Mind Thy Neighbor's Portfolio: A Network Approach to Contagion in the ETF Market*

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Abstract

The exchange-traded fund (ETF) market has become the most important development of the financial markets over the last decade. I show that the network of the ETF market — the linkages between ETFs based on portfolio weights — catalyzes the propagation of price dislocations, the gaps between prices and their fundamental values. Arbitrage trading induces price dislocations in connected ETFs, followed by strong responses in returns and subsequent reversals with a sizable effect of 4–6% per year. This is robust to controlling for arbitrage trading on its own mispricing and common factors. I reconfirm the effects with the Fed announcement of the Bond ETF purchase in March 2020. The findings suggest that arbitragers create externalities from trading. Finally, the ETF market works as a stabilizer for price dislocations, but induced returns can incur unexpected fluctuations.

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1 Introduction

Exchange-traded funds (ETFs) were born in the aftermath of 1987's Black Monday and were introduced into the market in 1993. Today, there are around 2,000 ETFs valued at $4 trillions in asset under management (AUM). In the United States, the number of ETFs might surpass that of stocks. As the ETF market continues to grow and replaces mutual funds, the linkages between ETFs and underlying assets, as well as those among ETFs, continue to increase. One wonders how price discovery in individual assets is affected by trading flows into and out of ETFs, once these bundled flows outweigh those targeting the underlying assets individually. Given the range of and overlap between different ETFs, arbitrage activity targeting price dislocations[1] is bound to have spill-over effects across the ETF universe.

Throughout this paper, I study how price dislocation on one fund affects other funds. I answer questions such as (i) Does arbitrage activity targeting on price dislocations induce contagion across ETFs? In particular, how do mispricing and return respond? and (ii) What is the nature of shock propagation in the ETF market? In the ETF market, arbitragers help the market to adjust supply and demand of ETF shares. For instance, an arbitrager in the primary market will sell its shares and buy its underlying assets to capture arbitrage opportunity when an ETF exhibits premium (ETF price $>$ value). To sell its shares, the arbitrager receives new shares from the ETF issuer, which is called creation, in exchange for a basket of underlying securities. This increases supply of ETF shares in the market.[2] This series of actions affects underlying assets. What happens to the *other* ETFs that share common securities?

To fix ideas, let us consider a simple scenario. Suppose there are two ETFs, A and B. They share some common underlying assets. First, if a demand shock at the ETF level hits ETF B and generates a premium (ETF B price $>$ value), the arbitrager will sell ETF B and

[1]The difference between ETF price and NAV (net asset value, or the sum of underlying assets' values), alternatively known as mispricing, NAV deviation, or premium.

[2]Conversely, the arbitrager will buy ETF shares and deliver it to the issuer in order to sell its underlying assets when an ETF exhibits a discount (ETF price $<$ value). This decreases supply of its shares, which is called redemption. See Figure 1 and Appendix C for details.

buy the underlying assets. Then, its neighbor ETF A's value will increase due to buying pressures on common underlying assets, which leads to ETF A's discount (ETF A price $<$ value) or a decrease in its premium. Going forward, the price of ETF A will increase so that arbitrage opportunity in A dissipates (ETF A price=value), which generates a positive return in ETF A.[3] Given this mechanism and conjecture, I study mainly two effects: Firstly, an increase in arbitrage activity in the neighbor funds creates a discount in the main fund via the adjustment in its fundamental value. Secondly, an increase in arbitrage activity in the neighbor funds leads to positive return in the main fund following an induced discount.[4]

I provide the first evidence on these two contagion effects and show that arbitrage activity induces mispricings to propagate through the network of the ETF market. This arbitrage-induced returns are followed by strong reversals in one to three weeks, which suggests that it is driven by trading. The effects are strong especially at longer horizons. In the short term, the effect of arbitrage activity on its own mispricing is stronger than the contagion effects from the neighbor funds. My findings are economically meaningful and statistically large. In the Equity ETF market, a one standard deviation increase in the contagion measure induces unexpected returns of 4–6% annually. Even in terms of alphas controlling Fama-French five (FF5) factors, it induces unexpected returns of around 4% annually. These results are not driven by competing explanations and can be causal. With an instrumental variable exploiting the rebalancing days of underlying portfolios, an increase in creation activity after the rebalancing induces a discount in the main fund. I quantify these effects, finding a network multiplier of 0.821 for contagion in terms of price dislocations and a network multiplier of -1.829 for contagion in terms of returns. These indicate that the ETF market stabilizes shocks for mispricing, while it can exacerbate shocks for returns. It can generate unexpected short-term returns with oscillating signs across ETFs. The pass-through for mispricing is 1/10, while it is 1–1.8 for returns. Further, a diff-in-diff study in the Bond ETF

[3] One could argue that there will be another arbitrage activity that buys ETF A, which pushes up ETF A's price.

[4] These are also described by the diagram in Section 3.1

market reconfirms the contagion effect, finding the contagion effect of an order of 20–30 bps.

Methodologically, I directly construct a time-varying network across ETFs with more than 1 billion portfolio weights. Based on a dataset covering 37% of the U.S. ETF market, I compute a pairwise *commonality* between each pair of funds among top 100 equity ETFs to construct this network. I combine this pairwise commonalities with measures for arbitrage activities by the contracted arbitragers, APs (authorized participants) in the primary market, and other arbitragers in the secondary market. I apply this method to the Bond ETF market under the stress during the COVID-19 crisis in a subsequent empirical design.[5]

I further employ the following empirical strategies to test whether the contagion effects are driven by network interconnectedness. To differentiate the effects of arbitrage trading on mispricing of one fund from arbitrage trading on the neighbor fund, I first control arbitrage activities on the main funds' mispricing. Second, I run placebo tests to confirm that induced price dislocation and returns are in fact catalyzed by the network, not a random choice of funds and noise. Third, I support my findings with different identifications, standard instrumental variable, granular instrumental variable (GIV; Gabaix and Koijen, 2020a) and diff-in-diff. Using different outcome variables, such as NAV returns and abnormal returns controlling FF5, I test to see whether the contagion effect is in fact coming from common underlying assets and arbitrage activity. Finally, I estimate a spatial autoregressive model, taking account of special dependencies across funds to eliminate the possibility of results driven by correlated shocks.

The literature has actively studied transmission of shocks by ETFs. Ben-David et al. (2018) study how ETF ownership increases the volatility of underlying stocks. Their findings support that the demand shocks in the ETF market translate into non-fundamental price changes for the underlying securities. Baltussen et al. (2019) show that the nature of index returns has changed due to index-linked products such as ETFs. Shim (2019) documents that ETF arbitragers trade underlying assets based on weights rather than fundamentals.

[5] See Figure 2

Compared to other types of fund flows, passive ETFs' effects on underlying assets seem to have greater impact (Dannhauser and Pontiff, 2019). Given the evidences that support a greater role of ETFs on price discoveries of underlying assets, my paper further extends this chain of propagation *across* ETFs and provides evidence at the ETF level. I propose a method to systematically capture this contagion.

The other important branch of the literature is about the roles and mechanism of ETF arbitrage. It links them to limit to arbitrage (Shleifer and Vishny, 1997, Gromb and Vayanos, 2010). For example, Pan and Zeng (2019) study the authorized participants' dual role as bond dealer and ETF arbitrager, and its conflict. Evans et al. (2019) study the implications of operational shorting. In contrast, my paper sheds light on a different consequence of arbitrage activity in the ETF market, that is, how arbitrage activity on one fund generates externalities and affects other funds' prices and fundamental values.

From more general and broader viewpoints, my paper offers a network perspective on the intertwined ETF market. Lettau and Madhavan (2018) lay out basics of ETFs and Madhavan (2014) reviews the literature and develops a canonical model of price dynamics in ETFs. Theoretically, Bhattacharya and O'Hara (2018) study how ETFs affect the informational efficiency of their underlying assets and how they induce herding behaviors. Malamud (2015) develops the general equilibrium model of the ETF market. Chinco and Fos (2019) analyse the complexity of ETFs. Anadu et al. (2018) suggest evidence of indexing on comovements and price distortions is mixed. For liquidity, Rappoport W. and Tuzun (2020) study the joint dynamics of ETF mispricing and liquidity with panel vector autoregressions. Converse et al. (2020) suggest that greater ETF ownership has amplified the global financial cycle in the emerging markets. For price deviations, Petajisto (2017) documents mispricing across different classes of ETFs; my paper partially explains how price dislocations could change.

In relation to the recent stress in the Bond ETF market due to the COVID-19 crisis, Falato et al. (2020) examine outflows of both mutual funds and ETFs and O'Hara and Zhou (2020) study the microstructure of liquidity provision in the corporate bond market.

Boyarchenko et al. (2020) evaluate the corporate credit facilities and multiple dimensions of primary and secondary market functioning in a granular manner. Haddad et al. (2020) argue that it is the result of extreme selling pressure by investors in safe and liquid debt ETFs. In contrast, this paper exploits the Fed announcements of the Bond ETF purchase to reconfirm the channel I establish with the Equity ETFs.

Furthermore, I contribute to the literature in the networks and finance. Theoretical works study financial contagion extensively (e.g., Elliott et al., 2014; Acemoglu et al., 2015). The network structure of firms and industries on the stock market has been analyzed by many papers (e.g., Gofman et al., 2018; Gofman, 2013; Herskovic, 2018). Another growing strand of papers tries to link international trade networks to asset prices (e.g., Du et al., 2018; Richmond, 2019; di Giovanni and Hale, 2020; Auer et al., 2020). In contrast, this paper is the first to study the network structure of the ETF market. On the econometric side, I estimate a spatial autoregressive model, similar to those used in other papers (Herskovic et al., 2013; Denbee et al., 2018; di Giovanni and Hale, 2020).

The literature on the linkages of institutional investors' stock holdings has not considered ETFs. Anton and Polk (2014) show the degree of shared ownership forecasts cross-sectional variation in return correlation. Greenwood and Thesmar (2011) propose fragility and applies it to mutual fund ownership to study price volatility and comovements. As opposed to these papers and the studies on flow-induced contagion (e.g., Coval and Stafford, 2007; Lou, 2012), I propose *arbitrage trading–induced* contagion, which is testable only in the ETF market.[6]

In terms of financial stability, the implication of this paper is threefold: Firstly, the network structure of the ETF market is shock-absorbing for price dislocations, while induced returns can fluctuate. Central banks need to be aware of this contagion effect. USD 289 billions of Equity ETFs are sitting on the balance sheet of the Bank of Japan, as of March 31st, 2020. An eventual tapering and unwinding of their positions must consider the inter-

[6]The closest form of mutual fund to a ETF is closed-end fund (CEF), which trades on the exchange. However, there is no explicit arbitrage mechanism, that is, creation/redemption by authorized participants in the primary market of ETFs. Further, sizes of those AUMs are small compared to ETFs and it is hard to claim a plausible mechanism for such contagion.

connectedness of ETFs. Secondly, my findings highlight a role of ETF trading in contributing to the market fluctuations in a higher frequency, while Gabaix and Koijen (2020b) study the origin of the stock market fluctuation, based on quarterly data. Thirdly, Stambaugh (2014) points out that individual ownership in the equity market declined, as well as noise trading, which left less room for active management to correct prices. However, given a drastic shift from active to passive investment with ETFs, noises could arise differently in a world over which passive investment dominates. My findings indeed suggest that price discovery in the growing ETF market is distorted by contagion effects.

The paper proceeds as follows. In Section 2, I elaborate on methodologies and data employed to test questions. Section 3 describes the main channel that I exploit for analysis and presents the main results in the Equity ETF market, followed by their application to recent events in the Bond ETF market. In Section 4, I provide robustness and extension from different perspectives: Section 4.1 to examine if the network weights really matter, Section 4.2 to see if it is not driven by other underlying factors or a different channel, Section 4.3 to support causal arguments, Section 4.4 to apply spatial estimation, and Section 4.5 to examine subsamples. Limitation of this version of the study are discussed in Section 5. Finally, Section 6 concludes.

2 Methodology and Data

Data

The data are constructed from several sources. ETF-level variables such as price and trading volume are from Bloomberg, while underlying asset-level variables are from CRSP. Additional data on transaction costs for underlying assets such as Daily Cost to Borrow Score are obtained from Markit. Daily portfolio weights to construct the network are from ETF Global, from 2012 to 2017.

To construct the dataset, I employ the following steps. First, I constrain the ETF sample by geography, asset class, and type. I limit it to funds in North America, equity funds, and non-synthetic vanilla funds. Therefore, some peculiar types of ETFs, such as leveraged and inverse products, are excluded from the sample for the sake of comparison and external validity. Second, I rank those equity ETFs from those that existed in 2012, based on a dollar trading volume and select the top 100 of them (therefore, there are no funds that appears or dies in the middle of the sample). This results in a coverage of 37% of the entire U.S. ETF market in terms of AUM, valued at $1.2 trillion and consisting of 99 U.S.-listed equity funds and 1 U.S.-listed Canadian equity market fund. The issuers of ETFs and the leading market makers are shown in Figure 4.

For the Bond ETF sample, I use data from 2019 to July 31st, 2020. Starting with 419 U.S.-listed Fixed Income ETFs, excluding sovereign-themed funds and leveraged products leaves 292 ETFs among those that exist at the beginning of 2020 after merging with portfolio constituents data. Further, I use TRACE data to compute liquidity levels of underliers. Table 1 presents summary statistics for both Equity and Bond ETF samples.

Extracting Networks

First, I describe the methodology for the construction of the ETF network. Using portfolio weights of the top 100 Equity ETFs, I compute the time-varying network. Every t, I look at all the pairs of ETFs, roughly 5,000. Each ETF has approximately 300 stocks on average in its holdings, which accrues to more than 1 million weights every day and more than 1 billion weights for the entire period. For a given pair of ETFs, I construct the following commonality between fund i and fund ℓ, where $i, \ell \in \{1, 2, ..., M\}$:

$$\mathbf{d}_t(i,\ell) = \sum_{j=1}^{N} w_{j,t}^{(i)} \log(w_{j,t}^{(\ell)})$$

$$w_{j,t}^{(i)}\text{: holding weight of stock } j \text{ in ETF } i\text{, in period } t$$

This quantity, $\sum_{j=1}^{N} w_{j,t}^{(i)} \log(w_{j,t}^{(\ell)})$, is the link between ETF A and ETF B that determines the lower bound of log deviation of net asset value in ETF A due to contagion from ETF B (see Appendix

D). At the same time, this is tightly linked to cross-entropy.[7] Typically, we negate this quantity to get cross-entropy, $H(p,q) = -\sum_i p_i \log q_i$, and often use it as a loss function to minimize. High commonality corresponds to low entropy and low commonality to high entropy. This measure gives high value to skewed funds and penalizes dispersed funds in the neighborhood of fund i. Based on this measure, I construct the following spatial matrices for every t.

$$\boldsymbol{D}_t = \begin{pmatrix} \mathbf{d}_t(1,1) & \dots & \mathbf{d}_t(1,M) \\ \vdots & \ddots & \vdots \\ \mathbf{d}_t(M,1) & \dots & \mathbf{d}_t(M,M) \end{pmatrix}$$

Further, after normalizing, I convert the matrices to row stochastic and later combine them with either primary or secondary market arbitrage measures. This yields Figures 4-a and 4-b, which show the topology of this ETF network and price dislocations in each ETF. Figure 4-a shows the price dislocations one week before the flash crash on August 24, 2015.

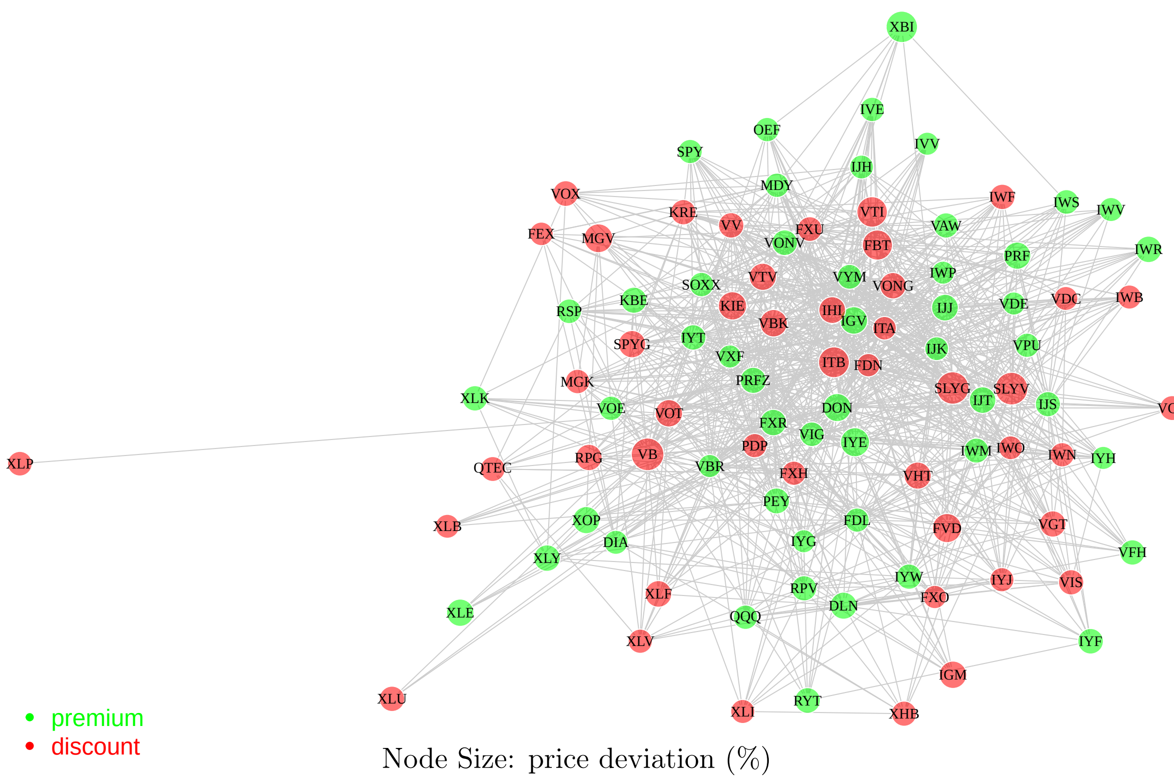
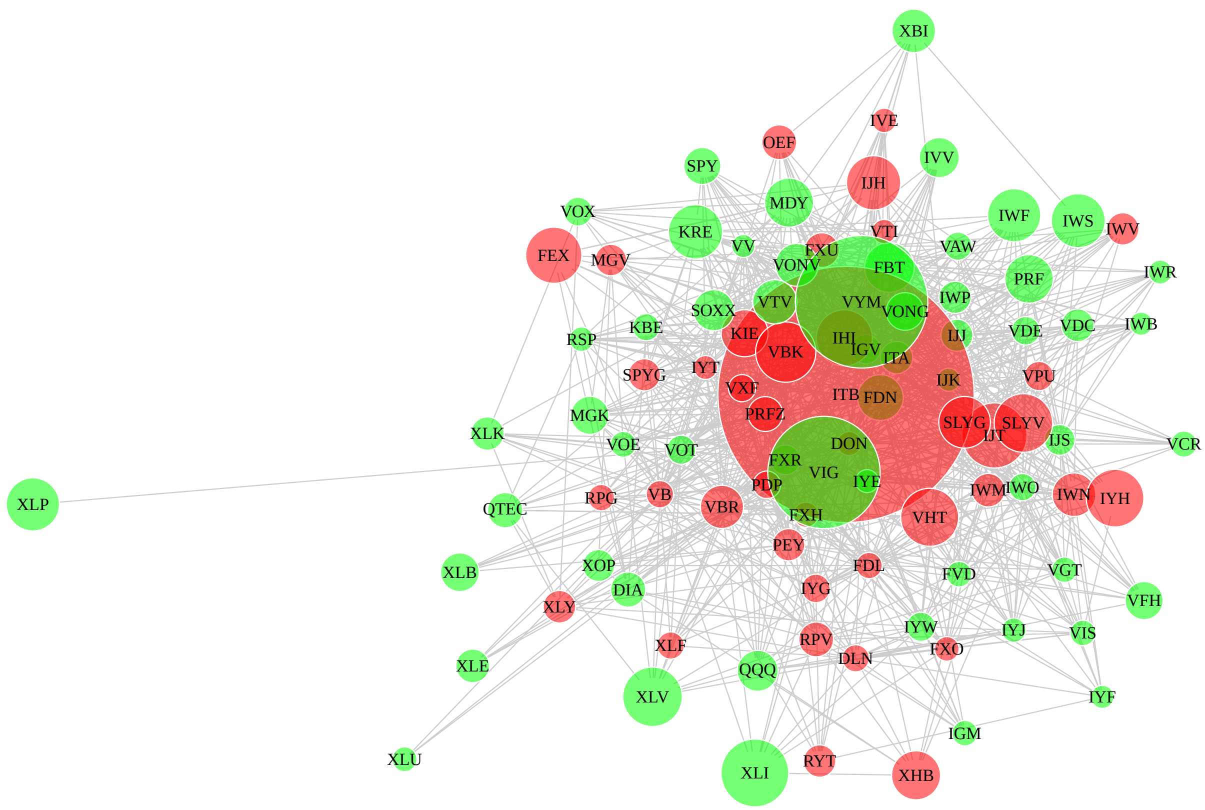


Figure 4-a: **Small Price Dislocation before the Crash**

[7] A symmetry of measure is not required as the purpose of this measure is to see how trading on neighbor funds as a whole matters to fund i.

Figure 4-b, below, shows the price dislocation after the crash; large price dislocations are in the center. Interestingly, the crash affected SPY a lot immediately after the market opened and yet the mispricing for SPY is negligible at the end of the day. In contrast, the funds in the center, which have high commonality with the other funds, exhibit large price dislocations.[8]



Node Size: price deviation (%)

Figure 4-b: **Large Oscillating Price Dislocation after the Crash**

The size of a node (circle) indicates the mispricing of each fund at the end of the day in percentage points; those funds, which track a large set of underlying stocks, tend to locate themselves at the periphery, e.g. SPY, IVV, and IWV, as they are balanced with large N and far away from many other funds. Another observation is about the *signs* of price dislocations; the direction of numerous price dislocations flips in many funds while large price

[8]For instance, ITB is a home construction sector fund and VYM is a high–dividend yield fund.

dislocations occur. This will be explained by the empirical analysis and the estimations of network parameters that follow.

3 Empirical Analysis

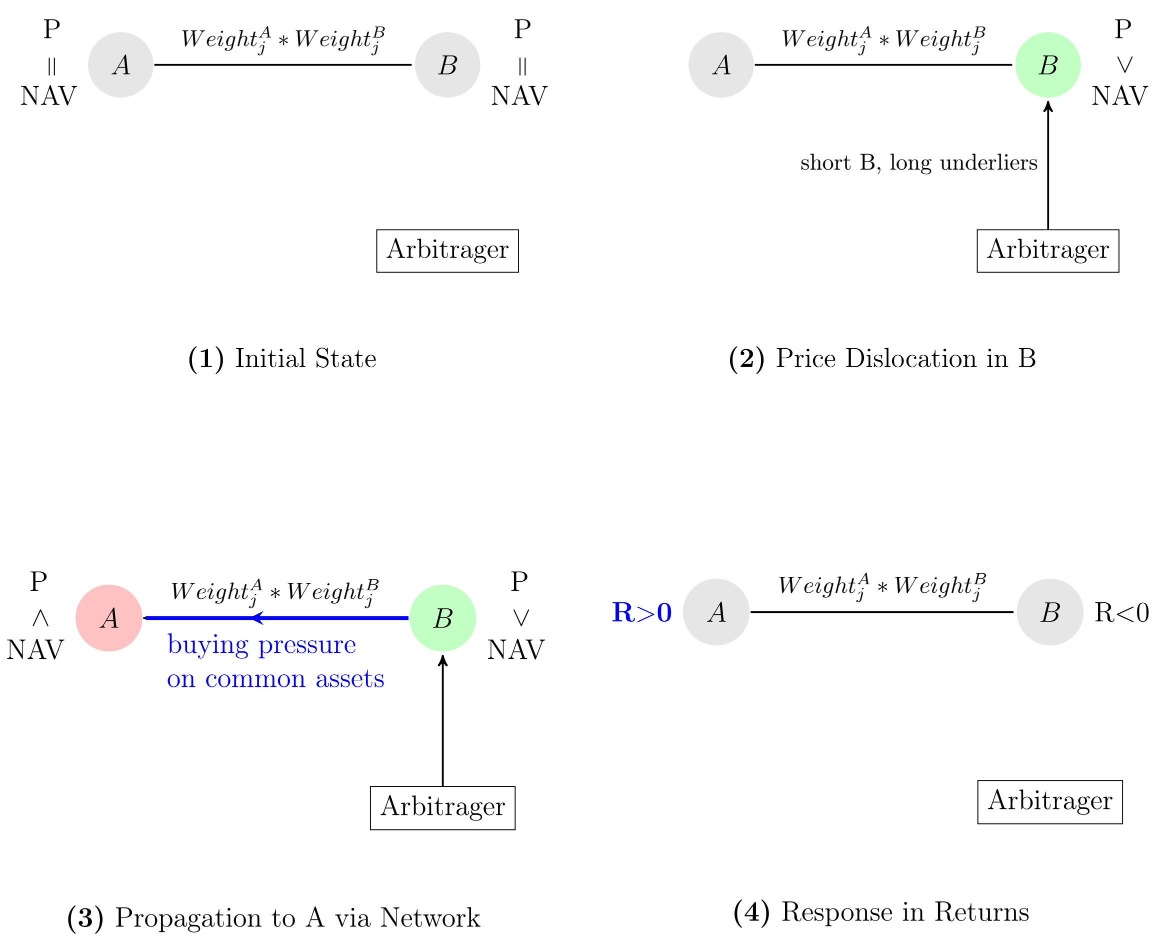
In this section, I examine how arbitrage activity on the neighbor funds that are linked through the network affects the main fund's mispricing and its returns. To make the hypotheses explicit, I first describe the channel that I exploit to capture this contagion. Then, I present the main findings on mispricing and returns. Further, I reconfirm the contagion effects I find in the Equity ETF market using the supplementary Bond ETF sample. In the following Section 4, I demonstrate robustness with a placebo test and specifications using alternative returns. I present extensions, including causal identifications; estimation of spatial models to discriminate from alternative explanations; and subsample results.

3.1 Channel of Arbitrage-Induced Contagion

The hypotheses I test are the subsequent action of an ETF arbitrager, its effect on price dislocations in ETFs, and a conjecture on responses in returns. Suppose there are two ETFs, A and B. First, if a demand shock at the ETF level hits ETF B and generates a premium (ETF B price $>$ value), the arbitrager will sell the ETF and buy the underlying assets to capture arbitrage. Then, its neighbor ETF A's value will increase due to buying pressures on common underlying assets, which leads to ETF A's discount (ETF A price $<$ value) or a decrease in its premium. Going forward, the price of ETF A will increase so that arbitrage opportunity in A dissipates (ETF A price=value), which generates a positive return in ETF A. This is visually captured by Figure 5, below. The way the arbitrager takes on arbitrage activity has been discussed in the literature (see Appendix C for details). The focus of my examination is summarized in states (3) and (4) in the figure, that is, propagation to the neighbor fund A and its induced return as a response.

Figure 5: **Arbitrage Creates Propagation of Price Dislocations and Unexpected Returns**

P stands for the price of the ETF; NAV for its net asset value; and $NAV^B \equiv \sum^N Weight_j^B * Price_j$, where $Weight_j^A$ is a portfolio weight of ETF A on underlying stock j. Initially, a shock hits ETF B at the ETF level and creates the premium. The initial assumption of no price deviations in both ETFs is not big; deviations and changes after state (2) can be regarded as relative changes compared to the initial deviations in state (1).



There are other possible scenarios and those are checked in the robustness excercises and with controls in the empirical analysis. For instance, an arbitrager might sell B and buy A without creating price pressures on the underlying assets if she finds a pair of very similar ETFs. In the robustness exercise, I show the main results hold even if I exclude a set of very similar funds, which track the same underlying indices and I also document that this arbitrage-induced returns take place at the NAV level, not just at the ETF price level. Another possible scenario is that the common shock hits both ETF A and B - such concerns are considered with several specifications and econometric methods in Section 4.

3.2 Main Results

To test the aforementioned channel, I construct two key variables using an extracted network, one for arbitrage activities in the primary market, the other for overall arbitrage activities in both the primary and secondary market (see Figure 1). First, I aggregate creation-redemption activities of ETF ℓs that are linked to fund i through the network, $\mathbf{D}_t$, by pairwise commonality measure, $\mathbf{d}_t(i, \ell)$. $Creation/Redemption_{t,\ell}$ is positive when an authorized participant creates shares and negative when he redeems shares.

$$Neighbor\ AP\ Activity_{t,i} = \sum_{\ell \neq i} \mathbf{d}_t(i, \ell) * \underbrace{(Creation/Redemption_{t,\ell}) * NAV_{t,\ell}}_{\$ \text{ Primary Market Activity}}$$

This variable corresponds to the primary market arbitrage. It is stated in dollars, as it is the dollar volume that creates price impact on the underlying stocks regardless of various ETFs with different numbers of outstanding shares. Throughout my exercises, I first smooth daily arbitrage activities on each fund ℓ over a week up to each period t and further aggregate across M-1 funds using the network weights, as arbitrage activity at a daily level can be sparse or noisy.[9] Second, in a similar fashion, I aggregate mispricing in fund ℓ that is linked to fund i through the network by pairwise measure, $\mathbf{d}_t(i, \ell)$.

[9] Authorized participants in the primary market tend to take arbitrage when mispricing becomes large enough, in comparison to arbitragers in the secondary market. This is probably because one faces a creation unit, i.e. minimum units of shares needed to run a transaction with ETF sponsor to profit from price dislocations (see Appendix C for details).

$$Neighbor\,Mispricing_{t,i} = \sum_{\ell \neq i} \mathbf{d}_t(i,\ell) * \underbrace{(p^{etf}_{t,\ell} - NAV_{t,\ell}) * SharesOutstanding_{t,\ell}}_{\text{\$ Proxy for Overall Arbitrage Opportunities}}$$

Among the other covariates, $Net\,Fund\,Flow_{i,t}$ is creation/redemption shares of fund i, scaled by NAVs. This takes account of the ETF arbitrager's activity on the mispricing of fund i, not that of neighbor funds. I control the time variation and the fund heterogeneity by time fixed effect (day t) and ETF fixed effect (fund i). With this construction, the variables capture how prone each fund is to contagion (for characteristics of this contagion measure, see Figure 5). Using these variables, I test the following regression:

$$\begin{aligned} Mispricing_{i,t+1} = \alpha_i + \alpha_t + \theta^{NAPA} \cdot Neighbor\,AP\,Activity_{i,t} + \theta^{NMisp} \cdot Neighbor\,Mispricing_{i,t} \\ + \beta^{NFF} \cdot Net\,Fund\,Flow_{i,t} + \sum^{K} \xi^k \cdot CONTROL^k_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Table 2 first documents the induced discount in a main fund, affected by the network. Arbitrage activities in *neighbor* funds ℓ create a discount in a main fund i. Comparing the proxy for the primary market activity, $Neighbor\,AP\,Activity_t$, and the proxy for overall arbitrage opportunities, $Neighbor\,Mispricing_t$, only the latter shows significance. This is probably because taking arbitrage in the secondary market is more frequent, while the primary market is exclusive to APs; thus, the latter probably captures overall buying pressure better than the former.

Table 2: **Mispricing and Arbitrage-Induced Contagion**

The table presents regressions of a period ahead mispricing of ETFs on the contagion measures for arbitrage trading on neighbor funds (the first two rows) and on the proxies for arbitrage trading on its own mispricing (the second two rows). For liquidity, $Bid\text{-}Ask\,Spread_t$ controls for ETF-level liquidity and $Composite\,BAS_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds respectively without using commonality $d_{i,j}$. Variables are standardized. Standard errors are clustered and reported in parentheses. All specifications include day and fund fixed effects. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

	$Mispricing_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Neighbor AP Activity$_t$	0.090	0.101	0.101	0.104	0.114	0.116
	(0.068)	(0.068)	(0.068)	(0.068)	(0.070)	(0.071)
Neighbor Mispricing$_t$	−0.306***	−0.312***	−0.320***	−0.312***	−0.315***	−0.323***
	(0.091)	(0.090)	(0.091)	(0.090)	(0.092)	(0.093)
Net Fund Flow$_t$		0.198***	0.195***	0.198***	0.198***	0.195***
		(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Trading Volume$_{t-1}$			0.485***			0.493***
			(0.123)			(0.123)
AUM$_{t-1}$			−0.344			−0.283
			(0.294)			(0.298)
Bid-Ask Spread$_t$				0.129**		0.134**
				(0.054)		(0.054)
Composite BAS$_t$					−0.067**	−0.067*
					(0.034)	(0.034)
Mispricing$_t$	0.614***	0.599***	0.596***	0.596***	0.598***	0.592***
	(0.119)	(0.119)	(0.118)	(0.118)	(0.119)	(0.118)
Mispricing$_{t-1}$	0.579***	0.578***	0.575***	0.576***	0.578***	0.572***
	(0.075)	(0.073)	(0.073)	(0.073)	(0.073)	(0.072)
Average AP Activity$_t$	−0.265	−0.037	−0.050	−0.036	−0.060	−0.071
	(0.384)	(0.284)	(0.287)	(0.283)	(0.283)	(0.285)
Average Mispricing$_t$	0.548	0.528	0.534	0.518	0.528	0.525
	(0.422)	(0.423)	(0.420)	(0.422)	(0.420)	(0.416)
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Observations	137,962	137,780	137,780	137,780	137,523	137,523
Adjusted R^2	0.095	0.096	0.096	0.096	0.096	0.097

$Neighbor\,Mispricing_t$ consistently finds negative coefficients throughout all the specifications, predicting a discount in a next period. I find the same when I perform the exercise with a contemporaneous dependent variable. In terms of economic magnitude, this contagion effect has larger magnitude, daily 0.323 bps per a one standard deviation increase in the contagion measure, than the effect from net fund flow into its own fund, daily 0.195 bps. On the other covariates, first, the coefficient on $Net\,Fund\,Flow_t$ and coefficients on lagged mispricings are all positive, which suggests that mispricing persists for a while and therefore the creation of ETF shares still forecasts positive mispricing in the next period.[10] ETF-level bid-ask spread positively predicts mispricing in the next period, which suggests that lower liquidity coincides with higher mispricing, which is natural given that a higher spread will impede the profitability of ETF arbitrage. On the other hand, lower liquidity at an underlying security level negatively predicts mispricing, suggesting that the liquidity premium pushes up the NAV value, creating thinner price dislocation between the ETF price and NAV. Next, I examine response of returns after arbitrage trading on neighbor funds changes mispricing in fund i.

$$\begin{aligned} Return_{i,t+k} = \alpha_i + \alpha_t + \theta^{NAPA} \cdot Neighbor\,AP\,Activity_{i,t} + \theta^{NMisp} \cdot Neighbor\,Mispricing_{i,t} \\ + \beta^{NFF} \cdot Net\,Fund\,Flow_{i,t} + \beta^{Misp} \cdot Mispricing_{i,t} + \sum^{K} \xi^k \cdot CONTROL^k_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

I specify the regression as above. *Return* is a period return from $t+k-1$ to $t+k$, where $k \in \{1, 2, 3, 5, 7, 14, 21\}$. In addition to including fund and date fixed effects, covariates, and controls, I add $Mispricing_{i,t}$, fund i's price dislocation in bps, to control responses of returns to arbitrage activities on fund i as well as the net fund flow of fund i.

[10]This is in line with the point Madhavan (2014) makes, that is, the premium still exhibits positive autocorrelation that increases with staleness and the slowness with which arbitrageurs correct pricing errors.

Table 3: **Returns and Arbitrage-Induced Contagion**

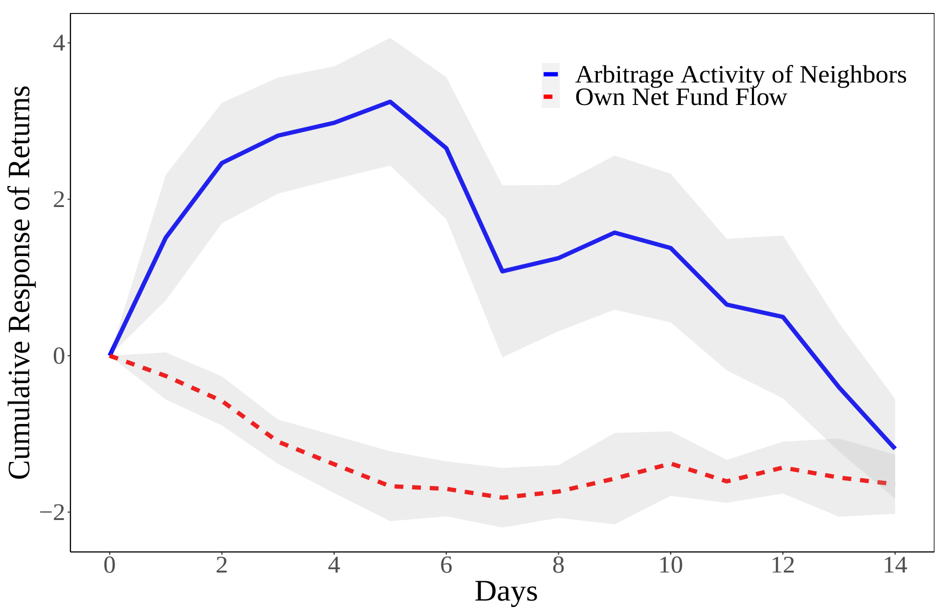
The table presents regressions of ETF returns, R_{t+k}, on the contagion measures for arbitrage trading on neighbor funds (the first two rows) and on the proxies for arbitrage trading on its own mispricing (the second two rows). For liquidity, $\textit{Bid-Ask Spread}_t$ controls for ETF-level liquidity and $\textit{Composite BAS}_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $\textit{Average Mispricing}_t$ and $\textit{Average AP Activity}_t$ simply take averages over all mispricing and net fund flow of the other funds respectively without using commonality $d_{i,j}$. Controls other than shown includes lagged return and lagged mispricing. Columns (1)–(7) vary by the number of periods ahead, k. Variables are standardized. Standard errors are clustered and reported in parentheses. All specifications include day fixed effects. The results are robust to adding fund fixed effects, to Fama-MacBeth specification, and to Bootstrapped standard errors. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

	Return						
	$t+1$	$t+2$	$t+3$	$t+5$	$t+7$	$t+14$	$t+21$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\textit{Neighbor AP Activity}_t$	1.509***	0.954**	0.350	0.270	−1.575***	−0.786**	−1.288***
	(0.410)	(0.394)	(0.379)	(0.416)	(0.561)	(0.326)	(0.487)
$\textit{Neighbor Mispricing}_t$	0.962	1.420**	0.824	1.384**	2.468***	1.803**	−2.217**
	(0.603)	(0.685)	(0.713)	(0.603)	(0.654)	(0.847)	(0.886)
$\textit{Net Fund Flow}_t$	−0.259*	−0.319**	−0.521***	−0.281	−0.113	−0.085	−0.323**
	(0.154)	(0.160)	(0.145)	(0.228)	(0.194)	(0.193)	(0.152)
$\textit{Mispricing}_t$	−4.270***	−0.026	−0.003	−0.344	−0.325	−0.215	0.261
	(0.836)	(0.176)	(0.226)	(0.322)	(0.201)	(0.218)	(0.222)
$\textit{Bid-Ask Spread}_t$	0.248*	−0.068	0.080	−0.086	−0.137	−0.273	0.126
	(0.148)	(0.123)	(0.155)	(0.182)	(0.114)	(0.196)	(0.120)
$\textit{Composite BAS}_t$	0.404**	0.252*	0.144	0.215	0.252	0.139	0.215
	(0.202)	(0.133)	(0.139)	(0.174)	(0.183)	(0.165)	(0.208)
$\textit{Trading Volume}_{t-1}$	−0.356	−0.268	−0.068	−0.581	−0.557	−0.414	−0.126
	(0.481)	(0.444)	(0.486)	(0.529)	(0.490)	(0.459)	(0.580)
$\textit{AUM}_{t-1}$	−0.248	−0.250	−0.466	−0.073	−0.124	−0.179	−0.387
	(0.454)	(0.437)	(0.479)	(0.486)	(0.497)	(0.457)	(0.533)
$\textit{Average AP Activity}_t$	−0.019	0.404	−0.388	−0.366	0.277	0.799	0.311
	(1.174)	(1.201)	(1.022)	(0.848)	(1.301)	(0.863)	(0.902)
$\textit{Average Mispricing}_t$	−1.261	−0.353	0.559	−0.141	−2.448	−4.894*	−0.673
	(1.943)	(1.901)	(2.382)	(1.716)	(1.860)	(2.654)	(1.849)
Time FE	✓	✓	✓	✓	✓	✓	✓
Control	✓	✓	✓	✓	✓	✓	✓
Observations	137,597	137,597	137,597	137,597	137,597	137,597	137,597
Adjusted R^2	0.695	0.690	0.681	0.675	0.668	0.641	0.620

Table 3 confirms (i) the induced discount in fund i further leads to a positive response in returns, as conjectured in Figure 5, panel (4), and (ii) their reversals. Taking (i) and (ii) together, it suggests that this response in return is driven by trading. In detail, $Neighbor\ AP\ Activity_{i,t}$ positively predicts returns for $t+1$ and $t+2$.[11] From $t+7$, it predicts return negatively, up to $t+21$, showing reversals.[12] Similarly, $Neighbor\ Mispricing_{i,t}$ positively predicts returns in $t+2$ and up to $t+14$. In $t+21$, it predicts return negatively as a reversal. This strong reversal in return response to the arbitrage activity of the neighbor, in contrast with return response to own net fund flow, is captured in the following Figure 8, below.

Figure 8: **Response of Returns**

The figure shows cumulative response of returns to two independent variables, $Neighbor\ AP\ Activity_t$ and $Net\ Fund\ Flow_t$. Coefficients are estimated up to $t+21$ in a model with the same specification as equation 2, except that I include only the primary market arbitrage measures and exclude the general arbitrage opportunity measure.



[11]One of the reasons why effects last for a while is related to the settlement operations, which can take up to 3 days in general (see Appendix C for details). Also, it is related to operational shorting. That is, APs can sell new ETF shares, while opting delay the physical share creation. Some APs create shares immediately, but some can wait to reassess the trade imbalances in the following days. They can delay even up to T+6 in some cases (see Evans et al. (2019) for details).

[12]This is consistent with the findings in Ben-David et al. (2018) that demand shocks in the ETF market generates a mean-reverting component to stock prices and the half-life of convergence of prices to the initial level is about 10 days

The finding that the neighbor mispricing variable predicts an initial positive response in returns slightly later than the neighbor AP arbitrage variable suggests that the secondary market arbitrage on a linked fund ℓ persists for a longer period. This is in line with the fact that taking an arbitrage position in the secondary market requires the arbitrager to hold positions for a longer period than APs in the primary market, who can close NAV deviations quickly.

On the other covariates, coefficients on $Net\,Fund\,Flow_t$ are negative, which confirms the effects documented in the literature, i.e., the extra supply of ETFs adjusted by APs in the primary market dampens ETF price. The sign on $Mispricing_t$, being negative, suggests that positive arbitrage opportunities, represented by mispricing, are followed by shorting of ETFs; therefore, it predicts negative returns going forward.

On economic magnitudes and time persistence of contagion effects, first, I compare the first two rows, the contagion effects from trading on neighbor fund j, and the third and forth rows, the effect of arbitrage activity on its own fund i. At $t+1$, the largest economic magnitudes shown are the result of trading on its own mispricing, daily 4.270 bps. The second is $Neighbor\,AP\,Activity_t$, arbitrage on the linked funds ℓ, daily 1.509 bps per a one standard deviation increase in the contagion measure. This reflects a standard network propagation, that effects from neighbors are weaker than its own. In contrast, after $t+2$ and up to $t+21$, the contagion measures show consistently larger economic magnitude, 0.954 bps per a one standard deviation increase in the contagion measure, with statistical significance, whereas the effects from arbitrage activities on its own fund i are weaker, 0.319 bps, with statistical significance. This contrast is even more clear if I compare $Neighbor\,Mispricing_t$ and $Mispricing_t$. The coefficients for $Mispricing_t$ have no economic significance after $t+1$, while coefficients for $Neighbor\,Mispricing_t$ have large economic significance of 1.384–2.468 bps. Importantly, those magnitudes are larger than coefficients on the contagion measure with the previous specification of mispricing as the dependent variable.

Alternative Hypotheses

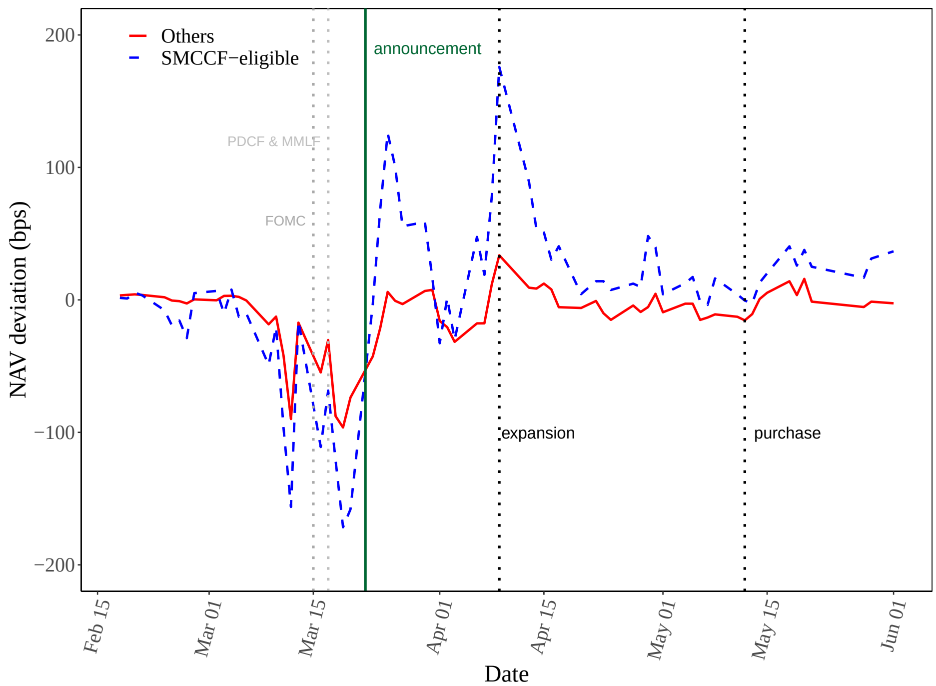
This arbitrage-induced return could be driven by other possibilities. For instance, common ETF market-level shocks might trigger changes in price dislocations and returns across ETFs. Factor structures in underlying assets may drive those results. Arbitrage opportunities might trigger trading involving only ETFs. To distinguish my findings from alternative hypotheses and explanations, I run various robustness and identifications, concluding that my findings are robust and not driven by other possibilities. See Section 4.1 for placebo tests to see if network weights indeed matter and are not driven by random or common shocks, Section 4.2 for regressions with returns replaced by different definitions (NAV Return and Alpha), Section 4.3 for a series of causal tests, and Section 4.4 for an estimation of a model considering spatial dependencies across entities.

Application: Network Effects in the Bond ETF market

In this subsection, I exploit a recent policy intervention to measures the contagion effects in the Bond ETF market. My purpose is to re-confirm the contagion effect and channel I find with the Equity ETF setting by applying the same method to the Bond ETF market, which extends the validity of the previous findings in the Equity ETF market. What I use is the differences in commonalities with the eligible ETFs among the non-eligible ETFs that were not targeted by the Fed purchase directly. Figure 9, below, shows the recent market reactions in the Bond ETF market in 2020.

Figure 9: **Surge in Premium after the Fed's SMCCF Announcement**

The figure shows the market reaction of price dislocations in the Bond ETF market in 2020. The first gray dotted line shows the actions by the Fed, which consist of interest rate cuts, Treasury and MBS purchases. A second gray line shows the launch of the Primary Dealer Credit Facility (PDCF) and Money Market Mutual Fund Liquidity Facility (MMLF). A green line shows the timing of an announcement on the Secondary Market Corporate Credit Facility (SMCCF). The following two black dotted line shows the timing of the announcement on the expansion of SMCCF to high yield on April 9th and the actual purchase on May 12nd. SMCFF-eligible (blue dotted line) includes 16 eligible Bond ETFs that exist in the sample. Others (red line) include 276 non-targeted Bond ETFs.



A series of actions by the Federal Reserve is as follows: On March 15th, the Fed announced an interest rate cut, treasury bill purchase, and MBS purchase at a meeting of the Federal Open Market Committee (FOMC), on March 15th. It purchased $40 billion in Treasury inflation-protected securities (TIPS) on March 16th. In the following week, on March 23rd, it announced two additional interventions, the Primary Market Corporate Credit Facility (PMCCF) and Secondary Market Corporate Credit Facility (SMCCF).[13] The purpose of PMCCF was to purchase bonds or portions of syndicated loans of investment grade firms. The SMCFF was to target ETFs with broad exposure to the U.S. investment grade corporate bond market and investment grade corporate bonds. On April 9th, it was expanded to in-

[13]see `https://www.newyorkfed.org/newsevents/news/markets/2020/20200417` for details.

clude ETFs with broad exposure to the U.S. high-yield corporate bond market and corporate bonds that were rated at least BBB-/Baa3 as of March 22nd but downgraded subsequently. The initial allocation of the equity will be $50 billion toward the PMCCF and $25 billion toward SMCCF. At the announcement, actual purchases were scheduled to begin in May, but it in fact started on May 12th. The actual ETFs that the Fed purchased so far are 16 ETFs[14] and they mostly match with those eligible ETFs that were expected as below.

	Eligible ETFs
Investment Grade	LQD, VCIT, VCSH, IGSB, IGIB, SPSB, SPIB, USIG, VCLT, BSCL
High Yield	HYG, JNK, HYLB, USHY, SHYG, BKLN, SJNK, ANGL, HYS, BSJL
	ETFs purchased by the Fed (as of Aug 31st, 2020)
Investment Grade	LQD, IGIB, IGSB, SPSB, SPIB, VCIT, VCSH, USIG
High Yield	ANGL, HYG, HYLB, JNK, USHY, SHYG, SLQD, USHY

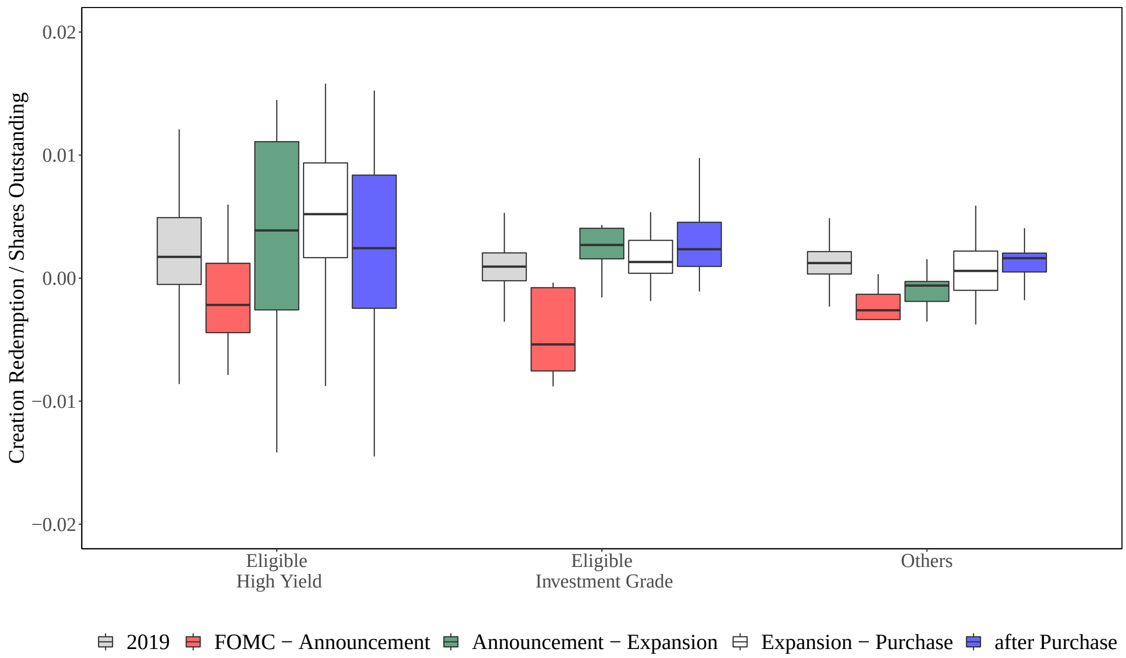
Many investors seemed to have front-run. What is notable is that the surge in premium is primarily around the SMCCF announcement, not the actual purchase, which occurred later. Further, arbitrage activity has increased or at least redemption has stopped after the SMCCF announcement while premium surges[15] (see Figure 10, below).

[14] see `https://www.federalreserve.gov/publications/reports-to-congress-in-response-to-covid-19.htm` for details.

[15] Regarding arbitrage activities during these months, Laipply and Madhavan (2020) find no evidence of destabilizing arbitrage activities, that is, the AP sells ETFs *below* NAV while she delivers bonds at NAV, resulting a loss. Their findings suggest that ETFs were functioning effectively during this stress, providing price discovery. Also, they estimate intrinsic value of NAVs, instead of the official closing NAVs, and find that the absolute size of premium/discounts do not significantly differ as compared to one using the official closing NAVs.

Figure 10: **Increase in the Creation of ETFs after the Fed's SMCCF Announcement**

The figure shows creation and redemption activities, representing primary arbitrage activities in the Bond ETF market during 2020, benchmarked to arbitrage activity throughout 2019. Eligible High Yield and Investment Grade include the eight high-yield ETFs and the eight investment grade bond ETFs that were expected to be purchased by the Fed, respectively; Others include 276 Bond ETFs in the data. FOMC–Announcement: 03/15/2020–03/22/2020; Announcement–Expansion: 03/23/2020–04/08/2020; Expansion–Purchase: 04/09/2020–05/11/2020; after Purchase: 05/12/2020 and afterwards.



As my main interest is in re-confirming the contagion effects rather than assessing the direct impact of the Fed purchase, I exploit this event to see how prone those non-eligible ETFs ("Others" category in Figure 10) that were *not* targeted but connected to the eligible ETFs ("High Yield" and "Investment Grade" categories) are to spill-overs from arbitrage activity placed on the eligible ETFs. Arbitrage activities of those ETFs are also shown in Figure 11, along with NAV deviations.

I use the following empirical designs. First, I apply the same method detailed in Section 2 to construct commonality between targeted and non-targeted ETFs and to further compare high-commonality ETFs and low-commonality ETFs among non-targeted ETFs. To separately measure both effects from the first announcement and the subsequent announcement of expansion, I use two-step tests. (i) For the March 23rd announcement, I compute each average commonality of the remaining 284 funds to the eligible investment grade ETFs (8 out of 10 identified are in the sample) and run a diff-in-diff study to test if high commonality non-eligible funds get larger contagion effects than low commonality non-eligible funds. The estimation period is from March 15th to April 9th, 2020. (ii) For the April 9th expansion announcement, I similarly compute each average commonality of the remaining 276 funds to the eligible high-yield ETFs (8 out of 10 identified are in the sample) and run a diff-in-diff study as the first test. The estimation period is from April 1st to May 11th, 2020. To a large extent the two groups have parallel trends before the announcement. Figure 12 shows the reactions of NAV deviations in the high- and low-commonality ETFs that are connected to eligible ETFs via their underlying network. Liquidity was greatly affected hugely in the corporate bond market, as documented in O'Hara and Zhou (2020). I control both liquidty at the ETF level and underlying asset level. *Composite Amihud*$_{t-1}$ is an aggregated version of the Amihud measure (Amihud, 2002) for a basket of securities. The results are in Table 4, below.

I find that after the announcement, non-targeted ETFs that have high commonality with the eligible ETFs had smaller price dislocations or discounts as compared to low-commonality ETFs (Panel A). This can be explained by the arbitrage activity (i.e., creation) that kicks in on the eligible ETFs as their premium surges, pushing up the NAV of non-targeted ETFs with high-commonality relative to those with low commonality. Thus, non-targeted ETFs with high-commonality get a decrease in price dislocation (i.e., a discount). These can also be confirmed in Figures 10 and 11. One might be concerned about weak creation/redemption activities after the announcement, but creation activities resumed as premium in those eligible ETFs increased, in particular in the Investment-Grade category. Creation activity did not resume in the Others category.

Table 4: **Network Effects of Fed's SMCCF Announcement**

The table shows results from diff-in-diff-style regressions exploiting variations in commonality among non-targeted funds when SMCCF was announced in the Bond ETF market. $D\{\textit{High Commonality to Eligible}\}$ is constructed based on the same network topology construction, $\mathbf{d}_t(i,\ell) = \sum_{j=1}^{N} w_{j,t}^{(i)} \log(w_{j,t}^{(\ell)})$, as the Equity ETFs (see Section 2) and by ranking non-targeted ETFs based on their average commonalities to the eligible funds, $\frac{1}{\#of Eligible} \sum_{\ell \in Eligible} \mathbf{d}_t(i,\ell)$. The sample in Panel A is after the introduction of an interest rate cut and Treasury purchase and before the announcement of expansion, between March 15th and April 8th, 2020. The result is robust to changing the beginning of the sample to after PDCF and MMLF. The sample in Panel B is a week after the first announcement and before the purchase, between April 1st and May 11st, 2020. Controls include lagged variables of mispricing and net fund flow other than those shown below. Standard errors are clustered and reported in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Panel A: Announcement

	Mispricing (%)					
	t	$t+1$	$t+2$	$t+3$	$t+7$	$t+14$
	(1)	(2)	(3)	(4)	(5)	(6)
D{*Announcement*}*D{*High Commonality to Eligible*}	-0.273^{***}	-0.253	0.041	-0.054	0.189^{***}	0.099^{*}
	(0.069)	(0.187)	(0.164)	(0.218)	(0.059)	(0.051)
D{*High Commonality to Eligible*}	0.212^{***}	0.206	-0.002	0.043	-0.209^{***}	-0.132^{***}
	(0.055)	(0.157)	(0.159)	(0.194)	(0.056)	(0.042)
$\textit{BA Spread}_{t-1}$	-0.008	-0.022^{***}	-0.003	-0.017	-0.015	-0.023^{**}
	(0.006)	(0.006)	(0.008)	(0.011)	(0.013)	(0.011)
$\textit{Composite Amihud}_{t-1}$	0.030	0.068	0.095^{*}	0.108^{*}	0.088^{***}	0.067^{**}
	(0.042)	(0.055)	(0.056)	(0.055)	(0.033)	(0.029)
Maturity Exposure (<1y)	0.018	0.026	0.019	0.011	-0.005	0.015
	(0.020)	(0.022)	(0.027)	(0.021)	(0.019)	(0.012)
Maturity Exposure (1-3y)	0.002	-0.014	-0.016	-0.027	-0.035	-0.020
	(0.028)	(0.033)	(0.035)	(0.032)	(0.034)	(0.020)
Maturity Exposure (3-5y)	-0.047	-0.033	-0.033	-0.044	-0.014	0.039^{*}
	(0.038)	(0.041)	(0.041)	(0.041)	(0.038)	(0.021)
Time FE	✓	✓	✓	✓	✓	✓
Control	✓	✓	✓	✓	✓	✓
Observations	4,564	4,561	4,558	4,555	4,543	4,282
Adjusted R^2	0.631	0.490	0.316	0.285	0.234	0.165

Panel B: Expansion

	Mispricing (%)					
	t	t+1	t+2	t+3	t+7	t+14
	(1)	(2)	(3)	(4)	(5)	(6)
D{*Expansion*}*D{*High Commonality to Eligible*}	-0.003	-0.001	-0.002	-0.003	0.010	0.020^{**}
	(0.019)	(0.019)	(0.017)	(0.017)	(0.014)	(0.010)
D{*High Commonality to Eligible*}	-0.007	-0.013	-0.013	-0.014	-0.022^{*}	-0.029^{***}
	(0.019)	(0.018)	(0.017)	(0.018)	(0.012)	(0.008)
$\textit{BA Spread}_{t-1}$	-0.001	-0.005^{***}	-0.001	-0.001	-0.0001	-0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$\textit{Composite Amihud}_{t-1}$	0.005	0.025	0.030	0.046^{*}	0.021	-0.006
	(0.019)	(0.023)	(0.027)	(0.023)	(0.014)	(0.009)
Maturity Exposure (<1y)	0.009	0.020^{*}	0.028^{***}	0.036^{***}	0.045^{***}	0.062^{***}
	(0.010)	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)
Maturity Exposure (1-3y)	0.005	-0.001	0.003	0.001	0.006	0.002
	(0.017)	(0.017)	(0.016)	(0.017)	(0.014)	(0.013)
Maturity Exposure (3-5y)	-0.001	0.004	0.007	0.004	0.003	-0.016
	(0.010)	(0.012)	(0.014)	(0.015)	(0.013)	(0.012)
Time FE	✓	✓	✓	✓	✓	✓
Control	✓	✓	✓	✓	✓	✓
Observations	6,174	5,927	5,925	5,923	5,915	5,411
Adjusted R^2	0.630	0.511	0.443	0.392	0.395	0.277

Further, I test again for the second announcement of expansion (Panel B) and find that statistical evidence of contagion effects in regard to the second announcement is weak. One potential reason could be that it was relatively safer products, as opposed to high-yield products, that were facing large selling pressures before the announcement and hence the reaction. Another potential reason could be that market participants might have expected high-yield ETFs were going to be included in the purchase even after the first announcement. Although it is a challenge to entirely separate out the effects of PDCF and MMLF from the effects of the SMCCF Announcement, the result in Panel A is robust to alternative designs: (a) construct commonality of non-eligible ETFs to both eligible investment grade ETFs and high-yield ETFs, (b) extending the end of the event study period up to May 11th, 2020, (c) changing the beginning of the sample from March 15th to after PDCF and MMLF. Lastly, I find that the actual purchase did not have statistically significant effects.

4 Robustness and Extensions

4.1 Placebo Test

In this subsection, I document placebo tests that show that the results are not driven by common shocks among ETFs or the shocks that randomly chosen funds can generate. Table 5, compares the coefficients obtained by placebo specifications with the baseline specification with neighbor contagion measures. *Average* variables simply take the average over all mispricing and creation/redemption of the other funds, respectively, without using commonality $d_{i,j}$. *Random* variables instead randomly pick half of the other funds at every period and average over them. This random selection of ETFs will test whether the network weights indeed matter. Using only average variables without fixed effects, the regressions in column (1) and (7) find that average mispricing across funds is *positively* related to fund i's mispricing with statistical significance. This is the opposite sign of the coefficient I find on the neighbor contagion measures (columns (6) and (12)). This positive coefficient simply reflects common components of the ETF market, such as aggregate risk factors, aggregate risk appetite, and common shocks. In fact, once I control time fixed effects in columns (2) and (8), statistical significance vanishes. I find the same for different choices of explanatory variables, presented in columns (3)–(5) and columns (9)–(11). Only when a model uses the network weighted mispricing and creation/redemption variables,they are statistically significant and survive both fixed effects. This confirms that the network does indeed matter.

4.2 Alternative Returns

To confirm that this response in return is driven through the channel in Figure 5, I test it with two alternative definitions of returns: NAV return and abnormal return after controlling Fama-French five factors. Table 6 presents the results. With NAV return, surprisingly, the contagion measures show *larger* economic significance, daily 1.356 bps per a one standard deviation increase in the contagion measure, than the fund i Net Fund Flow, 0.507 bps, while $Mispricing_t$ shows very weak significance. This confirms that the channel of arbitrage-induced contagion takes place through adjustments in NAVs.

With abnormal return, ETF return has a similar economic significance for ETF return as baseline regressions. At $t+1$, its fund i arbitrage measure, $Mispricing_t$ has a magnitude of daily 4.186 bps, whereas $Neighbor\ Mispricing_t$ is 1.178 bps. Also, R^2 drops significantly with abnormal return to 0.16–0.19, even with time fixed effects as compared to R^2 in the specification with both standard return and NAV return, around 0.69. This suggests that some portion of variability is driven by common factors, but findings suggest that this contagion effects remain strong, with daily 1.466 bps, even after taking into account factors. Comparing these results with Table 3 suggests that the contagion effect is indeed operates through NAV as conjectured in Figure 5 (3) and it is slightly weaker than the effect of the contagion measure when I use ETF return.[16] Importantly, this confirms that the response in returns is not driven by common risk factors.

[16]This is in line with the finding in Madhavan (2014) that ETF return volatility will exceed that of NAV returns.

4.3 Causal Identification

4.3.1 Instrumental Variable

One of the possible concerns for the channel I test is that common underlying shocks drive both the mispricing of fund i and the mispricing of the neighbor funds j. In addition to the statistical significance I find controlling aggregate risk factors and fixed effects, I further establish causal interpretation with the aid of instrumental variables. Figure 13 shows the relation between net fund flow and rebalancing days for the funds that rebalance and those that do not.

It indicates that the arbitrage activity of authorized participants starts plummeting first from $t = -2$ days before the rebalancing day up to a day before. On the rebalancing day, net fund flow jumps as the uncertainty about an underlying basket of portfolios resolves. This behavior of the arbitrager is in line with the mechanism of primary market arbitrage. As the arbitrager needs to trade a basket of underlying assets in the portfolio, he is less willing to do trades on days right before the rebalancing. Using this exogenous variation around rebalancing days, I construct an instrumented contagion variable, $\widehat{Neighbor\ AP\ Activity}_{t,i}$, in the following manner. The first and second stages are as follows.

$$Creation/Redemption_{t,\ell} * NAV_{t,\ell} = \alpha_t + \beta * \mathbb{1}_{t,\ell}\{Rebalance_{t,\ell}\} + \epsilon_t$$

$$\widehat{Neighbor\ AP\ Activity}_{t,i} = \sum_{\ell \neq i} \mathbf{d}_t(i,\ell) * \widehat{Creation/Redemption_{t,\ell} * NAV_{t,\ell}}$$

The construction of $\widehat{Neighbor\ Mispricing}_{t,i}$, corresponding to the overall arbitrage activities, simply replaces the net fund flow, the dependent variable in the first stage regression, by mispricing of the funds. By construction, these two constructed variables are relatively highly correlated ($\rho = 0.56$); although it is not optimal to run them together, they are juxtaposed in column (3).

Table 7: **Instrumental Variable Regression**

The table shows results from 2SLS IV regressions exploiting the exogenous rebalancing of portfolios. Each ETF is rebalanced periodically rebalancing as are the underlying indices. Controls include net fund flow, lagged mispricing, trading volume, bid-ask spread, and AUM. Variables are standardized. Standard errors are clustered and reported in parentheses. $^{*}p$<0.1, $^{**}p$<0.05, $^{***}p$<0.01. The dependent variable is in basis points.

	$Mispricing_{t+1}$		
	(1)	(2)	(3)
$\widehat{NeighborAPActivity_{t,i}}$	-0.080^{**}		-0.032
	(0.033)		(0.046)
$\widehat{NeighborMispricing_{t,i}}$		-0.103^{***}	-0.082^{*}
		(0.030)	(0.044)
Control	✓	✓	✓
FE	✓	✓	✓
Observations	137,778	137,778	137,778
Adjusted R^2	0.044	0.044	0.044

Interestingly, after using exogenous variation in rebalancing, the contagion variable corresponding to the primary market activities shows statistical significance (column (1)), in contrast to the baseline regression without an instrument in Table 2. The second contagion variable corresponding to the overall arbitrage activities shows somewhat weaker economic significance with an instrument, as compared to Table 2. These results together suggests that the arbitrage-induced price dislocations seem to be causal.

4.3.2 Granular Instrumental Variable (GIV)

I employ Gabaix and Koijen (2020a) to study contagion effects in the ETF market, using the granular residual[17] and exploiting its skewed size distribution. This enables an estimation to use the idiosyncratic shocks from the large entities, which are relevant to the ETF market as a whole. First, I obtain residuals from the regression of a dependent variable on controls, $\delta_{i,t+1} = a + bX_t + e_{i,t+1}$. Controls include the same set of variables as the main regressions from Tables 2 and 3. Using residuals from the first regression, $e_{i,t}$, and the key variables, net

[17]Granular residual has been recently used in another paper, di Giovanni et al. (2020)

fund flow of its own fund i and net fund flow of neighbor funds, I get estimates of η_t^x, factor exposures. Further, I construct GIV as

$$Z_t^\delta = \delta_{\Gamma_t} := \delta_{St} - \delta_{Et} = u_{St} - u_{Et}$$

where $\delta_{St} := \sum_{i=1}^{M} S_i \delta_{i,t}$, $S_i := \frac{AUM_i}{\sum^M AUM_i}$, $\delta_{Et} := \sum_{i=1}^{M} \frac{1}{N}\delta_{i,t}$, $X_{St} := \sum_i S_i X_{i,t}$, and $\delta_{i,t} := Mispricing_{i,t}$. The last equality comes from $\delta_{St} = \tilde{\eta}_t + u_{St}$ and $\delta_{Et} = \tilde{\eta}_t + u_{Et}$. $\tilde{\eta}_t$ is a common shock to mispricing. A key condition for the GIV estimator, Z_t^δ, to work is a size distribution of the industry. In the case of the ETF market, the excess Herfindahl is, $h := \sqrt{-\frac{1}{100} + \sum_{i=1}^{100} S_i^2} \approx 0.25$ and the entities are concentrated at a relatively high level based on their AUMs (see Figure 14). With Z_t^δ, η_t^x, and additional controls W_t, I estimate a multiplier, M, by

$$\delta_{St} = M^\delta Z_t^\delta + a'\eta_t^x + b'X_{St} + c'W_t + e_t' \tag{3}$$

Table 8, below, presents its result. From the table, M^{misp} is 0.795 for the specification with mispricing in column (1). This indicates a spillover effect of $\gamma^{misp} = 1 - \frac{1}{M^{misp}} = -0.26$. To interpret, suppose the average mispricing across funds is 10 bps and some shock multiples mispricing in a particular fund by 2; an initial shock creating a positive price dislocation (premium) of 10 bps to a particular fund with a relative size of 0.5 in the ETF market could create, $\gamma^{Misp} M^{Misp} S_i u_i = -0.26 * 0.795 * 0.5 * 10bps = -1.03bps$, price discount for the other funds in the short term. This suggests that price dislocations in the ETF market are shock-absorbing and the shock to one fund induces price distortions in the opposite direction in the other funds.

Table 8: **Granular Instrumental Variable Estimation**

The table shows results from GIV regressions. The first two lines shows multipliers, **M**, and the coefficients estimated for Z_t and Z_t^{hetero} separately. Z^{hetero} adjusts for heteroskedasticity. Controls include lagged dollar trading volume, lagged bid-ask spread, lagged composite bid-ask spread, lagged AUM, lagged mispricing (lagged return for (3) and (4)), and Fama-French five factors. Lagged bid-ask spread controls for ETF-level liquidity and lagged composite bid-ask spread controls for security-level liquidity. Standard errors are clustered and reported in parentheses. η_1 and η_2 are factor exposures. $^{*}p<0.1$; $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

	$Mispricing_{t+1}$		$Return_{t+2}$	
	(1)	(2)	(3)	(4)
Z_t	0.795***		−1.008***	
	(0.051)		(0.313)	
Z_t^{hetero}		0.821***		−1.829***
		(0.056)		(0.314)
η_1	0.052	0.073	0.145	0.199
	(0.044)	(0.045)	(2.094)	(2.082)
η_2			−7.888***	−5.856***
			(2.097)	(2.103)
Control	✓	✓	✓	✓
Observations	1,399	1,260	1,399	1,260
Adjusted R^2	0.304	0.634	0.028	0.077

On the other hand, M^{Ret} is -1.008 and -1.829 for the specification with ETF return as the dependent variable in columns (3) and (4), respectively. In turn, γ^{Ret} is 1.99 and 1.54 for columns (3) and (4), respectively. This indicates that if the average return across funds is 10 bps and some shock multiplies the return by 2, the average return increases to 20 bps without contagion, whereas it changes to -0.08bps and -8.29 bps, respectively ($\Delta Ret = -10.08bps = M^{Ret} * 10bps * 1$ and $\Delta Ret = -18.29bps$) in the presence of contagion. This surprising oscillating effects of contagion is in line with what is conjectured in Figure 5. Further, this is in line with the reduced-form baseline regressions in Table 3; the contagion measure for arbitrage activity on the neighbor fund, *Neighbor AP Activity*$_t$, and the measure for arbitrage activity on its own price dislocation, *Net Fund Flow*$_t$, predict future returns with opposite signs. In other words, an initial shock of 100 bps to a particular fund with a relative size of 0.5 in the ETF market could create, $\gamma^{Ret} M^{Ret} S_i u_i = 1.99 * -1.008 * 0.5 * 100bps = -100.296bps$ and

$\gamma^{Ret} M^{Ret} S_i u_i = 1.546 * -1.829 * 0.5 * 100bps = -144.381bps$, a shock with the opposite sign to the other funds in the market in the short term. This suggests, surprisingly, that the contagion effects in return terms can be an amplifier in contrast to mispricing, which is self-correcting. It can create an unexpected short-term return of the same magnitude or a greater relative to an initial shock, in the opposite direction.

4.4 Spatial Estimation

Some of the concerns about this type of contagion effects are the reflection problem (Manski, 1993) and correlated shocks. First, a shock to fund A can affect fund B, while a shock to fund B can affect fund A through the underlying network. Therefore, it is important to consider such spatial dependencies. Second, it can be difficult to distinguish spillover effects from fund B to fund A's return from effects on fund A's return due to correlated shocks. To address to these potential concerns, I estimate spatial models instead of using the granular instrumental variable in this section. I use the spatial autoregressive model (henceforth, SAR), described below.

$$Mispricing_{i,t} = \alpha_t^{\text{day}} + \alpha_i^{\text{fund}} + \sum_{k=1}^{K} \beta_k^{\text{fund}} x_{i,t}^k + \gamma \sum_{i \neq j} \mathbf{d}_{ij} Mispricing_{j,t} + \epsilon_{i,t}$$

$$\sim iid\, \mathcal{N}\left(0, \sigma_i^2\right), \quad i = 1, \ldots, M, \quad t = 1, \ldots, T$$

The key feature of the model is that it controls spatial correlation of a dependent variable and estimates the network parameter, γ. Rewriting in a matrix form (see Appendix E for details),

$$\mathbf{Y} = \boldsymbol{\alpha}\mathbf{F} + \mathbf{X}\boldsymbol{\beta} + \gamma \left(I_T \otimes \boldsymbol{D}_M\right) \mathbf{Y} + \varepsilon \tag{4}$$

For the network parameter, γ, to be identified, we need the condition that $\boldsymbol{D}$, $\boldsymbol{D}^2$, and $\boldsymbol{I}$ are linearly independent (see Bramoulle et al., 2009). This condition is met in the sample, which allows me to estimate a model by concentrated log-likelihood (Elhorst, 2003, Elhorst, 2010)

Figure 11: **Network Multiplier for Mispricing**

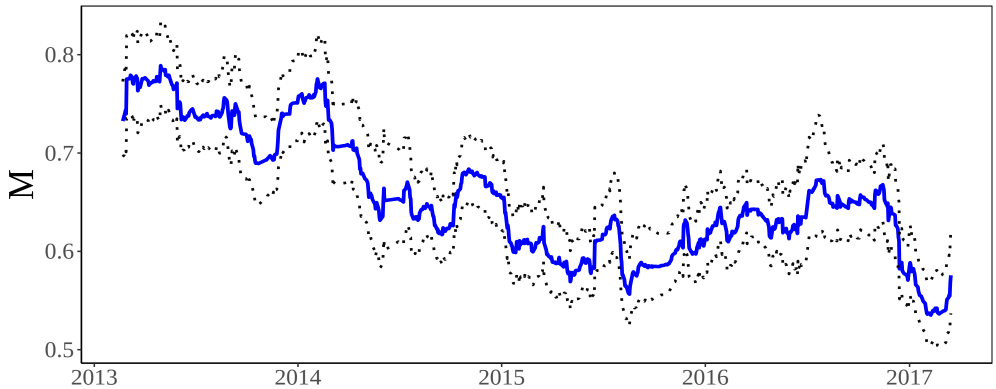


Figure 11 above shows a network multiplier, M $(= \frac{1}{1-\gamma})$, from rolling estimations of equation 4. This consistently shows that the multiplier is in a range between 0.8 and 0.5, suggesting that three things. First, contagion on mispricing is intact even after taking account of spatial dependencies through the network and, therefore, correlated shocks are not driving results. Second, contagion on mispricing is consistently self-stabilizing over time, though its magnitude is time-varying. Lastly, the magnitude is in the same ballpark as multipliers estimated by the granular instrumental variable, shown in Table 8.

4.5 Subsamples

4.5.1 Premium vs. Discount

Table 11 presents the results. I split the sample into the premium sample and discount sample by an initial sign of mispricing at t in each fund. Comparing the premium sample ($P_t > V_t$) in (1), (2), and (3) with the discount sample ($V_t > P_t$) in (4), (5), and (6), it suggests that the contagion effects are stronger in both statistical significance and economic magnitude in the discount sample. In (1), the contagion effect is statistically not significant, whereas the effect of creation/redemption from arbitrage activity on its own price dislocation is a daily 0.5–3.8 bps increase in the contagion measure. In contrast, in (2) and (3), the contagion effect is daily 1.3 bps, whereas the effect of arbitrage activity on its own price dislocation is less than half of that, 0.5 bps. In contrast, the discount sample already shows much stronger significance both economically and statistically already from the $t+1$ period; at $t+1$, the contagion effect is daily 3.8 bps, whereas the effect of arbitrage activity on its own price dislocation is less than that, 3.6 bps. This is because price dislocations in the discount sample get further pushed away by arbitrage-induced contagion when the linked funds exhibits positive mispricing, which creates more room for the NAV of fund i to bounce back, and hence a larger move in subsequent reactions in fund i's return.

4.5.2 Composition

Table 12-a presents a variant of the baseline return regression, in which the sample is split based on the category of ETFs. In each subsamples, I exclude a particular category of ETFs one by one to confirm that the findings are not driven by a particular category of ETFs. As compared to the benchmark findings in Table 3, where a one standard deviation increase in the contagion measure leads to a 1.509 bps increase in return, excluding the funds focused on either Sector or Growth shows higher contagion effects than the benchmark, suggesting that those funds exhibit smaller contagion effects (columns (2) and (5)). On the other hand, excluding the fund focused on Strategy, Value, or Small Caps exhibits much smaller contagion effects (columns (3), (6), and (7)). All in all, the contagion effects are robust to subsamples; this confirms that the findings are not driven by a particular subset of ETFs.

4.5.3 Year

Table 12-b presents a variant of the main return regression, where its sample is split by year. I create the subsamples by halving the sample into two and also creating a sample that excludes 2015, the year in which there was a flash crash. (1) is without 2015, (2) is between 2012 and 2014, and (3) is between 2015 and 2017. In the first two subsamples, $Neighbor\ AP\ Activity_t$ consistently shows statistical significance. This confirms the contagion effects are not purely

driven by market stresses such as the 2015 crash. In contrast, in the third subsample (3), $Neighbor\ Mispricing_t$ seems to capture the contagion effects very strongly, with a 2.789 bps increase per a one standard deviation increase in the contagion measure. This is almost as twice as the benchmark result in Table 3 and suggests that the contagion effects in recent years are stronger and are coming more from arbitrage trading on the secondary market than the primary market.

4.6 Fama-Macbeth

I further confirm these results with a standard Fama-Macbeth regression in Table 13 and find the same pattern; the effects from arbitrage trading on its own mispricing, an induced *negative* return, come first and then the contagion effects from arbitrage trading on neighbor funds arrive later with a *positive* return.

5 Limitation

In this section, I elaborate on points I have not explored in detail either because of the scope of the paper or the limitations of the data sets. First, I have not examined the formations of networks, which occurs when new ETFs are introduced into the market. In the analyses, I fixed ETFs in the sample so that there is no new network formation or elimination of existing networks. Second, I take networks as given in many parts of the paper. Though I address endogeneity concerns about creation/redemption activity and price dislocations with exogenous shocks in the Equity ETF part and by fixing the network weights before the experiment in the Bond ETF part, network weights can still be affected by contagion effects. Those contagion effects are forward-looking, take effects in a slightly lagged manner, and they are probably endogenous over time.

6 Conclusion

In this paper, I study how arbitrage-induced price dislocations propagate through the ETF network and lead to responses in returns. I first show that arbitrage activity targeting on mispricing in neighbor funds induces price dislocation in the main fund with an opposite sign. I show the strong response of returns and their subsequent reversals following the induced mispricing in both the primary and secondary markets. These unexpected returns and their reversals suggest that this is driven specifically by trading.

Second, I show that the underlying network does indeed matter. Without using information from the ETF network, it fails to show contagion effects. I further confirm this with NAV returns and abnormal returns, establishing that this contagion occurs via changes in the values of underlying assets. To discriminate from alternative explanations and support causality, I introduce different identifications. Regardless of identification strategies, the evidence supports the mechanism of arbitrage-induced contagion in the Equity ETF market; I reconfirm it the Bond ETF market.

While I focus on the contagion effects that stem from the proliferation of ETFs and associated tradings, another interesting venue to explore is the aspect of competition and the introduction of ETFs into the market. There is room to study new ETFs from the perspective of how introduction affects the market and how existing ETFs get terminated.

The notion that the ETF market is a potential systemic risk or a bubble is half wrong and half correct. A systemic risk is limited in that price dislocations in the ETF market act as a shock stabilizer, meaning that shocks wane across ETFs. In this sense, an original intention of the SEC report after 1987's Black Monday, which led to the birth of ETFs, proved correct: ETFs provide a cheaper and safer form of portfolio insurance. However, the findings also suggest that ETF prices can face short-term unexpected returns and subsequent reversals both at the ETF and the underlying asset levels. This complements the previous literature that argues volatility of underlying assets is distorted by ETFs, in that price discovery of ETFs is directionally distorted by arbitrage trading via the underlying network.

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A. Other Tables

Table 1: **Summary Statistics**

The table shows summary statistics. Mispricing is defined as $Price - NAV$. AUM is $SharesOutstanding * NAV$. Short Interest is scaled by Shares Outstanding. Net Fund Flow(EOD) is $\Delta Shares * NAV$ at the end of day, Net Fund Flow(BOD) for NAV at the beginning of the day. Bid-Ask Spread is on the fund level. Composite BAS is on the underlying asset level. Equity ETFs are in daily frequency from 2012 to 2017, for the top 100 equity ETFs. The Bond ETF sample is from 2019 to July 2020, including 292 funds.

		Panel A:	Equity ETFs	2012–2017				
Variable	mean	SD	min	25%	50%	75%	max	n
Return (1d, %)	0.055	0.983	-13.495	-0.420	0.082	0.586	13.469	138,162
Mispricing (bps)	0.69	6.69	-241.64	-2.26	0.76	3.54	462.72	138,162
abs(Mispricing) (bps)	4.09	5.33	0.00	1.38	2.95	5.21	462.72	138,162
Mispricing (mil, $)	0.26	6.77	-368.38	-0.44	0.08	0.84	313.60	138,162
abs(Mispricing) (mil, $)	2.21	6.40	0.00	0.22	0.64	1.82	368.38	138,162
AUM (mil, $)	7,889.89	20,574.86	37.06	963.50	2,336.12	6,630.30	279,733.19	138,162
Creation Unit (k)	47.01	20.93	25.00	50.00	50.00	50.00	200.00	137,662
Bid-Ask Spread (bps)	3.86	5.46	0.00	1.71	2.86	4.57	880.32	138,162
Composite BAS (bps)	3.81	3.57	0.00	1.92	2.59	4.32	169.16	137,905
Total Expence (%)	0.27	0.18	0.04	0.12	0.24	0.43	0.76	136,928
Put Vol (k)	28.58	180.95	0.00	0.00	0.00	0.16	7,007.41	110,034
Call Vol (k)	14.84	106.53	0.00	0.00	0.00	0.06	4,928.74	134,165
Short Interest (%)	0.08	0.18	0.00	0.00	0.01	0.06	3.86	49,585
Trading Volume (mil, $)	393.02	2,317.48	0.01	5.72	18.97	93.92	96,122.80	138,162
Net Fund Flow (EOD, mil, $)	3.73	237.09	-10517.94	0.00	0.00	4.38	28735.68	137,979
Net Fund Flow (BOD, mil, $)	2.97	247.63	-35,888.17	0.00	0.00	3.60	34,263.67	138,162
		Panel B:	Bond ETFs	2019–2020				
Variable	mean	SD	min	25%	50%	75%	max	n
Return (1d, %)	0.001	1.575	-47.708	-0.106	0.019	0.154	242.792	70,710
Mispricing (bps)	1.65	119.22	-2,785.61	-2.98	5.99	19.39	9,175.62	70,710
abs(Mispricing) (bps)	31.24	115.07	0.00	4.93	12.54	27.45	9,175.62	70,710
Mispricing (mil, $)	0.17	41.01	-3,277.95	-0.02	0.07	0.77	1,739.63	70,710
abs(Mispricing) (mil, $)	5.13	40.68	0.00	0.05	0.24	1.53	3,277.95	70,710
AUM (mil, $)	2,511.33	6,752.26	0.00	40.89	174.85	1,523.77	77,820.96	70,710
Creation Unit (k)	67.27	41.50	20.00	50.00	50.00	100.00	500.00	70,710
Bid-Ask Spread (bps)	2.062	53.799	0.001	0.093	0.316	0.936	9573.223	70,710
Total Expence (%)	0.36	0.34	0.00	0.13	0.25	0.48	2.38	68,118
Put Vol (k)	16.38	66.81	0.00	0.01	0.03	0.78	1160.21	4,861
Call Vol (k)	5.10	19.72	0.00	0.01	0.02	0.21	605.92	5,307
Short Interest (%)	0.01	0.04	0.00	0.00	0.00	0.01	0.58	28,883
Trading Volume (mil, $)	588.32	2,267.87	0.00	7.06	35.34	260.64	63,894.09	70,574
Net Fund Flow (EOD, mil, $)	1.74	61.81	-6,375.70	0.00	0.00	0.00	2,842.84	70,467

Table 5: **Placebo Tests**

The table shows the results of a comparison between placebo specification and the baseline specifications for both mispricing and return. *Average* variables on the RHS simply averages quantities of the other ETFs every period, instead of using the network weights, $d_{i,j,t}$. For instance, $Average\,Mispricing_t = \sum \frac{1}{M-1}(p^{etf}_{t,\ell} - NAV_{t,\ell}) * Shares\,Outstanding_{t,\ell}$. Instead, *Random* variables randomly choose the other ETFs in the market every period and average over their mispricing and creation/redemption. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. T-statistics, reported in parentheses, are based on clustered standard errors. The dependent variable is in basis points.

	$Mispricing_{t+1}$						$Return_{t+2}$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Average Mispricing$_t$	0.315***	−0.004					2.171***	0.773				
	(17.486)	(0.000)					(8.201)	(0.000)				
Random Mispricing$_t$			0.005						−0.219			
			(0.000)						(0.000)			
Average Cre/Redemp$_t$				0.029						1.141		
				(0.000)						(0.000)		
Random Cre/Redemp$_t$					0.031						0.365	
					(0.000)						(0.000)	
Neighbor Mispricing$_t$						−0.742***						1.402**
						(-8.214)						(1.823)
Neighbor AP Arbitrage$_t$						0.054						1.459***
						(0.857)						(2.715)
Fund FE						✓						✓
Time FE		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Observations	138,062	138,062	138,062	138,062	138,062	138,062	138,162	138,162	138,162	138,162	138,162	138,162
Adjusted R^2	0.002	0.055	0.055	0.055	0.055	0.079	0.0005	0.690	0.690	0.690	0.690	0.690

Table 6: **Alternative Returns**

The table presents regressions of alternative returns, R_{t+k}, on the contagion measures for arbitrage trading on neighbor funds (the first two rows) and on the proxies for arbitrage trading on its own mispricing (the second two rows). The LHS variable is replaced by either *NAV Return* or *Abnormal Return* controlling Fama-French five, respectively in (1)–(3) and (4)–(6). Controls not shown in the table are lagged NAV return for columns (1)–(3) and lagged abnormal return for (4)–(6). The LHS variables of columns (1)–(3) and (4)–(6), respectively, vary by the number of periods ahead, k, up to $t+3$. For liquidity, $Bid\text{-}Ask\ Spread_t$ controls for ETF-level liquidity and $Composite\ BAS_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $Average\ Mispricing_t$ and $Average\ AP\ Activity_t$ simply take averages over all mispricing and net fund flow of the other funds, respectively, without using commonality, $d_{i,j}$. Standard errors are clustered and reported in parentheses. All specifications include fund and day fixed effects. Variables are standardized. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

	NAV Return			*Abnormal Return (FF5)*		
	t+1	t+2	t+3	t+1	t+2	t+3
	(1)	(2)	(3)	(4)	(5)	(6)
$Neighbor\ AP\ Activity_t$	1.356***	0.892**	0.354	−0.291	−0.102	0.011
	(0.399)	(0.380)	(0.388)	(0.329)	(0.290)	(0.290)
$Neighbor\ Mispricing_t$	1.110*	1.175*	0.619	1.178**	1.466**	1.063**
	(0.582)	(0.675)	(0.659)	(0.540)	(0.617)	(0.526)
$Net\ Fund\ Flow_t$	−0.507***	−0.304*	−0.453***	−0.265*	−0.392***	−0.429***
	(0.160)	(0.173)	(0.131)	(0.142)	(0.152)	(0.131)
$Mispricing_t$	1.817*	0.067	0.046	−4.186***	0.236	−0.188
	(0.974)	(0.172)	(0.229)	(0.891)	(0.148)	(0.259)
$Bid\text{-}Ask\ Spread_t$	0.064	−0.084	0.068	0.175	0.002	−0.101
	(0.158)	(0.123)	(0.152)	(0.129)	(0.074)	(0.134)
$Composite\ BAS_t$	0.812***	0.419**	0.145	0.438	0.171	0.194
	(0.282)	(0.180)	(0.274)	(0.282)	(0.170)	(0.187)
$NAV\ Return_{t-1}$	0.206	−0.444	−1.155**			
	(0.442)	(0.491)	(0.489)			
$Alpha_{t-1}$				−0.613**	−1.095***	−0.391**
				(0.279)	(0.306)	(0.174)
$Trading\ Volume_{t-1}$	0.178	−0.921*	−0.204	0.546	−0.437	0.451
	(0.489)	(0.505)	(0.531)	(0.461)	(0.363)	(0.403)
AUM_{t-1}	−5.813***	−4.829***	−5.480***	−4.647***	−3.689***	−4.500***
	(0.913)	(0.913)	(0.909)	(0.802)	(0.736)	(0.756)
$Average\ AP\ Activity_t$	0.078	0.590	−0.286	0.957	1.187	0.017
	(1.164)	(1.162)	(0.958)	(0.769)	(0.779)	(0.806)
$Average\ Mispricing_t$	0.102	0.346	2.057	−1.241	0.356	0.211
	(1.961)	(1.704)	(2.807)	(1.422)	(1.163)	(1.655)
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Control	✓	✓	✓	✓	✓	✓
Observations	137,623	137,623	137,623	137,523	137,423	137,323
Adjusted R^2	0.699	0.695	0.686	0.168	0.184	0.193

Table 11: **Subsample: Premium vs. Discount**

The table presents a variant of the baseline return regression, where its sample is split by the directions in initial price dislocations of ETFs. Columns (1), (2), and (3) refer to the sample of funds with an initial *premium*. Columns (4), (5), and (6) refer to the sample of funds with an initial *discount*. Controls not shown in the table include lagged returns. For liquidity, $Bid\text{-}Ask\,Spread_t$ controls for ETF-level liquidity and $Composite\,BAS_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds, respectively, without using commonality $d_{i,j}$. All specifications include fund and day fixed effects. Variables are standardized. Standard errors are clustered and reported in parentheses. $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$. The dependent variable is in basis points.

	Return					
	$P_t - V_t > 0$			$P_t - V_t < 0$		
	$t{+}1$	$t{+}2$	$t{+}3$	$t{+}1$	$t{+}2$	$t{+}3$
	(1)	(2)	(3)	(4)	(5)	(6)
$Neighbor\ AP\ Activity_t$	−0.073	1.267**	1.262**	3.794***	0.365	−0.422
	(0.521)	(0.554)	(0.593)	(0.763)	(0.693)	(0.703)
$Neighbor\ Mispricing_t$	0.564	−0.681	−0.529	1.131	2.598***	2.220*
	(0.990)	(1.094)	(0.907)	(0.942)	(0.845)	(1.139)
$Net\ Fund\ Flow_t$	−0.542***	−0.452	−0.455***	−0.008	−0.185	−0.666***
	(0.192)	(0.290)	(0.164)	(0.210)	(0.235)	(0.251)
$Mispricing_t$	−3.881***	−0.123	−0.139	−3.554***	0.365	0.204
	(0.656)	(0.254)	(0.569)	(0.733)	(0.298)	(0.361)
$Trading\ Volume_{t-1}$	1.353*	−1.444*	−0.564	0.401	−0.338	−0.049
	(0.755)	(0.828)	(0.772)	(0.821)	(0.813)	(0.810)
AUM_{t-1}	−6.373***	−5.746***	−4.089***	−5.565***	−4.188***	−7.484***
	(1.225)	(1.469)	(1.217)	(1.316)	(1.067)	(1.543)
$Bid\text{-}Ask\ Spread_t$	−0.010	−0.411**	0.083	0.391*	0.153	0.129
	(0.199)	(0.178)	(0.282)	(0.226)	(0.181)	(0.224)
$Composite\ BAS_t$	0.118	0.348	0.221	1.268**	0.471	0.093
	(0.321)	(0.231)	(0.251)	(0.494)	(0.309)	(0.381)
$Average\ AP\ Activity_t$	0.693	0.280	−0.826	−1.446	0.629	0.068
	(1.186)	(1.300)	(1.453)	(1.421)	(1.395)	(1.783)
$Average\ Mispricing_t$	−4.083*	2.635	2.356	−2.669	−3.840	2.909
	(2.099)	(2.827)	(3.549)	(3.314)	(3.531)	(3.456)
Fund FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Control	✓	✓	✓	✓	✓	✓
Observations	73,535	73,535	73,535	64,088	64,088	64,088
Adjusted R^2	0.705	0.698	0.695	0.687	0.683	0.669

Table 12-a: **Subsample: By Composition**

The table shows a variant of the baseline return regression, where its sample is split by excluding certain categories of ETFs respectively. Column (1) excludes the ETFs that are substitutes, i.e., the ETFs that tracks the same underlying indices. Exclusions: IVV, VOO, MDY, SLYG, SLYV, VTWO, VXF. Column (2) excludes the sector funds. Column (3) excludes strategy ETFs, i.e., the funds that takes specific selection strategies such as high-dividend yield stocks. Column (4) excludes the broad market ETFs that track Russel and SP500. Columns (5)–(8) exclude the growth stock-themed fund, the value stock–themed fund, the small cap stock–themed fund, and the large cap stock–themed fund, respectively. For liquidity, $Bid\text{-}Ask\,Spread_t$ controls for ETF-level liquidity and $Composite\,BAS_t$ controls for security-level liquidity, aggregated to each basket of underlying securities. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds, respectively, without using commonality $d_{i,j}$. Controls not shown includes lagged returns. Standard errors are clustered and reported in parentheses. All specifications include fund and day fixed effects. Variables are standardized. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Dependent variable is in basis points.

	$Return_{t+1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ex. Substitutes	ex. Sector	ex. Strategy	ex. Broad Equity	ex. Growth	ex. Value	ex. Small	ex. Large
$Neighbor\ AP\ Activity_t$	1.334***	1.647***	1.249***	1.493***	1.551***	1.280***	1.114**	1.506***
	(0.444)	(0.360)	(0.460)	(0.423)	(0.480)	(0.474)	(0.505)	(0.419)
$Neighbor\ Mispricing_t$	0.776	−0.301	1.099	0.793	0.814	0.724	0.838	0.695
	(0.673)	(0.419)	(0.722)	(0.619)	(0.674)	(0.705)	(0.715)	(0.617)
$Net\ Fund\ Flow_t$	−0.301*	0.037	−0.203	−0.307*	−0.364**	−0.333**	−0.332**	−0.304*
	(0.158)	(0.118)	(0.167)	(0.161)	(0.169)	(0.164)	(0.161)	(0.157)
$Mispricing_t$	−3.727***	−4.147***	−4.838***	−4.254***	−3.901***	−3.897***	−3.744***	−4.240***
	(0.918)	(1.414)	(0.271)	(0.922)	(0.958)	(0.946)	(0.932)	(0.898)
$Trading\ Volume_{t-1}$	0.659	0.519	0.729	0.790	0.740	0.597	0.850	0.718
	(0.559)	(0.433)	(0.533)	(0.557)	(0.628)	(0.585)	(0.578)	(0.554)
AUM_{t-1}	−6.124***	−5.300***	−5.503***	−6.022***	−6.373***	−6.452***	−6.387***	−6.239***
	(0.982)	(0.908)	(0.955)	(1.005)	(1.055)	(1.115)	(1.008)	(1.011)
$Bid\text{-}Ask\ Spread_t$	0.212	0.025	0.321**	0.242	0.242	0.162	0.191	0.216
	(0.146)	(0.173)	(0.152)	(0.152)	(0.152)	(0.160)	(0.157)	(0.148)
$Composite\ BAS_t$	0.824***	0.038	0.843**	0.819***	0.815***	0.792**	0.907***	0.756**
	(0.299)	(0.248)	(0.332)	(0.301)	(0.316)	(0.331)	(0.315)	(0.304)
$Average\ AP\ Activity_t$	1.232	−0.953	11.905*	−0.084	−0.145	−0.043	0.245	−0.081
	(1.397)	(1.115)	(6.384)	(1.112)	(1.169)	(1.063)	(1.106)	(1.124)
$Average\ Mispricing_t$	−0.759	1.056	−4.333	−1.112	−0.694	−0.574	−0.537	−0.786
	(1.919)	(1.494)	(7.657)	(1.901)	(1.957)	(1.932)	(1.887)	(1.857)
Fund FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Control	✓	✓	✓	✓	✓	✓	✓	✓
Observations	129,387	74,276	122,637	129,436	121,047	119,811	125,276	133,449
Adjusted R^2	0.684	0.868	0.678	0.692	0.674	0.675	0.681	0.690

Table 12-b: **Subsample: By Year**

The table shows a variant of the baseline return regression, where its sample is split by time. Column (1) refer to the sample without 2015, during which a flash crash took place on August 24th. Column (2) refers to the period between 2012-2014 and (3) refers to the period between 2015 and 2017. Column (4) refers to the sample without 2017. $Bid\text{-}Ask\,Spread_t$ controls for ETF-level liquidity, while $Composite\,BAS_t$ and $Composite\,DCBS_t$ control for security-level liquidity, aggregated to each basket of underlying securities. $CompositeDCBS_t$ is not available after 2015 at my institution. $Average\,Mispricing_t$ and $Average\,AP\,Activity_t$ simply take averages over all mispricing and net fund flow of the other funds respectively without using commonality $d_{i,j}$. Controls not shown includes lagged returns. Standard errors are clustered and reported in parentheses. All specifications include fund and day fixed effects. Variables are standardized. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. The dependent variable is in basis points.

	$Return_{t+1}$			
	(1)	(2)	(3)	(4)
	ex. 2015	2012-2014	2015-2017	ex. 2017
Neighbor AP Activity$_t$	1.391***	1.697***	1.103	2.798***
	(0.428)	(0.567)	(0.696)	(0.601)
Neighbor Mispricing$_t$	1.098	−1.459*	2.789***	0.106
	(0.770)	(0.778)	(1.005)	(0.664)
Net Fund Flow$_t$	−0.220	−0.392	−0.294	−0.312*
	(0.172)	(0.253)	(0.325)	(0.184)
Mispricing$_t$	−4.133***	−5.202***	−3.399***	−4.524***
	(0.966)	(0.733)	(1.086)	(0.903)
Trading Volume$_{t-1}$	0.581	−0.089	1.326	0.907
	(0.577)	(0.776)	(0.814)	(0.609)
AUM_{t-1}	−5.953***	−7.770***	−9.293***	−7.361***
	(1.202)	(1.792)	(1.804)	(0.978)
Bid-Ask Spread$_t$	0.263*	0.332*	−0.034	0.242
	(0.149)	(0.179)	(0.325)	(0.159)
Composite BAS$_t$	0.657**	1.282**	0.319	1.282***
	(0.301)	(0.504)	(0.314)	(0.480)
Composite DCBS$_t$		−0.326		
		(0.467)		
Average AP Activity$_t$	0.202	1.775	−1.237	0.648
	(1.332)	(2.323)	(1.558)	(1.405)
Average Mispricing$_t$	−1.600	−3.231	0.916	−1.502
	(2.516)	(3.595)	(3.932)	(2.042)
Fund FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Control	✓	✓	✓	✓
Observations	113,169	64,933	72,690	113,444
Adjusted R^2	0.678	0.717	0.676	0.714

Table 13: **Fama-Macbeth Regression**

The table shows the results of fama-macbeth regressions with different horizons raging from $t + 1$ to $t + 30$. The coefficients represents the relationship between cumulative returns of ETFs, $R_{t \to t+k}$, and the contagion measures (the first two rows) and the effects from arbitrage trading on its own (the second two rows), respectively. Controls include trading volume, bid ask spread (for ETF itself), composite bid-ask spread (for underlying assets), AUM, and lagged returns. Columns (1)-(8) vary by horizon, k. T statistics are reported in parentheses. Variables are standardized. *p<0.1; **p<0.05; ***p<0.01. Dependent variable is in basis points.

	$R_{t \to t+k}$							
	t+1	t+2	t+3	t+5	t+7	t+14	t+21	t+30
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Neighbor APActivity$_t$	0.248	0.193	1.180	0.750	1.506	5.775**	8.945***	9.055**
	(0.53)	(0.29)	(1.42)	(0.68)	(1.18)	(3.09)	(4.1)	(3.31)
Neighbor Mispricing$_t$	0.434	0.933	-0.413	-0.302	-0.608	-0.058	2.775	2.975
	(0.95)	(1.42)	(-0.51)	(-0.3)	(-0.52)	(-0.03)	(1.29)	(1.12)
Mispricing$_t$	-3.649***	-3.7***	-3.632***	-4.155***	-4.559***	-4.746***	-4.161***	-4.758***
	(-17.05)	(-12.74)	(-9.23)	(-8.83)	(-8.46)	(-6.38)	(-4.49)	(-4.43)
Net Fund Flow$_t$	-0.379	-0.519	-1.075 *	-1.53**	-1.824**	-1.797	-1.772	-1.211
	(-1.43)	(-1.42)	(-2.38)	(-2.62)	(-2.68)	(-1.88)	(-1.58)	(-0.94)
Control	✓	✓	✓	✓	✓	✓	✓	✓
N	100	100	100	100	100	100	100	100
Adjusted R^2	0.131	0.129	0.128	0.126	0.121	0.120	0.118	0.114

B. Other Figures

Figure 1: **ETF Market**

The figure illustrates how arbitrager in the ETF market, in particular Authorized Participants (APs), play roles in the primary and the secondary markets. APs are licenced entities, which are often investment banks and trading firms, and they voluntarily engage in creation/redemption activities when price dislocation between ETF price and NAV widens.

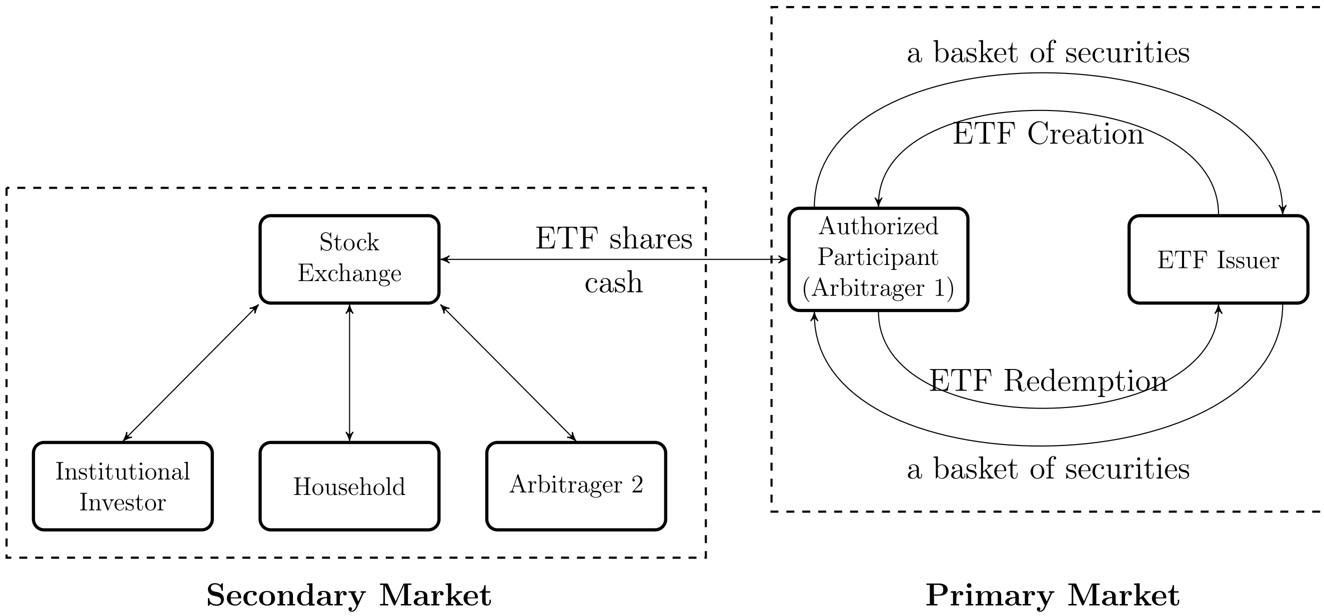
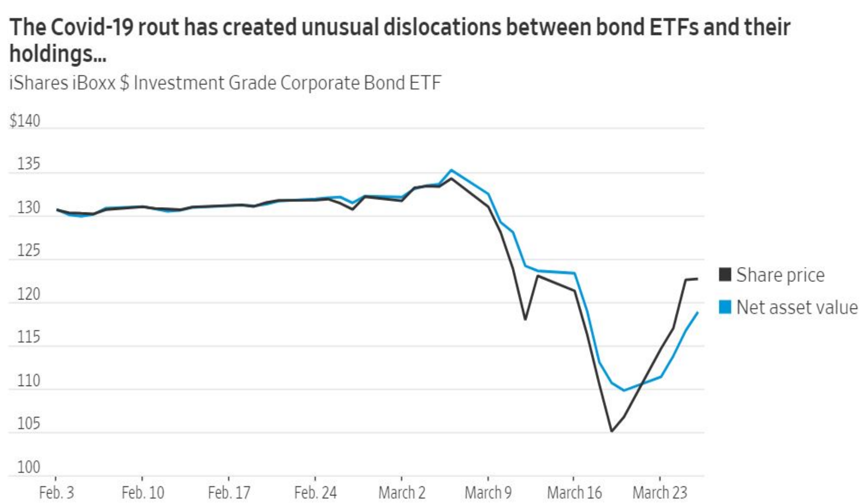


Figure 2: **Price Dislocation during the COVID-19 Crisis**



Source: Wall Street Journal

Figure 3: **Premium and Dispersion in Top 100 Equity ETFs**

The left panel shows the total traded premium and the premium for the top 100 Equity ETFs. Total traded premium is defined as the product of dollar trading volume and price dislocation (premium/discount), aggregated to a monthly basis. Premium per ETF is calculated as price dislocation minus bid-ask spread and aggregated with value weights based on the AUM of ETFs to a monthly basis. The right panel shows cross-sectional dispersion and volatility of return for TOP 100 ETFs. Cross-sectional dispersion is average monthly dispersion across ETFs with equal weights. Volatility of return is the value weight average of rolling time-series volatilities with 30-day windows.

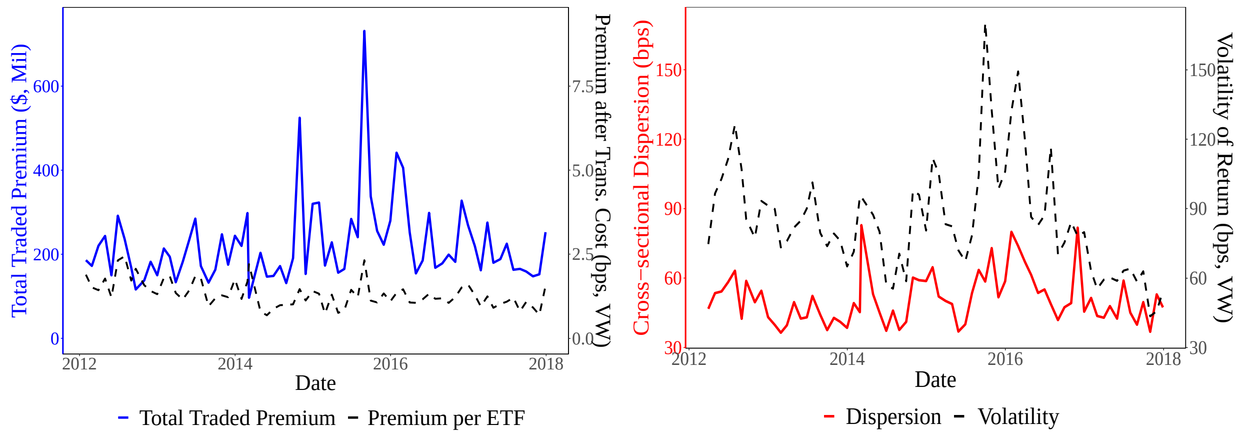


Figure 4: **Issuer and Market Makers in Top 100 Equity ETFs**

The left panel shows how many ETFs each issuer has for the top 100 ETFs. The right panel shows the fractions of fund-date N, in which each entity is a lead market maker maker throughout the sample, 2012–2017.

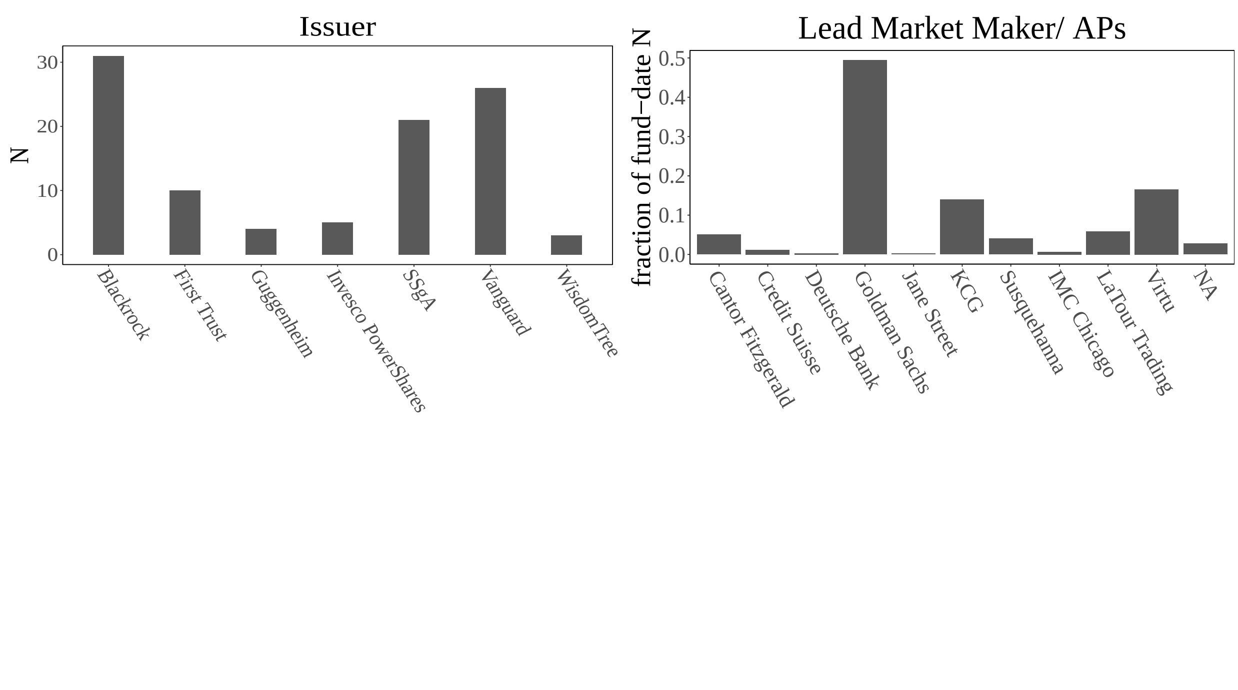


Figure 5: **Contagion Index by Category**

The figure shows a classified presentation of the average contagion index, which captures how prone each ETF is to contagion effects from neighbor ETFs. They are classified by the category of ETFs. Style refers to mid-cap funds and those ETFs with some focus on particular sectors (but not fully limited to). Strategy refers to high-dividend yield funds and dividend-themed funds. The contagion index is defined as $\mathbf{Contagion}_i = \sum_t \sum_{\ell \neq i} \mathbf{d}_t(i, \ell) * (Creation/Redemption_{t,\ell}) * NAV_{t,\ell}$ for each ETF. All variables are standardized.

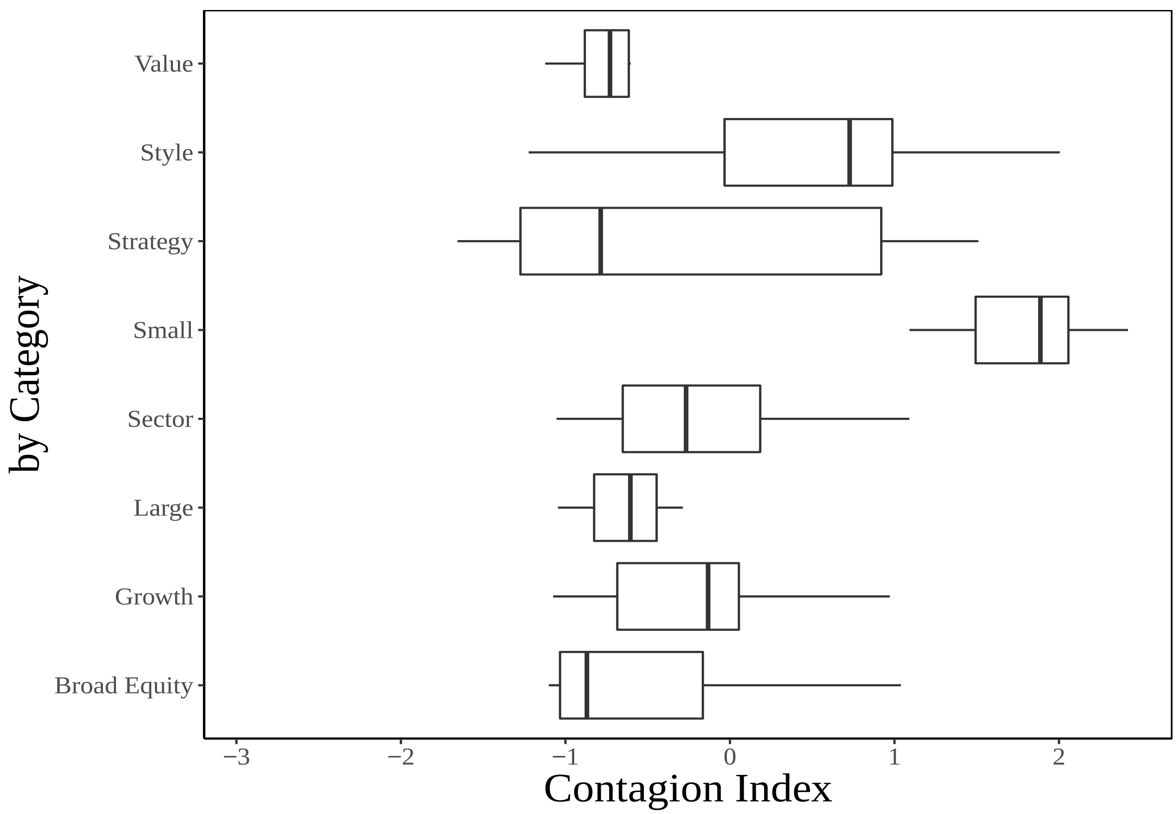


Figure 11: **Primary Market Activity around Fed Announcement**

The figure shows market reactions of Bond ETFs before and after the SMCCF announcement by the Fed. The High Yield category includes eight major high-yield bond ETFs, eligible for the Fed purchase, and the Investment Grade category includes eight major investment-grade bond ETFs, eligible for the Fed purchase, respectively. Others include the other 276 bond ETFs.

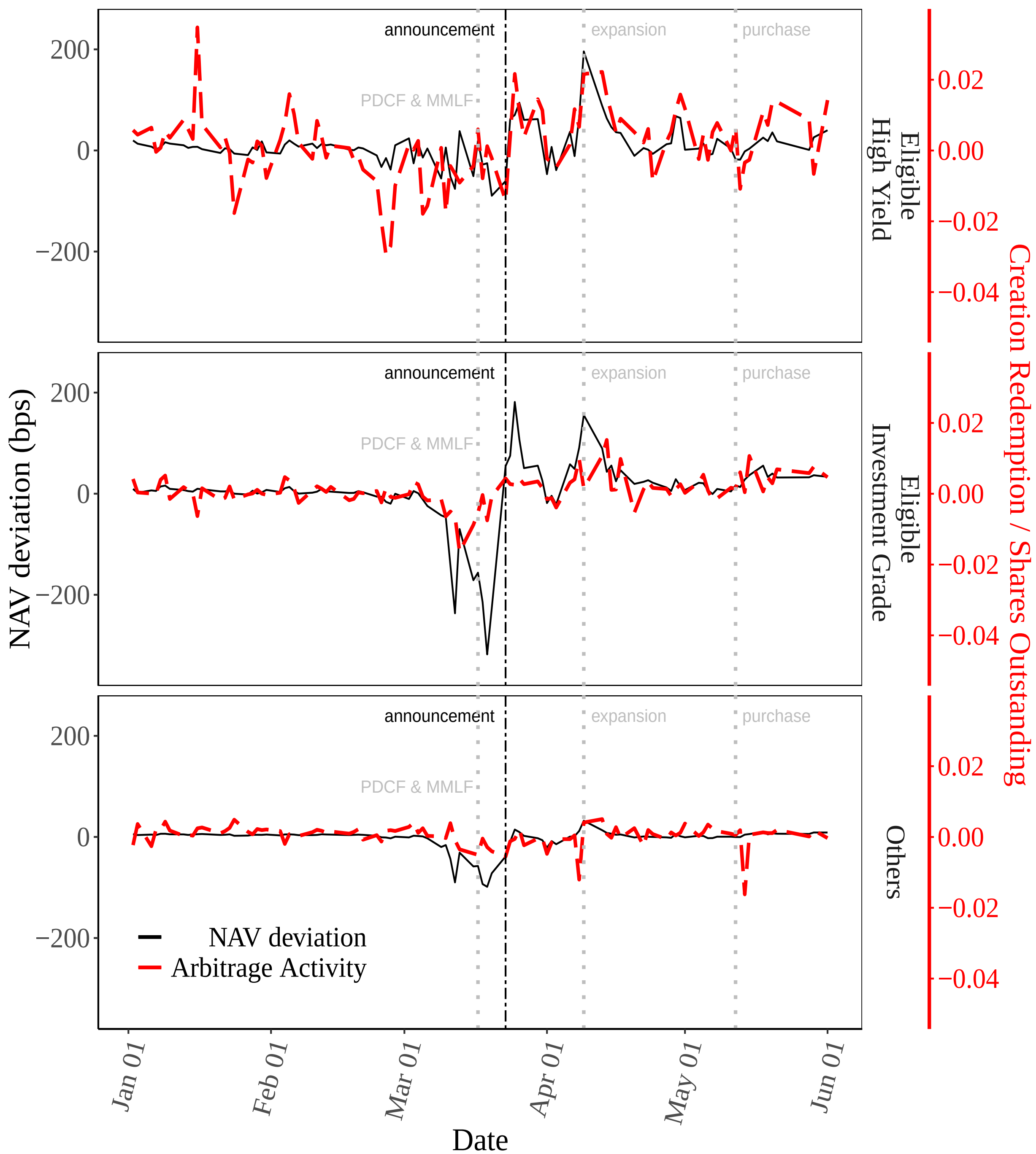
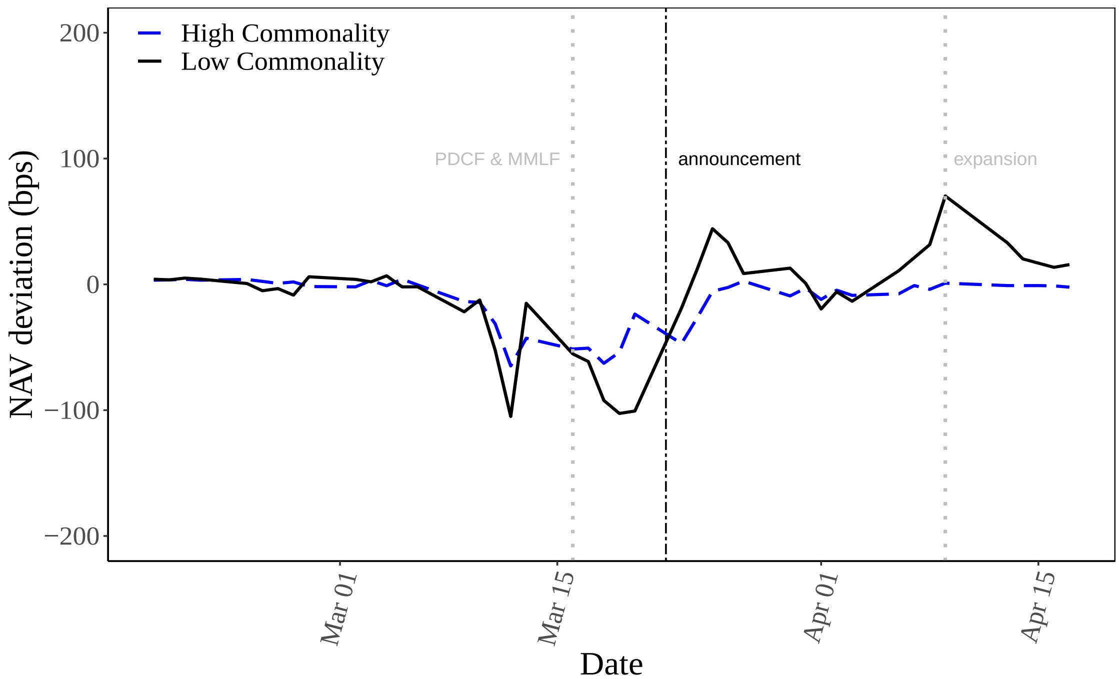


Figure 12: **Network Effects in Non-targeted Funds**

The figure shows the market reactions of non-targeted Bond ETFs before and after the SMCCF announcement by the Fed. High-commonality and low-commonality funds are computed based on the network topology, **D**, with the same construction as the one used in the Equity ETF part. By first computing commonality, **d(i,j)**, between non-targeted funds i and targeted funds j and averaging over j, non-targeted ETFs are split into three bins. I use **d** at the beginning of the year so as to prevent the network from becoming affected by the market distress that began in March 2020.



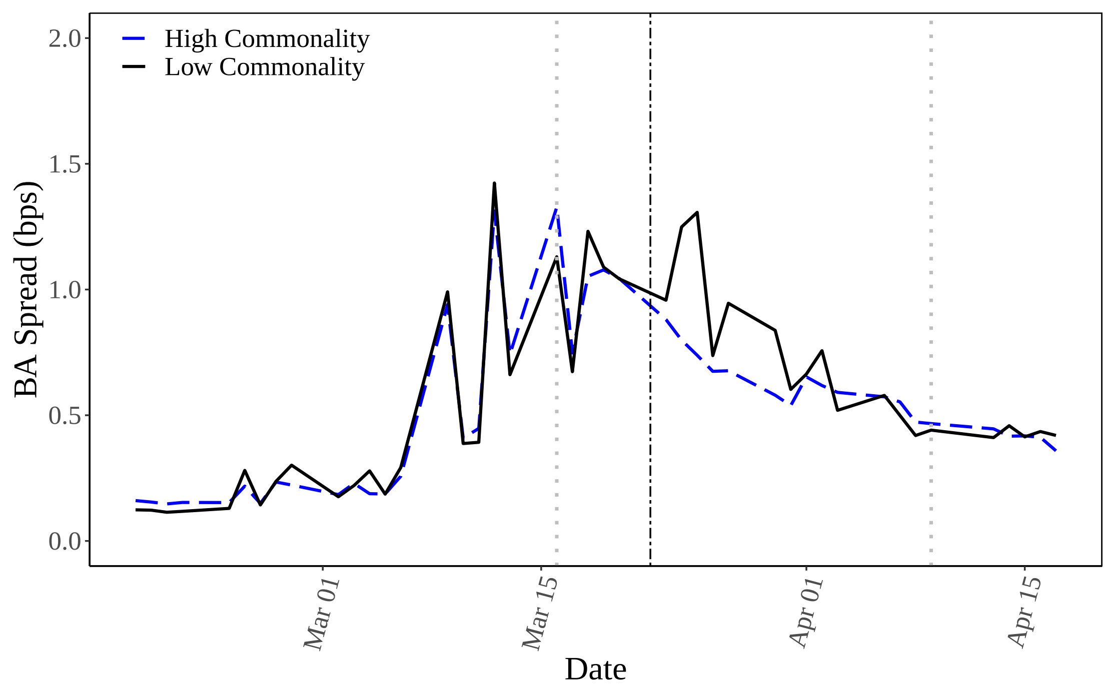


Figure 13: **Flow Waits for Uncertainty to Resolve before Index Rebalancing**

This figure shows the average net fund flow of Equity ETFs for two groups that are split based on whether or not each fund faces rebalancing. A blue line shows the average net fund flow of rebalancing funds from five days earlier and up to five days after each rebalancing day. The sample is 2012–2017.

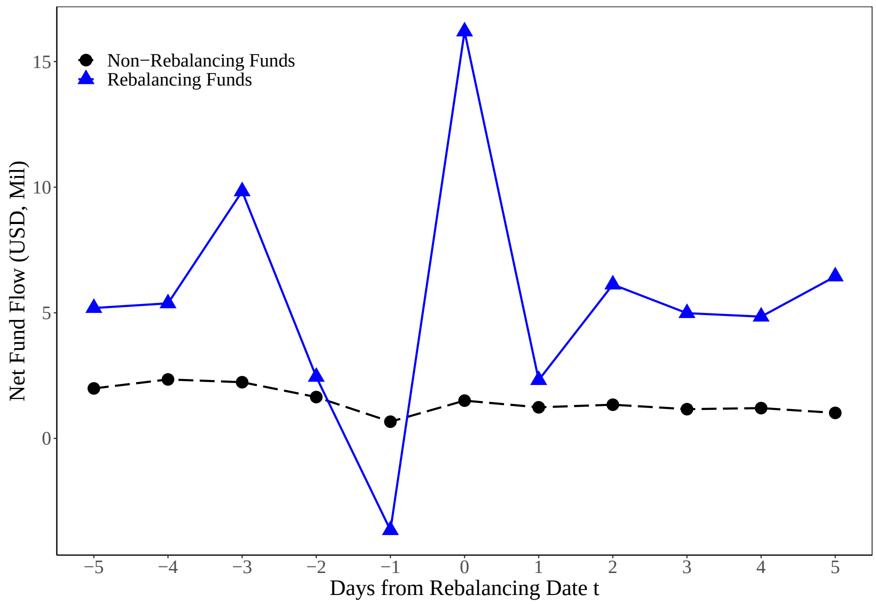
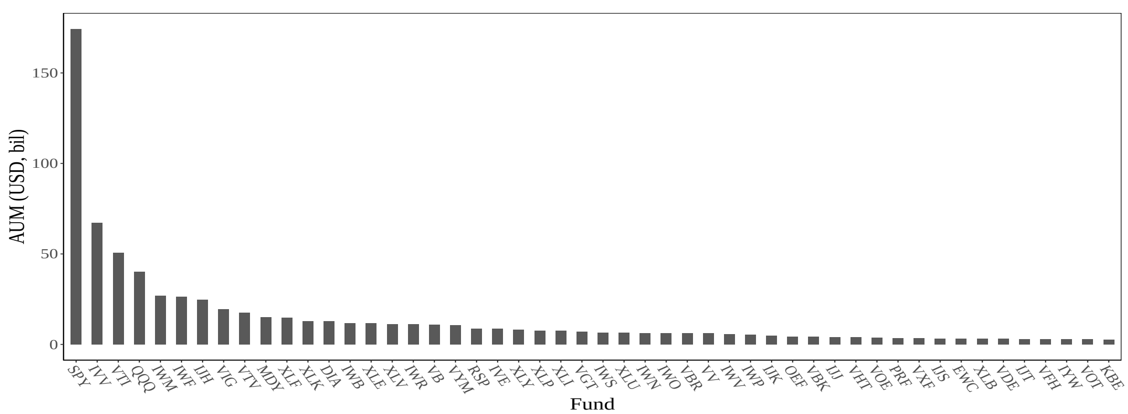


Figure 14: **Skewed Size Distribution of Top 50 ETFs**

This figure shows the AUM of the top 50 Equity ETFs during the sample period. The excess Herfindahl is $h := \sqrt{-\frac{1}{100} + \sum_{i=1}^{100} S_i^2} \approx 0.25$ and they are concentrated at a relatively high level.



C. Primary Market Arbitrage

This section describes the primary market arbitrage carried out by APs. It is reported that registered APs are typically 30–40 entities per one ETF and 5 are active on average at each point in time (see Blackrock (2017) for details). Authorized participants tend to be either large financial institutions or specialized market makers. The authorized participant does not have an obligation to engage in market-making activities, or AP activities.

The authorized participant takes arbitrage when the fund SPY exhibits the premium, $ETFPrice > NAV$, by gathering the basket of underlying stocks and delivering it to the ETF sponsor in return for an ETF share ("in-kind" ETF creation).[18] For this transaction, the AP needs to make orders following *creation units* specified by the ETF. In the top 100 Equity ETF sample, it is typically a block of either 25k or 50k shares. For instance,

$$\begin{aligned}\$\mathit{Profit} =& (\mathit{NAV\ of\ ETF})*(\ |\mathit{Premium/Discount\ after\ TC}|\ ) \\ & *(\mathit{Creation\ Unit})*\mathrm{X} - \mathit{Creation\ Fee}\end{aligned}$$

Creation Fee is a fee that the AP needs to pay per participating day, i.e., a day when the AP engages in creation/redemption activity. For example, a dollar profit for engaging in the creation of SPY when it exhibits 10 bps premium and is traded at USD 200 is (\$200)*(10bps)*(50K)*X − min{\$3000, 10bps*50k*\$200}, paying a creation fee. The fee is the smaller of USD 3000 or 10bps of traded price of the ETF. This creation fee is specified by the ETF issuer and documented in its prospectus.[19] The AP can scale this transaction by *X*.

In terms of settlements, it can take up to T+3 days. First, at T, the AP submits orders to the ETF distributor with a 4:00 p.m. (ET) deadline for domestic equity ETFs, based on the portfolio composition file. This creation/redemption (C/R) order will be processed

[18] For a market maker, profit is not necessarily the premium, but the deviation of the ETF price from the expected value. See detailed discussion in Madhavan (2014).

[19] Source: State Street

via NSCC.[20] Second, the ETF agent deliver instructions to NSCC for C/R with a 8.00 p.m. (ET) deadline. In turn, NSCC distributes a file of accepted C/R instructions to the ETF agent and the AP. Third, at T+1, the AP and the ETF agent reconcile the information of C/R instructions. By the midnight of T+1, NSCC guarantees the settlement. Fourth, at T+2, NSCC distributes their consolidated trade summary reports and send instructions to DTC (Depository Trust Company). Lastly, from the late evening of T+2 to T+3, DTC can sweep the electronic books of parties involved and settle the transactions untill 3:10 p.m. (ET).[21]

[20] Domestic fixed-income securities and some of their ETFs are also NSCC-eligible. However, many domestic fixed-income ETFs are processed outside NSCC. In this case, APs post collateral to protect the ETF and its shareholders from failures in delivery. On the other hand, certain types of ETFs such as those of international securities, Treasuries, and U.S. government agency securities are not NSCC-eligible.

[21] See Antoniewicz and Heinrichs (2014) for further details.

D. Commonality Function

Assuming linear a price impact on the price of underlying stocks when the ETF arbitrage with a dollar amount of trade, $w_j^B V_{j,t}^B$, takes place on ETF B, $p_{j,t+1} = p_{j,t} + \gamma \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}}$, the net asset value (= fundamental value) of ETF A after the arbitrage activity is

$$
\begin{aligned}
V_{t+1}^A &= \sum^N w_j^A p_{j,t+1} \\
&= \sum^N w_j^A \Big(p_{j,t} + \gamma \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}}\Big)
\end{aligned}
$$

where w_j^B is the weight on stock j in ETF B, $V_{j,t}^B$ is the net asset value of ETF B, $MktCap_{j,t}$ is the market cap of stock j, and γ is the parameter that represents the strength of the price impact on stock j. With this after-arbitrage net asset value of ETF A, V_{t+1}^A, expressing log deviation of V_{t+1}^A relative to the value prior to the arbitrage activity yields the following expression with the aid of Taylor expansion and Jensen's inequality:

$$
\begin{aligned}
log\Big(\frac{V_{t+1}^A}{V_t^A}\Big) &= log\Big(1 + \frac{\gamma \sum^N w_j^A \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}}}{V_t^A}\Big) \\
&\approx k + (1-\rho)\Big(log\gamma \sum^N w_j^A \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}} - logV_t^A\Big) \\
&\geq k + (1-\rho)\Big(\underbrace{\sum^N w_j^A log(w_j^B)}_{\substack{\text{the link between A and B} \\ \text{that affects A's deviation}}} + log\gamma + \sum^N w_j^A log\Big(\frac{V_{j,t}^B}{MktCap_{j,t}}\Big) - logV_t^A\Big)
\end{aligned}
$$

where

$$
\rho \equiv \frac{1}{1 + exp\Big(\overline{log\gamma \sum^N w_j^A \frac{w_j^B V_{j,t}^B}{MktCap_{j,t}}} - \overline{V_t^A}\Big)}
$$

$$
k \equiv -log\rho - (1-\rho)log\Big(\frac{1}{\rho} - 1\Big)
$$

Therefore, a distance function used to define commonality in the paper, $d_{AB} \equiv \sum^N w_j^A \log(w_j^B)$, is the link between ETF A and ETF B that determines the lower bound of log deviation of the net asset value of ETF A due to contagion from ETF B.

E. Definitions

$$\mathbf{F} = (I_T \otimes \mathbf{1}_M, \mathbf{1}_T \otimes I_M),$$

$$\boldsymbol{D}_M = \tfrac{1}{T}\Sigma_{t=1}^T \boldsymbol{D}_{M,t},$$

$$\boldsymbol{\alpha} := (\alpha_1^{day}, \ldots, \alpha_T^{day}, \alpha_1^{fund}, \ldots, \alpha_M^{fund})', \boldsymbol{\beta} := (\beta_1, \ldots, \beta_K)'$$

$$\mathbf{Y} := (y_{1,1}, \ldots, y_{M,1}, \ldots, y_{i,t}, \ldots, y_{1,T}, \ldots, y_{M,T})'$$

$$\varepsilon := (\epsilon_{1,1}, \ldots, \epsilon_{M,1}, \ldots, \epsilon_{i,t}, \ldots, \epsilon_{1,T}, \ldots, \epsilon_{M,T})'$$

$$\mathbf{X} = \begin{pmatrix} x_{1,1}^1 & \ldots & x_{1,1}^k & \ldots & x_{1,1}^K \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m,1}^1 & \ldots & x_{m,1}^k & \ldots & x_{m,1}^K \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{M,T}^1 & \ldots & x_{M,T}^k & \ldots & x_{M,T}^K \end{pmatrix}$$