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Financial Intermediary Funding Constraints and Segmented Markets: Evidence from SMCCF ETF Purchases*

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Abstract

This paper examines a quasi-natural experiment to study the effect of balance sheet frictions among financial intermediaries on the pricing and liquidity of segmented asset markets. Corporate bond ETF purchases by the Federal Reserve through the Secondary Market Corporate Credit Facility (SMCCF) beginning in May 2020 were extremely large, likely alleviating inventory capacity constraints for authorized participants (APs) who were counterparties to those transactions. Other ETFs not purchased by the Fed—but overlap in their underlying bond holdings with purchased ETFs—exhibit significant positive price reaction within seconds of the transaction. Bonds held by ETFs purchased by the Fed also exhibit a significant and positive price reaction as well as improved liquidity on the day of the transaction. We offer additional evidence that these reactions reflected the effects of the purchases on AP balance sheet liquidity. The paper's findings support the view that the inclusion of ETFs in the SMCCF had broader "spillover" effects in stabilizing markets beyond the ETFs directly targeted by the program. More broadly, our paper provides strong evidence that the "health" of financial intermediaries has important implications for the liquidity and prices of the securities that they trade. *JEL Codes: G12, G14, G23.*

Keywords: Financial intermediaries, authorized participants, corporate bond ETFs, corporate bonds, Covid-19, Federal Reserve, regulatory interventions.

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1. Introduction

Many financial market activities pass through a relatively small number of intermediaries. While these intermediaries can insulate the financial system from adverse market conditions (Chodorow-Reich, Ghent, and Haddad, 2021), they can also magnify shocks when they face funding constraints (Duffie, 2016; Andersen, Duffie & Song, 2019; Hebert, 2020). During crisis periods, these issues can be especially problematic for illiquid asset markets, where the concentration of intermediaries is generally higher and, in turn, the role of potentially capital-constrained intermediation has greater importance.

This issue is particularly evident for U.S. exchange-traded funds, or ETFs, where the top five authorized participants (APs) account for 67.2% of total aggregate creation and redemption volume, and especially in U.S. corporate bond markets, where the top five APs account for 90.1%. During the onset of the Covid-19 pandemic in March 2020, regulators and policymakers expressed concerns about the liquidity conditions facing APs in corporate bond ETFs, including whether stress in the balance sheets of these intermediaries can further destabilize the broader underlying corporate bond market.[1]

In our paper, we ask some important and related questions. Specifically, do intermediaries that experience balance sheet constraints contribute to the propagation of severe shocks? If so, what is the path of transmission across asset markets during such periods? And, from a policy standpoint, how do regulatory interventions quell these effects beyond the primary securities

[1] For examples of these concerns, see Zuckerman, Gillers and Verlaine (2020). As an alternative view, if the capital constraints of intermediaries are relatively unimportant in U.S. corporate bond markets, interventions at the intermediary level could be expected to be less impactful than simply purchasing the underlying corporate bonds. The Fed program for purchasing corporate bond ETFs was presumably based on the belief that intermediaries efficiently provide bond-level liquidity to markets.

markets that are usually targeted for such interventions (e.g., the direct intervention of the Fed in purchasing corporate bonds during the early months of the COVID pandemic)?

We address these questions by examining a quasi-natural experiment where large intermediaries operating in segmented but connected asset markets – namely, the corporate bond and corporate bond ETF markets – experienced sizable, positive balance sheet liquidity shocks. Specifically, the Federal Reserve (henceforth, the Fed) conducted large-scale secondary market purchases of ETFs from APs through its Secondary Market Corporate Credit Facility (SMCCF).[2]

A unique aspect of these ETF purchases is that the identity of the ETF, the identity of the AP selling to the Fed, and the timing of the transactions were known only to the Fed and the ETF seller at the time. All of the transactions were conducted with entities that registered with the Fed prior to trading, and the identities of these counterparties remained confidential until several weeks after most of the transactions took place. An important issue to explore is whether these Fed purchases of ETFs may have eased balance sheet constraints for sellers (APs), who held large corporate bond inventories and faced difficult market conditions following March 2020.

If the balance sheets of ETF APs, as intermediaries, are central to their trading of ETFs (as a result of their optimal inventory levels of ETFs and their underlying bonds), we would expect that constrained balance sheets of APs will potentially lead to corresponding constraints on these APs in providing market liquidity in their ETFs and underlying corporate bonds. Accordingly, this paper focuses on intraday ETF and daily bond price reactions in order to identify the immediate causal effect of the Fed trades on other ETFs not directly related to the transaction. We document evidence that Fed SMCCF trades led to "spillover" effects to other ETFs covered by the same AP

[2] Although the SMCCF was announced in March 2020 in response to the massive shocks to financial markets due to the Covid-19 pandemic, the facility did not begin purchasing ETFs on the open market until May 12, 2020, and corporate bonds until June 15, 2020.

seller—and to corporate bonds held by such other ETFs—including those that did not overlap with Fed-purchased ETFs. To our knowledge, our paper is the first to provide direct evidence of the transmission of balance-sheet constraints of an important intermediary—ETF APs—through the liquidity of different, and presumably segmented, markets linked through that intermediary.

Key to our study is that APs of corporate bond ETFs also serve as market-makers in the underlying corporate bonds of these ETFs, and that the SMCCF program represents an unprecedented examination of these intermediaries in an environment where the identification of effects is clear. That is, with a particular AP, ETF, date/time of purchase, and size of purchase unknown to the market (but, to us as econometricians) in real-time, we are able to cleanly separate the general effect of the announcement of the program from its effect on APs associated with specific target ETFs (and their underlying corporate bonds), by leveraging daily data on the underlying holdings of ETFs associated with different APs.[3]

Our empirical design facilitates causal inference of the propagation of intermediary balance sheet shocks across different asset markets—ETFs and their underlying bond holdings—using intraday data on pricing in each market as well as SMCCF purchases. We use difference-in-differences estimators to pin down the effects of the Fed's transactions. Specifically, our analysis focuses on the price reaction of *other* ETFs within a 15-minute period before and after the transaction, based on the degree of overlap in daily bond holdings with the ETF purchased by the Fed.[4] The focus on the overlap in underlying holdings, especially that for other ETFs (not SMCCF-purchased) with the same AP, allows us to directly assess the potential transmission effects to other

[3] A large literature examines the impact of ETFs on their underlying holdings, though few have directly examined the role of APs. These studies include Hamm (2014), Israeli et al. (2017), Chang et al. (2014), Coles et al. (2020), Chinco & Fos (2021), Ben-David et al. (2018) and Saglam et al. (2020). An exception is Pan and Zeng (2020), who show that bond inventories of APs can mediate the transmission of bond market liquidity to bond ETF prices.

[4] In particular, we use the cosine similarity of bond holdings between ETFs based on daily holdings data. Other studies, which pose related questions in other contexts, use a similar approach (Hanley & Hoberg, 2010; Hanley & Hoberg 2012; Sias et al., 2016; Girardi et al., 2021).

ETFs (and their underlying holdings) due to the associated liquidity shock on corporate bond markets of an SMCCF purchase of a particular ETF from a particular AP. The high frequency data and narrow estimation window allow us to directly attribute the effects to the APs involved in the SMCCF transactions. More importantly, this approach mitigates the influence of fundamental factors related to market expectations of potential Fed support for particular ETFs, or for individual corporate bonds, which began a few weeks later under the SMCCF. To account for other potential biases associated with rapidly changing, even intraday, fundamental and market factors associated with that period, we employ fixed effects in our regression models to purge any time-varying factors associated with ETF characteristics (i.e., ETF-date) and the timing of the Fed trade (i.e., transaction date-time).

Our main results are summarized as follows. We start by examining the intraday effects of the Fed purchases on ETF prices. ETFs with a higher degree of overlapping holdings with the ETF traded by the Fed exhibit stronger positive price reactions within 15 minutes of the Fed's purchase. The estimates remain stable with and without the inclusion of control variables and fixed effects, suggesting that the results are unlikely to be driven by time-varying heterogeneity related to the ETF. Consistently, we show that the ETFs purchased by the Fed also exhibit a positive price reaction to the transaction.

We next examine *daily* corporate bond prices and provide evidence consistent with our primary finding. Here, we find that corporate bond ownership, by ETFs purchased by the Fed, has a positive and significant association with underlying bond price reaction to the Fed transactions. In these tests, we address potential endogeneity concerns by using fixed effects to account for time-varying bond issuer factors, including credit risk, as well as time-invariant bond issue factors. Importantly, these specifications limit the influence of omitted variables associated with ETF selection of the underlying bonds. We argue that these results are the first evidence that the intraday ETF test results are not only related to pricing effects on the underlying bond holdings, but are also evidence of balance sheet constraints of the AP sellers associated with the Fed transactions.

We provide three sets of additional tests to evaluate the AP intermediary balance sheet channel. First, we examine the effect of the Fed purchases on ETF and corporate bond market liquidity. Encumbered capital may inhibit arbitrageurs from facilitating liquidity for markets in which they participate (Gromb & Vayanos, 2002), and the Fed purchases may have helped to alleviate AP balance sheet constraints. For the bond-level tests, we find that bond ownership by the ETFs purchased by the Fed has a positive and significant association on various measures of bond liquidity in response to the Fed purchases.[5] Specifically, we show that bonds with a higher level of ownership by ETFs purchased by the Fed have lower bid-ask spreads and Amihud (2002) illiquidity measures on the day of the transaction. However, for the intraday ETF tests, we find that the overlap measure has an insignificant effect on non-targeted ETF bid-ask spreads. The asymmetry in the results for the intraday ETF tests may reflect the mechanism used by APs in the Fed transactions. APs likely needed to create new ETF shares with the fund sponsor using existing corporate bond inventories for the Fed purchases given the size of the transactions. ETF market makers were unaware that the purchases were associated with the Fed, nor would they have been able to infer associated activities in the primary ETF markets. In contrast, AP sellers were likely to also be dealers in the underlying corporate bond markets.

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[5] There are other empirical studies that examine the effect of ETFs on market liquidity, though they generally consider demand shocks by a broader set of market participants. For example, Saglam, et al. (2020) uses major stock index reconstitutions to show that stocks with greater ETF ownership is associated with relatively better liquidity conditions during normal periods, but worse during stress periods. Our analysis differs from these studies, as we focus on shocks affecting a narrow set of market participants (i.e., SMCCF-targeted APs) on balance sheet constraints. Moreover, because these shocks were not observable to other market participants at the time, it is unclear how they may have affected broader demand on the margins that we study.

Second, we conduct additional bond-level tests to distinguish the effects on ETFs that are associated with APs not involved in the Fed trades. Specifically, we decompose bond ownership by ETFs with seller APs versus others. This identification strategy allows us to differentiate the effects on the underlying holdings of other ETFs that share a common AP versus other APs. Here, we find that corporate bond price reactions have a significant, positive association with the holdings of the ETF that is traded by the Fed, as well as the holdings of other ETFs that are associated with the seller AP. And, the holdings of ETFs associated with other (non-SMCCF-targeted) APs have a mostly insignificant effect. Moreover, we further distinguish the effects of the seller AP by decomposing bond ownership, based on portfolio similarity with the ETF traded the Fed. We find comparable effects for ETFs with low and high portfolio similarity that are associated with the seller AP, and, again, find mostly insignificant results for ETFs associated with other APs. These results suggest that the liquidity shock associated with the Fed purchase not only improved the ability of the seller AP to provide support for bonds associated with the underlying holdings of the ETF purchased by the Fed, but also to other bonds in the underlying holdings of the same-AP.

Finally, we examine the effect of Fed transactions on ETF arbitrage activities, specifically on creations and redemptions. Most ETF arbitrage activities are undertaken by APs (Madhavan, 2016), as such activities critically depend on access to the primary ETF markets. Secondary market illiquidity in the underlying corporate bond market can be a limit to arbitrage, even if there are dislocations between ETF prices and underlying bond prices that would otherwise prove profitable for an AP. To examine if the Fed's intervention reduced these limits to arbitrage, we adapt tests developed by Pan and Zeng (2020) to incorporate the effects of the transaction on corporate bond market liquidity as described above. We focus on the interaction between the degree of overlapping holdings with the ETF traded by the Fed and relative ETF mispricing, or ETF NAV premiums. We document a positive association between the interaction and net creation volumes in the day following the Fed trade, suggesting that the Fed transaction had a beneficial effect on AP arbitrage activities, in addition to the other effects we describe above. These results are consistent with Pan and Zeng (2020), who focus on the pre-Covid-19 period and use a different measure of AP balance sheet constraints.

A growing body of literature has examined the role of financial intermediaries' balance sheet frictions on mispricing and market liquidity conditions in various asset markets (Gromb & Vayanos, 2002; Lewis, Longstaff & Petrasek, 2017; Du, Tepper & Verdelhen, 2018; Boyarchenko et al., 2018; Gromb & Vayanos, 2018; Siriwardane, 2018; Pan & Zeng, 2020; Cenedese, Corte & Wang, 2021; Haddad & Muir, 2021). Our paper contributes to this literature by examining the role of large financial intermediaries in the propagation of shocks and the pathway of transmission between markets that they support.

Our findings also have implications on the literature that studies the effects of large-scale asset purchase programs. Similar to the approach used in this study, Swanson (2021) use intraday stock price analysis to identify the causal effect of such programs compared to other forms of unconventional monetary policies. Closer to this study, there are recent studies have focused central bank ETF purchases in Japan (Barbon & Gianinazzi, 2019; Charoenwong, Morck & Wiwattanakantag, 2021) and in the U.S. (O'Hara & Zhou, 2020; Gilchrist et al., 2020; Falato, Goldstein & Hortaçsu, 2021; Boyarchenko, Kovner & Shachar, 2022). For example, Boyarchenko, Kovner, and Shachar (2022) study the effects of such programs on market issuances of bonds by corporations. As with this study, they examine corporate bond price reactions to the Fed ETF purchases. In contrast, our study focuses on secondary market effects for other ETFs not directly involved in the transaction but are also linked to the AP seller. More generally, this paper contributes to this literature by documenting the broader transmission of effects beyond the specific securities that were targeted through the intermediary balance sheet channel.

The balance of our paper is organized as follows: Section 2 describes the data and provides institutional details about the SMCCF. Section 3 outlines the research design. Section 4 presents the results on the intraday ETF tests. Section 5 describes the results for the corporate bond tests. Section 6 discusses the results on AP creation and redemption activities. Section 7 concludes.

2. Data and Institutional Details

This paper draws on several data sources to measure the effects of interest. First, we collect data on the Fed's purchases of corporate bond ETFs from the SMCCF Transaction-specific Disclosures.[6] The data disclosed by the SMCCF contain several important pieces of information at the transaction level. For each transaction, the SMCCF discloses the ETF ticker purchased, the purchase date, the number of shares purchased, and the price per share. In total, the SMCCF made 926 discrete purchases spanning 16 ETFs over the period from May 12 to July 23, 2020.[7]

[See Table 1]

Although the Fed does not disclose the timestamps of its transactions, we are able to identify 571 of the SMCCF purchases using intraday trade data from Maystreet (f/k/a Thesys). For each ETF-day in the list of SMCCF purchases, we download the entire set of intraday executions. For each of the 926 discrete purchases by the Fed, we seek a unique match based on four variables: date, ticker, price, and quantity. If an SMCCF purchase matches exactly one execution on all four

[6] See disclosures from the Federal Reserve Board (https://www.federalreserve.gov/monetarypolicy/smccf.htm) and the Federal Reserve Bank of New York (https://www.newyorkfed.org/markets/secondary-market-corporate-credit-facility) for full details on the SMCCF. Broadly speaking, the SMCCF was an effort by the Fed during the Covid-19 crisis to provide support to the U.S. corporate bond market, in turn to provide support to U.S. corporations.
[7] See Appendix Figure 1 for a brief timeline of the SMCCF.

dimensions, we count that as a matched trade. By matching the SMCCF purchases to intraday data, we are then able to characterize the intraday environment, including the trade timestamp (to the microsecond), the prevailing national best bid and offer (NBBO) of the ETF at the time of the purchase, and whether the trade was executed on an exchange or was reported to a trade-reporting facility. The remaining balance of transactions cannot be matched on at least two of the four dimensions and are, thus, dropped from the analysis.[8] Table 1 summarizes the purchases, and Figure 1 plots the distribution of matched trades by intraday timestamp and trade size.

[See Figure 1]

Once we have the set of matched purchases with intraday characteristics, we expand our focus to compare with other (non-SMCCF-purchased) corporate bond ETFs on the same days, as well as expanding the analysis to SMCCF-purchased ETFs on days when they were not purchased by the Fed. We compile a list of 120 U.S. corporate bond ETFs from Morningstar, including the 16 ETFs purchased by the SMCCF and 104 ETFs not purchased by the SMCCF. For each ETF, both purchased and not purchased by the Fed, we collect daily, security-level portfolio holdings data from Morningstar. Using these holdings data, we compute a measure of portfolio overlap between the bond holdings of any two ETFs in our sample on a given day. Section 3.3 provides more detail on how this similarity measure is used in our empirical analysis.

For further detail on the holdings of the ETFs, we collect data on corporate bonds from multiple sources. For daily prices of corporate bonds, we use the pricing service estimates from

[8] A large fraction of the remaining unmatched trades appears to be reported as aggregates of execution algorithms conducted by the agent (BlackRock) that split the trades into smaller purchases. This inference is based on the fact that all of the matched trades have two-decimal prices, but all of the unmatched trades have four-decimal prices. Consequently, the size distribution for the transactions with two-decimal prices (matched) is shifted to the left, relative to that with four-decimal prices (unmatched) in Figure 1. Additionally, some of the unmatched trades report share quantities larger than any execution for the relevant ETF-day. Identifying the components of these aggregated trades is effectively a two-dimensional subset sum problem (share quantity & VWAP) for each unmatched trade. Finding a unique solution to this problem for each unmatched trade appears to be computationally infeasible.

Intercontinental Exchange/Bank of America Merrill Lynch (ICE BAML). We do this because the ICE BAML data has an advantage over transaction data, such as TRACE, in that end-of-day quotes are provided for all bonds regardless of whether a transaction occurred at that time. ICE BAML also provides bond-level data, such as credit ratings.

We complement these daily price estimates with transaction data on corporate bonds from TRACE, which allows us to derive many of the bond liquidity measures used in the analysis. For daily characteristics of ETFs, we collect prices, NAVs, flows, shares and market value outstanding from Bloomberg.[9] For tests of daily flows, we join these daily data with measures of overlapping holdings.

Another important component of our analysis is the role of authorized participants (APs) as intermediaries between an ETF and its underlying holdings. To study the role of APs, we collect data from SEC Form N-CEN filings as of 2019.[10] These filings require each ETF to disclose, on an annual basis, the list of financial institutions that are registered APs with the fund. Then, for each AP, the fund's sponsor must report how much dollar volume the AP created and/or redeemed, even if the number is zero. We use this information to identify the active APs of each ETF, and to identify which ETFs have overlapping primary APs.

[See Figure 2]

We match the counterparty data for SMCCF purchases disclosed in the first SMCCF data release with AP data disclosed in the SEC Form N-CEN filings to examine how much of the SMCCF's purchases were from APs of the respective ETFs.[11] As Figure 2 shows, the vast majority

[9] Pan & Zeng (2020) attest that Bloomberg's daily ETF data is most accurate, particularly on shares outstanding, which is an important component of measuring ETF fund flows.
[10] The use of N-CEN filings is relatively novel (Arora et al. (2020)), and ours is the first to use N-CEN data to connect ETF markets to underlying asset markets through the APs.
[11] The SMCCF disclosures do not explicitly identify their counterparties on a trade-level granularity; rather, they aggregate across all SMCCF buying activity to list the total purchase volume from each counterparty (aggregated

of initial SMCCF ETF purchases were transacted with APs. It is important to highlight some notable omissions from the list of SMCCF counterparties: namely, the SMCCF did not purchase *any* ETFs from lead market makers (LMMs) or designated liquidity providers (DLPs).[12] The contrast between APs and LMMs/DLPs is important because it provides insight into how the SMCCF targeted its activity to optimize policy impact – and in turn, our analysis of SMCCF choices speaks to deeper, fundamental questions about the role of intermediaries that connect segmented markets.

[See Table 2]

For our intraday analysis of SMCCF purchases in Section 4.1, we use a three-way data panel based on the ETF, the Fed purchase event, and time interval levels. We construct the panel starting with pairwise combinations of each of the 571 matched purchase events and each of the 120 eligible corporate bond ETFs, which produces 68,520 event-ETF pairs.[13] Note that these combinations represent every eligible ETF at the purchase time of a particular ETF purchased by the SMCCF, across all purchases of all ETFs by the SMCCF—which is key to our identifying tests in Section 4. For every 15-second interval on the range of [*t*-15 minutes, *t*+15 minutes] around a matched purchase event at time *t*, we observe the NBBO of each ETF. This data is obtained for all intervals within the total 30-minute time period around each transaction, or 121 15-second intervals. Finally, we augment the 68,520 event-ETF pairs with the price data. That is, each

across all ETFs purchased from that counterparty). The first disclosure, released on May 28, 2020, contains purchases aggregated at the counterparty level across May 12, 13, 14, 15, and 18, 2020.

[12] LMMs and DLPs are market participants registered with NYSE Arca and Nasdaq, respectively, to provide intraday liquidity on the secondary trading market for particular tickers. The firms that are either LMMs or DLPs for the 16 Fed-traded ETFs are Jane Street, Susquehanna, and Virtu. Of these three secondary market makers, none is a primary AP for any of the Fed-purchased ETFs. Furthermore, only Virtu conducts any amount of creation/redemption activity in the 16 Fed ETFs, with a market share of less than 1% each in ANGL and USIG. It is also worth noting that the analysis of AP vs. LMM/DLP counterparties is derived directly from SMCCF & N-CEN disclosures for all SMCCF transactions and, thus, is not a result of the intraday trade-matching procedure.

[13] Note that in the intraday data, 5 of the 120 ETFs are not observed during our sample period (BSCU, BSJS, HYBB, HYXF, and VCEB).

observation of the panel contains the timestamp of the interval, the ticker that was purchased by the SMCCF, the ticker that is being observed, the NBBO of the ticker that is being observed, and the overlap between the holdings of the purchased ETF and those of the observed ETF. We use the NBBO to compute 15-second log returns of the midquote and 15-second changes in the bid-ask spread, i.e., the difference between the log bid and log ask. Summary statistics of the key variables for the intraday analysis (cosine similarity, returns, spread changes) are shown in Table 2. We use a similar (but not identical) approach for 'placebo' tests.[14]

3. Research Design

3.1. Authorized Participants and the Fed Purchases

Bond ETF authorized participants (APs) serve a multi-faceted role as financial intermediaries that engage in ETF arbitrage while serving as market makers in the underlying corporate bond markets.[15] They create and redeem ETF shares by purchasing a lower-priced underlying basket of bonds (or, alternatively, lower-priced ETF shares) to deliver to the ETF sponsor. In exchange, the APs receive higher-priced, newly created ETF shares (alternatively, the higher-priced basket of bonds), which can be sold or delivered to settle a prior short sale to close out the trade.[16]

Given that APs have contractual obligations to perform their market-making activities in the corporate bond markets, but not for their ETF arbitrage activities, APs may not necessarily

[14] See Section 4.2 for details on how we construct placebo tests.
[15] All primary APs that we identified for the sample of corporate bond ETFs used in the analysis also serve as primary bond dealers.
[16] Market regulations also allow APs to use shorting to satisfy excess demand in the secondary markets, where APs are allowed to sell ETF shares they have not yet created (Evans et al. (2021)). This mechanism, in principle, would allow SMCCF sellers to offload corporate bond inventories from their balance sheets by naked short selling ETF shares (that they do not own) to the SMCCF: the AP would use the in-kind creation window to deliver underlying bonds to the ETF sponsor and, in turn, use the newly created ETF shares to settle the ETF short sale.

provide liquidity in ETF markets even when doing so in the underlying corporate bond markets, particularly during stress periods. Considering the relative illiquidity of corporate bond markets, APs may choose to carry corporate bond inventories to avoid incurring high trading costs due to liquidity mismatch issues between the ETFs and their underlying bonds. APs may accumulate bond inventories during prolonged periods of stress conditions in corporate bond markets, though they may be constrained by inventory costs and ETF investor demand.[17]

[See Figure 3]

While we do not have information on AP-level inventories, we can indirectly infer their corporate bond inventories from public FR 2004 disclosures on aggregate primary dealer activities. Primary dealer inventories, which include those of large APs, rose dramatically following March 2020, as shown in Figure 3. Dealer inventories increased further during May 2020, before falling during June 2020. The aggregate inventory changes were driven primarily by investment grade bonds, though the pattern is similar for high-yield bonds. The relatively high inventories suggest that APs may have faced balance sheet constraints in the lead-up to the opening of the SMCCF.

We conjecture that the SMCCF purchases represented a significant, positive liquidity shock to AP balance sheets. As described in the next section, these ETF purchases were abnormally large. And, APs that carried large inventories of corporate bonds likely faced difficulty in reducing their exposure in a timely manner without incurring a significant price impact during the first months of the COVID crisis of 2020.

[17] Other studies provide supportive evidence. For example, using pre-pandemic data, Goldstein and Hotchkiss (2020) find that most dealer roundtrip trades are completed within the same day. However, the top corporate bond dealers are relatively more likely to take bonds into inventory for longer periods of time, and this effect is pronounced during stress periods. These dealers generally correspond with the largest APs for corporate bond ETFs.

Given the size of the corporate bond inventories held by these authorized participants, the Fed purchases likely afforded these APs an opportunity to dispose of them at a relatively lower price impact than would have been possible without such intervention – both at the end of the trading day, by delivering the bonds to the ETF sponsor, and during the trading day, because of the impact of the ETF purchase on bond market liquidity. APs would have been able to fulfill such large orders by exchanging their bond inventories with the fund sponsor to create new ETF shares. Accordingly, the Fed purchases likely enabled these AP sellers to substantially bolster their balance sheet capacities, enhancing their ability to provision liquidity in the corporate bond markets.

Using these events, we examine how these non-fundamental shocks to financial intermediary balance sheets propagate to ETF and corporate bond markets. Namely, our tests focus on the price and liquidity reactions of other corporate bond ETFs that were not purchased by the Fed, as well as bonds held by ETFs that had the same AP, but were not purchased by the Fed. By focusing on these other ETFs, we are able to study propagation effects associated with AP balance sheet frictions. The liquidity provided by the Fed purchases may have enabled these authorized participants to improve their market-making capacity associated with the underlying holdings of the ETFs that were purchased. Given that these ETFs had overlapping holdings with other ETFs not purchased by the Fed, we seek to determine whether there were spillovers to the other ETFs through their holdings; that is, the SMCCF transactions may have had "multiplier effects" through other ETFs and corporate bonds.

An important potential confounding factor to our analysis is that, once disclosed, the Fed purchases may have created informational spillovers related to the types of ETFs, and, in turn, corporate bonds, that the SMCCF would likely target. In particular, the Fed did not begin to purchase corporate bonds until well after it began purchasing ETFs. The underlying assets associated with the purchased ETFs may have informed sophisticated market participants on which corporate bonds were expected to be purchased when the SMCCF began their bond program. In other words, SMCCF purchases may have also represented a non-fundamental demand shock associated with the Fed's plan to support the corporate bond markets, hindering our ability to cleanly identify the supply effect. We discuss this challenge in the following section.

3.2. Identification Strategy

We start the analysis by examining the effects of overlapping holdings in ETFs not purchased by the Fed. Specifically, we construct a measure of overlapping holdings, or *ETFOverlap,* based on the cosine similarity between the Fed ETF and other ETFs using daily, security-level holdings. We choose to use the overall ETF portfolio rather than the creation and redemption securities basket primarily because the baskets are not fixed and may differ based on the AP.[18] For example, Cohen et al. (2021) show that securities used for creation purposes can vary broadly and are negotiated by individual APs with the ETF sponsor. Additionally, the baskets used for creation purposes differ in some cases from baskets used for redemptions.

For several reasons, we employ cosine similarity over other approaches. First, cosine similarity is simple and easy to interpret. The measure is bounded between zero and one, where higher values correspond with greater similarity. Second, cosine similarity has been extensively used in the existing literature as a measure of portfolio similarities such as mutual funds (Wermers, 1994), insurers (Girardi et al., 2021), hedge funds (Sias et al., 2016), endowments (Aragon et al., 2021), and so on. Third, cosine similarity allows us to capture the relative weighting of individual

[18] Thus, the overlap of securities actually traded is ex-ante probabilistic, rather than deterministic when baskets deviate from full ETF holdings.

securities of two portfolios, as opposed to schemes that focus only on the reference or target portfolio. Relatedly, because cosine similarity places more weight on holdings that comprise a larger portion of a fund's holdings, the use of cosine similarity diminishes the importance of any differences between a fund's holdings and its basket components, since the largest holdings are most likely to feature in the basket composition anyway. We also consider alternative approaches and find qualitatively similar results, suggesting that our findings are not sensitive to our choice of overlapping holdings measures.

Our analysis focuses on the price reaction of the ETF associated with the Fed purchase, henceforth, "Fed ETF." Our identification strategy helps us to isolate non-fundamental shocks associated with AP balance sheet frictions. We conduct tests using intraday data to study ETF price and liquidity effects within minutes of the Fed purchase, mitigating the influence of fundamental factors. Because the Fed purchases were negotiated directly with the AP sellers, other market participants were unlikely to have knowledge at the time of the purchase, limiting the influence of other non-fundamental factors associated with investor demand. As such, we focus on tight estimation windows centered around the time of the Fed purchase. Given that only the AP seller has knowledge about the purchase, the AP may be able to use the information to inform prices of other ETFs based on their holdings immediately after the transaction takes place.[19] Because of this, we expect the effects to hold for both other ETFs based on cross bond holdings.

We expect the source of pricing effects in the ETFs not associated with the Fed purchase, henceforth, "non-Fed ETFs," to directly correspond with appreciation in the underlying corporate bond holdings of the ETF purchased by the Fed through overlapping bond holdings. It is unclear, however, whether there might be any effect on the *liquidity* of non-Fed ETFs based on their overlap

[19] Madhavan, Laippily, and Sobczyk (2016) provide background information on intraday ETF pricing models and their implementation in practice.

in holdings with the Fed ETF. We may expect no association between *ETFOverlap* and ETF liquidity for multiple reasons. Foremost, APs have no contractual obligation to provide liquidity in either primary markets (daily creation and redemption of ETF shares with the fund sponsor) or secondary markets (intraday trading of ETF shares with other market participants). It is also worth noting that none of the secondary-market ETF market makers were included in the list of eligible sellers to the SMCCF.[20] Additionally, while it is conceivable that APs could step in to support ETFs when market makers cannot, it is unclear why it should correspond with the overlapping holdings measure.

To further drill down into the sources of the variation captured by the intraday ETF tests, we conduct additional tests on daily corporate bond yields. While our tests, thus far, have focused on the holdings of ETFs purchased by the Fed, these new tests focus on holdings of other ETFs that are also associated with the AP seller, and those that are not. Specifically, we examine whether corporate bond yields react differently based on holdings of the ETF purchased by the Fed, other ETFs not purchased by the Fed, but supported by the AP seller, and other ETFs supported by other APs, scaled by issue size. A positive and significant effect on bond yields associated with the holdings of other non-Fed-purchased ETFs with the same AP seller, controlling for the holdings of the Fed ETF holdings, would be consistent with the balance sheet channel. If the results are due to the informational spillover channel, we would expect the holdings of other ETFs unrelated to the AP seller to exhibit a similar price reaction.

We also address concerns that the AP seller may use information about a particular ETF purchase by the Fed to infer potential future corporate bond trades by the SMCCF. While it is

[20] By "secondary-market ETF market makers," we mean, specifically, the list of lead market makers (LMMs) for NYSE Arca-listed ETFs in our sample and designated liquidity providers (DLPs) for Nasdaq-listed ETFs in our sample. These lists are publicly available and include firms such as Jane Street, Susquehanna, and Virtu.

unlikely that APs would risk using such information to inform their trading strategies, given that it is explicitly prohibited,[21] it is still possible, given that violations are difficult to prove. We modify our tests to directly address this issue. Namely, we distinguish holdings by other ETFs of the AP seller based on whether they have low or high holdings overlap with the ETF purchased by the Fed. Larger effects for the holdings of the same-AP, high overlap ETFs would be consistent with an AP using information about the Fed transaction for trading purposes in the underlying bonds, while comparable effects between the holdings of the same-AP low and high overlap ETFs would be consistent with the balance sheet channel.

In our final set of tests, we examine APs' reactions to SMCCF purchases in their creation and redemption activities. As with our other tests, we focus on ETFs that were not purchased by the Fed. We adapt the methodology developed by Pan and Zeng (2020) to test whether the interaction between an ETF's NAV premium and the degree of its overlapping holdings with the Fed ETF is significantly associated with net creation activities. Higher NAV premiums may be associated with greater profitability in ETF arbitrage activities. ETFs associated with a higher degree of overlapping holdings are likely to have experienced greater improvements in liquidity in their underlying bond holdings liquidity due to the Fed purchase. As such, we expect the interaction the have a positive effect on net ETF creation activities.

3.3. Sample Construction and Model Specifications

For the intraday ETF tests, we utilize an event study design that allows us to compare the effects of overlapping holdings across ETFs for each Fed transaction. We begin the sample construction by identifying time stamps associated with each Fed transaction, then construct a

[21] See rules and policies governing participation in the SMCCF: https://www.newyorkfed.org/markets/primary-and-secondary-market-faq/corporate-credit-facility-faq.

panel of corporate bond ETFs, excluding the ETF purchased by the Fed, for the time period beginning 15 minutes prior to the transaction and concluding 15 minutes after the transaction. We populate the panel with ETF price quotes at 15-second increments. The resulting data structure is a three-dimensional panel formed on the ETF-, Fed transaction-, and time-levels.

For ETF *i*, Fed transaction *j,* and time *t*, our baseline regression model used for the intraday ETF tests is specified as follows:

$$R_{i,j,t} = \alpha \times ETFOverlap_{i,j} \times FedTrade_{j,t} + \boldsymbol{\tau_{i \times j}} + \boldsymbol{\tau_t} + \varepsilon_{i,j,t} \tag{1}$$

The dependent variable, $R_{i,j,t}$, is the 15-second return based on the difference in the natural log of the mid-price-quote for ETF i from time *t-1* to *t*. $ETFOverlap_{i,j}$ is the cosine similarity of ETF i's market valuation of holdings compared to those of the ETF involved in the Fed transaction, j, as of the end of the previous day. $FedTrade_{j,t}$ is a dummy taking value one if the Fed transaction occurred as of time *t*, and zero otherwise. The model also includes two-way interactive fixed effects for ETF i and Fed transaction event j, as well as date and time *t*. The inclusion of the fixed effects purges the effects of time-varying ETF characteristics as well as those of intraday changes in market and fundamental conditions. Given the transaction and time fixed effects, the non-interacted $ETFOverlap_{i,j}$ and $FedTrade_{j,t}$ terms are spanned by the interaction terms, and, so, are dropped when estimated. Also, we address potential cross-sectional dependence issues that are common to event studies by double-clustering the standard errors used to construct the test statistics on the Fed transaction-ETF- and Fed transaction-date-levels (Petersen (2009)).

Equation (1) describes a difference-in-differences estimator that exploits the ETF price reaction based on the degree of overlapping holdings with the ETF purchased by the Fed. A positive coefficient on the interaction term (i.e., $\alpha > 0$) indicates that the differential returns between ETFs with high and low underlying holdings overlap are larger following a particular Fed

[See Figure 4]

transaction. A significant challenge that has limited prior studies examining the effects of financial intermediary balance sheet frictions on fund performance is accounting for the influence of time-varying fund factors that can potentially bias results. For example, $ETFOverlap_{i,j}$ may be correlated with other fund factors related to trading strategies and risk exposures that may also affect fund performance. Our tests account for time-varying fund heterogeneity through the inclusion of Fed transaction event-ETF fixed effect, allowing us to cleanly identify estimates for $ETFOverlap_{i,j}$. Additionally, the Fed transaction event-time fixed effects mitigate the influence of any intraday market factors.

In addition to ETF returns, we also consider ETF liquidity. In those specifications, we replace the dependent variable in Equation (1) with the changes in the bid-offer spread over 15-second intervals, calculated as the first difference in the natural log of the ask price less the natural log of the bid price for ETF *i* from time *t-1* to *t*. The model specifications for these tests are otherwise identical.

4. Intraday Test Results

4.1. Intraday Effects of SMCCF Purchases

As documented in Section 2, we identify over half of the SMCCF's purchases of corporate bond ETFs on the intraday tape. This raises several questions about the intraday characteristics of SMCCF purchases and their effects on ETFs, where we focus the first part of our analysis. Figure 4 shows the intraday behavior of ETFs purchased by the SMCCF. The prices shown are averages across transactions, weighted by the size of each SMCCF purchase, and normalized such that the trade price paid by the SMCCF for the ETF is 100.

[See Figure 4]

In Figure 4, we see that the average bid, ask, and midquote prices of ETFs purchased by the SMCCF do not move substantially during the 15 minutes prior to the trade time. Then, after the SMCCF purchases an ETF (at event time t=0), the price of the ETF rises by more than one basis point over the post-trade 15 minutes.[22] The normalization of the trade price to $100.00 also indicates that SMCCF purchases, on average, are very close to the bid price, suggesting that the SMCCF was able to fill most of its purchases without crossing the spread. Equivalently, it shows that the Facility's counterparties were willing to pay the bid-ask spread to sell to the Facility, suggesting that those counterparties may have been constrained, and perceived SMCCF purchases as an opportunity to reduce balance sheet constraints (in return for a sale at the bid). From Figure 4, we can infer that SMCCF purchases were not anticipated by the market, supporting that they represent exogenous shocks.

Next, we formalize and extend our intraday analysis to examine the effects of SMCCF purchases on *other* corporate bond ETFs, as laid out in Section 3. In our least-restrictive specification (the left-most column of Table 3), we do not use any of the fixed effects shown in Eq. (1) of Section 3.3. In the next specification, we use interactive fixed effects between the ETF and the ETF associated with the Fed purchase, i.e., Observed ETF × Fed ETF. This controls for any time-invariant differences between ETF pairs.[23] In the third specification, we use two-way fixed effects associated with the ETF and the Fed purchase event, i.e., Observed ETF and Fed

[22] In unreported regression analysis, we find that the price increase is statistically significant at the 1% level.. We note, here, that all trades that we identify on the intraday tape were transacted off-exchange and reported to a FINRA trade reporting facility (TRF). The rules of the TRF require off-exchange trades to be reported within 10 seconds of execution; thus, these trades appeared on the public intraday tape nearly immediately.

[23] For example, these fixed effects would capture separately the time-invariant differences between the following three cases: Case 1: LQD is traded, and prices of JNK are observed. Case 2: LQD is traded, and prices of ANGL are observed. Case 3: ANGL is traded, and prices of LQD are observed. Also note that "Observed ETF" fixed effects and "Traded ETF" fixed effects are subsumed by these joint fixed effects.

Trade, respectively. This specification allows us to control for event-specific variation between SMCCF purchases, and for time-invariant variation between Observed ETFs.[24]

Our most stringent specification (right-most column) uses highly granular fixed effects to account for several potential sources of endogeneity. One is an interactive fixed effect associated with the ETF and the Fed purchase event, i.e., Observed ETF × Fed Trade, which subsumes all other fixed effects used in the first three specifications. Because each event contains information about a particular date, time, and purchased ETF, the Observed ETF × Fed Trade fixed effect captures information about ETF pairs that varies by event, which also subsumes the $ETFOverlap$ variable in the regression specification. However, these fixed effects do not capture information about ETF pairs that changes during the event (hence, why the interaction term survives). In addition to the Observed ETF × Fed Trade fixed effect, we also add a fixed effect associated with each time interval, i.e., Date × Time, which soaks up any variation in market-wide conditions that vary within the event time window, measured at each 15-second interval, averaged across all events for a particular date. Consequently, this set of fixed effects subsumes the $Trade$ variable, since it is effectively a market-wide data point at each time interval. With these fixed effects, we are able to focus on within-event, within-observed-ETF variation as prices change over the 30-minute event window.

[See Table 3]

Table 3, Panel (a) shows the results of this test, where $Y_{i,j,t}$ is log return over a 15-second interval during event window [t-15 to t+15] minutes, while Panel (b) shows the results of this test where $Y_{i,j,t}$ is changes in the log spread. Panel (a) of Table 3 shows that SMCCF purchases have

[24] Note that the event-level fixed effects will capture any variation in overall market conditions between trades, including two trades on different dates, two trades at different times on the same date, and two trades in the same traded ETF.

positive intraday price effects on other corporate bond ETFs with overlapping holdings. This result is not an artifact of the purchased ETF itself (since the panel for each purchase only includes ETFs $i \neq j$), and is robust to different specifications and different levels of granularity in the fixed effects used. This result suggests that the SMCCF's purchases of corporate bond ETFs had spillover effects to other ETFs not purchased by the Facility. This result is both statistically and economically significant: a one-standard-deviation increase in *ETFOverlap* is associated with a 16.6 to 17.3% higher annualized return.[25]

Panel (b) of Table 3 indicates that SMCCF purchases have no significant effect on the intraday liquidity of other corporate bond ETFs. This result may be surprising at first glance. However, given that the Fed did not target secondary-market ETF liquidity providers as SMCCF eligible sellers, it is not obvious that intraday ETF liquidity should be affected by the Fed's purchases. Plus, given that corporate bond ETFs usually exhibit higher intraday liquidity than the bonds they hold, it need not be the case that holdings liquidity should bind on ETF liquidity. Relatedly, APs may not even hold material inventories of bond ETFs on their balance sheet; hypothetically, the Fed could target APs with large inventories of the underlying bonds, and the APs could create new ETF shares with the underlying assets and deliver ETF shares to the Fed without ever holding the ETF. Appendix Table 1 shows that the results are qualitatively similar (for both Panels (a) and (b)) when using an alternative measure of overlapping holdings between ETFs that equal-weights holdings, suggesting that the results are not driven by the exact definition of overlap between ETFs.[26] By using this alternative measure of overlapping holdings as a robustness check, we address the potential concern that cosine similarity may be influenced by

[25] The annualized return is calculated by multiplying the standard deviation of *ETFOverlap* (0.198) by the regression coefficient on the interaction term (2.124-2.212 x 10^{-6}, across specifications) for 15-second log returns, and then multiplying by 4*60*6.5*252 (=393,120).
[26] The economic significance ranges from an annualized return of 15.7 to 16.0%.

day-to-day fluctuations in bond prices (which may perturb portfolio weights), and the related concern that illiquid corporate bonds are being marked-to-model, which could generate another source of noise in corporate bond ETFs' portfolio weights.

[See Table 4]

We next examine whether these findings persist over longer estimation windows in order to help assess temporal microstructure explanations. Panel (a) of Table 4 shows the results for a 30-minute post-trade window, while Panel (b) shows the results for a 60-minute post-trade window.[27] Both panels expand on the baseline setting of Table 3 by using two post-trade indicators (as opposed to one in Table 3), which allows us to capture any potential reversal effects that might occur in the window following the first 15 minutes post-trade. In both panels of Table 4, we see that the intraday price impact spillover effects are quantitatively similar to those shown in Table 3. Furthermore, we find no evidence for intraday reversals, suggesting that these spillover effects are not merely artifacts of microstructure noise.

[See Table 5]

Next, to examine the extent to which the effects documented in Table 3 might vary over the course of the SMCCF program, we split the sample into subperiods, then re-estimate the most stringent specification from Table 3 over each subperiod. The results are shown in Table 5. Panel (a) of Table 5 shows that the spillover price effects of SMCCF purchases are strongest during the first week of the Facility's operations, and that these effects rapidly diminish over time. These findings are consistent with the interpretation that prior to SMCCF purchases, the APs (the Facility's counterparties, by and large) experienced balance sheet constraints, and that the ETF purchase helped to alleviate these constraints. An alternative, not mutually exclusive

[27] For Panel (b), we remove Fed trades transacted after 3:00pm to avoid the undue influence of after-hours market prices on the results.

interpretation, is that the effects disappeared after the first disclosures on May 29 because the disclosures eliminated a lot of uncertainty about the nature of the Facility's purchases. However, the disclosure hypothesis cannot explain why the effects began to attenuate prior to the first disclosure. Panel (b) of Table 5 provides further evidence that the SMCCF did not have any significant intraday liquidity effects on other corporate bond ETFs.

4.2. Intraday Placebo Tests

One important possibility we address is whether these intraday spillover effects from SMCCF purchases are simply a 'large trade' effect. Most of the SMCCF transactions are quite large: the median dollar volume (share volume) among the transactions we are able to match to the intraday tape is $2.2 million (43 thousand shares). To test whether the SMCCF purchases are important in some way, above and beyond their typically large trade sizes, we compile a set of large trades not involving the SMCCF to examine as a 'placebo' test. To identify these placebo trades, we employ intraday transaction data for the 16 ETFs purchased by the SMCCF. First, we use data from the week of April 27 to May 1, 2020 to avoid the influence of announcement effects (and their prior leakage), given that it was the last week before the Federal Reserve Bank of New York (FRBNY) announced that the SMCCF would become operational. For each of the 16 ETFs, we calculate the 99.9th percentile of trade size (in dollars) for all trades between 9:45am and 3:45pm (to avoid market open and close effects). This results in 936 trades for the week of April 27 – May 1. Given that this week preceded the SMCCF trading period, we know that none of these trades are SMCCF transactions.

[See Figure 5]

[See Figure 6]

Keeping the same 99.9th percentile thresholds from the week of April 27, we repeat this exercise for the week of May 11-15, the first week that the SMCCF began its purchases. This results in 893 trades for the week of May 11-15. Determining which are SMCCF purchases requires a few steps. There are 132 SMCCF purchases during the May 12-15 period. Of these 132 purchases, we are able to identify 82 of them on the intraday tape (62%). Seventy-eight of these 82 purchases exceed the size threshold and appear in the sample of 893 large trades from May 11-15, so they are a definitive "Yes" (to the question, "Is this transaction an SMCCF purchase?").

For the remaining 815 trades, the goal is to identify as many trades as possible that cannot be SMCCF purchases, in order to compile a 'control' group of trades. There are 124 trades in the sample on Monday, May 11 (the day before the SMCCF began trading), so those trades are a definitive "No." For May 12-15, classifying trades as a definitive "No" is a function of the uncertainty around the SMCCF trades that cannot be identified on the tape. If, for a given date and ticker, there are no unmatched SMCCF trades, then we know that every other trade in the sample is a "No" for that date/ticker. Alternatively, if there are one or more unmatched trades in an ETF on a particular date, then we can only definitively mark other trades as a "No" if the share quantity exceeds the largest unmatched SMCCF trade for that date/ticker.

The result of this classification process is that for the 893 large trades from May 11-15, there are 78 known SMCCF trades, 271 known non-SMCCF trades, and 544 unclassifiable trades. Figure 5 shows the size and time distribution of the placebo trades, separately for the week of April 27 (Panel (a)) and the week of May 11 (Panel (b)). Figure 6 compares the trades from May 11-15 with the SMCCF trades from May 12-15 and the SMCCF trades from May 18 – July 23.

[See Table 6]

Once we compile the placebo large trades, this enables several tests. First, in Table 6, we repeat our analysis from Table 3, but using the set of placebo trades from April 27 – May 1, which are all non-SMCCF trades. Panel (a) of Table 6 shows that, across several specifications, the large placebo trades (in ETFs later traded by the SMCCF) had no intraday spillover price effects to other corporate bond ETFs. This table shows that the results we find on SMCCF trades were not just large trade effects. Additionally, Panel (b) of Table 6 shows that large placebo trades had no intraday liquidity effects. Appendix Table 2 shows that these conclusions hold when using the alternative measure of overlapping holdings.

[See Table 7]

However, to make a more direct comparison between SMCCF and non-SMCCF trades, we repeat this placebo exercise for the sample of large trades over the week of May 11-15. Table 7 is analogous to Panel (a) of Table 6, and shows that, without distinguishing SMCCF and non-SMCCF trades, the overall effect of large trades is insignificant during this period.[28] However, if the analysis is conditioned on trade classification, then the strong intraday spillover price effects of SMCCF purchases reappear, as was shown in Table 6. When removing these purchases from the sample, the results for known non-SMCCF trades exhibit a small but statistically significant negative price impact, consistent with more typical expectations for large block trades (Keim & Madhavan (1996)). For unclassifiable trades, the results are statistically insignificant. These results are shown in Table 8.[29]

[See Table 8]

[28] Liquidity effects are also insignificant (table not shown), consistent with other results in Panel (b) of Tables 3, 5, and 6. Appendix Table 3 provides similar results to Table 7 when using the alternative measure of overlapping holdings.

[29] The spillover effects of SMCCF trades are much stronger in magnitude than those of the non-SMCCF trades, and this result is consistent across both measures of overlapping holdings. However, the result on non-SMCCF trades is *not* robust to the alternative measure of overlapping holdings, as shown in Appendix Table 4, suggesting that it may be more noise than signal.

Tables 7 and 8 provide evidence that the results that we find on intraday spillover price effects from SMCCF purchases are not simply driven by large trade effects. Furthermore, Table 8 demonstrates that these results are not simply driven by market-wide date effects (e.g., the FRBNY announces the SMCCF and all corporate bond ETF transactions are positively affected). Instead, these findings are consistent with the interpretation that the Fed's purchases of corporate bond ETFs provided relief to balance sheet constraints faced by APs prior to the SMCCF intervention.

5. Daily Bond-Level Tests

A crucial part of our analysis on intermediaries in segmented asset markets, naturally, is to examine spillover effects from one market to another market that is connected by these intermediaries. In this particular setting, we examine the effects of SMCCF trades on the underlying corporate bond market. In our baseline tests, we examine the direct effects by estimating bond price reactions to the Fed purchases on bonds held by the Fed ETFs. We next build on those tests to examine the indirect effects associated with the intermediary balance channel, namely focusing on holdings of other ETFs that are also associated with the seller AP.

Given that reliable intraday bond quote data is unavailable, we collect daily data from several sources to compile a rich view of the relation between ETFs, APs, and bonds. For any given day, we observe which ETFs hold certain quantities of corporate bonds and how ETF holdings of corporate bonds change from day to day. We use this information to study bond price reactions on the day of the Fed purchase.[30]

[30] We restrict our analysis to same-day price reactions for at least two reasons. First, because of rapidly changing market and fundamental conditions associated with the sample period, there may be other factors that could confound detection of longer-term effects. Second, many of the SMCCF ETF purchases were clustered within a short period of time. Because the holdings of the purchased ETFs effectively span the entire U.S. corporate bond market, the key explanatory variables in our analysis are unlikely to have sufficient variation when broadening the analysis window, limiting the power of the tests.

Our baseline tests are based on the following regression model:

$$\ln(1 + OAS)_{i,t} = \beta_1 \%FedETF_{i,t-1} + \Phi_{i,t} + \varepsilon_{i,t} \quad (2)$$

The dependent variable, or $\ln(1 + OAS)_{i,t}$, is the natural log of one plus the end-of-day option-adjusted spread based on ICE BAML quote data for bond *i* on date *t*. $\%FedETF_{i,t-1}$ is defined as the percent of the market value of the bond held by the ETF purchased by the SMCCF on date *t*, based on the most recent information available, as of date *t-1*. On other dates (when a Fed trade did not take place), the measure takes value zero. Given that the holdings of ETFs purchased by the SMCCF as a whole generally span the corporate bond markets, alternative approaches that rely on indicator variables to denote the treatment are unlikely to provide sufficient variation to detect any effects. Finally, we include two-way fixed effects on the issuer-date and issue levels to mitigate the influence of time-varying issuer and time-invariant issue heterogeneity.

The baseline model is augmented to directly investigate the intermediary balance sheet channel. For these tests, we are interested in capturing how the Fed trade responses in the underlying bonds vary by AP commonality. Specifically the baseline tests are modified to examine the effects of bond ownership associated with other ETFs not traded by the Fed, but covered by the same AP that sells to the Fed. Corporate bond ETFs are classified as either high or low overlap based on how much the overall holdings of the ETF overlap with the holdings of ETFs traded by the SMCCF.[31] Additionally, corporate bond ETFs are classified as having the same primary AP as the ETF traded by the SMCCF, or having a different primary AP as the ETF traded by the SMCCF. Thus, we break %ETF into different subgroups: $\%ETF_{i,t-1}^{HighOverlap}$, $\%ETF_{i,t-1}^{LowOverlap}$, $\%ETF_{i,t-1}^{HighOverlap,SameAP}$, $\%ETF_{i,t-1}^{HighOverlap,OtherAP}$, $\%ETF_{i,t-1}^{LowOverlap,SameAP}$, and

[31] Naturally, ETFs that are directly traded by the SMCCF count as *HighOverlap* in this setting.

$\%ETF_{i,t-1}^{LowOverlap,OtherAP}$. $\%ETF_{i,t-1}^{Fed}$ We use two granular sets of fixed effects: Issuer × Date fixed effects, which allow us to interpret results both within-issuer and within-date, and also bond issue fixed effects, which control for any time-invariant variation between specific bond issues.

5.1. Baseline Results

[See Table 9]

Table 9 shows that bond ownership associated with the holdings of the ETF traded by the Fed has a significantly negative association with corporate bond yield spreads (a positive association with corporate bond prices).[32] That is, on days when the Fed trades occurred, bond yield spreads decline for the holdings of the ETF traded by the Fed. These results suggest that the price reactions to the Fed trades are linked to changes in prices in the underlying holdings of the ETF.

We next consider heterogeneity in the corporate bond price reactions and to what extent these price reactions reflect information about the SMCCF corporate bond purchase program. Namely, we check whether the results are driven by bond characteristics associated with eligibility in the SMCCF corporate bond program. Towards this end, we use alternative specifications to Equation (2) to consider how the effects differ based on the set of bonds that were not expected to be directly purchased by the SMCCF when the facility began to purchase corporate bonds.

The Fed provided information on corporate bond eligibility prior to the SMCCF, though an ETF's composition of ineligible bonds did not preclude an ETF's eligibility for the SMCCF. However, APs may have taken into consideration bond eligibility in their responses to the SMCCF

[32] Inclusion of fixed effects significantly attenuate the point estimates, as expected, though these point estimates remain negative and statistically significant.

ETF purchases. *NotCovered* is a dummy associated with corporate bonds that were rated as high-yield, or had remaining maturities in excess of five years. In these tests, we consider whether the results remain after inclusion of the *NotCovered* variables along with its interaction with *%FedETF*. We also consider whether ETF ownership irrespective of the holdings of the ETF traded by the Fed has a similar effect. For those specifications, we also include *%AllETF*, defined as the percentage of the market value of the bond held by all ETFs, as well as its interaction with *NotCovered*. Columns (3) and (4) display the results. Across both specifications, the *%FedETF* coefficient remains negative and statistically significant, and is relatively larger in absolute magnitude, compared to that of Column (2). The interaction term between *%FedETF* and *NotCovered* is positive and statistically significant, indicating that the effects are muted for high yield bonds and bonds with long maturities. However, the sum of the coefficients remains negative, and is statistically significant at the 1% level. Finally, the effect of *%AllETF* and its interaction term are both statistically insignificant, indicating that the effects are not more generally driven by ETF bond ownership. These results suggest that the corporate bond price reactions were pervasive, though stronger for bonds eligible for the SMCCF bond purchase program.

[See Table 10]

We next examine the effects on bond illiquidity. The dependent variable in Equation (2) is exchanged for three common measures of bond illiquidity: daily bond turnover (*Turnover*), effective bid-ask spreads (*Bid-Ask*), and the Amihud (2002) measure of bond illiquidity (*Amihud*) based on the theoretical model of Kyle (1985). Table 10 displays the results. We use the same specifications as in Columns (3) and (4) from Table 9 for all of the measures. Across all the specifications, we find consistent evidence that *%FedETF* has a positive effect on bond liquidity.

These results suggest that the corporate bond price reactions, as well as those for the intraday ETF prices, are related, to some degree, to changes in liquidity of the underlying bond holdings.

5.2. Common AP Results

[See Table 11]

Table 11 shows the bond price reaction, measured as the natural log of one plus the daily option-adjusted bond spread for bond i on date t $\left(ln(1 + OAS)_{i,t}\right)$, as a function of ETF ownership of bond i on date t-1. Across the different specifications, we break ETF ownership into the different subgroups mentioned above. In columns (1) and (2), we compare the bond price levels in bonds with higher ownership by high-overlap ETFs (1) and bond price levels in bonds that that have higher ownership by low-overlap ETFs (2). These results show that bonds with higher ownership by high-overlap ETFs have lower yield spreads (higher prices), and that this effect is roughly 10 times the magnitude for high-overlap ETF ownership, compared to low-overlap ETF ownership.

In columns (3) through (6), we further divide the ETF ownership by level of holdings overlap and AP commonality. The coefficients on $\%ETF_{i,t-1}^{HighOverlap,SameAP}$ and $\%ETF_{i,t-1}^{HighOverlap,OtherAP}$, across columns (3), (5), and (6), suggest that the price effect on underlying bonds for high-overlap ETFs is actually driven by having a common primary AP as an SMCCF-traded ETF. In other words, if bond *i* has a high degree of ownership by ETFs that have substantial holdings overlap with SMCCF-traded ETFs, and those same ETFs also have a common AP with SMCCF-purchased ETFs, then bond *i* has a lower yield spread on the day of the SMCCF purchase. However, if bond i has a high degree of ownership by high-overlap ETFs, but those ETFs do *not* have a common AP with SMCCF-traded ETFs, then the positive price effect of the holdings overlap disappears. This result provides evidence in favor of our interpretation that APs' balance sheets were constrained, and that the SMCCF trades of corporate bond ETFs provided relief to these APs' balance sheets, and in turn, that this relief was transmitted to the bond market as improved intermediation capacity for bonds supported by the APs. Additionally, these results suggest that a pure holdings-based spillover channel is not sufficient to explain the shock propagation we document, because holdings alone should produce a significantly negative coefficient on $\%ETF_{i,t-1}^{HighOverlap,OtherAP}$.

The results on $\%ETF_{i,t-1}^{LowOverlap,SameAP}$ and $\%ETF_{i,t-1}^{LowOverlap,OtherAP}$ are even more notable, and help to distinguish further between the holdings-overlap channel and the common-AP channel. In columns (4), (5), and (6), we find a significant negative coefficient on $\%ETF_{i,t-1}^{LowOverlap,SameAP}$, equivalent in magnitude to the coefficient on $\%ETF_{i,t-1}^{HighOverlap,SameAP}$. Concretely, this finding means that for a bond that is owned by low-holdings-overlap ETFs with a common AP as an SMCCF-traded ETF, the decrease in yield spread is nearly equivalent to the decrease for a bond owned by high-holdings-overlap ETFs with a common AP as an SMCCF-traded ETF.

To be clear, this finding is not consistent with a holdings-based shock propagation story alone, but instead is highly suggestive of the importance of APs as intermediaries in segmented markets. As AP constraints are relaxed by SMCCF trades of corporate bond ETFs, balance sheet space is freed up, allowing for more intermediation capacity across all bonds that the AP supports, regardless of whether they overlap with the holdings of SMCCF-traded ETFs or not.

6. Daily ETF Flow Test Results

To take our analysis one step further, we examine whether SMCCF purchases are associated with higher net inflows to corporate bond ETFs. This question is important, because it examines the most irreplaceable feature of APs; namely, their unique ability to create or redeem ETF shares in the primary market. Other firms do not have to be an AP to trade corporate bonds in the secondary bond market or to trade corporate bond ETFs in the secondary ETF market. However, only APs have the right (without obligation) to exchange large baskets of corporate bonds for ETF shares. Furthermore, it is the primary creation/redemption market where APs provide the most direct connection between the two secondary markets. Thus, our study of intermediaries in connected markets is incomplete without examining daily net flows to corporate bond ETFs.

We set up this analysis as a two-dimensional daily panel, where each observation is at the ETF-day level. For each observation, we compute $NAV\ Prem_{i,t}$, which is the premium, measured in basis points, of the closing price of ETF *i* on date *t* over the NAV of ETF i on date *t*. Thus, when the ETF price is higher than the NAV, then $NAV\ Prem_{i,t} > 0$. Conceptually, the $NAV\ Prem_{i,t}$ represents an arbitrage opportunity for APs: when the price is higher than the NAV, the AP should be able to earn a profit by buying low (the underlying bonds, usually) and selling high (selling or short selling the ETF, usually). However, if APs are constrained, they may not have sufficient balance sheet capacity to exploit these arbitrage opportunities. Thus, we measure $AvgOverlap_{i,t}$ for each ETF, i, on each date, *t*, as the weighted average portfolio holdings overlap between ETF i and the SMCCF-purchased ETFs on date *t*. Consistent with our intraday approach, we exclude the Fed-purchased ETF in order to focus our results on the spillover effects to other ETFs. Lastly, the dependent variable, $Net\ Flows_{i,t}$, is measured in basis points as the dollar value of net inflows to ETF i on date *t*, divided by the market capitalization of ETF i on date *t*. We also include date fixed effects and ETF fixed effects in our approach. We estimate the following specification:

$$Net\ Flows_{i,t} = \gamma_1 \times NAV\ Prem_{i,t-1} + \gamma_2 \times AvgOverlap_{i,t-1} \tag{3}$$
$$+ \gamma_3 \times NAV\ Prem_{i,t-1} \times AvgOverlap_{i,t-1} + \boldsymbol{\Phi_{i,t-1}} + \xi_{i,t-1}$$

In our estimation procedure, we use Driscoll-Kraay (1998) standard errors that are robust to date clustering, ETF clustering, and common correlated disturbances across date and ETF clusters.[33] Table 12 shows the results for this test.

[See Table 12]

Across all specifications in Table 12, the coefficient on the interaction term, γ_3, is positive and significant. This result is suggests that the improvements in AP balance sheet liquidity improved intermediation capacity, allowing APs to better capture arbitrage opportunities involving price dislocations between corporate bond ETFs and their underlying holdings. As shown in Table 12, this result is robust when expanding the sample period to include a longer estimation window.

As a robustness check, we repeat the analysis of daily ETF net flows using a three-dimensional daily panel, where each observation is at the ETF-purchased ETF-day level. The variables are defined similarly, except for the overlap measure, referred to in these tests as $Overlap_{i,j,t}$, which is defined as the bilateral cosine similarity between the holdings of ETF i (observed) and ETF j (purchased) on date t, just as in Tables 3-8. The results of this robustness check are shown in Appendix Table 5. This robustness check demonstrates that the results in Table 12 are not driven by the aggregation of measures of overlapping holdings between more than two ETFs. The three-dimensional setting provides further evidence supporting a positive interaction between the NAV premium and overlapping holdings with ETFs purchased by the SMCCF.

[33] This procedure requires the econometrician to choose a bandwidth for estimating autocovariances in the Bartlett kernel, and we follow the commonly used Newey and West (1994) rule that $bandwidth = m + 1$, where $m = floor\left(4(T/100)^{2/9}\right)$ and T is the number of days in the panel. Thus, in the long panel where $T = 145$, bandwidth = 5, and in the subsample where $T = 51$, bandwidth = 4.

7. Conclusion

This paper examines the effects of financial intermediaries' balance sheet frictions, and how they can propagate through connected asset markets. We do so by examining a quasi-natural experiment where APs experienced sizable, positive balance sheet liquidity shocks, and examine its effects on the ETF markets, corporate bond markets, and ETF arbitrage activities. We document four key findings: One, that SMCCF purchases of certain corporate bond ETFs generated intraday spillover price effects on a relatively short horizon (within 15 minutes) to other corporate bond ETFs with overlapping holdings. Two, that these intraday spillover effects are not simply an artifact of large trade size nor of market-wide improvement over time. Three, that corporate bonds with more exposure to the APs of SMCCF-purchased ETFs experienced exhibited lower yield spreads (higher prices), regardless of the degree of holdings overlap between ETFs. And four, that ETFs with greater overlap with SMCCF-purchased ETFs experience higher net inflows the day after closing at a price premium to NAV.

Our findings demonstrate how positive inventory shocks to a small number of intermediaries in a concentrated market (the corporate bond ETF market) can spread broadly and quickly to many other funds in the corporate bond ETF market, and furthermore to another asset market (corporate bond market) connected through these intermediaries. To our knowledge, this is the first study that provides evidence for the propagation of shocks on large intermediaries across multiple asset markets, providing evidence of systemic effects. The paper also provides evidence on the effectiveness of the SMCCF, and how the facility helped ameliorate balance sheet stress of those intermediaries and had impact beyond only the ETFs that it targeted.

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Tables and Figures

Table 1: Summary of SMCCF ETF Purchases

This table summarizes the Fed's purchases of ETFs through the SMCCF, spanning the period May 12 – July 23, 2020. For each of the 16 ETFs purchased by the SMCCF, this table provides the following information: the ticker of the ETF (Ticker), the total number of purchases made by the SMCCF in that ETF (Total Trades), the number of purchases in an ETF that we are able to identify on the intraday tape (Matched Trades), the average size of an SMCCF purchase in that ETF, in millions of dollars (Avg. Trade Size – Total), and the average size of an SMCCF purchase in that ETF, in millions of dollars, restricted to the subsample of purchases that we are able to match to the intraday tape (Avg. Trade Size – Matched). The last two columns summarize the market conditions at the time of the purchase, averaged over all of the purchases in an ETF that we are able to match to the intraday tape: the size of the prevailing bid-ask spread, scaled to the midquote price, in basis points (Avg. Spread), and the placement of the SMCCF purchase price relative to the prevailing midquote price – a negative number means that the purchase occurred below the midquote – scaled to the midquote price, in basis points (Avg. Placement). All averages are equal-weighted within each ETF.

Ticker	Total Trades	Matched Trades	Avg. Trade Size ($M, Total)	Avg. Trade Size ($M, Matched)	Avg. Spread (bps)	Avg. Placement (bps)
ANGL	39	35	0.81	0.86	8.43	-1.31
HYG	49	27	6.42	4.77	1.22	-0.47
HYLB	47	41	1.63	1.55	2.39	-0.93
IGIB	71	50	6.73	5.01	2.32	-0.99
IGSB	81	49	8.33	5.62	1.84	-0.85
JNK	58	19	9.20	7.07	0.99	-0.70
LQD	65	18	36.14	17.28	0.77	-0.50
SHYG	49	40	0.59	0.53	2.33	-1.45
SJNK	18	17	1.72	1.74	3.93	-2.43
SLQD	28	15	1.55	1.31	3.88	-1.42
SPIB	81	53	5.84	5.25	2.88	-1.33
SPSB	79	53	3.53	2.88	3.20	-1.54
USHY	51	44	1.16	1.13	4.09	-1.76
USIG	77	51	2.30	1.56	3.42	-1.05
VCIT	56	16	24.82	14.85	1.08	-0.40
VCSH	77	43	19.40	9.55	1.22	-0.67

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Table 2: Summary Statistics for Intraday ETF Analysis

There are three key variables we need to define for the intraday ETF analysis. One dependent variable variable is the 15-second change in the natural log of the midquote, or *Δlog(midquote)*. The midquote is measured as the average of the prevailing national best bid and ask at time *t* (sourced from Maystreet) for ETF *i* during an observation window for an SMCCF purchase of ETF *j*. At each point in time in our observation window (every 15 seconds, from 15 minutes prior to the trade to 15 minutes post-trade, with purchase time set to *t*=0), we calculate the natural log of the midquote. Then, for each time interval *t*, we measure the change in the natural log of the midquote from *t*-1 to *t*. Another dependent variable is the 15-second change in the log spread, or *Δ(log(ask)-log(bid))*. The log spread is defined (at time *t* for ETF *i* during an observation window for an SMCCF purchase of ETF *j*) as the difference between the natural log of national best ask price (*log(ask)*) and the natural log of the national best bid price (*log(bid)*). Then, for each time interval *t*, we measure the change in the log spread from *t*-1 to *t*. A primary explanatory variable is *ETFOverlap*. $ETFOverlap_{i,j,t}$ measures the degree of overlap in the holdings of ETF i (the ETF whose prices we are observing) compared to those of ETF j (the ETF that is purchased by the SMCCF), as defined by the cosine similarity between their holdings. This measure is naturally scaled from 0 (no overlap) to 1 (perfect overlap). Statistics shown for *Δlog(midquote)* and *Δ(log(ask)-log(bid))* are multiplied by 10^6 for readability. Statistics shown for *ETFOverlap* are reported in the original scaling.

Variable	Min	1Q	Median	Mean	3Q	Max	SD
Δlog(midquote)	-3755.23	0.00	0.00	0.11	0.00	3638.16	124.35
Δ(log(ask)-log(bid))	-7296.44	0.00	0.00	-0.62	0.00	7062.52	207.71
ETFOverlap	0.00	0.00	0.00	0.12	0.19	1	0.20

Return to text.

Table 3: Baseline Regression Results for Intraday ETF Reactions

In Panel (a), the dependent variable is the 15-second change in the natural log of the midquote, or *Δlog(midquote)*, as defined in Table 2. In Panel (b), the dependent variable is the 15-second change in the log spread, or *Δ(log(ask)-log(bid))*, as defined in Table 2. In both panels, the two main explanatory variables are $ETFOverlap_{i,j,t}$ and $Trade_t$. $ETFOverlap_{i,j,t}$ is defined as in Table 2. $Trade_t$ is a binary indicator variable that equals one at time t ≥ 0, and zero, otherwise. In all specifications, the set of observed ETFs included in the sample excludes the ETF that is directly purchased by the SMCCF. The sample date range is May 12 – July 23, 2020. For each specification, we observe prices every 15 seconds on the observation window $[t-15, t+15]$ where t is measured in minutes relative to the time of the SMCCF purchase, denoted t = 0. In the least-restrictive specification (left-most column), we use no fixed effects. In the next specification, we use Observed ETF × Fed ETF fixed effects, which controls for any time-invariant differences between ETF pairs. In the third specification, we use Event fixed effects and Observed ETF fixed effects. In the most-restrictive specification (right-most column), we use Observed ETF × Fed Trade fixed effects and Date × Time Interval fixed effects. Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

Panel (a): Intraday ETF Price Reaction

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δlog(midquote)*			
ETFOverlap × Trade	2.124** (0.852)	2.124** (0.852)	2.124** (0.849)	2.212*** (0.841)
ETFOverlap	-1.942*** (0.614)	-1.521 (1.149)	-2.199*** (0.634)	
Trade	-1.039*** (0.243)	-1.039*** (0.243)	-1.039*** (0.218)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	7,669,440	7,669,440	7,669,440	7,669,440
R^2	0.0000	0.0002	0.0019	0.0101

Panel (b): Intraday ETF Liquidity Reaction

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δ(log(ask)-log(bid))*			
ETFOverlap × Trade	-0.422 (0.447)	-0.422 (0.447)	-0.422 (0.447)	-0.426 (0.452)
ETFOverlap	0.223 (0.285)	-0.136 (0.786)	-0.247 (0.295)	
Trade	0.390*** (0.137)	0.390*** (0.137)	0.390*** (0.136)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	7,669,440	7,669,440	7,669,440	7,669,440
R^2	0.0000	0.0001	0.0000	0.0025

Return to text.

Table 4: Intraday ETF Price Reaction, Extended Post-Trade Estimation Windows

The set-up and variable definitions in Table 4 are identical to those in Tables 2 and 3, except as follows: In Panel (a), $Trade_{0\text{-}30}$ is a binary indicator variable equal to one for all $t \geq 0$; zero otherwise. $Trade_{15\text{-}30}$ is a binary indicator variable equal to one for all $t > 15$; zero otherwise. The observation window for Panel (a) is $[t-15, t+30]$. In Panel (b), $Trade_{0\text{-}60}$ is a binary indicator variable equal to one for all $t \geq 0$; zero otherwise. $Trade_{15\text{-}60}$ is a binary indicator variable equal to one for all $t > 15$; zero otherwise. The observation window for Panel (b) is $[t-15, t+60]$. For Panel (b), we drop SMCCF purchases that transact after 3:00pm to avoid the influence of after-hours markets on the results. Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

Panel (a): 30-Minute Post-Trade Estimation Window

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δlog(midquote)*			
ETFOverlap × $Trade_{0\text{-}30}$	2.129** (0.851)	2.129** (0.851)	2.129** (0.850)	2.215** (0.860)
ETFOverlap × $Trade_{15\text{-}30}$	1.904 (1.348)	1.911 (1.351)	1.941 (1.351)	1.848 (1.430)
ETFOverlap	-1.940*** (0.614)	-3.137*** (0.915)	-2.245*** (0.663)	
$Trade_{0\text{-}30}$	-1.038*** (0.243)	-1.038*** (0.243)	-1.038*** (0.224)	
$Trade_{15\text{-}30}$	-1.347*** (0.453)	-1.348*** (0.455)	-1.380*** (0.472)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	11,483,630	11,483,630	11,483,630	11,483,630
R^2	0.0000	0.0001	0.0002	0.0048

Panel (b): 60-Minute Post-Trade Estimation Window

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δlog(midquote)*			
ETFOverlap × $Trade_{0\text{-}60}$	1.966** (0.884)	1.966** (0.884)	1.966** (0.882)	2.097** (0.873)
ETFOverlap × $Trade_{15\text{-}60}$	0.239 (0.732)	0.239 (0.731)	0.239 (0.730)	0.119 (0.717)
ETFOverlap	-1.771*** (0.639)	-2.202** (0.862)	-1.687*** (0.645)	
$Trade_{0\text{-}60}$	-0.907*** (0.253)	-0.907*** (0.253)	-0.907*** (0.24)	
$Trade_{15\text{-}60}$	0.097 (0.208)	0.097 (0.208)	0.097 (0.200)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	17,735,700	17,735,700	17,735,700	17,735,700
R^2	0.0000	0.0001	0.0007	0.0085

Return to text.

Table 5: Intraday ETF Reactions by Date Range

Table 5 takes the most stringent specification from Table 3 (right-most column), with the same data and variable definitions, and repeats it in subsamples of the data, divided by different date ranges, as shown in each specification of each panel. As before, in all specifications, the set of observed ETFs included in the sample excludes the ETF that is directly purchased by the SMCCF. Refer to the caption on Tables 2 and 3 for more details. Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

Panel (a): Intraday ETF Price Reaction

	(1)	(2)	(3)
Dependent Variable:	*Δlog(midquote)*		
ETFOverlap × Trade	8.398*** (2.232)	3.855*** (1.270)	0.522 (1.096)
Dates	May 12-15	May 18-29	June 1 – July 23
Fed Trade × Observed ETF FEs	YES	YES	YES
Date × Time Interval FEs	YES	YES	YES
N	1,092,240	1,545,120	5,032,080
R^2	0.0076	0.0075	0.0111

Panel (b): Intraday ETF Liquidity Reaction

	(1)	(2)	(3)
Dependent Variable:	*Δ(log(ask)-log(bid))*		
ETFOverlap × Trade	-0.633 (1.203)	0.078 (0.803)	-0.519 (0.580)
Dates	May 12-15	May 18-29	June 1 – July 23
Fed Trade × Observed ETF FEs	YES	YES	YES
Date × Time Interval FEs	YES	YES	YES
N	1,092,240	1,545,120	5,032,080
R^2	0.0022	0.0030	0.0025

Return to text.

Table 6: Intraday ETF Reactions for Placebo Trades, April 27 – May 1

Table 6 takes Table 3, with the same variable definitions, and repeats it using the sample of placebo trades from April 27 – May 1, 2020. Placebo trades were identified by the following procedure: For each ETF ticker purchased by the SMCCF from May 12 – July 23, we looked at all trades between 9:45am and 3:45pm in those tickers for the week of April 27 – May 1 and selected all trades above the 99.9th percentile (by within-ticker trade size in dollars). Those trades comprise the sample for Table 6, and as in Table 3, in all specifications, the set of observed ETFs included in the sample excludes the ETF that is traded. Refer to the caption on Table 3 for more details. Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

Panel (a): Intraday ETF Price Reaction

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δlog(midquote)*			
ETFOverlap × Trade	0.236 (1.351)	0.236 (1.348)	0.236 (1.350)	0.153 (1.379)
ETFOverlap	0.374 (1.237)	-4.497 (8.732)	1.843 (1.121)	
Trade	1.957** (0.965)	1.957** (0.965)	1.957** (0.956)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	12,242,880	12,242,880	12,242,880	12,242,880
R^2	0.0000	0.0005	0.0003	0.0089

Panel (b): Intraday ETF Liquidity Reaction

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δ(log(ask)-log(bid))*			
ETFOverlap × Trade	-2.390 (4.082)	-2.390 (4.082)	-2.390 (4.080)	-2.636 (4.128)
ETFOverlap	2.384 (3.929)	30.245 (30.628)	2.159 (2.379)	
Trade	6.208** (2.778)	6.208** (2.771)	6.208** (2.740)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	12,242,880	12,242,880	12,242,880	12,242,880
R^2	0.0000	0.0006	0.0007	0.0102

Return to text.

Table 7: Intraday ETF Price Reaction for Placebo Trades, May 11-15

Table 7 takes Panel (a) of Table 6, with the same data and variable definitions, and repeats it using the sample of placebo trades from May 11-15, 2020. The procedure for identifying placebo trades during the week of May 11-15 is identical to that for the week of April 27 – May 1, with one exception: the 99.9th percentile trade size cutoffs are taken from the week of April 27 – May 1, in order to avoid any confounding effects from the trade size distribution changing over the different weeks. Refer to the captions on Tables 3 and 6 for more details. Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δlog(midquote)*			
ETFOverlap × Trade	1.239 (0.926)	1.239 (0.921)	1.239 (0.921)	1.236 (0.892)
ETFOverlap	-1.631** (0.669)	11.995** (5.187)	-1.273* (0.685)	
Trade	0.404* (0.224)	0.404* (0.223)	0.404* (0.215)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	11,865,000	11,865,000	11,865,000	11,865,000
R^2	0.0000	0.0003	0.0009	0.0070

Return to text.

Table 8: Intraday ETF Price Reaction for Placebo Trades, May 11-15, by Fed Trade Status

Table 8 takes the most stringent specification (right-most column) of Table 7, with the same data and variable definitions, and repeats it by splitting the sample into three subsamples: trades that are known to be SMCCF purchases (Fed Trades = "Yes"), trades that are known not to be SMCCF trades (Fed Trades = "No"), and trades that cannot be assigned a definitive label (Fed Trades = "Unsure"). Refer to the captions on Tables 3 and 7 for more details. Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

	(1)	(2)	(3)
Dependent Variable:		*Δlog(midquote)*	
ETFOverlap × Trade	7.989*** (2.279)	-1.984* (1.138)	1.696 (1.260)
Fed Trades	Yes	No	Unsure
Fed Trade × Observed ETF FEs	YES	YES	YES
Date × Time Interval FEs	YES	YES	YES
N	1,038,960	3,579,960	7,246,080
R^2	0.0079	0.0079	0.0066

Return to text.

Table 9: ETF Bond Ownership and Corporate Bond Yields

The table displays the results of regression models where the dependent variable is the natural log of one plus the daily option-adjusted bond spread, or *ln(1+OAS)*, for bond *i* on date *t*. $\%FedETF_{i,t-1}$ is defined as the percent of the market value of the bond held by the ETF purchased by Fed on date *t* based on the most recent information available as of date *t-1*. On other dates when a Fed purchase did not take place, the measure takes value zero. *NotCovered* is a dummy associated with corporate bonds that were rated as high-yield or had remaining maturities in excess of five years. *%AllETF* is defined as the percentage of the market value of the bond held by all ETFs on date *t*. Standard errors are reported in parentheses and are double-clustered on the bond issue and date levels. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	$ln(1+OAS)_t$			
$\%FedETF_{t-1}$	-0.195***	-0.034***	-0.062***	-0.063***
	(0.034)	(0.007)	(0.010)	(0.010)
$NotCovered_{t-1}$			-0.001***	-0.001**
			(0.000)	(0.001)
$\%FedETF \times NotCovered_{t-1}$			0.052***	0.051***
			(0.008)	(0.008)
$\%AllETF_{t-1}$				-0.002
				(0.015)
$\%AllETF_{t-1} \times NotCovered_{t-1}$				0.012
				(0.017)
Bond FE	YES	YES	YES	YES
Issuer × Date FE	NO	YES	YES	YES
N	1,049,065	847,452	847,452	847,452
R^2	0.956	0.993	0.993	0.993

Return to text.

Table 10: ETF Bond Ownership and Corporate Bond Illiquidity

The table displays the results of regression models where the dependent variables are different measures of bond liquidity. These three measures are daily bond turnover (*Turnover*), effective bid-ask spreads (*Bid-Ask*), and the Amihud measure of bond illiquidity (*Amihud*) from Amihud (2002) based on the theoretical model of Kyle (1985). $\%FedETF_{i,t-1}$ is defined as the percent of the market value of the bond held by the ETF purchased by Fed on date *t* based on the most recent information available as of date *t-1*. On other dates when a Fed purchase did not take place, the measure takes value zero. *NotCovered* is a dummy associated with corporate bonds that were rated as high-yield or had remaining maturities in excess of five years. *%AllETF* is defined as the percentage of the market value of the bond held by all ETFs on date *t*. Standard errors are reported in parentheses and are double-clustered on the bond issue and date levels. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$Turnover_t$	$Turnover_t$	$Bid\text{-}Ask_t$	$Bid\text{-}Ask_t$	$Amihud_t$	$Amihud_t$
$\%FedETF_{t-1}$	-0.003	0.012*	-1.746***	-1.947***	-0.023***	-0.023***
	(0.005)	(0.007)	(0.549)	(0.596)	(0.006)	(0.006)
$NotCovered_{t-1}$	0.001	0.000	-0.016	-0.030	0.000	0.000
	(0.001)	(0.001)	(0.024)	(0.038)	(0.000)	(0.000)
$\%FedETF_{t-1} \times NotCovered_{t-1}$	-0.008**	-0.012***	0.632*	0.598*	0.007	0.006
	(0.004)	(0.004)	(0.343)	(0.357)	(0.006)	(0.006)
$\%AllETF_{t-1}$		-0.094***		0.967		0.001
		(0.021)		(0.831)		(0.010)
$\%AllETF_{t-1} \times NotCovered_{t-1}$		0.022		0.491		0.010
		(0.024)		(0.852)		(0.011)
Bond FE	YES	YES	YES	YES	YES	YES
Issuer × Date FE	YES	YES	YES	YES	YES	YES
N	242,816	242,816	242,816	242,816	847,452	847,452
R^2	0.4720	0.4730	0.5500	0.5500	0.3020	0.3020

Return to text.

Table 11: Bond Price Reactions Based on Common APs and Bond Holdings Overlap

The table displays the results of regression models where the dependent variable is the natural log of one plus the daily option-adjusted bond spread, or *ln(1+OAS)*, on date *t*. *%ETF* is the percentage of the market valuation of bond *i* held by ETFs as of date *t-1* on days when Fed ETF transactions take place, and zero otherwise. *%ETF* is decomposed based on holdings by ETFs with a high (low) degree of holdings overlap with the ETF purchased by the Fed, or *HighOverlap* (*LowOverlap*), and with the same (different) AP as the ETF purchased by the Fed, or *SameAP* (*OtherAP*). Issuer-date and issue fixed effects are included in all the specifications. Standard errors are reported in parentheses and are double-clustered on the bond issue and date levels. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$ln(1+OAS)_t$					
$\%ETF^{HighOverlap}_{i,t-1}$	-0.114***					
	(0.030)					
$\%ETF^{LowOverlap}_{i,t-1}$		-0.018*				
		(0.010)				
$\%ETF^{HighOverlap,SameAP}_{i,t-1}$			-0.124***		-0.122***	-0.107***
			(0.031)		(0.031)	(0.023)
$\%ETF^{HighOverlap,OtherAP}_{i,t-1}$			-0.078		-0.059	-0.078
			(0.074)		(0.077)	(0.058)
$\%ETF^{LowOverlap,SameAP}_{i,t-1}$				-0.113**	-0.110**	-0.108***
				(0.046)	(0.044)	(0.041)
$\%ETF^{LowOverlap,OtherAP}_{i,t-1}$				0.017	0.000	-0.041**
				(0.014)	(0.015)	(0.016)
$\%FedETF_{i,t-1}$						-0.035***
						(0.008)
Bond FE	YES	YES	YES	YES	YES	YES
Issuer × Date FE	YES	YES	YES	YES	YES	YES
N	830,848	830,848	830,848	830,848	830,848	830,848
R^2	0.993	0.993	0.993	0.993	0.993	0.993

Return to text.

Table 12: Daily ETF Net Flows

The dependent variable, $Net\ Flows_{i,t}$, is measured in basis points as the dollar value of net inflows to ETF i on date t, divided by the market capitalization of ETF i on date t. $NAV\ Prem_{i,t}$ is the premium, in basis points, of the closing price of ETF i on date t over the NAV of ETF i on date t. $AvgOverlap_{i,t}$, for each ETF i on each date t, is the weighted average portfolio holdings overlap between ETF i and the SMCCF-purchased ETFs on date t. The results in the table are differentiated by different sample periods (either April 1 – June 15, 2020 or January 1 – July 31, 2020). All specifications include date fixed effects and ETF fixed effects. All specifications use Driscoll-Kraay (1998) standard errors that are robust to date clustering, ETF clustering, and common correlated disturbances across date and time clusters. Bandwidth choice for estimating autocovariances in the Bartlett kernel follows the Newey-West (1994) rule of bandwidth = m + 1, where m = floor($4*(T/100)^{2/9}$). In this case, T = 145 → m = 4 → bandwidth = 5. (Or T = 51 → m =3 → bandwidth = 4.) Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent Variable:	*Net Flows$_t$*	
NAV Prem$_{t-1}$	0.452*	0.184***
	(0.265)	(0.062)
AvgOverlap$_{t-1}$	-293.995**	-67.409
	(126.857)	(65.176)
AvgOverlap$_{t-1}$ × NAV Prem$_{t-1}$	4.746**	2.457**
	(1.922)	(1.025)
Dates	Apr 1 – Jun 15	Jan 1 – Jul 31
Date FEs	YES	YES
ETF FEs	YES	YES
N	5,379	15,324
R^2	0.0015	0.0011

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Figure 1: SMCCF Trade Sizes and Trade Times

This figure illustrates the distribution of the SMCCF ETF purchases on two dimensions: the sizes of the trades and their times of day. The top-left panel plots the joint distribution of time-of-day (horizontal axis) and trade size in dollars (vertical axis) for the subset of SMCCF purchases that can be matched to the intraday tape. The time axis runs from 9:30am (left red line) to 4:00pm (right red line). The trade size axis runs from $10,000 to $100,000,000 (log-scaled). The top-right panel plots the trade size distribution as a histogram for all SMCCF ETF trades, including both those trades that can be matched to the intraday tape, and those that cannot. The horizontal trade size axis runs from $10,000 to $100,000,000 (log-scaled). The bottom two panels take the top-right panel and split it into two subsamples: the distribution of trade size for trades that can be matched to the intraday tape (bottom left) and the distribution of trade size for trades that cannot be matched to the intraday tape (bottom right).

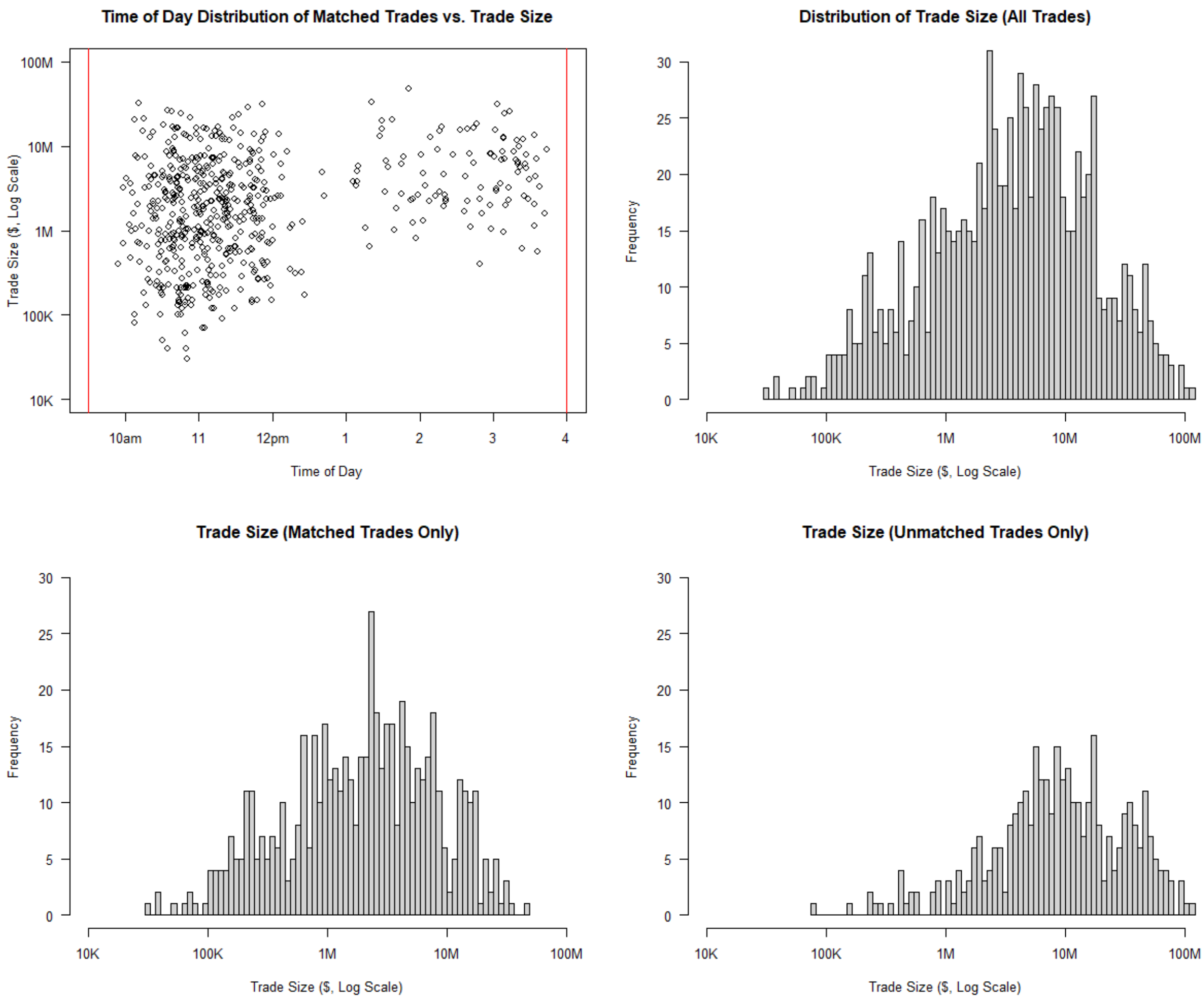

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Figure 2: ETF Sellers

The figure displays data from the SMCCF disclosures showing the dollar amount of ETFs sold to the Fed by seller (in millions). Dark blue shaded bars are sellers that have been identified to be an AP of at least one of the ETFs purchased by the Fed as of May 18, 2020 (according to the Fed disclosure of Mary 28, 2020). Light yellow shaded bars are sellers that could not be identified as an AP for any of the ETFs.

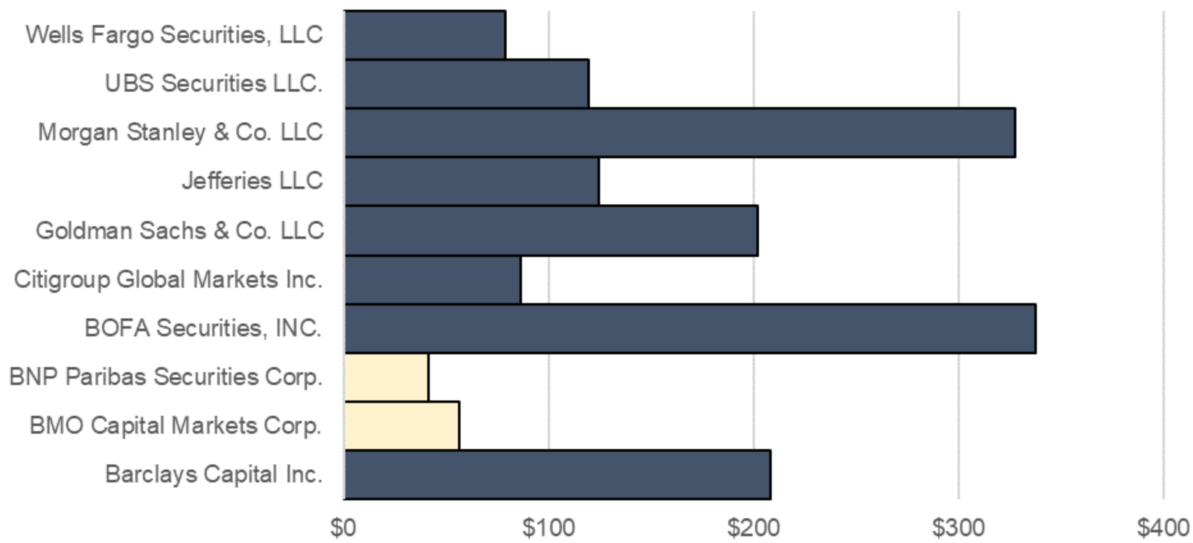

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Figure 3: Primary Dealer Corporate Bond Inventories

This figure displays weekly corporate bond inventories of primary dealers from the public FR 2004 disclosures from January 2020 through June 2021. Aggregate inventories are decomposed based on investment grade and high yield corporate bond security holdings.

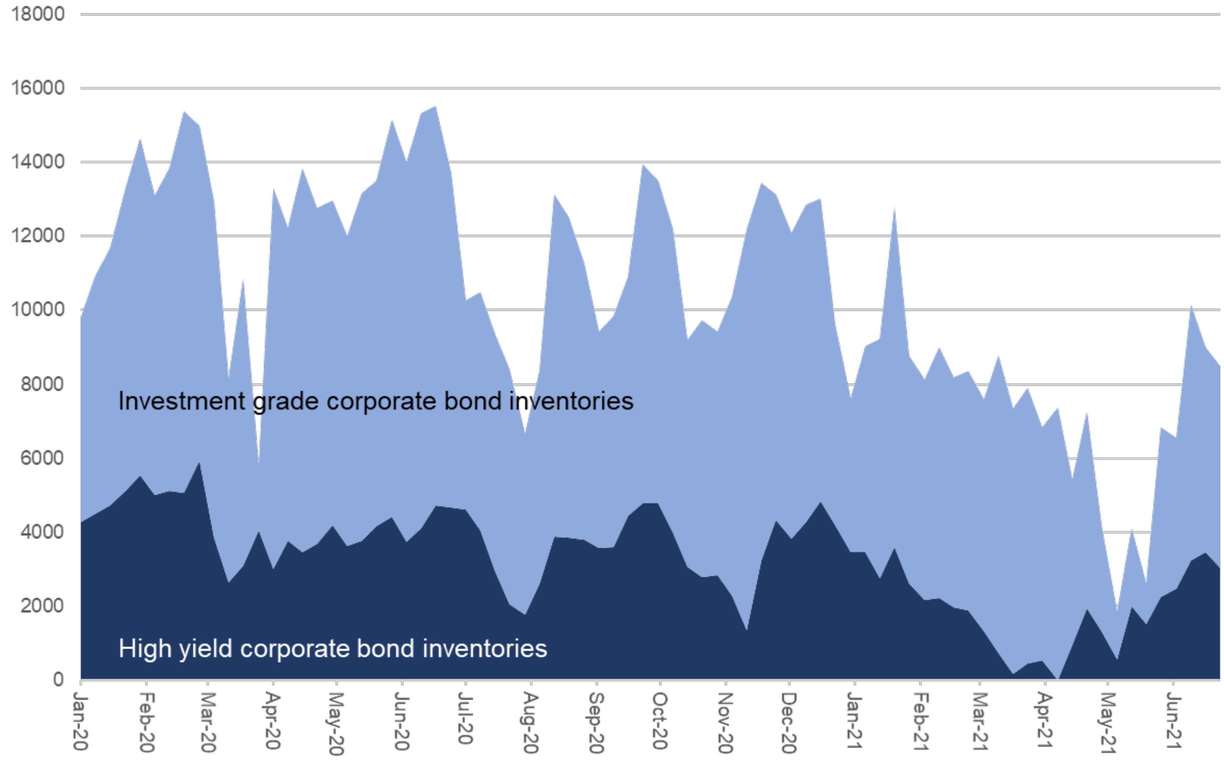

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Figure 4: Intraday Price Reaction of ETFs Purchased by the SMCCF

This figure shows the intraday price reaction of ETFs that are purchased by the SMCCF. The x-axis is time, measured in minutes and normalized so that the transaction time is t = 0. The x-axis ranges from t= -15 (15 minutes prior to the trade) to t = 15 (15 minutes post-trade). The time resolution is 15-second intervals, so there are 60 time intervals before and after the trade. The y-axis shows prices, normalized so that the purchase price of the transaction is p = 100.00. The national best bid price is shown as the solid blue line, the national best ask price is shown as the solid red line, and the midquote is shown as the purple dotted line. Bid, ask, and midquote prices are weighted averages, weighted at each time interval by the trade size (in dollars) of each SMCCF purchase identified on the intraday tape (n=571). Bid and ask prices are sourced from direct feeds of all lit exchanges, as aggregated by Maystreet.

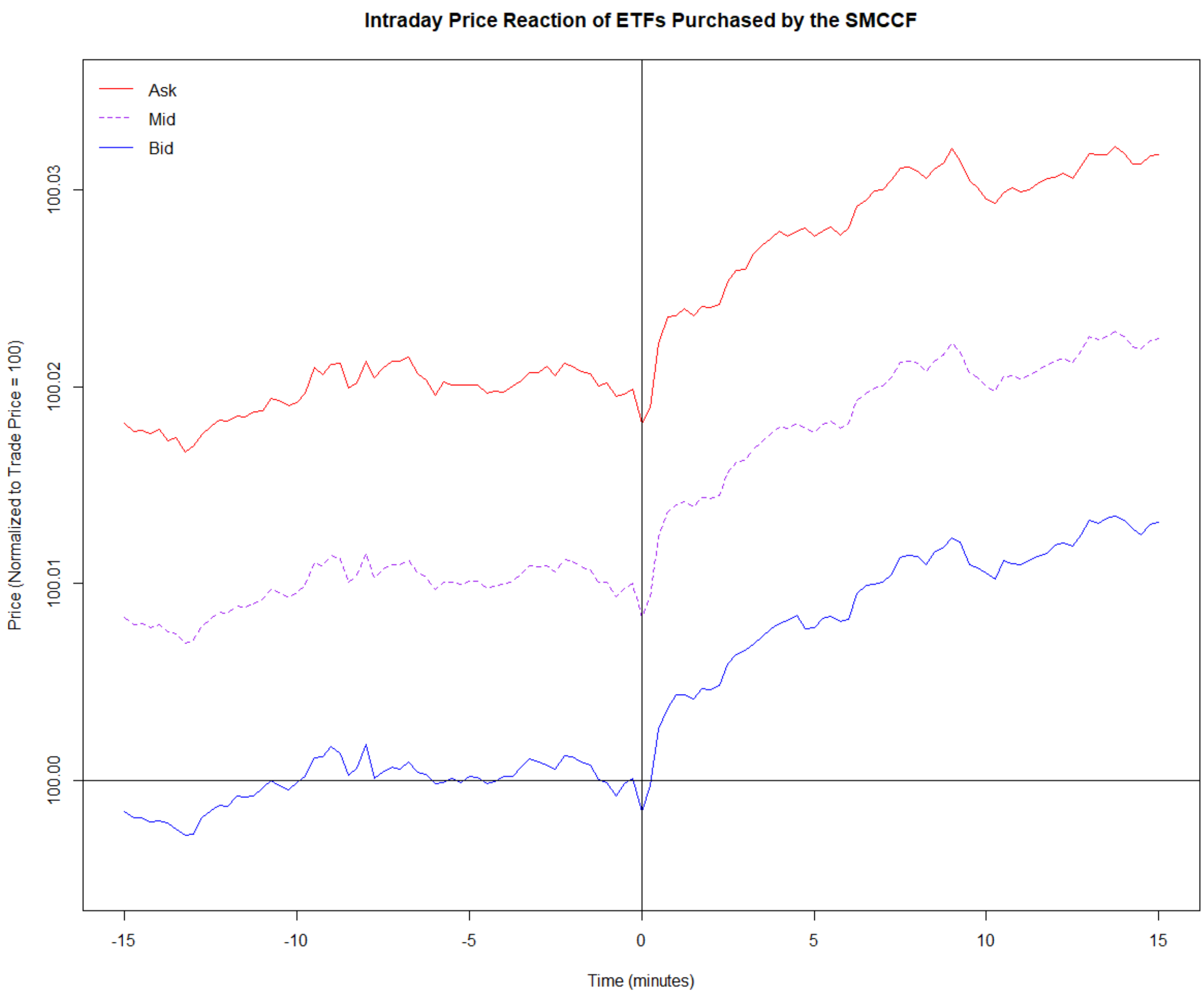

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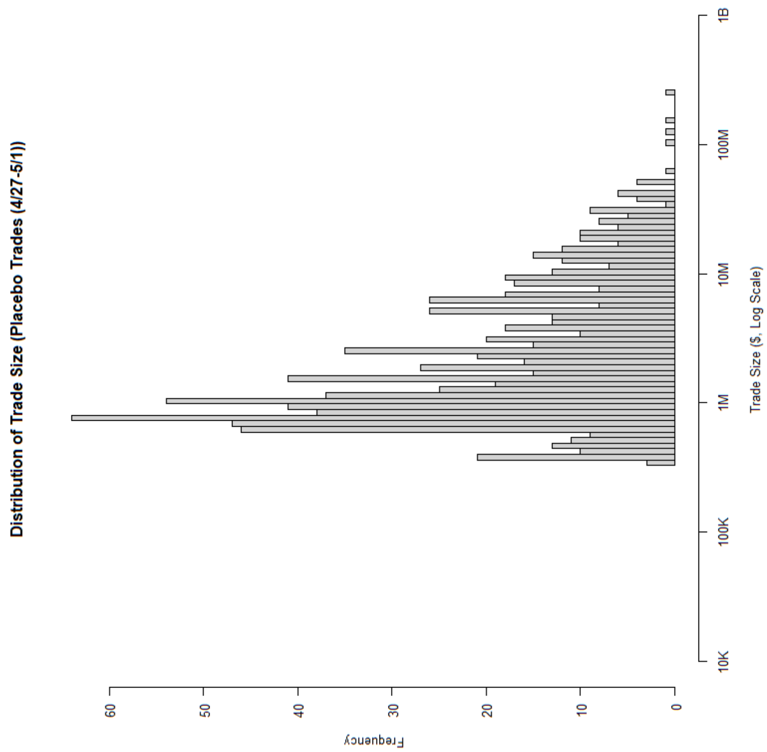
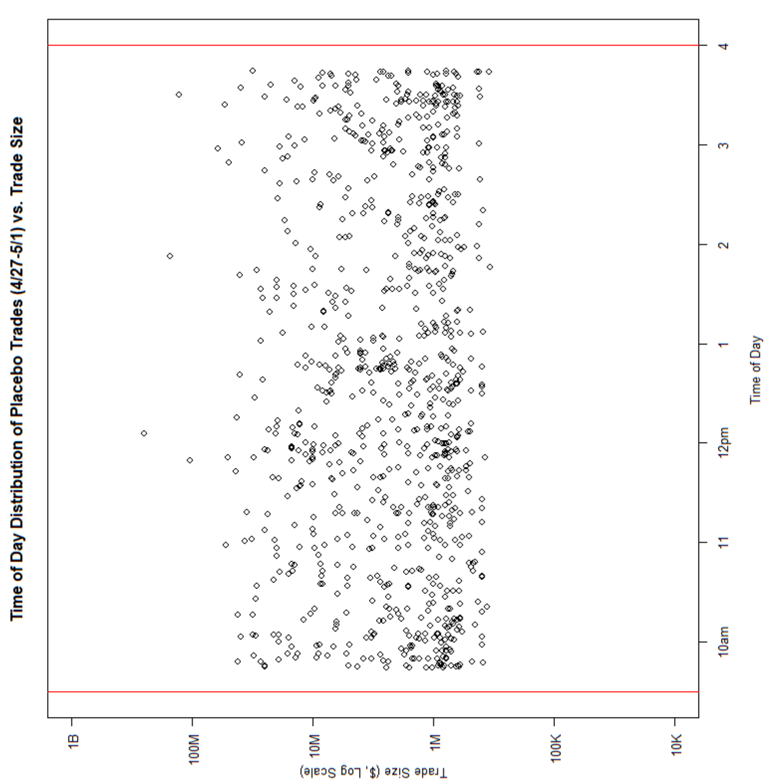
Figure 5: Size and Time Distribution of Placebo Trades

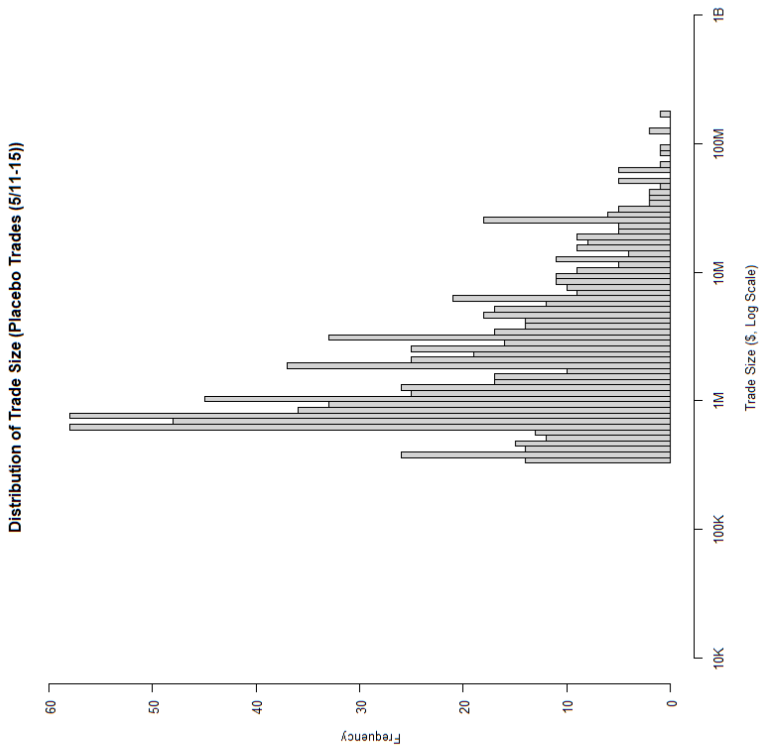
This figure shows the size distribution and time distribution of the ‘placebo’ trades from two different weeks: the week of April 27 – May 1, 2020 (Panel (a)) and the week of May 11-15 (Panel (b)). Placebo trades were identified by the following procedure: For each ETF ticker purchased by the SMCCF from May 12 – July 23, we looked at all trades between 9:45am and 3:45pm in those tickers for the week of April 27 – May 1 and selected all trades above the 99.9th percentile (by within-ticker trade size in dollars). The resulting trades are plotted in the top row as follows: the top left panel shows time of day on the x-axis, with 9:30am indicated by the left red line, and 4:00pm indicated by the right red line. The y-axis shows the size of each trade, in dollars, log-scaled. The top right panel shows the histogram of trade size, in dollars, log-scaled. The procedure is repeated for the week of May 11-15 with one caveat: the 99.9th percentile trade size cutoffs are taken from the week of April 27 – May 1, in order to avoid any confounding effects from the trade size distribution changing over the different weeks. The panels show that the distribution of large trades (by time or size) was largely unchanged between the week of April 27 – May 1 and the week of May 11-15.

Panel (a): Week of April 27 – May 1, 2020





Panel (b): Week of May 11-15



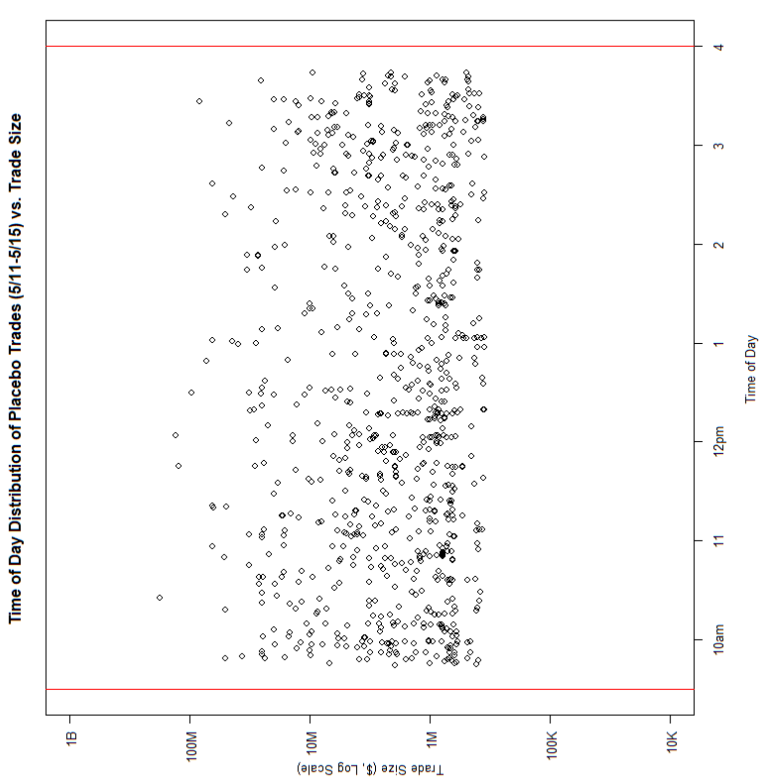


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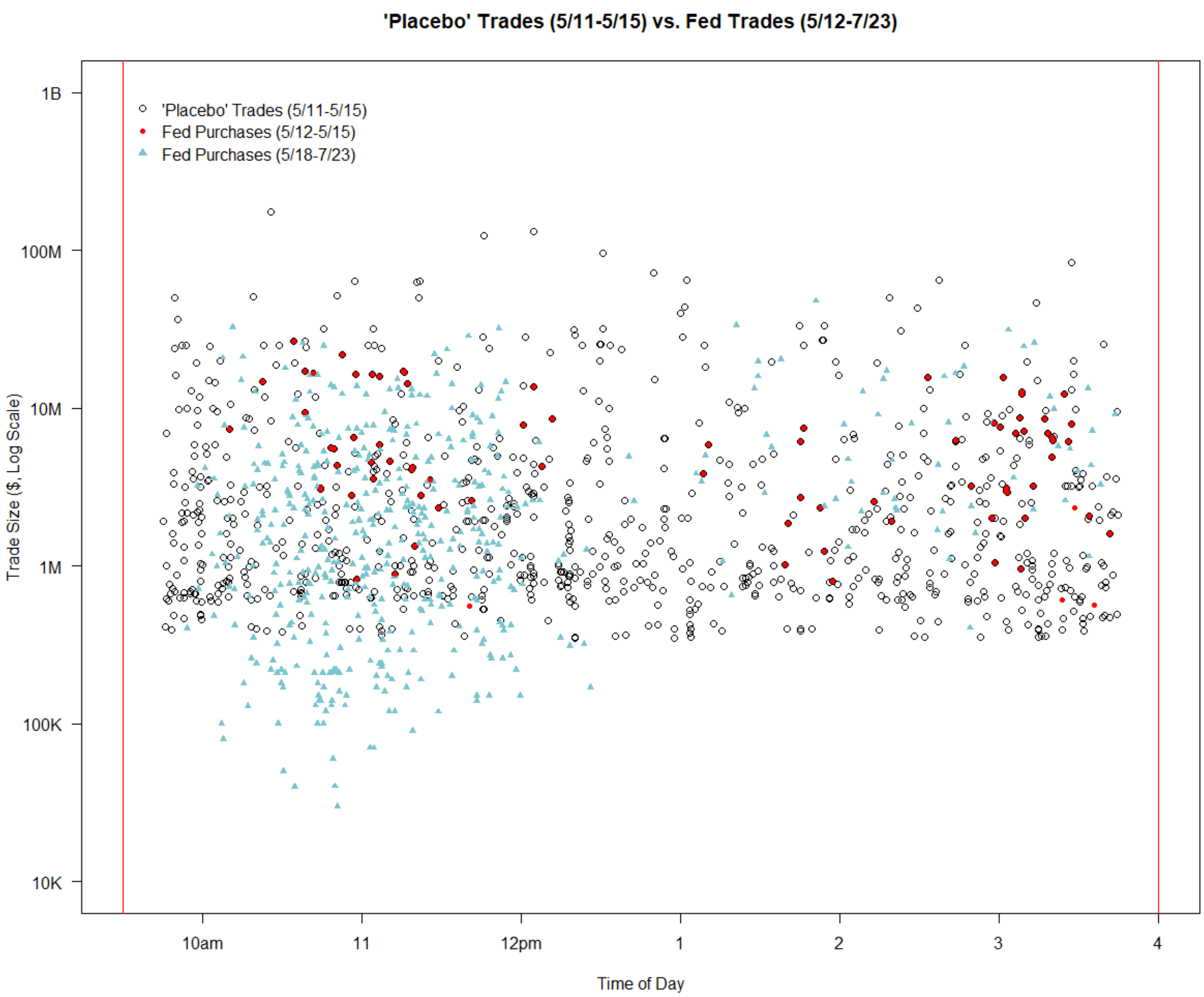
Figure 6: SMCCF Trades vs. Placebo Trades

This figure shows the trade-size distribution (in dollars, log-scaled) against the time-of-day distribution for three different groups of trades. The black circles show the size and time distribution of the placebo trades for the week of May 11-15, 2020. These trades are selected by the following procedure: First, the size threshold (in dollars) for the 99.9th percentile is calculated using trades from the week of April 27 – May 1. This size threshold is calculated separately for each of the ETFs that are purchased at least one time by the SMCCF in subsequent weeks. Given these size thresholds, they are applied to all trades in the same ETFs for the week of May 11-15. The trades that pass the 99.9th percentile are shown in the black circles in the figure above. The solid red dots indicate SMCCF trades of ETFs during the period May 12-15 that can be identified on the intraday tape. It is important to note that these SMCCF trades can (and do) appear in the 'placebo' trade sample. When a placebo trade is also identified as an SMCCF purchase, that trade appears in the scatterplot as a red dot outlined by a black circle. Lastly, the solid blue triangles indicate SMCCF trades from the period May 18 – July 23 that can be identified on the intraday tape. This figure illustrates an important point: namely, that the SMCCF purchases were large, but not so large as to fall outside the range of commonly large trades. This reinforces our argument that SMCCF trades were not immediately obviously SMCCF purchases to other market participants observing trades being reported on the intraday tape, consistent with the interpretation that SMCCF purchases, on a short-horizon basis, were plausibly exogenous shocks to the ETF market and could not be inferred to be SMCCF trades.



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Appendix

Appendix Table 1: Baseline Intraday ETF Spillovers, Equal-Weight Overlap Measure

The set-up and variable definitions in Appendix Table 1 are identical to those in Table 3, except that in this table, *ETFOverlap* is defined using a measure that equal-weights holdings when trying to assess the degree of overlapping holdings between two ETFs (as opposed to giving more weight to holdings that have higher portfolio shares, as does cosine similarity). Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

Panel (a): Intraday ETF Price Reaction

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δlog(midquote)*			
ETFOverlap × Trade	1.142*** (0.398)	1.142*** (0.398)	1.142*** (0.397)	1.121*** (0.392)
ETFOverlap	-0.811*** (0.288)	-1.639** (0.690)	-1.119*** (0.315)	
Trade	-1.063*** (0.262)	-1.063*** (0.261)	-1.063*** (0.235)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	7,669,440	7,669,440	7,669,440	7,669,440
R^2	0.0000	0.0002	0.0019	0.0101

Panel (b): Intraday ETF Liquidity Reaction

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δ(log(ask)-log(bid))*			
ETFOverlap × Trade	-0.125 (0.255)	-0.125 (0.255)	-0.125 (0.255)	-0.144 (0.261)
ETFOverlap	-0.027 (0.175)	-1.595*** (0.584)	-0.199 (0.182)	
Trade	0.371*** (0.141)	0.371*** (0.141)	0.371*** (0.140)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs		YES		YES
N	7,669,440	7,669,440	7,669,440	7,669,440
R^2	0.0000	0.0001	0.0000	0.0025

Appendix Table 2: Intraday ETF Reactions for Placebo Trades, April 27 – May 1

This table is the same as Table 6, with the exception that ETFOverlap is defined using an alternative measure that equal-weights the holdings of each ETF (as opposed to cosine similarity, which gives more computational weight to holdings with higher portfolio weights). Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

Panel (a): Intraday ETF Price Reaction

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δlog(midquote)*			
ETFOverlap × Trade	1.501 (1.128)	1.501 (1.125)	1.501 (1.129)	1.416 (1.117)
ETFOverlap	-0.953 (1.069)	-0.805 (3.656)	-0.136 (0.665)	
Trade	1.679** (0.847)	1.679** (0.846)	1.679** (0.837)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	12,242,880	12,242,880	12,242,880	12,242,880
R^2	0.0000	0.0005	0.0003	0.0089

Panel (b): Intraday ETF Liquidity Reaction

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δ(log(ask)-log(bid))*			
ETFOverlap × Trade	3.108 (5.017)	3.108 (5.016)	3.108 (5.021)	2.839 (4.955)
ETFOverlap	-3.599 (4.965)	-2.663 (8.922)	-2.516 (3.943)	
Trade	5.271** (2.370)	5.271** (2.365)	5.271** (2.340)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	12,242,880	12,242,880	12,242,880	12,242,880
R^2	0.0000	0.0006	0.0007	0.0102

Appendix Table 3: Intraday ETF Price Reaction for Placebo Trades, May 11-15

This table is the same as Table 7, with the exception that ETFOverlap is defined using an alternative measure that equal-weights the holdings of each ETF (as opposed to cosine similarity, which gives more computational weight to holdings with higher portfolio weights). Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

	(1)	(2)	(3)	(4)
Dependent Variable:	*Δlog(midquote)*			
ETFOverlap × Trade	0.791 (0.557)	0.791 (0.555)	0.791 (0.556)	0.811 (0.546)
ETFOverlap	-1.103*** (0.403)	20.118 (20.668)	-0.715* (0.406)	
Trade	0.384 (0.240)	0.384 (0.239)	0.384* (0.229)	
Observed ETF × Fed ETF FEs		YES		
Observed ETF FEs			YES	
Fed Trade FEs			YES	
Fed Trade × Observed ETF FEs				YES
Date × Time Interval FEs				YES
N	11,865,000	11,865,000	11,865,000	11,865,000
R^2	0.0000	0.0003	0.0009	0.0070

Appendix Table 4: Intraday ETF Price Reaction for Placebo Trades, May 11-15, by Fed Trade Status

This table is the same as Table 8, with the exception that ETFOverlap is defined using an alternative measure that equal-weights the holdings of each ETF (as opposed to cosine similarity, which gives more computational weight to holdings with higher portfolio weights). Standard errors are reported in parentheses and are double-clustered at the Event × Observed ETF level and the Date × Time Interval level. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively. All coefficients and standard errors are multiplied by 10^6 for readability.

	(1)	(2)	(3)
Dependent Variable:		*Δlog(midquote)*	
ETFOverlap × Trade	4.523*** (1.191)	-1.172 (0.736)	1.122 (0.809)
Fed Trades	Yes	No	Unsure
Fed Trade × Observed ETF FEs	YES	YES	YES
Date × Time Interval FEs	YES	YES	YES
N	1,038,960	3,579,960	7,246,080
R^2	0.0079	0.0079	0.0066

Appendix Table 5: Alternative Specification for Daily ETF Net Flows

Appendix Table 5 replicates Table 12, except here a three-way panel based on date, observed ETF, purchased ETF is used instead of the two-way panel based on date and observed ETF. The variables in Appendix Table 5 are defined as in Table 12 with the exception of $ETFOverlap_{i,j,t}$, which is defined here as the bilateral cosine similarity between the holdings of ETF i (observed) and ETF j (purchased) on date t. The date range for all specifications is May 12 – July 23, which matches the date range for SMCCF purchases of ETFs. All specifications exclude cases where ETF i is purchased by the SMCCF on date t. As in Table 12, all specifications use Driscoll-Kraay (1998) standard errors that are robust to date clustering, ETF clustering, and common correlated disturbances across date and time clusters. Bandwidth choice for estimating autocovariances in the Bartlett kernel follows the Newey-West (1994) rule. Statistical significance levels are denoted as ***, **, and * for significance at the 1%, 5%, and 10% levels, respectively.

	(3)	(4)
Dependent Variable:	*Net Flows$_t$*	
NAV Prem$_{t-1}$	0.777 (0.505)	0.760 (0.498)
ETFOverlap$_{t-1}$	19.451 (172.700)	18.813 (175.311)
ETFOverlap$_{t-1}$ × NAV Prem$_{t-1}$	2.385** (1.200)	2.566** (1.277)
Date FEs	YES	YES
ETF × Purchased ETF FEs	YES	YES
Date × Purchased ETF FEs		YES
N	62,044	62,044
R^2	0.0015	0.0015

Appendix Figure 1: Timeline of the SMCCF

This figure shows a brief timeline of key SMCCF events, overlaid on the daily purchase volume of ETFs (in millions of dollars) by the SMCCF. Data sourced from releases by the Fed (FRB) and the Federal Reserve Bank of New York (FRBNY).