3-2022

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This Draft: March 2022

*We thank Byoung Kang, Charles Lee, Giorgio Valente, and seminar participants at the Hong Kong Institute for Monetary and Financial Research for their helpful comments. Frank Weikai Li gratefully acknowledges financial support from the Hong Kong Institute for Monetary and Financial Research. This paper represents the views of the author(s), which are not necessarily the views of the Hong Kong Monetary Authority, the Hong Kong Institute for Monetary and Financial Research, or its Board of Directors or Council of Advisers. The above-mentioned entities except the author(s) take no responsibility for any inaccuracies or omissions contained in the paper.

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Abstract

Capital constraints of financial intermediaries can affect liquidity provision. We investigate whether these constraints spillover and consequently cause contagion in the degree of *market efficiency* across assets managed by a common intermediary. Specifically, we provide evidence of strong comovement in pricing gaps between ETFs and their constituents for ETFs served by the same lead market maker (LMM). The effects are stronger for ETFs that are more illiquid and volatile, when the underlying constituents of the ETFs are more costly to arbitrage, and for LMMs with more constrained capital. Using extreme disruptions in debt markets during COVID-19 as an experiment, we show that non-fixed income ETFs serviced by LMMs managing a larger fraction of fixed income ETFs experience greater pricing gaps. Overall, our results indicate that intermediaries' constraints indeed influence comovements in pricing efficiencies.

JEL classification: G12, G14, G21, G23

Keywords: ETFs, financial intermediaries, capital constraints

1 Introduction

How do financial intermediaries affect financial market prices? This issue has gathered considerable momentum in recent years. While much research has focused on how intermediaries affect risk premia, we propose instead that these agents can cause co-movements in the degree of *market efficiency*. Specifically, we show that capital constraints of intermediaries can cause contagion in the efficiency of prices across markets in which the intermediaries have a key presence.

Studies on intermediary-based asset pricing link movements in asset prices and risk premia to frictions in financial intermediation. Empirical studies that provide evidence supporting intermediary-based asset pricing include Adrian et al. (2014) and He et al. (2017), who construct a proxy for the intermediary stochastic discount factor (SDF) that explains the cross-sectional variation in asset returns. Despite the theoretical appeal of the idea, however, there is ongoing debate on the reasons for the connection between intermediary balance sheet capacity and asset returns. One key identification challenge is an omitted variable problem. For example, some argue that the relation between intermediary balance sheet capacity and asset prices is spurious, and is driven by macroeconomic factors, time-varying sentiment or risk aversion (Baron and Xiong, 2017; Gomes et al., 2019; Santos and Veronesi, 2021).

In this paper, we use exchange-traded funds (ETFs) as a laboratory to test whether the funding constraints of intermediaries affect comovements in pricing efficiency. Using a comprehensive sample of ETFs listed on US exchanges over the period from 2012 to 2020, we show that (i) pricing gaps co-move within ETFs managed by the same lead ETF market maker (LMM) and (ii) they widen when these LMMs face greater funding constraints. A host of additional tests indicate that these phenomena are causal, running from intermediaries to price efficiency. Thus, we provide support for the proposition that capital constraints do drive pricing efficiency across assets.

Why study the ETF market? There are three reasons. First, this market allows us to differentiate intermediary-specific capital constraints from aggregate funding constraints (both observed and unobserved). We can test a sharper prediction of intermediary asset pricing theories that intermediary-specific constraints have a larger impact on prices when intermediaries are more likely to be the "marginal" investor (Baron and Muir, 2021). Second, when compared to other financial assets, pricing efficiency in ETFs is cleanly defined — the pricing of ETFs should perfectly replicate the value of their underlying assets. Third, ETFs have grown quickly in both size and scope. As of the end of 2020, there were 2,204 ETFs with total assets under management of around $5.4 trillion in US.[1] The sheer size and economic importance of the ETF market suggests that understanding the determinants of ETF pricing (in)efficiency is important.

The ETF LMMs, along with other authorized participants (APs), are responsible for ensuring that ETF prices do not deviate significantly from their net asset value (NAV). If LMMs observe any significant premium or discount between an ETF's price and its NAV, they conduct arbitrage activities by taking long (short) positions on the relatively undervalued (overvalued) side. However, arbitrage is capital-intensive and LMMs are subject to capital constraints. Given that an LMM typically needs to maintain the law of one price in many ETFs, a natural equilibrium prediction is that the pricing gap between ETFs and their constituents will co-move across the different ETFs served by the same LMM. The rationale is that if one ETF experiences a higher level of (absolute) pricing gaps due to an exogenous demand shock, the LMM will direct more capital towards that ETF to exploit the mispricing opportunity.[2] Consequently, less capital will be available to maintain the law of one price for other ETFs managed by the same LMM. Moreover, the comovement of ETF

[1]Source: 2021 Investment Company Factbook.

[2]The LMMs rationally allocate capital to correct ETF mispricing until the marginal benefit of arbitrage per unit of capital is equalized across different ETFs. When one ETF's price moves away from its intrinsic value due to exogenous reasons, the marginal benefit of arbitrage for that ETF becomes greater.

mispricing should be stronger when the LMM faces more binding capital constraints.

To test these ideas, we utilize ETF LMM data for January 2012 to December 2020. We measure ETF mispricing by the ETF premium, defined as the absolute value of the percentage deviation of the price from its net asset value. To ensure that the LMM-level mispricing comovement is not driven by commonality in mispricing across all ETFs, we further orthogonalize the premium with respect to its non-LMM counterpart, and use the residual premium as our variable of interest in most of our empirical tests. We regress each ETF's daily (residual) premium on the average counterpart across all ETFs sharing the same LMM, excluding the focal ETF, in our baseline model. We control for a list of ETF characteristics that may affect ETF mispricing, and include ETF fixed effects to ensure that our result is not influenced by persistent differences in the level of mispricing across ETFs. We also include asset-day fixed effects, where "asset" refers to the specific asset class to which the focal ETF belongs. The inclusion of this fixed effect helps alleviate the concern that the LMM-level comovement in ETF mispricing might be driven by investors' correlated (time-varying) demand for ETFs belonging to the same asset class.

We identify a strong comovement in premium among ETFs sharing the same LMM. The coefficient estimate on the premium is 1.72 (t-stat. = 18.9). This suggests that a one-standard deviation increase in the average premium of non-focal ETFs managed by the same LMM leads to a 1.72 bps increase in the focal ETFs' premium, equivalent to 7.5% of its standard deviation. Since an average LMM manages assets of ETFs of around \$155 billion during our sample period, a one standard deviation increase in the premium results in a dollar cost of \$26.7 million to investors who trade ETFs managed by the LMM on inopportune days.[3]

To show that LMMs play a causal role, we conduct an event study around the days when an ETF changes its LMM. Anecdotal evidence suggests that a change of LMM typically occurs when the LMM decides to retreat from market making due to high regulatory costs

[3]Our estimate provides a lower bound for the effect of LMM-specific capital constraints on the pricing of ETFs. The effect of common LMM constraints on ETF mispricing is removed via the inclusion of asset-day fixed effects and the construction of the residual premium.

in the ETF market-making business.[4] It can be reasonably assumed that a change of LMM for an *individual* ETF is relatively exogenous to the ETF's unobserved characteristics that may drive comovement in premium. Using an event-study approach, we find that the focal ETF's premium comovement with that of its old LMM reduces significantly from a pre-level of 1.15 bps to a magnitude of close-to-zero after the ETF switches to a new LMM. The pre- and post-difference in comovement is 0.99 bps, with a t-stat. of 4.50. Meanwhile, the focal ETF exhibits stronger comovement with that of its new LMM after the switching. The comovement with the new LMM increases by a magnitude of 1.50 bps (t-stat. = 3.06) from its pre-level of 0.22 bps (t-stat. = 1.23). Importantly, the absence of comovement in the premium between the focal ETF and the new LMM *before* the switching and the presence of comovement *after* the switching, together suggest that our finding is unlikely to be explained by market-wide funding constraints that unanimously affect all ETFs.

Next, we examine heterogeneity in pricing efficiency contagion due to the LMM effect. Intuitively, ETFs with higher return volatility, lower liquidity, and smaller market cap should require more costly liquidity provision from their LMMs to maintain the law of one price. We interact these ETF characteristics with non-focal average LMM premium. We find that the interaction terms are significantly positive for ETF volatility and illiquidity, and significantly negative for ETF size, consistent with our conjecture that comovement is stronger for ETFs that are more costly to arbitrage. We also predict that pricing efficiency comovement should be more pronounced when the underlying assets of the ETF are more costly to arbitrage. To test this idea, we restrict our sample to ETFs with U.S. equity as the underlying asset. Aggregating stock-level bid-ask spreads, return volatility, and lendable supply at the ETF level as proxies of arbitrage costs, we find that the LMM-level comovement effect is stronger for ETFs with underlying assets being more costly to arbitrage.

We expect the comovement to be stronger when the LMM faces more severe capital

[4] For example, Goldman Sachs retreated from ETF lead market making in July 2017: https://www.reuters.com/article/us-goldman-sachs-etf-idUSKBN1A92LN.

constraints. We construct three measures to capture LMM-specific capital constraints: the intensity of creation/redemption activities on the ETF over the prior month, the total market capitalization of ETFs managed by the LMM, and the number of active APs for each ETF in a year. We then regress the focal ETF's premium on the interaction between the LMM-specific capital constraint proxies and the non-focal average LMM premium. Consistent with our conjecture, we find stronger ETF premium comovement when the LMM faces more binding capital constraints.

To provide causal evidence that LMM-specific capital constraints drive comovement in ETF pricing inefficiencies, we conduct a difference-in-differences (DiD) test around COVID-19, using the fact that fixed income ETFs experienced unprecedented large discounts during the COVID-19 market sell-off (Falato et al., 2021; Haddad et al., 2021). The idea is that LMMs who manage relatively more fixed income ETFs likely experience more binding capital constraints during the COVID-19 pandemic. We hypothesize that non-fixed income ETFs managed by such constrained LMMs should experience greater pricing gaps, compared to ETFs that are managed by less constrained LMMs. The advantage of this setting is that COVID-19 pandemic is largely an exogenous shock that originates outside the financial sector. Our results are consistent with our prediction. The DiD analysis provides evidence that negative shocks to LMMs' capital constraints led to increased ETF pricing gaps. The results also have important policy implications in showing that inefficiencies in one segment of the ETF market can spillover to other segments through the sharing of common intermediaries.

We conduct several robustness tests. First, we conduct subsample analyses conditional on the level of aggregate funding constraints. We use three proxies for constraints: the VIX, the credit spread, and the intermediary capital ratio of He et al. (2017). Subsample tests reveal that ETF premium comovement is similarly strong and significant during both periods of tightened and loosening aggregate funding constraints. It suggests that the role of LMM-specific capital constraints is independent from the impacts of aggregate funding constraints. Second, we find similar results when using alternative fixed effects specifications. Third, we conduct our baseline analysis for ETFs that track different assets, and find that our central result holds for all types of ETFs except one (those tracking currencies).

Aside from providing evidence for pricing efficiency contagion across financial intermediaries (the LMM pathway), our study also has implications for investors who use ETFs as building blocks to construct investment portfolios (Abraham et al., 2019). One key advantage of ETFs is that diversification across different asset classes, countries, and factors is easy, even for small retail investors with limited amount of capital. For example, many popular robo-advisors such as Wealthfront and Betterment use ETFs to manage the wealth of investors. The excess return comovement we document, however, suggests that the benefits of diversification may be circumscribed if the returns of ETFs tracking different asset classes are excessively correlated, especially during periods when financial intermediaries have more severe funding constraints.

One important caveat of our setting is that we focus mainly on the LMMs of ETFs. Although an LMM is typically the most important financial intermediary with a duty to provide liquidity and maintain the law of one price, an ETF can potentially have other APs simultaneously providing liquidity. However, the presence of other APs should only weaken the role of the LMM, and bias us against finding any LMM-level comovement effect. Using information on APs reported in SEC N-CEN filings, we indeed find that the presence of active APs can mitigate the impact of the LMMs' capital constraints. Furthermore, Arora et al. (2020) show that the market of authorized participants is highly concentrated, with 8 (3) APs accounting for around 80% of total gross creations and redemptions of equity (fixed income) ETFs in 2019. The high concentration suggests that capital constraints may also be an issue for APs if they need to simultaneously manage a large number of ETFs.

The rest of the paper proceeds as follows. In Section 2, we describe the institutional background of the ETF arbitrage mechanism and the contributions of our paper to the literature. In Section 3, we introduce the data and define the variables. In Section 4, we examine the comovement in ETF mispricing and test several cross-sectional predictions. We discuss robustness tests and additional analyses in Section 5. We conclude in Section 6.

2 Institutional background and literature

In Subsection 2.1, we describe the institutional background of ETF arbitrage and the role of LMMs in maintaining the law of one price for ETFs. In Subsection 2.2, we review the related literature and highlight the paper's contribution.

2.1 *Institutional background of ETF arbitrage*

Exchange-traded funds (ETFs) are passive investment vehicles that seek to mimic the returns of baskets of securities. ETFs offer better liquidity than index funds and, unlike index funds, are traded on the stock exchanges. ETFs are traded on both the primary and secondary markets. On the secondary market, ETFs are actively traded by both institutional investors and retail investors, with the price of an ETF determined by supply and demand. As a result, the price of an ETF can diverge from the NAV of its underlying assets. To minimize the divergence between the price of the ETF and its NAV, the ETF sponsor reports the indicated NAV of the ETF's underlying assets every 15 seconds during the trading day. By doing so, the ETF sponsor helps facilitate the arbitrage activities that take place in both the primary and secondary markets.

On the primary market, institutions known as lead market makers (LMMs), along with other authorized participants (APs), play a critical role in facilitating the functioning of the ETF ecosystem. They create and redeem ETF units to ensure that an ETF's market price and NAV are closely linked. For example, RBC Capital Markets, one of the LMMs in our sample, mentions that LMMs "fulfill other important roles in addition to providing liquidity and maintaining market equilibrium they also help to ensure the market price of each ETF unit reflects the value of its underlying securities intraday."[5] While other APs can typically trade as they please, firms acting as LMMs must consistently offer competitive buy-and-sell quotes for their assigned ETFs, and they receive rebates on exchange fees. As Figure 1 illustrates, when the ETF trades at a premium relative to the price of the underlying basket of assets, APs buy the underlying assets, exchange them for "creation units" from the ETF sponsor, and sell those units on the secondary market, thereby harvesting the spread between the price of the ETF and that of the underlying assets. By exerting downward pressure on the price of the ETF and upward pressure on the price of the underlying assets, such arbitrage activity reduces the ETF price premium. Conversely, when the ETF trades at a discount relative to the price of the underlying basket of assets, APs buy the ETFs on the secondary market, redeem them through the ETF sponsor for baskets of underlying securities, and offload the underlying securities in the market, thereby earning the spread between the price of the underlying securities and that of the ETF. By exerting upward pressure on the price of the ETF and downward pressure on the price of the underlying assets, such arbitrage activity narrows the ETF price discount.

On the secondary market, arbitrageurs such as hedge funds and high-frequency traders can take advantage of the price differential between the ETF and the underlying basket of securities without accessing the primary market. When the price of the ETF exceeds (falls below) that of the underlying assets, the arbitrageur can take a long (short) position in the underlying basket of assets, short (go long in) the more expensive ETF, and hold the position until convergence occurs. Of course, since convergence does not always take place (the mispricing could diverge further), such activities may not be considered arbitrage in the strictest sense of the word. Moreover, short sales constraints may prevent arbitrageurs from conducting such activities in the first place. For these reasons, even though arbitrageurs can engage in ETF mispricing correction in the secondary market, the LMMs and APs can do so with much lower arbitrage risk.

[5] https://www.rbcgam.com/documents/en/articles/what-is-the-role-of-the-market-maker-for-etfs.pdf.

2.2 *Related literature and paper contributions*

First, our paper is related to the literature on intermediary-based asset pricing. One of the key predictions from these studies is that liquidity provision by financially constrained intermediaries is a main driver of co-movement in the pricing efficiency of intermediated assets (e.g., Adrian et al., 2014; He et al., 2017).[6] Although prior studies find supportive evidence for intermediary-based asset pricing, they typically focus on the aggregate funding constraints and are subject to omitted variable concerns, i.e., the relationship between intermediary balance sheet capacity and asset prices could be spurious, driven by macroeconomic factors or time-varying sentiment or risk aversion (Baron and Xiong, 2017; Gomes et al., 2019; Santos and Veronesi, 2021). Some papers even reverse the idea, using the common component of market inefficiencies as a measure of financial market dislocation and linking it to aggregate funding constraints (Pasquariello, 2014; Rösch et al., 2017).

Some recent studies emphasize the role of individual intermediaries' capital constraints on the pricing efficiency of certain assets. For example, in the foreign exchange market, Du et al. (2018) show that deviations from covered interest rate parity are particularly strong for contracts that appear on banks' balance sheets at the end of the quarter. Utilizing a regulation reform in the United Kingdom on the leverage ratio of dealers, Cenedese et al. (2021) provide similar evidence. Lewis et al. (2021) find strong commonality in the mispricing of corporate bonds guaranteed by the full faith and credit of the United States, which can be explained by dealer funding costs.

Different from these studies that focus on mispricing within a single asset class, we investigate pricing efficiency comovement across ETFs tracking all major asset classes, including US equities, global equities, fixed income securities, commodities, currencies, and real estate. Indeed, a disaggregated analysis shows that our central result holds in virtually all asset classes. Further, using the debt market disruption during COVID-19 as an exogenous

[6] Other related studies on intermediary-based asset pricing include but are not limited to He et al. (2019), Baron and Muir (2021), Goldberg and Nozawa (2021), and Haddad and Muir (2021).

shock to LMMs' capital constraints, we show inefficiency contagion across ETFs tracking different assets via the common LMM link. A key differentiating factor in our paper is that since the price of an ETF should perfectly replicate the value of its underlying assets, pricing efficiency in ETFs is cleanly defined. We thus offer more direct evidence on the causal relationship between financial intermediaries' capital constraints and the pricing efficiency of intermediated assets.

Second, our paper contributes to the burgeoning literature that examines the impact of rising ETFs on financial markets. Although the introduction of ETFs substantially lowered management fees and introduced greater intraday trading flexibility for investors, practitioners and academics alike have expressed concerns about the potential negative effects of ETFs. Some recent evidence suggests that ETFs can increase systemic risk, induce non-fundamental volatility and excess co-movement, and impede price discovery for individual constituent stocks (Israeli et al., 2017; Ben-David et al., 2018; Da and Shive, 2018). On the other hand, some studies document that ETFs can improve the price efficiency of the underlying stocks, by allowing investors to exploit stock mispricing through hedging (Huang et al., 2021) and facilitate the transmission of systematic information into the underlying stocks' prices (Bhojraj et al., 2020; Glosten et al., 2021). While previous studies mostly focus on the impact of ETFs on the underlying constituent securities, few examine whether the price formation process is efficient at the ETF level and what factors may improve or impede the efficient pricing of ETFs. This is an important question as, like all other assets, ETFs may be subject to non-fundamental demand shocks that drive prices temporarily from their fundamental value.

Among the few studies that examine price inefficiencies at the ETF level, Petajisto (2017) finds that ETF prices significantly deviate from their NAVs, particularly for ETFs holding illiquid securities. Similarly, Bae and Kim (2020) document that illiquid ETFs have large tracking errors. Brown et al. (2021) show, theoretically and empirically, that creation and redemption activities (ETF flows) provide signals of non-fundamental demand shocks and negatively predict future ETF returns. Pan and Zeng (2019) and Gorbatikov and Sikorskaya (2021) provide evidence that ETF arbitrage is limited by the balance sheet space constraints of authorized participants. Our paper differs as we focus on the comovement of mispricing across ETFs, instead of focusing on the level of mispricing. The comovement of ETF mispricing is higher for those LMMs with more severe capital constraints, which reveals the non-trivial role of LMMs in the price formation process of ETFs.

Finally, our study is also related to the literature on the excess return comovement among firms or funds sharing similar characteristics, such as firms headquartered in the same state (Pirinsky and Wang, 2006); stocks belonging to the same indices (Barberis et al., 2005; Greenwood, 2008; Boyer, 2011); stocks priced at similar levels (Green and Hwang, 2009); firms covered by similar sets of analysts (Israelsen, 2016); stocks held by a common set of mutual funds (Anton and Polk, 2014); stocks that pay dividends (Hameed and Xie, 2019); and hedge funds sharing the same prime broker (Chung and Kang, 2016). One challenge in interpreting these excess return comovement studies is that it is often difficult to distinguish whether return comovement is driven by correlated fundamentals or by noise traders' demands. In other words, it is difficult (if not impossible) to establish whether the return comovement is indeed excessive (Grieser et al., 2020). The advantage of our setting is that we can directly observe a model-free measure of mispricing, which allows us to rule out fundamental or information-based explanations for the comovement of the mispricing across ETFs. Moreover, differing from previous studies that focus on the demand-side factors in driving return comovement, we focus on the supply-side by examining the liquidity provision role of LMMs.

3 Data and summary statistics

In this section, we provide detailed descriptions on the data and main variables used in our paper. We also show the time series patterns of ETF mispricing.

3.1 *Data*

Our ETF LMM data are from ETF Global, which covers all ETFs listed in the US with no survivorship bias. ETF Global is a leading and independent provider of ETF data. It offers detailed ETF data including the NAV, share price, shares outstanding, flows, bid/ask prices, volume, inception date and LMMs of ETFs. We verify the data (and correct any data errors) on ETF prices, shares outstanding, and bid-ask spreads using data from CRSP security files. We confirm the ETF NAV information using CRSP mutual fund data. Our sample period is from January 1, 2012 to December 31, 2020. Our final sample includes 3,848 ETFs with broad regional coverage including Emerging Markets, Developed Markets, Asia-Pacific, Europe, Global Ex-U.S., Global, and North America. In terms of asset class coverage, around 70% of the ETFs are equity ETFs, with the remaining asset classes including commodity, currency, fixed income, real estate, and multi-assets.

Panel A in Table 1 shows that there are 18 LMMs in our sample. The list of LMMs matches the LMM names provided by NYSE Arca.[7] Some LMMs in our sample are broker-dealers such as Goldman Sachs and Credit Suisse, while others are market makers affiliated with hedge funds such as Citadel Securities and Jane Street. The average number of ETFs managed by each LMM varies from three to 364, and the total size of ETFs managed by each LMM varies from $1 billion to $634.5 billion. The largest LMM in our sample, in terms of the number of ETFs managed, is Goldman Sachs, which on average runs 280 ETFs, totaling $634.5 billion.

3.2 *Variables construction and summary statistics*

Our main variable of interest is the premium of an ETF, calculated as (ETF Price − ETF NAV)/ETF NAV.[8] Since the absolute deviation of ETF price from its NAV, regardless

[7]https://www.nyse.com/products/nyse-arca-market-making

[8]Following Petajisto (2017), we call this measure an ETF premium even though it could be either a premium or a discount.

of the direction, determines an LMM's arbitrage opportunities, we take the absolute value of the ETF premium, raw $|Premium|$, as a measure of ETF mispricing. To make sure the comovement in ETF raw $|Premium|$ is not simply driven by aggregate funding constraints, we orthogonalize each ETF's raw $|Premium|$ with respect to its non-LMM raw $|Premium|$, by estimating the following regression:

$$\text{raw } |Premium|_{i,t} = \beta_0 + \beta_1 \text{non-LMM raw } |Premium|_{i,t} + \epsilon_{i,t}, \tag{1}$$

where non-LMM raw $|Premium|_{i,t}$ is the average raw $|Premium|$ across all ETFs managed by LMMs that are different from that of the focal ETF i. For each ETF, we use the full sample to estimate Equation (1) and take the regression residual $\epsilon_{i,t}$ as the main variable of interest, $|Premium|_{i,t}$. Essentially, we allow each ETF to have a differential exposure to market-wide mispricing factors.

In our empirical analyses, we control for several ETF characteristics.[9] $Log(Size)$ is the natural logarithm of an ETF's market capitalization. $Turnover$ is the daily dollar trading volume of an ETF scaled by its market capitalization (in bps), estimated using data from the prior month. $BidAsk$ is the difference between ask and bid quotes scaled by the average of bid and ask quotes (in bps), estimated using data from the prior month. STD is the standard deviation of daily ETF returns estimated using data from the prior month. Summary statistics for our main variables are in Panel B of Table 1. The mean and standard deviations of ETF raw $|Premium|$ are 25.5 and 32 bps, respectively. By construction, ETF $|Premium|$ has a mean close to zero. The standard deviation of $|Premium|$ is large with a magnitude of 22.8 bps, suggesting that a large degree of variation in ETF $|Premium|$ is not explained by market-wide mispricing factors. The last two columns in Panel A of Table 1 show the average ETF raw $|Premium|$ by LMMs. There is considerable cross-sectional variation in the average ETF raw $|Premium|$ across different LMMs, ranging from

[9]The Appendix provides detailed description of main variables used in the paper.

the tightest 5 bps of Latour Trading to the widest 48.4 bps of CLP.

We also construct three measures to capture time-varying LMM-specific capital constraints. *Creation* captures the intensity of creation or redemption activities of an LMM, estimated using daily observations in the prior month. Daily creation or redemption activity is calculated as the absolute percentage change in ETF shares outstanding in a given day, scaled by shares outstanding, averaged across all ETFs managed by the LMM. $Log(Mktcap\ of\ ETFs)$ is the natural logarithm of the total market capitalization of ETFs managed by the LMM. *#Active AP* is the number of active APs for the ETF in a given year, as reported in form N-CEN. To control for aggregate funding constraints, we also include several macroeconomic variables. VIX is the CBOE volatility index; the credit spread (CS) is the difference between Moody's BAA yield and the yield on 10-year constant maturity Treasury bond; and HKM is the intermediary capital ratio of He et al. (2017).

3.3 *Time series patterns*

Before we examine in depth the relationship between individual LMMs' capital constraints and ETF mispricing, we first investigate the aggregate pattern of ETF mispricing. Panel A of Figure 2 plots the number and total size of ETFs (in billions USD) managed by an average LMM in our sample. The figure shows that on average, the total assets under management (AUM) of ETFs managed by an average LMM increased from \$106 billion to \$226 billion from 2012 to 2020 (as indicated by the blue line). This aggregate trend suggests that an average LMM needs to manage ETFs with increasing total market cap over time, and if their capital does not grow at the same pace, LMMs will face tightening capital constraints over time. In Panel B of Figure 2, we plot the average raw and residual $|Premium|$ along with the CBOE Volatility Index (VIX). We find a strong comovement between the VIX index and the average raw $|Premium|$, with a correlation coefficient of around 0.6. Since the raw $|Premium|$ is a proxy for the expected returns from ETF arbitrage, the pattern is consistent with the notion that expected returns from liquidity provision and arbitrage opportunity increase with aggregate risk aversion. The time-series variation in raw $|Premium|$ is consistent with Nagel (2012), in which he shows that the expected returns from liquidity provision in equity markets is highly predictable with the VIX index. In contrast to the time-varying pattern of raw $|Premium|$, the green line plots the average residual ETF $|Premium|$ over time. It is clear from the figure that the residual $|Premium|$ is quite stable throughout the sample period, suggesting that the measure of residual $|Premium|$ mostly captures the idiosyncratic components of ETF mispricing.

4 Results

In Subsection 4.1, we conduct a baseline analysis investigating comovement in pricing efficiency for ETFs sharing the same LMM. We supplement the baseline panel regression results with event studies based on ETFs switching LMM in Subsection 4.2. In Subsections 4.3 and 4.4, we conduct cross-sectional tests conditional on ETF characteristics and measures of LMM-specific capital constraints, respectively. In Subsection 4.5, we conduct a DiD analysis of ETF premium around the period of the COVID-19 market sell-off.

4.1 *Baseline regression*

Our baseline test is to run panel regressions of each ETF's daily $|Premium|$ on the equal-weighted average $|Premium|$ of all ETFs sharing the same LMM, controlling for a set of ETF characteristics that may affect the ETF $|Premium|$. This regression framework has been used to test excess return comovement among stocks sharing similar characteristics (Pirinsky and Wang, 2006; Green and Hwang, 2009). The regression specification is as follows:

$$\begin{aligned} |Premium|_{i,j,t} = \beta_0 + \beta_1 \text{LMM } |Premium|_{i,t} + \beta_2 \text{non-LMM } |Premium|_{i,t} \\ + \beta_3 X_{i,t} + \alpha_i + \gamma_{j,t} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where LMM $|Premium|_{i,t}$ is the average daily $|Premium|$ across all ETFs (excluding the focal ETF i itself) that share the same LMM as the focal ETF. In some specifications without time-fixed effects, in order to absorb any residual comovement due to market-wide factors, we also control for non-LMM $|Premium|_{i,t}$, which is the average $|Premium|$ of all ETFs served by an LMM that is different from that of the focal ETF. $X_{i,t}$ is a set of control variables, including ETF size ($Log(Size)$), ETF turnover ($Turnover$), ETF bid-ask spread ($BidAsk$), and ETF return volatility (STD). To facilitate comparison across different variables, we standardize all independent variables to have a mean of zero and a standard deviation of one. The observations are at the ETF-day levels. In most specifications, we also include ETF fixed effects (α_i) and $Asset \times Day$ fixed effects ($\gamma_{j,t}$), where $Asset$ refers to the specific asset class to which the ETF belongs. Note that the inclusion of $Asset \times Day$ fixed effects absorbs any time-varying change in ETF premium at the asset class level, and hence also absorbs the non-LMM $|Premium|_{i,t}$. This helps address the concern that the comovement is due to investors' correlated (time-varying) demand for ETFs belonging to the same asset class. We double cluster the standard errors at the ETF and Day levels.

Table 2 reports the results. Columns (1) to (4) consider the raw $|Premium|$, while columns (5) to (8) the residual $|Premium|$. Across different specifications, the coefficients on LMM $|Premium|_{i,t}$ are significantly positive, which is consistent with our hypothesis. For example, column (1) shows that the coefficient on LMM raw $|Premium|_{i,t}$ is 8.34 bps (t-stat. = 20.21), when estimated without any fixed effects. This suggests that a one-standard deviation increase in LMM raw $|Premium|_{i,t}$ is associated with an 8.34 bps increase in the focal ETF's raw $|Premium|$. In contrast, the coefficient on Non-LMM raw $|Premium|_{i,t}$ is much lower at 0.95 bps (t-stat. = 2.69). The last two rows of Table 2 show a significant difference between the coefficients of LMM raw $|Premium|_{i,t}$ and non-LMM raw $|Premium|_{i,t}$. We next add a set of ETF characteristics and the ETF fixed effects. The results in column (2) show that the coefficient of LMM raw $|Premium|_{i,t}$ decreases slightly to 5.66 bps (t-stat. = 14.37). When we include both the $Asset \times Day$ and ETF fixed effects, the results in column (4) show that the coefficient of LMM raw $|Premium|_{i,t}$ is 2.41 (t-stat. = 12.74). The declining pattern in the coefficient estimates of LMM raw $|Premium|_{i,t}$ suggests that a non-trivial part of the comovement in ETF mispricing is driven by market-wide factors. One caveat is that part of the market-wide factors could be driven by LMMs' systematic capital constraints. Hence, our estimate in column (4) provides a lower bound for the effect of LMM-specific capital constraints on the mispricing comovement of ETFs.

Focusing on the coefficients on the control variables, we find that the estimates are consistent with theories of limits to arbitrage (Shleifer and Vishny, 1997). For example, the negative coefficient on $Log(Size)$ in column (4) suggests that larger ETFs have lower levels of mispricing, potentially because there are more arbitrageurs in the secondary market for larger ETFs. The positive coefficient on bid-ask spread ($BidAsk$) indicates that ETF mispricing is greater for ETFs with lower liquidity, consistent with the evidence in Bae and Kim (2020). Similarly, the positive coefficient on STD is consistent with the notion that, when the ETF return is more volatile, it is more costly for arbitrageurs to take large arbitrage positions to correct mispricing. As a result, the equilibrium level of mispricing is higher for such ETFs.

We next run the same regressions using the residual $|Premium|$, which further accounts for each ETF's differential exposure to market-wide mispricing factors. Across all specifications, we find in columns (5) to (8) that the coefficients on LMM $|Premium|_{i,t}$ are positive and highly significant, while that on non-LMM $|Premium|_{i,t}$ becomes insignificant. Importantly, since the residual $|Premium|_{i,t}$ already removes the effects of market-wide factors on individual ETF mispricing, the coefficient estimates of LMM $|Premium|_{i,t}$ are quite stable across different specifications, with estimated coefficients ranging from 1.68 to 2.12 bps. In terms of economic magnitude, when both the ETF and $Asset{\times}Day$ effects are included, the coefficient on LMM $|Premium|_{i,t}$ in column (8) suggests that a one standard deviation increase in LMM $|Premium|_{i,t}$ is associated with a 1.72 bps increase in the focal ETF's residual $|Premium|$. Since the standard deviation of residual $|Premium|$ is 22.8

bps, a 1.72 bps is equivalent to 7.5% of its standard deviation. Given that for our sample an average LMM manages ETFs with total assets of around $155 billion, a one standard deviation increase in LMM $|Premium|$ results in a dollar cost of $26.7 million for investors who trade ETFs managed by the LMM on inopportune days. For an average ETF, the losses resulting from ETF mispricing accumulate to $6.34 million in a given year.[10]

Overall, the baseline results are consistent with our hypothesis that there exists a strong comovement in the mispricing component of ETFs served by the same LMM. Since the residual $|Premium|$ mainly captures the idiosyncratic component of ETF mispricing, we focus on the residual $|Premium|$ as the variable of interest in the subsequent analyses to provide insight on the importance of LMM-specific capital constraints. All the empirical results are robust when estimated using the raw $|Premium|$, and are sometimes even stronger than the results based on the residual $|Premium|$.

4.2 *Identification based on ETFs switching LMM*

Our panel regression results show a strong comovement in the idiosyncratic component of ETF $|Premium|$ among ETFs sharing the same LMM. One might be concerned, however, that the comovement in ETF mispricing is driven by self-selection of LMMs. That is, LMMs select the list of ETFs to make markets based on some unobservable (to an econometrician) ETF characteristics, and these ETF characteristics may lead to comovement in ETF mispricing due to correlated investor demand. To show that LMMs play a causal role in the comovement of ETF mispricing, we conduct event studies around the days when ETFs change their LMMs. Anecdotal evidence suggests that a change of LMM typically occurs when the LMM decides to retreat from market making due to high regulatory costs in operating as an LMM. For example, Goldman Sachs retreated from the ETF lead market making business in July 2017 due to the high regulatory and operation costs. As a result, we can reasonably assume that a change of LMM for an *individual* ETF is relatively exogenous

[10] This assumes that the average size of an ETF is $147.6 million and there are 250 trading days in a year.

to the ETF's unobserved characteristics that drive mispricing comovement.

We identify 1,264 events where an ETF changed its LMM. We choose a window of $[-120, 120]$ trading days, with day 0 as the date on which the ETF changed its LMM. We then regress the residual $|Premium|$ on the average residual $|Premium|$ of the ETFs that are managed by its old and new LMMs. In Figure 3, we plot the regression coefficients of LMM (raw) $|Premium|_{i,t}$ around the event days, where the coefficient for each event day is estimated using the $[-3, 3]$ trading day window surrounding it. The upper graph in the figure shows the regression coefficients estimated using the raw $|Premium|$ and the lower graph shows the estimations for the residual $|Premium|$. The red line indicates the coefficient of the old LMM (raw) $|Premium|_{i,t}$ while the blue line indicates the coefficient of the new LMM (raw) $|Premium|_{i,t}$. The figure clearly demonstrates that, after an ETF changes its LMM, its mispricing comoves to a lesser extent with that of ETFs managed by the old LMM, while the mispricing becomes more correlated with those of ETFs managed by the new LMM.

Next, we confirm this pattern in formal regressions using the specification below:

$$\begin{aligned} |Premium|_{i,j,t} = \beta_0 + \beta_1 LMM_{old}\,|Premium|_{i,t} + \beta_2 Post_t * LMM_{old}\,|Premium|_{i,t} \\ +\beta_3 LMM_{new}\,|Premium|_{i,t} + \beta_4 Post_t * LMM_{new}\,|Premium|_{i,t} + \\ \beta_6 Post_t + \beta_7 X_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where $LMM_{old}\,|Premium|_{i,t}$ ($LMM_{new}\,|Premium|_{i,t}$) is the average residual $|Premium|$ of ETFs managed by the old (new) LMM before (after) switching. $Post_t$ is a dummy variable that equals one for the days after an ETF changes its LMM. $X_{i,t}$ is the same set of ETF-level controls as those in Eq. (2). In some specifications, we also include macroeconomic factors, returns on the Fama-French five factors (Fama and French, 2015) and the Fama-French ten industry portfolios to control for correlated demand shocks to ETFs belonging to the same style or sector (Wahal and Yavuz, 2013).

Table 3 reports the results. Consistent with our predictions, we find that the coefficients on $Post{*}LMM_{old}\ |Premium|_{i,t}$ are negative and significant across all specifications. Column (1) shows that the coefficient on $LMM_{old}\ |Premium|_{i,t}$ is 1.17, while the coefficient on $Post{*}LMM_{old}\ |Premium|_{i,t}$ is -0.93 (t-stat. = -3.72). The economic magnitude suggests that the mispricing comovement with other ETFs served by the old LMM reduces by around 80% after the ETF switches to a new LMM. On the other hand, we find the coefficients on $Post *$ $LMM_{new}\ |Premium|_{i,t}$ are positive and significant across all specifications, suggesting that ETF mispricing becomes more closely correlated with other ETFs served by the new LMM after switching. Importantly, we find that the coefficients on $LMM_{new}\ |Premium|_{i,t}$ are statistically insignificant across all specifications, suggesting that the mispricing comovement is unlikely driven by the self-selection effects of LMMs. Column (1) of Table 3 shows that the coefficient on $LMM_{new}\ |Premium|_{i,t}$ is 0.268 (t-stat. = 1.42), while the coefficient on $Post * LMM_{new}\ |Premium|_{i,t}$ is 1.44 (t-stat. = 2.94). Overall, the absence of comovement *before* the switching and the presence of comovement *after* the switching between the focal ETF's mispricing and that of the new LMM show that the excess comovement of ETF mispricing is indeed driven by these ETFs sharing the same LMM.

4.3 *Cross-sectional heterogeneity*

In this subsection, we examine the heterogeneous effects of ETF mispricing comovement conditional on the characteristics of the focal ETF. Our main hypothesis is that the capital constraints of LMMs have a greater impact on mispricing comovement for those ETFs that are more costly to arbitrage. To test such a hypothesis, in Subsection 4.3.1, we discuss subsample analyses for ETFs covering different regions. In Subsections 4.3.2 and 4.3.3, we use ETF characteristics and those of their constituents as proxies for arbitrage costs.

4.3.1 *ETFs with different regional coverage*

We begin by examining cross-sectional heterogeneity in ETF mispricing comovement conditional on their regional coverage. As reported in Table 4, comovement in ETF mispricing is pervasive across ETFs with different geographical coverage, with the estimated coefficients on LMM $|Premium|$ ranging from the lowest of 0.46 for North America to the highest of 3.41 for Asia-Pacific. The economic magnitude of the estimated coefficients is consistent with the notion that market efficiency comovement is higher for ETFs that are more costly to arbitrage. In particular, columns (1) and (2) show that the comovement for emerging markets ETFs is 15% higher than that of the developed markets ETFs. Columns (3) to (6) show that ETFs with the highest level of comovement are Asia-Pacific ETFs, followed by Global Ex-U.S. and Europe ETFs. Not surprisingly, North American ETFs have the lowest level of comovement. In untabulated results, we find that the average level of the (absolute) premium is also the highest for Asia-Pacific and Emerging Markets ETFs, and is the lowest for the North America ETFs. The lower level of the premium and comovement for North-America ETFs may be due to the existence of many non-LMM arbitrageurs in this ETF segment, with the correction of mispricing being less reliant on LMMs.

4.3.2 *Characteristics of ETFs*

We next examine cross-sectional heterogeneity in pricing efficiency comovement conditional on the characteristics of ETFs. We hypothesize that the effect of intermediary capital constraints on ETF mispricing comovement is stronger for ETFs that are most costly to arbitrage. Intuitively, smaller ETFs and ETFs with higher return volatility and lower liquidity may require more costly liquidity provision from their LMMs to maintain the law of one price. When the LMM decides to correct mispricing for an ETF that is more costly to arbitrage, the ETF would demand a greater capital commitment per unit of mispricing correction, resulting in a larger capital withdrawal from other ETFs. As a result, we should expect to find a stronger comovement effect for ETFs that are more costly to arbitrage. Table 5 reports the results when we interact LMM $|Premium|$ with ETF characteristics that capture their arbitrage costs. The results are consistent with our conjecture. Column (1) shows that the comovement is weaker for ETFs with larger market capitalization. Columns (2) and (3) show that the effect is more pronounced for ETFs with higher return volatility and higher bid-ask spread, respectively. The economic effect is also non-trivial. Taking bid-ask spread as an example, column (3) shows that for a one-standard deviation increase in an ETF's bid-ask spread, the impact of LMM $|Premium|$ on its own $|Premium|$ is 16.5% greater.

4.3.3 *Arbitrage frictions of ETFs' underlying constituents*

Since ETF arbitrage requires LMMs (and other arbitrageurs) to take positions in both the ETF and its underlying basket securities,[11] another cross-sectional prediction is that the comovement in pricing efficiency should be stronger when the ETF's underlying assets are, on average, more costly to arbitrage. To test this hypothesis, we focus on ETFs with underlying assets of US equity, for which we can measure the arbitrage costs of the underlying constituents. We use three measures of such costs: the bid-ask spread ($Spread\ CS$), stock return volatility ($Volatility$), and lendable supply ($Supply$). We construct stock-level bid-ask spreads following the approach of Corwin and Schultz (2012).[12] We obtain stock lendable supply (lendable shares divided by total shares outstanding) from Markit Securities Finance (formerly Data Explorer) database. Both a higher bid-ask spread and higher return volatility indicate more severe arbitrage frictions, while a greater lendable supply in the

[11]LMMs need to create (redeem) shares of an ETF and simultaneously enter into an opposite direction of trades for the underlying constituents when the ETF is traded at a premium (discount).

[12]The Corwin and Schultz (2012) spread estimate is based on two reasonable assumptions. First, daily high-prices are almost always buyer-initiated trades and daily low-prices are almost always seller-initiated trades. The ratio of high to low prices for a day therefore reflects both the fundamental volatility of the asset and its bid-ask spread. Second, the component of the high-to-low price ratio that is due to volatility increases proportionately with the length of the trading interval while the component due to bid-ask spreads do not. Corwin and Schultz (2012) show via simulations that, under realistic conditions, the correlation between their spread estimates and true spreads is about 0.9.

securities lending market indicates less constrained short selling. We first aggregate the stock-level arbitrage cost measures to the ETF level, and then interact these measures with LMM $|Premium|_{i,t}$, to test the incremental effect of arbitrage frictions on ETF mispricing comovement.

Table 6 reports the results. Consistent with our hypothesis, columns (1) and (2) show that the interactions between LMM $|Premium|_{i,t}$ and $Spread\ CS$ and $Volatility$ are significantly positive, and column (3) indicates that the interaction between LMM $|Premium|_{i,t}$ and $Supply$ is significantly negative. The economic effect is also meaningful. Taking bid-ask spread as an example, column (1) shows that for a one-standard deviation increase in the average bid-ask spread of an ETF's underlying stocks, the impact of LMM $|Premium|$ on ETF $|Premium|$ is 41.5% greater. These results support our hypothesis that the comovement in pricing efficiency is more pronounced when the LMM faces higher costs in taking arbitrage positions in an ETF's underlying assets.

4.4 *The role of LMM-specific capital constraints*

Intermediary-based asset pricing theories suggest that comovement in pricing efficiency should be driven by the limited balance sheet capacity of financial intermediaries. In this subsection, we test this key prediction by examining the comovement conditional on LMM-specific capital constraints. Intuitively, when an LMM faces limited arbitrage capital, the pricing gap in one ETF managed by an LMM can spread to pricing gaps in other ETFs for which the LMM is responsible. Hence, we expect LMM-specific capital constraints to have an contagious effect on the comovement in ETF pricing efficiency.

We use three variables to measure LMM-specific capital constraints. Our first measure, $Creation$, is the creation and redemption activities of an LMM over the prior month. This measure is motivated by our hypothesis that, if an LMM conducts arbitrage activities for one ETF, it will result in less arbitrage capital for the remaining ETFs managed by the same LMM. For ETFs, arbitrage can be measured by creation and redemption activities as reflected in percentage changes in shares outstanding (Brown et al., 2021). A higher value of $Creation$ indicates that less arbitrage capital is left for the focal ETF. Since the mispricing of ETFs might not only be affected by the same-day arbitrage activity, but also by the arbitrage capital tied up in arbitrage activities days ago, for each day t we estimate the LMM creation and redemption activity as the average absolute percentage change in ETF shares outstanding in the $[t-30, t-1]$ window, equally weighted across all ETFs managed by the LMM, excluding the focal ETF.

The second measure, $Log(Mktcap\ of\ ETFs)$, is the natural logarithm of the total market capitalization of all ETFs managed by the LMM. The idea is intuitive: if the LMM needs to simultaneously provide liquidity for ETFs with larger total market capitalization, then it has less capital devoted to correcting pricing gaps for each individual ETF.[13]

Our last measure is the number of active APs for each ETF in a year, where active APs create or redeem shares for the ETF at any point in time. In addition to LMMs, APs also play an important role in maintaining the law of one price for ETFs. To construct this measure, we collect information on ETFs' active APs from SEC N-CEN filings. We create a variable, $Log(1/\#Active\ APs)$, calculated as the natural logarithm of one divided by the number of active APs, constructed using filings data from the last fiscal year.

Following the baseline specification, we then interact each measure with LMM $|Premium|_{i,t}$ to estimate the incremental effect of LMM-specific capital constraints on comovement in ETF pricing efficiency. ETF fixed effects and $Asset{\times}Day$ fixed effects are included in all the regression specifications. Table 7 reports the results. Consistent with our hypothesis, we find that the interaction terms are significantly positive for all three measures of LMM capital constraint. For example, column (2) reports that the estimated coefficient on the

[13]The total market capitalization of ETFs served by the LMM can also be viewed as a proxy for the LMM's (in)attention. However, most ETFs are traded on electronic exchanges, such as NYSE Arca, with LMMs adopting algorithmic trading for ETFs. For these reasons, attention constraint is unlikely the major reason for the ETF mispricing comovement effect we find.

interaction between $Log(Mktcap\ of\ ETFs)$ and LMM $|Premium|_{i,t}$ is 0.324 (t-stat. = 8.70). The economic magnitude indicates that, for a one standard deviation increase in the $Log(Mktcap\ of\ ETFs)$ of an LMM, the impact of LMM $|Premium|$ on the focal ETF's $|Premium|$ is 17.6% greater. Overall, the results support intermediary-based asset pricing theories that ETF mispricing comovement is more pronounced when the LMM-specific capital constraint is more binding.

4.5 *DiD Analysis of ETF premium during COVID-19 pandemic*

We conduct a difference-in-differences (DiD) estimation around the COVID-19 market sell-off to examine whether intermediary capital constraints amplify the comovement in the ETF premium. During that period, the ETF market experienced unprecedented levels of pricing gaps, especially for fixed income ETFs. In Panel A of Figure 4, we plot the average raw $|Premium|$ for ETFs tracking different asset classes from January 2020 to June 2020. The shaded area indicates the period when COVID-19 caused significant financial market turmoil, which runs from February 20, 2020, to April 30, 2020, following Pástor and Vorsatz (2020). As the figure shows, the average absolute premium for all types of ETFs widened dramatically during the crisis period, with the effect being most pronounced for fixed income ETFs. The average absolute premium for fixed income ETFs increases from 14.9 bps on February 1 to 156.7 bps at the peak of the crisis on March 20. This is consistent with recent studies documenting a significant disruption to the fixed income market during the COVID-19 pandemic (Falato et al. (2021); Haddad and Muir (2021)). In Panel B of Figure 4, we show that the widening pricing gap is mainly manifested as a discount (i.e., the prices of ETFs traded below their NAV), potentially because ETFs are the type of asset that investors chose to liquidate first in the cash crunch due to their superior liquidity and trading convenience.

Our DiD exploits the fact that fixed income ETFs experienced the largest $|Premium|$ during the COVID-19 pandemic. The idea is that LMMs who need to manage a larger fraction of fixed income ETFs likely face more binding capital constraints during the pandemic. As predicted by our hypothesis, non-fixed income ETFs managed by more constrained LMMs should experience greater pricing gaps, compared to non-fixed income ETFs that are managed by less constrained LMMs. The advantage of this setting is that the COVID-19 pandemic is largely an exogenous shock to the ETF market that originates outside of the financial sector. As a result, LMMs are unlikely to anticipate the widening ETF premium during this period, which ensures the close-to-random assignment between the more and less constrained LMMs.

We conduct the DiD estimation using the following specification:

$$\text{raw } |Premium|_{i,j,t} = \beta_0 + \beta_1 COVID_t + \beta_2 FI\ Weight_i * COVID_t + \beta_3 X_{i,t} + \alpha_i + \epsilon_{i,t}, \quad (4)$$

where $COVID_t$ is a dummy indicating the post-treatment period, which equals one for the period from February 20, 2020 to April 30, 2020, and zero otherwise. $FI\ Weight_i$ is the continuous treatment variable defined at ETF-level, which is calculated as the market capitalization of fixed income ETFs managed by the focal ETF's LMM scaled by the total market capitalization of all ETFs managed by the LMM. Importantly, we measure $FI\ Weight_i$ at the end of 2019 (i.e., before the start of the COVID-19 pandemic). The coefficient of interest is the interaction between $FI\ Weight_i$ and $COVID_t$, which captures the effect on the $|Premium|$ of non-fixed income ETFs due to their LMMs managing fixed income ETFs during the sample period. $X_{i,t}$ is the same set of control variables as in the baseline regression in Eq. (2). We also control for ETF fixed effects (α_i) in all specifications, which subsume the effect of $FI\ Weight_i$.

Table 8 reports the DiD results. Our sample period is from January 1, 2020, to June 30, 2021. In the regression for column (1), we only include the $COVID_t$ dummy, which has a coefficient of 20.46 (t-stat. = 7.70). This is consistent with Figure 4, where ETFs on average experienced widening pricing gaps during the market sell-off. We next add the treatment variable $FI\ Weight_i$ and its interaction with $COVID_t$. Column (2) shows that coefficient of $FI\ Weight_i$*$COVID_t$ is significantly positive, consistent with our prediction. In column (3), we find similar results after including control variables and $Asset{\times}Day$ fixed effects in the regression, with the latter absorbing the $COVID_t$ dummy. The economic effect is also meaningful. For example, the estimated coefficient of $FI\ Weight_i$*$COVID_t$ in Column (3) is 9.35 (t-stat. = 2.88). The economic magnitude suggests that for a non-fixed income ETF managed by an LMM with a 75% weight in fixed income ETFs, the increase in its $|Premium|$ during the sample period is 4.68 bps higher than ETFs managed by an LMM with only 25% in fixed income ETFs.

In sum, the DiD test indicates that negative shocks to LMMs' capital constraints causally lead to increased ETF pricing gaps. From a policy perspective, the result suggests that inefficiencies in one segment of the ETF market can potentially spillover to other segments through the common LMM linkage.

5 Robustness and additional analyses

In this section, we discuss several robustness tests. Subsection 5.1 provides further evidence that the impact of LMM-specific capital constraints is different from that of aggregate funding constraints. In Subsection 5.2, we re-estimate the baseline regression with alternative sets of fixed effects. In Subsection 5.3, we conduct our baseline tests separately for different asset classes.

5.1 *Subperiod analysis*

Our evidence in Section 4 indicates that LMMs play a key role in driving the mispricing comovement for ETFs under their umbrella. However, it is possible that LMMs face more severe capital constraints when aggregate funding constraints tighten. To differentiate from previous studies that focus on the role of aggregate funding constraints, in this subsection we conduct subperiod analysis conditional on measures of aggregate funding constraints.

We use the VIX index, the credit spread (CS), and the intermediary capital ratio of He et al. (2017) (HKM) as proxies for aggregate intermediary constraints. Higher values of VIX and CS, and lower values of HKM indicate tightened aggregate intermediary constraints. We divide the sample into halves based on each of the three measures and conduct the baseline regression in Eq. (2) for two subperiods, with High (Low) indicating periods with tightened (loosening) aggregate funding constraints.

Table 9 shows that the coefficients on LMM $|Premium|_{i,t}$ are positive and significant with similar economic magnitudes in both periods. For example, columns (1) and (2) show that the coefficients on LMM $|Premium|_{i,t}$ are 1.644 (t-stat. = 17.22) and 1.758 (t-stat. = 17.63) in subperiods with a low and high VIX, respectively. The pattern is similar when we use the credit spread (CS) and intermediary capital ratio (HKM) as proxies for aggregate funding constraints. Overall, the results suggest that the role of LMM-specific capital constraints in driving comovement in ETF pricing efficiency is independent from the impacts of aggregate funding constraints.

5.2 *Alternative fixed effects specifications*

Our main empirical specification includes both ETF and $Asset{\times}Day$ fixed effects. The inclusion of $Asset{\times}Day$ fixed effects helps alleviate the concern that the LMM-level comovement in ETF pricing efficiency is driven by investors' correlated (time-varying) demand for ETFs belonging to the same asset class. In Table 10, we report the baseline results using panel regressions with alternative sets of fixed effects. In the regression for column (1), we include $Category{\times}Day$ fixed effects, where $Category$ denotes the detailed style category that the ETF belongs to, including Sector, Broad Equity, and Corporate Bonds. In the regression for column (2), we control for $Region{\times}Day$ fixed effects, where $Region$ refers to the geographical focus of the ETF. In the regression for column (3), we include $Exchange \times Day$ fixed effects, where $Exchange$ denotes the stock exchange in which the ETF is listed. In the regression for columns (4) and (5), we include $Issuer \times Day$ and $Distributor \times Day$ fixed effects, respectively, where $Issuer$ and $Distributor$ refer to the issuer and distributor of the ETF. We also control for ETF fixed effects and the same set of ETF-level characteristics as in Eq. (2). Across all specifications, the coefficients of LMM $|Premium|$ are positive and significant, with coefficients ranging from 1.447 to 1.723 and t-statistics ranging from 15 to 19. Overall, the LMM-level comovement in pricing efficiency is robust to an array of alternative fixed effects. The results suggest that the pricing gap comovement among ETFs sharing the same LMM cannot be explained by investors' correlated (time-varying) demand for ETFs belonging to the same categories, regional coverage, exchanges, issuers, or distributors.

5.3 *Comovement in pricing efficiency across asset classes*

We next conduct our baseline analyses for ETFs tracking different assets, including equities, fixed income securities, real estate, commodities, currencies, and multi-assets. For this test, since we focus on ETFs within each asset class, we include ETF and Day fixed effects in the regressions. In Table 11, we find that the LMM-level comovement in ETF residual $|Premium|$ is significant for ETFs tracking all assets except currencies. The coefficients of LMM $|Premium|$ range from the lowest of 0.269 for currencies to the highest of 2.16 for real estate. The findings suggest that the notion of capital constraints of individual financial intermediaries influencing comovement in pricing efficiencies holds across asset classes.

6 Conclusion

How do financial intermediaries affect the efficiency of prices in the assets they manage? In this paper, we use ETFs and their lead market makers (LMMs) as a setting to investigate the posed question. We find strong comovement in pricing gaps between ETFs and their constituents, among ETFs served by the same LMM. Additional tests based on changes in ETFs' LMMs provide causal evidence that the excess comovement in ETF premium is indeed due to these ETFs sharing the same LMM. Specifically, for ETFs that change their LMMs, we find that their pricing gaps comove less with those of the ETFs served by their previous LMMs, and more with that of the ETFs served by their new LMMs. We also conduct a difference-in-differences test around COVID-19 pandemic, driven by the observation that fixed income ETFs had large pricing gaps around this event. We find that LMMs that manage relatively more fixed income ETFs (and thus are likely more constrained) experience greater ETF pricing gaps in their non-fixed income ETFs. An ancillary implication of this result is that efficiencies in one segment of the ETF market can spillover to other segments through sharing common intermediaries.

Our evidence suggests that LMMs play an important role in the pricing efficiencies of ETFs. Consistent with theories of intermediary-based asset pricing, the comovement in pricing efficiency among ETFs is more pronounced when the ETF and its underlying constituents are more costly to arbitrage, and for LMMs with more constrained capital. Our results validate the role of intermediaries and their capital constraints in the efficiency of financial market prices.

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Appendix. Variable definitions

This table reports the definitions of main variables used in the paper.

Variable	Definition
raw $\lvert Premium\rvert_{i,t}$	The absolute value of an ETF's raw premium, defined as |(ETF Price – ETF NAV)/ETF NAV|.
LMM raw $\lvert Premium\rvert_{i,t}$	Equal-weighted average raw $\lvert Premium\rvert_{i,t}$ of all ETFs sharing the same lead market maker as the ETF *i*, excluding the focal ETF *i*.
non-LMM raw $\lvert Premium\rvert_{i,t}$	Equal-weighted average raw $\lvert Premium\rvert_{j,t}$ of all ETFs managed by a lead market maker that is different from that of the focal ETF *i*.
$\lvert Premium\rvert_{i,t}$	We orthogonalize each ETF's raw |*Premium*| with respect to its non-LMM raw |*Premium*|, by estimating the following regression: raw $\lvert Premium\rvert_{i,t} = a + b * \text{Non} - \text{LMM raw } \lvert Premium\rvert_{i,t} + \varepsilon_{i,t}$. An ETF's $\lvert Premium\rvert_{i,t}$ is captured by the residual terms $\varepsilon_{i,t}$.
LMM $\lvert Premium\rvert_{i,t}$	Equal-weighted average $\lvert Premium\rvert_{i,t}$ of all ETFs sharing the same lead market maker as the ETF *i*, excluding the focal ETF *i*..
non-LMM $\lvert Premium\rvert_{i,t}$	Equal-weighted average $\lvert Premium\rvert_{j,t}$ of all ETFs managed by a lead market maker that is different from that of the focal ETF *i*.
LMM_{OLD} $\lvert Premium\rvert_{i,t}$	Equal-weighted average |*Premium*| of all ETFs managed by the ETF's old LMM, excluding the focal ETF *i* itself. Old LMM is the lead market maker just before the ETF changes its lead market maker.
LMM_{NEW} $\lvert Premium\rvert_{i,t}$	Equal-weighted average |*Premium*| of all ETFs managed by the ETF's new LMM, excluding the focal ETF *i* itself. New LMM is the lead market maker just after the ETF changes its lead market maker.
Log (Size)	The natural logarithm of an ETF's market capitalization.
STD	The standard deviation of daily ETF returns estimated using data from the prior month.
BidAsk	The difference between ask and bid quotes scaled by the average of bid and ask quotes (in bps.), estimated as of the end of the prior month.
Turnover	Daily dollar trading volume of an ETF scaled by its market capitalization (in bps.), estimated using daily data from the prior month.
Creation	Average daily creation and redemption activity for the LMM, estimated over the [-30, -1] window. The Day *t* creation or redemption activity is calculated as the absolute percentage change in ETF shares outstanding on that day, scaled by shares outstanding as of day *t-1*, averaged across all ETFs managed by the LMM.
Log (Mktcap of ETFs)	Natural logarithm of the total market capitalization of ETFs managed by the LMM.
#Active AP	The number of active authorized participants for the ETF, as reported in form N-CEN
VIX	The CBOE volatility index.
CS	Credit spread = Moody's BAA Yield – Yield on Treasury 10-year constant maturity.
HKM	The intermediary capital ratio of He, Kelly, and Manela (2017).

Figure 1. Illustration of arbitrage on ETF price and net asset value deviation

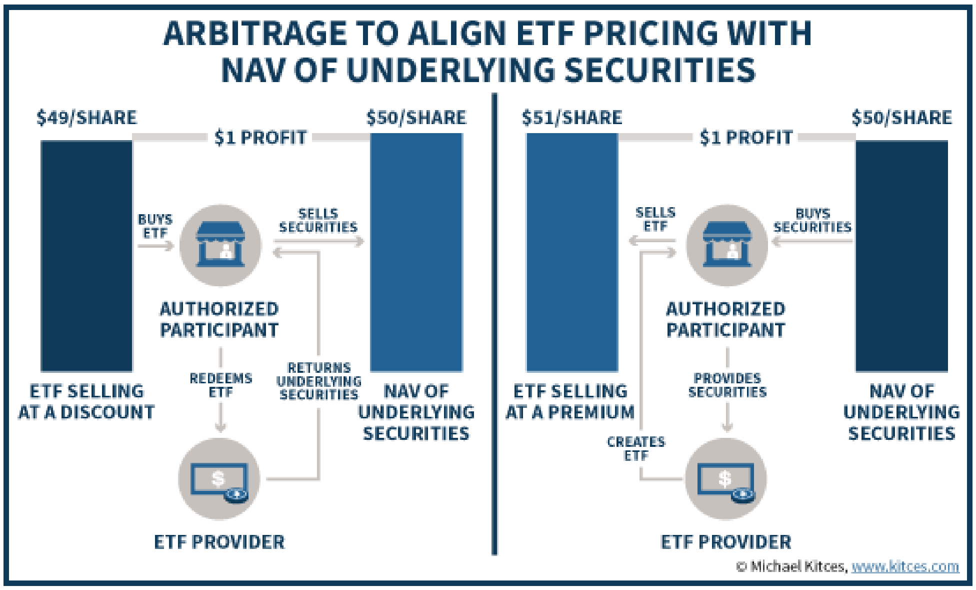
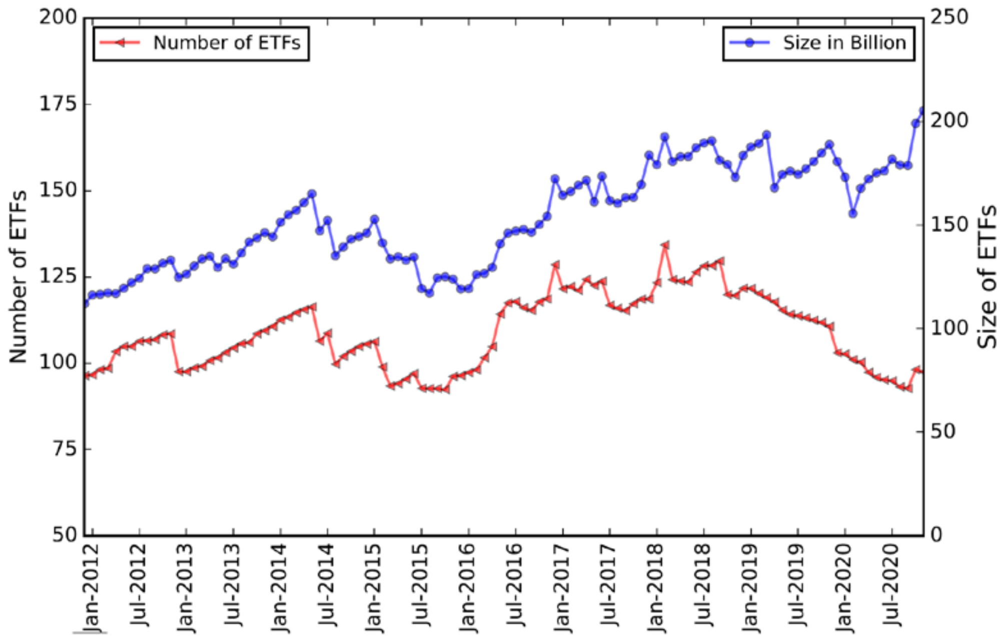
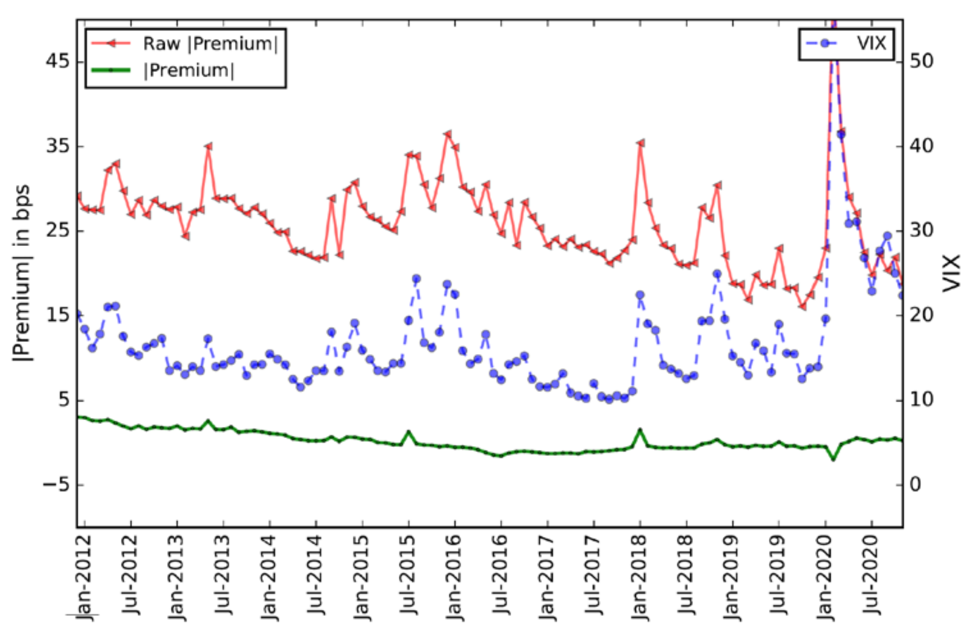


Figure 2. Number and total size of ETFs managed by an average LMM, and ETF premium over Time

Panel A shows the number and total size of ETFs (in billions USD) managed by an average lead market maker in our sample. Panel B shows the equal-weighted average raw |*Premium*| and residual |*Premium*| for each month. On the right axis, the blue dotted line shows the level of the VIX. The sample period runs from January 2012 to December 2020.



Panel A: Coverage of ETFs by an average LMM



Panel B: Average absolute ETF premium

Figure 3. Comovement in |Premium| when ETFs change the lead market makers

This figure reports the comovement in the (absolute) ETF premium with those of other ETFs served by the old and new lead market makers (LMMs) over the [-120, 120] trading days around the change of LMM. LMM_{OLD} $|Premium|$ (LMM_{NEW} $|Premium|$) is the average absolute premium of ETF i's old (new) LMM, excluding ETF i itself. Old (new) LMM is the lead market maker before (after) the ETF changes its LMM. For each trading day around the event, we use a [-3, +3] trading day window to estimate the regression below and then plot the coefficients estimates of *b* and *c*. The shaded area is the 95% confidence interval. The upper graph shows the regression coefficients estimated using raw |*Premium*| and the lower graph shows the estimations for the residual |*Premium*|.

$$|Premium|_{i,t} = a + b * LMM_{OLD}|Premium|_{i,t} \quad + c * LMM_{NEW}|Premium|_{i,t} + \varepsilon.$$

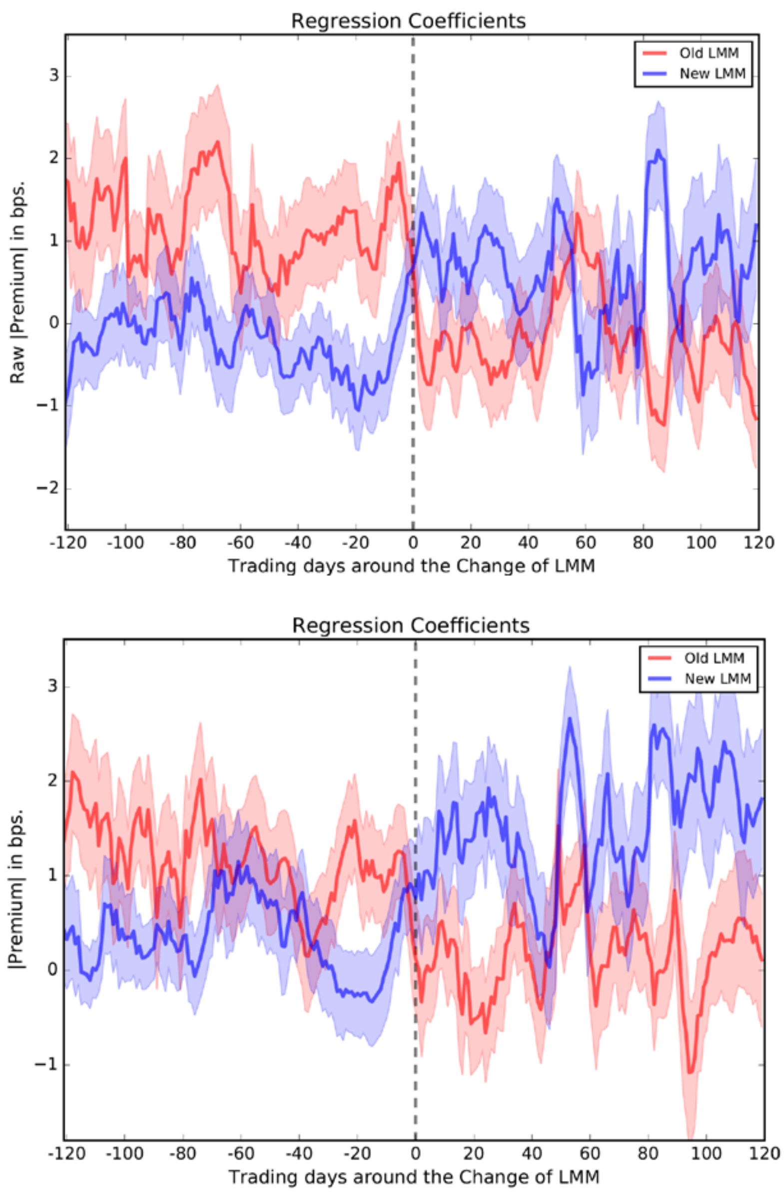
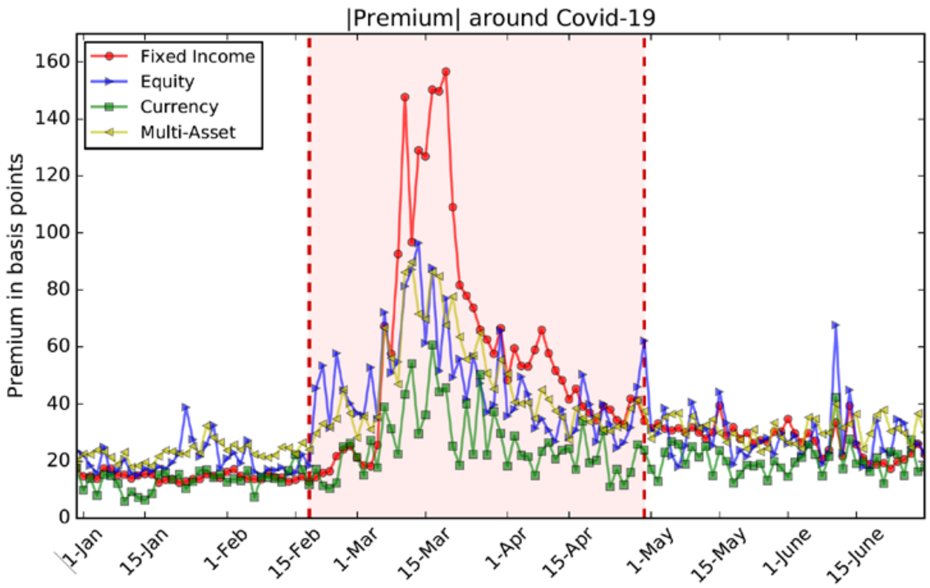


Figure 4. ETF premium during COVID-19 pandemic

Panel A (Panel B) of this figure shows the average absolute (signed) premium for ETFs tracking different assets from January 1, 2020 to June 30, 2020. The shaded area denotes the COVID-19 pandemic period, which runs from February 20, 2020, to April 30, 2020.

Panel A: Average Absolute Premium for Different Types of ETFs



Panel B: Average Signed Premium for Different Types of ETFs

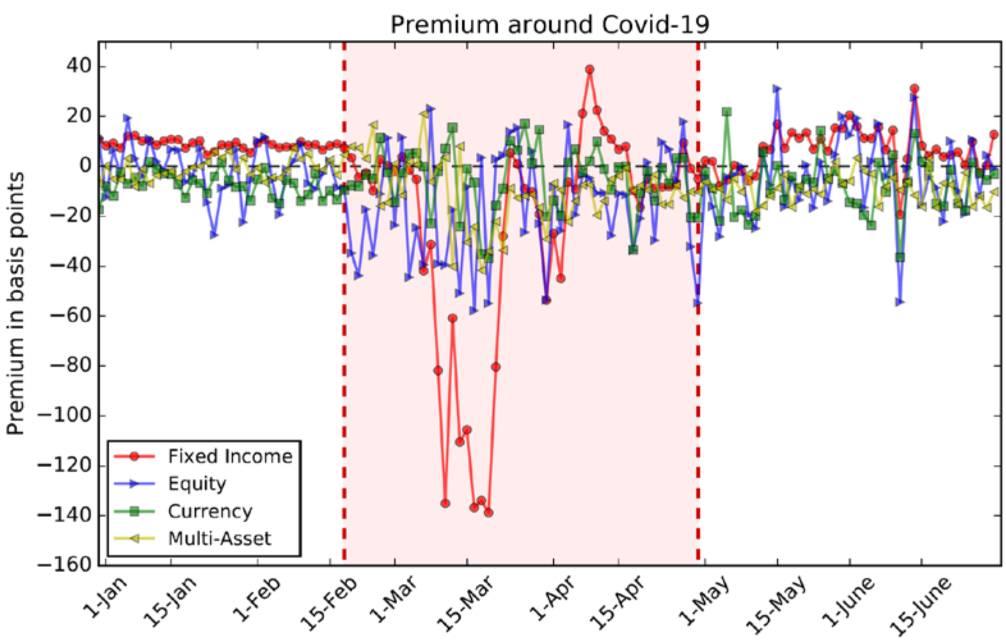


Table 1. Summary Statistics

Panel A lists the information about the lead market makers (LMMs) in our sample. We first calculate the number and size (in billions USD) of ETFs, as well as the equal-weighted average (raw) |*Premium*| of ETFs managed by each LMM at the daily level. We then report the time series average statistics of these variables from January 2012 to December 2020. Panel B shows the summary statistics of the main variables. Raw |*Premium*| is the absolute value of ETF premium in bps. |*Premium*| is the residual |*Premium*|, which is the regression residual of |*Premium*| on the non-LMM |*Premium*|. LMM (raw) |*Premium*| is the equal-weighted average (raw) |*Premium*| of all ETFs sharing the same LMM (in bps.). *Log (Size)* is the natural logarithm of an ETF's market capitalization. *Turnover* is an ETF's daily dollar trading volume scaled by its market capitalization (in bps). *STD* is the standard deviation of daily ETF return. *BidAsk* is the difference between ask and bid quotes scaled by the average of bid and ask quotes (in bps). *Turnover, STD,* and *BidAsk* are estimated using daily observations from prior month. We winsorize the continuous variables at 1% and 99% levels. See the Appendix for variable definitions.

Panel A. List of Lead Market Makers

LMM	#ETF	Size (billion USD)	Raw |Premium|	|Premium|
Goldman Sachs	280	634.5	20.56	-0.97
KCG	364	489.5	30.92	1.41
Virtu Financial	203	377.6	17.25	-0.43
Jane Street	209	316.3	33.99	1.75
Susquehanna	215	302.6	29.06	0.16
IMC Chicago	105	204.2	16.71	0.42
Cantor Fitzgerald	109	122.2	26.31	0.35
Latour Trading	25	97.1	5.08	-0.05
Pundion	23	74.2	22.24	2.40
Credit Suisse	38	63.0	21.48	-1.13
RBC Capital Markets	32	37.7	19.17	0.15
Citadel	22	32.6	14.80	-0.78
Deutsche Bank	19	17.3	19.11	-0.32
Flow Traders	10	12.9	26.15	0.73
Societe Generale	9	6.4	23.78	-2.81
Wolverine Trading	5	4.1	19.01	-0.21
CLP	3	1.4	48.38	0.77
C&C Trading	4	1.0	31.91	-4.72

Panel B. Summary Statistics of Main Variables

Variable	N	Mean	Std	Q1	Median	Q3
raw |*Premium*| (bps)	2,946,278	25.48	31.99	4.44	12.59	33.21
|*Premium*| (bps)	2,946,278	-0.02	22.80	-10.46	-1.90	5.81
LMM raw |*Premium*| (bps)	2,946,278	25.74	9.51	19.20	24.81	31.04
LMM |*Premium*| (bps)	2,946,278	-0.02	3.33	-1.96	-0.28	1.62
Log (Size)	2,946,278	18.81	2.27	17.16	18.77	20.38
STD (percent)	2,946,278	0.83	0.60	0.44	0.72	1.09
BidAsk (bps)	2,946,278	0.24	0.27	0.06	0.14	0.30
Turnover (bps)	2,946,278	3.95	5.73	0.91	1.93	4.18

Table 2. LMM-level comovement in ETFs' raw and residual |Premium|

This table reports the regression estimates of ETF daily raw |*Premium*| and residual |*Premium*| on the equal-weighted average raw |*Premium*| and residual |*Premium*| for all ETFs sharing the same LMM (excluding the focal ETF itself). Columns (1) - (4) show the results for ETFs' raw |*Premium*|, while columns (5) - (8) show the results for ETF's residual |*Premium*|. Controls include the contemporaneous non-LMM (raw) |*Premium*|, ETF size, ETF turnover, ETF bid-ask spread, and ETF return volatility. All independent variables are standardized with a mean of zero and a standard deviation of one. We include ETF and *Asset*Day* fixed effects as indicated. Standard errors are double clustered at the ETF and Day level. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See the Appendix for variable definitions. The sample period is from January 1, 2012 to December 31, 2020.

Dep.Var = Raw |Premium|					Dep.Var = |Premium|				
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
non-LMM raw |*Premium*| (a)	0.954***				non-LMM |*Premium*| (a)	-0.06			
	(2.69)					(-0.73)			
LMM raw |*Premium*| (b)	8.343***	5.664***	5.553***	2.406***	LMM |*Premium*| (b)	2.123***	1.997***	1.684***	1.716***
	(20.21)	(14.37)	(13.58)	(12.74)		(21.37)	(20.87)	(18.64)	(18.89)
Log (Size)		-0.232	-0.494	-3.031***	*Log (Size)*		-2.989***	0.872***	-3.321***
		(-0.59)	(-1.25)	(-8.71)			(-9.99)	(8.89)	(-9.94)
STD		2.100***	2.137***	2.272***	*STD*		-0.364***	0.798***	1.991***
		(5.40)	(4.04)	(10.03)			(-4.04)	(7.73)	(12.14)
BidAsk		11.215***	11.195***	7.018***	*BidAsk*		6.210***	2.701***	6.558***
		(31.02)	(30.61)	(26.38)			(25.22)	(18.92)	(25.70)
Turnover		2.773***	2.827***	0.474***	*Turnover*		0.326**	0.233***	0.404***
		(6.37)	(6.39)	(3.43)			(2.56)	(3.50)	(3.14)
*Asset*Day* FE	N	N	Y	Y	*Asset*Day* FE	N	N	Y	Y
ETF FE	N	Y	N	Y	ETF FE	N	Y	N	Y
Observations	2,946,278	2,946,278	2,946,278	2,946,278	Observations	2,946,278	2,946,278	2,946,278	2,946,278
R-squared	0.008	0.215	0.230	0.454	R-squared	0.008	0.036	0.038	0.059
(b)-(a)	7.388***				(b)-(a)	2.184***			
F-stat.	(10.13)				*F*-stat.	(20.06)			

Table 3. Comovement in |Premium| when ETFs change the lead market makers

This table shows the comovement in ETF $|Premium|$ with the equal-weighted average $|Premium|$ of ETFs served by their old and new LMMs. The sample includes ETF-Day observations within the [-120, 120] trading days around the 1,266 events when an ETF changes its LMM. We include the same set of controls as in Table 2. LMM_{OLD} $|Premium|$ (LMM_{NEW} $|Premium|$) is the equal-weighted average $|Premium|$ of ETF i's old (new) LMM, excluding ETF i itself. Old (new) LMM is the LMM before (after) the ETF changes its LMM. *Post* is a dummy variable that equals one on the day (and the day after) an ETF changes its LMM. We also control for returns on the five Fama-French factors and the ten Fama-French industries as indicated. All independent variables are standardized with a mean of zero and a standard deviation of one. The standard errors are clustered at the event levels. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See the Appendix for variable definitions.

	Dep. Var = |Premium|				
	(1)	(2)	(3)	(4)	(5)
LMM_{OLD} $\|Premium\|$	1.167***	1.210***	1.176***	1.146***	1.146***
	(4.39)	(4.93)	(4.41)	(3.94)	(3.86)
*Post**LMM_{OLD} $\|Premium\|$	-0.932***	-0.967***	-0.951***	-0.997***	-0.994***
	(-3.72)	(-4.21)	(-4.37)	(-4.49)	(-4.50)
LMM_{NEW} $\|Premium\|$	0.268	0.242	0.226	0.225	0.222
	(1.42)	(1.34)	(1.28)	(1.25)	(1.23)
*Post**LMM_{NEW} $\|Premium\|$	1.441***	1.567***	1.575***	1.510***	1.499***
	(2.94)	(2.94)	(2.93)	(3.09)	(3.06)
Post	0.424	0.774	0.477	0.534	0.552
	(1.14)	(1.18)	(0.62)	(0.72)	(0.76)
Log (Size)		1.520***	1.488***	1.485***	1.485***
		(4.40)	(4.21)	(4.18)	(4.18)
STD		0.449	0.443	0.452	0.453
		(1.60)	(1.63)	(1.62)	(1.62)
BidAsk		3.191***	3.190***	3.192***	3.193***
		(7.19)	(7.29)	(7.32)	(7.33)
Turnover		-0.436***	-0.437***	-0.440***	-0.441***
		(-3.49)	(-3.89)	(-3.85)	(-3.85)
Controls of Aggregate Funding Constraints			Y	Y	Y
FF 5 factors				Y	Y
FF 10 Industries					Y
Observations	189,471	189,432	189,432	189,432	189,432
R-squared	0.005	0.02	0.02	0.02	0.02

Table 4. Cross-sectional heterogeneity: ETFs covering different regions

This table reports the regression estimates of ETF daily |*Premium*| on the equal-weighted average |*Premium*| of all ETFs sharing the same LMM. The sample includes US-listed ETFs covering different geographic regions. We control for the contemporaneous ETF size, turnover, return volatility, and the bid-ask spread. All independent variables are standardized with a mean of zero and a standard deviation of one. ETF and *Asset*Day* fixed effects are included in the regressions. Standard errors are double clustered at ETF and Day level. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See the Appendix for variable definitions. The sample is from January 1, 2012 to December 31, 2020.

	Dep.Var = |Premium|						
	Emerging Markets	Developed Markets	Asia-Pacific	Europe	Global Ex-U.S.	Global	North America
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LMM |*Premium*|	3.144***	2.728***	3.411***	2.634***	2.518***	1.340***	0.461***
	(6.13)	(6.37)	(8.33)	(6.37)	(5.37)	(8.25)	(7.86)
Log (Size)	-2.911	-6.042***	-1.717	-3.432**	-3.574***	-2.684***	-3.008***
	(-1.59)	(-5.20)	(-1.44)	(-2.20)	(-2.93)	(-3.51)	(-7.52)
STD	1.822*	1.028	5.063***	4.008***	1.847*	1.970***	0.465**
	(1.84)	(0.81)	(9.70)	(4.28)	(1.87)	(5.43)	(2.33)
BidAsk	5.004***	8.221***	5.384***	5.656***	6.464***	6.104***	7.479***
	(7.88)	(11.86)	(6.72)	(8.44)	(8.40)	(13.22)	(15.45)
Turnover	1.001	0.336	1.167***	1.298***	0.279	0.459	-0.048
	(1.59)	(0.61)	(3.65)	(4.06)	(0.47)	(1.22)	(-0.36)
*Asset*Day* FE	Y	Y	Y	Y	Y	Y	Y
ETF FE	Y	Y	Y	Y	Y	Y	Y
Observations	140,640	123,448	220,273	152,249	155,741	524,352	1,550,826
R-squared	0.162	0.212	0.156	0.223	0.156	0.093	0.107

Table 5. Cross-sectional heterogeneity: ETF characteristics

This table reports the ETF mispricing comovement effect conditional on ETF characteristics. The coefficients of interest are the interaction between LMM |*Premium*| and ETF characteristics, including the logarithm of ETF market capitalization (column (1)), ETF return volatility (column (2)), and ETF bid-ask spread (column (3)). All independent variables are standardized with a mean of zero and a standard deviation of one. ETF and *Asset*Day* fixed effects are included in the regressions. Standard errors are double clustered at the ETF and Day level. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See the Appendix for variable definitions. The sample is from January 1, 2012 to December 31, 2020.

	Dep. Var. = |Premium|		
	(1)	(2)	(3)
LMM |*Premium*|	1.704***	1.682***	1.719***
	(18.68)	(18.84)	(18.91)
*Log (Size)**LMM |*Premium*|	-0.283***		
	(-3.30)		
*STD**LMM |*Premium*|		0.232***	
		(4.15)	
*BidAsk**LMM |*Premium*|			0.284***
			(3.23)
Log (Size)	-3.315***	-3.325***	-3.335***
	(-9.94)	(-9.95)	(-10.02)
STD	1.994***	1.983***	1.993***
	(12.17)	(12.12)	(12.16)
BidAsk	6.551***	6.554***	6.528***
	(25.70)	(25.68)	(25.84)
Turnover	0.390***	0.404***	0.400***
	(3.03)	(3.14)	(3.13)
*Asset*Time* FE	Y	Y	Y
ETF FE	Y	Y	Y
Observations	2,946,278	2,946,278	2,946,278
R-squared	0.059	0.059	0.059

Table 6. Cross-sectional heterogeneity: Arbitrage costs of ETFs' constituents

This table reports the effects of arbitrage costs for ETFs' constituent securities on co-movement in ETF pricing gaps. We restrict the sample to US equity ETFs, for which we can measure arbitrage costs of the constituent stocks. *Spread CS* is the bid-ask spread calculated following the method of Corwin and Schultz (2012). *Volatility* is the daily stock return volatility within a month. Lendable supply (*Supply*) is the lendable shares from Markit divided by total shares outstanding. All independent variables are standardized with a mean of zero and a standard deviation of one. ETF and Asset*Day fixed effects are included. Standard errors are double clustered at the ETF and Day level. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See the Appendix for variable definitions. The sample is from January 1, 2012 to December 31, 2020.

	Dep. Var.= |Premium|		
	(1)	(2)	(3)
LMM |*Premium*|	0.344***	0.344***	0.371***
	(5.18)	(5.19)	(5.31)
Spread CS	0.626***		
	(2.65)		
LMM |*Premium*|**Spread CS*	0.143**		
	(2.49)		
Volatility		0.723***	
		(2.70)	
LMM |*Premium*|**Volatility*		0.131**	
		(2.43)	
Supply			0.402
			(0.93)
LMM |*Premium*|**Supply*			-0.254***
			(-2.68)
Log (Size)	-2.331***	-2.324***	-2.212***
	(-5.85)	(-5.85)	(-5.86)
STD	0.185	0.084	0.219
	(0.85)	(0.37)	(1.03)
BidAsk	5.226***	5.228***	5.234***
	(9.39)	(9.42)	(9.88)
Turnover	0.315	0.317	0.357*
	(1.49)	(1.53)	(1.68)
Time FE	Y	Y	Y
ETF FE	Y	Y	Y
Observations	844,539	844,539	809,313
R-squared	0.071	0.071	0.07

Table 7. LMM-specific capital constraints

This table reports the effects of LMM-specific capital constraints on ETF mispricing comovement. In the regression for column (1), the LMM-specific capital constraint is measured by the creation and redemption pressures faced by the LMM over the prior month (*Creation*). For each day *t,* we estimate the LMM creation and redemption activity as the average absolute percentage change in ETF shares outstanding in the window of [*t*-30, *t*-1], equally weighted across all ETFs managed by the LMM, excluding the focal ETF. In the regression for column (2), the LMM-specific capital constraint is measured by the natural logarithm of total market capitalization of all ETFs managed by the LMM (*log(Mktcap of ETFs)*). In the regression for column (3), *Log(1/#Active APs)* inversely measures the number of other APs available to alleviate LMM constraints. It is the natural logarithm of one over the number of active APs, estimated using SEC N-CEN filings data from last fiscal year. Active APs are those APs that create or redeem shares for the ETF at any point in time. Other controls are the same as for Table 2. All independent variables are standardized with a mean of zero and a standard deviation of one. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. See the Appendix for variable definitions. In columns (1) and (2), the sample period is from January 1, 2012 to December 31, 2020. In column (3), the sample period is from July 1, 2017 to December 31, 2020.

Dep. Var.= |Premium|			
	(1)	(2)	(3)
LMM |*Premium*|	1.648***	1.841***	1.824***
	(18.20)	(18.70)	(11.82)
Creation	0.015		
	(0.75)		
*Creation**LMM |*Premium*|	0.046**		
	(2.01)		
Log (Mktcap of ETFs)		0.158	
		(1.10)	
*Log (Mktcap of ETFs)**LMM |*Premium*|		0.324***	
		(8.70)	
Log (1/#Active APs)			0.452
			(1.20)
*Log (1/#Active APs)**LMM |*Premium*|			0.365***
			(2.88)
Log (Size)	-3.224***	-3.250***	-2.863***
	(-9.71)	(-9.72)	(-3.28)
STD	1.876***	1.877***	0.659**
	(9.96)	(9.99)	(2.46)
BidAsk	6.293***	6.282***	2.985***
	(25.31)	(25.31)	(7.45)
Turnover	0.434***	0.437***	0.561***
	(3.52)	(3.53)	(3.47)
*Asset*Day* FE	Y	Y	Y
ETF FE	Y	Y	Y
Observations	2,943,920	2,946,278	666,913
R-squared	0.059	0.06	0.114

Table 8. DiD analysis of ETF |Premium| during COVID-19 pandemic

This table reports the results from a difference-in-differences estimation of ETF |*Premium*| around the COVID-19 pandemic. The sample includes only non-fixed income ETFs. The sample period is from January 1, 2020, to June 30, 2020. *COVID* is a dummy variable that equals one for period from February 20, 2020, to April 30, 2020. *FI Weight* is calculated as the market capitalization of fixed income ETFs managed by the focal ETF's LMM scaled by the total market capitalization of all ETFs managed by the LMM. We calculate the *FI Weight* for each LMM based on the observations in December 2019. The coefficient of interest is the interaction of *COVID* and *FI Weight*, which identifies the mispricing of ETFs managed by LMMs with high fixed income ETF exposure with that of ETFs managed by LMMs with low fixed income ETF exposure during the COVID-19 pandemic period. All independent variables are standardized with a mean of zero and a standard deviation of one. We include ETF and *Asset*Day* fixed effects as indicated. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively.

Dep. Var = Raw |Premium|			
	Sample of Non-Fixed Income ETFs		
	(1)	(2)	(3)
COVID	20.464***	17.257***	
	(7.70)	(7.34)	
*FI Weight*COVID*		11.655***	9.350***
		(3.82)	(2.88)
Log (Size)			-3.209
			(-1.45)
STD			-1.304
			(-0.93)
BidAsk			3.665***
			(6.36)
Turnover			1.266***
			(3.23)
ETF FE	Y	Y	Y
*Asset*Day* FE			Y
Observations	152,170	152,170	152,170
R-squared	0.436	0.436	0.527

Table 9. Subperiod analysis conditional on aggregate funding constraints

This table reports subperiod results stratified by levels of aggregate funding constraints. The regression specification follows Table 2. We divide the sample into halves based on *VIX*, credit spread (*CS*), and the intermediary capital ratio (*HKM*) of He, Kelly, and Manela (2017). High (Low) indicates periods with tightened (loosened) aggregate funding constraints. All independent variables are standardized with a mean of zero and a standard deviation of one. See the Appendix for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. The sample period is from January 1, 2012 to December 31, 2020.

	Dep. Var = |Premium|					
	VIX		*Credit Spread*		*HKM*	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
LMM |*Premium*|	1.644***	1.758***	1.706***	1.678***	1.699***	1.694***
	(17.22)	(17.63)	(16.70)	(16.49)	(17.16)	(16.10)
Log (Size)	-2.401***	-4.086***	-3.028***	-3.863***	-3.575***	-3.330***
	(-5.98)	(-10.89)	(-7.50)	(-8.98)	(-8.50)	(-8.03)
STD	2.678***	1.667***	2.121***	2.012***	2.433***	1.547***
	(11.40)	(9.93)	(11.31)	(9.91)	(12.51)	(7.49)
BidAsk	7.374***	5.799***	6.280***	6.737***	6.453***	6.375***
	(22.73)	(21.83)	(21.63)	(19.94)	(22.33)	(18.90)
Turnover	0.432***	0.287**	0.634***	0.128	0.759***	0.18
	(2.64)	(2.05)	(4.24)	(0.76)	(4.87)	(1.28)
*Asset*Day* FE	Y	Y	Y	Y	Y	Y
ETF FE	Y	Y	Y	Y	Y	Y
Observations	1,512,415	1,433,863	1,671,942	1,274,334	1,716,307	1,229,971
R-squared	0.07	0.07	0.064	0.08	0.066	0.083

Table 10. Alternative specifications

This table presents results of the baseline regression model in Table 2 with an alternative set of fixed effects. Category denotes the detailed style category to which the ETF belongs, including Sector ETF, Broad Equity ETF, and Corporate Bond ETF. Region refers to the geographical focus of the ETF. Exchange denotes the exchange on which the ETF is listed. Issuer and Distributor refer to these entities for the relevant ETF. All independent variables are standardized with a mean of zero and a standard deviation of one. See the Appendix for variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. The sample period is from January 1, 2012 to December 31, 2020.

	Dep. Var.= |Premium|				
	(1)	(2)	(3)	(4)	(5)
LMM |*Premium*|	1.531***	1.510***	1.723***	1.447***	1.616***
	(16.99)	(19.01)	(18.15)	(15.06)	(17.10)
Log (Size)	-3.348***	-3.129***	-2.954***	-3.162***	-3.273***
	(-9.93)	(-9.75)	(-8.82)	(-9.05)	(-9.67)
STD	1.904***	1.248***	1.330***	1.325***	1.270***
	(10.04)	(6.64)	(7.24)	(7.17)	(6.86)
BidAsk	6.249***	6.473***	6.417***	6.425***	6.455***
	(25.14)	(26.14)	(24.88)	(26.09)	(25.87)
Turnover	0.472***	0.501***	0.503***	0.565***	0.489***
	(3.88)	(4.13)	(4.04)	(4.51)	(3.90)
ETF FE	Y	Y	Y	Y	Y
Other FE	Category*Day	Region*Day	Exchange*Day	Issuer*Day	Distributor*Day
Observations	2,916,565	2,944,228	2,762,151	2,903,629	2,885,229
R-squared	0.081	0.101	0.048	0.105	0.064

Table 11. Comovement in |Premium| for ETFs tracking different assets

This table presents results of the baseline regression model of Table 2 for ETFs tracking different assets. We regress ETF |*Premium*| on the equal-weighted average |*Premium*| of all ETFs sharing the same LMM (excluding the focal ETF itself). Controls include ETF size, turnover, bid-ask spreads, and return volatility. All independent variables are standardized with a mean of zero and a standard deviation of one. We include ETF and Day fixed effects as indicated. Standard errors are double clustered at the ETF and Day level. *, **, and *** indicate significance at the 10%, 5%, and 1% two-tailed levels, respectively. The sample period is from January 1, 2012 to December 31, 2020.

	Dep. Var.= |Premium|					
	Commodities	Currencies	Equities	Fixed income	Real estates	Multi-asset
	(1)	(2)	(3)	(4)	(5)	(6)
LMM |*Premium*|	1.126***	0.269	1.910***	1.096***	2.163***	0.976***
	(2.69)	(0.90)	(16.94)	(6.77)	(3.49)	(3.38)
Log (Size)	0.329	-1.066	-3.740***	-2.568**	-4.909***	-0.482
	(0.15)	(-0.66)	(-10.63)	(-2.54)	(-3.35)	(-0.34)
STD	5.826***	7.791***	1.772***	1.114	2.241***	3.078***
	(7.46)	(4.78)	(10.41)	(1.17)	(2.68)	(3.77)
BidAsk	7.610***	3.997***	6.139***	8.990***	5.886***	6.083***
	(4.47)	(7.25)	(20.30)	(14.14)	(4.40)	(5.85)
Turnover	-0.482	0.221	0.678***	-0.471	-0.526	-0.482
	(-0.57)	(1.01)	(5.50)	(-1.21)	(-1.13)	(-0.41)
ETF FE	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y
Observations	57,191	32,546	2,121,625	534,083	71,459	129,374
R-squared	0.188	0.202	0.041	0.116	0.09	0.072