Two APs Are Better Than One: ETF Mispricing and Primary Market Participation

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May 2, 2022

Abstract

Exchange-traded funds (ETFs) depend on arbitrageurs to correct deviations between a fund's price and its fair value. ETFs have designated brokers, or authorized participants (APs), who have a unique right to create and redeem ETF shares, and who can thus trade on ETF mispricing without risk. Using novel regulatory filings, we provide the first description of the US ETF-AP network. It has a dense core and a sparse periphery, and the observed creation/redemption volumes are highly concentrated. The level of mispricing in a US equity ETF is negatively related to the fund's network diversity, especially during times of high market volatility. Funds that share more APs exhibit stronger mispricing comovement. We theoretically show that diverse networks help mitigate the effect of shocks to AP-specific arbitrage costs. We highlight the importance of AP balance sheet usage costs in ETF markets by exploiting the Federal Reserve's purchases of bond ETFs in 2020.

JEL Classification: G12, G14, G21, G23

Keywords: exchange-traded funds, authorized participants, limits of arbitrage, prime brokers, SMCCF.

*We thank Nina Boyarchenko, Svetlana Bryzgalova, Caitlin Dannhauser, Rebecca De Simone, Francisco Gomes, Bruce Iwadate, Howard Kung, Ananth Madhavan, Thomas Marta, Narayan Naik, Anna Pavlova, Stephen Schaefer, Dimitri Vayanos, Kumar Venkataraman, Yao Zeng, and seminar participants at the AFA 2022, FMA 2021, London Business School finance seminar, NFA 2021, and Young Scholars Finance Concortium 2022 for helpful comments. For valuable insights into ETF primary markets, we are grateful to Keshava Shastry from the DWS Group and to other ETF practitioners.

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1 Introduction

Exchange-traded funds (ETFs) are an extremely successful financial innovation. They have attracted over \$5.4 trillion in the US by the end of 2020[1] and democratized diversified access to various markets and asset classes. Despite this rapid growth, very little is known about the primary markets of ETFs, where ETF shares are supplied, or the authorized participants (APs) of these markets who have exclusive rights to create and redeem ETF shares. The primary market helps an ETF maintain intraday liquidity and keeps the ETF share price close to its underlying value, i.e., the net asset value of the fund. During the COVID-19 crisis, however, many funds saw large mispricing.[2] On March 13, 2020, the price of the SPDR S&P 500 ETF (SPY), the largest ETF in the industry, diverged from its underlying basket by 0.8%.[3]

Several papers have explored the importance of the arbitrage mechanism in ETF primary markets.[4] However, due to the lack of appropriate data, this literature has focused on a representative AP. To the best of our knowledge, ours is the first paper to provide a comprehensive description of US ETF primary markets and to suggest that AP heterogeneity affects ETF mispricing. Using novel regulatory filings, we characterize the network of ETF-AP connections as one with a dense core and a sparse periphery. The primary markets of US ETFs significantly differ in diversity, composition, and in the concentration of trading activity. We establish that the level of mispricing in a US equity ETF is related to the fund's primary market features, especially during times of stress.

We propose a mechanism behind the empirical findings: diverse primary markets mitigate the effect of shocks to AP-specific arbitrage costs. In our model of ETF arbitrage, equilibrium mispricing depends on the number of participating arbitrageurs and their average costs. We present evidence that AP-specific costs matter for ETF mispricing in the data. In particular, we observe stronger mispricing comovement for funds that share more APs. Finally, we highlight the importance of AP balance sheet usage costs in ETF markets by exploiting the Federal Reserve's purchases of bond ETFs in 2020.

We exploit the new regulatory N-CEN filings to characterize the primary markets of ETFs in the US. Starting from June 1, 2019, all ETFs are required to report the structure

[1]Compared to \$0.2 trillion in 2004, according to Investment Company Factbook (ICF) data: https://www.ici.org/system/files/2021-05/2021_factbook.pdf. According to the ICF, ETFs now account for 18% of investment company assets in the US.

[2]For a study of mispricing in bond ETFs during the COVID-19 turmoil, see, for example, Haddad, Moreira, and Muir (2021).

[3]With an \$88.8 bln trading volume on March 13, 2020, this divergence amounts to hundreds of millions of dollars on a single day. This assumes that all volume is traded at a price 0.8% lower than the NAV. The exact magnitude is \$88.8 bln $\times$ 0.8% $\approx$ \$710 mln.

[4]See, for example, Malamud (2015), Ben-David, Franzoni, and Moussawi (2018), and Pan and Zeng (2019).

and activity of their primary markets to the US Securities and Exchange Commission (SEC). More specifically, ETFs provide the SEC with details about the identities of the authorized participants who are registered with them, and about the annual trading volume of each AP. We use this information to construct the ETF-AP network, where APs are considered as connected to a fund if they have a registered relationship.

Our first contribution is the description of ETF primary markets. The network of ETF-AP connections is not very dense on average – as of 2019, 48% of all potential connections were formed. It is not a random graph: there is a notably dense core and a sparse periphery. This network structure leads to considerable cross-sectional variation in fund-level primary market characteristics. The majority of ETF-AP links are inactive: in only one-fifth of cases does an AP create or redeem shares of a connected ETF. The median ETF has connections with 22 (out of 50) APs; only four of these connections are active.[5] We also document a strong persistence of the ETF-AP relationships: 97% of ETF-AP connections in 2019 were maintained in 2020.

Next, we describe brokers with a unique right to operate in the ETF primary markets. Most APs are bank-affiliated brokers, and some are global systemically important banks (G-SIBs). Out of 50 APs operating in the market, 15 are responsible for 98% of creations and redemptions, and the top three APs generate half of that total volume.[6] However, most of the authorized participants in our sample are prime brokers, who create or redeem ETF shares on behalf of their clients.[7] Thus, the observed AP-level volume is the aggregate for the AP and its customers and we argue that the ultimate arbitrageur market is not as concentrated as it may seem in N-CEN filings.

As our second contribution, we relate mispricing in US equity ETFs to the number and composition of their connections with APs. Using several measures of primary market size and diversity, we show that ETFs with more diverse primary markets experience significantly lower mispricing in the cross-section. To address reverse causality, we first show that ETF mispricing is not a significant predictor of future AP registrations and activity in the fund. Second, we argue that the ETF-AP relationships are persistent and that they did not have time to react to the market disturbances caused by COVID-19. Hence, we regress the 2020 ETF mispricing levels on the 2019 primary market features. A one standard deviation increase in the number of APs that are registered in a fund translates into a 15% lower

[5] Aquilina, Croxson, Valentini, and Vass (2020) documented a similar level of activeness for European ETF markets.

[6] This analysis does not include designated market makers, as they have a different agreement with funds and are paid for providing liquidity.

[7] By law, only self-clearing brokers can become APs in US ETFs. So even large institutional investors who do not self-clear cannot participate in ETF primary markets directly. For details, see SEC rule 6c-11: https://www.sec.gov/rules/final/2019/33-10695.pdf and Laipply and Madhavan (2020).

average daily mispricing. Importantly, the effect primarily comes from days with a high level of financial market stress, when primary markets are likely to be marginal.[8] Correspondingly, only on such days is there a pass-through of primary market transaction costs to mispricing. Our results are robust to using different mispricing measures and definitions of market stress, and including additional fund-level controls or benchmark index fixed effects.

We also study ETF flows as a key measure of activity in ETF primary markets. In particular, we estimate the sensitivity of ETF flows to mispricing. The literature has considered this sensitivity as a measure of how well ETF primary markets function.[9] Consistent with the previous findings, we see that flows are highly sensitive to mispricing. We document a novel fact that the flow-premium sensitivity is higher for ETFs with larger primary markets, which suggests that the properties of ETF-AP networks contribute to the efficacy of the arbitrage mechanism.

We argue that the relationship between an ETF's primary market features and its mispricing is driven by the arbitrageur-specific costs of transactions in ETFs. The costlier that arbitrage for ETF secondary market participants, the more the observed mispricing is determined by the structure of the primary market. To elucidate the mechanism, we construct a static model with two identical assets that are traded by price-taking investors in segmented markets and by oligopolistic arbitrageurs who bear costs based on the size of the gross arbitrage position. An investor demand shock generates mispricing between the assets. Arbitrageurs' activity depends on the size of the demand shock in comparison to their costs and to the costs of their competitors. The equilibrium level of mispricing is defined by the number of participating arbitrageurs and by their average costs. We illustrate that in our model, a larger and more diverse pool of potential arbitrageurs makes mispricing less sensitive to changes in costs for a given arbitrageur or to the exclusion of certain arbitrageurs from the market.

We present evidence for heterogeneity in AP costs assumed in our model. We relate the observed level of mispricing to AP features that are likely to pick up differences in arbitrage costs, such as AP total assets, primary market trading volume and centrality, and the number of prime brokerage clients.[10] We find that all these features are negatively related to mispricing even conditional on the number of active APs. This is consistent with the prediction of our model that funds with lower costs among available arbitrageurs have

[8]Secondary market arbitrageurs can also trade on ETF mispricing. However, in contrast to APs, for whom the arbitrage is riskless due to their exclusive right to create and redeem ETF shares, secondary market arbitrage is subject to the risk of further divergence between ETF price and NAV.

[9]See, for example, Pan and Zeng (2019) and Dannhauser and Hoseinzade (2021).

[10]Following Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020), we use regulatory ADV filings in order to link APs in our sample to their clients.

lower mispricing.

If shocks to AP-specific costs matter in ETF markets, the mispricing of ETFs sharing the same APs should comove. In the data, the correlation of mispricing between two ETFs in our US equity sample is related to the commonality in their active AP network. On low-stress days, this commonality does not contribute to correlation in ETF mispricing. On high-stress days, however, having twice as many common active APs is associated with 6 percentage points higher correlation. The magnitude is conditional on ETFs having similar benchmark indices, belonging to the same fund family or investment category, and after including both funds' fixed effects. Finally, we find no significant relationship between mispricing correlation and the number of common active APs for funds with large networks.

Balance sheet usage costs are a likely driver of heterogeneity in arbitrage costs in ETF markets.[11] Since most APs in our sample are regulated entities that offer institutional brokerage services, regulatory costs are likely to contribute to the balance sheet usage costs that such APs charge. Therefore, the regulatory costs enter into arbitrageurs' optimization problem and feed into equilibrium mispricing.

To shed some light on the importance of balance sheet costs, we study the mispricing of equity ETFs during the announcement and implementation of the Federal Reserve's Secondary Market Corporate Credit Facility (SMCCF). Concerned by plummeting corporate bonds during the first weeks of March 2020, the Federal Reserve announced several stabilizing programs. One of them, the SMCCF, was to provide liquidity to the secondary bond market through purchases of bonds and bond ETFs. These purchases were made through primary dealers and involved several APs from our US equity ETF sample. During the implementation of the program, AP capital was used to purchase bond ETF shares to satisfy the demand of the Federal Reserve. All else equal, allocation of room for the Federal Reserve's purchases required the capital to be shifted internally to a bond desk and, hence, raised the break-even condition for equity ETF trades.[12] Thus, we expect higher mispricing among equity ETFs whose APs are highly exposed to the Fed's purchasing program.

Consistent with this hypothesis, we find that funds whose APs are more engaged in the SMCCF program exhibit higher mispricing during the implementation period. The effect is economically small but statistically significant. Importantly, we see that the result is concentrated in ETFs with less diverse primary markets and on days when secondary market arbitrageurs are less likely to step in. We observe no effect during the same period in 2019.

[11] The literature shows that regulatory constraints impede intermediation in many financial markets. See, for example, Fleckenstein and Longstaff (2020) and Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020).

[12] We rely on the assumption that capital within financial institutions is slow-moving (Duffie (2010) and Siriwardane (2019)).

This result represents a spillover from the bond to equity ETF primary markets, which again highlights the interconnectedness of funds through APs in their primary markets.

We explore alternative explanations for the relationship between an ETF's primary market features and its mispricing. In particular, we consider binding equity capital constraints, arbitrageur disagreement in evaluating arbitrage opportunities, and limits to arbitrageurs' attention. We find little support for these channels in our data.

Our results highlight potential contagion in ETF primary markets. First, the relationship between the primary market characteristics and ETF mispricing concentrates in high-risk times, making ETFs susceptible to shocks to their APs. Second, mispricing of two funds comoves more if they share more APs, consistent with shock propagation. Finally, our results imply that the Federal Reserve's bond ETF buying program had spillovers in equity ETF markets.

Related literature. Our paper is related to the literature on exchange-traded funds, limits to arbitrage, and networks in financial markets.

ETFs have attracted significant academic interest, which has primarily focused on ETFs' asset pricing implications. Specifically, Ben-David, Franzoni, and Moussawi (2018) argue that equity ETFs amplify non-fundamental shocks and increase volatility in ETFs' underlying securities. Malamud (2015) theoretically shows that primary market arbitrage may propagate shocks. Israeli, Lee, and Sridharan (2017) and Cong (2016) argue that increased ETF ownership leads to less informative pricing due to higher trading costs, higher return comovement, and lower future earnings responses. Box, Davis, Evans, and Lynch (2021) exploit high-frequency data to argue against the propagation of nonfundamental shocks to ETF underlying securities. Evans, Moussawi, Pagano, and Sedunov (2017) discuss the effect of ETF shorting on underlying liquidity and price efficiency. The literature has also documented the impact of ETFs in other asset classes.[13] Even though many of these papers posit that nonfundamental shocks are propagated due to the activity of authorized participants in ETF primary markets,[14] the empirical analysis of these markets is very scarce.[15]

The paper most related to our work is Pan and Zeng (2019). The authors study the primary markets of the two largest corporate bond ETF issuers in the US to show that the quality of the arbitrage mechanism depends on APs' inventory management motives. We use a more comprehensive dataset to characterize the primary markets of US ETFs across

[13] In particular, on corporate bonds (e.g., Dannhauser (2017) and Bhattacharya and O'Hara (2017)) and VIX futures (Dong (2016) and Todorov (2019)).

[14] Consistent with that, Brown, Davies, and Ringgenberg (2020) use ETF flows as signals of non-fundamental demand shocks.

[15] A recent exception is contemporaneous work-in-progress by Zurowska (2022). Raddatz (2021) also uses N-CEN data but with a focus on corporate bond ETFs and COVID-19 turmoil.

all asset classes. Our results suggest that mispricing outcomes are related to the balance sheet usage costs of APs even for US domestic equity ETFs.[16]

ETF mispricing has attracted researcher attention since the early days of the industry (Elton, Gruber, Comer, and Li (2002) and Engle and Sarkar (2006)). Petajisto (2017) documents deviations in ETF prices and argues that these deviations remain economically significant even after adjusting for the stale components in fund NAVs. More recently, Bae and Kim (2020) document that better ETF liquidity leads to lower mispricing. We find that the liquidity of ETF shares is related to the structure of its primary markets and that mispricing is higher for ETFs with less diverse primary markets controlling for ETF liquidity. This, along with the findings of Bae and Kim, suggests that ETF primary market diversity has a direct and an indirect effect on ETF mispricing.[17]

Academics and regulators have recognized the potential of systemic risk arising from ETFs' primary markets. Dannhauser and Hoseinzade (2021) study the Taper Tantrum episode, and document a flow-induced bond-price pressure that originates from ETF arbitrage. Shim and Todorov (2021) compare redemption mechanisms in mutual funds and ETFs, and show that APs may act as a buffer between ETF markets and an ETF's underlying assets. Cohen, Laipply, Madhavan, and Mauro (2021) provide further insights into the functioning of the primary markets for fixed income ETFs during the COVID-19 crisis. Neither of these papers considers the structure of ETF primary markets. Aquilina, Croxson, Valentini, and Vass (2020) use a proprietary dataset[18] to describe the primary market for EU-domiciled ETFs. The authors observe that, despite high market concentration, alternative liquidity providers step in during times of stress. Our data also suggest a high degree of concentration in the US primary market. However, we also point out a significant institutional difference between the US and European ETF markets: APs in the US are required to be self-clearing firms. This means that the volumes attributed to the largest prime brokerage firms may represent the activity of a larger number of arbitrageurs.[19] Moreover, we find that funds with lower primary market concentration are more resilient in times of stress, as measured by mispricing.

[16]There is minimal liquidity mismatch between these ETFs and their underlying stocks.

[17]Khomyn, Putnins, and Zoican (2020) abstract away from mispricing to study ETF liquidity. Their paper models APs as competitive market makers, and argues that the ETF bid-ask spread only depends on the activity of the ETF's *secondary* market and on the liquidity of the ETF's underlying assets. We document cross-sectional differences in the liquidity of ETFs with different primary market structures, which suggests that this view of ETF liquidity might be incomplete. We leave a more detailed analysis of liquidity provision in different primary market structures to future research.

[18]This dataset is based on a one-time regulatory request from the Financial Conduct Authority in the UK.

[19]More specifically, the volume captures the clients of the prime broker and other subsidiaries of the broker's holding company.

Our paper also contributes to the literature on limits of arbitrage.[20] There is a growing body of evidence that regulatory capital constraints result in deviations from the no-arbitrage price in many asset markets.[21] The list includes but is not limited to prominent covered interest rate parity violations (Du, Tepper, and Verdelhan (2018))[22] and the basis in the interest rate futures market (Fleckenstein and Longstaff (2020)).[23] In this line of work, the most related paper is Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020), which shows that the break-even condition for many types of bank-intermediated arbitrage is affected by the post-crisis regulation. Our results suggest that regulatory costs may also manifest in the deviation of the ETF price from its NAV.

Finally, our paper contributes to the literature on the role of networks in financial markets. Di Maggio, Kermani, and Song (2017) show that ties between corporate bond dealers define the level of spreads that dealers charge and that this effect is more pronounced during periods of market stress. Li and Schuerhoff (2019) document that central dealers in municipal bond markets charge double round-trip markups, but that they also provide immediacy. Centrality and concentration are shown to be important in other OTC markets, e.g., CDS (Peltonen, Scheicher, and Vuillemey (2014)) and asset-backed securities (Hollifield, Neklyudov, and Spatt (2017)). We are the first to describe the network of exchange-traded funds and their authorized participants in the US and to document the implications of broker heterogeneity and fund connectedness for ETF mispricing. It is important to understand the incentives for agents in the ETF-AP network, which has a different structure than most OTC markets.

The rest of the paper is organized as follows. In Section 2, we describe the ETF market and the role of APs in correcting ETF mispricing. Section 3 describes our data sources. We characterize the network of ETF-AP connections and define fund-level primary market features in Section 4. Section 5 links primary market features with ETF mispricing. Section 6 builds a theoretical model of the costly ETF arbitrage and empirically demonstrates the importance of AP cost heterogeneity for ETF mispricing. Section 7 concludes.

[20] This literature studies the asset pricing implications of short-selling costs (e.g., Duffie (1996)), leverage constraints (e.g., Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2008)), and of constraints on equity capital (Shleifer and Vishny (1997) and He and Krishnamurthy (2013)). Gromb and Vayanos (2010) and He and Krishnamurthy (2018) offer a comprehensive review of this literature. Though our model in Section 6.1 shares many of the features of Gromb and Vayanos (2002) and Fardeau (2020), we make arbitrage costly instead of including arbitrageur wealth constraints. We motivate our model with differences in the institutional setup of ETF markets.

[21] There are also theoretical models of dealers' balance sheets, e.g., Andersen, Duffie, and Song (2018).

[22] However, Augustin, Chernov, Schmid, and Song (2020) document that only one-third of CIP deviations can be associated with the limits of arbitrage.

[23] Several papers attribute price dislocations during COVID-19 to balance sheet constraints, e.g., He, Nagel, and Song (2021) and Chen, Liu, Sarkar, and Song (2020).

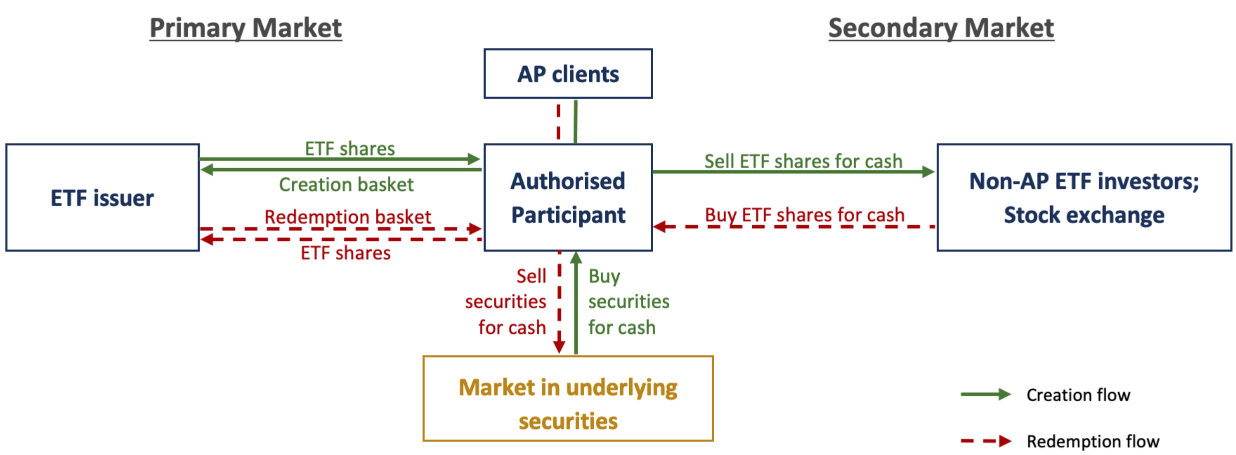
2 Institutional Setup

2.1 ETF Infrastructure

Exchange-traded funds provide intra-day liquidity and exposure to a basket of securities, and require the coexistence of two markets: ETF shares are traded on a centralized exchange (the secondary market), while the supply of shares can be adjusted daily in the over-the-counter market (the primary market). As with closed-end funds, the ETF share price on the secondary market may deviate from its fundamental net asset value per share (NAV). The primary market is designed to limit such mispricing.

Authorized participants (APs) are specialized broker-dealers who have an exclusive right to operate in the primary ETF market, and so they play a critical role in the functioning of ETFs. As shown in Figure 1, an AP has to deliver a creation basket to the ETF issuer in order to create new ETF shares. The ETF portfolio manager makes the composition of the basket publicly available before the start of a trading day.[24] If an AP does not have the shares required by the basket, they will purchase them on the respective market, e.g., the exchange for equities and over-the-counter market for bonds. Converting the basket into ETF shares happens at the end of the trading day, and is called an 'in-kind' creation, as opposed to a 'cash' creation when an ETF accepts the cash value of the basket instead of the constituent securities. The basket is always valued using the end-of-day fund NAV.[25]

Figure 1: AP-centric ETF Infrastructure



To become an AP, a broker must enter into a legal agreement with a fund. This

[24]ETFs typically reserve the right to decline redemption/creation orders but generally choose to do so only if a basket is considerably misaligned. Custom baskets are less common for equity ETFs so we abstract from this in our analysis.

[25]Further details of the ETF markets are outlined in Lettau and Madhavan (2018).

agreement creates a right (but not an obligation) for APs to create and redeem ETF shares.[26] Though both ETFs and APs share the legal costs of such agreements, ETFs do not pay their APs.[27] Furthermore, APs have to pay a transaction fee on every creation or redemption order. Thus, APs are financial intermediaries who can operate in both the primary and secondary markets of an ETF, and who profit from any deviation between ETF share price and NAV.

Importantly, to become an AP, a broker must be a member of a clearing agency that is registered with the US Securities and Exchange Commission.[28] This means that a broker must be able to act as a clearing firm instead of submitting trades to an external clearing firm, and that the number of brokers who can become an AP in the US ETF market is formally limited. However, any market participant acting through a prime broker who is also an AP can access the primary ETF market for a commission. Throughout the paper, we refer to such market participants as AP clients (depicted together with APs in Figure 1).

2.2 ETF Mispricing

ETF mispricing arises when the secondary market share price deviates from its net asset value per share. Since underlying constituents and ETF shares are both traded on exchanges and are very liquid, mispricing for equity ETFs is easily measurable.

We define mispricing as the absolute value of a fund's premium, following the standard approach in the literature:

$$Mispricing_{ft} = |premium_{ft}| = \left| \frac{P_{ft} - NAV_{ft}}{NAV_{ft}} \right|, \tag{1}$$

where P_{ft} is the share price of fund f on day t and NAV_{ft} is the fund's NAV. The fund trades at a premium when its price is above the NAV, while a negative premium means that the fund trades at a discount to its NAV. We use daily closing prices throughout the paper.[29] However, (1) only provides a proxy for the intraday mispricing observed by market participants using real-time intraday NAVs.

[26] Pan and Zeng (2019) argue that the inventory-management incentive of APs in bond ETFs can clash with their incentive to correct an ETF's mispricing. Since APs have no obligation to a fund, they might choose to create or redeem shares in a way that actually increases mispricing.

[27] In that sense, APs are different from market makers (MMs), who are paid to maintain liquidity in ETF shares on the secondary market. In our dataset, market makers are almost never the same entities as APs.

[28] The regulatory definition is as follows: "AP is a broker-dealer that is also a member of a clearing agency registered with the Commission, and which has a written agreement with the Exchange-Traded Fund or Exchange-Traded Managed Fund or one of its designated service providers that allows it to place orders to purchase or redeem creation units."

[29] We confirm in the Appendix that our results go through with midpoint prices.

The deviations between an ETF's share price and its NAV represent a textbook arbitrage opportunity for authorized participants of the fund. As an example, consider a case when an ETF share price is above its NAV. Having noticed the divergence, an AP can immediately enter a transaction on two sides, that is, buy the basket of underlying securities and sell ETF shares in the secondary market ('lock in the spread'). The AP then delivers the basket to the ETF in exchange for the ETF shares, which they then use to close the short position. Since the conversion always happens at NAV, there is no risk to the AP.

For AP i to be willing to trade one basket of ETF shares (a minimum order size), a break-even condition for the level of mispricing in the shares of fund f on date t has to be satisfied:

$$Mispricing_{ft} > \frac{Transaction\, Fee_f}{Basket\, Size_f \times NAV_{ft}} + c_{ft} + c_{it}. \tag{2}$$

$Transaction\, Fee_f$ is the dollar amount that ETF f charges an AP for creating or redeeming one basket of shares, and $Basket\, Size_f$ is the number of shares in one basket of fund f. c_{ft} are other ETF-specific costs, e.g., expected price impact or short-selling, while c_{it} are AP-specific costs. The latter make break-even condition (2) different across APs.

There are various economic drivers of differences in AP arbitrage costs. Importantly, APs in our sample are regulated entities, so most of them have balance sheet costs.[30] Activities outside of AP business may generate synergies and thus reduce AP-specific costs. For example, inventory that is used in an institutional brokerage business may be cross-utilized in the ETF creation/redemption process. Finally, some APs in our sample are proprietary trading firms and market makers, whose advanced trading technologies may also reduce their arbitrage costs. We characterize the relationship between ETF mispricing and AP costs more formally through a model in Section 6.1.

Because ETF shares are traded on an exchange, any secondary market arbitrageur can benefit from ETF mispricing. An investor could take opposite positions in an ETF and in its underlying basket, and then realize profits when the mispricing corrects. Such a trade would be costly, as the ETF basket might include thousands of securities, as well as risky, given that the ETF price and NAV could diverge even further. Therefore, even though the secondary market participants can engage in correcting ETF mispricing, the APs (or their clients) are in a unique position to do so without risk.

[30] Some APs are global systemically important banks (G-SIBs). The literature has shown that regulatory costs disincentivize banks' arbitrage activities (see, for example, Fleckenstein and Longstaff (2020) and Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020)). We provide further details in Section 6.

3 Dataset

3.1 N-CEN Filings and ETF Data

In our analysis, we use the new regulatory filings called N-CEN forms. The N-CEN form is used for annual reports filed pursuant to rule 30a-1 under the Act (17 CFR 270.30a-1).[31] This regulation is one in a series of investment company reporting modernization reforms that were adopted by the US Securities and Exchange Commission (SEC) between 2016 and 2019. All entities were required to comply with the new reporting as of June 1, 2019.

The N-CEN form captures information about the structure, organization, and general activities of management investment companies. In particular, funds are required to report details on their organization, directors, legal proceedings, principal underwriters, accounting, share class structure, securities lending, investment advisers, transfer agents, pricing services, custodians, and brokers.

Exchange-traded funds are also required to fill out Part E of the form, which captures information about the fund's primary market, e.g., its registered authorized participants (name, central registration depository (CRD) number, legal entity identifier (LEI), the dollar value of fund shares that were redeemed and purchased during the fiscal year, whether the AP was required to post collateral with the fund), creation units (size, average and standard deviation of the cash percentage, transaction fees, the fiscal year return difference to the benchmark (benchmark provider, annualized tracking difference, and tracking error), and whether the fund shares are only redeemed in kind.[32] ETFs report all APs with which they have legal agreements, even if a broker is inactive throughout an entire reporting period. Inactive brokers are reported to have creation and redemption volumes of zero.

We download and parse all available N-CEN forms from the SEC EDGAR system.[33] We select the last available filing in a given reporting period.[34] Details on the merging procedure are in Appendix A.2.

We aggregate authorized participants to the holding company level. The AP identifier reported in N-CEN forms (LEI) refers to a separate legal entity. These entities can be geographical subsidiaries, acquired companies, or clearing firms. However, they still operate

[31] The official description of the form is available on the website of the SEC: https://www.sec.gov/files/formn-cen.pdf.

[32] These requirements are defined in rule 22e-4 of the SEC, available here: https://www.sec.gov/rules/final/2016/33-10233.pdf.

[33] We include all N-CEN and N-CEN/A forms available in EDGAR as of April 01, 2021.

[34] Funds' reports are based on their fiscal years. The majority of ETFs have December 31 as their fiscal year-end. If a fund published amended forms, we use the last available amendment.

under one brand and do not have independent financing.[35] Furthermore, these legal entities do not specialize in asset classes or sectors, and we do not observe individual trading desks. We use the reported AP names to aggregate the data and then manually check the holding company structure on Factset. In our sample, 39 out of the 50 holding companies have only one legal entity.

We use CRSP and Morningstar for the standard ETF data. Details on how we merge datasets and what filters we impose to arrive at the final sample of 438 equity ETFs are in Appendix A.4.

3.2 Other Data Sources

Stock EPS announcements come from I/B/E/S, and we use the macroeconomic calendar from Factset. The OFR Financial Stress Index and VIX come from Federal Reserve Economic Data (FRED).

AP data come from several sources. We use Factset to link the AP legal entities with their holding companies. We also get data on public APs' total assets and market equity from Factset (all in USD). For private APs, we take the total assets from annual reports submitted to the SEC. We use the 2020 list of global systemically important banks (G-SIBs) from the Financial Stability Board (FSB) to classify the APs.[36] We obtain information on services APs provide, such as institutional brokerage and clearing, from their websites. Finally, we characterize prime brokerage clients of APs by linking our data to ADV forms as described in Appendix A.5.

All the data on the Secondary Market Corporate Credit Facility (SMCCF) are from the Federal Reserve's website.[37]

4 Characterizing the ETF Primary Markets in the US

In this section, we provide the first insights into the US ETF primary markets by characterizing ETF-AP connections and AP activity. We provide summary statistics for the APs and ETFs, define primary market features at a fund level, and discuss how these features relate to the basic ETF characteristics.

In the general description of ETF primary markets, we consider ETFs across all

[35] A notable example is the Virtu Financial Inc. holding company, with five LEIs. We provide a detailed description of Virtu in Appendix A.3.

[36] Available on the FSB website: https://www.fsb.org/2020/11/fsb-publishes-2020-g-sib-list/.

[37] https://www.federalreserve.gov/monetarypolicy/smccf.htm

underlying asset classes in 2019. Our sample includes 1,913 ETFs from 114 fund families.[38] More specifically, we have 815 US equity ETFs (from 90 families), 467 International Equity ETFs (from 53 families), and 354 bond ETFs (both government and corporate from 45 families).[39]

4.1 Authorized Participants

APs are subsidiaries of large financial conglomerates or of specialized trading firms. The majority are bank holding companies. Some APs have US banking subsidiaries, while others are foreign banks with broker-dealer branches in the US. The rest are proprietary trading firms.

In total, 50 authorized participants operate in the US ETF markets. The top 15 APs are responsible for 97.5% of the ETF primary market activity. Table 1 provides summary statistics for these top 15 APs, sorted by the annual creation/redemption volume.[40] The most active AP (Bank of America) brings about almost a fourth of the volume, and the top three APs are responsible for almost a half.

AP activity in the ETF primary markets looks concentrated, yet most APs in the US are also institutional brokers who provide their clients with access to ETF creations/redemption process. APs in the US are required to be self-clearing, so most investors cannot gain direct access to ETF primary markets and trade via their prime brokers. For example, most of the volume from the Bank of America comes from its Merrill Lynch Professional Clearing Corp. subsidiary, which offers prime brokerage services. Therefore, the volumes we report in Table 1 are the aggregate of trading activity for each AP and its clients. The second column in Table 1 indicates which APs do not offer institutional brokerage services.[41] We call them 'direct investors' as they are likely to trade for their own account.

[38] ETFs are typically issued by investment management companies under a fund family brand (or ETF series) such as SPDR or iShares.

[39] The remaining 277 funds are classified in Morningstar as 'Allocation', 'Alternative', 'Commodities', or with no classification.

[40] For the full list of authorized participants, with information about the total assets of their ultimate owners, see Appendix Table A1.

[41] Namely: Citadel, Flow Traders, Virtu, Jane Street, and Hudson River Trading.

Table 1: Descriptive Statistics by Authorised Participant (AP)

The table provides the summary statistics for 15 authorized participants most active in the primary markets for all US ETFs in 2019, sorted from most to least active. Total volume is measured as a dollar volume of creations and redemptions combined in the full N-CEN dataset. Total equity volume is the same for equity ETFs. AP data are aggregated to the holding company level. 'Direct investor' is 'No' if AP offers prime brokerage services. HHI is the Herfindahl-Hirschman Index computed as $HHI = \sum_{i \in N} flow\_share_i^2 \in [0, 1]$, with N as the number of funds the AP traded with.

AP Name	**Direct investor**	**Total volume, $ billion**	**Total equity volume, $ billion**	**Cumulative share, %**	**Registered in funds, no.**	**Registered in families, no.**	**Active in funds, %**	**Active in families, %**	**HHI in funds**
Bank of America	No	963.3	588.4	23.5	1851	101	84	94	0.03
Goldman Sachs	No	605.6	455.9	38.3	1684	76	50	78	0.11
ABN Amro	No	475.1	468.5	49.9	1346	25	21	68	0.18
JPMorgan	No	414.9	209.2	60.0	1727	92	53	86	0.02
Morgan Stanley	No	277.6	256.7	66.8	1460	33	22	64	0.05
SG Americas	No	209.5	200.7	71.9	1483	38	14	58	0.34
Citadel	Yes	201.5	199.0	76.9	1670	73	35	68	0.05
Credit Suisse	No	170.6	87.2	81.0	1738	86	40	78	0.02
Virtu	Yes	134.7	117.0	84.3	1622	90	44	77	0.02
Citigroup	No	109.2	93.4	94.0	1512	35	20	51	0.04
UBS	No	108.2	59.5	90.0	1593	51	22	45	0.05
Deutsche Bank	No	91.0	84.6	91.9	1574	63	11	43	0.15
BNP Paribas	No	85.4	84.9	93.9	1384	28	6	32	0.09
Barclays	No	85.2	72.2	96.0	1243	21	9	48	0.23
RBC	No	62.5	33.4	97.5	1648	65	23	45	0.04

4.2 The ETF-AP Connections

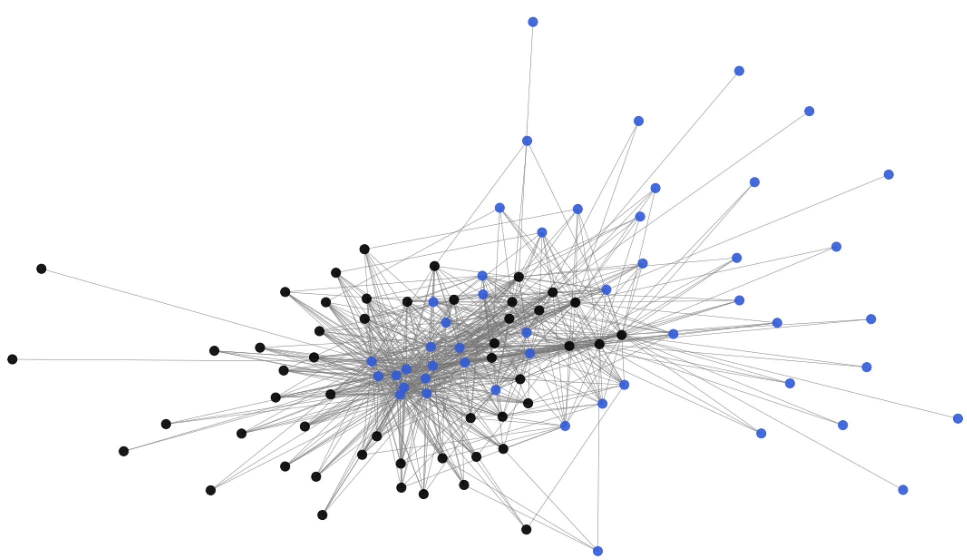
In this section, we describe the ETF-AP connections in the U.S. ETF primary markets. More specifically, we characterize them as a network and document its basic properties, such as density and persistence. For US equity funds, we define several features that reflect the size, activity, and diversity of the ETF primary markets.

4.2.1 The Basic Network Description

One can think of the body of ETF-AP connections as a network. In particular, the ETF-AP network is bipartite – it has two types of agents (ETFs and APs), and the observed links only connect agents of different types. We say that an ETF and an AP have a *registered connection* if they sign a legal agreement allowing the AP to create and redeem shares of the ETF. If an AP executes a non-zero volume of creations/redemptions during a fiscal year, we call the connection *active*.

Figure 2 presents the network graph for registered connections. For purposes of exposition, it shows ETF Family - AP connections. At a Family-AP level, the density of the network is 22.4% – of the 5,700 potential connections, only 1,277 are established. A median AP is connected to 13 fund families, and a median family has connections with 9 APs.

Figure 2: ETF-AP Network: Registered Connections



Nodes: AP holding company (blue) and ETF families (black).

The network has a notably dense core and a sparse periphery. The largest AP (Bank of America) is connected to 101 of 114 families, and four other top APs are connected to more than 70 families. The variation in connectedness is considerable even among the top 15 APs: several of the brokers work with fewer than 30 funds. On the ETF side, there are three families connected with 41 (of 50 total) APs. The periphery is quite sparse, where four APs are connected to one family and three families are connected to a single AP. 70 families are connected to 10 or fewer APs.

At the fund level, the network has a similar core-periphery structure. The density of 47.6% (45,505 out of 95,650 potential connections) is considerably higher than the density at the family level, which suggests that funds in the largest families are the most connected. The median AP has the right to operate in 931 ETFs, while the median ETF is connected to 22 APs. AP-ETF connections are likely to be established for the whole family at once – for 942 out of the 1,277 registered family-AP connections, APs operate in all funds of the family.

Though the ETF-AP network is quite dense, less than one-fifth of the connections are active. Moreover, the primary market activity is concentrated in the largest APs. For the median AP, just 1.5% of connections are active, and 15 APs did not create or redeem any ETF shares during 2019. The network of active connections between APs and ETF families is plotted in Figure 3. A median ETF has just four active APs. The activity of APs within funds is very concentrated: For over 65% of the funds, one AP is responsible for more than half of all creations and redemptions, and for 11%, all creations and redemptions are executed by a single AP.

The relationships in primary markets appear to be relatively stable, with the network saturating slowly over time. In 2019, 1,639 of the 40,518 missing ETF-AP connections were established, and 1,186 of the 40,136 existing connections were destroyed.[42] This gives a net of 453 established connections per year, or a 1.1% network growth from 2019 to 2020.[43] Similarly, we see a net 2% increase in the number of active connections in 2020.

Networks with a dense core and sparse periphery are common in OTC financial markets.[44] Even though the ETF-AP network is bipartite and OTC network models are not directly applicable, some of the forces contributing to the formation of dense cores in OTC markets can still be active in our setting. For example, there might be benefits to concentrated intermediation due to lower inventory risk (Wang (2016)). We conjecture that the observed structure arises due to the lower unit inventory costs when an AP trades in several

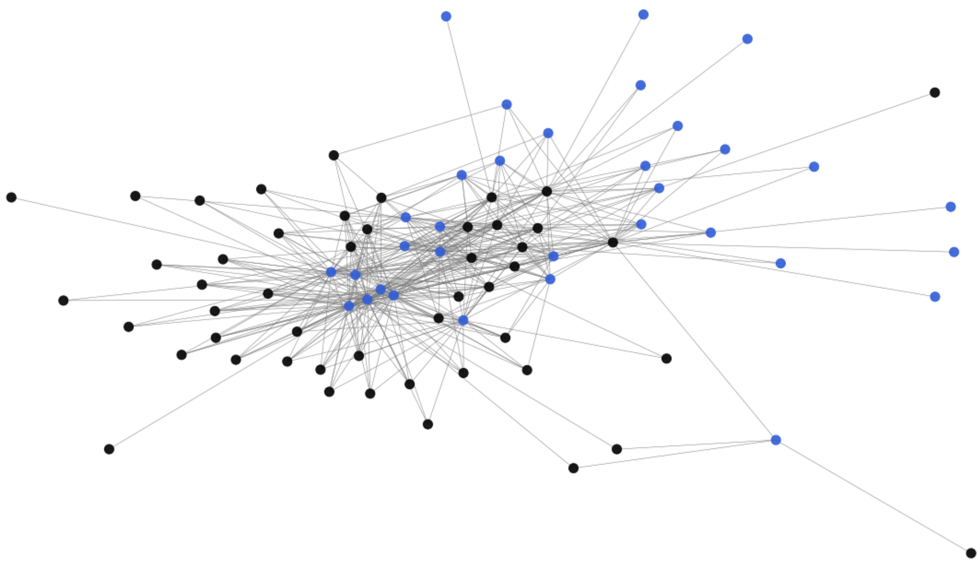
[42]There are no obvious costs for maintaining an established legal connection. We leave the study of broken connections to future research.

[43]Here, we only account for the 1,730 funds and 49 APs reporting in both 2019 and 2020, and ignore network changes from delisted or created funds and from AP entries or exits.

[44]Examples include corporate bonds (Di Maggio, Kermani, and Song (2017)), municipal bonds (Li and Schuerhoff (2019)), CDS (Peltonen, Scheicher, and Vuillemey (2014)), and asset-backed securities (Hollifield, Neklyudov, and Spatt (2017).

ETFs, and from the high legal costs of connecting to a new fund. When establishing a connection, an AP weighs the costs against the expected benefits from trading. The high legal costs of establishing a connection then contribute to the sparse periphery. We leave the formal treatment of the ETF-AP network formation to future research, when more data on the evolution of ETF-AP relationships becomes available.

Figure 3: ETF-AP Network: Active Connections



Nodes: AP holding company (blue) and ETF families (black).

4.2.2 ETFs

Our main goal is to explore the relationship between ETF primary markets and *US Equity* ETF mispricing, so from here onwards we restrict our attention to this part of the ETF universe. Table A2 in the Appendix provides the summary statistics for ETFs in our sample.[45]

The size distribution of US equity ETFs is highly skewed: the average fund is almost ten times larger than the median fund that has around $600 mln in assets. At the end of 2019, a median fund is slightly older than 12 years and receives 35bps in annual fees from investors. The median net creation is equal to 5.8% of the assets under management per year, suggesting overall growth in the US equity ETF industry. The annual primary market volume for a median fund (creations and redemptions combined) is about as large as the total assets under management. The secondary market is even more active: the median

[45]We provide summary statistics for International Equity ETFs and Bond ETFs in Appendix Table A3.

annual trading volume is twice the size of the primary market.[46]

4.2.3 The Cross-Sectional Differences in ETF Primary Markets

To compare primary markets of different funds, we construct the following descriptive features at a fund level: fund connectedness, primary market activity and diversity, and the share of direct investors in primary market volume.

Connectedness reflects the importance of a given node in a network. We measure fund connectedness as the logarithm of the number of registered connections with APs. In the context of ETF primary markets, a fund's connectedness is a proxy for the number of potential arbitrageurs and liquidity providers.

We define *primary market (PM) activity* as the logarithm of the number of APs that are active in a fund over a given year.[47] This measure reflects the number of active arbitrageurs rather than the number of potential arbitrageurs (registered APs). As such, it is consistent with the literature on OTC networks where only active connections are observable. Given that we call APs active when they traded at least once throughout a year, our measure is an upper bound for the true level of activity.

To measure the primary market diversity of an ETF, we use a function of the Herfindahl-Hirschman Index (HHI) that is based on the trading shares of APs in the fund. A higher HHI reflects a fund's higher concentration of creation/redemption activity, which might imply lower competition and that a fund is dependent on a particular broker. Therefore, (1 - HHI) measures *PM diversity*.

Finally, we consider a share of direct investors in ETF primary market activity. As described above, most APs operate as institutional brokers and their trading volume reported in N-CEN filings is an aggregate of all clients. Furthermore, the costs of brokerage services may affect clients' arbitrage activity (see, for example, Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020)). *Share of direct PM volume* reflects trading on direct investors' own accounts and is, therefore, less likely to be subject to similar intermediation costs.

Panel A of Table 2 reports the summary statistics for primary market features at an ETF level. Consistent with the network description provided in Section 4.2.1, there is considerable cross-sectional variation for all primary market features. The features are also persistent: the cross-sectional correlation between 2019 and 2020 is 54% for the share of direct PM volume, 61% for PM diversity, 91% for PM activity, and close to 99% for connectedness.

[46] The descriptive statistics of our sample are in line with those published by the 2020 Investment Company Fact Book, available here: https://www.icifactbook.org/.

[47] Formally, we use $ln(1+N)$ for connectedness and $ln(1+N_{act})$ for PM activity. The logarithm captures the decreasing effect of an additional AP on the size of the primary market.

Table 2: ETF Primary Market Features

Panel A documents the summary statistics for the network features in the sample of 438 US equity ETFs in 2019. The primary market features are defined in Section 4.2.3. Panel B provides the pairwise cross-sectional correlations for the primary market features. Panel C reports regression estimates of ETF primary market features on fund characteristics. Fund characteristics include: logarithm of fund size (in $mln), logarithm of age (in days), logarithm of creation basket size (in $), transaction fee, net expense ratio, dummy for whether ETF shares can be redeemed through an in-kind transaction only, benchmark index volatility of daily returns in 2019, average daily turnover of ETF shares on exchange in 2019, and total PM turnover scaled by fund size. Transaction fee is the average of creation and redemption fees. In Panel C, all regressions include Morningstar Investment Category fixed effects, and t-statistics based on HAC-robust standard errors are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

Panel A

	Mean	Median	St. Dev.	p1	p99
Fund connectedness	3.30	3.50	0.49	1.61	3.74
PM activity	2.05	2.08	0.52	0.69	3.09
PM diversity	0.64	0.69	0.19	0.00	0.89
Share of direct PM volume	0.21	0.18	0.16	0.00	0.72

Panel B

	(1)	(2)	(3)
(1) Fund connectedness			
(2) PM activity	0.425***		
(3) PM diversity	0.368***	0.791***	
(4) Share of direct PM volume	0.050	0.087	0.273***

Panel C

	Primary market features			
	PM activity	PM diversity	Fund connectedness	Share of direct PM volume
Ln(Size)	0.151***	0.030***	-0.054***	-0.012**
	(13.57)	(4.57)	(-3.58)	(-2.02)
Ln(Age)	0.159***	0.058***	0.468***	0.008
	(5.21)	(3.27)	(11.33)	(0.49)
Ln(Basket Size)	-0.126***	-0.041**	0.139***	-0.020
	(-4.61)	(-2.58)	(3.77)	(-1.35)
Transaction Fee	-0.011**	-0.006*	0.033***	0.007**
	(-2.03)	(-1.81)	(4.66)	(2.55)
Net Expense Ratio	-0.003***	-0.001	-0.004***	-0.001**
	(-3.66)	(-1.26)	(-3.36)	(-2.44)
Turnover	1.564***	0.437**	0.591	-0.622***
	(4.78)	(2.30)	(1.34)	(-3.53)
In-Kind ETF dummy	-0.030	-0.035**	-0.120***	-0.007
	(-1.13)	(-2.22)	(-3.31)	(-0.47)
Benchmark index st.dev. %	0.003	0.001	0.003	0.003
	(0.60)	(0.18)	(0.42)	(1.04)
Average spread, bps	-0.006***	-0.002**	-0.007***	-0.003***
	(-3.75)	(-2.26)	(-3.54)	(-3.41)
Total annual PM turnover	1.311**	0.173	2.364***	0.824**
	(2.17)	(0.49)	(2.89)	(2.53)
Observations	438	438	438	438
Within R^2, %	73.7	33.0	47.5	12.6

As suggested by Panel B of Table 2, PM activity, diversity, and connectedness are highly correlated with each other. Direct investors contribute to PM diversity but their volume share is not related to the size of the primary market or PM activity in general.

4.2.4 Primary Market Features and Fund Characteristics

We complete the section by documenting how primary market features are related to basic fund characteristics and which fund characteristics predict APs' future registration and activity in the cross-section.

We start by running a cross-sectional regression of fund primary market features on fund characteristics. Panel C of Table 2 reports results.

As follows from columns (1) and (2), on average, APs are more active in larger and older funds, which is consistent with the gradual formation of ETF-AP relationships. ETF liquidity as measured by average bid-ask spread is also strongly associated with AP activeness. This may reflect the fact that APs prefer to come to the most liquid ETFs first, but also may be the result of improvements in fund liquidity due to APs' participation. Also, there are more active APs in funds with a larger turnover. Net expense ratio is negatively associated with AP activeness, that is, funds with larger and more diverse primary markets are cheaper to end investors. Finally, the larger the primary market transaction fees[48] and the creation basket size, the less active fund APs are.

Column (3) illustrates how fund features relate to connectedness. First, the link with fund age is much more pronounced. Conditional on age, the relationship between connectedness and size is negative. Second, unlike measures related to activeness, fund connectedness is positively related to fees and basket size. It is plausible that more connected ETFs, all else equal, are able to set larger basket sizes and extract higher fees in their primary markets.

Unlike the other primary market features, the share of direct investors is not related to the fund's age (column (4)). All other things equal, this share is higher in smaller, cheaper, and more liquid funds. Note, however, that the total explanatory power of all fund characteristics (as measured by R^2) is quite small for the share of direct investors (compared to the other primary market features).

To further explore what determines APs' decisions to register or become active in a certain fund, we run cross-sectional tests at the connections level. Appendix Table A6 explores which ETF characteristics as of 2019 predict new connections and activity of APs in 2020. New ETF-AP registrations strongly depend on whether the AP is already registered with the ETF family and fund age. Whether an AP is active in the ETF in 2020 is

[48] Appendix A.1 provides details on how we compute the measure of primary market transaction fees.

predominantly determined by being active in 2019, both in ETF and ETF family. Fund size and share turnover also increase the probability of being active in 2020. In addition to these characteristics, a higher expense ratio predicts lower primary market volume. Importantly, average ETF mispricing in 2019 is not a significant predictor of future AP registrations or activity. These results are similar for panel regression estimates with AP and investment category fixed effects and probit regression estimates without fixed effects.

Taken together, our results suggest that ETFs with larger and more diverse primary markets are older, larger, more actively traded in the secondary market, and cheaper to end investors. It is cheaper to create and redeem shares of such ETFs as well. ETF family-level connectedness and fund age strongly predict future AP registrations, while fund size and AP past activity in the fund are the best predictors of future AP activity and primary market volumes.

5 Primary Markets and Mispricing in US Equity ETFs

In this section, we investigate the relationship between ETF primary market properties and mispricing in the cross-section of US equity funds. We find that funds with larger and more diverse primary markets are less mispriced on average, even after controlling for ETF characteristics. Relying on the persistence of the ETF-AP relationships, we show that having a more diverse primary market in 2019 is associated with less mispricing in 2020. This relationship manifests itself on days with high financial stress. We also document that the sensitivity of primary market flows to premium in ETF shares is higher in larger networks. Finally, we show that the correlation of mispricing between two ETFs depends on the commonality of their primary markets.

5.1 How Mispriced Are US Equity ETFs?

On average, equity ETFs are fairly priced. Panel B of Table A2 in the Appendix reports the summary statistics for the premium and mispricing of ETF shares in our sample. We compute ETF mispricing using the definition in Equation (1). The cross-sectional mean of the daily premium is virtually zero and the mean of mispricing is 7bps. For comparison, the mean daily tracking error[49] of funds in our sample is below 4bps.

Our estimates of mispricing are consistent with those in Petajisto (2017). The paper documents that for an average equity ETF, mispricing is close to zero but that its volatility

[49]Tracking error is calculated as the standard deviation of the daily difference between the return on ETF shares and the return on ETF benchmark.

is large. Similar to Petajisto, we evaluate total dollar deviation due to inefficient prices in our sample. Such deviation is defined as the absolute difference between the dollar volume at the close price and the dollar volume at NAV, aggregated annually. We see that, across asset classes, the deviations amounted to $32 billion in 2019 and $80 billion in 2020 (compared with the estimate of $40 billion a year for 2007-2014 provided by Petajisto).

5.2 ETF Network Features and Mispricing in 2019

To study the relationship between ETF primary market features and mispricing, we estimate the following specification in the cross-section of 438 US Equity ETFs in 2019:

$$Mispricing_f = \beta \times Primary\,Market\,feature_f + \boldsymbol{\gamma}'\boldsymbol{X_f} + \alpha_{MS} + \epsilon_f, \tag{3}$$

where $Mispricing_f$ is the average daily mispricing of fund f in 2019. $Primary\,Market\,feature_f$ is one of the four features defined in Section 4.2.3.

There are several sources of potential omitted variable bias in equation (3). First, APs could be more likely to register with ETFs that are older. Second, direct investors are likely to trade in cheaper and more liquid ETFs.[50] Therefore, in all regression specifications, we control for funds' age, fees, and liquidity (bid-ask spread). APs are also more likely to be active in larger ETFs with more secondary market demand, so we control for fund size and the turnover of ETF shares. We include further fund characteristics which are related to the fund's primary market features, as shown in Table 2, Panel C.

The resulting set of controls, $\boldsymbol{X_f}$, includes the logarithm of size, the logarithm of age, the logarithm of creation basket size, transaction fees, the net expense ratio, a dummy for whether fund shares can only be redeemed in-kind, the average bid-ask spread of the ETF in 2019, the benchmark index volatility in 2019, and the average turnover of ETF shares on the exchange in 2019.[51] α_{MS} are Morningstar Investment Category fixed effects.[52]

As Table 3 reports, ETFs with more active and diverse primary markets experienced less mispricing in 2019. The better connected the ETF, the less its shares are mispriced. Mispricing is also lower for ETFs with a lower concentration of primary market volume (higher PM diversity) and with a larger share of direct PM volume. The magnitudes are

[50] This interpretation is consistent with practitioners' views on the typical ETF lifecycle: as an ETF matures, more brokers join its network. See, for example: https://www.franklintempleton.com/articles-us/liberty-shares/etf-capital-markets-desk-trading-arbitrage-and-the-new-etf.

[51] Chosen controls are broadly consistent with previous studies of the cross-section of ETF mispricing such as Bae and Kim (2020).

[52] Adding these fixed effects barely affects our estimates throughout the paper, but we keep them to account for varying complexity in ETF management and pricing that is not picked up by our controls.

similar across network features and economically small: a one standard deviation increase in PM activity decreases daily mispricing by 1bps (or 15%).

Table 3: ETF Primary Market Features and Mispricing in 2019

This table reports the results of estimating the following specification:

$$Mispricing_f^{2019} = \beta \times Primay\,Market\,feature_f + \gamma' \boldsymbol{X_f} + \alpha_{MS} + \epsilon_f$$

The regression is estimated on a cross-section of 438 US equity ETFs in 2019. The dependent variable is the average ETF mispricing in 2019, which is the absolute value of the relative premium of ETF share price over its net asset value per share. Fund characteristics include: logarithm of fund size (in \$mln), logarithm of age (in days), logarithm of creation basket size (in \$), transaction fee (in bps), in-kind redemption dummy, net expense ratio (in bps), average bid-ask spread of the ETF in 2019, benchmark index volatility of daily returns in 2019, and average daily turnover of ETF shares on exchange in 2019. Transaction fee is the average of creation and redemption fees. Primary market features are defined in Section 4.2.3. All regressions include Morningstar Investment Category fixed effects. t-statistics based on robust standard errors are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	PM activity	PM diversity	Connectedness	Share of direct PM volume
Panel A: Without controls for fund characteristics				
Primary market feature	-6.133***	-13.111***	-3.745***	-5.149***
	(-14.48)	(-10.28)	(-7.32)	(-2.96)
Within R^2, %	33.6	20.4	11.5	2.1
Panel B: With controls for fund characteristics				
Primary market feature	-3.176***	-4.983***	-0.374	-3.437***
	(-4.84)	(-4.32)	(-0.74)	(-2.76)
Within R^2, %	57.7	57.3	55.4	56.1

Primary market features are also positively associated with the liquidity of ETF shares. In Appendix Table A4, we show that bid-ask spreads are lower for funds with more diverse networks.[53] This result is a natural consequence of an AP's role as a liquidity provider of ETF shares. The larger number of those liquidity providers operate in ETF primary markets and the less ETF relies on a particular provider, the narrower the bid-ask spread.

One may have a concern that our controls for the characteristics of underlying assets are not sufficient: the observed relationship between the primary market features and ETF mispricing may be driven by the preference of APs for certain equity sectors. Therefore, we verify our results in a setting with benchmark index fixed effects (see Table A5 in the

[53]In unreported analyses on daily data similar to those in Section 5.3, we see that the network is also more important for ETF liquidity on high-FSI days.

Appendix). We find that, even within the same benchmark, primary market features are negatively related to mispricing.

The positive relationship between ETF mispricing and the fund network diversity in 2019 could potentially be driven by reverse causality. On the one hand, to maximize arbitrage profits, APs are more likely to register with ETFs that are more mispriced on average. On the other hand, APs could prefer to register with less mispriced ETFs if such ETFs were demanded by APs' clients. In Appendix Table A6 we found that past mispricing has a negative but insignificant effect on future AP registrations and activity. However, since we only have two cross-sections of data, our tests in Table A6 may lack power. To make sure that our results are not driven by contemporaneous network changes, we take a fund's network as it was in 2019 and explore the mispricing implications in the 2020 daily panel.

5.3 ETF Primary Market Features and Mispricing in 2020

We document that ETFs with large and diverse networks in 2019 experience less daily mispricing in 2020. Using the OFR Financial Stress Index (FSI), we show that the effect is concentrated in high-stress days, which suggests that primary market connections matter most when ETF investors might care about it the most.

We estimate the following specification on daily data in 2020:

$$\begin{aligned} Mispricing_{f,t} = &\beta_1 \times Primary\,Market\,feature_f \times D_t^{Low\,FSI} \\ &+ \beta_2 \times Primary\,Market\,feature_f \times D_t^{High\,FSI} \\ &+ \boldsymbol{\gamma_1'} \boldsymbol{X_{f,t}} \times D_t^{Low\,FSI} + \boldsymbol{\gamma_2'} \boldsymbol{X_{f,t}} \times D_t^{High\,FSI} \\ &+ \boldsymbol{\delta_1'} \boldsymbol{Y_f} \times D_t^{Low\,FSI} + \boldsymbol{\delta_2'} \boldsymbol{Y_f} \times D_t^{High\,FSI} \\ &+ \alpha_{MS} + \alpha_t + \epsilon_{f,t}, \end{aligned} \tag{4}$$

where $Mispricing_{f,t}$ is the mispricing of fund f shares on day t. $Primary\,Market\,feature_f$ is one of the four features defined in Section 4.2.3 as of 2019. $D_t^{High\,FSI}$ equals 1 when the daily FSI on day t is positive (or stress above average, as per OFR definition).[54] Correspondingly, $D_t^{Low\,FSI}$ equals 1 when the daily FSI on day t is negative. $\boldsymbol{X_{f,t}}$ is a vector of fund characteristics on day t: the bid-ask spread of the ETF shares and its square, the benchmark index return and its square, and the turnover of ETF shares on the exchange.[55] $\boldsymbol{Y_f}$ is

[54] FSI is positive for 30% of observations in 2020, or on 75 out of 253 days.

[55] We report results for the winsorized $Mispricing_{f,t}$, daily bid-ask spread, and turnover (all at the 99.5^{th} percentile), but our findings are not sensitive to winsorization. We include squared spread and benchmark return to capture nonlinearities that might be important in high-stress times. Our results are qualitatively similar without these controls.

a vector of fund characteristics: the logarithms of size and age (as of 2019), the logarithm of creation basket size, transaction fees, the net expense ratio, a dummy for whether fund shares can only be redeemed in-kind, and the benchmark index volatility in 2019. α_{MS} are Morningstar Investment Category fixed effects and α_t are date fixed effects.

In equation (4), β_1 estimates the average cross-sectional effect of a given network feature on ETF mispricing on days when FSI is negative (low stress); β_2 estimates the average cross-sectional effect on days when FSI is positive (high stress). We include interactions of all controls to make sure that the estimates of β_1 and β_2 are conditional on potentially different loadings of mispricing on fund characteristics. For example, such a specification takes into account the fact that mispricing is even larger on high-stress days for less liquid ETFs. Results are qualitatively similar in a specification without control interactions.

As Table 4 reports, all four network features measured in 2019 are associated with lower mispricing in 2020. This result corroborates our findings in Section 5.2, which alleviates the concern that the relationship we are documenting is driven by network changes in response to relative mispricing in 2020. Moreover, the results in Panel (B) of Table 4 indicate that the relationship between network features and ETF mispricing only manifests on high-FSI days.

To provide further evidence of primary markets' importance in eliminating arbitrage, in Panel (B) of Table 4 we address the relation between fund mispricing and primary market transaction fees. If mispricing is eliminated by the secondary market participants, its observed level should not be related to primary market fees. On the contrary, if primary market arbitrageurs are marginal in correcting mispricing, then these fees should be reflected in the observed mispricing (see breakeven condition (2)). The data fully support this logic: primary market fees are highly statistically significant only in periods with high FSI. This result suggests that primary market arbitrageurs are marginal in stressful times.

We subject our results to a battery of robustness tests. Our findings are similar if we measure ETF mispricing using midpoint prices as shown in Appendix Table A7. Furthermore, in Appendix Table A8, we show that PM activity and diversity are important for both small and large ETFs (as defined by median fund size). Connectedness matters for small funds only, while the share of direct PM volume is only important for large ETFs. Results are also robust to including benchmark index fixed effects (see Panels C and D of Table A5 in the Appendix), extending to the 2019 daily sample, using VIX instead of FSI as a proxy for days with more costly secondary market arbitrage, defining high-stress dummy using a top quartile or tercile of FSI, double-clustering standard errors by fund and date, and controlling for fund family size and further fund-level characteristics, such as total primary

Table 4: ETF Primary Market Features and Mispricing in 2020

This table reports the results of daily panel regressions of the end-of-day fund mispricing on network characteristics. Panel A reports the estimate of β for the following specification (pooled high- and low-stress days):

$$Mispricing_{f,t} = \beta \times Primary\,Market\,feature_f + \boldsymbol{\gamma}'\boldsymbol{X_{f,t}} + \boldsymbol{\delta}'\boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

Panel B reports the estimates of β_1 and β_2 for

$$\begin{aligned} Mispricing_{f,t} =& \beta_1 \times Primary\,Market\,feature_f \times D_t^{Low\,FSI} + \beta_2 \times Primary\,Market\,feature_f \times D_t^{High\,FSI} + \\ &+ \boldsymbol{\gamma_1'}\boldsymbol{X_{f,t}} \times D_t^{Low\,FSI} + \boldsymbol{\gamma_2'}\boldsymbol{X_{f,t}} \times D_t^{High\,FSI} + \boldsymbol{\delta_1'}\boldsymbol{Y_f} \times D_t^{Low\,FSI} + \boldsymbol{\delta_2'}\boldsymbol{Y_f} \times D_t^{High\,FSI} + \alpha_{MS} + \alpha_t + \epsilon_{f,t} \end{aligned}$$

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices. All network features are as of 2019. Daily $D^{High\,FSI}$ equals 1 when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). $D^{Low\,FSI} = 1$ when the daily Financial Stress Index is negative. Last row of the table reports results of a t-test that $\beta_2 - \beta_1 = 0$. Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. Primary market features are defined in Section 4.2.3, these features are demeaned before we build the interaction variable. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	PM activity	PM diversity	Connectedness	Share of direct PM volume
Panel A: Primary market features as of 2019, no interactions				
Primary market feature	-1.605**	-2.405*	-0.976**	-1.843
	(-2.40)	(-1.82)	(-2.17)	(-1.27)
Observations	109,134	109,134	109,134	109,134
Within R^2, %	16.3	16.3	16.3	16.3
Panel B: Primary market features as of 2019, interactions with FSI				
Primary market feature $\times D^{Low\,FSI}$	-0.920	-1.398	-0.711	-1.014
	(-1.57)	(-1.24)	(-1.65)	(-0.76)
Primary market feature $\times D^{High\,FSI}$	-3.495***	-5.092**	-1.705**	-4.003**
	(-3.27)	(-2.31)	(-2.58)	(-1.98)
Transaction fee $\times D^{Low\,FSI}$	0.057	0.056	0.077*	0.070
	(1.23)	(1.19)	(1.73)	(1.54)
Transaction fee $\times D^{High\,FSI}$	0.313***	0.327***	0.406***	0.365***
	(3.60)	(3.60)	(4.71)	(3.94)
Observations	109,134	109,134	109,134	109,134
Within R^2, %	16.9	16.9	16.8	16.8
Primary market feature High-Low	-2.575***	-3.694**	-0.994*	-2.989**
	(-3.29)	(-2.22)	(-1.93)	(-2.32)

market turnover in 2019 and ETF derivatives availability.[56]

Our findings corroborate the fact that ETF mispricing is higher in times of market turmoil (Madhavan and Sobczyk (2016)), and we document that this increase is weaker for funds with larger and more diverse networks. Using European data, Aquilina, Croxson, Valentini, and Vass (2020) show that some of the usual ETF liquidity providers may become inactive during a crisis, but that alternative providers could step in. This would suggest that larger networks enlarge the pool of potential arbitrageurs. In our data, however, we do not observe an increase in the number of active APs during 2020.[57] One potential explanation is the institutional difference between the US and European markets: In the US, arbitrageur substitution could happen between prime broker clients rather than across prime brokers. In addition to that, our theoretical analysis in Section 6.1 implies that the substitution of arbitrageurs depends on their cost distribution and that most of the activity is likely to be accommodated by APs who were active prior to the crisis.

5.4 ETF Primary Market Flows and Mispricing

Next, we explore how ETF primary market structure relates to the actual capital flows in ETF primary markets. We document that higher PM activity translates into larger sensitivity of ETF flows to fund mispricing. Similar to Pan and Zeng (2019) and Dannhauser and Hoseinzade (2021), we use past ETF premium as a proxy for perceived arbitrage opportunities and study the sensitivity of daily ETF net flows to these arbitrage opportunities. Daily net flows are of key interest because they characterize activity in ETF primary markets, even though they are a noisy proxy for arbitrage activity of APs.[58]

As Table 5 documents, we find that US equity ETF flows, measured as relative changes in ETF shares outstanding, are highly sensitive to arbitrage opportunities. On average, a fund sees an inflow if its shares are priced at a premium to its NAV, consistent with arbitrageurs buying a relatively underpriced basket and converting it to ETF shares. Similar to the results of Pan and Zeng for bond ETFs, we see that this sensitivity goes down

[56] Appendix Table A9 shows that estimates are very similar when additional fund characteristics are included.

[57] This is based on unreported tests. Although there is no significant change in the number of active APs, the number of registered APs, PM diversity and share of direct PM volume grew in 2020. We only observe annual AP activity, which limits the conclusions that can be drawn from this analysis.

[58] Some of the flows are originated by ETF end investors and not arbitrageurs. These are typically institutions placing orders large enough that they require APs' help in executing them. However, such investors seek to gain exposure to the ETF basket so they should trade at the lowest available price. We expect them to buy ETF shares on the exchange when the shares are underpriced and through an AP otherwise. Similarly, investors should sell on the exchange when the shares are overpriced and to an AP otherwise. We explore the implications of such trading using 13F institutional ownership of ETFs in Section 6.4. Our analysis suggests that investor flows do not contribute to ETF flow-premium sensitivity.

Table 5: ETF Flows and Mispricing

This table reports the results of daily panel regressions of the primary market flows on end-of-day fund mispricing. We estimate the following specification:

$$Flow_{f,t} = \beta \times Premium_{f,t-1} + \boldsymbol{\gamma}'\boldsymbol{X_{f,t-1}} + \boldsymbol{\delta}'\boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is daily net flow (percentage change in fund shares outstanding). The main independent variable is lagged ETF premium, i.e., the relative premium of ETF share price over its net asset value per share (in percent). Daily $D^{High\,FSI}$ equals 1 ($D_t^{Low\,FSI} = 0$) when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). PM activity is the demeaned log number of APs with nonzero primary market volume in 2019. Daily (lagged) controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF daily flows, percent		
	(1)	(2)	(3)
ETF premium	0.420***		0.502***
	(10.31)		(10.77)
ETF premium $\times D^{Low\,FSI}$		0.569***	
		(9.60)	
ETF premium $\times D^{High\,FSI}$		0.332***	
		(6.64)	
PM activity			-2.895
			(-1.33)
ETF premium × PM activity			0.224***
			(3.30)
Observations	108,047	108,047	108,047
Within R^2, %	0.7	0.7	0.8
ETF premium High-Low		-0.237***	
		(-3.37)	

in high-stress times.[59]

Importantly, we document that the flow-premium sensitivity is higher if the activity in ETF's PM network is higher. Since the coefficient on the interaction with the number of active APs is large and positive, more activity in the network is associated with a higher sensitivity of ETF flows to perceived arbitrage opportunities. This result suggests that PM activity contributes to the efficacy of the arbitrage mechanism. Consistent with this view,

[59]We define high-stress times as days with a positive OFR Financial Stress Index, but the results are similar if we use VIX instead. Furthermore, our model in Section 6.1 provides a different explanation for this pattern: If arbitrageur costs rise in high-stress times, the number of active APs decreases and lowers flow sensitivity to a demand shock.

our model in Section 6.1 predicts that the sensitivity of arbitrage trading to demand shocks increases in the number of active APs.

6 ETF Mispricing and AP-specific Costs

In this section, we suggest an explanation for our findings. We formulate a model in which arbitrage between identical assets is limited due to costs of arbitrage as well as a limited number of potential arbitrageurs. Equilibrium mispricing in such a model depends on the degree of imperfect competition and the average arbitrage costs. We present further empirical evidence corroborating the importance of the second component (arbitrage costs) in our data. We argue that the number of potential arbitrageurs is important for ETF mispricing as long as it helps mitigate shocks to AP-specific costs.

Our model is agnostic on the nature of AP-specific arbitrage costs. As we discussed in Section 2.2, one can think of many sources of cost heterogeneity across APs in ETF markets: differences in inventory costs stemming from activities outside AP business, balance sheet usage costs (regulatory costs channel), differences in risk management and trading technology – and our data do not allow us to fully differentiate between them. However, the tests in this section are most consistent with the regulatory costs channel.

In ETF markets, regulatory costs may matter in at least two ways. First and most intuitive, these costs were shown to affect inventory management of bond dealers, hence bond liquidity and, ultimately, bond ETF arbitrage incentives (Pan and Zeng (2019)). APs are highly regulated entities: most of them are banks and almost half are global systemically important banks. We therefore expect them to incur the highest regulatory costs.[60] Second, when an AP offers institutional brokerage services, regulatory costs are likely to contribute to the brokerage charges. We refer to such costs as balance sheet usage costs throughout the paper.

Also, prime brokers may have different margin requirements and dynamically adjust them on days with high market stress. Such heterogeneity in required margins is observationally equivalent to our results: higher required margins impede arbitrage.[61] However,

[60] More specifically, they are required to maintain higher capitalization ratios. The literature has connected these banks' ability to provide balance sheet space for arbitrage activities to capital restrictions, see, e.g. Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020). Prior literature has also shown that leverage ratio regulations impede the matched-book intermediation of banks (Correa, Du, and Liao (2020)), and that the provision of short-term funding cannot be fully substituted for by reserves (Copeland, Duffie, and Yang (2021)). Furthermore, Copeland, Duffie, and Yang also point out that the quantitative easing helps relax the scarcity of reserves but only at the cost of a more binding leverage ratio.

[61] In support of this view, we see that our results are stronger for ETFs with benchmark volatility above the sample median (see Appendix Table A17).

positions in physically replicated ETFs are usually easily cross-collateralized with their underlying baskets. Moreover, recent literature documented that in various markets Value-at-Risk constraints (what makes margins sensitive to high-stress times) are not as binding under the regulations that were introduced in the aftermath of the Global Financial Crisis (Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020)). For these two reasons, we lean towards the importance of costs rather than margins for ETF mispricing, even though both costs and funding liquidity are very similar in our setup, and both highlight the pass-through of regulatory costs in ETF markets.

6.1 The Model of Costly ETF Arbitrage

We consider a one-period, two-date model of arbitrage that is similar to the models in Gromb and Vayanos (2002) and Fardeau (2020). In our model, oligopolistic arbitrageurs compete to eliminate the mispricing between two segmented markets. Agents make investment decisions on date 1 and obtain profits on date 2. We assume that the dynamic concerns of APs related to correcting mispricing are negligible, and that the process of eliminating ETF mispricing can be modeled as a sequence of one-period games.

The key feature of our model is that the arbitrage costs are assumed to be proportional to the gross arbitrage position size. Such a cost structure implies that both active and inactive arbitrageurs co-exist in equilibrium. We solve for the pure strategy Nash equilibrium and derive the expression for equilibrium mispricing as a function of arbitrageur costs. In the model, changes in AP costs produce a weaker effect on mispricing for funds with larger primary markets.

6.1.1 Model Setup

There are two asset markets. Each market consists of one riskless asset with a unit return and one risky asset, A or B. Risky assets pay uncertain but identical dividends on date 2, $\delta_2^A = \delta_2^B = \delta_2$. These dividends are distributed as $\delta_2 \sim \mathcal{N}(\delta, \sigma^2)$. The assets are in equal positive net supply, $s_A = s_B = s$. On date 1, the assets are traded at prices p_A and p_B.

Each market is populated by a unit mass of price-taking investors. We assume an exogenous market segmentation: some investors are only able to invest in asset A and the riskless asset (A-type investors), while others are only able to invest in asset B and the riskless asset (B-type investors).[62] Investors derive utility from their wealth on date 2. For

[62] This assumption is standard in the literature and is required to generate mispricing.

tractability, we assume investors have CARA utility with the risk-aversion coefficient γ:

$$U_i(w_{i,2}) = \mathbb{E}_1\left[-exp(-\gamma w_{i,2})\right], \quad i = A, B$$

On date 2, investors receive an endowment proportional to the dividends: $u_i\delta_2$. The proportionality coefficient u_i is different for the two investor types, and is known on date 1. Following Gromb and Vayanos (2002), we assume for simplicity that $u_A = -u_B = u$.

Investors solve the following maximization problem:

$$\begin{aligned} &\max_{y_{i,1}} \mathbb{E}_1\left[-exp(-\gamma w_{i,2})\right] \\ &s.t. \quad w_{i,2} = w_{i,1} + y_i(\delta_2 - p_{i,1}) + u\delta_2. \end{aligned} \tag{5}$$

In the absence of other market participants, the solution of this maximization problem and the market clearing condition $y_i = s_i$ provide the expressions for equilibrium prices and for mispricing:

$$p_A = \delta - \gamma\sigma^2(s+u),$$

$$p_B = \delta - \gamma\sigma^2(s-u),$$

$$Misp_1^{NoArb} \equiv p_B - p_A = 2u\gamma\sigma^2.$$

The expected endowments on date 2 are a shock to investor demand on date 1. The demand for the risky security is lower if the dividend payment is positively correlated with the endowment. Without loss of generality, we assume that u is positive, and thus without arbitrageurs $p_A < p_B$.[63] The resulting mispricing on date 1 is proportional to the size of the demand shock, the risk aversion, and the variance of the dividends.

Next, we introduce the discrete number $N \geq 1$ of the price-setting agents, or arbitrageurs. These arbitrageurs operate in markets A and B, and generate profits by buying cheaper security and simultaneously selling the more expensive one. Arbitrageurs are risk-neutral and seek to maximize their profits. Importantly, arbitrageurs are only allowed to implement pure arbitrage strategies, i.e., they are forbidden from taking any risk associated with future dividends. Thus, for arbitrageur n, the demand for security A must be equal in magnitude and opposite in sign to the demand for security B: $x_n^A = -x_n^B \equiv x_n$.[64] Finally, we assume that arbitrageur n pays fixed costs C_n per gross invested dollar. Thus, the total costs to arbitrageur n are equal to $C_n|x_n|(p_B + p_A)$.

Arbitrageurs compete to eliminate mispricing in a Cournot oligopoly setup, and solve

[63] Note that in the absence of market segmentation, A- and B-type investors could perfectly insure each other.

[64] Similar to Gromb and Vayanos (2002).

the following maximization problem:[65]

$$\begin{aligned} &\max_{x_n} \left[x_n(p_B - p_A) - C_n|x_n|(p_B + p_A)\right] \\ s.t. \quad & p_A = \delta - \gamma\sigma^2 \left(s - \sum_{k=1}^{N} x_k + u\right) \\ & p_B = \delta - \gamma\sigma^2 \left(s + \sum_{k=1}^{N} x_k - u\right). \end{aligned} \tag{6}$$

Substituting prices, we end up with the following unconstrained problem for arbitrageur n:

$$\max_{x_n} \left[x_n \gamma\sigma^2 \left(u - \sum_{k=1}^{N} x_k\right) - C_n|x_n|\bar{p}\right], \tag{7}$$

where $\bar{p} \equiv \delta - \gamma\sigma^2 s$ is the average of p_A and p_B.

6.1.2 Model Equilibrium

In this subsection, we solve for the model equilibrium and formulate its main properties. The proposition below describes the equilibrium of the model. The proof is provided in Appendix B.

Proposition 1

Assume that N arbitrageurs solve maximization problem (7), and that all of them incur different costs such that: $C_1 \leq C_2 \leq ... \leq C_N$.

Then,

(a) Problem (7) has a unique pure strategy Nash equilibrium:
If $C_1 \geq \frac{u\gamma\sigma^2}{\bar{p}}$, then there is no trading.
If $C_1 < \frac{u\gamma\sigma^2}{\bar{p}}$, then arbitrageurs $1, ..., n$ with C_n such that

$$C_n < \frac{u\gamma\sigma^2}{n\bar{p}} + \frac{1}{n}\sum_{k=1}^{n-1} C_k \tag{8}$$

trade, while arbitrageurs $n+1, ..., N$ are inactive.

(b) For trading arbitrageurs, the equilibrium allocations are:

$$x_i = \frac{1}{1+N_{act}}u + \frac{1}{1+N_{act}}\frac{\bar{p}}{\gamma\sigma^2}\sum_{\substack{k\neq i \\ k\in act}} C_k - \frac{N_{act}}{1+N_{act}}C_i\frac{\bar{p}}{\gamma\sigma^2}, \tag{9}$$

[65] Note that equilibrium demand functions and prices do not depend on whether arbitrageurs convert securities or establish a long-short position.

where N_{act} is the number of active arbitrageurs.

The equilibrium mispricing is equal to

$$Misp_1 = \frac{2u\gamma\sigma^2}{1 + N_{act}} + \frac{2\bar{p}}{1 + N_{act}} \sum_{j \in act} C_j. \tag{10}$$

The level of mispricing (10) depends on the number of arbitrageurs and on their trading costs. The first term is the level of mispricing without arbitrageurs (recall that $Misp_1^{NoArb} = 2u\gamma\sigma^2$) weighted by $1 + N_{act}$, and the second term corresponds to the pass-through of arbitrageurs' trading costs. Notably, when the number of arbitrageurs increases (given the average level of costs), the second term prevails. In the limiting case of infinitely many actively trading arbitrageurs, mispricing does not depend on the initial demand shock u, and is determined solely by costs. In the case of zero costs, all arbitrageurs trade actively, but mispricing still exists and is only eliminated when the number of arbitrageurs becomes infinitely large.

6.1.3 Illustration: Uniform Cost Distribution

Proposition 1 provides the general solution for the arbitrageurs' maximization problem. However, under an arbitrary cost structure, equilibrium allocations and mispricing cannot be expressed as a function of exogenous variables in a closed form. Thus, in this subsection, we consider a specific cost structure that allows us to express mispricing as a function of demand shock u, investors' risk-aversion γ, dividend variance σ, the number of arbitrageurs N, and arbitrageurs' costs. A and B markets are an ETF and its underlying asset, respectively.

We model the ETF primary market as N arbitrageurs with costs uniformly distributed on $[\underline{C}; \overline{C}]$.[66] That is, $C_i = \underline{C} + \frac{\overline{C} - \underline{C}}{N} i$ for $i = 1, ..., N$. The secondary market consists of S identical arbitrageurs with C^S costs. As seen from Proposition 1, in equilibrium, the secondary market arbitrageurs are all actively trading or are all inactive, depending on the relative parameter values.

If the secondary market is large and active, the equilibrium mispricing is primarily determined by its costs C^S. In fact, it follows from Proposition 1 that if the number of arbitrageurs in secondary market S is large enough, no arbitrageurs from the primary market with costs higher than C^S are active in equilibrium. n denotes the number of primary market arbitrageurs with costs below or equal to C^S. The equilibrium mispricing, according to (10),

[66] For the problem to have a non-trivial solution, it must hold that $\underline{C} < \frac{u\gamma\sigma^2}{\bar{p}}$.

equals:

$$Misp = \frac{2u\gamma\sigma^2}{1+n+S} + \frac{2\bar{p}}{1+n+S}\left(SC^S + n\underline{C} + \frac{\overline{C}-\underline{C}}{N}\frac{n(n+1)}{2}\right).$$

When S increases, $Misp$ tends to $2\bar{p}C^S$.

If, on the contrary, the costs of arbitrage for the secondary market are prohibitively high, mispricing will be determined by the structure of primary market. The general formula for mispricing is:[67]

$$\begin{aligned} Misp =& \frac{2u\gamma\sigma^2}{1+N_{act}} + \bar{p}(\overline{C}-\underline{C})\frac{N_{act}}{N} + 2\bar{p}\underline{C}\frac{N_{act}}{1+N_{act}} = \\ =& \frac{2u\gamma\sigma^2}{1+N_{act}} + 2\bar{p}\frac{N_{act}}{N}\left(\frac{\overline{C}+\underline{C}}{2} + \underline{C}\left(\frac{N}{1+N_{act}} - 1\right)\right) \end{aligned} \tag{11}$$

where $N_{act} = \left[\frac{1}{2}\left(\sqrt{1+\frac{8N(u\gamma\sigma^2-\underline{C}\bar{p})}{\bar{p}(\overline{C}-\underline{C})}}-1\right)\right]$, and where square brackets denote the integer part.

As follows from (11), larger primary market networks (i.e., a larger N) induce lower equilibrium mispricing while higher average arbitrage costs (i.e., $\frac{\overline{C}+\underline{C}}{2}$) result in higher mispricing, which is consistent with the empirical results in Section 5. In periods of high volatility, when the costs of establishing an arbitrage position are higher (especially for secondary market participants, who cannot simply convert one security into the other and need to wait before prices converge to extract profits), the observed mispricing is determined by primary market properties.

Next, we consider what happens to equilibrium mispricing when the leading arbitrageur (i.e., the arbitrageur with the lowest costs) is driven out of the market. As follows from the above, the difference in mispricing would be small with the large and active secondary market, and would move towards zero as the number of secondary market arbitrageurs increases. If the secondary market is not active, the mispricing increase is equal to[68]

$$\Delta Misp = \frac{N_{act}}{1+N_{act}}\frac{2\bar{p}(\overline{C}-\underline{C})}{N},$$

where $N_{act} = \left[\frac{1}{2}\left(\sqrt{1+\frac{8N(u\gamma\sigma^2-\underline{C}\bar{p})}{\bar{p}(\overline{C}-\underline{C})}}-1\right)\right]$. With a larger ETF primary network N (given average costs), the effect on mispricing of the leading arbitrageur's exit is lower. This model prediction is in line with the empirical results in Section 6.3 below. When the lead arbitrageur

[67] The proof is provided in Appendix C.

[68] When the leading arbitrageur is driven out, another arbitrageur with higher costs may or may not step in, depending on model parameters. Here, we consider the case when she steps in. The other case can be solved similarly.

of an equity ETF is engaged in the Federal Reserve's SMCCF Program, the costs of using the balance sheet space increase; this increase keeps the equity ETF arbitrage from being profitable. The arbitrageur is thus inactive in the ETF's primary market, and the equilibrium mispricing for the equity ETF increases. This effect is stronger for ETFs with less diverse networks.

6.2 AP Heterogeneity and ETF Mispricing

The general formula for equilibrium mispricing (10) predicts that, all else equal, the observed level of mispricing is defined by the number of active arbitrageurs and the average arbitrage costs at an ETF level. In this section, we discuss the relative importance of competition versus average costs and provide further evidence for AP heterogeneity that we assume in the model.

6.2.1 The Actual Concentration in ETF Primary Markets

As we described earlier, one cannot characterize the number of arbitrageurs in ETF markets by the number of active or registered APs. First, any investor can trade on ETF mispricing on the secondary market (exchange). Second, even though the observed number of primary market participants is limited, a larger number of arbitrageurs can trade in ETF primary markets through APs. Therefore, to gauge the actual degree of concentration in these markets, one needs to take into account such indirect primary market participants. We do so by looking into the size of APs' prime brokerage clientele with a help of ADV filings.

Specifically, we follow Jiang (2021) and Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020) to identify connections between hedge fund advisors and their prime brokers in the US and then link prime brokers to APs in our sample. We hence assume that only hedge fund clients could potentially trade on ETF mispricing. Details on data collection are in Appendix A.5.

According to the ADV data, a median AP has 12 clients with $1,32 trillion in gross assets. Prime brokerage connections are fairly concentrated, that is, clients of one AP overlap little with the clients of another. We find that the number of unique clients who can access a median ETF in our sample is as high as 1,147, with the first and 99^{th} percentiles at 263 and 1,978, respectively. Therefore, given the size of AP clientele, the imperfect competition channel is unlikely quantitatively important for ETF mispricing.

6.2.2 Evidence on Importance of AP-Specific Costs

Next, we study the relationship between AP-specific costs and ETF mispricing. In the absence of measurements of arbitrage costs, we use observable AP characteristics that are likely to be related to such costs, namely: AP size (total assets at a holding company level in 2019), total AP primary market volume (the 2019 volume as reported in N-CEN filings), AP centrality in the equity ETF-AP network (the 2019 PageRank centrality),[69] and the size of AP prime brokerage clientele (according to ADV filings as we described above). We therefore assume that arbitrage costs are lower when an AP is larger, more connected with equity ETFs, has a higher primary market volume and more prime brokerage clients.

To test model prediction (10) with respect to AP costs, we simply regress the daily mispricing on each AP feature, similar to our analysis in Section 5.3, additionally controlling for the number of active APs. As earlier, all features are projected to the ETF level: we take the simple average of each AP feature across the active APs of the fund. As Panel B of Table 6 reports, all four AP features are negatively related to ETF mispricing. These results emphasize that the composition of APs in ETF primary market (not only their number) is related to ETF mispricing.

6.2.3 ETF Primary Market and Mispricing Comovement

We also exploit information about AP identities to provide further evidence on the importance of AP heterogeneity. If shocks to AP-specific costs get passed through to mispricing, we expect that the mispricing of ETFs sharing the same APs will comove. Consistent with that, we show that the correlation of mispricing between two ETFs in our US equity sample is related to the commonality in their active AP network.

We explore whether the correlation of mispricing between two ETFs in our US equity sample is related to the number of common active APs. Results are reported in Table 7. If two ETFs have twice as many *common* active APs, the correlation of their daily mispricing in 2020 is almost 4 percentage points higher on average. The magnitude is conditional on ETFs having similar benchmark indices, belonging to the same fund family or investment category, and after including both funds' fixed effects. This result is fully driven by high-stress times when having twice as many common active APs is associated with 5 percentage points higher correlation. Finally, we find no significant relationship between mispricing correlation and the number of common active APs for funds with a larger than the median number of active APs.

[69]It is the most widespread measure of centrality in the network literature. According to PageRank centrality, a node is important if it is highly connected or if it is linked to highly connected nodes, adjusted by the number of these influential nodes' connections.

Table 6: ETF Mispricing and AP Heterogeneity

This table reports the results of daily panel regressions of the end-of-day fund mispricing on primary market characteristics (averaged AP features):

$$Mispricing_{f,t} = \beta \times AP\,feature_f + \boldsymbol{\gamma}'\boldsymbol{X_{f,t}} + \boldsymbol{\delta}'\boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

Panel A does not include the conrol for PM activity while Panel B does.

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices. All AP features and PM activity are as of 2019. Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. The AP features are defined in Section 6.2. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	Active AP size	Active AP volume	Active AP centrality	Average no. clients
Panel A: Not controlling for PM activity				
AP feature	-0.536***	-1.799***	-333.309***	-1.069***
	(-4.10)	(-4.24)	(-5.32)	(-3.32)
Observations	109,134	109,134	109,134	109,134
Within R^2, %	16.6	16.6	16.7	16.5
Panel B: Controlloing for PM activity				
AP feature	-0.484***	-1.807***	-310.081***	-0.943***
	(-3.66)	(-4.51)	(-4.91)	(-2.83)
PM activity	-1.006*	-1.627***	-0.970*	-1.007
	(-1.68)	(-2.79)	(-1.66)	(-1.61)
Observations	109,134	109,134	109,134	109,134
Within R^2, %	16.6	16.8	16.7	16.6

Table 7: ETF Primary Market and Mispricing Correlation

This table reports the results of estimating the following specification:

$$Correlation(Mispricing_i, Mispricing_j) = \beta \times Common\ Active\ APs_{ij} + \gamma' Controls_{ij} + \epsilon_{ij}$$

The regression is estimated on a cross-section of pairs of US equity ETFs in 2020. The dependent variable is the correlation of daily mispricing of two ETFs (i and j). *Common Active APs* measure equals the log of one plus the number of APs active in both funds of the pair.

In column (3), the correlation is estimated within March 2020 to June 2020 for high FSI months (i.e., months with positive FSI for the majority of trading days) and on the rest of 2020 for low FSI months. The specification includes high-FSI dummies and interactions with all pair controls as well.

In column (4), only ETFs with the number of active APs above 7 (sample median) are included into the test.

$Controls_{ij}$ include pair characteristics: benchmark returns correlation, a dummy for whether the funds have the same benchmark, a dummy for whether funds belong to the same family, a dummy for whether funds belong to the same Morningstar investment category.

All columns except for (1) include fixed effects for each fund in the pair. t-statistics based on standard errors double clustered by fund i and fund j are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing correlation			
	(1)	(2)	(3)	(4)
Common Active APs	0.074***	0.050***		0.007
	(7.16)	(5.66)		(0.45)
Common Active APs × Low-FSI months			-0.010	
			(-1.26)	
Common Active APs × High-FSI months			0.075***	
			(7.57)	
Sample	All	All	All	No. APs $\geq$ 7
Observations	87,571	87,571	175,142	23,653
Adjusted R^2	7.3	37.9	49.6	38.9
Fund i + Fund j FE	No	Yes	Yes	Yes

6.3 Evidence From the Federal Reserve's Bond-Buying Program

To provide more insight into the nature of AP-specific costs, we show that the ETFs most exposed to the Federal Reserve's bond ETF purchase program through their APs also experience higher mispricing. We interpret this result as evidence of the pass-through of the APs' regulatory balance sheet usage costs. Our results also highlight the interconnectedness of funds in their primary market networks, as mispricing in US *equity* ETFs is affected by the Federal Reserve's purchases of US *bond* ETFs.

We hypothesize that the implementation of the SMCCF program had an adverse spillover effect on *equity* ETF mispricing.[70] During the implementation of the program, AP capital was involved in purchasing bonds in order to satisfy the demand of the Federal Reserve (see details in Appendix Tables A10 and A11). As most active APs are banks that comply with banking regulations (in particular, Basel III), allocating space to bond purchases on their balance sheet is costly. Moreover, capital *within* financial institutions may also be slow-moving (Siriwardane (2019) and Duffie (2010)). Taken together, these two observations suggest that allocation of room for the Federal Reserve's purchases shifts the capital internally to a bond desk and, hence, raises the break-even condition for equity ETF trades. For funds whose APs are involved in the program, this leads to higher mispricing, especially during high-FSI days when APs are marginal. The effect is expected to be more pronounced for funds whose APs are more exposed to the program (relative to their usual operations in the bond ETF market). Additionally, some effects may be observed during the run-up period, as it may take time for APs to reallocate capital across specific desks.

To test our hypothesis, we construct the measure of an AP's relative exposure to the program using data on ETF purchases.[71] For each AP, we divide the total dollar volume of bond ETFs bought by the Federal Reserve through the given AP during the first five weeks of the program by the total volume of the AP's primary market activity in bond ETFs in 2019 (scaled by 5/52 to allow comparison with the five-week period):

$$AP\,Exposure_i = \frac{FED\,ETF\,Purchases_i}{Total\,Bond\,ETF\,Volume\,2019_i}. \tag{12}$$

We interpret this measure as a proxy for the adjustment that is required to the AP's books

[70] A comprehensive overview of the program is offered in Boyarchenko, Kovner, and Shachar (2020). We provide details relevant to our test in Appendix A.6.

[71] One limitation of our analysis is that we cannot deduct expected volumes by the seller in real time. In other words, the balance sheet space requirement expected by the APs at the time of the Federal Reserve's announcement was different from the eventually needed space. More specifically, the SMCCF was underutilized: According to the Federal Reserve's website, the SMCCF size peaked at around $14 billion instead of the announced $250 billion. This might be the reason for the observed spillovers during the announcement period.

relative to the normal level of activity. To study mispricing at a fund level, we use the exposure of AP that was most active in the fund in 2019 (lead AP).[72] AP-level exposures are reported in Appendix Table A10 and descriptive statistics of the fund-level exposure in our final sample are shown in Appendix Table A12.

A potential concern with our measure of exposure is that the denominator in definition (12) might not be a relevant comparison metric for the size of the purchases. If the Fed's buy order is small enough, an AP may be able to source the necessary bond ETF shares from the secondary market, which would less likely require the use of any balance sheet space. In Appendix Table A13, we show, however, that bond ETFs with larger SMCCF trades experience contemporaneous inflows.[73] This suggests that APs had to tap into ETF primary markets.

The negative spillover effect on the equity ETF mispricing of AP exposure to the SMCCF implies a positive β coefficient in the following regression, estimated during the program implementation:

$$Mispricing_{f,t} = \beta \times Lead\,AP\,Exposure_f + \boldsymbol{\gamma}'\boldsymbol{X_{f,t}} + \boldsymbol{\delta}'\boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}, \tag{13}$$

where $Mispricing_{f,t}$ is mispricing of fund f shares on day t. $\boldsymbol{X_{f,t}}$ is a vector of fund characteristics on day t, and $\boldsymbol{Y_f}$ is a vector of fund characteristics as of 2019 (see Section 5.3). α_{MS} are Morningstar Investment Category fixed effects and α_t are date fixed effects.

We find that funds with lead APs who are more engaged in the Federal Reserve's purchasing program exhibit higher mispricing during the program implementation. In column (1) of Panel A in Table 8, we estimate Equation (13) on the implementation sample from May 12 to June 17, 2020. The β coefficient is positive and statistically significant. The economic effect, however, is quite small: the average *Lead AP Exposure* adds an average of 0.15 basis points to the mispricing of related equity funds. During the announcement period, the effect on mispricing is similar in magnitude to the effect of implementation (column (2)). This suggests some anticipatory adjustment to the balance sheet, consistent with slow moving capital. There is no effect during the placebo period (column (3)).

In order to test whether the effect stems from high-FSI periods, when other arbitrageurs are less likely to get involved, we interact the exposure variable with the FSI value in column (4), similar to our earlier analyses. We see that during days with higher FSI, the effect is twice as strong.

[72] Any AP can potentially correct ETF mispricing. Correspondingly, we see that the spillovers are concentrated in funds with fewer previously active APs.

[73] Our tests include fund and date fixed effect and go through when we consider all funds or funds with nonzero Fed purchases only.

Table 8: Mispricing and AP Exposure to FED Bond-Buying Program

This table reports the results of estimating the following specification:

$$Mispricing_{f,t} = \beta \times Lead\,AP\,Exposure_f + \boldsymbol{\gamma}'\boldsymbol{X_{f,t}} + \boldsymbol{\delta}'\boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

where $Lead\,AP\,Exposure_f$ is $AP\,Exposure$ of the lead AP of the fund. $AP\,Exposure_j$ is AP j's exposure to the program, that is, the amount of bond ETF purchases through this AP relative to the total bond ETF primary market volume of this AP in 2019:

$$AP\,Exposure_j = \frac{FED\,ETF\,Purchases_{AP_j}}{Total\,Bond\,ETF\,Volume\,2019_j}$$

The regression is estimated on a daily panel of US equity ETFs in the respective period. The announcement period ('Announc') is from March 23, 2020 to May 11, 2020; the implementation period ('Impl') is from May 12, 2020 to June 17, 2020; the placebo period ('Placebo') is from May 12, 2019 to June 17, 2019. We describe the program and the construction of FED shocks in more detail in Section 6.3. FSI is the daily value of the OFR Financial Stress Index. No. of active APs is as of 2019 and 7 is its median value. All regressions include controls for fund characteristics: logarithms of size and age (as of 2019), logarithm of creation basket size, transaction fee, net expense ratio, in-kind redemption dummy, daily bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points				
Sample	Impl	Announc	Placebo	Impl	Impl
	(1)	(2)	(3)	(4)	(5)
Lead AP exposure	1.49***	1.95**	0.55	0.83**	
	(3.06)	(2.05)	(0.65)	(2.10)	
Lead AP Exposure × FSI				0.75**	
				(2.24)	
Lead AP Exposure × No. of active APs $\leq$ 7					2.11***
					(2.80)
Lead AP Exposure × No. of active APs > 7					0.59
					(1.30)
Observations	11,232	15,118	10,748	11,232	11,232
Within R^2, %	21.8	18.4	20.2	21.9	21.9

Finally, we explore whether a larger ETF-AP network helps mitigate the spillover effect of shocks to lead APs. We interact the exposure variables with a dummy that equals one if the number of active APs in the fund is above the sample median of 7.[74] The effect is only present in the subsample of funds with a smaller number of active APs.

Our results contribute to the literature on the mispricing and liquidity effects of COVID-19. Haddad, Moreira, and Muir (2021) attribute the normalization of debt markets to the Federal Reserve's announcement of bond purchases. Similarly, O'Hara and Zhou (2021) argue that the liquidity normalization effects of the Federal Reserve's facilities materialized in late March 2020 and at the announcement of the SMCCF. They do not find any

[74] Results are similar if we use the number of registered APs and its median instead.

changes to corporate bond liquidity at the start of bond ETF purchases. Laipply and Madhavan (2020) argue that the large dislocations in corporate bond ETFs in March stemmed from the staleness of NAV, and that the ETF arbitrage mechanism has functioned well throughout the pandemic.[75] Iwadate (2021) documents contagion between ETFs with similar underlying assets. None of these papers considers differences in ETF primary market networks or spillovers to equity ETFs.

6.4 Alternative Channels

In this section, we explore alternative explanations for our findings. We show that it is unlikely that our results are driven by equity capital constraints of arbitrageurs, differences in arbitrageurs' evaluations of ETF mispricing, and limits to arbitrageur attention.

6.4.1 Capital Constraints

Capital constraints are one of the well-known limits to arbitrage. In our setup, primary market size could be correlated with the availability of arbitrage or end ETF investor capital. Thus, a smaller primary market might imply a smaller amount of available arbitrage capital, hence larger observed mispricing. We therefore look for evidence that capital constraints are binding in ETF markets.

First, with limited capital, if an arbitrageur has a better arbitrage opportunity elsewhere in the ETF network, she will forgo eliminating mispricing in a particular ETF. We build a measure of arbitrage opportunities for fund APs elsewhere in the ETF network and do not see that larger outside opportunities[76] are associated with higher mispricing or lower flow-premium sensitivity. Test details and results are reported in Appendix Table A15. In short, there is no evidence that outside arbitrage opportunities within the ETF universe are positively related to fund mispricing.

Second, as we discussed in Section 5.4, trades originating from end ETF investors may coincide with arbitrage flows. Specifically, when ETF shares are traded at a premium on the exchange, an investor seeking to gain exposure to the ETF would purchase them through an AP, thus triggering a creation. The only difference from AP's perspective is that she would sell ETF shares to the client and charge a commission rather than selling at a premium on

[75] Relatedly, Dannhauser and Hoseinzade (2021) explore the flow-induced pressure from the ETF arbitrage mechanism in corporate bond markets during the Taper Tantrum. They show that funds with the smallest amount of mispricing also saw the largest AP activity, suggesting an effective arbitrage mechanism.

[76] Our main measure of available arbitrage opportunities for a given ETF-AP pair is the dollar amount needed to close mispricing net of fees in all the funds where the AP is active, except the fund itself. We assume linear price impact and use Amihud (2002) illiquidity as the measure of price impact. See Table A15 for details.

the exchange. Hence, if the arbitrage capital is not sufficient, APs may use client orders to benefit from mispricing. In that case, the flow-premium sensitivity should increase with the flows of end ETF investors. However, we do not see such an increase using interactions with changes in 13F institutional ownership (reported in Appendix Table A16).

6.4.2 NAV Calculation Disagreement

Beyond limits to arbitrage explanations, we conjecture that arbitrageurs' disagreement on real-time fund NAV could lead to the importance of networks as arbitrageurs would then have different evaluations of arbitrage opportunities. Indeed, for larger primary markets, there is a higher chance that some arbitrageurs will have an evaluation of mispricing higher than their break-even level.

First, this concern is relatively muted for US equities as they are liquid and continuously priced. Second, we confirm that our results still hold even for funds where disagreement is less likely. In Appendix Table A18, we split our sample into funds with a 'simpler' benchmark weighting (in particular, with market weights, modified market weights, and equal weights) and all other funds (e.g., whose benchmark requires estimated quantities such as risk factors). Results are very similar in these two subsamples, except for the coefficient of direct PM volume share, which is only significant for funds with 'simpler' benchmarks. Furthermore, in Appendix Table A19, we subsample ETFs by their Morningstar Style Box position in several ways and find that the network is almost equally important on high-FSI days across all subsamples. All in all, we do not find support for the importance of arbitrageurs' disagreement in our data.

6.4.3 Arbitrageurs' Inattention

We also explore whether arbitrageurs' inattention may explain the importance of larger primary markets. Even though arbitrageurs with access to ETF primary markets are sophisticated and technologically savvy market players, they might not be able to attend to every arbitrage opportunity.[77]

To assess the importance of inattention for ETF mispricing, we separate our 2020 daily subsample into high-inattention and low-inattention days based on three different inattention measures.[78] As suggested by Appendix Table A20, the coefficients on PM activity on low- and

[77] Inattention has been shown to have effects in markets with sophisticated investors, such as mutual fund managers (Kacperczyk, Nieuwerburgh, and Veldkamp (2016)).

[78] First, we separate Fridays as days with higher inattention, as suggested by Dellavigna and Pollet (2009). Second, we consider days with higher than the median number of stock-level earnings announcements (Hirshleifer, Lim, and Teoh (2009)). Third, we use key macroeconomic data announcements (Savor and Wilson (2014)). See the details in Table A20.

high-FSI days are only slightly larger in magnitude on high-inattention days. Importantly, ETF primary market size is still as strongly related to mispricing on low-inattention days as in our baseline results. Therefore, we do not see strong limits to arbitrageur attention with respect to ETF mispricing, at least for the chosen inattention measures.

7 Conclusion

Exchange-traded funds depend on creation and redemption activity in their primary markets. In this paper, we provide the first insight into the structure of the US ETF primary markets using novel N-CEN regulatory filings.

We document that the network of ETF-AP connections has a dense core and a sparse periphery. There is considerable variation in the number of connections held by US equity ETFs, and in the concentration of these ETFs' primary market activity. APs also differ from each other in their connectedness to funds, and in how much they are regulated.

ETF markets are a good laboratory to study the limits to arbitrage: mispricing is measurable, and only a limited number of market participants can trade on it risklessly. We show that the level of mispricing in an ETF is related to fund network features, especially in high-stress times and during short-selling halts on ETF shares. Our findings suggest that AP balance sheet usage costs contribute to ETF mispricing. We further corroborate this channel using the Federal Reserve's purchases of bond ETFs in 2020. Regulatory costs have been shown to affect no-arbitrage relationships in many asset markets. Our results indicate the presence of these costs in liquid markets, and suggest that costs are passed directly to ETF investors.

Our results highlight potential fragility in ETF primary markets since we find that primary market characteristics relate to ETF mispricing in high-risk times and mispricing of two funds comoves more if they share more APs. It seems important to us to conduct similar studies in markets with a higher liquidity mismatch between an ETF and its underlying basket, such as corporate bonds. Furthermore, we highlight that the specifics of the US regulations make interpretation of N-CEN filings harder: because many APs are prime brokers, the actual degree of concentration in the US ETF primary markets is still obscure. Our findings therefore call for more detailed regulatory data on ETF primary markets to facilitate further scientific inquiry in this direction.

The scope of our questions has been limited by time series availability. With only several observed cross-sections of the ETF-AP relationships, we cannot address questions on primary markets evolution or the effects of network changes on fund mispricing and other characteristics. We see these questions as very promising avenues for future research.

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A Appendix

A.1 Details on Fee Calculations

In N-CEN data, fees are reported in a non-unified way because funds use different fee schedules:

1. Dollars per creation unit (flat fee with respect to the price of ETF but not the number of units) – type *fee1*

2. Dollars for one or more creation units purchased on the same day (flat fee with respect to both the price and number of units) – *fee2*

3. A percentage of the value of each creation unit (proportional) – *fee3*

Fee3 is proportional and therefore easily comparable. We translate *fee1* by dividing it by the average basket value (average NAV times basket size) over the year. We use *fee2* as the upper boundary (it will be maximal in % terms if only one unit is traded). Finally, we compute both the maximum and the minimum of the reported (non-zero) fees to get a range for excess mispricing.

Moreover, transaction fee schedules may be asymmetric for creations/ redemptions and cash/in-kind transactions. We compute both averaged metrics as well as separate ones to pick up this asymmetry.

A.2 Details on N-CEN Parsing and Merge With Morningstar

We first merge all N-CEN subfiles on CIK, SeriesID, and 'filed as of date'. We remove files that were not 'live' or were for index/mutual funds. We remove cases when the filing was applicable for less than 12 months. Out of the remaining multiple filings per year, we keep the last one. Multiple filings arise due to updates, typically filed under form name 'N-CEN/A'. We correct the ticker for series 'S000060899' to 'RENW'. This leaves us with 2308 unique fund names.

We merge (1) Morningstar (MS) static variables and (2) MS-SEC map on SecId (Morningstar fund identifier). Then we link the merged MS file to N-CEN dataset on 'Ticker'. Furthermore, we merge this to average annual prices from MS both on SecId and year. The resulting file has 2894 tickers.

In this dataset, we clean AP names to get 'AP_firm' (AP holding company name) and extract 'AP_id' (for that we use 'LEI', legal entity identifier). We use Factset to trace parent holding companies for each broker. We remove missing names and missing

'AP_id' and aggregate trading volumes to ticker-'AP_id' level. We manually clean cases with duplicate funds per ticker (BCI, QTUM, KFYP, ADRE, GTO, JPIN, SDY). Then we normalize fee data from N-CEN using reported basket sizes and average annual prices from MS (to express all fees in % of creation unit value). This results in our ETF-AP annual panel with 2116 unique tickers.

A.3 Structure of Virtu Financial Inc.

In our dataset, Virtu Financial has the following LEIs.

- 549300$XG5LFGN1IGYC$71 is Virtu Financial Ireland, a registered investment firm under the Market in Financial Instruments Directive, and its primary regulator is the Central Bank of Ireland.
- 54930088$MP91YZQJT$494 is Virtu Financial Bd Llc, a wholly owned broker-dealer subsidiary of Virtu Financial.
- 5493006$FX0HRYU3G2R$47 is Virtu Financial Capital Markets , is another broker-dealer subsidiary of Virtu Financial (this and the one above are registered U.S. broker-dealers, and their primary regulators include the SEC, the Chicago Stock Exchange and FINRA).
- 549300$RA02N3BNSWBV$74 is Virtu Americas Llc, which was formed upon acquisition of KCG Holdings Inc. in April 2017. This is a clearing firm.
- 549300$S41SMIODVIT$266 is Virtu Itg Llc which was formed upon acquisition of ITG by Virtu in March 2019.

The company describes its subsidiaries, their regulation, and financial interconnectedness in its report to the SEC.[79]

A.4 ETF Data

A.4.1 Sources of ETF Data

We use CRSP and Morningstar for our standard ETF data. A fund's total net assets (TNA) and daily returns for NAV and ETF share price come from the CRSP stock file and the CRSP Mutual Fund Database. Details on parsing the CRSP data are in Appendix A.4.2.

[79] Available at https://www.sec.gov/Archives/edgar/data/1592386/000104746915001003/a2219372zs-1a.htm.

Fund fees, benchmarks, investment categories, and other static data come from Morningstar, as do our daily benchmark returns. Fund benchmarks and fund families (identified with *Branding Name*) are a static snapshot from September 2020. We take daily fund shares outstanding from Morningstar.[80] We merge CRSP and Morningstar by fund ticker; details of this merge are in Appendix A.2. We take ETF short interest from Compustat. We use Thomson Reuters s34 tables to compute 13F institutional ownership of ETF shares,[81] and use Brian Bushee's classification (Bushee (1998)) to split institutional ownership into transient, dedicated, and quasi-indexer. To compute holdings-level measures, we use monthly fund holdings from CRSP Mutual Fund Database.

A.4.2 Details on Preparing ETF Data in CRSP

We need both data on ETF stock and ETF assets, which we get from CRSP via WRDS.

The first is the exchange data available in CRSP stock files, we set the share code (SHRCD) to '73' to get a list of ETF PERMNOs. From daily stock file we get stock price, stock price return, outstanding shares (updated monthly), trading volume, bid, ask, high price, and low price. There are 3278 unique PERMNOs.

The second is CRSP fund database and we find funds that ever had 'et_flag' equal 'F' to get all 'crsp_fundno' for ETFs. From the same table we get tickers and Lipper style. We manually correct 4 tickers and 2 cusips for 4 funds. There are 3071 unique crsp_fundno.

We left-join fund numbers to daily PERMNO-level data on historical CUSIP and summary date (quarterly frequency). Then, we left-join daily NAV fund returns (NAV returns) by fund number and date. We drop funds with missing tickers. We also restrict the sample to after 2015. This results in 2686 tickers. All of these have price and NAV data.

A.4.3 Filters

Our dataset is limited to ETFs for which we can merge N-CEN forms, i.e., 2,181 of the available ETFs in Morningstar (2,894 tickers). We use this entire ETF universe to describe our network.

In our tests, we focus on US domestic equity ETFs. We exclude funds with less than $10 million in assets, with net expense ratios higher than 3%, with a low correlation between Morningstar and CRSP returns (below 95%), and that are younger than one year. We only

[80] Shares outstanding are reported with a lag in Morningstar. We lead the values by one day to align fund flows with Bloomberg data.

[81] We thank Luis Palacios, Rabih Moussawi, and Denys Glushkov for making their code publicly avaiable on WRDS.

consider ETFs that are physically replicated and that have a confirmed benchmark.[82] We exclude funds that are inverse, leveraged, or fund-of-funds. US domestic equity funds are defined by the US category group of Morningstar. To correct for classification errors, we drop funds with the words 'foreign', 'world', 'relative', 'global', and 'preferred' in the Morningstar category name. We also exclude funds with portfolio allocation to non-US equity of over 50% and to bonds of over 1%, on a net basis. The final sample of plain US domestic equity ETFs is 438 funds.

[82] We manually check whether the benchmark in Morningstar aligns with the investment objective of the fund. The excluded funds represent 0.3% of the original Morningstar ETF sample.

Table A1

AP holding company	Ticker	Total Assets, $bln	Market Cap, $bln	G-SIB	Primary Dealer	Direct investor	Number of entities (LEI)
ABN AMRO Bank (DR)	ABN (NL)	421000.0	17114.5	No	No	No	2
Bank of America	BAC (US)	2444300.0	316770.7	Yes	Yes	No	4
Bank of Montreal	BMO (CA)	648380.0	48106.3	No	Yes	No	2
Barclays PLC	BARC (GB)	1510500.0	42107.8	Yes	Yes	No	1
BNP Paribas	BNP (FR)	2333000.0	74043.6	Yes	Yes	No	2
Canadian Imperial Bank of Commerce	CM (CA)	495760.0	35768.0	No	No	No	1
Cetera Financial Group Inc.		178.6		No	No	No	1
CF & Company Holdings LP		19662.9		No	Yes	No	2
Citigroup Inc	C (US)	1957000.0	171315.0	Yes	Yes	No	2
Commerzbank AG	CBK (DE)	520430.0	7753.0	No	No	No	1
Cowen Inc	COWN (US)	5221.7	538.5	No	No	No	1
Credit Suisse Group AG	CSGN (CH)	813030.0	35297.3	Yes	Yes	No	2
Daiwa Securities Group Inc.	8601 (JP)	220670.0	7750.4	No	Yes	No	1
Depository Trust Company (DTCC)				No	No	No	1
Deutsche Bank AG	DBK (DE)	1456600.0	17284.7	Yes	Yes	No	1
First Southwest Bancorporation Inc				No	No	No	1
Flow Traders NV	FLOW (NL)	7583.0	1119.5	No	No	Yes	1
FMR LLC (Fidelity)		89437.0*		No	No	No	1
GFH HFEVA LLC (Citadel)		34346.0		No	No	Yes	2
Goldman Sachs Group Inc.	GS (US)	993000.0	84282.1	Yes	Yes	No	3
Hilltop Holdings Inc	HTH (US)	15244.0	2295.5	No	No	No	1
HSBC Holdings PLC	HSBA (GB)	2715200.0	119075.1	Yes	Yes	No	1
Hudson River Trading LLC		4061.8		No	No	Yes	1
Industrial and Commercial Bank of China	1398 (HK)	4322500.0	70480.6	Yes	No	No	1
ING Groep NV	INGA (NL)	1001000.0	46794.1	Yes	No	No	1
Interactive Brokers Group Inc	IBKR (US)	71676.0	22325.5	No	No	No	2
Intesa Sanpaolo	ISP (IT)	916100.0	46001.2	No	No	No	1
Itau Unibanco Holding SA Pfd	ITUB4 (BR)	408760.0	83942.8	No	No	No	1
Jane Street Group LLC		16090.2		No	No	Yes	1
Jefferies Financial Group	JEF (US)	49686.0	6604.4	No	Yes	No	1
JPMorgan Chase & Co	JPM (US)	2687400.0	437736.6	Yes	Yes	No	3
Macquarie Group Limited	MQG (AU)	144670.0	21446.3	No	No	No	1
Mitsubishi UFG Financial Group Inc	8306 (JP)	3117700.0	69948.1	Yes	No	No	1
Mizuho Financial Group	8411 (JP)	1988400.0	39205.3	Yes	Yes	No	1
Morgan Stanley	MS (US)	896800.0	84960.1	Yes	Yes	No	1
National Bank of Canada	NA (CA)	214140.0	19356.7	No	No	No	1
Natixis	KN (FR)	576030.0	13999.4	No	No	No	1
NatWest Group PLC	NWG (GB)	957800.0	38811.1	No	Yes	No	1
Nomura Holdings Inc	8604 (JP)	407580.0	16426.7	No	Yes	No	1
Peak6 LLC		205.3		No	No	No	1
Royal Bank of Canada	RY (CA)	1087200.0	153507.3	Yes	Yes	No	1
Societe Generale	GLE (FR)	1522500.0	27583.2	Yes	Yes	No	2
State Street Corporation	STT (US)	245610.0	28900.2	No	No	No	2
Stifel Financial Corp	SF (US)	24854.0	6034.4	No	No	No	1
The Bank of New York Mellon Corporation	BK (US)	381510.0	46072.9	Yes	No	No	2
The Bank of Nova Scotia	BNS (CA)	826390.0	66370.6	Yes	Yes	No	1
The Toronto-Dominion Bank	TD (CA)	1076800.0	98467.2	Yes	Yes	No	1
UBS Group AG	UBSG (CH)	972200.0	45246.3	Yes	Yes	No	1
Virtu Financial Inc	VIRT (US)	9609.0	3105.7	No	No	Yes	5
Wedbush Inc		6661.6*		No	No	No	1
Wells Fargo & Co	WFC (US)	1936000.0	226773.6	Yes	Yes	No	1

Table A2: US Equity ETF Summary Statistics

The table provides summary statistics for the sample of 438 US Equity ETFs. Size, age, expense ratio and benchmark characteristics are reported as of December 31st, 2019. Trading volumes, basket sizes and convertion fees are reported based on funds' 2019 fiscal years. Panels A and B are for 2019, and Panel C is for daily 2020 data. p1 and p99 stand for the 1^{st} and 99^{th} percentile, respectively.

US Equity ETFs	Mean	Median	St. Dev.	p1	p99
Panel A					
Size, $mln	5615.6	611.0	21365.4	13.1	87066.5
Age, years	10.8	12.1	5.6	1.9	21.1
Expense Ratio (net), bps	32.9	35.0	19.3	3.0	70.0
Benchmark index return, annual %	26.8	27.2	8.8	-3.2	50.3
Benchmark index st. dev., annual %	14.9	14.0	4.2	9.1	34.3
ETF share turnover, annual %	388.9	186.9	918.2	21.5	3015.4
Basket size, $mln	3.2	2.5	2.5	0.3	12.1
Basket size, 1000s of shares	46.0	50.0	13.8	10.0	100.0
Creation fee, bps	3.2	2.2	3.8	0.0	18.4
Redemption fee, bps	2.9	2.0	3.1	0.0	14.3
Total annual creation volume, % of size	101.8	50.9	164.1	0.0	785.5
Total annual redemption volume, % of size	69.2	42.0	119.9	4.1	402.6
Net annual creation volume, % of size	32.6	5.8	99.8	-62.8	407.7
Average spread, bps	10.4	6.2	18.6	0.7	51.4
In-kind redemption, dummy	0.41	0.00	0.49	0.00	1.00
Panel B					
Average premium, daily bps	0.1	0.2	4.4	-11.6	12.4
Average absolute premium, daily bps	6.6	4.9	5.8	2.0	28.3
Premium st.dev., annualized, bps	136.3	99.2	125.5	40.0	752.9
Tracking error, annualized, bps	59.5	11.4	130.2	2.2	450.0
Total mispricing st.dev., annualized, bps	187.1	124.9	188.3	52.6	1061.3
Panel C					
Premium, daily bps	-0.6	-0.0	15.2	-58.3	49.6
Absolute premium, daily bps	9.2	5.2	13.9	0.0	80.5
Net fund flow, daily bps	1.8	0.0	93.7	-444.4	500.0
Spread, daily bps	14.6	9.2	18.4	0.5	102.4
Benchmark index return, daily %	0.1	0.2	2.6	-9.2	7.9
ETF share turnover, daily %	1.6	0.5	3.7	0.0	21.3
OFR Financial Stress Index	-0.4	-1.6	3.4	-4.1	9.8

Table A3: ETF Summary Statistics

The table provides summary statistics for the International Equity and Bond parts of the ETF universe. We only include funds that are physically replicated and not leverage, inverse, or funds-of-funds. Size, age, expense ratio and benchmark characteristics are reported as of December 31st, 2019. Trading volumes, basket sizes and convertion fees are reported based on funds' 2019 fiscal year. p1 and p99 stand for the 1^{st} and 99^{th} percentile, respectively.

International Equity ETFs (278 funds)	Mean	Median	St. Dev.	p1	p99
Size, $mln	2806.55	226.85	9793.73	12.40	67137.70
Age, years	9.02	7.94	5.61	1.55	23.82
Expense Ratio, bps	44.45	48.00	21.87	3.00	92.00
Benchmark index return, 1y, %	19.63	20.37	9.21	-12.19	45.23
Benchmark index std. dev., 1y, %	12.53	11.43	4.55	6.30	27.26
Annual trading volume, % of size	465.88	202.77	814.88	45.53	3880.50
Basket size, $mln	3.78	2.24	4.59	0.44	30.43
Basket size, 1000s of shares	96.10	50.00	89.47	25.00	600.00
Creation fee, bps	14.15	8.58	15.38	0.00	75.96
Redemption fee, bps	13.59	8.46	15.63	0.00	76.90
Total annual creation volume, % of size	101.40	25.50	429.62	0.00	1304.08
Total annual redemption volume, % of size	48.12	26.02	158.56	0.00	328.23
Net annual creation volume, % of size	53.28	2.55	281.79	-58.08	1020.45
Average spread, bps	22.27	15.99	22.33	1.76	120.33
In-kind redemption, dummy	0.28	0.00	0.45	0.00	1.00
Bond ETFs (122 funds)	Mean	Median	St. Dev.	p1	p99
Size, $mln	5395.59	1046.50	9979.97	22.00	48455.80
Age, years	8.63	9.19	4.11	1.28	17.45
Expense Ratio, bps	18.80	15.00	12.99	3.50	56.00
Benchmark index return, 1y, %	10.07	8.91	5.07	2.12	23.89
Benchmark index std. dev., 1y, %	3.38	2.62	2.85	0.11	16.13
Annual trading volume, % of size	324.36	200.96	448.02	21.55	2424.38
Basket size, $mln	4.18	2.76	3.49	0.88	14.15
Basket size, 1000s of shares	74.59	50.00	40.78	25.00	200.00
Creation fee, bps	5.19	1.99	10.43	0.00	49.89
Redemption fee, bps	3.13	0.90	9.11	0.00	50.65
Total annual creation volume, % of size	81.49	50.55	109.12	1.99	350.05
Total annual redemption volume, % of size	40.15	22.38	56.61	0.00	289.20
Net annual creation volume, % of size	41.33	26.81	100.38	-56.05	316.18
Average spread, bps	9.64	5.69	14.78	0.91	44.38
In-kind redemption, dummy	0.20	0.00	0.41	0.00	1.00

Table A4: ETF Network Features and ETF Liquidity

This table reports the results of estimating the following specification

$$Spread_f^{2019} = \beta \times Network\,feature_f + \boldsymbol{\gamma}'\boldsymbol{X_f} + \alpha_{MS} + \epsilon_f$$

The regression is estimated on a cross-section of 438 US equity ETFs in 2019. The dependent variable is the average bid-ask spread of ETF share in 2019. Fund characteristics include: logarithm of fund size (in $mln), logarithm of age (in days), logarithm of creation basket size (in $), transaction fee (in bps), in-kind redemption dummy, net expense ratio (in bps), benchmark index volatility of daily returns in 2019, and average daily turnover of ETF shares on exchange in 2019. Transaction fee is the average of creation and redemption fees. The network features are defined in Section 4.2.3. All regressions include Morningstar Investment Category fixed effects. t-statistics based on robust standard errors are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	Average ETF bid-ask spread in 2019, basis points			
	PM activity	PM diversity	Connectedness	Share of direct PM volume
Panel A: Without controls for fund characteristics				
Network feature	-13.061***	-24.697***	-9.041***	-7.868**
	(-14.34)	(-8.79)	(-8.43)	(-2.10)
Within R^2, %	33.0	15.6	14.5	1.0
Panel B: With controls for fund characteristics				
Network feature	-5.854***	-6.471**	-4.629***	-10.562***
	(-3.56)	(-2.21)	(-3.81)	(-3.44)
Within R^2, %	39.9	38.7	40.1	39.8
Panel C: With controls for fund characteristics and mispricing in 2019				
Network feature	-0.296	1.680	-2.739***	-3.270
	(-0.21)	(0.68)	(-2.71)	(-1.26)
Within R^2, %	58.7	58.7	59.4	58.8

Table A5: ETF Network Features and Mispricing: Benchmark Index Fixed Effects

This table reports the results of cross-section and daily panel regressions on a subsample of 46 US Equity ETFs with non-unique benchmarks. Panels A and B present results for cross-sectional regressions of the end-of-day fund mispricing on network characteristics in 2019:

$$Mispricing_{f,2019} = \beta \times Network\,feature_{f,2019} + \boldsymbol{\gamma}' \boldsymbol{X_{f,2019}} + \alpha_{BM} + \epsilon_f$$

Panel A does not include fund-level controls. Panel B includes primary market fees, logarithm of creation basket size and average bid-ask spread on the ETF share.

Panels C and D present results for daily panel regressions of the end-of-day fund mispricing in 2020 on network characteristics as of 2019:

$$Mispricing_{f,t} = \beta \times Network\,feature_f + \boldsymbol{\gamma}' \boldsymbol{X_{f,t}} + \alpha_{BM} + \alpha_t + \epsilon_{f,t}$$

Panel C does not include fund-level controls. Panel D includes primary market fees, logarithm of creation basket size and bid-ask spread on the ETF share.

All regressions include Benchmark Index fixed effects. Panels C and D include date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	PM activity	PM diversity	Connectedness	Share of direct PM volume
Panel A: Cross-section 2019, without controls				
Network feature	-2.274***	-6.006***	-2.330***	-1.006
	(-7.87)	(-4.32)	(-6.89)	(-0.54)
Observations	46	46	46	46
Within R^2, %	86.5	74.0	84.0	57.2
Panel B: Cross-section 2019, with controls				
Network feature	-1.452***	-2.834**	-1.492**	-2.963**
	(-2.80)	(-2.11)	(-2.59)	(-2.38)
Observations	46	46	46	46
Within R^2, %	88.6	87.2	88.2	87.7
Panel C: Panel 2020, without controls				
Network feature	-3.775***	-8.638***	-4.728***	-5.971***
	(-3.95)	(-3.33)	(-7.34)	(-3.13)
Observations	11,636	11,636	11,636	11,636
Within R^2, %	2.7	1.2	3.7	0.5
Panel D: Panel 2020, with controls				
Network feature	-1.809***	-3.610**	-2.931***	-6.125***
	(-2.78)	(-2.31)	(-3.73)	(-4.34)
Observations	11,636	11,636	11,636	11,636
Within R^2, %	5.3	5.1	5.6	5.5

Table A6: ETF Characteristics and ETF-AP Connections in 2020

This table reports the results of estimating the following specification:

$$Y_{ij} = \boldsymbol{\gamma}' Pair\,Chars_{ij} + \boldsymbol{\delta}' Fund\,Chars_i + \epsilon_{ij}$$

The regression is estimated on a cross-section of ETF-AP pairs of 432 US equity ETFs in 2020. Columns (1), (2), (5), (6), (9) and (10) report panel regression estimates while columns (3), (4), (7) and (8) report probit estimates.

We use the following variables as a dependent variable Y_{ij}: a dummy that equals 1 if AP j has a registered connection with ETF i in 2020 (columns (1)-(4)), a dummy that equals 1 if AP j created or redeeemed shares of ETF i in 2020 (columns (5)-(8)), and $log(1 + PM\,volume_{ij})$ where $PM\,volume_{ij}$ is the total primary market volume traded by AP j in ETF i in 2020. Correspondingly, the sample is limited to connections not existing in 2019 in columns (1)-(4) and to connections existing in 2019 in columns (5)-(10).

$Pair\,Chars_{ij}$ include pair characteristics: a dummy that equals 1 if AP j created or redeeemed shares of ETF i in 2019, a dummy that equals 1 if AP j was active in any ETF of the family of ETF i in 2019, a dummy that equals 1 if AP j was registered in any ETF of the family of ETF i in 2019.

$Fund\,Chars_i$ include our baseline fund characteristics: logarithm of fund size (in $mln), logarithm of age (in days), logarithm of creation basket size (in $), transaction fee, net expense ratio, dummy for whether ETF shares can be redeemed through an in-kind transaction only, benchmark index volatility of daily returns in 2019, average daily turnover of ETF shares on exchange in 2019, - as well as average fund mispricing and bid-ask spread in 2019. Transaction fee is the average of creation and redemption fees.

Columns (1), (2), (5), (6), (9) and (10) include AP and Morningstar Investment Category fixed effects and t-statistics based on standard errors double clustered by fund and AP. Columns (3), (4), (7) and (8) do not include fixed effects and t-statistics are based on robust standard errors. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF-AP pair characteristic in 2020:									
	AP is registered				AP is active				AP's PM volume	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AP active in family dummy	-0.078	-0.072	-0.213**	-0.129	0.054***	0.028*	0.908***	0.964***	1.006***	0.355
	(-0.77)	(-0.72)	(-2.20)	(-1.31)	(3.73)	(1.91)	(17.22)	(18.16)	(3.67)	(1.29)
AP registered in family	0.209**	0.189**	1.011***	0.934***						
	(2.48)	(2.28)	(18.89)	(16.25)						
Active pair dummy					0.425***	0.354***	1.812***	1.737***	8.333***	6.641***
					(9.29)	(8.52)	(56.84)	(52.95)	(9.32)	(8.65)
ETF mispricing		-16.091		-67.372		-20.609		-63.109		-187.542
		(-1.39)		(-0.79)		(-1.36)		(-0.84)		(-0.69)
Ln(Size)		-0.010		-0.086***		0.024***		0.073***		0.625***
		(-1.50)		(-4.38)		(4.76)		(5.73)		(5.52)
Ln(Age)		0.042**		0.313***		0.004		-0.169***		0.146
		(2.03)		(5.73)		(0.39)		(-4.74)		(0.77)
Ln(Basket Size)		0.005		-0.040		-0.008		-0.018		-0.044
		(0.56)		(-0.85)		(-0.95)		(-0.60)		(-0.29)
Transaction Fee		8.160		53.799		-16.681		-114.459**		-242.589
		(0.78)		(0.62)		(-1.13)		(-2.04)		(-0.86)
Net Expense Ratio		-8.730*		-71.119***		-8.015**		-12.456		-169.576***
		(-1.69)		(-4.43)		(-2.29)		(-1.13)		(-2.81)
Turnover		0.111		1.421***		0.566***		1.524***		13.019***
		(0.63)		(2.96)		(3.95)		(5.73)		(4.39)
In-Kind ETF dummy		-0.027		-0.247***		0.007		0.042		0.137
		(-1.28)		(-4.65)		(0.82)		(1.29)		(0.81)
Benchmark index st. dev.		-0.067		-0.811		0.094		0.489		0.557
		(-0.57)		(-1.14)		(0.73)		(1.13)		(0.23)
Average spread		0.033		-0.208		0.043		0.143		1.390
		(0.96)		(-0.44)		(0.69)		(0.37)		(1.21)
Observations	8,811	8,811	8,812	8,812	12,355	12,355	12,356	12,356	12,355	12,355
Within R^2, %	8.8	10.7			21.5	26.0			23.9	31.1
Pseudo R^2, %			9.4	12.0			39.7	40.8		
Sample	Not registered in 2019				Registered in 2019					

Table A7: ETF Network Features and Mispricing in 2020: Mispricing Measured Using Bid-Ask Midpoints

This table reports the results of daily panel regressions of the end-of-day fund mispricing on network characteristics. Panel A reports the estimates for the following specification:

$$Mispricing_{f,t} = \beta \times Network\, feature_f + \boldsymbol{\gamma}' \boldsymbol{X_{f,t}} + \boldsymbol{\delta}' \boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

Panel B reports the estimates for

$$\begin{aligned} Mispricing_{f,t} = \beta_1 \times Network\, feature_f \times D_t^{Low\, FSI} + \beta_2 \times Network\, feature_f \times D_t^{High\, FSI} + \\ + \boldsymbol{\gamma_1'} \boldsymbol{X_{f,t}} \times D_t^{Low\, FSI} + \boldsymbol{\gamma_2'} \boldsymbol{X_{f,t}} \times D_t^{High\, FSI} + \boldsymbol{\delta_1'} \boldsymbol{Y_f} \times D_t^{Low\, FSI} + \boldsymbol{\delta_2'} \boldsymbol{Y_f} \times D_t^{High\, FSI} + \alpha_{MS} + \alpha_t + \epsilon_{f,t} \end{aligned}$$

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated using bid-ask spread mid points. All network features are as of 2019. Daily $D^{High\, FSI}$ equals 1 when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). $D^{Low\, FSI} = 1$ when the daily Financial Stress Index is negative. Last row of the table reports results of a t-test that $\beta_2 - \beta_1 = 0$. Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. The network features are defined in Section 4.2.3, these features are demeaned before we build the interaction variable. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	PM activity	PM diversity	Connectedness	Share of direct PM volume
Panel A: Network feature as of 2019				
Network feature	-0.474	-0.177	-1.031**	-2.716**
	(-0.92)	(-0.17)	(-2.48)	(-2.04)
Observations	109,134	109,134	109,134	109,134
Within R^2, %	19.8	19.8	20.0	20.0
Panel B: Interactions with FSI				
Network feature $\times D^{Low\, FSI}$	0.120	0.800	-0.744*	-1.639
	(0.24)	(0.86)	(-1.93)	(-1.31)
Network feature $\times D^{High\, FSI}$	-1.754**	-2.113	-1.625***	-4.569***
	(-2.53)	(-1.34)	(-2.78)	(-2.74)
Transaction fee $\times D^{Low\, FSI}$	0.023	0.024	0.035	0.029
	(0.51)	(0.55)	(0.81)	(0.65)
Transaction fee $\times D^{High\, FSI}$	0.208**	0.218**	0.277***	0.242***
	(2.37)	(2.45)	(3.40)	(2.65)
Observations	109,134	109,134	109,134	109,134
Within R^2, %	21.0	21.0	21.2	21.2
Network feature High-Low	-1.873**	-2.913**	-0.881**	-2.930***
	(-3.75)	(-2.57)	(-2.06)	(-3.08)

Table A8: ETF Network Features and Mispricing in 2020: Size Subsamples

This table reports the results of daily panel regressions of the end-of-day fund mispricing on network characteristics. Panels report the estimates for the following specification:

$$Mispricing_{f,t} = \beta_1 \times Network\,feature_f \times D_t^{Low\,FSI} + \beta_2 \times Network\,feature_f \times D_t^{High\,FSI} + \\ + \boldsymbol{\gamma_1'} \boldsymbol{X_{f,t}} \times D_t^{Low\,FSI} + \boldsymbol{\gamma_2'} \boldsymbol{X_{f,t}} \times D_t^{High\,FSI} + \boldsymbol{\delta_1'} \boldsymbol{Y_f} \times D_t^{Low\,FSI} + \boldsymbol{\delta_2'} \boldsymbol{Y_f} \times D_t^{High\,FSI} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

Panel A reports results for small funds, i.e., funds smaller than the median fund as of the end of 2019. Panel B reports results for large funds.

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices. All network features are as of 2019. Daily $D^{High\,FSI}$ equals 1 when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). $D^{Low\,FSI} = 1$ when the daily Financial Stress Index is negative. Last row of each panel reports results of a t-test that $\beta_2 - \beta_1 = 0$. Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. The network features are defined in Section 4.2.3, these features are demeaned before we build the interaction variable. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	PM activity	PM diversity	Connectedness	Share of direct PM volume
Panel A: Small Funds				
Network feature $\times D^{Low\,FSI}$	-1.581*	-1.892	-0.420	-0.834
	(-1.89)	(-1.34)	(-0.60)	(-0.45)
Network feature $\times D^{High\,FSI}$	-5.040***	-5.698*	-2.161**	-2.546
	(-2.93)	(-1.94)	(-2.01)	(-0.84)
Transaction fee $\times D^{Low\,FSI}$	0.112*	0.107	0.133**	0.123*
	(1.67)	(1.57)	(1.97)	(1.88)
Transaction fee $\times D^{High\,FSI}$	0.303***	0.332***	0.459***	0.384***
	(2.74)	(2.79)	(3.69)	(3.12)
Observations	54,510	54,510	54,510	54,510
Within R^2, %	12.9	12.8	12.7	12.6
Network feature High-Low	-3.459***	-3.806*	-1.740**	-1.712
	(-2.78)	(-1.69)	(-2.29)	(-0.89)
Panel B: Large Funds				
Network feature $\times D^{Low\,FSI}$	-0.806**	-0.910	-0.340	-0.056
	(-2.46)	(-1.17)	(-1.09)	(-0.08)
Network feature $\times D^{High\,FSI}$	-2.059**	-4.331**	-0.771	-4.168***
	(-2.57)	(-2.13)	(-0.96)	(-3.19)
Transaction fee $\times D^{Low\,FSI}$	0.005	0.013	0.015	0.021
	(0.13)	(0.30)	(0.38)	(0.50)
Transaction fee $\times D^{High\,FSI}$	0.393***	0.398***	0.440***	0.413***
	(4.68)	(4.75)	(5.59)	(4.85)
Observations	54,624	54,624	54,624	54,624
Within R^2, %	9.8	9.7	9.6	9.7
Network feature High-Low	-1.253*	-3.422**	-0.431	-4.111***
	(-1.83)	(-2.16)	(-0.67)	(-3.63)

Table A9: ETF Network Features and Mispricing in 2020, Additional Controls

This table reports the estimates for specification

$$Mispricing_{f,t} = \beta_1 \times PM\,activity_f \times D_t^{Low\,FSI} + \beta_2 \times PM\,activity_f \times D_t^{High\,FSI} + \\ + \boldsymbol{\gamma_1'} \boldsymbol{X_{f,t}} \times D_t^{Low\,FSI} + \boldsymbol{\gamma_2'} \boldsymbol{X_{f,t}} \times D_t^{High\,FSI} + \boldsymbol{\delta_1'} \boldsymbol{Y_f} \times D_t^{Low\,FSI} + \boldsymbol{\delta_2'} \boldsymbol{Y_f} \times D_t^{High\,FSI} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices. *PM activity* is as of 2019. Daily $D^{High\,FSI}$ equals 1 when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). $D^{Low\,FSI} = 1$ when the daily Financial Stress Index is negative. Last row of the table reports results of a t-test that $\beta_2 - \beta_1 = 0$. In columns (1)-(8), we include control variables in addition to the baseline controls desctibed in Table 4. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM activity $\times D^{Low\,FSI}$	-0.740	-1.131*	-0.916	-0.927	-1.202**	-0.710	-0.931	-0.885
	(-1.25)	(-1.75)	(-1.56)	(-1.58)	(-2.23)	(-1.15)	(-1.60)	(-1.49)
PM activity $\times D^{High\,FSI}$	-3.310***	-3.594***	-3.522***	-3.327***	-3.533***	-3.183***	-3.478***	-3.419***
	(-3.24)	(-3.00)	(-3.29)	(-3.11)	(-3.24)	(-3.05)	(-3.24)	(-3.14)
IOR $\times D^{Low\,FSI}$	-1.791**							
	(-2.54)							
IOR $\times D^{High\,FSI}$	-1.819*							
	(-1.91)							
Short interest ratio $\times D^{Low\,FSI}$		0.062***						
		(2.84)						
Short interest ratio $\times D^{High\,FSI}$		0.067						
		(1.60)						
Tracking error $\times D^{Low\,FSI}$			-0.896					
			(-0.12)					
Tracking error $\times D^{High\,FSI}$			-14.853					
			(-1.49)					
Holdings ILLIQ $\times D^{Low\,FSI}$				56.846**				
				(2.14)				
Holdings ILLIQ $\times D^{High\,FSI}$				424.208***				
				(3.45)				
ETF ILLIQ $\times D^{Low\,FSI}$					0.433***			
					(2.66)			
ETF ILLIQ $\times D^{High\,FSI}$					-0.015			
					(-0.09)			
Ln(Family size) $\times D^{Low\,FSI}$						-0.190		
						(-1.44)		
Ln(Family size) $\times D^{High\,FSI}$						-0.288*		
						(-1.82)		
Option traded dummy $\times D^{Low\,FSI}$							0.100	
							(0.36)	
Option traded dummy $\times D^{High\,FSI}$							-0.126	
							(-0.27)	
PM turnover $\times D^{Low\,FSI}$								-0.029
								(-1.37)
PM turnover $\times D^{High\,FSI}$								-0.047
								(-1.46)
Observations	109,134	100,279	109,134	108,723	106,605	109,134	109,134	109,134
Within R^2, %	17.1	17.3	16.9	17.3	17.4	17.0	16.9	16.9
PM activity High-Low	-2.570***	-2.463***	-2.605***	-2.401***	-2.331***	-2.472***	-2.546***	-2.534***
	(-3.28)	(-2.76)	(-3.33)	(-3.13)	(-2.95)	(-3.06)	(-3.25)	(-3.15)

A.5 Details on ADV Data

We use ADV forms from the SEC website submitted in 2020 in order to characterize the prime brokerage business of APs in 2019.[83] Specifically, we take the last report for each company in 2020. We keep filings from investment companies that advise at least one hedge fund according to the classification in Schedule D Part 7B1 of the ADV forms and have more than 80% of AUM from hedge fund clients (as in Jiang (2021)). For each prime broker, we compute the number of clients and the gross asset value. A 'client' in our sample is therefore an investment advisor (defined by a unique SEC number in ADV forms).

We aggregate prime brokers into holding companies, consistent with how we process N-CEN filings. We end up with 160 unique prime brokers and 2,447 clients in 2019 (for comparison, Boyarchenko, Eisenbach, Gupta, Shachar, and Tassel (2020) follow the same algorithm and report 2,250 advisors and 152 prime brokers in 2018). A median prime broker in our sample has two clients with \$3.5 billion in gross assets, though the distribution is highly skewed. 44% of clients have only one broker and 90% have up to four prime brokers. Clients with larger asset bases tend to have more prime brokers.

[83] ADV forms are submitted annually by investment advisors with more than 15 U.S. clients or more that \$25 million in assets under management. Data are available here: https://www.sec.gov/foia/docs/form-adv-archive-data.htm.

A.6 Details on the Federal Reserve's Bond-Buying Program

During the first weeks of the COVID-19 crisis in March of 2020, the US corporate bond market plummeted. This drop forced the Federal Reserve to design several stabilizing programs. In particular, on March 23, the Federal Reserve established the Secondary Market Corporate Credit Facility[84] (SMCCF) to provide liquidity to the secondary market through the purchases of individual bonds and bond ETFs. The program was scheduled to start on May 12, 2020, and was to last through the end of 2020. According to the announcement on April 9, $25 billion would be allocated to the SMCCF. Taking into account the potential leverage of 10 to one, the size of SMCCF alone could have reached up to $250 billion.[85]

The SMCCF could only buy bonds and ETFs from so-called 'Eligible Sellers'. Eligible Sellers were institutions that operated primarily in the United States and that satisfied certain certification requirements.[86] At the beginning of the program, the SMCCF mostly traded with primary dealers, but later started considering other eligible counterparties. Appendix Table A10 presents the list of authorized participants from our sample that were actively engaged in the SMCCF's purchases of bond ETFs. Out of 50 APs operating in the ETF industry during 2019-2020, 17 actively sold bond ETFs to the Federal Reserve. The aggregate ETF and bond purchases through all eligible sellers are reported in Table A11. We only include APs that traded with the Federal Reserve in the first five weeks of the program (from May 12 to June 15), when the SMCCF was only buying ETFs. Between June 16 and July 27, the SMCCF bought both ETFs and individual bonds. After July 28, it only purchased bonds. In our analysis, we focus on the first five weeks of the program because that is when most of the ETF purchases took place and because the amount of bond purchases is small enough that we can measure the amount purchased through each AP.[87]

[84] https://www.federalreserve.gov/monetarypolicy/smccf.htm

[85] The Federal Reserve explicitly stated, however, that SMCCF purchases would be adjusted based on 'sustained improvement in market functioning:' https://www.newyorkfed.org/markets/secondary-market-corporate-credit-facility/secondary-market-corporate-credit-facility-seller-certification.

[86] For details, see: https://www.newyorkfed.org/markets/secondary-market-corporate-credit-facility/secondary-market-corporate-credit-facility-seller-certification.

[87] The volume of an eligible seller reported by the Federal Reserve is the total of bond and bond ETF purchases. To be able to compare with the trading volume of APs in 2019, we need to focus on ETF transactions. Therefore, we pick the first five weeks of the program, when bond purchases were smaller than ETF purchases. If we take the first week only, when no bonds were purchased, we miss a considerable share of ETF purchases. If we include all purchases up to July 30, we might mismeasure the balance sheet space allocated to ETFs (assuming the more likely substitution from bond ETFs to equity ETFs instead of substitution between bond ETFs and bonds). Our subsampling choices are also limited by the aggregation in the Fed's reporting: Amounts by AP are reported for periods May 12 to May 18, May 19 to June 17, June 18 to June 29, and June 30 to July 30.

Table A10: APs as Sellers in the SMCCF

The table provides the summary statistics for the APs' participation in the Fed's bond ETF purchases within the SMCCF between May 12 and June 17, 2020. *Amount* refers to the nominal value of bond ETFs that were purchased by the Fed via the AP. The exposure to the program is computed as: $AP\,Exposure_i = \frac{FED\,ETF\,Purchases_i}{Total\,Bond\,ETF\,Volume\,2019_i}$. Four APs are not assigned an exposure because they did not have any bond ETF activity in 2019.[a] *Lead* is equal to 1 if AP ever appears as the most active AP of a US equity ETF in our sample.

AP holding company	**Amount, \$mln**	**N of trades**	***AP Exposure***	***Lead***
Bank of America	937.53	109	0.04	1
Barclays PLC	776.18	80	0.63	1
Bank of Montreal	330.31	19	-	0
BNP Paribas	452.80	60	9.38	1
Citigroup Inc	532.47	41	0.60	1
Daiwa Securities Group Inc	2.70	1	-	0
Deutsche Bank AG	3.70	2	0.00	1
Goldman Sachs Group Inc	585.31	38	0.06	1
Jefferies Financial Group	567.96	57	1.00	0
JPMorgan Chase & Co	297.93	30	0.02	1
Mizuho Financial Group	207.75	23	15.09	1
Morgan Stanley	1010.38	110	0.94	1
Royal Bank of Canada	594.16	24	0.23	1
The Bank of Nova Scotia	519.76	48	-	0
The Toronto-Dominion Bank	4.38	1	-	0
UBS Group AG	122.45	8	3.75	1
Wells Fargo & Co	281.91	34	40.13	1

[a]Our results are not sensitive to that because we only consider lead AP exposures.

Table A11: Traded Amounts by Eligible Seller in the SMCCF

The table provides the summary statistics for the seller participation in the Fed's bond ETF and bond purchases within the SMCCF between May 12 and July 30, 2020.[a] *Amount by period* refers to the nominal value of bond ETFs or bonds that were purchased by the Fed via the seller. Traded amounts by seller come from the Federal Reserve's website.[b] Only APs with positive amount between May 12 and June 17 are included in our sample in Table A10.

Eligible seller	**AP**	**Amount by period, $mln**			
		May 12 - May 18	May 19 - June 17	June 18 - June 29	June 30 - July 30
Amherst Pierpont Securities	N		73.03	289.24	255.25
Bank of America	Y	337.40	600.13	136.70	150.02
Barclays PLC	Y	208.05	568.12	148.37	181.96
Bank of Montreal	Y	56.38	273.93	98.54	27.50
BNP Paribas	Y	41.21	411.59	123.49	91.05
Cantor Fitzgerald	Y				8.73
Citigroup Inc	Y	86.36	446.12	152.57	132.23
Daiwa Securities Group Inc	Y		2.70	7.27	15.66
Deutsche Bank AG	Y		3.70	22.57	28.16
Goldman Sachs Group Inc	Y	201.80	383.52	83.31	230.20
HSBC Holdings Plc	Y			10.22	3.16
Jefferies Financial Group	Y	124.73	443.22	133.12	56.49
JPMorgan Chase & Co	Y		297.93	132.81	147.83
Mizuho Financial Group	Y		207.75	172.64	80.43
Morgan Stanley	Y	327.16	683.22	323.90	346.71
NatWest Group PLC	Y		2.71		15.96
Royal Bank of Canada	Y		594.16	83.19	130.19
Societe Generale	Y				12.20
The Bank of Nova Scotia	Y		4.38	42.79	58.37
The Toronto-Dominion Bank	Y		3.19	12.80	51.83
UBS Group AG	Y	119.75	203.29	117.86	16.98
Wells Fargo & Co	Y	78.61	519.76	211.61	254.47
Total Fed purchases, $ mln		1,581.46	5,722.45	2,369.16	2,371.35
ETF share in purchases, %		100.0	92.5	43.9	22.0

[a] There were no ETF purchases after July 30, 2020.

[b] https://www.federalreserve.gov/monetarypolicy/smccf.htm

Table A12: ETF-Level AP Exposure Statistics

The table provides summary statistics for the AP exposure to the SMCCF at the ETF level. AP j's exposure to the program, that is, the amount of bond ETF purchases through this AP relative to the total bond ETF primary market volume of this AP in 2019 is computed as:

$$AP\,Exposure_j = \frac{FED\,ETF\,Purchases_{AP_j}}{Total\,Bond\,ETF\,Volume\,2019_j}$$

Lead AP Exposure is $AP\,Exposure_j$ for the lead AP of the fund. p1 and p99 stand for the 1^{st} and 99^{th} percentile, respectively.

	Mean	Median	St. Dev.	p1	p99
Lead AP exposure	0.10	0.03	0.29	0.00	0.93

Table A13: Fed SMCCF Purchases and Bond ETF Flows

The table reports the estimate of β for the following specification:

$$Flow_{f,t} = \beta \times SMCCF\,flow_f + \boldsymbol{\gamma}'\boldsymbol{X_{f,t}} + \alpha_f + \alpha_t + \epsilon_{f,t}$$

The regression is estimated on a daily panel of 124 US bond ETFs in 2020. The dependent variable is daily ETF fund flow, percentage change in the number of fund shares. The main independent variable is $SMCCF\,flow$, the number of shares purchased by the SMCCF divided by the number of shares the day before. Column (3) reports intensive margin results only, i.e., on a subsample of 16 ETFs whose shares the SMCCF purchased. We report these purchases by fund in Appendix Table A14. In column (4), we interact $SMCCF\,flow$ with time dummies: $D^{ETF\,only} = 1$ in May 12 to May 18, $D^{Mostly\,ETFs} = 1$ in May 19 to June 17 and $D^{Mostly\,bonds} = 1$ in June 18 to July 30. Daily controls $\boldsymbol{X_{f,t}}$ include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF daily flow			
	(1)	(2)	(3)	(4)
SMCCF flow	2.316***	2.123***	2.089**	
	(4.89)	(4.52)	(2.47)	
SMCCF flow $\times D^{ETF\,only}$				1.577***
				(4.21)
SMCCF flow $\times D^{Mostly\,ETFs}$				2.668***
				(4.86)
SMCCF flow $\times D^{Mostly\,bonds}$				-1.770
				(-0.77)
Observations	31,213	31,213	3,526	31,213
Adjusted R^2	3.2	4.2	15.1	4.3
Sample	All bond ETFs	All bond ETFs	SMCCF only	All bond ETFs
FE	Fund and Date	Fund and Date	Fund and Date	Fund and Date
Clusters	Fund	Fund	Fund	Fund
Daily controls	No	Yes	Yes	Yes

Table A14: Traded Amounts by ETF in the SMCCF

The table provides the summary statistics for the Fed's bond ETF and bond purchases through the SMCCF. *Total flow* refers to a simple sum of percentage flows over different dates (shares purchased divided by shares outstanding the day before). Traded amounts by ETF come from the Federal Reserve's website.[a]

ETF name	**Ticker**	**Amount purchased, $mln**		**Total flow, %**
		Total	Purchased in May 12 - June 17	
VanEck Vectors Fallen Angel High Yield Bond	ANGL	31.4	27.9	1.62
iShares iBoxx High Yield Corporate Bond	HYG	314.5	240.4	1.30
Xtrackers US Dollar High Yield Corporate Bond	HYLB	76.8	56.2	1.61
iShares Intermediate-Term Corporate Bond	IGIB	477.6	390.7	5.22
iShares Short-Term Corporate Bond	IGSB	675.1	606.0	4.01
SPDR Bloomberg Barclays High Yield Bond	JNK	533.6	411.9	4.69
iShares iBoxx US Dollar Investment Grade Corporate Bond	LQD	2,349.0	1854.0	4.68
iShares 0-5 Year High Yield Corporate Bond	SHYG	29.1	23.3	0.71
SPDR Bloomberg Barclays Short Term High Yield Bond	SJNK	31.1	22.6	0.89
iShares 0-5 Year Investment Grade Corporate Bond	SLQD	43.5	43.5	2.12
SPDR Portfolio Intermediate Term Corporate Bond	SPIB	473.4	413.5	7.88
SPDR Portfolio Short Term Corporate Bond	SPSB	279.2	244.8	4.33
iShares Broad US Dollar High Yield Corporate Bond	USHY	59.2	48.4	1.17
iShares Broad US Dollar Investment Grade Corporate Bond	USIG	177.2	148.5	3.90
Vanguard Intermediate-Term Corporate Bond	VCIT	1,390.2	1011.5	4.46
Vanguard Short-Term Corporate Bond	VCSH	1,494.1	1331.8	5.62
Total		8,434.8	6,875.0	

[a] https://www.federalreserve.gov/monetarypolicy/smccf.htm.

Table A15: AP Activity and Arbitrage Opportunities

This table reports the results of daily panel regressions of the end-of-day fund mispricing and primary market inflows on different measures of outside arbitrage opportunities available for fund's APs.

Panel A reports the estimate of β for the following specification:

$$Mispricing_{f,t} = \beta Outside\,opportunity_{f,t} + \gamma' \boldsymbol{X_{f,t}} + \boldsymbol{\delta}' \boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices.

Panel B reports the estimates of β_1, β_2 and β_3 for

$$Flow_{f,t} = \beta_1 Prem_{f,t-1} + \beta_2 Outside\,opportunity_{f,t} + \beta_3 Prem_{f,t-1} \times Outside\,opportunity_{f,t} + \gamma' \boldsymbol{X_{f,t-1}} + \boldsymbol{\delta}' \boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

The dependent variable is daily net flow (percentage change in fund shares outstanding).

The size of arbitrage opportunity of AP j in fund f is defined as

$$Outside\,opportunity_{f,j,t} = \frac{FeeAdj\,Mispricing_{f,t-1}}{ILLIQ^{ETF}_{f,2019} + ILLIQ^{BM}_{f,2019}}$$

where $FeeAdj\,Mispricing_{f,t-1}$ is a daily fund mispricing minus the primary market transaction fee, $ILLIQ^{ETF}_{f,2019}$ and $ILLIQ^{BM}_{f,2019}$ are Amihud illiquidity measures of the ETF and the underlying portfolio measured on daily data for 2019.

To compute all arbitrage opportunities for AP j, we sum arbitrage opportunities across all funds in which this AP was active in 2020:

$$Outside\,opportunity_{j,t} = \sum_{f \in active} Outside\,opportunity_{f,j,t}$$

To aggregate arbitrage opportunities available to all APs to the fund level, we weigh them by APs' primary market volumes in 2020.

The regressions are estimated on a daily panel of 432 US equity ETFs in 2020. Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. All regressions include Morningstar Investment Category, date and lead AP fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	All opportunities, all APs	Best opportunity, all APs	All opportunities, lead AP	Best opportunity, lead AP
Panel A: Daily mispricing				
Outside opportunity	-0.837*	-0.768	-0.301	-0.271
	(-1.81)	(-0.56)	(-0.93)	(-0.29)
Observations	108,649	108,649	108,649	108,649
Within R^2, %	14.7	14.7	14.7	14.7
Panel B: Daily inflow				
Premium	0.498***	0.501***	0.496***	0.500***
	(5.63)	(5.68)	(5.63)	(5.68)
Outside opportunity	-8.389**	0.768	-7.394**	0.239
	(-1.97)	(0.24)	(-2.38)	(0.08)
Premium × Outside opportunity	-0.027	-0.031	-0.034	-0.074
	(-0.39)	(-0.28)	(-0.62)	(-0.72)
Observations	108,037	108,037	108,037	108,037
Within R^2, %	0.3	0.3	0.3	0.3

Table A16: ETF Flow-Premium Sensitivity and Institutional Ownership Changes

This table reports the results of daily panel regressions of the primary market flows on lagged end-of-day fund mispricing. We estimate the following specification:

$$Flow_{f,t} = \beta \times Premium_{f,t-1} + \phi \times Premium_{f,t-1} \times \Delta IOR_{f,q} + \kappa \times \Delta IOR_{f,q} + \boldsymbol{\gamma}' \boldsymbol{X_{f,t-1}} + \boldsymbol{\delta}' \boldsymbol{Y_f} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

The regression is estimated on a daily panel of 434 US equity ETFs in 2019 and Q1 2020. The dependent variable is daily net flow (percentage change in fund shares outstanding). The main independent variable is lagged ETF premium, i.e., the relative premium of ETF share price over its net asset value per share (in percent). $\Delta IOR_{f,q}$ is quarterly change in 13F institutional ownership ratio, and $\Delta IOR^{TRA}_{f,q}$ and $\Delta IOR^{QIX}_{f,q}$ are changes in its transient and quasi-indexer components, respectively. Daily (lagged) controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF daily flows, percent			
	(1)	(2)	(3)	(4)
ETF premium	0.502***	0.431***	0.443***	0.429***
	(12.71)	(9.52)	(9.45)	(9.50)
ETF premium $\times \Delta IOR$		-0.245		
		(-0.66)		
ΔIOR		33.403***		
		(4.65)		
ETF premium $\times \Delta IOR^{TRA}$			-1.392	
			(-1.48)	
ΔIOR^{TRA}			19.975*	
			(1.87)	
ETF premium $\times \Delta IOR^{QIX}$				-0.441
				(-0.65)
ΔIOR^{QIX}				39.772***
				(3.68)
Observations	215,845	134,228	134,228	134,228
Within R^2, %	0.6	0.6	0.5	0.6

Table A17: ETF Network Features and Mispricing in 2020: Benchmark Volatility Subsamples

This table reports the results of daily panel regressions of the end-of-day fund mispricing on network characteristics. Panels report the estimates for the following specification:

$$Mispricing_{f,t} = \beta_1 \times Network\,feature_f \times D_t^{Low\,FSI} + \beta_2 \times Network\,feature_f \times D_t^{High\,FSI} + \\ + \boldsymbol{\gamma_1'} \boldsymbol{X_{f,t}} \times D_t^{Low\,FSI} + \boldsymbol{\gamma_2'} \boldsymbol{X_{f,t}} \times D_t^{High\,FSI} + \boldsymbol{\delta_1'} \boldsymbol{Y_f} \times D_t^{Low\,FSI} + \boldsymbol{\delta_2'} \boldsymbol{Y_f} \times D_t^{High\,FSI} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

Panel A reports results for funds with benchmark volatility lower than the one of the median fund, as of the end of 2019. Panel B reports results for funds with higher benchmark volatility.

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices. All network features are as of 2019. Daily $D^{High\,FSI}$ equals 1 when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). $D^{Low\,FSI} = 1$ when the daily Financial Stress Index is negative. Last row of each panel reports results of a t-test that $\beta_2 - \beta_1 = 0$. Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. The network features are defined in Section 4.2.3, these features are demeaned before we build the interaction variable. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	PM activity	PM diversity	Connectedness	Share of direct PM volume
Panel A: Low BM Volatility Funds				
Network feature $\times D^{Low\,FSI}$	1.143	0.588	-0.650	-0.880
	(1.53)	(0.40)	(-0.92)	(-0.48)
Network feature $\times D^{High\,FSI}$	-0.388	-3.286	-0.167	-3.304
	(-0.33)	(-1.21)	(-0.19)	(-1.39)
Transaction fee $\times D^{Low\,FSI}$	0.058	0.048	0.063	0.050
	(0.89)	(0.78)	(0.95)	(0.81)
Transaction fee $\times D^{High\,FSI}$	0.391***	0.386***	0.412***	0.406***
	(3.33)	(3.25)	(3.66)	(3.49)
Observations	54,520	54,520	54,520	54,520
Within R^2, %	19.1	19.1	19.1	19.1
Network feature High-Low	-1.531	-3.874*	-0.482	-2.424*
	(-1.58)	(-1.77)	(-0.60)	(-1.85)
Panel B: High BM Volatility Funds				
Network feature $\times D^{Low\,FSI}$	-2.594***	-3.837**	-1.156**	-1.011
	(-3.59)	(-2.15)	(-2.11)	(-0.55)
Network feature $\times D^{High\,FSI}$	-6.799***	-8.006**	-2.762***	-4.990
	(-4.43)	(-2.41)	(-3.16)	(-1.54)
Transaction fee $\times D^{Low\,FSI}$	0.059	0.039	0.075	0.072
	(1.06)	(0.62)	(1.25)	(1.24)
Transaction fee $\times D^{High\,FSI}$	0.208*	0.222*	0.343***	0.294**
	(1.82)	(1.80)	(2.89)	(2.16)
Observations	54,614	54,614	54,614	54,614
Within R^2, %	14.5	14.0	13.9	13.7
Network feature High-Low	-4.205***	-4.170*	-1.606**	-3.979*
	(-3.74)	(-1.79)	(-2.38)	(-1.79)

Table A18: ETF Network Features and Mispricing in 2020: Benchmark Weighting Subsamples

This table reports the results of daily panel regressions of the end-of-day fund mispricing on network characteristics. Panels report the estimates for the following specification:

$$Mispricing_{f,t} = \beta_1 \times Network\,feature_f \times D_t^{Low\,FSI} + \beta_2 \times Network\,feature_f \times D_t^{High\,FSI} + \\ + \boldsymbol{\gamma_1'} \boldsymbol{X_{f,t}} \times D_t^{Low\,FSI} + \boldsymbol{\gamma_2'} \boldsymbol{X_{f,t}} \times D_t^{High\,FSI} + \boldsymbol{\delta_1'} \boldsymbol{Y_f} \times D_t^{Low\,FSI} + \boldsymbol{\delta_2'} \boldsymbol{Y_f} \times D_t^{High\,FSI} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

Panel A reports results for funds with 'simple' benchmark weighting methodology, i.e., equal, market value or modified market value weighted benchmarks. Panel B reports results for all other funds.

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices. All network features are as of 2019. Daily $D^{High\,FSI}$ equals 1 when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). $D^{Low\,FSI} = 1$ when the daily Financial Stress Index is negative. Last row of each panel reports results of a t-test that $\beta_2 - \beta_1 = 0$. Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. The network features are defined in Section 4.2.3, these features are demeaned before we build the interaction variable. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points			
	PM activity	PM diversity	Connectedness	Share of direct PM volume
Panel A: 'Simple' benchmark weighting				
Network feature $\times D^{Low\,FSI}$	-1.037	-3.591*	-1.753**	-2.192
	(-1.45)	(-1.76)	(-2.38)	(-1.20)
Network feature $\times D^{High\,FSI}$	-2.577**	-5.717*	-2.391***	-7.043***
	(-2.20)	(-1.66)	(-2.61)	(-2.68)
Observations	63,136	63,136	63,136	63,136
Within R^2, %	20.9	20.9	21.1	21.0
Network feature High-Low	-1.540	-2.126	-0.638	-4.851***
	(-1.53)	(-0.85)	(-0.77)	(-2.75)
Panel B: 'Complex' benchmark weighting				
Network feature $\times D^{Low\,FSI}$	-0.962	-1.169	0.306	0.073
	(-1.22)	(-0.97)	(0.49)	(0.04)
Network feature $\times D^{High\,FSI}$	-4.778**	-6.773**	-2.301*	-1.219
	(-2.56)	(-2.49)	(-1.97)	(-0.42)
Observations	45,492	45,492	45,492	45,492
Within R^2, %	12.1	12.1	11.9	11.8
Network feature High-Low	-3.816***	-5.604**	-2.607***	-1.292
	(-2.88)	(-2.58)	(-3.27)	(-0.68)

Table A19: ETF Network Features and Mispricing in 2020, by Style Box Position

This table reports reports the estimates of β_2 of specification:

$$Mispricing_{f,t} = \beta_1 \times PM\,activity_f \times D_t^{Low\,FSI} + \beta_2 \times PM\,activity_f \times D_t^{High\,FSI} +$$
$$+ \boldsymbol{\gamma_1'} \boldsymbol{X_{f,t}} \times D_t^{Low\,FSI} + \boldsymbol{\gamma_2'} \boldsymbol{X_{f,t}} \times D_t^{High\,FSI} + \boldsymbol{\delta_1'} \boldsymbol{Y_f} \times D_t^{Low\,FSI} + \boldsymbol{\delta_2'} \boldsymbol{Y_f} \times D_t^{High\,FSI} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}$$

in subsamples of US equity ETFs formed by excluding all funds in their Morningstar style box cell every month. For example, in row 'Large' and column 'Blend' we estimate the regression on all 'Mid' and 'Small' ETFs as well as 'Large' 'Value' and 'Growth'. The last row and column exlude the entire style or size category, e.g. all 'Large' ETFs.

The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices. PM activity is as of 2019. Daily $D^{High\,FSI}$ equals 1 when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). $D^{Low\,FSI} = 1$ when the daily Financial Stress Index is negative. Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	Blend	**Growth**	**Value**	All size
Large	-4.300***	-3.196***	-4.001***	-4.839***
	(-3.55)	(-2.79)	(-3.32)	(-3.05)
Mid	-3.556***	-3.765***	-3.711***	-4.197***
	(-3.02)	(-3.17)	(-3.14)	(-2.81)
Small	-2.733***	-2.872***	-3.574***	-1.925**
	(-3.09)	(-2.74)	(-3.21)	(-2.35)
All style	-3.326***	-2.655**	-4.623***	
	(-2.93)	(-2.07)	(-3.18)	

Table A20: ETF Network Features and Mispricing in 2020: Inattention

This table reports the results of daily panel regressions of the end-of-day fund mispricing on network characteristics:

$$
\begin{aligned}
Mispricing_{f,t} = {} & \beta_1 \times PM\,activity_f \times D_t^{Low\,FSI} \times D_t^{Low\,Inatt} + \beta_2 \times PM\,activity_f \times D_t^{Low\,FSI} \times D_t^{High\,Inatt} + \\
& + \beta_3 \times PM\,activity_f \times D_t^{High\,FSI} \times D_t^{Low\,Inatt} + \beta_4 \times PM\,activity_f \times D_t^{High\,FSI} \times D_t^{High\,Inatt} + \\
& + \boldsymbol{\gamma_1'} \boldsymbol{X_{f,t}} \times D_t^{Low\,FSI} + \boldsymbol{\gamma_2'} \boldsymbol{X_{f,t}} \times D_t^{High\,FSI} + \boldsymbol{\delta_1'} \boldsymbol{Y_f} \times D_t^{Low\,FSI} + \boldsymbol{\delta_2'} \boldsymbol{Y_f} \times D_t^{High\,FSI} + \alpha_{MS} + \alpha_t + \epsilon_{f,t}
\end{aligned}
$$

The regression is estimated on a daily panel of 432 US equity ETFs in 2020. The dependent variable is ETF mispricing, absolute value of the relative premium of ETF share price over its net asset value per share, estimated with close prices. PM activity is as of 2019. Daily $D^{High\,FSI}$ equals 1 when the daily Financial Stress Index is above 0 (stress above average, as per OFR definition). $D^{Low\,FSI} = 1$ when the daily Financial Stress Index is negative. Daily $D^{High\,Inatt}$ equals 1 when the inattention dummy for the day equals 1, $D^{Low\,Inatt}$ equals 1 otherwise. The penultimate and last rows of the table report results of t-tests that $\beta_2 - \beta_1 = 0$ and $\beta_4 - \beta_3 = 0$, respectively.

Friday inattention dummy equals 1 on Fridays, and 0 otherwise. *Stock announcements* inattention dummy equals 1 if the number of stock-level EPS announcements during the day was above the sample median (32), and 0 otherwise (according to I/B/E/S). *Macro announcements* inattention dummy equals 1 if during the day there was at least one of the key macro announcements (Savor and Wilson (2014)), and 0 otherwise.

Daily controls include bid-ask spread on the ETF share and its square, daily benchmark index return and its square, and daily turnover of ETF shares on the exchange. Other controls are fund characteristics: logarithms of fund size and age (as of 2019), benchmark index volatility of daily returns in 2019, logarithm of creation basket size, PM transaction fee and net expense ratio (in bps), and in-kind redemption dummy. Transaction fee is the average of creation and redemption fees. All regressions include Morningstar Investment Category and date fixed effects. t-statistics based on standard errors clustered by fund are in parentheses. Significance levels are marked as: *p<0.10; **p<0.05; ***p<0.01.

	ETF mispricing, basis points		
	Friday	Stock announcements	Macro announcements
$PM\,activity \times D^{Low\,FSI} \times D^{Low\,Inatt}$	-0.977*	-0.755	-0.865
	(-1.68)	(-1.23)	(-1.48)
$PM\,activity \times D^{Low\,FSI} \times D^{High\,Inatt}$	-0.680	-1.118*	-1.296**
	(-1.10)	(-1.96)	(-2.05)
$PM\,activity \times D^{High\,FSI} \times D^{Low\,Inatt}$	-3.463***	-2.851**	-3.470***
	(-3.22)	(-2.42)	(-3.23)
$PM\,activity \times D^{High\,FSI} \times D^{High\,Inatt}$	-3.623***	-3.931***	-3.739***
	(-3.11)	(-3.81)	(-3.18)
Observations	109,134	109,134	109,134
Within R^2, %	16.9	17.0	16.9
$PM\,activity \times D^{Low\,FSI}$ High-Low Inattention	-0.297*	0.363*	0.431*
	(-1.86)	(1.90)	(1.88)
$PM\,activity \times D^{High\,FSI}$ High-Low Inattention	0.160	1.080**	0.268
	(0.29)	(2.33)	(0.44)

B Proof of Proposition 1

We start with writing down FOC for problem (7):

$$\gamma\sigma^2\left(u - \sum_{k\neq n} x_k\right) - 2\gamma\sigma^2 x_n - C_n\bar{p}sign(x_n) = 0. \tag{14}$$

Recall that $\bar{p} = \delta - \gamma\sigma^2 s$ is the average of p_A and p_B, or the price of both assets in the absence of demand shock u.

The maximization problem (7) contains an absolute value $|x_n|$, making the maximization function non-differentiable at zero. Thus the solution of the problem belongs to the set of FOC roots augmented by zero.

B.1 Step 1

First, we observe that if FOC is satisfied at some non-zero x_n, then zero allocation cannot be a solution to the maximization problem.

Indeed, one can geometrically present the maximization function as a combination of two downward parabolas intersecting at zero. The vertexes of these two parabolas, which are the only potential roots for FOC, have non-negative ordinates. It means that the profit calculated at FOC roots (if it exists) is always non-negative, compared to the exactly zero profit at 0, and it is strictly positive if the solution is non-zero.

It also follows from the geometrical representation that FOC can potentially have zero, one or two solutions. In case of two solutions, one would be positive and one would be negative.

B.2 Step 2

We next show that in equilibrium arbitrageurs cannot sell short a cheaper security, i.e., negative FOC solutions $x_n < 0$ cannot exist in equilibrium for any n.

We start by rearranging terms in the FOC (14) to obtain the expression for x_n:

$$x_n = u - \sum_{k=1}^{N} x_k - C_n\frac{\bar{p}}{\gamma\sigma^2}sign(x_n) \tag{15}$$

Summing these equations for all n such that FOC is satisfied and rearranging terms, we obtain the expression for $\sum_{k\in active} x_k$, where the set of active agents includes those with

$x_k \neq 0$ and we denote its size as N_{act}:

$$\sum_{k \in act} x_k = \frac{N_{act}}{1+N_{act}} u - \frac{\bar{p}}{(1+N_{act})\gamma\sigma^2} \sum_{k \in act} C_k sign(x_k).$$

For all non-active agents, $x_k = 0$, so $\sum_{k \in active} x_k = \sum_{k=1}^{N} x_k$ and hence

$$\sum_{k=1}^{N} x_k = \frac{N_{act}}{1+N_{act}} u - \frac{\bar{p}}{(1+N_{act})\gamma\sigma^2} \sum_{k \in act} C_k sign(x_k). \tag{16}$$

Substituting the latter into the expression for x_n, we obtain

$$x_n = \frac{1}{1+N_{act}} u - \frac{C_n \bar{p}}{\gamma\sigma^2} sign(x_n) + \frac{\bar{p}}{(1+N_{act})\gamma\sigma^2} \sum_{k \in act} C_k sign(x_k). \tag{17}$$

Now, consider two potential options for x_n. First, assume that at the optimum all x_n are non-positive, some of them being strictly negative. Consider the expression (16) for the sum of all allocations. The first term on the right-hand side is positive as $u > 0$. The second term is positive as well, because by assumption $sign(x_k) = -1$ for all active agents. But by initial assumption, the left-hand side is negative. Thus, it is a contradiction.

Second, assume that at the optimum $x_i > 0$ and $x_j < 0$ for some i, j. The difference $x_j - x_i$ should thus be negative. Write down this difference explicitly using (17):

$$x_j - x_i = \frac{C_j \bar{p}}{\gamma\sigma^2} + \frac{C_i \bar{p}}{\gamma\sigma^2} > 0,$$

which is again a contradiction.

Therefore, at the optimum we can only have non-negative allocations $x_n \geq 0$.

B.3 Step 3

In the next step, we show that if an arbitrageur is active in equilibrium, then all arbitrageurs with lower or equal costs must also be active. We start by assuming the contrary and show that the best response for the agent with zero allocation is positive.

Assume that $x_i > 0$ and $C_i \geq C_j$. The best response for agent j is either positive x_j satisfying FOC or zero x_j if FOC has no positive solutions. We now search for a positive solution for FOC of agent j.

From (15) (assuming positive x_j):

$$x_j = \frac{u}{2} - \frac{1}{2} \sum_{k \neq j} x_k - \frac{C_j \bar{p}}{2\gamma\sigma^2}.$$

$\sum_{k \neq j} x_k$ can be expressed from the FOC for agent i, as $x_i > 0$:

$$\sum_{k \neq j} x_k = u - x_i - \frac{C_i \bar{p}}{\gamma \sigma^2}.$$

Substituting it into the formula for x_j, we get:

$$x_j = \frac{1}{2} x_i + (C_i - C_j) \frac{\bar{p}}{2\gamma\sigma^2},$$

$x_i > 0$ and $C_i \geq C_j$, so x_j (the best response of agent j) is positive. Hence, zero allocation is not an equilibrium strategy for this agent.

B.4 Step 4

So far, we have shown that all potential equilibria have the following structure: m agents with the lowest costs invest actively, all others do not invest at all. In the next step, we prove that for a given set of parameters, multiple equilibria cannot exist. In other words, if there exists an equilibrium with $x_i > 0$ and $x_j > 0$, then there could not exist an equilibrium with $x_i > 0$ and $x_j = 0$.

Assume that both strategies are equilibria. Denote $x_i > 0, x_j > 0$ as Equilibrium 1 and $x_i > 0, x_j = 0$ as Equilibrium 2.

As $x_{j,1} > 0$, $x_{j,1}$ satisfies FOC, so

$$x_{j,1} = \frac{u}{1 + N_1} + \frac{\bar{p}}{(1 + N_1)\gamma\sigma^2} \sum_{k \neq j} C_k - \frac{N_1 C_j \bar{p}}{(1 + N_1)\gamma\sigma^2},$$

where N_1 is the total number of active agents in Equilibrium 1.

Now, solve for the best response of player j in Equilibrium 2. As before, we will figure out whether its FOC has a positive solution. If it does, this solution must satisfy the following:

$$x_{j,2} = \frac{u}{2} - \frac{1}{2} \sum_{k \neq j} x_{k,2} - \frac{C_j \bar{p}}{2\gamma\sigma^2}.$$

We find $\sum_{k \neq j} x_{k,2}$ by summing up FOCs for $x_{k,2}$:

$$\sum_{k \neq j} x_{k,2} = \frac{N_1 - 1}{N_1} u - \frac{\bar{p}}{N_1 \gamma \sigma^2} \sum_{k \neq j} C_k,$$

where we used that the number of active agents in Equilibrium 2 is $N_2 = N_1 - 1$.

Next, substitute $\sum_{k \neq j} x_{k,2}$ into the equation for $x_{j,2}$:

$$x_{j,2} = \frac{u}{2N_1} + \frac{\bar{p}}{2N_1\gamma\sigma^2}\sum_{k\neq j} C_k - \frac{C_j\bar{p}}{2\gamma\sigma^2} = \frac{1+N_1}{2N_1}x_{j,1} > 0$$

as $x_{j,1} > 0$. So we found a positive FOC solution for agent j in Equilibrium 2, so $x_j = 0$ is not an equilibrium, by contradiction.

B.5 Step 5

So far we have proved that the pure strategy Nash equilibrium in model (7) is unique, if exists at all. Now we conclude the proof of part (a) of Proposition 1 by characterising the equilibrium for each set of parameters.

If costs are very high even for the agent with minimal costs, then nobody invests in equilibrium. The best response for agent 1 is:

$$x_1 = \frac{u}{2} - \frac{C_1\bar{p}}{2\gamma\sigma^2} > 0 \qquad iff \qquad C_1 < \frac{u\gamma\sigma^2}{\bar{p}}. \tag{18}$$

We can write a similar expression for agent $m > 1$ (recall that agents are ordered with respect to their costs, so m denotes both the index and the number of active agents):

$$x_m = \frac{u}{m+1} + \frac{1}{m+1}\frac{\bar{p}}{\gamma\sigma^2}\sum_{j\neq m} C_j - \frac{C_m\bar{p}}{\gamma\sigma^2}\frac{m}{m+1} > 0 \quad iff \quad C_m < \frac{u\gamma\sigma^2}{m\bar{p}} + \frac{m-1}{m}\overline{C_{act,m}}, \tag{19}$$

where $\overline{C_{act,m}}$ is the average costs for agents $i < m$.

The number N_{act} of active agents in equilibrium is thus determined by (18) and (19). If C_n is the largest cost for which (19) is satisfied, then in equilibrium agents 1, 2, ..., n take non-zero positions, and others are inactive. The equilibrium allocations are given by:

$$x_i = \frac{1}{1+n}u + \frac{1}{1+n}\frac{\bar{p}}{\gamma\sigma^2}\sum_{\substack{k\leq n\\ k\neq i}} C_k - \frac{n}{1+n}C_i\frac{\bar{p}}{\gamma\sigma^2}.$$

It is easy to see that $x_i > 0$ if (19) holds for all i from 1 to n and for all $i > n$ zero trading is the equilibrium best response.

B.6 Step 6

Finally, to find the expression for the equilibrium mispricing, recall from (6) that

$$p_B - p_A = 2u\gamma\sigma^2 - 2\gamma\sigma^2\sum_k x_k.$$

To obtain the expression for mispricing, substitute the sum of arbitrageur allocations from (16):

$$Misp_1 = \frac{2u\gamma\sigma^2}{1+N_{act}} + \frac{2\bar{p}}{1+N_{act}} \sum_{k\in act} C_k.$$

This constitutes part (b) of Proposition 1.

C Proof of Equation (11)

Use formula (8) to find the number of active arbitrageurs. In case of a uniform cost distribution, the inequality takes the following form:

$$\underline{C} + \frac{n(\overline{C}-\underline{C})}{N} < \frac{u\gamma\sigma^2}{n\bar{p}} + \frac{1}{n}\sum_{k=1}^{n-1}\left(\underline{C} + \frac{k(\overline{C}-\underline{C})}{N}\right).$$

Expand the sum:

$$\underline{C} + \frac{n(\overline{C}-\underline{C})}{N} < \frac{u\gamma\sigma^2}{n\bar{p}} + \frac{n-1}{n}\underline{C} + \frac{(n-1)(\overline{C}-\underline{C})}{2N},$$

$$n^2 + n - \frac{2N}{(\overline{C}-\underline{C})}\frac{u\gamma\sigma^2 - \underline{C}\bar{p}}{\bar{p}} < 0.$$

By assumption, $\underline{C} < \frac{u\gamma\sigma^2}{\bar{p}}$, hence, according to the Vieta's formula, the quadratic form on the left-hand side has two real solutions, one positive and one negative. To find the maximal integer n satisfying the inequality, we should solve for the positive root of the following equation and take the integer part of the solution:

$$x^2 + x - \frac{2N}{(\overline{C}-\underline{C})}\frac{u\gamma\sigma^2 - \underline{C}\bar{p}}{\bar{p}} = 0,$$

$$x_{1,2} = \frac{-1 \pm \sqrt{1 + \frac{8N(u\gamma\sigma^2 - \underline{C}\bar{p})}{(\overline{C}-\underline{C})\bar{p}}}}{2},$$

$$n_{max} = \left[\frac{1}{2}\left(\sqrt{1 + \frac{8N(u\gamma\sigma^2 - \underline{C}\bar{p})}{(\overline{C}-\underline{C})\bar{p}}} - 1\right)\right].$$

Substituting n_{max} and the costs into the mispricing formula (10), we obtain equation (11).