM in the entire equity ETF market at the end of 2020. Institutions are mainly interested in holding the largest (and presumably most liquid) ETFs.[24] We expect institutional investors are better positioned to take advantage of mispricing to amplify the influence of ETF liquidity on price efficiency, and the effect is greater in large ETFs.

To test the prediction, we construct two dummy variables: *Ins Indicator* and *Large*. *Ins Indicator* equals 1 if institutional ownership is in the top quintile of the sample, and *Large* equals to 1 if the AUM of the ETF is in the top quintile. We regress ETF price efficiency on ETF liquidity, *Ins Indicator*, *Large*, and the triple interaction among them. The regression model is:

$$\begin{aligned} \textit{Price Efficiency}_{i,t} = {} & \beta_0 + \beta_1 \textit{Liq}_{i,t} \times \textit{Ins Indicator}_{i,t} \times \textit{Large}_{i,t} + \beta_2 \textit{Liq}_{i,t} \times \textit{Ins Indicator}_{i,t} \\ & + \beta_3 \textit{Ins Indicator}_{i,t} \times \textit{Large}_{i,t} + \beta_4 \textit{Liq}_{i,t} \times \textit{Large}_{i,t} + \beta_5 \textit{Liq}_{i,t} + \beta_6 \textit{Ins Indicator}_{i,t} \\ & + \beta_7 \textit{Large}_{i,t} + \beta_8 \textit{Liq\_Mismatch}_{i,t} + \gamma X_{i,t} + \eta \textit{ETF}_i + \lambda \textit{Day}_t + \varepsilon_{i,t}, \end{aligned} \tag{18}$$

Table 12 presents the results of the regressions. We find that the coefficient of the triple interaction is negative and significant in most cases, which provides evidence for our conjecture that institutional ownership amplifies the influence of ETF liquidity on price efficiency, and the effect is greater for large ETFs.

We conduct an additional test to investigate the role of breadth of ownership or ownership concentration on the impact of liquidity on price efficiency. We use total shares to standardize the number of holders and capture the breadth of ownership of ETFs. We define *Shares per Holder* as the total shares divided by the number of holders. The larger *Shares per Holder*, the more concentrated the holder structure. We divide the sample into two groups according to whether *Shares per Holder* is larger than the top quartiles (more concentrated) or smaller than the top quartiles (less concentrated), and rerun

[24] We provide descriptive statistics in Panel B of Table 2 to support our statement. We find that institutional investors' holdings account for more than 65% in the top 20% ETFs by AUM, and institutional holdings decline to only about 30% for the bottom 40% ETFs based on AUM.

TABLE 11 Short selling, liquidity, and price efficiency.

	Deviation				*Persistence*			
	QSpread	*ESpread*	*Depth*	*Amihud*	*QSpread*	*ESpread*	*Depth*	*Amihud*
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Liq × *Short*	0.118***	0.126***	0.097***	0.079***	0.044**	0.042**	0.026**	0.101***
	(9.872)	(10.735)	(14.357)	(5.227)	(2.253)	(2.151)	(2.350)	(4.095)
Short	−0.047***	−0.047***	−0.025***	−0.041***	−0.031***	−0.031***	−0.036***	−0.022**
	(−7.327)	(−7.485)	(−4.093)	(−6.270)	(−2.941)	(−3.022)	(−3.630)	(−2.000)
Liq	−0.202***	−0.197***	−0.033***	−0.091***	−0.008***	−0.009***	−0.036***	−0.034***
	(−41.254)	(−40.126)	(−5.026)	(−24.260)	(−5.006)	(−9.059)	(−3.351)	(−5.552)
Liq_Mismatch	0.301***	0.197***		0.449***	0.575***	0.551***		0.489***
	(10.586)	(14.044)		(10.795)	(14.286)	(14.243)		(12.568)
AUM	−0.189***	−0.189***	−0.117***	−0.218***	−0.176***	−0.176***	−0.148***	−0.161***
	(−20.735)	(−20.802)	(−19.374)	(−23.818)	(−11.442)	(−11.445)	(−14.960)	(−10.457)
Volatility	0.012	0.013	0.007	−0.002	−0.131***	−0.131***	−0.053***	−0.118***
	(1.356)	(1.465)	(1.147)	(−0.244)	(−8.824)	(−8.823)	(−5.392)	(−7.869)
Volume	−0.207***	−0.207***	−0.203***	−0.174***	−0.053***	−0.053***	−0.070***	−0.086***
	(−29.538)	(−29.622)	(−37.411)	(−23.751)	(−4.511)	(−4.527)	(−7.909)	(−6.979)
Constant	0.366**	0.373**	−0.156	0.631**	−0.813***	−0.813***	−0.195	−1.229**
	(2.129)	(2.171)	(−0.559)	(2.013)	(−2.800)	(−2.798)	(−0.426)	(−2.333)
ETF fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	99,626	99,626	99,626	99,626	99,626	99,626	99,626	99,626
Adj. R^2	0.457	0.456	0.450	0.450	0.273	0.273	0.273	0.273

Note: This table reports coefficient estimates of daily regressions of exchange-traded fund (ETF) price efficiency on short selling, ETF liquidity, and an interaction between the two variables. The regression model is:

$$Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} \times Short_{i,t} + \beta_2 Short_{i,t} + \beta_3 Liq_{i,t} + \beta_4 Liq\_Mismatch_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t}, \quad (17)$$

where *Price Efficiency* denotes two variables: *Deviation* and *Persistence*. *Liq* × *Short* is the interaction between liquidity and the dummy variable for short selling. *Short* is a dummy variable for short selling that equals 1 if the ETF is listed on the securities lending list published by the exchanges on that trading day, and 0 otherwise. *Liq* denotes four explanatory variables: relative quote spread (*QSpread*, Columns 1 and 5), relative effective spread (*ESpread*, Columns 2 and 6), market depth (*Depth*, Columns 3 and 7), and Amihud illiquidity (*Amihud*, Columns 4 and 8). *Liq_Mismatch* denotes three variables: absolute relative *QSpread* (*Rel(QSpread)*), absolute relative *ESpread* (*Rel(ESpread)*), and absolute relative *Amihud* (*Rel(Amihud)*). In this test, we remove ETFs that have never been listed on the securities lending lists by exchanges. The dependent variables are *Deviation* in Columns 1–4 and *Persistence* in Columns 5–8. The dependent variables and liquidity variables are standardized by subtracting the mean and dividing by the standard deviation. All regression specifications include ETF and day fixed effects. The standard errors are double-clustered at the ETF and day levels; *t*-statistics are given in parentheses. Appendix A provides variable definitions.

**$p < 0.05$; ***$p < 0.01$.

TABLE 12 Institutional ownership, ETF size, liquidity, and price efficiency.

	Deviation				*Persistence*			
	QSpread	*ESpread*	*Depth*	*Amihud*	*QSpread*	*ESpread*	*Depth*	*Amihud*
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Liq × Ins Indicator × Large	−0.026**	−0.062**	−0.072***	−0.712***	−0.034***	−0.011***	−0.006	0.079***
	(−2.432)	(−2.106)	(−5.135)	(−6.316)	(−3.294)	(−4.424)	(−0.317)	(3.895)
Liq × Ins Indicator	−0.010**	−0.009*	−0.070***	−0.042***	−0.020***	−0.017**	−0.119***	−0.069***
	(−2.115)	(−1.764)	(−5.583)	(−11.172)	(−2.684)	(−2.253)	(−6.572)	(−11.521)
Ins Indicator × Large	−0.000	0.014	−0.058***	−0.050***	−0.347***	−0.300***	−0.139***	−0.045***
	(−0.004)	(0.638)	(−5.217)	(−6.290)	(−8.095)	(−9.188)	(−8.718)	(−7.951)
Liq × Large	−0.058	−0.069	−0.097	−0.715***	−0.873	−0.763	0.052	−0.190***
	(−1.056)	(−1.342)	(−0.988)	(−6.318)	(−0.351)	(−0.584)	(0.718)	(−3.898)
Liq	−0.134***	−0.143***	−0.108***	−0.201***	−0.014**	−0.007***	−0.008***	−0.871***
	(−9.783)	(−8.873)	(−13.064)	(−10.899)	(−2.162)	(−3.092)	(−3.646)	(−3.425)
Ins Indicator	0.010	0.011	0.012	0.028	0.093	0.092	0.043	0.094
	(1.450)	(1.534)	(0.119)	(0.168)	(0.657)	(0.619)	(0.108)	(0.738)
Large	−0.050***	−0.091***	−0.103**	−0.009***	−0.060***	−0.095***	−0.074***	−0.081***
	(−7.394)	(−8.387)	(−9.178)	(−6.768)	(−7.889)	(−6.391)	(−7,342)	(−8.646)
Liq_Mismatch	0.472**	0.438***		0.276***	0.032***	0.032***		0.007***
	(2.109)	(4.332)		(3.986)	(4.419)	(3.762)		(4.385)
Control variables	Included	Included	Included	Included	Included	Included	Included	Included
ETF fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	129,939	130,029	129,939	225,670	129,939	130,029	129,939	225,670
Adj. R^2	0.157	0.169	0.133	0.233	0.222	0.221	0.273	0.223

Note: This table reports coefficient estimates of daily regressions of exchange-traded fund (ETF) price efficiency on institutional ownership, ETF liquidity, and the dummy variable of ETF assets under management (AUM). The regression model is:

$$\begin{aligned} \textit{Price Efficiency}_{i,t} = \ & \beta_0 + \beta_1 \textit{Liq}_{i,t} \times \textit{Ins Indicator}_{i,t} \times \textit{Large}_{i,t} + \beta_2 \textit{Liq}_{i,t} \times \textit{Ins Indicator}_{i,t} + \beta_3 \textit{Ins Indicator}_{i,t} \\ & \times \textit{Large}_{i,t} + \beta_4 \textit{Liq}_{i,t} \times \textit{Large}_{i,t} + \beta_5 \textit{Liq}_{i,t} + \beta_6 \textit{Ins Indicator}_{i,t} + \beta_7 \textit{Large}_{i,t} + \beta_8 \textit{Liq\_Mismatch}_{i,t} \\ & + \gamma X_{i,t} + \eta \textit{ETF}_i + \lambda \textit{Day}_t + \varepsilon_{i,t}, \end{aligned} \tag{18}$$

where *Price Efficiency* denotes two variables: *Deviation* and *Persistence*. *Liq × Ins Indicator × Large* is the triple interaction among liquidity, the dummy variable of institutional ownership, and the dummy variable of ETF size. *Ins Indicator* equals 1 if institutional ownership is in the top quintile of the sample, and 0 otherwise. *Large* equals 1 if the AUM of the ETF is in the top quintile of the sample, and 0 otherwise. *Liq* denotes four explanatory variables: relative quote spread (*QSpread*, Columns 1 and 5), relative effective spread (*ESpread*, Columns 2 and 6), market depth (*Depth*, Columns 3 and 7), and Amihud illiquidity (*Amihud*, Columns 4 and 8). *Liq_Mismatch* denotes three variables: absolute relative *QSpread* (*Rel(QSpread)*), absolute relative *ESpread* (*Rel(ESpread)*), and absolute relative *Amihud* (*Rel(Amihud)*). The dependent variables and liquidity variables are standardized by subtracting the mean and dividing by the standard deviation. All regression specifications include ETF and day fixed effects. The standard errors are double-clustered at the ETF and day levels; *t*-statistics are given in parentheses. Appendix A provides variable definitions.

**$p < 0.05$; ***$p < 0.01$.

TABLE 13 Adjusted price efficiency: Using ETF closing midquote prices and NAVs of peer groups.

Variable	*QSpread* (1)	*ESpread* (2)	*Depth* (3)	*Amihud* (4)	*QSpread* (5)	*ESpread* (6)	*Amihud* (7)
Dependent variable: *Adj1 Deviation*							
Liq	−0.053***	−0.053***	−0.018***	−0.033***	−0.051***	−0.050***	−0.203***
	(−34.178)	(−32.844)	(−20.149)	(−19.873)	(−32.117)	(−19.378)	(−13.729)
Liq_Mismatch					0.075***	0.103***	0.037***
					(13.275)	(8.988)	(19.887)
Dependent variable: *Adj1 Persistence*							
Liq	−0.004***	−0.004***	−0.016***	−0.022***	−0.005***	−0.004***	−0.018***
	(−3.986)	(−4.773)	(−4.217)	(−3.648)	(−3.798)	(−5.263)	(−3.331)
Liq_Mismatch					0.002***	0.001***	0.001***
					(3.312)	(4.429)	(3.563)
Control variables	Included	Included	Included	Included	Included	Included	Included
ETF fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the effect of exchange-traded fund (ETF) liquidity on adjusted price efficiency. The regression models are:

$$\text{Adj1 } Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t},$$

$$\text{Adj1 } Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} + \beta_2 Liq\_Mismatch_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t},$$

where *Adj1 Price Efficiency* denotes *Adj1 Deviation* and *Adj1 Persistence*. We calculate adjusted price efficiency using ETF closing midquote prices and estimated net asset values (NAVs) (see Section 6.2 for details). *Liq* denotes four explanatory variables: relative quote spread (*QSpread*, Columns 1 and 5), relative effective spread (*ESpread*, Columns 2 and 6), market depth (*Depth*, Column 3), and Amihud illiquidity (*Amihud*, Columns 4 and 7). *Liq_Mismatch* denotes three variables: absolute relative *QSpread* (*Rel(QSpread)*), absolute relative *ESpread* (*Rel(ESpread)*), and absolute relative *Amihud* (*Rel(Amihud)*). The dependent variables and liquidity variables are standardized by subtracting the mean and dividing by the standard deviation. All regression specifications include ETF fixed effects and day fixed effects. The standard errors are double-clustered at the ETF and day levels; *t*-statistics are given in parentheses. Appendix A provides variable definitions.
***$p < 0.01$.

the regressions. The results are reported in Internet Appendix Table I3. Results are consistent with our conjecture that the impact of liquidity on price efficiency is larger for ETFs with more concentrated ownership.

6.2 | Robustness tests

Deviations calculated using the difference between ETF closing price and NAV may be inaccurate because of stale ETF closing price or NAV, in which case the price deviation is artificial and biased (Broman, 2020; Petajisto, 2017). However, our sample includes only ETFs with underlying stocks that are A-listed shares, which may alleviate some of the concerns about stale NAVs. ETFs and their underlying securities that are traded with different closing times, and illiquid high-yield bonds are excluded from our sample. However, the closing price and NAV may still be stale because of poor liquidity. To resolve the issue of stale closing prices and NAVs, we adjust the calculation of closing prices and NAVs to arrive at a more accurate measure of true price dislocation.

TABLE 14 Transaction-costs-adjusted price efficiency measure.

Variable	QSpread (1)	ESpread (2)	Depth (3)	Amihud (4)	QSpread (5)	ESpread (6)	Amihud (7)
Depdent variable: *Adj Deviation*							
Liq	−0.450***	−0.309***	−0.225***	−0.113***	−0.413***	−0.308***	−0.109***
	(−112.263)	(−88.979)	(−38.445)	(−33.121)	(−64.915)	(−53.918)	(33.585)
Liq_Mismatch					0.060***	0.007	0.044***
					(7.451)	(1.007)	(8.844)
Dependent variable: *Adj Persistence*							
Liq	−0.132***	−0.108*	−0.127***	−0.014***	−0.101***	−0.064***	−0.009**
	(−4.162)	(−1.950)	(−19.810)	(−18.094)	(−13.637)	(−8.131)	(−2.047)
Liq_Mismatch					0.063***	0.053***	0.003**
					(17.421)	(8.512)	(2.388)
Control variables	Included	Included	Included	Included	Included	Included	Included
ETF fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the effect of exchange-traded fund (ETF) liquidity on transaction costs adjusted price efficiency. The regression models are:

$$\text{Adj2 } Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t},$$

$$\text{Adj2 } Price\ Efficiency_{i,t} = \beta_0 + \beta_1 Liq_{i,t} + \beta_2 Liq\_Mismatch_{i,t} + \gamma' X_{i,t} + \eta ETF_i + \lambda Day_t + \varepsilon_{i,t},$$

where *Adj2 Price Efficiency* denotes the two adjusted dependent variables: *Adj Deviation* and *Adj Persistence*. *Liq* denotes four explanatory variables: relative quote spread (*QSpread*, Columns 1 and 5), relative effective spread (*ESpread*, Columns 2 and 6), market depth (*Depth*, Column 3), and Amihud illiquidity (*Amihud*, Columns 4 and 7). *Liq_Mismatch* denotes three variables: absolute relative *QSpread* (*Rel(QSpread)*), absolute relative *ESpread* (*Rel(ESpread)*), and absolute relative *Amihud* (*Rel(Amihud)*). The dependent variables and liquidity variables are standardized by subtracting the mean and dividing by the standard deviation. All regression specifications include ETF fixed effects and day fixed effects. The standard errors are double-clustered at the ETF and day levels; *t*-statistics are given in parentheses. Appendix A provides variable definitions.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

We follow Petajisto (2017), who uses the average price of a group of similar ETFs that track the identical index to control for stale pricing of the underlying assets and resolve the issue of stale NAVs.[25] We recognize that ETFs that track the same underlying index may have different price points, so simply using the average of these prices is not the right approach. For clarification, the following are the exact steps used to measure adjusted price efficiency:

Step 1. Group ETFs according to whether ETFs track the same index, and each peer group contains at least three different ETFs.

Step 2. Simulate the NAV of ETFs using the equal-weighted change in daily prices of ETFs in the peer group.

Step 3. Replace the NAV of ETF *i* with simulated NAV using the price change computed in Step 2, and calculate the difference between ETF price (midquote) and simulated NAV.

[25]We make some improvements based on Petajisto (2017), as the ETF price we use is the midquote of the closing prices rather than the closing price.

We use adjusted price efficiency and replicate our main analyses in Table 3. Table 13 reports our results. They remain highly significant and consistent with our earlier findings, which indicates that the effect of liquidity on deviation is robust after purging the effect of stale pricing.[26]

In addition, transaction costs in a round-trip arbitrage are a key determinant of whether arbitrage will take place. If the premium and discount are smaller than the transaction costs, there is no incentive for arbitragers. The market could be perfectly efficient while ETFs trade at a persistent discount relative to NAV simply because fees are extracted. Hence, we modify deviation (our price efficiency measure) to be the difference between the ETF price and the NAV of its underlying securities minus the trading costs of a round-trip arbitrage strategy.

As shown in Appendix B, the transaction costs for trading when ETFs are at a premium or a discount are different. The creation and redemption fees are generally a fixed amount of 1000–2000 yuan per transaction, which is negligible given the size of the transaction in million yuan. Thus, we ignore the fees for creation and redemption. The transaction costs in a round-trip arbitrage trading are 0.04% when ETFs are traded at a premium, but 0.13% when ETFs are traded at a discount. The equal-weighted (value-weighted) mean of transaction cost adjusted deviation is 0.533 (0.197) based on numbers reported in Panel A of Table 1.

We replicate the analysis in Table 3 using the adjusted deviations. Table 14 reports the results. We continue to find significant effects of all liquidity measures on the adjusted deviations.

These results reveal that our findings are robust to how deviation is measured. Using both Petajisto's (2017) approach to adjust for stale ETF prices and NAVs, and the transaction-cost-adjusted deviation measure, we continue to find that liquidity has a strong impact on price efficiency.

7 | CONCLUSION

The popularity of ETFs continues to grow globally, and the size of the ETF market has risen dramatically in China. We are the first to report two interesting observations about the Chinese ETF market, which differs significantly from the ETF markets of the United States and other developed countries. First, Chinese equity ETFs experience substantial price inefficiency; price deviations are approximately 25 times larger and 10 time more persistent than in the United States. Second, Chinese equity ETFs lack liquidity and are actually less liquid than their underlying assets. Is illiquidity a key factor hindering the price efficiency of equity ETFs in China? If so, what contributes to the illiquidity in Chinese ETFs? We address these questions by examining the relation between price efficiency and liquidity in Chinese equity ETF markets, as well as the influence of arbitrage restrictions and ownership structures.

We begin by showing that ETFs with higher liquidity have lower price deviation and shorter deviation persistence, and that these effects persist after controlling for liquidity mismatch. A quasi-natural experiment based on the addition of liquidity service providers addresses endogeneity concerns and lends support to a causal interpretation between liquidity and price efficiency. We show that ETFs with greater arbitrage activity have lower price deviation and shorter deviation persistence. Apart from being exchange traded with real-time prices, a unique feature of ETFs is their open-ended structure via the share creation/redemption process, which adds another layer of liquidity in addition to secondary market trading volume. Using the new policy implemented on the SZSE as our setting, we find that the improvement in the arbitrage environment increases arbitrage activity and ETF price efficiency. In addition, we find that ETFs with short selling allowed have significantly higher liquidity and price efficiency than ETFs with short-selling restrictions. The impact of liquidity on ETF price efficiency is weaker for ETFs with short-selling restrictions lifted. Furthermore, the effect of weakened arbitrage restrictions on ETF price efficiency is stronger for ETFs with lower liquidity and higher transaction costs.

[26]Alternatively, we compare the premium of ETF *i* with the equal-weighted premium of other funds in the same peer group and use the absolute value of the peer-adjusted premium to replace our deviation measure. We thank an anonymous referee for this suggestion.

Finally, we address the role of ownership structure on price efficiency. We find that institutional investors can improve price efficiency and have a stronger impact on price efficiency for more liquid ETFs. Similarly, we find that the impact of liquidity on price efficiency is larger for ETFs with more concentrated ownership.

Overall, these results support the argument that ETF illiquidity and lack of arbitrage are important drivers of price inefficiency of Chinese equity ETFs. We suspect that the lack of ETF liquidity in China may also be closely associated with investor awareness and acceptance of ETFs, a financial innovation with many potential advantages but a relatively short history in China. With the development of a wide range of Chinese ETFs (e.g., sector ETFs, fixed-income ETFs) and fund sizes, we expect the Chinese ETF market to gain more participants and ETFs to become an increasingly popular investment vehicle in the future. Given the potential effects of price inefficiency on market risk and volatility, future market reforms and regulations must help improve ETF liquidity and encourage arbitrage activity. In particular, the current state of ETF price efficiency in China suggests that policies and rules that further improve ETF price efficiency are essential to the continued growth of the ETF market in China.

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REFERENCES

Agarwal, V., Hanouna, P., Moussawi, R., & Stahel, C. W. (2019). *Do ETFs increase the commonality in liquidity of underlying stocks?* (Working Paper). Georgia State University.

Allen, F. (2012). Trends in financial innovation and their welfare impact: An overview. *European Financial Management*, *18*(4), 493–514.

Allen, F., & Gale, D. (1994). *Financial innovation and risk sharing*. MIT Press.

Bae, K., & Kim, D. (2020). Liquidity risk and exchange-traded fund returns, variances, and tracking errors. *Journal of Financial Economics*, *138*(1), 222–253.

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do ETFs increase volatility? *Journal of Finance*, *73*(6), 2471–2535.

Bhattacharya, A., & O'Hara, M. (2018). *Can ETFs increase market fragility? Effect of information linkages in ETF markets* (Working Paper). City University of New York.

Box, T., Davis, R., Evans, R., & Lynch, A. (2021). Intraday arbitrage between ETFs and their underlying portfolios. *Journal of Financial Economics*, *141*(3), 1078–1095.

Broman, M. S. (2020). Local demand shocks, excess comovement and return predictability. *Journal of Banking & Finance*, *119*, Article 105910.

Broman, M. S., & Shum, P. (2018). Relative liquidity, fund flows and short-term demand: Evidence from exchange-traded funds. *Financial Review*, *53*(1), 87–115.

Brown, D. C., Davies, S. W., & Ringgenberg, M. C. (2020). ETF arbitrage, non-fundamental demand, and return predictability. *Review of Finance*, *25*(4), 937–972.

Cespa, G., & Foucault, T. (2014). Illiquidity contagion and liquidity crashes. *Review of Financial Studies*, *27*(6), 1615–1660.

Chordia, T., Roll, R., & Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of Financial Economics*, *87*(2), 249–268.

Da, Z., & Shive, S. (2018). Exchange traded funds and asset return correlations. *European Financial Management*, *24*(1), 136–168.

Dow, J. (1998). Arbitrage, hedging, and financial innovation. *Review of Financial Studies*, *11*(4), 739–755.

Duffie, D., & Rahi, R. (1995). Financial market innovation and security design: An introduction. *Journal of Economic Theory*, *65*(1), 1–42.

Edmans, A., Fang, V. W., & Zur, E. (2013). The effect of liquidity on governance. *Review of Financial Studies*, *26*(6), 1443–1482.

Engle, R. F., & Sarkar, D. (2006). Premiums-discounts and exchange-traded funds. *Journal of Derivatives*, *13*(4), 27–45.

Ernst, T. (2020). *Stock-specific price discovery from ETFs* (Working Paper). University of Maryland.

Glosten, L. R., Nallareddy, S., & Zou, Y. (2021). ETF activity and informational efficiency of underlying securities. *Management Science*, *67*(1), 22–47.

Gorbatikov, E., & Sikorskaya, T. (2021). *Two APs are better than one: ETF mispricing and primary market participation* (Working Paper). London Business School.
Hasbrouck, J. (2003). Intraday price formation in U.S. equity index markets. *Journal of Finance*, *58*(6), 2375–2399.
Holden, C. W., & Nam, J. (2017). *Market accessibility, corporate bond ETFs, and liquidity* (Research Paper No. 18-1). Kelley School of Business. Available at SSRN: https://ssrn.com/abstract=3083257
Huang, S., O'Hara, M., & Zhong, Z. (2021). Innovation and informed trading: Evidence from industry ETFs. *Review of Financial Studies*, *34*(3), 1280–1316.
Jain, A., Jain, C., & Jiang, C. X. (2021). Active trading in ETFs: The role of high-frequency algorithmic trading. *Financial Analysts Journal*, *77*(2), 66–82.
Kaminska, I. (2011, September 19). Europe's fragmented ETF settlement system. *Financial Times*. http://www.ft.com/cms/s/0/2cef77ae-d00b-11e0-81e2-00144feabdc0.html
Lijnse, B., & Scholtes, C. (2010). The fragmentation of the European ETF market. *Journal of Indexes*, *13*(2), 22–25. https://www.etf.com/docs/magazine/2/2010_164.pdf
Madhavan, A. (2012). Exchange-traded funds, market structure, and the flash crash. *Financial Analysts Journal*, *68*(4), 20–35.
Madhavan, A., & Sobczyk, A. (2016). Price dynamics and liquidity of exchange-traded funds. *Journal of Investment Management*, *14*(2), 86–102.
Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2013). ETF arbitrage: Intraday evidence. *Journal of Banking & Finance*, *37*(9), 3486–3498.
Merton, R. C. (1992). Financial innovation and economic performance. *Journal of Applied Corporate Finance*, *4*(4), 12–22.
Miller, M. H. (1986). Financial innovation: The last twenty years and the next. *Journal of Financial and Quantitative Analysis*, *21*(4), 459–471.
Pan, K., & Zeng, Y. (2019). *ETF arbitrage under liquidity mismatch* (Working Paper). Harvard University.
Petajisto, A. (2017). Inefficiencies in the pricing of exchange-traded funds. *Financial Analysts Journal*, *73*(1), 24–54.
Piccotti, L. R. (2018). ETF premiums and liquidity segmentation. *Financial Review*, *53*(1), 117–152.
Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics*, *42*(1–2), 35–52.
Roll, R., Schwartz, E., & Subrahmanyam, A. (2007). Liquidity and the law of one price: The case of the futures-cash basis. *Journal of Finance*, *62*(5), 2201–2234.
Sağlam, M., Tuzun, T., & Wermers, R. R. (2020). *Do ETFs increase liquidity?* (Working Paper). University of Cincinnati.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX A: VARIABLE DEFINITIONS

Variable	Definition	Frequency	Source
Price Efficiency	Price efficiency measures of exchange-traded funds (ETFs)		
Deviation (%)	Absolute difference between the ETF closing price and net asset value (NAV), divided by NAV and multiplied by 100; see Equation (1)	Daily	Wind
Premium (%)	If ETF price > NAV, *Premium* = *Deviation*; otherwise, *Premium* = 0; see Equation (1a)	Daily	Wind
Discount (%)	If ETF Price < NAV, *Discount* = *Deviation*; otherwise, *Discount* = 0; see Equation (1b)	Daily	Wind
Persistence	Number of days in each run of *Premium* (*Discount*) in the same direction	Daily	Wind

Variable	Definition	Frequency	Source
Liq	Liquidity measures of ETFs		
QSpread (%)	Average time-weighted relative quoted spread, which is the difference between bid and ask prices divided by the quote midpoint, multiplied by −100	Daily	Resset
ESpread (%)	Average trade-weighted relative effective spread; effective spread is the absolute difference between the trade price and the quote midpoint of the associated price divided by the quote midpoint, multiplied by −100	Daily	Resset
Depth	Natural logarithm of the sum of bid price multiplied by volume and ask price multiplied by volume	Daily	Resset
Amihud	Ratio of daily absolute return (in percentage) to trading volume (in million yuan) on that day, multiplied by −1	Daily	Wind
WLiq	Value-weighted liquidity measures of the underlying portfolio		
WQSpread (%)	Value-weighted *QSpread* of the underlying portfolio; the weight of an individual security is the value the security has in the underlying basket held by the ETF according to the daily portfolio composition file (PCF)	Daily	Resset
WESpread (%)	Value-weighted *ESpread* of the underlying portfolio; the weight of an individual security is the value the security has in the underlying basket held by the ETF according to the daily PCF	Daily	Resset
WAmihud	Value-weighted *Amihud* of the underlying portfolio; the weight of an individual security is the value the security has in the underlying basket held by the ETF according to the daily PCF	Daily	Resset
Rel(Liq)	Relative liquidity measures between the value-weighted underlying portfolio and ETF		
Rel(QSpread)	Log difference of *QSpread* between the value-weighted underlying portfolio and ETF	Daily	Resset
Rel(ESpread)	Log difference of *ESpread* between the value-weighted underlying portfolio and ETF	Daily	Resset
Rel(Amihud)	Log difference of *Amihud* between the value-weighted underlying portfolio and ETF	Daily	Resset
Liq_Mismatch	Absolute value of relative liquidity; see Equation (7a)	Daily	Resset
Arbitrage activities			
Absolute Flow (%)	Ratio of total creation and redemption shares to average shares outstanding at the beginning and end of the quarter, multiplied by 100	Quarterly	China Stock Market & Accounting Research (CSMAR)
Ownership structure			
Institutional Ownership (%)	Ratio of shares held by all institutional investors to total shares outstanding, multiplied by 100	Half year	Wind
Dummy variables			
Post1	*Post1* equals 1 if the trading day is after the addition of market makers to the ETF, and 0 otherwise	Daily	CSMAR
Treat1	*Treat1* equals 1 if an ETF has at least one market maker, and 0 otherwise	Daily	CSMAR
Post2	*Post2* equals 1 if the trading day is after October 21, 2019, when the Shenzhen Stock Exchange (SZSE)	Daily	CSMAR

(Continues)

Variable	Definition	Frequency	Source
	announced new creation and redemption rules, and 0 otherwise		
Treat2	*Treat2* equals 1 if an ETF is cross-market, where the tracked index of the ETF includes both Shanghai Stock Exchange (SSE-) and SZSE-listed stocks, and 0 otherwise	Daily	CSMAR
Short	*Short* equals 1 if an ETF is on the securities lending list published by the exchanges on that trading day, and 0 otherwise	Daily	Resset
Ins Indicator	*Ins Indicator* equals 1 if *Institutional Ownership* is in the top quintile of the sample in the period, and 0 otherwise	Half year	Wind
Large	*Large* equals 1 if the assets under management (AUM) of the ETF are in the top quintile of the sample in the period, and 0 otherwise	Half year	Wind
Control variables			
AUM	Natural logarithm of ETF close price times shares outstanding	Daily	Wind
Volatility	Standard deviation of 5-min prices during a day	Daily	Resset
Volume	Natural logarithm of the daily number of shares traded	Daily	Wind
Related variables			
Turn (%)	Trading volume divided by shares outstanding and multiplied by 100	Daily	Wind
Age	Calendar year minus the year of ETF inception	Yearly	CSMAR
Fee (%)	Annual expense ratio in percentage	Yearly	CSMAR
Price	Daily close price	Daily	Wind

APPENDIX B: TRANSACTION COSTS IN ROUND-TRIP ARBITRAGE TRADING

	Stock		Exchange-traded fund				
	Buy	Sell	Creation	Redemption	Buy	Sell	Transaction costs
Stamp duty	0.00%	0.10%			0.00%	0.00%	
Transfer fee	0.02%	0.02%			0.00%	0.00%	
Commission	0.01%	0.01%	0–1000	0–1000	0.01%	0.01%	
Premium	0.03%		0–1000			0.01%	0.04%
Discount		0.13%		0–1000	0.01%		0.14%