Do Designated Market Makers Matter for ETFs?

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Abstract

This paper examines the controversial role of Exchange-Traded Fund (ETF) Designated Market Makers (DMMs), motivated by the contentious debate prior to their implementation. A theoretical market microstructure framework is presented to analyze the behavior of ETF DMMs and the impact of their trading on the ETF market. Using a unique dataset from China that includes the exact DMM inauguration events and high-frequency trading data, the authors provide new empirical evidence that supports the theoretical framework. Our findings suggest that the introduction of DMMs can significantly enhance ETF liquidity and price efficiency, increase trading volume, while having a limited impact on ETF prices. The effect on ETF liquidity is more pronounced in funds with low liquidity and small market cap compared to those with high liquidity and large market cap. The evidence also shows that DMMs continue to provide liquidity during fund-level distressed conditions, but not during market-wide extreme distressed conditions. Furthermore, DMMs can help ETFs in both surviving and thriving, benefiting various market participants. Specifically, The inauguration of DMMs led to a 41.5% reduction in the bid-ask spread, a 54% increase in the turnover rate, and a 16.8% decrease in the magnitude of ETF premiums. Moreover, during the top 5% of extremely distressing times, ETFs with DMMs exhibit an average spread of 91 basis points, which is not significantly different from ETFs without DMMs. ETFs with DMMs experience fewer liquidations (9.2%) compared to those without DMMs (28.3%) and show a high average growth rate of 65.87% in market value over the six months following the introduction of DMMs. These results emphasize the importance of DMMs for ETFs and the need for better regulation, providing valuable insights for policy implications.

Keywords: Designated market maker; ETFs; Liquidity provision; Market structure

JEL: G11, G15, G17

1. Introduction

The role of Designated Market Makers (DMMs) has been a long-standing and central question in financial market structure. Despite the extensive literature on the topic of DMMs in the stock market, including works by Grossman and Miller (1988), Seppi (1997), Venkataraman and Waisburd (2007), Panayides (2007), Anand et al. (2009), Clark-Joseph et al. (2017), Bessembinder et al. (2015, 2020), and Theissen and Westheide (2020), there has been limited research on DMMs in the rapidly expanding Exchange-Traded Fund (ETF) market. This is despite the widespread popularity of ETFs among market participants, as evident in their tremendous growth in trading volume and assets under management (AUM) over the past two decades,[1] as well as the differing role of DMMs in the ETF market compared to the stock market.

ETFs are traded similarly to stocks, but the market making process for them can be fundamentally different from that of stocks. While the true value of a stock cannot be observed, the net asset value (NAV) of an ETF is usually visible to market participants, offering inherent arbitrage opportunities that draw in voluntary liquidity providers. This is especially true in the era of electronic trading, and some market participants view DMMs as a relic of the pre-electronic trading era, previously referred to as specialists on the NYSE, feeling that voluntary liquidity is already sufficient. Particularly, Authorized Participants (APs) play a crucial role in the creation and redemption process of ETFs and are naturally essential for their liquidity, raising questions about the necessity of DMMs for enhancing liquidity provision and market quality in ETF markets. Additionally, ETFs tend to attract greater endogenous liquidity and arbitrage activity compared to stocks due to their unique inherent arbitrage mechanism and low trading costs, which appeals to High-Frequency Traders (HFTs) (c.f. Ben-David et al., 2018; Dannhauser and Hoseinzade, 2022).

[1]In 2022, the global AUM invested in ETFs reached a remarkable 10 trillion U.S. dollars, with a substantial increase from the 276 ETFs in 2003 to 8,754 in 2022. In the U.S. equity market, the ETF asset class accounted for over 30% of the market's trading volume (Ben-David et al., 2018).

Moreover, the DMMs of an ETF can change its inventory through redemption and selling underlying components or accumulating inventory through buying underlying components and creating ETF shares, potentially creating a more competitive environment in the ETF market compared to the stock market. The significant differences between the ETF and stock markets indicate that the financial consequences and economic issues associated with the implementation of DMMs in the stock market from previous research may not be directly applicable to ETF markets. This underscores the importance of a study that bridges the gap in the literature.

Not surprisingly, the introduction of DMMs in the ETF market sparked a contentious debate at the U.S. Securities and Exchange Commission (SEC). Prior to the launch of the first ETF DMM program, the NASDAQ and NYSE Arca exchanges proposed a rule change in 2012 through the Market Quality Program aimed at improving market quality. The proposal prompted numerous comments from both academic and industry experts. While supporters claimed that the introduction of DMMs would not have a significant impact on security prices and NASDAQ declared that the proposal would be a "win for all" including ETF sponsors, companies, market makers, and investors, many commentators voiced strong opposition to the proposal, citing concerns about the necessity of DMMs in light of the central role played by APs in ETF liquidity,[2] and *"the potential to distort market forces"* since *"incentivized trading resulting from such arrangements obfuscates true supply and demand by creating volume"*, leading to *"manipulation and an unfair market place"*.[3]

The debate at the time was largely hypothetical, as there was neither existing theoretical guidance on ETF DMMs nor empirical evidence available prior to the launch of the program, and the opinions expressed by both sides were either informed only by previous studies on DMMs in stock markets or based on hypothetical speculation. However, more than a decade after the program's

[2] Reference to page 34 of U.S. SEC release No. 34-67411.

[3] See footnote 132, pages 31 and 32 of U.S. SEC release No. 34-67411, and comment letters providing views on the proposal to implement the NASDAQ Market Quality Program.

operation following SEC's favorable decision, the role of DMMs in the ETF market still remains largely unexamined. With the advantage of hindsight, this study aims to shed light on the effects of DMMs on the ETF market and the benefits or drawbacks they offer to market participants.

Building upon prior literature, we first propose a theoretical framework to motivate the study of the role of DMMs in the ETF market. Our model incorporates key features such as the presence of informed and uninformed traders, the market maker's dynamic approach of clearing inventory through bid and ask prices, the unique and inherent ETF arbitrage opportunity, and the DMM's subsidies for a trade from the exchange, along with their obligation to post bid and ask prices within a certain spread. To accommodate this constraint obligation, the DMM sets bid and ask prices such that the spread remains within the prescribed range. Conceptually, the market maker is effectively offering a call option to the informed trader at the ask price and a put option to the informed trader at the bid price. To offset this loss, the market maker profits from the noise trader and the subsidies received from the exchanges. Under the classic assumptions of the Black-Scholes model, we derive analytical expressions and propose several testable hypotheses that may have significant implications for investors and important policy implications for exchanges and regulators.

Guided by the theoretical motivations, we also empirically investigate the role of DMMs in shaping the liquidity and growth of ETFs. Empirically testing the impact of DMM implementation on market quality has been challenging in the literature, as the inauguration dates of DMMs are not publicly disclosed in the U.S. ETF market. Previous studies have utilized alternative identification methods, such as analyzing exchange technical glitches (Clark-Joseph et al., 2017) and examining DMM contract discontinuity (Bessembinder et al., 2020).[4] This study has a unique advantage in its ability to directly observe the impact of the exact DMM inauguration events, which is fully

[4] In a similar vein, Skjeltorp and Ødegaard (2015) investigate other markets that have already implemented similar programs in order to gain insights into the workings and effects of DMM programs for individual stocks, as the crucial information about the NASDAQ Market Quality Program is not accessible.

disclosed in the China's ETF market and manually collected by the authors from exchange records, providing the cleanest way to assess the impact. Specifically, we employ the difference-in-differences (DID) approach to capture changes in ETF liquidity related to the implementation of DMMs. In line with our theoretical predictions, our findings show a significant and positive impact of DMM inaugurations on the liquidity of ETFs. DMMs were found to increase the turnover rate by 54% and decrease the quoted spread and Amihud's illiquidity. Furthermore, DMMs boosted trading volume without significantly impacting ETF prices.

The positive impact of DMM programs on ETF liquidity is also supported by high-frequency trading data. We use tick-by-tick data to construct metrics of ETF secondary market trading activity and observe the changes around the inauguration of DMMs. Our results show increased trading activity and higher turnover per transaction in the ETF secondary market after the DMM program. To further test the role of DMMs in ETF liquidity, we also analyze one-minute-interval data from call auctions during every trading day. Since both APs and HFTs are inactive during these periods, examining the impact of DMMs in the call auctions helps minimize the potential interference from voluntary liquidity providers. Our investigation confirms that DMMs play a role in enhancing ETF liquidity during call auctions, particularly in ETFs with small market cap.

On top of boosting market activity, improving the liquidity of ETFs, and enhancing the price efficiency of ETFs, we also document that DMMs help ETFs to survive and grow. Our research indicates that ETFs with DMMs undergo fewer liquidations compared to those without DMMs and exhibit a high average growth rate of 65.87% in market value over the six months following the introduction of DMMs, accompanied by a significant increase in market capitalization. Additionally, our findings suggest that DMMs play a crucial role in the success and growth of ETFs, with a more pronounced effect in small-cap ETFs, which aligns with our model and previous studies by Sabourin (2006) and Bessembinder et al. (2015). Although our empirical work focuses on China's

ETF market, it also offers valuable insights into more general ETF markets, as ETFs have a similar structure and DMM programs have largely uniform regulations across markets. Moreover, the DID analysis eliminates various confounding factors, resulting in more robust estimates of the effects of DMM programs.[5] These results emphasize the value of DMMs in ETF markets and suggest that they play a crucial role in supporting the survival and growth of small ETFs, thus promoting the development of the ETF ecosystem.

To resolve the debates surrounding the potential adverse effects of introducing DMMs to ETF markets, we investigate whether the presence of DMMs in ETF markets influences ETF prices or NAVs. Unlike the value-enhancing effects observed in stocks near the announcement date of liquidity provision contracts (Venkataraman and Waisburd, 2007; Anand et al., 2009), we find no evidence of abnormal returns or cumulative abnormal returns in ETFs around the introduction of DMMs compare to ETFs without DMMs. This finding suggests that DMMs are not a disruptive force in the ETF market, as the inherent arbitrage mechanism restricts the ability of market makers to manipulate ETF prices.

While DMMs are commonly perceived as obligated liquidity providers, the participation requirements established by the exchange are not binding and are often measured by a participation rate of no less than a certain threshold. For example, in the China's ETF market, DMMs are expected to have a participation rate of no less than 80% during call auctions[6] and no less than 60% during continuous trading.[7] This means that DMMs are not fully obligated to participate in the market all the time, although their participation is always encouraged by the exchange through subsidies. Given their perceived role as the obligated liquidity providers but with non-binding par-

[5] See, for instance, Beck et al. (2010), Nunn and Qian (2011), Moser and Voena (2012), and Greenstone and Hanna (2014).

[6] This rate is computed by dividing the number of days a market maker participates in the call auction by the number of trading days in the evaluation period of call auction.

[7] This rate is computed by dividing the length of the time interval a market maker participates in the continuous trading by the length of time interval in the evaluation period of continuous trading.

ticipation requirements established by the exchanges, It is important for investors and regulators to understand the effectiveness of ETF DMM programs during times of stress on fund level and extreme market conditions. We show that DMMs play a positive role in most instances when the distressed condition is limited to the fund level. Additionally, the financial market crash in China in 2015 provides a valuable opportunity to evaluate the role of DMMs in extremely distressed market conditions.[8] Analysis of data from the 2015 crash period, when both APs and HFTs quickly left the ETF market, reveals little evidence of improved ETF liquidity due to DMM intervention. By conducting a regression of ETF relative spread using a DMM dummy variable, a dummy variable for the quantiles of ETF market-wide spread, and their interaction over the whole sample period, our results confirm that DMMs are reluctant to provide liquidity during extremely distressed market conditions, in line with the findings from the 2015 Chinese financial market crash. This suggests that the current incentive mechanism for DMM programs is not adequate in inspiring DMMs to serve as a last line of liquidity defense during times of extreme stress.

Finally, we assess the potential profits for different participants in the ETF market. To gauge the benefits to ETF investors, fund issuers, DMMs, APs, and exchanges, we use proxies such as the trading costs (ETF relative spread), market capitalization, the product of ETF bid-ask spread and trading volume, fund flows, and trading volume of ETFs. Our analysis reveals that all these participants benefit from the DMM program, further demonstrating the value of the liquidity provision provided by DMMs to the ETF market. Interestingly, it is worth noting that our findings also provide strong evidence of DMMs enhancing ETF price efficiency, which is related to the enhanced liquidity resulting from the DMM program. This function, however, is not included in the DMM's affirmative obligation.

[8] The 2008 financial crisis had a widespread impact on financial markets, but DMMs were not yet introduced to major ETF markets. The COVID-19 related market crash in 2020, while significant, did not have the same lasting impact as the 2015 crash in China.

Our research makes several substantial contributions to the existing literature. Firstly, we contribute to the growing area of study on the vital market structure of ETFs and are relevant to the extensive literature on the optimality of exclusively endogenous liquidity provision in modern financial markets (c.f. Hendershott and Riordan, 2013; Conrad et al., 2015; Kirilenko et al., 2017; Baldauf and Mollner, 2020; Bongaerts and Van Achter, 2021). Recent studies have focused on the role of APs in ETF markets. For example, Pan and Zeng (2017) highlight that the inventory management motives of APs significantly impact the quality of arbitrage. Brown et al. (2021) demonstrate that AP activities can provide signals of non-fundamental shocks. Aquilina et al. (2020) provide insights into APs' participation in the ETF primary market. Gorbatikov and Sikorskaya (2021) characterize the network of AP connections and find that ETF mispricing is related to the network features of APs. Unlike these studies, our research offers a complementary perspective on the ETF market structure by highlighting the role of exogenous liquidity providers, specifically DMMs, who cannot be replaced by normal APs and HFTs. Our work goes beyond evaluating the impact of DMMs on traditional market quality measures, and to the best of our knowledge, is the first paper that systematically examines the value of liquidity provision from DMMs in the ETF market.

Importantly, our theoretical framework and empirical analyses emphasize the importance of considering the necessity and rationality of DMMs. Much of the existing literature focuses on whether DMMs can improve market quality or asset values (Venkataraman and Waisburd, 2007; Anand et al., 2009; Bessembinder et al., 2015). In an era where liquidity is increasingly provided by market participants without formal obligations as DMMs, market quality is becoming less dependent on DMM activities. This suggests that DMMs may not be essential for trading securities. However, our analyses support the importance and rationale of DMMs in the modern finance market, offering a new perspective on this issue by highlighting the role of DMMs in promoting the survival and success of small-cap securities, which is a crucial but often overlooked aspect.

Additionally, our study contributes to the literature on the stability of liquidity provision from DMMs. In recent years, there has been a growing interest in the stability of liquidity provision from DMMs (Anand and Venkataraman, 2016; Kirilenko et al., 2017; Brogaard et al., 2018; Aquilina et al., 2020). Currently, the incentives specified in DMMs' market maker programs in the major ETF markets do not require them to provide liquidity throughout the trading day, leading to the possibility that DMMs may not offer a narrow bid-ask spread during market distress. Our findings on the behavior of DMMs during extreme market stress provide direct evidence that DMMs may not take the risk to provide narrow bid-ask spreads when the markets are in distress, as long as they can meet their market making obligations during normal times. This discussion about the stability of liquidity provision from DMMs is crucial and has significant implications for exchanges and regulators.

Our research also provides new insights into the heterogeneous effects of the introduction of DMMs on market quality across assets with varying characteristics. It is widely understood that the trading costs of many small and newer ETFs can be unpredictable (Amihud and Mendelson, 1986; Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005). The DMM program provides incentives for market makers that were not present under previous market rules, encouraging them to bear these costs. Our findings on the heterogeneous impact of the introduction of DMMs on liquidity have important implications for financial policy regarding the optimal regulation of market makers.

The remaining sections proceed as follows. Section 2 offers background information, establishes the theoretical framework, and formulates hypotheses. Section 3 outlines the data and methodology utilized. Section 4 presents the key empirical findings. Section 5 provides additional discussions on the robustness and regulatory implications of the study. Section 6 concludes this study.

2. Model and Hypothesis Development

2.1. ETF Market and Liquidity Providers

The proper functioning of ETF markets requires collaboration among multiple market participants. A comprehensive overview of the key players in the ETF market and their respective roles is depicted in Figure 1. Three market segments are involved in the operation of ETFs, including the primary market for ETFs, the secondary market for ETFs, and the trading markets for the component securities of the ETFs' underlying benchmarks. After the ETF sponsor has established the ETF's investment objective and operational strategy, APs exchange a basket of the underlying index's securities with the sponsor to create units of the ETF, making the ETF shares available for investment. APs, motivated by arbitrage profits, respond to demand for ETF shares in the secondary market by submitting requests to either create shares or redeem the basket securities of the index with the sponsor (Brown et al., 2021). It's important to note that, without sufficient profit incentive, APs may not participate in this activity, and therefore could potentially have a negative impact on liquidity provision by exacerbating liquidity shortages.

HFTs serve as another form of voluntary liquidity providers to ETFs. They engage in profit-seeking activities through both the arbitrage of ETFs and their component assets and the pursuit of price differences based on ETF price trends. A growing body of literature is investigating the role and value of high-frequency and algorithmic trading, and the findings suggest that these forms of trading have dominated the provision of liquidity in security markets and enhanced market quality during normal times (Hendershott et al., 2011; Brogaard et al., 2014; Li et al., 2021). However, there is a valid concern regarding the continuation of their immediate liquidity provision during times of stress. Studies by Anand and Venkataraman (2016) have revealed that endogenous liquidity providers often withdraw from security markets during such periods. Kirilenko et al. (2017) find that HFTs did not take on large, risky inventories during the flash crash of May 6, 2010, even when faced with large liquidity imbalances and temporary selling pressure, but did not significantly alter their inventory dynamics.

APs and HFTs are key liquidity providers in ETF markets, but they do not have any formal obligation to do so. To address this, several exchanges, including NASDAQ, NYSE Arca in the US and Shanghai Securities Exchange (SSE), and Shenzhen Securities Exchange (SZSE) in China, have implemented DMM programs for ETFs. Unlike the voluntary and endogenous liquidity provided by APs and HFTs, DMM liquidity is obligated and exogenous, who have obligations to provide liquidity to the market by maintaining bid and ask prices for a certain percentage of times. Thus, exchanges offer incentives such as subsidies most commonly in the form of rebate on transaction fees to compensate for the cost of fulfilling such obligations and encourage DMM compliance with their obligations, while APs and HFTs do not receive any such benefits or incentives. Table 1 highlights the behavior patterns of these three participants. Understanding their different obligations, incentives, and actual roles is crucial in the ETF market.

2.2. Theoretical Framework

Kyle (1985) proposed a market microstructure model in which an informed trader with private information about an asset's value trades against a group of uninformed market participants through a continuous double auction. In this auction, both buyers and sellers can submit limit orders at any time, and the informed trader can trade based on their information by submitting informed trades to the market.

Bessembinder et al. (2015, 2020) extended this framework to consider stock DMMs as liquidity providers who enter into contracts with firms to provide liquidity in the market for their stocks. These contracts specify the terms under which the DMM will provide liquidity, such as the minimum size and frequency of orders, and may include incentives for the DMM to meet these terms. The framework demonstrates that these contracts can impact both the value of the firm and the market quality of the stock.

To apply these microstructure models to the context of an ETF DMM, we set up a simplified one-period model. We begin with a general market maker (MM) model and add features specific to the ETF market DMMs. At $t = 0$, the true value of the ETF, v_0, is publicly known. The MM posts a bid price, B, and an ask price, A. Following the characterization of informed and noise traders in Kyle (1985) and Easley et al. (1996), the MM is aware of the probability of the incoming trader being a noise trader, denoted as o, as well as the distribution of the trader's preference shock, e, and the distribution of the value shock, r, when posting these prices.

At $t = 1$, there is a probability of o that the incoming trader is a noise trader with a preferred value of $E \times v_0 = exp(e) \times v_0$, which does not affect the fundamental value of the ETF. The preference shock setting is consistent with that of Glosten and Milgrom (1985) who introduced a "pure preference parameter" for liquidity traders. The trader will buy if $exp(e) \times v_0$ is larger than A and sell if $exp(e) \times v_0$ is smaller than B. There is a probability of (1-o) that the incoming trader is informed. The trader knows that the true value is $R \times v_0 = exp(r) \times v_0$ and will buy if $exp(r) \times v_0$ is larger than A and sell if $exp(r) \times v_0$ is smaller than B. The value shock, $exp(r)$, known by the informed trader, will permanently change the value of the ETF.

At time $t = 2$, the true value is revealed. The market maker clears inventory. Due to competition in market making, *ex-ante*, the market maker posts the bid and ask prices so that her expected profit is zero. Without any constraint, the market maker sets the ask price based on the expectation of making zero profit when selling a share. The expected profit of the market maker, conditional on a trade at the ask price, is:

$$E(Profit) = o[prob(Ev_o > A)(A - v_o)] - (1 - o)[prob(Rv_o > A)E(Rv_o - A) \mid (Rv_o > A)].$$

Intuitively, the MM is effectively giving away a call option to the informed trader at the strike price of A. To make up for this loss, the MM profits from the noise trader. Similarly, the market maker sets the bid price so as to achieve zero expected profit when he buys a share. The expected profit of the market maker, conditional on a trade at the bid price, is given by:

$$E(Profit) = o[prob(Ev_o < B)(v_o - B)] - (1-o)[prob(Rv_o < B)E(B - Rv_o) \mid (Rv_o < B)].$$

In essence, the market maker is giving away a put option to the informed trader, while compensating for the loss by profiting from the noise trader.

When a DMM is introduced into the ETF market, the exchange provides a subsidies for each trade, which can enable the DMM to lower the ask price and raise the bid price. However, the DMM also has an obligation to maintain the bid and ask prices within a specified spread. The DMM must therefore adjust the bid and ask prices to keep the spread within the specified limit, while taking into account the subsidies provided by the exchange.

As becoming DMM is a competitive process, if the subsidy is denoted as s, then:

$$E(Profit) = o[prob(Ev_o > A)(s + A - v_o)] - (1-o)[prob(Rv_o > A)E(Rv_o - A - s) \mid (Rv_o > A)]$$
$$+ o[prob(Ev_o < B)(s + v_o - B)] - (1-o)[prob(Rv_o < B)(B - Rv_o - s) \mid (Rv_o < B)] = 0.$$
$$\textit{subject to } A \text{ - } B \leq \textit{ given spread.}$$

Compared to the case without subsidy, the expected profit of DMM will increases if A and B do not change. If the DMM sets the expected profit as zero, she can increase the bid price B and lower the ask price, A. Furthermore, the constraint that A - B must be less than or equal to the given spread may also lead to a reduction in the average bid-ask spread. Additionally, for the ETF market, the underlying basket has an aggregated ask price (A_u) and an aggregated bid price (B_u).

To prevent arbitrage, the posted bid (B) cannot be higher than A_u and the posted ask (A) cannot be lower than B_u.

To simplify the model, we assume that the preference shock experienced by the noise trader ($E = exp(e)$) follows a lognormal distribution, and the value shock ($R = exp(r)$) also follows a lognormal distribution. Utilizing the classic Black-Scholes assumptions and normalizing the time to maturity, the following expressions are obtained:

$$A = v_o[o\Phi(d_{2e}) + (1-o)\Phi(d_{1r})]/[o\Phi(d_{2e}) + (1-o)\Phi(d_{2r})]$$

$$B = v_o\,[o\Phi(-d_{2e}) + (1-o)\Phi(-d_{1r})]\,/\,[o\Phi(-d_{2e}) + (1-o)\Phi(-d_{2r})]$$

where $d_{2e} = \ln(v_o/A)/\sigma_e - 0.5\sigma_e$, $d_{1r} = \ln(v_o/A)/\sigma_r + 0.5\sigma_r$, and $d_{2r} = d_{1r} - \sigma_r$.

In the case where $\sigma_e = \sigma_r$, $A = v_o[o+(1-o)\Phi(d_{1r})/\Phi(d_{2r})]$ and $B = v_o[o+(1-o)\Phi(-d_{1r})/\Phi(-d_{2r})]$. If the probability of an informed trader is zero, then $A = v_o$ and $B = v_o$. A higher probability of an informed trader is likely to result in a higher ask price, as $\Phi(d_{1r})$ is greater than $\Phi(d_{2r})$. This effect is directly related to the term o, and there is also an indirect effect, as A affects d_{1r} and d_{2r}. If σ_r increases, the call option given to the informed trader by the DMM becomes more expensive and the DMM posts a higher ask price to compensate for the potential loss, as reflected in the $\Phi(d_{1r})/\Phi(d_{2r})$ term. The difference between d_{1r} and d_{2r} increases as σ_r increases. A higher probability of an informed trader is likely to result in a lower bid price, as $\Phi(-d_{1r})$ is smaller than $\Phi(-d_{2r})$. This effect is also directly related to the term o, and there is also an indirect effect, as B affects d_{1r} and d_{2r}. If σ_r increases, the put option given to the informed trader by the DMM becomes more expensive and the DMM posts a lower bid price to compensate, as reflected in the $\Phi(-d_{1r})/\Phi(-d_{2r})$ term. The difference between $-d_{1r}$ and $-d_{2r}$ increases as σ_r increases.

2.3. Hypothesis Development

Based on the theoretical framework presented, we formulate several testable hypotheses. As mentioned earlier, DMMs are incentivized to provide bid and ask prices continuously, thus maintaining a fair and orderly market through mechanisms like rebates, resulting in a consistent supply of liquidity. Meanwhile, other market participants may not be as committed to providing liquidity and may withdraw during uncertain conditions, which can lead to decreased liquidity and negative effects on ETF investors, such as wider bid-ask spreads, lower trading volumes, and increased volatility. More specifically, the DMM's subsidy can increase the bid price B and lower the ask price A relative to the case without subsidy. Furthermore, the constraint that $A - B$ must be less than or equal to the given spread can also help reduce the average bid-ask spread. The lower bid-ask spread can attract more noise traders to participate in trades, thereby increasing the trading volume of the market. These arguments lead to the following hypothesis.

Hypothesis 1. *The introduction of DMMs in the secondary market will result in improved liquidity for ETFs.*

The NAV of an ETF is determined by calculating the weighted sum of the prices of its individual component stocks. The impact of ETF DMMs on the prices of individual stocks is likely to be minimal. Furthermore, the creation and redemption mechanisms of an ETF prevent the ETF market price from straying too far from its NAV. Therefore, we conjecture that the DMMs in the secondary market do not have a significant effect on the ETF price or its NAV. This hypothesis can be stated as follows.

Hypothesis 2. *The introduction of DMMs in the ETF secondary market does not affect the level of either the ETF price or the NAV.*

Since the ask price must be greater than the bid price, a subsidy will have limited impact when the bid-ask spread is already small (e.g., one tick size). However, when the spread is large, the subsidy can have a significant effect and the constraint on the given spread obligation of the DMM may further reduce the bid-ask spread, assuming that the DMM is fulfilling its contractual obligations. Therefore, we hypothesize that the impact of DMMs on the bid-ask spread is greater when the liquidity of the ETF is poor, given the DMM's greater role in providing liquidity. Specifically, we propose the following hypothesis.

Hypothesis 3. *The impact of DMMs on ETFs is more pronounced when ETF liquidity is poor, but not in an extremely distressed condition, compared to when liquidity is adequate.*

Due to the given bid-ask spread constraint, the DMM may decide not to make the market if the profit break-even bid-ask spread is larger than this constraint, particularly in cases of extreme market distress when the bid-ask spread widens significantly. Hence, we postulate that under the current incentive mechanism of market making activities, DMMs are likely to be cautious about providing liquidity in such circumstances. This leads us to the following hypothesis.

Hypothesis 4. *DMMs are cautious to provide liquidity during extreme market distress under the current market making incentives.*

3. Data and Methodology

3.1. DMM Program in China's ETF market

The first ETF in China was listed on February 23, 2005, almost fifteen years after the launch of the first ETF in the United States. Despite this late start, China's ETF market has experienced a rapid growth in both AUM and the number of funds, with the official launch of the DMMs program in the same year as the U.S. market. As shown in Figure 2, the growth of the China's ETF market has been substantial. As outlined in the guidelines released by the SSE and SZSE, there are specific quotation requirements for ETFs of different asset classes. For example, the minimum required amount of stock ETFs is 200,000 RMB, and the maximum bid-ask spread is 0.01 RMB. Additionally, regardless of ETF asset class, DMMs must meet three requirements: 1) The average amount per trade documented by the DMM account is not less than 50,000 RMB.[9] 2) The participation rate during the call auction shall not be less than 80%.[10] 3) The participation rate during the continuous trading shall not be less than 60%.[11] These obligations evidently distinguish DMMs from other voluntary providers of liquidity. To entice market makers to fulfill their obligations, China's exchanges wave part of fees to DMMs' trading activities of ETFs. However, there is no public document revealing the detail of the specific subsidizing mode to DMM's market making activities.

3.2. Data and Sample

Our sample of ETFs was collected from the Shanghai Stock Exchange and the Shenzhen Stock Exchange and includes all equity ETFs from January 2012 to June 2021. After removing ETFs that track foreign indices, those with inadequate data, and those that have always had DMMs since their listing (as this would distort the results of our difference-in-differences regression), our final sample consisted of 144 ETFs, which represent a significant majority of the China's ETF market capitalization. Out of the 144 ETFs in our sample, 97 had introduced market makers by June 2021. It's worth noting that these introductions occurred on various dates.

To explore the channels of DMM impact on ETF markets, we use two types of high-frequency intraday data. The first set is tick-by-tick data, which is used to measure the activity of the

[9]This amount is computed by the ratio of the total amount of trading recorded in a DMM's account to the number of all its trading.

[10]This rate is computed by dividing the number of days a market maker participates in the call auction by the number of trading days in the evaluation period of call auction.

[11]This rate is computed by dividing the length of the time interval a market maker participates in the continuous trading by the length of time interval in the evaluation period of continuous trading.

ETF secondary market and is obtained from the RESSET and WIND databases. The other set is one-minute interval data, which is obtained from the RESSET database and used to calculate the turnover and trading volume of ETFs during the closing call auction. Our data on daily prices, NAV, shares outstanding, and ETF characteristics were obtained from the WIND database. To determine whether an ETF had introduced a market maker, we conducted a search of all fund announcements containing the keywords "market makers" and "liquidity provision". Through this process, we were able to identify the exact date on which an ETF introduced market makers.

In Table 2, we present the descriptive statistics of the key variables. The average market capitalization of the 144 ETFs in our sample is 2064 million RMB, with a relatively wide distribution as the market capitalization of the 75th percentile is still smaller than the mean. The average age of the ETFs in our sample is 4.4 years. On average, the daily returns of the ETFs in our sample have positive means and medians each month.

3.3. Variables

3.3.1. Dummy Variables of DID Regression

The main variable of our DID regressions, the indicator of DMMs, is denoted as D_DMM. It equals one during all months in which an ETF has a DMM and equals zero otherwise. Specifically, for ETFs that did not have a DMM before June 2021, D_DMM remains equal to zero for the entire sample period. For ETFs that introduced a DMM at some point during the sample period, D_DMM equals one starting from the month in which the DMM was introduced.

3.3.2. Measurement of ETF Liquidity

Following Broman and Shum (2018), we focus on three lquidity metrics of ETF secondary market: the proportional quoted spreads, Amihud's illiquidity, and turnover. Particularly, the quoted spread is defined as:

$$Quoted\ spread_{i,t} = \frac{1}{N_t}\sum_{d=1}^{N_t}\log\frac{2(Ask_{i,d} - Bid_{i,d})}{Ask_{i,d} + Bid_{i,d}}, \tag{1}$$

where N_t is the number of trading days in month t, $Ask_{i,d}$ is the ask price, and $Bid_{i,d}$ is the bid price at the close of trading day d for ETF i.

The Amihud's illiquidity (also called price impact) is computed as:

$$Price\ impact_{i,t} = \frac{1}{N_t}\sum_{d=1}^{N_t}\log\frac{|R_{i,d}|}{YVolume_{i,d}}, \tag{2}$$

where $R_{i,d}$ and $YVolume_{i,d}$ are the closing mid-quote return expressed (in percentage) and the RMB volume (in millions) for ETF i on trading day d, respectively. We set $\left|R_{i,d}\right|$ to 0.01% if it is less than 0.01%. This setting can significantly alleviate the impact of zero returns and extremely small returns without altering the sequence of size for the non-zero observations of price impact since the smallest observation of actual $\left|R_{i,d}\right|$ is 0.018% which is a little higher than 0.01%. The Amihud's price impact is a measurement of illiquidity of security.

The turnover is calculated as:

$$Turnover_{i,t} = \frac{1}{N_t}\sum_{d=1}^{N_t}\log\frac{Volume_{i,d}}{Share_{i,d}}, \tag{3}$$

where $Volume_{i,d}$ is the share volume on day d for ETF i, and $Share_{i,d}$ is the shares outstanding of ETF i on day d.

As shown in the definition, the quoted spreads and the Amihud's illiquidity inversely reflect the liquidity of ETFs in the secondary market, while the turnover computed from Eq.(3) positively reflects the liquidity.

3.3.3. Measurement of ETF Market Activity

Following Chordia et al. (2011) and Friederich and Payne (2015), we use the number of transactions and the turnover per transaction as the metrics of secondary market activity. We start by counting the number of transactions of an ETF in each day. Then, we compute the average number of shares per transaction in each day. Third, after dividing the average number of shares per transaction in each day by the shares outstanding, we get the average turnover per transaction in each day. Finally, we average the daily metrics in each month.[12]

When it comes to ETF primary market, we use the coefficient of variation for shares outstanding (Box et al., 2019) to measure the level of market activity, $CVshare_{i,t}$, which is computed as:

$$CVshare_{i,t} = \frac{\sigma_{i,t}^{share}}{\mu_{i,t}^{share}}, \tag{4}$$

where $\sigma_{i,t}^{share}$ and $\mu_{i,t}^{share}$ are the standard deviation and mean, respectively, of ETF i's daily total number of shares outstanding during month t. A high level of $CVshare_{i,t}$ is associated with a high frequency of ETF shares being redeemed or created, thus corresponding to a high level of ETF activity in the primary market.

3.3.4. Measurement of ETF Price Efficiency

We measure the price efficiency of ETFs by two metrics: the absolute value of ETF premium and the frequency of extreme observations of ETF premiums during a month. The premium of ETF i in d is computed by the real-time price and the indicative optimized portfolio value (IOPV) of ETFs:

$$Premium_{i,d} = Price_{i,d}/IOPV_{i,d} - 1. \tag{5}$$

[12] Apparently, all else being equal, an ETF over a month with more trading days tends to have more transactions, and if there are several days for holidays or festivals in a month, this effect increases. Therefore, we average the total amount by the number of trading days.

We choose 30 and -30 basis points as the thresholds because the normal arbitrage cost of ETFs traded in China's market is approximately 30 basis points. Therefore, the observations of premiums higher than 30 basis points or smaller than -30 basis points are defined as extreme observations. For the metrics, high magnitude corresponds to low price efficiency of ETF market.

3.3.5. Other Variables

We also compute some other variables that serve as control variables or grouping variables, including the best bid-ask spreads, monthly turnover, shares outstanding, monthly volume, market caps, ETF age, ETF return, fund flows, and the realized volatility in each month. We compute the fund flows of an ETF in a day by dividing the difference between ETF outstanding shares in the day and in the previous day by the shares outstanding in the previous day, then average the daily fund flows in each month to get the month-frequency observation. The realized volatility of ETF prices is computed by:

$$Realized\ volatility_{i,t} = \frac{1}{N_t} \sum_{d=1}^{N_t} Rclose_{i,d}^2, \tag{6}$$

where $Rclose_{i,d}$ is the return computed by closing price for ETF i on trading day d in month t.

3.4. Methodology

We employ the DID approach to assess the association between the gradual introduction of DMMs and market quality in China's ETF market. The regression is expressed as:

$$Y_{i,t} = \alpha + \beta\, D_{i,t} + \delta\, X_{i,t} + A_i + B_t + \upsilon_{i,t}. \tag{7}$$

In Eq.(7), $Y_{i,t}$ is a measure of market quality in month t for ETF i, $X_{i,t}$ is a set of time-varying fund-level variables, A_i and B_t are vectors of fund and month dummy variables that account for fund and month fixed effects, and $\upsilon_{i,t}$ is the error term. $D_{i,t}$ is a dummy variable that equals one in the months after fund i introduces market maker and zero otherwise. Therefore, the coefficient β reveals the impact of the introduction of market makers.

4. The Impacts of DMMs on ETF Market

4.1. Do DMMs Enhance ETF liquidity?

To test Hypothesis 1, we focus on the changes in ETF liquidity surrounding the introduction of DMMs. In this section, we first analyze the overall liquidity of ETFs around the DMM program during the entire sample period (January 2012 to June 2021). Then, we explore the heterogeneity of DMMs' impact on ETF liquidity. Finally, we use end-of-day call auction trading data to eliminate any potential impact from APs and HFTs on our results.

4.1.1. Main Results

We use a DID approach to test whether DMMs fulfill their basic obligations by measuring the changes in ETF liquidity around the introduction of market makers. In Table 3, we examine the impact of DMMs on ETF liquidity using three indicators: quoted spread, Amihud's illiquidity, and turnover. As shown, all dummy variables for the introduction of DMMs are significant, with four of the six having a significance level of 1%. For example, column (1) shows that the entry of market makers led to a reduction in the quoted spread, as indicated by the coefficient of -0.527. The coefficients of Amihud's illiquidity and turnover, as shown in columns (3) and (5), are also statistically and economically significant. Furthermore, after controlling for monthly turnover, market capitalization, ETF premium, ETF returns, ETF price, the realized volatility of ETF returns, and fund age, as shown in columns (2), (4), and (6), the results remain similar. In particular, the coefficients for the dummy of market makers are -0.415, -0.492, and 0.54 when liquidity is measured by quoted spread, Amihud's illiquidity, and turnover, respectively. To summarize, the introduction of DMMs to ETFs enhances ETF liquidity, suggesting that DMMs can play a role in increasing ETF liquidity even with the presence of authorized participants, who have a critical impact on ETF liquidity.

Examining the dynamic changes of ETF liquidity around the introduction of DMMs can provide further evidence on their potential impact. To do this, we use a standard regression model that includes a series of dummy variables to trace the month-by-month effects of DMMs' introduction on ETF market quality and activity metrics. We follow the approach used in Sun and Abraham (2021) and consider the entire set of relative-time indicators in the regression, but only report the results from $t-5$ to $t+10$, following the original event-study analysis of Beck et al. (2010). These results are plotted in Figure 3.

Figure 3 illustrates three key points: changes in ETF liquidity did not precede the introduction of DMMs, the impact of DMMs' introduction on the improvement of ETF liquidity materializes very quickly, and this influence is persistent. For instance, as shown in Figure 3, the coefficients on the DMMs' introduction dummy variables are insignificantly different from zero for all months before DMMs' introduction, with no trends in ETF liquidity prior to DMMs' introduction. Moreover, note that ETF liquidity increases immediately after DMMs' introduction. The impact of DMMs' introduction on ETF liquidity levels off just after the introduction, indicating a steady and persistent effect on ETF liquidity.

Table 4 presents the results of joint significance tests for leads and lags. The values of F-stat in the first three columns show that there were no significant tendency before the introduction of DMMs, and the values in the last three columns show that there is significant tendency after the introduction of DMMs. Taken together, the parallel assumption test is past and there is indeed positive effect of introducing DMMs on ETF liquidity.

4.1.2. Evidence from the Market Activity

Provided the liquidity of ETF market are indeed enhanced after the DMM program, there must be more trading activities in the secondary market of ETFs. To test this conjecture, we now turn to the reactions of ETF micro-activity after the introduction of DMMs. Intuitively, the introduction of DMMs to ETF markets may directly influence market activity, such as the transactions of ETF shares in the secondary market and the creations or redemption activity in the primary market. These market activities are potentially the actual sources driving ETF liquidity to change. Table 5 tests this prediction.[13]

Consistent with our conjecture, the coefficients of D_DMM presented in Table 5 show that the market activity does register significant enhancement after the introduction of DMMs, particularly in the secondary market of ETFs. Specifically, the transaction of ETFs in the secondary market becomes more frequent, reflected by the significantly positive coefficients of 25.972 and 221.972 in columns (3) and (4). The increased market activity is also reflected by the enhanced average turnover per transaction shown by the significant and positive coefficients of D_DMM in columns (5) and (6). These findings shed light on the link between the enhancement of ETF liquidity and the changes of market activity of ETF secondary market. More explicitly, consistent with the interpretation of how DMMs create value for stocks (Menkveld and Wang, 2013), the presence of DMMs in ETF markets can facilitate more transactions of incumbent investors, and attract new investors due to the liquidity guarantee. Consequently, DMMs reduce the trading costs by retaining more counterparties to trade. Accordingly, ETF liquidity improves with more traders participating in the markets and a higher probability of delivering transactions.

[13] Due to the restrictions on retrieving the tick data, we have only collected the tick data of ETF trading from 2016 to 2019. Therefore, the regressions in this table only based on 2832 observations.

4.1.3. Evidence from ETF Price Efficiency

With DMMs present in the ETF secondary market, they can meet investors' demand for ETF shares more rapidly, alleviating the pressure on ETF prices. This leads to a quicker correction of ETF prices towards the price of basket securities. The presence of DMMs enhances ETF market liquidity, reducing liquidity risks and arbitrage costs. As a result, arbitrageurs react more actively to ETF premiums or discounts compared to the times without DMMs. The extreme observations of premium occur less, as arbitrageurs don't have to wait for the premium or discount to reach a very high level before offsetting their arbitrage costs. These changes are potentially beneficial in smoothing the variation of ETF prices and enhancing ETF price efficiency. Based on these reasons, we expect that introducing DMMs can not only enhance ETF liquidity, as expected, but also enhance ETF price efficiency. It should be noted that this function is not included in the DMM's affirmative obligation.

To test the above conjecture, we empirically examine the impact of introducing DMMs on the absolute premium of ETFs and the frequency of extreme premiums. As shown in columns (1) to (3) of Table 6, all the coefficients of the DMM indicator are negative and significant at the 5% or 1% level. After controlling for an array of variables, as shown in columns (2) and (4), the magnitude and significance of coefficients are also significantly negative and close to their counterparts in columns (1) and (3), respectively. These results suggest that introducing DMMs to ETF markets can enhance ETF price efficiency by reducing the magnitude of ETF premium and the frequency of extreme premiums.

4.1.4. Heterogeneity of DMMs' Impact on ETF Liquidity

To test the Hypothesis 3 that the impact of DMMs on ETFs is more pronounced when the ETF liquidity of ETFs is very poor than it is when the liquidity is adequate, we conduct quantile regressions of ETF liquidity on the DMM dummy. We run the regressions on 19 quantile levels

(Q5, Q10, ..., Q95) to acquire the coefficients of DMM dummy and then plot them in Figure 4. As shown in the figure, the distribution of the coefficients is inverted U-shape when the liquidity metrics positively correspond to liquidity. It indicates that, as the liquidity level of ETFs increases from the very poor level to a less poor level, and then to a very high level, the positive effect of DMMs on ETF liquidity increases first and then decreases.

It is reasonable to observe this heterogeneity of the impact of DMM on ETF liquidity. When the liquidity of ETFs is the extremely bad, making market for ETFs will incurring very high costs for DMMs, so DMMs are not active in providing liquidity for ETFs anymore. When the liquidity level increases to a less poor level, DMMs find it cheaper and easier to make market for ETFs than in the extremely poor level. When the liquidity is in a very high level, DMMs find it hard to enhance the liquidity even in this case they have sufficient inventory of securities to make the market. This characteristic is very instructive for the regulating of ETFs' market making.

We also examine the heterogeneity of DMMs' impact on ETF liquidity across funds with different market capitalizations. To do this, we perform a DID regression by introducing the interaction term between the DMM dummy and the market capitalization of each ETF into Eq.(7). Column (3) of Table 7 reveals a negative coefficient for the interaction term (-0.212), indicating that the boost in ETF turnover is more significant for funds with small market caps. The positive coefficients of the interaction terms in columns (1) and (2) (0.229 and 0.392, respectively) suggest that the reductions in ETF quoted spread and Amihud's illiquidity are also more pronounced for small-cap ETFs. These findings highlight the heterogeneous impact of DMMs on ETF liquidity across different funds, underscoring their potential to support the growth of small ETFs.

There are several potential reasons that could explain the heterogeneity of the impact of DMMs on ETF liquidity. Firstly, it is likely that liquidity for ETFs with big market cap and old age is already better than that for their counterparts with small market cap and young age. Therefore, the marginal increase of liquidity level in the latter ETFs after DMMs' introduction is more likely to be substantial and significant. This marginal contribution is similar to the notion that the utility of rewarding a sum of money to a low-income group is apparently higher than it is to a high-income group. Secondly, the characteristics of the ETF constituent assets may be a reason for the heterogeneity of impact. ETFs can be composed of a wide variety of assets, and these assets can have different liquidity profiles, trading characteristics, and risk levels. Therefore, the impact of DMMs on ETF liquidity may be more significant for certain types of ETFs depending on their underlying assets and the trading characteristics of those assets. Finally, the heterogeneity in the impact of DMMs on ETF liquidity may also be related to the association between asset volatility and equity capitalization. As asset volatility typically decreases with equity capitalization, small ETFs may benefit more from the presence of DMMs compared to ETFs with big capitalization.

4.1.5. Evidence from the Call Auction Period

The Chinese equity markets operate a hybrid structure combining call auctions with continuous trading, providing us a unique opportunity to examine the pure effect of DMMs. During call auctions, both the HFTs and APs are much less active than they are in continuous trading periods. Consequently, examining the impact of DMMs in the call auctions can largely minimize the potential interference of APs' and HFT' activities. Both the SSE and SZSE determine the opening prices with the market structure of call auctions from 9:15 a.m. to 9:25 a.m. After that, the two exchanges operate in the market structure of continuous trading from 9:30 a.m. to 2:56 p.m. Near the end of a trading day, the closing prices of equities traded in the SSE are still via the continuous trading, while the closing prices of equities traded in the SZSE are determined by the call auction trading from 2:57 p.m. to 3 p.m.

Since the closing auction accounts for a much higher fraction of the trading volume (Theissen and Westheide, 2020),[14] we investigate the impact of DMMs' participation on the closing auction. More importantly, the difference in the forming of closing price between the SSE (via continuous trading) and SZSE (via call auction) can just provide a comparison of DMMs' roles in the trading environments with and without APs' and HFTs' participation. Table 8 details the features of the main market participants during the formation of the closing price of ETFs in SSE and SZSE.

Due to the differences of participants of ETF market in the closing trading between SSE and SZSE, we expect that the ETFs in SZSE with DMMs will display better liquidity than ETFs without DMMs in the closing trading, while ETFs in SSE with DMMs will not. To test this conjecture, we conduct the DID regression on ETF liquidity by using the trading data during the closing of SSE's and SZSE's ETF markets.

We use one-minute interval data to construct the dependent variables: turnover and trading volume.[15] Specifically, we aggregate the trading volume of ETFs and average the effective spread after 2:57 p.m of each trading day to measure the daily liquidity of ETFs in each trading day. After this, we average the daily metrics among each month. Among the entire sample ETFs over the period from January 2012 to June 2021, 53 ETFs are traded in the manner of call auctions at the end of trading days, corresponding to 3342 monthly observations, remaining 91 ETFs (5476 observations) serving as the comparative samples which are traded in continuous manner.

We regress the turnover and trading volume of these 53 ETFs during the closing auctions on the DMM dummy. The results are presented in Table 9. As shown, the coefficients of D_DMM in columns (1) and (2) are always positive and significant. It suggest that introducing DMMs to ETFs can significantly improves ETF liquidity during the closing auctions. When regressing the trading volume on the D_DMM, we find a similar result (shown in columns (5) and (6) of Table 9):

[14] The closing auction has twice the trading volume of that during the opening auction in the China's ETF market.

[15] We did not test the quoted spread and Amihud's illiquidity in this period because quite a lot of the recorded ask and bid prices of SSE's ETFs during the 3 minutes of closing are missing or set to 0 in the database.

the positive impact of DMMs on the trading volume is very significant in all the 53 ETFs traded in the manner of call auctions at the end of closing trading. Such significant and positive effects of DMMs on ETF liquidity are not observed in the regressions based on the samples funds traded by the continuous manner in the SSE's closing trading period.

To summarize, even the trading in call auctions only account for a little fraction of the aggregate trading, DMMs still play a role in enhancing ETF liquidity during the periods of call auctions. Note that this result is estimated under a clean setting with rare activities of APs and HFTs, thus confirming that the observed liquidity enhancement in ETFs after the DMM programs is robust. These analyses provide convincing evidence supporting our Hypothesis 1.

4.2. Do DMMs Enhance Liquidity in Distressed Conditions?

Overall, our findings so far have shown that the introduction of DMMs is beneficial to ETF liquidity, but they don't detail DMMs' behaviors during unfavorable markets when liquidity is most needed. To test the Hypothesis 4 that DMMs are cautious to provide liquidity during the extremely distressed market conditions, we first utilize a typical market crash (the 2015 Chinese financial market crash) to test the role of DMMs in the extremely distressed market. After this, we text the role of DMMs in the more generalized distressed market condition, which is characterized by a very wide market-wide spread in ETF markets. Additionally, we use the quantile regressions to investigate the role of DMMs in the fund-level distressed condition, which is characterized by the very high quantile of ETF effective spread. Note that the fund-level distressed condition is identified by the high quantile of ETF's spread. Since the quantile regression in this subsection is to split the data into multiple quantiles according to the distribution of ETFs' effective spreads (not the market spread computed by all ETFs' spreads), the results estimated from different quantiles can just reveal the role of DMMs in the different fund-level conditions. Particularly, the results of Q95 (95% quantile) is corresponding to the very distressed fund-level conditions and the results of

Q5 (5% quantile) is corresponding to the very pleasure fund-level conditions with highly sufficient liquidity.

4.2.1. Evidence from the 2015 Chinese Financial Market Crash

The 2015 Chinese financial market crash provides a valuable opportunity to investigate this issue. We first tally the average relative spread of ETFs and compare between the crash and non-crash periods, and between ETFs with and without DMMs. The results are presented in Table 10. If DMMs continue providing liquidity for ETFs during the crash, we will observe narrower spreads in ETFs with DMMs than in those without DMMs.

As shown in Table 10, the relative spreads of both the ETFs with and without DMMs were getting wider during the market crash, indicating a significantly negative impact of this crash on ETF liquidity. Specifically, ETFs without DMMs have an mean relative spread of 0.0162 in the period of 2015 market crash, significant higher than the mean during the non-crash period. As for ETFs with DMMs during the 2015 market crash, their mean spread is also significantly wider than the average spread in other times. As shown Panel B, during the periods of non-crash, the average spread of ETFs with DMMs (0.009) is significantly smaller than that of ETFs without DMMs (0.0126) did not have narrower bid-ask spreads than their counterparts without DMMs. However, the difference between them falls to 0.0021 and is insignificant. This finding suggests that DMMs did not benefit ETF markets by improving ETF liquidity during 2015 market crash. This interpretation is predicated on the premise that there is no additional reward for DMMs offering bid and ask quotations to ETF markets during stressful times.

We then using a formal test on the impact of DMMs on ETF liquidity during this market crash. We estimate the relative spread around the crash by the standard DID regressions. Specifically, we construct the sample consisting of ETFs always had DMMs and ETFs did not have DMMs during the sample periods from September 2014 to February 2016. The regression model is:

$$Rspread_{i,t} = \alpha + \beta_1 Treat_{i,t} + \beta_2 Crash_{i,t} + \beta_3 Treat_{i,t} \times Crash_{i,t} + Controls_{i,t} + \upsilon_{i,t},$$

where $Rspread_{i,t}$ is the relative spread in month t for ETF i, $Treat_{i,t}$ is a dummy variable equaling one if an ETF has contracted with DMMs and zeros others, $Crash_{i,t}$ is a dummy variable equaling one if the current month is during the 2015 Chinese market crash (from June 2015 to February 2016) and zeros others. Therefore, the coefficient β_3 reveals the difference of relative spread between ETFs with DMMs and without DMMs during the market crash. The sample funds includes 62 ETFs. The results are presented in Table 11.

As shown in Table 11, the coefficients of $Crash$ is significantly positive as expected, indicating that all ETFs (with and without DMMs) will experience a high spread. However, the coefficient of the interaction term ($Treat \times Crash$) very small and insignificant, suggesting even the ETFs with DMMs could not benefit from the DMMs when the market is extremely distressed, consistent with the statistics present in Table 10.

4.2.2. Evidence from the Market-wide Distressed Conditions

To test the Hypothesis 3 that DMMs in a more general background of market crash, we sort the market condition into 20 levels by the averaging the relative spread of all the ETFs. After this, we distribute the observations of every ETFs relative spread to the corresponding groups if the level of the current market conditions is in a certain window. Thhen we tally the average relative spread of ETFs and compare between ETFs with and without DMMs. The results are presented in Table 12.

As shown in Table 12, the average spreads of ETFs without DMMs across all the windows of market spread are higher than those with DMMs. However, the differences are insignificant and very small when the market is in the extremely distressed conditions (above Q85), suggesting that DMMs are very unable to improve the liquidity of ETFs, consistent with the finding during 2015 market crash.

We also use another alternative to test whether DMMs would be willing to provide liquidity for ETFs during distressed markets under the current mechanism of DMM incentives. Specifically, we examine DMMs' behaviors by regressing ETF relative spread on the ETF DMM dummy, the dummy of the specific relative spread quantile of ETF market, and the interaction term between them. The regression is expressed as:

$$Rspread_{i,t} = \alpha + \beta\, D_{i,t} + \gamma\, D\_m_t + \theta\, D_{i,t} D\_m_t + \delta\, X_{i,t} + A_i + \upsilon_{i,t}. \tag{8}$$

In Eq.(8), $Rspread_{i,t}$ is the relative spread of ETF i in month t, D_m_t, equals one when the effective spread of ETF market over month t falls in a certain quantile and equals zero otherwise, and $X_{i,t}$ is a set of time-varying fund-level variables. The relative spread of ETF market in month t is the average relative spread of all ETFs over the month. We sort the market spreads into 20 groups according to ascending order. Then to test the role of DMMs when market spread falls in a certain quantile (e.g., 95% to 100%), we assign the value of D_m to one for the observations in the quantile and zero otherwise. If DMMs provide extra liquidity when ETF markets have wider spread than during other times, the coefficient of the interaction should be significantly negative. If DMMs provide less liquidity during the wide-spread time than during other times, we would expect to see a positive coefficient on the interaction term. If the sum of the coefficients on the DMM indicator and on the D_m is close to zero, then DMMs are not providing liquidity during the time in the quantile window.

As mentioned before, it is likely that DMMs are not willing to continue providing liquidity when

ETF markets have very wide spreads. The results of these regressions are summarized in Table 13. As expected, all the coefficients of DMM dummy in Table 12 are significantly negative. The coefficients of the interaction of D_DMM and D_m in the third columns different across the 19 quantile windows. Specifically, when the quantile window is below Q50, which corresponds to a very better level of market liquidity, the coefficient is positive, with nine of the ten coefficients are very significant, and all of them are less than the absolute values of their respective coefficients of the D_DMM. This evidence is consistent with the intuition that DMMs' positive impact on ETF liquidity is very weak. However, as the quantile window increases to the interval of relative poor liquidity (Q50$\sim$Q85), the coefficients of the interaction term become negative and some of them are significant. These positive interactions indicate that it is in those quantile windows of ETF market spread that the DMMs play their role in improving the liquidity of ETFs to the greatest extent. When the market spread comes to the top 15% window (Q85$\sim$Q100), the coefficients of $D\_DMM \times D\_m$ become positive, implying that DMMs provide less liquidity during this periods than during others.

The last third columns in Table 13 show the approximate estimates of ETFs' spread at the 19 quantile windows of market spread by using the regression results shown in columns (1) to (4). Particularly, as shown in column (4) of Table 13, during normal times, ETFs without DMMs have a spread of 0.011. During the top 10% extremely distressed times (measured by market-wide spread), ETFs without DMMs experience a spread of 0.0103 (0.0109 -0.0006). Meanwhile, ETFs with DMMs show an average spread of 0.0091 (0.0109 -0.0006 -0.0052 +0.004), 0.0012 less. These findings suggest that DMMs still provide some liquidity support during the top 10% most distressed market months, but not as strong as that during the other quantile windows as shown in columns (3) through (8).

The cross-row comparisons suggest that DMMs indeed are very reluctant to continue providing liquidity for ETFs when market conditions are extremely distressed. For example, as shown the column (7), the differences of spread between ETFs DMMs and without DMMs, which can show the policy effect of DMMs on ETF liquidity, vary form 0.0012 to 0.0065, and the smallest value is in the windows of Q90 $\sim$ Q100 and Q0 $\sim$ Q5. Also, taking into account the coefficients of interaction term, we conclude that DMMs are very disinclined to provide liquidity for an extremely distressed ETF market. Overall, the findings in Tables 10 to 13 provide supportive evidence for Hypothesis 4.

4.2.3. Evidence from the Fund-level Distressed Conditions

The empirical evidences in the previous two parts shows the behaviors of DMMs during the market-wide distressed conditions. But Can this conclusion apply to the fund-level distressed conditions? To test this, we run the regression of ETF relative spread on the ETF DMM dummy, the dummy of the specific relative spread quantile, and the interaction term between them. The regression is expressed as:

$$Rspread_{i,t} = \alpha + \beta\, D_{i,t} + \gamma\, D\_e_t + \theta\, D_{i,t} D\_e_t\ + \delta\, X_{i,t} + A_i + \upsilon_{i,t}. \tag{9}$$

In Eq.(9), $Rspread_{i,t}$ is the relative spread of ETF i in month t, D_e_t, equals one when the relative spread of the ETF i in month t falls in a certain quantile and equals zero otherwise, and $X_{i,t}$ is a set of time-varying fund-level variables. We sort ETF spreads into 20 groups according to ascending order. Then to test the role of DMMs when ETF spread falls in a certain quantile (e.g., 95% to 100%), we assign the value of D_e to one for the observations in the quantile and zero otherwise. The results of these regressions are summarized in Table 14.

As expected, all the coefficients of DMM dummy in Table 14 are significantly negative. The coefficients of the interaction of D_DMM and D_m in the third columns different across the 19 quantile windows. Specifically, when the quantile window is below Q60, which corresponds to a better level of market liquidity, the coefficient is positive and very significant, consistent with the intuition that DMMs' positive impact on ETF liquidity is very weak when ETF liquidity is in a high level. However, as the quantile window increases, the coefficients of the interaction term is smaller and smaller. This tendency indicates that DMMs provide extra liquidity when ETFs have wider spread than than in other times.

Columns (5) to (7) in Table 14 show the approximate estimations ETFs' spread at the 20 quantile windows of ETF spread by using the regression results shown in columns (1) to (4). As shown in column (4), during the top 5% extremely wide spread window, ETFs without DMMs experience a spread of 0.0325 (0.0231 +0.0094). Meanwhile, ETFs with DMMs show an average spread of 0.0298($= 0.0231+0.0094-0.0043+0.0016$), 0.0027 less. This difference exceeds eight of the other difference shown in columns (7). For the difference in the Q90$\sim$Q95 window, the magnitude is more substantial, exceeding all other differences in columns (7). These findings suggest that DMMs are still able and willing to make market for ETFs even the fund's spread reaches to a very high level. Conversely, as shown in the last two rows of Table 13, DMM are unable or unwilling to provide liquidity when there is a severe market-wide depression. The potential reason may be that a market-wide distressed condition seriously limit the DMMs to provide liquidity. In this case, DMMs find it hard to the replenish the inventory of ETF shares because the entire market is in a poor level conditions of liquidity. However, only the fund-level distressed condition is not so bad for DMMs to undertake their obligations of providing liquidity.

Taken the results of Tables 12, 13, and 14 together, we now have a clear view on the role of DMMs during the distressed conditions: when the the distressed condition is on the market-wide level, DMMs will probably hesitate to provide liquidity for ETFs. However, when the distressed condition is only on the fund level, DMMs are still able and willing to provide liquidity for ETFs.

4.3. Are DMMs Distorting ETF Markets?

To test the hypothesis that the level of ETF price or NAV is not affected by the introduction of DMMs in ETF secondary market, we examine whether there are changes in ETF price around DMMs' introduction. Specifically, we compute the abnormal returns (ARs) and cumulative abnormal returns (CARs) for a sample of 67 ETFs that contracted with designated liquidity providers between January 2012 and June 2021 and for a sample of matched ETFs that did not contract with liquidity providers during the same period. We identify the matched ETFs following the approach by Huang and Stoll (1996). For each sample ETF, the matched ETFs are selected from the pool of all ETFs that trade without DMMs in the secondary market on the DMMs' introduction day of the sample ETFs. After screening control ETFs, we compute a score (similar to Huang and Stoll (1996)) for each pair of sample and control ETFs by the following expression:

$$Score_m = \sum_{m=1}^{3} \left[\frac{x_m^{sample} - x_m^{control}}{0.5(x_m^{sample} + x_m^{control})} \right]^2, \tag{10}$$

where x_m is either any of the average price, average daily share volume, or market capitalization of an ETF over the trading days t_i - 106 to t_i - 6 (t_i is the inception day of ETF i).

The event window is from five days before the entry of DMMs to 22 days after the introduction day (t_i) of DMMs. We estimate the market model parameters by using returns of the CSI 300 Index and ETF market returns or NAV returns over the trading days t_i - 106 to t_i - 6. Scholes and Williams (1977) β is computed to adjust for infrequent trading. The results are presented in Table 15.[16]

As shown in the third column of Table 15, although the sample ETFs registered significant CARs in several days around the introduction of DMMs, it did not mean a negative effect of DMMs'

[16]Due to the limited space and high similarity of results, we only report the results based on ETF price, and the results based on NAV are available upon request.

introduction on ETF price, especially considering the value of ARs which do not significantly deviate from zero. Actually, as shown in column (4), such negative CARs also appeared to the matched ETFs which had not introduced DMMs during the event window. Therefore, the results shown in columns (5) and (6) reflect the real policy effect, as they have ruled out the possibility of market-wide trends affecting ETF price. As shown, almost all the differences between sample ETFs' CARs and matched ETFs' CARs are insignificant, with some positive and some negative values, indicating that introducing DMMs to the ETF market didn't affect the price of ETFs significantly.

Given that the ETF market is distinct from the stock market in several aspects, we are not surprised to observe insignificant values of CARs for the ETFs starting to be traded with DMMs compared with ETFs without DMMs. Note that ETFs have a unique structure that limits the possibility for market makers to manipulate ETF price. Moreover, as a basket of securities, an ETF is very likely to have less fundamental uncertainty and low information asymmetry than a single stock. Therefore, the result is consistent with the model implications of Bessembinder et al. (2015) that DMM contracts are more likely to be value-enhancing for stocks characterized by greater information asymmetry and more fundamental uncertainty. It therefore suggests that the entry of DMMs can improve ETF liquidity without causing significant movement of ETF price, suggesting our Hypothesis 2.

4.4. Do DMMs Help ETFs Survive or Thrive?

4.4.1. Evidence from ETF Liquidation

One may wonder whether ETFs with DMMs are more likely to survive than those without DMMs. To investigate this issue, we compare the statistics of survival status of ETFs with and without DMMs.[17] The results are presented in Table 16.

[17] Actually, the hazard model (Cox, 1972) is a very practical approach to analyze the survival status. However, we find it inappropriate for our sample ETFs, because the hazard model requires that the treat group must be treated

The sample funds in Table 16 include 151 stock ETFs in the period from the beginning of 2012 to June 2021. As shown in column (3), 24 ETFs were liquidated, leaving 127 surviving ETFs in June 2021. Among ETFs with DMMs, only nine of them had been liquidated, or 6.98%. This liquidation percent is much less than the liquidated ETFs without DMMs (28.3%). These statistics intuitively suggest that ETFs without DMMs are more inclined to suffer liquidation than ETFs with DMMs.

4.4.2. Evidence from ETF Growth

We also examine whether DMMs facilitate ETF growth by comparing the average market values of ETFs over the six months before introducing DMMs and over the six months after introducing DMMs. We use the product of ETF share price and the number of ETF shares instead of ETF AUM as our focus, because AUM is only available in quarters and lower frequency and thereby is inaccurate to capture the daily and monthly changes of ETF market value.[18] To capture the changes of ETF market values around DMMs' introduction, we only include ETFs with at least six months' observations before the introduction and at least six months' observations after the introduction, leaving 54 qualified ETFs in the final sample. The results are presented in Table 17.

As shown in Panel A of Table 17, ETF AUM after introducing DMMs registered a mean of 3.278 billion RMB, significantly higher than that of 2.861 billion RMB before introducing DMMs. Moreover, we document less liquidation of ETFs with DMMs than those without, and very high average growth rate (65.87%) of ETF market value over the six months after the introduction of DMMs. After splitting the ETFs into the small group (Panel B of Table 17) and big group (Panel C of Table 17) according to ETF average market value during the six months before introducing

before the subsequent follow-up visit, but our sample ETFs are gradually being introduced DMMs throughout the entire sample period.

[18]Since the shares of many ETFs are constantly changing, using the metrics averaged by the daily observations can reveal more details of the actual change.

DMMs, we find that the average growth rate of the small group is much higher than that of the big group, suggesting that DMMs' positive impact on ETF growth is more pronounced in ETFs with small market value.

To further confirm the positive impact of DMMs on ETF's growth, we regress the ETF's market cap on the DMM dummy. The result is shown in Table 18. Column (1) suggests that the introduction of DMMs induced an increment in ETF's market cap, indicated by the coefficient of 0.314. The coefficient of D_DMM shown in columns (2) is also statistically and economically significant when controlling for an array of time-varying fund-level factors, suggesting that DMMs can help ETF's market cap grow. Jointly, the results in Tables 16, 17, and 18 imply that DMMs can help ETF survive and grow.

4.5. Who Are the Prime Beneficiaries of ETFs' DMM Programs?

In this subsection, we directly test whether the participants in ETF markets can benefit from the DMM program. Specifically, we examine the trading costs, market cap, the product of ETF bid-ask spread and trading volume, fund flows, and trading volume to proxy for the benefits of ETF investors, fund issuers, market makers, APs, and exchanges around the introduction of DMMs, respectively. The results are presented in Table 19.

As shown in Table 19, the trading costs faced by investors, proxied by ETF effective spread, are reduced after the introduction of DMMs. Such a reduction of trading costs are very likely to enliven the market activity of ETFs. For the fund issuers, they also benefit from the introduction of DMMs, indicated by the results in columns (3) and (4) that ETF market cap grows significantly.[19] As for market makers, although there is no DMM before the program, we could approximate the

[19] We did not find any announcement or document regarding the change of management fee percentage during our sample periods, so the changes of compensation to the issuers around DMMs' introduction, which is computed by the changes of product of AUM and percentage management fee, can be approximately reflected by the changes of AUM.

profits of all market makers as a whole, including voluntary liquidity providers and DMMs, by the production of ETF bid-ask spread and trading volume. Columns (5) and (6) show that the profits of market makers significantly improve after introducing DMMs. Notably, this result is not contrary to the observed reduction in ETF spread, on the grounds that the increase in ETF trading volume has offset the negative impact of ETF spread on the profits of market makers. With regard to APs, we find in columns (7) and (8) that fund flows to ETFs experienced significant and positive inflows after introducing DMMs, suggesting that APs conduct more arbitrage activity between ETF primary and secondary markets. Finally, since there is no other information regarding the revenues of exchanges when promoting DMMs to ETF trading, we use the trading volume to approximately judge whether exchanges can benefit from DMM programs. Apparently, exchanges will benefit from higher trading volume of ETFs, and the results in columns (9) and (10) show a very significant and positive increase in ETF trading volume. Figure 5 also reveals the similar changing of those variables proxing the benefits of ETF market participants. In sum, the results shown in Table 19 and Figure 5 indicate that all the participants of ETF markets can benefit from the introduction of DMMs.

5. Additional Discussions

5.1. Addressing the Endogeneity Concern: Evidence from PSM-DID

To address the endogeneity concern of self-selection bias, we use the PSM-DID approach to reconduct all the DID regressions in Table 3, and the results (reported in Table 20) are qualitatively consistent with the results presented in Table 3. Specifically, we use the nearest-neighbor matching technique to find the most suitable observation matched with each observation of treatment sample. Both the DID regressions after phase-by-phase matching and cross-sectional matching are conducted in our unreported analyses. All the coefficients of DMM indicators estimated from

PSM-DID regressions have the same signs with their counterparts reported in our previous tables, and all of them are significant and have a slightly higher magnitude. Our examination shows that the liquidity is not significantly different between ETFs with and without DMMs in each month before the introduction of DMMs. It confirms that the changes of ETF liquidity are due to the DMMs' presence rather than the time trend, and our analyses based on the DID regressions are robust.

5.2. Diagnostic of Staggered DID Estimates

Since the results are estimated by the two way fixed staggered DID regressions which may have biases, one may the likelihood of biases of our estimates. Due to the following reasons, our results can provide relatively reliable estimates of the real effects of the DMM program in the China's ETF market. First, since our sample ETFs do not include those funds that are always treated (which will contaminate the results) and a third of the funds are never treated (which serve as clean comparison), the problematic comparison may receives a low weight in the overall staggered DID estimate. Second, we also use a strongly balanced panel to conduct all the empirical estimates of this study, and the results are qualitatively consistent with the reported findings.[20] Third, we conduct an alternative estimate of the changes of ETF liquidity around the DMM program applying the regression inverse-probability-weighted variants of Callaway and Sant'Anna (2021). The results are presented in Table 21. As shown in the table, all the coefficients of DMM dummy are significant and have the same signs with the estimates shown in Table 3, and only small differences occur to the results estimated by the two DID approaches. Thus, the biases of our regression results on the changes of ETF liquidity around DMM's introduction is not severed, and the conclusion drew from the DID regressions is reliable.

[20]The results based on a strongly balanced panel are available upon request.

5.3. Regulatory Implications

This study has several regulatory implications. First, although the liquidity provision of ETF markets is not mainly from DMMs, there should be an indispensable position for DMMs in the market structure of ETFs, as DMMs play various valuable roles that are beyond their primary obligations and cannot be substituted by APs and HFTs. In the electronic trading era, many market participants view DMMs as the relic of non-electronic trading. However, both our model and empirical evidence indicates that DMMs are very helpful forces to the ETF market. Therefore, it is highly recommended to preserve and introduce more DMMs to ETF markets.

Second, incentive mechanisms of ETF DMMs that do not specify normative terms of obligations for DMMs during distressed market periods could lead to DMMs' withdrawal from ETF markets during these periods. Therefore, exchanges or regulators should create additional incentives for market making activity during stressful periods to encourage DMMs to continue providing liquidity.

Third, regulators should notice that the policy effects of DMMs on ETF liquidity is approximately inverted U shape: when ETF liquidity is extremely poor or very adequate, DMMs' impact on the liquidity is very limited, and they sometimes will even consume the liquidity; when ETF liquidty is between these two extremely conditions, DMMs are willing and able to provide additional liquidity for the markets. It strongly implies that the DMM programs in ETF markets should be more targeted to the funds with poor liquidity, and for the funds with good liquidity, such programs is ineffective or even counterproductive to the policy objective.

Last, since DMMs can help ETFs survive and thrive, DMM policy should be targeted at those ETFs with small cap and the new funds. Across the major ETF markets in the world, although both the overall growth and trading volume of ETFs seem considerable, quite a substantial portion of assets and trading volume are concentrated on the flagship products. Meanwhile the liquidity, market cap, and trading volume of other ETFs are still at a low level, particularly for the new and small ETFs that may be more attractive as investment vehicles than many of the large and established ETFs. Promoting DMM programs toward those ETFs with small-cap and young fund age can also improve the ETF ecosystem.

6. Conclusions

This paper is the first comprehensive study to examine the disputable role of the designated liquidity provision in ETF markets by studying the changes in market characteristics around the introduction of DMMs. We find that DMMs can significantly enhance ETF liquidity and price efficiency during normal times. However, DMMs hesitate to provide liquidity for ETFs in the market-wide distressed conditions, but are still able and willing to provide liquidity for ETFs in the fund-level distressed conditions. Unlike the stock market, introducing DMMs to ETF markets does not significantly affect ETF price. Moreover, the enhancement of ETF liquidity is more pronounced in the small-cap ETFs, and further evidences show that DMMs can help the survival and success of ETFs. We also find that DMMs can benefit most ETF market participants. These findings provide new evidence for several branches of studies regarding market structure, market makers, market reactions, and market performance.

Our study provides a meaningful starting point for both comprehensive theoretical and empirical analyses of market makers' roles in ETF markets. Future studies could further investigate DMM behavior and its impact during stressful periods in the ETF market. For instance, does the participation of more DMMs benefit ETF trading and market quality? In ETFs with multiple DMMs, how do incumbent DMMs behave when faced with new entrants? Given that high-frequency trading in ETF markets accounts for a considerable portion of total trading activity, it would also be of great interest to employ intraday data to study the market quality or market reactions of ETFs associated with DMMs' behaviors. Moreover, future research could investigate whether the liquidity provision of DMMs affects the performance of ETF constituent securities, such as valuation level, expected return, liquidity, volatility, and information efficiency.

References

Acharya, V.V., Pedersen, L.H., 2005. Asset pricing with liquidity risk. *Journal of Financial Economics* 77, 375–410.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics* 17, 223–249.

Anand, A., Tanggaard, C., Weaver, D.G., 2009. Paying for market quality. *Journal of Financial and Quantitative Analysis* 44, 1427–1457.

Anand, A., Venkataraman, K., 2016. Market conditions, fragility, and the economics of market making. *Journal of Financial Economics* 121, 327–349.

Aquilina, M., Croxson, K., Valentini, G.G., Vass, L., 2020. Fixed income ETFs: Primary market participation and resilience of liquidity during periods of stress. *Economics Letters* 193, 109249.

Baldauf, M., Mollner, J., 2020. High-frequency trading and market performance. *The Journal of Finance* 75, 1495–1526.

Beck, T., Levine, R., Levkov, A., 2010. Big bad banks? The winners and losers from bank deregulation in the United States. *The Journal of Finance* 65, 1637–1667.

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

Bessembinder, H., Hao, J., Zheng, K., 2015. Market making contracts, firm value, and the IPO decision. *The Journal of Finance* 70, 1997–2028.

Bessembinder, H., Hao, J., Zheng, K., 2020. Liquidity provision contracts and market quality: Evidence from the New York Stock Exchange. *The Review of Financial Studies* 33, 44–74.

Bongaerts, D., Van Achter, M., 2021. Competition among liquidity providers with access to high-frequency trading technology. *Journal of Financial Economics* 140, 220–249.

Box, T., Davis, R.L., Fuller, K.P., 2019. ETF competition and market quality. *Financial Management* 48, 873–916.

Brogaard, J., Carrion, A., Moyaert, T., Riordan, R., Shkilko, A., Sokolov, K., 2018. High frequency trading and extreme price movements. *Journal of Financial Economics* 128, 253–265.

Brogaard, J., Hendershott, T., Riordan, R., 2014. High-frequency trading and price discovery. *The Review of Financial Studies* 27, 2267–2306.

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

Brown, D.C., Davies, S.W., Ringgenberg, M.C., 2021. ETF arbitrage, non-fundamental demand, and return predictability. *Review of Finance* 25, 937–972.

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-differences with multiple time periods. Journal of Econometrics 225, 200–230.

Chordia, T., Roll, R., Subrahmanyam, A., 2011. Recent trends in trading activity and market quality. *Journal of Financial Economics* 101, 243–263.

Clark-Joseph, A.D., Ye, M., Zi, C., 2017. Designated market makers still matter: Evidence from two natural experiments. *Journal of Financial Economics* 126, 652–667.

Conrad, J., Wahal, S., Xiang, J., 2015. High-frequency quoting, trading, and the efficiency of prices. *Journal of Financial Economics* 116, 271–291.

Cox, D.R., 1972. Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological)* 34, 187–202.

Dannhauser, C.D., Hoseinzade, S., 2022. The unintended consequences of corporate bond ETFs: Evidence from the Taper Tantrum. *The Review of Financial Studies* 35, 51–90.

Easley, D., Kiefer, N.M., O'hara, M., Paperman, J.B., 1996. Liquidity, information, and infrequently traded stocks. *The Journal of Finance* 51, 1405–1436.

Friederich, S., Payne, R., 2015. Order-to-trade ratios and market liquidity. *Journal of Banking & Finance* 50, 214–223.

Glosten, L.R., Milgrom, P.R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14, 71–100.

Gorbatikov, E., Sikorskaya, T., 2021. Two APs Are Better Than One: ETF Mispricing and Primary Market Participation. SSRN .

Greenstone, M., Hanna, R., 2014. Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review* 104, 3038–72.

Grossman, S.J., Miller, M.H., 1988. Liquidity and market structure. *The Journal of Finance* 43, 617–633.

Hendershott, T., Jones, C.M., Menkveld, A.J., 2011. Does algorithmic trading improve liquidity? *The Journal of Finance* 66, 1–33.

Hendershott, T., Riordan, R., 2013. Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis* 48, 1001–1024.

Huang, R.D., Stoll, H.R., 1996. Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. *Journal of Financial Economics* 41, 313–357.

Kirilenko, A., Kyle, A.S., Samadi, M., Tuzun, T., 2017. The flash crash: High-frequency trading in an electronic market. *The Journal of Finance* 72, 967–998.

Kyle, A.S., 1985. Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society* , 1315–1335.

Li, S., Wang, X., Ye, M., 2021. Who provides liquidity, and when? *Journal of Financial Economics* 141, 968–980.

Menkveld, A.J., Wang, T., 2013. How do designated market makers create value for small-caps? *Journal of Financial Markets* 16, 571–603.

Moser, P., Voena, A., 2012. Compulsory licensing: Evidence from the trading with the enemy act. *American Economic Review* 102, 396–427.

Nunn, N., Qian, N., 2011. The potato's contribution to population and urbanization: Evidence from a historical experiment. *The Quarterly Journal of Economics* 126, 593–650.

Pan, K., Zeng, Y., 2017. ETF arbitrage under liquidity mismatch. SSRN .

Panayides, M.A., 2007. Affirmative obligations and market making with inventory. *Journal of Financial Economics* 86, 513–542.

Pástor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642–685.

Sabourin, D., 2006. Are Designated Market Makers Necessary in Centralized Limit Order Markets?, in: AFA 2007 Chicago Meetings Paper.

Scholes, M., Williams, J., 1977. Estimating betas from nonsynchronous data. *Journal of Financial Economics* 5, 309–327.

Seppi, D.J., 1997. Liquidity provision with limit orders and a strategic specialist. *The Review of Financial Studies* 10, 103–150.

Skjeltorp, J.A., Ødegaard, B.A., 2015. When do listed firms pay for market making in their own stock? *Financial Management* 44, 241–266.

Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* 225, 175–199.

Theissen, E., Westheide, C., 2020. Call of duty: Designated market maker participation in call auctions. *Journal of Financial Markets* 49, 100530.

Venkataraman, K., Waisburd, A.C., 2007. The value of the designated market maker. *Journal of Financial and Quantitative Analysis* 42, 735–758.

Table 1: The Attributes of APs, DMMs, and HFTs

This table reports the attributes of APs, DMMs, and HFTs, three important types of market participants in ETF markets.

	APs	DMMs	HFTs
An indispensable part to ETF markets?	Yes	No	No
Have obligations to provide liquidity?	No	Yes	No
Receive rebates for providing liquidity?	No	Yes	No
Other features	Incentivized by arbitrage profits	Subject to DMM contract	Fast in and fast out

Table 2: Summary Statistics

This table reports the summary statistics of variables. The statistics are computed using data from January 2012 to June 2021. CVshare is the coefficient of variation for ETF shares.Volume is the monthly volume of ETFs. RV is the realized volatility of ETF daily return during a calendar month. Price is the logarithmic form of ETF share price. Market cap is expressed in millions RMB, shares outstanding and volume are expressed in millions of shares, the return and premium are expressed in %, the age is expressed in years, and the realized volatility is expressed in 0.0001. Each variable has 9061 observations.

Variables	Mean	S.D.	Q5	Q25	Q50	Q75	Q95
Quoted spread	-6.5619	1.2494	-8.6608	-7.4469	-6.6409	-5.5527	-4.5773
Amihud's illiquidity	-0.4299	3.1346	-6.1807	-2.5435	-0.1433	1.9097	4.272
Turnover	-6.1886	2.5802	-11.113	-7.6914	-5.8292	-4.2077	-2.7862
Relative spread	0.0090	0.0102	0.0006	0.0018	0.0049	0.0130	0.0292
Market cap	2064	5948	23	84	233	902	13110
Absolute premium	8.8149	53.383	0.0958	0.1934	0.5729	1.3645	30.541
Cvshare	0.0378	0.085	0	0.005	0.0143	0.0368	0.1449
RV	2.7164	2.9985	0.4457	0.9825	1.7295	3.296	8.3961
Price	0.4616	0.6633	-0.4006	0.0178	0.3603	0.8077	1.6945
Return	0.0634	0.3333	-0.398	-0.1239	0.0529	0.2253	0.6086
Volume	31.48	148.20	0.01	0.10	0.75	6.30	118.20
Age	4.4	3.16	0.3	1.8	3.9	6.5	10.1
Fund flow	0.0004	0.0278	-0.0118	-0.0022	-0.0003	0.0006	0.0100

Table 3: ETF Liquidity around DMMs' Introduction

This table reports the impact of DMMs' on ETF liquidity. The results are estimated by of one-month interval panel difference-in-differences approach. The sample funds includes 151 ETFs and the sample period is from January 2012 to June 2021. The dependent variables are three liquidity measures, including quoted spread, Amihud's illiquidity, and turnover. The indicator of DMMs, denoted by D_DMM, equals one during all months in which an ETF have DMMs and equals zero otherwise. CVshare is the coefficient of variation for shares outstanding, measuring the level of the primary market activity of ETFs. Price is the logarithmic form of ETF share price. RV is the realized volatility of ETF daily return during a calendar month. All regressions control for the fund and month fixed effects. The quoted spreads and Amihud's illiquidity inversely reflect the liquidity of ETFs in the secondary market, respectively, and the turnover positively reflects the liquidity. Standard errors are clustered at the fund and month level and t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Quoted spread		Amihud's illiquidity		Turnover	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
D_DMM	-0.527***	-0.415***	-0.910***	-0.492**	0.521**	0.540**
	(-4.88)	(-4.11)	(-3.55)	(-2.34)	(2.30)	(2.39)
CVshare		-0.534***		-2.615***		2.674***
		(-3.90)		(-6.67)		(5.98)
Market cap		-0.230***		-0.836***		-0.037
		(-6.91)		(-13.76)		(-0.55)
Price		-0.545**		-0.455		1.069*
		(-2.34)		(-0.86)		(1.88)
Absolute premium		0.001***		-0.004***		0.001**
		(2.70)		(-5.10)		(1.99)
Return		0.059		0.047		0.219
		(1.20)		(0.44)		(1.61)
RV		0.044***		0.063***		0.002
		(3.49)		(4.03)		(0.12)
Age		0.273*		0.369		-0.961**
		(1.92)		(1.16)		(-2.59)
Constant	-6.364***	-6.949***	-0.089	-1.633***	-6.384***	-5.616***
	(-158.87)	(-29.44)	(-0.94)	(-2.96)	(-76.07)	(-8.94)
Observations	9,061	9,061	9,061	9,061	9,061	9,061
R-squared	0.801	0.829	0.773	0.819	0.714	0.731
Fund FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES

Table 4: Joint Significance Tests for the Leads and Lags of DID Estimations

This table reports the F-stat and P-value of the joint significance tests for the leads and lags of DID estimations. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Statistics	Joint significance test for leads			Joint significance test for lags		
	Quoted spread	Amihud's illiquidity	Turnover	Quoted spread	Amihud's illiquidity	Turnover
F-stat	1.4719	1.5652	1.6369	2.9091***	4.8224***	2.062**
P-value	0.2054	0.1756	0.1559	0.0015	<0.0001	0.025

Table 5: ETF Market Activity around DMMs' Introduction

This table reports the results of DMMs' impact on the market activity of ETFs. The results are estimated by of one-month interval panel difference-in-differences approach. The dependent variables are the coefficient of variation for ETF shares outstanding (CVShare) which measures the market activity of ETF primary market, and two metrics of market activity of ETF secondary market, including the number of transactions and average turnover per transaction. The indicator of DMMs, denoted by D_DMM, equals one during all months in which an ETF have DMMs and equals zero otherwise. Price is the logarithmic form of ETF share price. RV is the realized volatility of ETF daily return during a calendar month. All regressions control for the fund and month fixed effects. Standard errors are clustered at the fund and month level and t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	CVshare	CVshare	Number of transactions	Number of transactions	Turnover per transaction	Turnover per transaction
D_DMM	0.009**	0.0058	275.630***	221.972***	0.120***	0.152***
	(2.124)	(1.614)	(3.268)	(2.789)	(2.793)	(3.843)
CVshare				35.067		0.155*
				(0.639)		(1.701)
Market cap		0.010***		163.948**		-0.138***
		(3.835)		(2.333)		(-2.907)
Price		-0.005		-49.142		0.275
		(-0.450)		(-0.168)		(1.421)
Absolute premium		-0.0001		2.4077		-0.0193***
		(-0.058)		(0.543)		(-6.366)
Return		0.004		20.894		0.039*
		(0.664)		(0.944)		(1.815)
RV		0.0001		0.4531***		-0.0001
		(1.426)		(2.829)		(-0.360)
Age		-0.040		-49.356**		0.147
		(-0.731)		(-2.015)		(0.709)
Constant	0.018***	0.265	186.235***	715.201***	0.101***	-1.108
	(24.719)	(0.823)	(14.883)	(6.358)	(14.800)	(-0.800)
Obs.	2,832	2,832	2,832	2,832	2,832	2,832
R-squared	0.091	0.098	0.878	0.890	0.312	0.346
Fund FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES

Table 6: ETF Price Efficiency around DMM's Introduction

This table reports the results of DID estimation on ETF price efficiency. The dependent variables are the absolute premium of ETFs and the frequency of extreme premium. The indicator of DMMs, denoted by D_DMM, equals one during all months in which an ETF have DMMs and equals zero otherwise. CVshare is the coefficient of variation for shares outstanding, measuring the level of the primary market activity of ETFs. Price is the logarithmic form of ETF share price. RV is the realized volatility of ETF daily return during a calendar month. All regressions control for the fund and month fixed effects. Standard errors are clustered at the fund and month level and t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Absolute premium		Frequency of extreme premium	
	(1)	(2)	(3)	(4)
D_DMM	-0.195**	-0.168**	-5.009***	-4.418***
	(-2.39)	(-2.47)	(-7.36)	(-6.57)
CVshare		0.120		-2.227***
		(0.50)		(-3.05)
Market cap		-0.109***		-1.094***
		(-3.52)		(-4.89)
Price		-0.029		-1.401
		(-0.17)		(-1.11)
Return		0.123		0.650**
		(0.85)		(2.42)
RV		0.190***		0.234***
		(6.45)		(4.82)
Age		0.312***		0.681
		(2.93)		(0.78)
Constant	0.822***	-0.307	11.779***	9.251***
	(27.79)	(-1.24)	(46.94)	(6.13)
Obs.	9,061	9,061	9,061	9,061
R-squared	0.409	0.501	0.698	0.713
Fund FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES

Table 7: Heterogeneity of DMMs' Impact on ETF Liquidity

This table reports the heterogeneous impacts of DMMs on ETF liquidity. The results are estimated by of one-month interval panel difference-in-differences approach. The dependent variables are three liquidity measures, including quoted spread, Amihud's illiquidity, and turnover. The indicator of DMMs, denoted by D_DMM, equals one during all months in which an ETF have DMMs and equals zero otherwise. CVshare is the coefficient of variation for shares outstanding, measuring the level of the primary market activity of ETFs. Price is the logarithmic form of ETF share price. RV is the realized volatility of ETF daily return during a calendar month. All regressions control for the fund and month fixed effects. The quoted spreads and Amihud's illiquidity inversely reflect the liquidity of ETFs in the secondary market, respectively, and the turnover positively reflects the liquidity. Standard errors are clustered at the fund and month level and t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Quoted spread	Amihud's illiquidity	Turnover
	(1)	(2)	(3)
D_DMM	-0.531***	-0.813***	0.561**
	(-5.16)	(-3.36)	(2.56)
CVshare	-0.439***	-2.340***	2.664***
	(-3.07)	(-5.33)	(6.02)
Market cap	-0.293***	-0.982***	0.097
	(-3.54)	(-3.47)	(0.57)
D_DMM×Market cap	0.229***	0.392*	-0.212*
	(4.81)	(1.91)	(-1.91)
Price	-0.753***	-1.188*	1.053*
	(-2.84)	(-1.75)	(1.93)
Absolute premium	0.001***	-0.003***	0.001*
	(3.06)	(-5.02)	(1.85)
Return	0.046	-0.030	0.207
	(0.88)	(-0.25)	(1.57)
RV	0.045***	0.072***	0.005
	(3.30)	(3.96)	(0.23)
Age	0.275*	0.205	-1.048***
	(1.78)	(0.54)	(-2.74)
Constant	-6.565***	0.005	-5.427***
	(-24.42)	(0.01)	(-8.34)
Obs.	9,061	9,061	9,061
R-squared	0.816	0.790	0.732
Fund FE	YES	YES	YES
Month FE	YES	YES	YES

Table 8: APs, HFTs, and DMMs during the Closing Trading of ETFs

This table characterizes the participation of APs, HFTs, and DMMs during the closing trading period in the two major exchanges of China (SSE and SZSE). 'Yes' indicates that it is very possible for the participants to participate the trading, and 'No' indicates that the participants are limited or reluctant to participate the trading.

	SSE	SZSE
Trading manner of closing	Continuous trading.	Call auction.
APs	Yes. Stay in the market to wait for the profitable arbitrage.	No. Arbitrage activities are limited by the trading manner of call auction.
HFTs	Yes. Stay in the market to wait for the profitable arbitrage opportunity.	No. Arbitrage activities are limited by the trading manner of call auction.
DMMs	No. Reluctant to provide liquidity during the closing period of market (high volatility).	Yes. Have obligations to participate the call auction trading.

Table 9: DMMs' Impact on ETF Liquidity during the Call Auction

This table reports the impacts of DMMs on ETF liquidity during the call auction by close of trading. The results are estimated by of one-month interval panel difference-in-differences approach. The dependent variables are effective spread and trading volume over the the call auction by close of trading. We collect the daily observations of the trading volume from the one-minute-interval data, and then average among each month. The indicator of DMMs, denoted by D_DMM, equals one during all months in which an ETF have DMMs and equals zero otherwise. CVshare is the coefficient of variation for shares outstanding, measuring the level of the primary market activity of ETFs. Price is the logarithmic form of ETF share price. RV is the realized volatility of ETF daily return during a calendar month. The sample period is from January 2012 to June 2021. All regressions control for the fund and month fixed effects. Standard errors are clustered at the fund and month level and t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Turnover				Trading volume			
	SZSE		SSE		SZSE		SSE	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_DMM	0.704**	0.914***	0.014	0.011	1.668***	0.993***	0.397	0.083
	(2.02)	(3.31)	(0.04)	(0.03)	(4.92)	(3.57)	(0.87)	(0.24)
CVshare		0.917**		2.843***		0.799*		2.788***
		(2.15)		(4.97)		(1.92)		(4.62)
Market cap		-0.279		0.147		0.633***		1.048***
		(-1.30)		(1.21)		(2.92)		(8.75)
Price		0.611		2.747**		-0.397		1.849
		(0.73)		(2.31)		(-0.47)		(1.55)
Absolute premium		-0.004***		0.004***		-0.001		0.006***
		(-7.87)		(4.26)		(-1.62)		(4.44)
Return		0.225*		0.075		0.113		-0.045
		(1.98)		(0.44)		(0.93)		(-0.25)
RV		0.050***		0.123***		0.056***		0.133***
		(2.88)		(3.86)		(3.40)		(4.10)
Age		0.235		0.245		0.487		0.541
		(0.46)		(0.44)		(0.96)		(0.96)
Constant	-18.121***	-19.316***	-13.494***	-15.401***	0.749***	0.854	5.338***	4.583***
	(-272.44)	(-23.88)	(-75.20)	(-15.16)	(11.70)	(1.07)	(24.14)	(4.52)
Obs.	3,342	3,342	5,476	5,476	3,342	3,342	5,476	5,476
R-squared	0.647	0.668	0.727	0.747	0.746	0.782	0.795	0.839
Fund FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 10: ETF Spreads around the 2015 Chinese Market Crash

This table presents the mean of relative spreads of ETFs in different groups and the results of the two sample t test. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: During the crash period v.s. not duirng the crash period			
	Not during the crash	During the crash	Difference	t-statistics
Without DMMs	0.0126	0.0162	-0.0036***	-5.3678
With DMMs	0.0090	0.0140	-0.0051***	-3.5636
	Panel B: With DMMs v.s. without DMMs			
	Without DMMs	With DMMs	Difference	t-statistics
Not during the crash	0.0126	0.0090	0.0036***	4.5705
During the crash	0.0162	0.0141	0.0021	1.5436

Table 11: DID estimation on ETF Spreads around the 2015 Chinese Market Crash

This table reports the results of whether ETFs with DMMs perform better than those whithout DMMs in the terms of relative spread when the market is under extremely distressed conditions (2015 Chinese market crash period). The results are estimated by standard difference-in-differences approach.

$$Rspread_{i,t} = \alpha + \beta_1 Treat_{i,t} + \beta_2 Crash_{i,t} + \beta_3 Treat_{i,t} \times Crash_{i,t} + Controls_{i,t} + \upsilon_{i,t}.$$

$Rspread_{i,t}$ is the relative spread in month t for ETF i, $Treat_{i,t}$ is a dummy variable equaling one if an ETF has contracted with DMMs and zeros others, $Crash_{i,t}$ is a dummy variable equaling one if the current month is during the 2015 Chinese market crash (from June 2015 to February 2016) and zeros others. Therefore, the coefficient β_3 reveals the difference of relative spread between ETFs with DMMs and without DMMs during the market crash. The sample funds includes 62 ETFs and the sample period is from September 2014 to February 2016 (Crash=0 in the months before June 2015 and Crash=1 if others). CVshare is the coefficient of variation for shares outstanding, measuring the level of the primary market activity of ETFs. Price is the logarithmic form of ETF share price. RV is the realized volatility of ETF daily return during a calendar month. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: ETF relative spread	
Variables	(1)	(2)
Treat	-0.0002	-0.0003
	(-0.24)	(-0.47)
Crash	0.0079***	0.0032***
	(10.34)	(4.37)
Treat×Crash	-0.0000	0.0007
	(-0.02)	(0.51)
CVshare		-0.0103***
		(-2.79)
Market cap		-0.0041***
		(-23.10)
Price		0.0007*
		(1.86)
Absolute premium		0.0000***
		(4.72)
Return		0.0004
		(0.57)
RV		0.0006***
		(6.62)
Age		0.0018***
		(2.59)
Constant	0.0096***	0.0002
	(25.47)	(0.12)
Observations	1099	1099
R-squared	0.103	0.454

Table 12: ETF Spreads during Different Quantile Windows of Market Spread

This table presents the mean of ETF relative spreads across the different quantile intervals of the relative spread of ETF market. The relative spread of ETF market in month t is the average relative spread of all ETFs over the month. The market spreads was sorted into 19 groups according to ascending order (since there is only one observations of D_DMM with the value of one within the interval of Q95~Q100, we merge this quantile interval with the interval of Q90~Q95 together). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Quantile interval of market spread	Without DMMs (1)	With DMMs (2)	Difference (3)	t value of t test (4)
0~5	0.0074	0.0020	0.0053***	18.7242
5~10	0.0075	0.0023	0.0052***	15.3585
10~15	0.0077	0.0029	0.0049***	12.6858
15~20	0.0083	0.0032	0.0051***	12.0720
20~25	0.0090	0.0039	0.0051***	8.0862
25~30	0.0088	0.0058	0.0030***	3.3681
30~35	0.0108	0.0076	0.0032***	3.0200
35~40	0.0106	0.0062	0.0044***	4.7777
40~45	0.0102	0.0051	0.0051***	6.7707
45~50	0.0121	0.0058	0.0063***	7.2330
50~55	0.0122	0.0085	0.0038***	2.8491
55~60	0.0135	0.0086	0.0050***	3.7449
60~65	0.0151	0.0101	0.0050***	3.0302
65~70	0.0137	0.0092	0.0045***	3.1077
70~75	0.0133	0.0088	0.0045***	2.8504
75~80	0.0138	0.0109	0.0029*	1.9185
80~85	0.0148	0.0107	0.0041**	2.2680
85~90	0.0169	0.0155	0.0013	0.5335
90~100	0.0136	0.0131	0.0005	0.2786

Table 13: ETF Spread in Different Conditions of ETF Market: DID Regression

This table presents the results of regressing ETF relative spread on the indicator of DMMs, indicator of the quantile of ETF market spread (D_m), and the interaction between them. The indicator of DMMs, denoted by D_DMM, equals one during all months when an ETF has DMMs and equals zero otherwise. D_m_t, equals one when the relative spread of ETF market over month t falls in a certain quantile and equals zero otherwise. The relative spread of ETF market in month t is the average relative spread of all ETFs over the month. The sample time spans from January 2012 to June 2021, including 9061 observations. The market spreads was sorted into 19 groups according to ascending order (since there is only one observations of D_DMM with the value of one within the interval of Q95∼Q100, we merge this quantile interval with the interval of Q90∼Q95 together). Then if we intend to test the role of DMMs when market spread falls in a certain quantile (e.g., 90% to 95%), we assign the value of D_m to one and zeros otherwise. DMM:Y, DMM:N, and Interval:Y, correspond to with DMMs, without DMMs, and within the current quantile interval, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Quantile interval	Regression results				ETF spread		
	D_DMM	D_m	D_DMM×D_m	Constant	DMM:N Interval:Y	DMM:Y Interval:Y	Diff.
	(1)	(2)	(3)	(4)	(5): (2)+(4)	(6): (1)+(3)+(5)	(7): (5)-(6)
0∼5	-0.0049***	-0.0050***	0.0037***	0.0110***	0.0060	0.0048	0.0012
	(-5.55)	(-5.28)	(4.12)	(24.92)			
5∼10	-0.0050***	-0.0048***	0.0037***	0.0110***	0.0062	0.0049	0.0013
	(-5.62)	(-5.61)	(4.96)	(24.93)			
10∼15	-0.0052***	-0.0045***	0.0039***	0.0111***	0.0066	0.0053	0.0013
	(-5.80)	(-6.08)	(5.99)	(24.72)			
15∼20	-0.0052***	-0.0038***	0.0036***	0.0111***	0.0073	0.0057	0.0016
	(-5.89)	(-5.58)	(6.15)	(24.69)			
20∼25	-0.0053***	-0.0026***	0.0021***	0.0110***	0.0084	0.0052	0.0032
	(-5.86)	(-3.73)	(6.44)	(24.46)			
25∼30	-0.0053***	-0.0026***	0.0026***	0.0110***	0.0084	0.0057	0.0027
	(-5.94)	(-4.17)	(3.74)	(24.64)			
30∼35	-0.0052***	-0.0002	0.0015**	0.0109***	0.0107	0.0070	0.0037
	(-5.82)	(-0.18)	(2.32)	(23.75)			
35∼40	-0.0052***	-0.0006	-0.0001	0.0109***	0.0103	0.0050	0.0053
	(-5.79)	(-1.11)	(-0.13)	(24.11)			
40∼45	-0.0052***	-0.0012***	0.0013***	0.0110***	0.0098	0.0059	0.0039
	(-5.85)	(-2.81)	(3.14)	(24.29)			
45∼50	-0.0052***	0.0009*	0.0001	0.0108***	0.0117	0.0066	0.0051
	(-5.80)	(1.80)	(0.26)	(24.02)			
50∼55	-0.0051***	0.0009	-0.0002	0.0109***	0.0118	0.0065	0.0053
	(-5.74)	(0.58)	(-0.25)	(24.28)			
55∼60	-0.0050***	0.0025***	-0.0010*	0.0107***	0.0132	0.0072	0.0060
	(-5.68)	(2.98)	(-1.69)	(24.09)			
60∼65	-0.0049***	0.0043***	-0.0010	0.0106***	0.0149	0.0090	0.0059
	(-5.55)	(2.81)	(-0.75)	(24.03)			
65∼70	-0.0050***	0.0022	-0.0015***	0.0108***	0.0130	0.0065	0.0065
	(-5.76)	(1.61)	(-4.12)	(24.73)			
70∼75	-0.0051***	0.0013	-0.0005	0.0108***	0.0121	0.0065	0.0056
	(-5.75)	(1.24)	(-0.48)	(24.29)			
75∼80	-0.0050***	0.0024***	-0.0008***	0.0108***	0.0132	0.0074	0.0058
	(-5.70)	(2.93)	(-2.76)	(24.39)			
80∼85	-0.0050***	0.0029**	-0.0011	0.0107***	0.0127	0.0066	0.0061
	(-5.64)	(2.36)	(-1.33)	(24.40)			
85∼90	-0.0048***	0.0052**	0.0012	0.0106***	0.0158	0.0122	0.0036
	(-5.53)	(2.40)	(0.52)	(25.74)			
90∼100	-0.0052***	-0.0006	0.0040**	0.0109***	0.0103	0.0091	0.0012
	(-5.80)	(-0.46)	(2.35)	(24.14)			

Table 14: ETF Spread in Different Conditions of Fund-level Liquidity: DID Regression

This table presents the results of regressing ETF relative spread on the indicator of DMMs, indicator of the quantile of ETF spread (D_e), and the interaction between them. The indicator of DMMs, denoted by D_DMM, equals one during all months when an ETF has DMMs and equals zero otherwise. D_m_t, equals one when the relative spread of an ETF over month t falls in a certain quantile and equals zero otherwise. The sample time spans from January 2012 to June 2021, including 9061 observations. The ETF spreads were sorted into 20 groups according to ascending order. Then if we intend to test the role of DMMs when the spread falls in a certain quantile (e.g., 95% to 100%), we assign the value of D_m to one and zeros otherwise. DMM:Y, DMM:N, and Interval:Y, correspond to with DMMs, without DMMs, and within the current quantile interval, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Quantile interval	Regression results				ETF spread		
	D_DMM	D_e	D_DMM×D_e	Constant	DMM:N Interval:Y	DMM:Y Interval:Y	Diff.
	(1)	(2)	(3)	(4)	(5): (2)+(4)	(6): (1)+(3)+(5)	(7): (5)-(6)
0∼5	-0.0057***	-0.0018***	0.0044***	0.0110***	0.0092	0.0079	0.0013
	(-5.88)	(-4.61)	(4.77)	(24.90)			
5∼10	-0.0054***	-0.0026***	0.0030***	0.0110***	0.0084	0.006	0.0024
	(-5.88)	(-4.84)	(3.42)	(24.76)			
10∼15	-0.0051***	-0.0032***	0.0020**	0.0110***	0.0078	0.0047	0.0031
	(-5.81)	(-4.86)	(2.16)	(24.86)			
15∼20	-0.0052***	-0.0033***	0.0022***	0.0110***	0.0077	0.0047	0.003
	(-5.84)	(-5.78)	(3.45)	(24.92)			
20∼25	-0.0052***	-0.0033***	0.0021***	0.0110***	0.0077	0.0046	0.0031
	(-5.89)	(-5.73)	(3.03)	(25.04)			
25∼30	-0.0053***	-0.0039***	0.0025***	0.0111***	0.0072	0.0044	0.0028
	(-5.98)	(-5.93)	(3.12)	(25.04)			
30∼35	-0.0053***	-0.0043***	0.0029***	0.0111***	0.0068	0.0044	0.0024
	(-5.96)	(-5.60)	(3.37)	(25.07)			
35∼40	-0.0053***	-0.0044***	0.0025**	0.0111***	0.0067	0.0039	0.0028
	(-5.96)	(-5.05)	(2.47)	(24.97)			
40∼45	-0.0054***	-0.0047***	0.0040***	0.0111***	0.0064	0.005	0.0014
	(-6.03)	(-6.43)	(4.80)	(24.78)			
45∼50	-0.0054***	-0.0042***	0.0033***	0.0111***	0.0069	0.0048	0.0021
	(-6.00)	(-5.87)	(3.39)	(24.78)			
50∼55	-0.0054***	-0.0040***	0.0035***	0.0111***	0.0071	0.0052	0.0019
	(-5.99)	(-6.11)	(2.89)	(24.63)			
55∼60	-0.0054***	-0.0038***	0.0029**	0.0111***	0.0073	0.0048	0.0025
	(-5.99)	(-5.73)	(2.26)	(24.68)			
60∼65	-0.0053***	-0.0035***	0.0007	0.0111***	0.0076	0.003	0.0046
	(-5.85)	(-5.03)	(0.39)	(24.54)			
65∼70	-0.0052***	-0.0028***	0.0013	0.0111***	0.0083	0.0044	0.0039
	(-5.79)	(-3.67)	(0.68)	(24.29)			
70∼75	-0.0053***	-0.0024***	0.0025	0.0110***	0.0086	0.0058	0.0028
	(-5.83)	(-3.11)	(1.26)	(24.13)			
75∼80	-0.0052***	-0.0014	0.0007	0.0110***	0.0096	0.0051	0.0045
	(-5.78)	(-1.53)	(0.27)	(23.86)			
80∼85	-0.0051***	0.0012	-0.0012	0.0108***	0.012	0.0057	0.0063
	(-5.77)	(1.32)	(-0.41)	(23.68)			
85∼90	-0.0050***	0.0045***	-0.0007	0.0106***	0.0151	0.0094	0.0057
	(-5.81)	(4.39)	(-0.22)	(23.91)			
90∼95	-0.0048***	0.0092***	-0.0023	0.0103***	0.0195	0.0124	0.0071
	(-5.94)	(9.66)	(-1.08)	(24.85)			
95∼100	-0.0043***	0.0231***	0.0016	0.0094***	0.0325	0.0298	0.0027
	(-6.04)	(18.27)	(1.37)	(29.26)			

Table 15: Abnormal Returns for ETFs around DMMs' Introduction

This table reports the abnormal returns (ARs) and cumulative abnormal returns (CARs) for a sample of 67 ETFs that contracted with designated liquidity providers between January 2012 and June 2021 and for matched ETFs that did not contract with liquidity providers during the estimate periods of their respect sample funds. The event window is from five days before the entry of DMMs in ETF market to 10 days after the introduction day (t_i) of DMMs. The market model parameters are estimated by using returns of the CSI 300 Index and ETF returns over the trading days $t_i - 106$ to $t_i - 6$. Scholes and Williams (1977) betas are computed to adjust for infrequent trading. Day 0 is the introduction day of DMMs. Two-sided t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Day	Sample ETFs		Matche ETFs		Sample ETFs - Matched ETFs	
	AR	CAR	AR	CAR	AR	CAR
	(1)	(2)	(3)	(4)	(5)	(6)
t-5	-0.2005	-0.2005	-0.0313	-0.0313	-0.1692	-0.1692
t-4	-0.2714	-0.4719**	-0.2034	-0.2347	-0.068	-0.2372
t-3	-0.3584**	-0.8303***	-0.2953	-0.53*	-0.0631	-0.3002
t-2	-0.1946	-1.0249**	-0.3662**	-0.8962**	0.1716	-0.1286
t-1	0.0645	-0.9603**	0.1978	-0.6984*	-0.1333	-0.2619
t	0.1537	-0.8066*	-0.0361	-0.7345*	0.1898	-0.0721
t+1	0.0141	-0.7925*	0.0329	-0.7016	-0.0188	-0.0909
t+2	0.0262	-0.7663*	-0.0362	-0.7378*	0.0624	-0.0285
t+3	-0.1598	-0.9261**	0.0347	-0.7032	-0.1945	-0.223
t+4	-0.1515	-1.0777***	-0.1204	-0.8236*	-0.0311	-0.2541
t+5	0.0126	-1.065**	-0.0703	-0.8938*	0.0829	-0.1712
t+6	0.101	-0.964**	0.1056	-0.7883	-0.0045	-0.1757
t+7	-0.1037	-1.0677**	-0.1696	-0.9579*	0.0659	-0.1098
t+8	0.147	-0.9207*	0.1623	-0.7956	-0.0153	-0.1251
t+9	0.0675	-0.8532*	-0.0145	-0.8101	0.0821	-0.0431
t+10	0.0891	-0.764	0.049	-0.7611	0.0402	-0.0029
t+11	0.0175	-0.7465	0.1899	-0.5712	-0.1724	-0.1753
t+12	0.1817	-0.5648	-0.008	-0.5793	0.1898	0.0144
t+13	0.2091	-0.3557	0.101	-0.4783	0.1082	0.1226
t+14	0.0139	-0.3418	-0.0264	-0.5047	0.0403	0.1629
t+15	0.2122	-0.1296	0.135	-0.3697	0.0772	0.2402
t+16	-0.4927**	-0.6222	-0.1108	-0.4806	-0.3818	-0.1417
t+17	-0.0654	-0.6877	0.1672	-0.3134	-0.2326	-0.3743
t+18	0.0106	-0.6771	-0.0535	-0.3669	0.0642	-0.3102
t+19	0.2257*	-0.4514	0.1413	-0.2256	0.0844	-0.2258
t+20	0.1353	-0.3161	0.1964	-0.0292	-0.0611	-0.2868
t+21	0.3349**	0.0188	0.3161**	0.2869	0.0187	-0.2681
t+22	0.3626**	0.3814	0.2954*	0.5823	0.0672	-0.2009

Table 16: DMMs and ETF Liquidation

Statistics	ETFs with DMMs	ETFs without DMMs	All ETFs
Number of all ETFs	98	53	151
Number of liquidated ETFs	9	15	24
Number of surviving ETFs	89	38	127
$\frac{Number\,of\,liquidated\,ETFs}{Number\,of\,all\,ETFs}$ (%)	9.2	28.3	15.9

Table 17: The Statistic for the Growth of ETF Market Value around DMMs' Introduction

This table reports the statistics of ETF market value around the introduction of DMMs. The presented market value in this table is the average market value of an ETF over the six months before introducing DMMs and over the six months after introducing DMMs. We split the sample ETFs into the small group and the big group according to ETF average market value during the six months before introducing DMMs. Panels A, B, and C show the results based on the entire sample, the small group, and the big group, respectively. The market value is expressed in billions RMB. We also test the difference between the mean of the difference of market value and 0. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Statistics	Market value before introducing DMM	Market value after introducing DMM	Difference of market value: (2)-(1)	Market value's growth rate(%) around DMMs' introduction: (3)/(1)
	(1)	(2)	(3)	(4)
Panel A: Entire sample				
Mean	2.861	3.278	0.417***	65.89
SD	6.489	6.849	0.846	232.00
Q5	0.041	0.050	-0.509	-62.04
Q25	0.127	0.164	0.007	4.70
Q50	0.386	0.559	0.099	23.70
Q75	1.503	2.017	0.550	56.66
Q95	16.920	20.650	2.052	194.70
Obs.	54	54	54	54
Panel B: ETFs with small market value				
Mean	0.141	0.216	0.075**	107
SD	0.0891	0.179	0.155	324.2
Q5	0.0398	0.0429	-0.0876	-64.6
Q25	0.0659	0.105	-0.0042	-3.153
Q50	0.127	0.164	0.0297	32.03
Q75	0.201	0.223	0.0994	87.99
Q95	0.347	0.696	0.349	302.9
Obs.	27	27	27	27
Panel C: ETFs with big market value				
Mean	5.581	6.34	0.759***	24.77
SD	8.394	8.724	1.092	33.18
Q5	0.44	0.539	-0.523	-27.67
Q25	0.864	1.231	0.0991	7.698
Q50	1.503	2.017	0.512	22.48
Q75	6.961	9.013	1.215	47.19
Q95	19.34	20.83	3.686	75.67
Obs.	27	27	27	27

Table 18: Market Cap of ETFs around DMMs' Introduction: DID Regression

This table reports the impact of DMMs on the market cap of ETFs. The results are estimated by one-month interval panel difference-in-differences approach. The dependent variable is the market cap of ETFs. The indicator of DMMs, denoted by D_DMM, equals one during all months in which an ETF have DMMs and equals zero otherwise. CVshare is the coefficient of variation for shares outstanding, measuring the level of the primary market activity of ETFs. Price is the logarithmic form of ETF share price. RV is the realized volatility of ETF daily return during a calendar month. All regressions control for the fund and month fixed effects. Standard errors are clustered at the fund and month level and t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	Dependent variable: market cap of ETFs	
	(1)	(2)
D_DMM	0.5105***	0.4811***
	(3.74)	(3.50)
CVshare		-0.4150**
		(-1.99)
Price		0.8099**
		(2.53)
Absolute premium		-0.0002
		(-0.33)
Return		0.0532
		(0.77)
RV		-0.0123
		(-1.08)
Age		0.2764
		(1.08)
Constant	-1.3866***	-2.1181***
	(-27.46)	(-5.09)
Obs.	9,061	9,061
R-squared	0.845	0.848
Fund FE	YES	YES
Month FE	YES	YES

Table 19: The Benefits of DMMs' Introduction to the Participants of ETF Markets

This table reports the results of one-month interval panel difference-in-differences estimation on the variables relevant to the benefits of the participants of ETF markets. The dependent variables are the trading costs (relative effective spread) in basis points, market cap in logarithm, the product of bid-ask spread and trading volume (in logarithm), fund flows, and trading volume of ETFs (in logarithm) to proxy for the benefits of ETF investors, fund issuers, market makers, APs, and exchanges around the introduction of DMMs, respectively. The indicator of DMMs, denoted by D_DMM, equals one during all months when an ETF has DMMs and equals zero otherwise. CVShares is the coefficient of variation for ETF shares outstanding. Price is the logarithmic form of ETF share price. Market cap is averaged among all the trading days of a certain month. RV is the realized volatility of ETF daily return during a calendar month. All regressions control for fund and month fixed effects. Standard errors are clustered at the fund and month level, and t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Investors		Fund issuers		DMMs		APs		Exchanges	
	ETF spread		Market cap		Spread×volume		Fund flow		Trading volume	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_DMM	-0.002**	-0.001*	0.510***	0.481***	0.548***	0.263**	0.001	0.003**	1.012***	0.615***
	(-2.15)	(-1.75)	(3.74)	(3.50)	(3.51)	(2.03)	(0.64)	(2.47)	(4.51)	(3.39)
CVshare		-0.003*		-0.415**		2.521***				3.095***
		(-1.86)		(-1.99)		(5.70)				(6.33)
Market cap		-0.001***				0.533***		-0.005***		0.806***
		(-4.30)				(11.61)		(-4.67)		(15.03)
Price		-0.002		0.810**		0.143		0.000		-0.254
		(-1.31)		(2.53)		(0.40)		(0.11)		(-0.53)
Absolute premium		0.000		-0.000		0.002**		0.000		0.004***
		(0.62)		(-0.33)		(2.37)		(1.29)		(6.45)
Return		0.000		0.053		0.194*		-0.003*		0.105
		(0.01)		(0.77)		(1.93)		(-1.76)		(0.98)
RV		0.001***		-0.012		0.087***		0.001***		0.032
		(4.57)		(-1.08)		(2.85)		(3.10)		(1.49)
Age		0.003**		0.276		-0.068		0.004		-0.439
		(2.46)		(1.08)		(-0.29)		(1.43)		(-1.51)
Constant	0.008***	0.001	-1.387***	-2.118***	11.312***	11.733***	0.000	-0.017***	-7.446***	-5.797***
	(29.88)	(0.48)	(-27.46)	(-5.09)	(196.15)	(30.83)	(0.50)	(-3.39)	(-89.65)	(-11.73)
Obs.	9,061	9,061	9,061	9,061	9,061	9,061	9,061	9,061	9,061	9,061
R-squared	0.597	0.654	0.845	0.848	0.696	0.751	0.037	0.064	0.802	0.855
Fund FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 20: ETF Liquidity and DMMs: PSM-DID Estimates

This table reports the regression results of DMMs' impact on ETF liquidity. The results are estimated by the PSM-DID estimation. Specifically, after the phase-by-phase matching, we conduct the DID regressions based on the samples selected from the matching. The dependent variables are three liquidity measures, including quoted spreads, Amihud's illiquidity, and turnover. The indicator of DMMs, denoted by D_DMM, equals one during all months in which an ETF have DMMs and equals zero otherwise. CVshare is the coefficient of variation for shares outstanding, measuring the level of the primary market activity of ETFs. Price is the logarithmic form of ETF share price. RV is the realized volatility of ETF daily return during a calendar month. All regressions control for the fund and month fixed effects. The quoted spreads and Amihud's illiquidity inversely reflect the liquidity of ETFs in the secondary market, respectively, and the turnover positively reflects the liquidity. Standard errors are clustered at the fund and month level and t-statistics appear in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Quoted spread	Amihud's illiquidity	Turnover
Variables	(1)	(2)	(3)
D_DMM	-0.5367***	-0.7437***	0.7956***
	(-4.4377)	(-3.0570)	(3.0855)
CVshare	-0.9415***	-4.3106***	4.2452***
	(-4.4322)	(-6.8275)	(6.0626)
Market cap	-0.2789***	-0.7949***	-0.0556
	(-7.9890)	(-12.0573)	(-0.7687)
Price	-0.4812*	-0.4074	1.0516*
	(-1.9630)	(-0.7349)	(1.6992)
Absolute premium	0.1454***	0.2092***	-0.2794***
	(3.7686)	(3.5234)	(-3.4664)
Return	0.0980*	-0.0135	0.2907**
	(1.8441)	(-0.1275)	(2.0764)
RV	0.0269**	0.0305	0.0478*
	(2.1580)	(1.6052)	(1.9456)
Age	0.3299**	0.4683	-1.1567***
	(2.0252)	(1.3335)	(-2.7570)
Obs.	6383	6383	6383
R-squared adj.	0.7854	0.7309	0.7329

Table 21: ETF Liquidity and DMMs: DID Estimates of Callaway and Sant'Anna (2021)

This table reports the regression results of DMMs' impact on ETF liquidity by applying the regression inverse-probability-weighted variants of Callaway and Sant'Anna (2021). The quoted spreads and Amihud's illiquidity inversely reflect the liquidity of ETFs in the secondary market, respectively, and the turnover positively reflects the liquidity. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dep. v	Coefficient	Std. err.	z-statistics	P>z
Quoted spread	-0.346**	0.145	-2.38	0.017
Amihud's illiquidity	-0.664**	0.320	-2.08	0.038
Turnover	0.601*	0.336	1.79	0.073

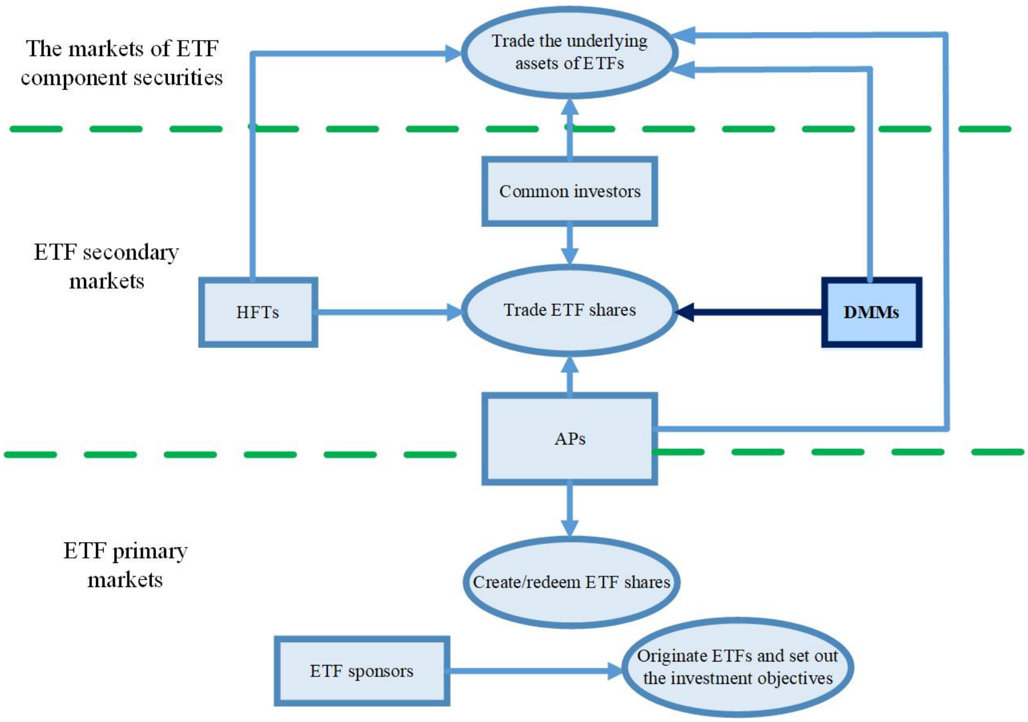


Figure 1: Functioning of ETFs

This figure illustrates the detail of the major ETF market participants and their main activities. The dashed lines indicate that only a portion of the corresponding participants have access to engaging the activities pointed by the arrow.

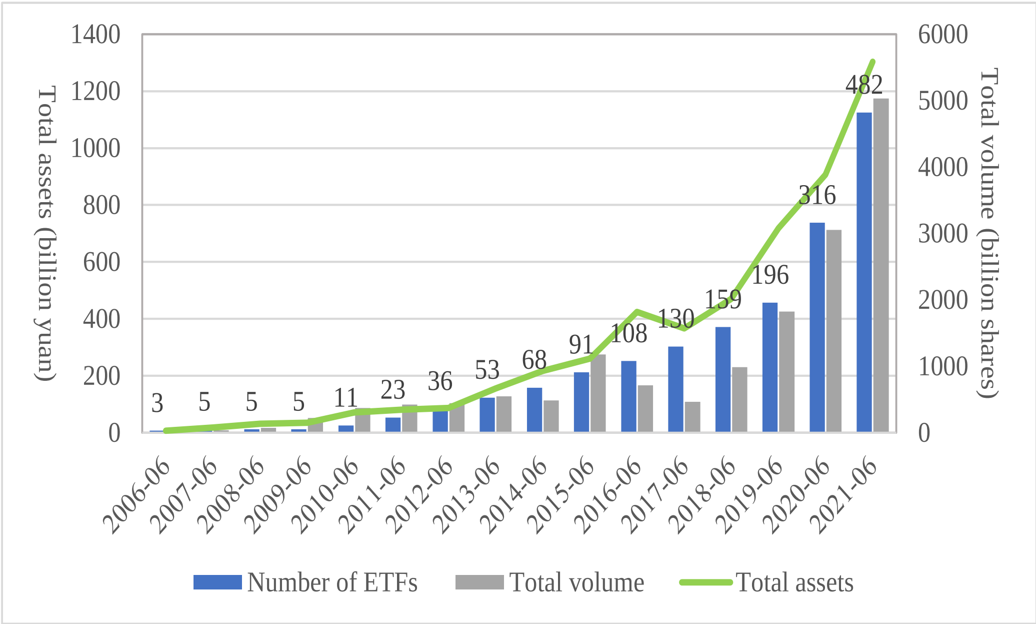
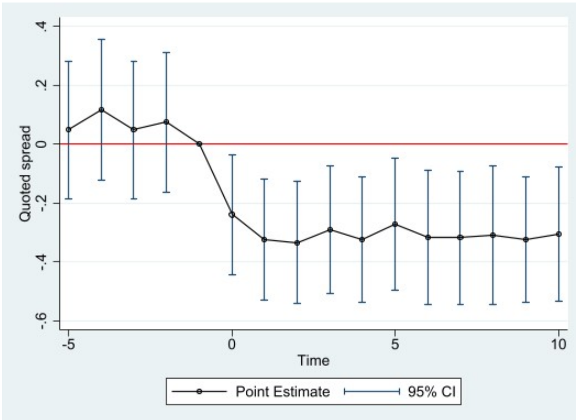
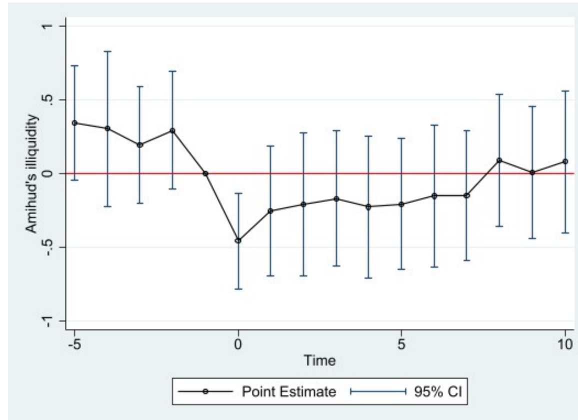


Figure 2: The Growth of China's ETF market

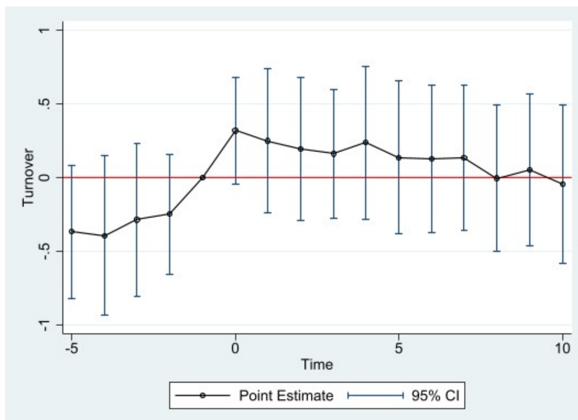
This figure illustrates the annual trading volume, total assets, and the number of all ETFs in the markets of mainland China. The numbers of ETFs are marked right above the bars. The left vertical axis represents the level of the total assets (expressed in billions RMB) of the entire ETF market in mainland China, and the right vertical axis represents the level of the trading volume of ETFs (expressed in billions of shares).



(a) Quoted spread



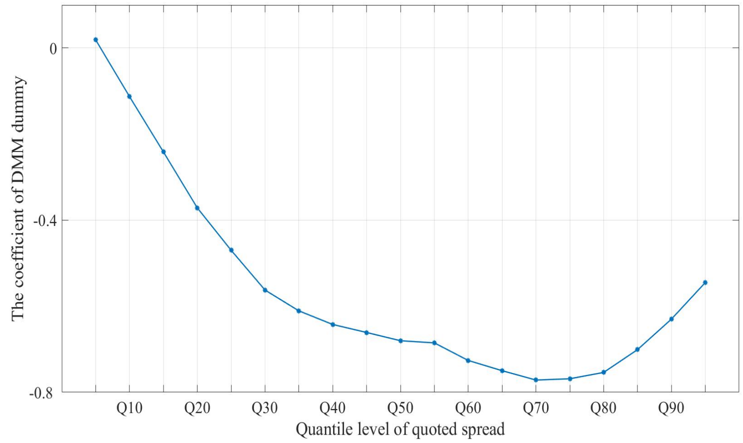
(b) Amihud's price impact



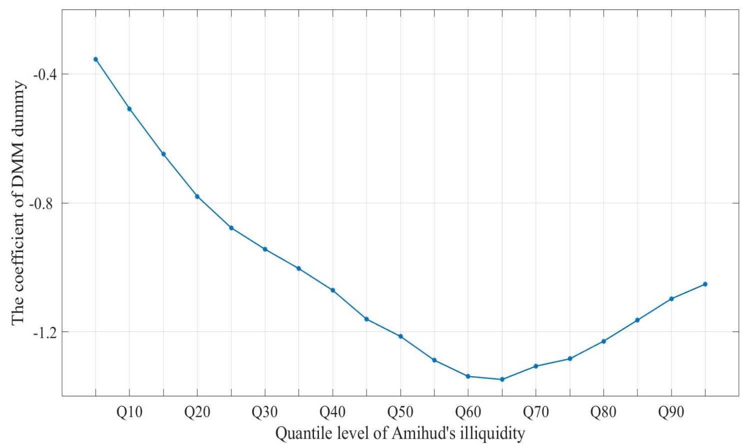
(c) Turnover

Figure 3: Dynamic Impact of DMMs' Introduction on ETF Liquidity

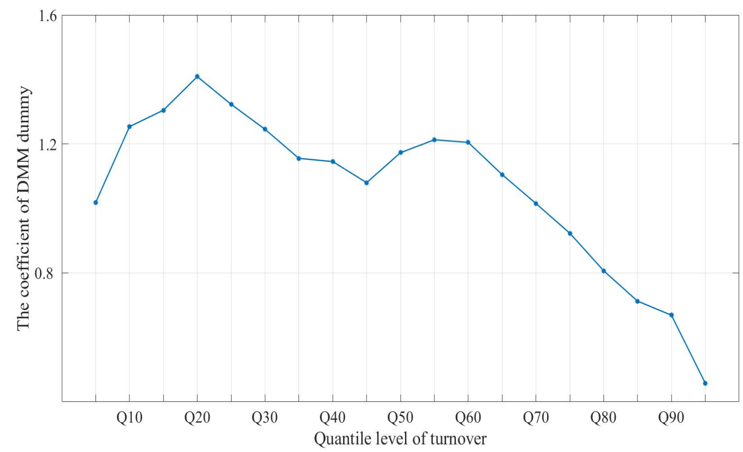
This figure plots the impact of the introduction of DMMs on ETF liquidity which is expressed in three metrics, including the quoted spread, Amihud's illiquidity, and turnover. All three metrics are computed by taking the average value of their respective daily observations during each month. We consider a fifteen-month window, spanning The dashed lines represent 95% confidence intervals, adjusted for fund and month level clustering. Following Sun and Abraham (2021), we consider the entire set of relative-time indicators in the regression, but report only those results from five months before the introduction of market makers until ten months after introduction, following the original event-study analysis of Beck et al. (2010).



(a) Quoted spread



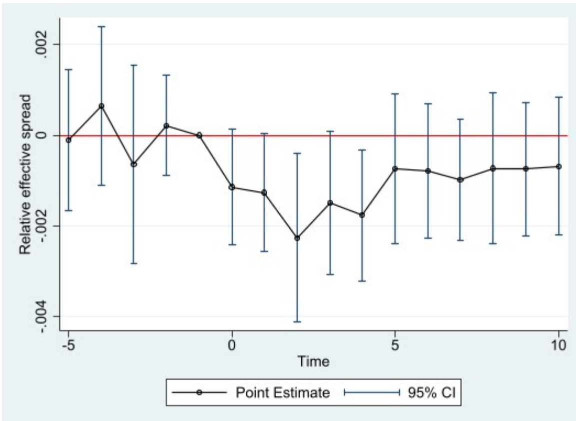
(b) Amihud's illiquidity



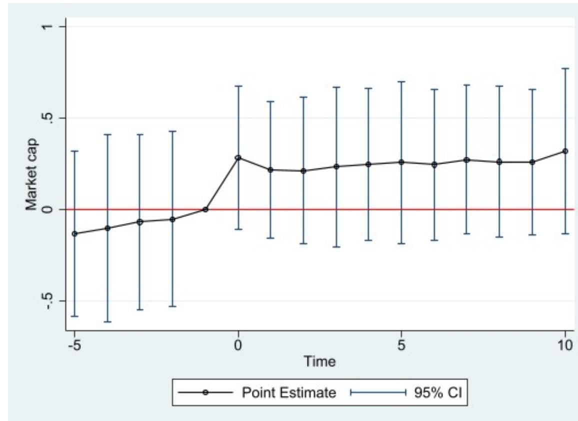
(c) Turnover

Figure 4: The Impact of DMMs on ETF Liquidity: Quantile Regression

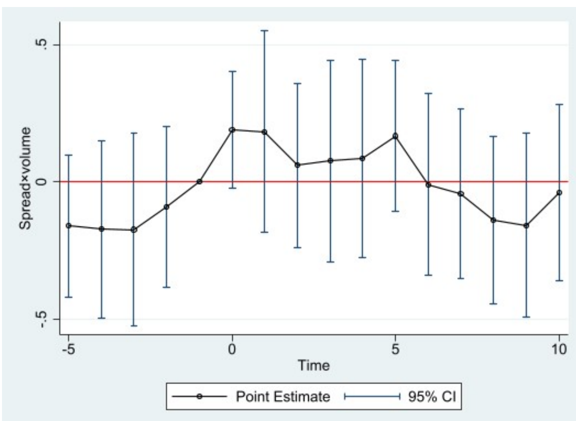
This figure plots the impacts of DMMs when ETF liquidity is at different levels. The results are estimated by of one-month interval panel difference-in-differences approach and quantile regression. The dependent variable is ETF's liquidity which is expressed in three metrics, including the quoted spread, Amihud's illiquidity, and turnover. the independent variable is the indicator of DMMs, denoted by D_DMM, and it equals one during all months in which an ETF have DMMs and equals zero otherwise. The control variables includes: the coefficient of variation for shares outstanding (measuring the level of the primary market activity of ETFs), market cap, ETF price, the realized volatility of ETF daily return during a calendar month, absolute premium, the fund age of ETFs, and ETF return.



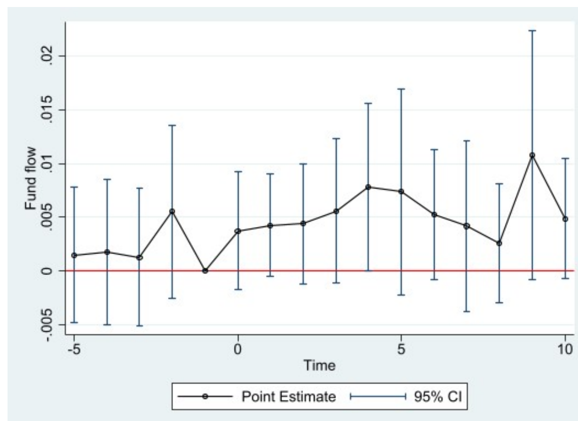
(a) Relative effective spread



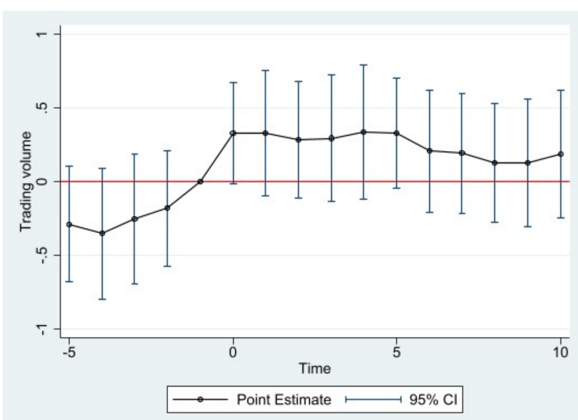
(b) Market cap



(c) Spread×volume



(d) Fund flow



(e) Trading volume

Figure 5: Dynamic Impact of DMMs' Introduction on the Benefit of ETF Market's Participants

This figure plots the impact of the introduction of DMMs on ETF investor, fund issuers, DMMs, APs, and exchanges. The metrics of their benefits are approximately proxied by relative effective spread, market cap, the product of bid-ask spread and trading volume, fund flow, and trading volume, respectively. We consider a fifteen-month window, spanning The dashed lines represent 95% confidence intervals, adjusted for fund and month level clustering. Following Sun and Abraham (2021), we consider the entire set of relative-time indicators in the regression, but report only those results from five months before the introduction of market makers until ten months after introduction, following the original event-study analysis of Beck et al. (2010).