The Economics of ETF Redemptions

Han Xiao[1]

Pennsylvania State University

December 29, 2022

[1] Xiao is at the Smeal College of Business, Pennsylvania State University, University Park, PA 16802, hxx15@psu.edu. I am indebted to Charles Cao (Co-chair), Tim Simin (Co-chair), Mihail Velikov, Brent Ambrose, and Bill Kracaw for their invaluable guidance and advice. I thank Mehmet Canayaz, Yong Chen, Lin Cong, Hannes Gerstel, Simon Gervais, Stefano Giglio, Matt Gustafson, Haim Kassa, Ahn Le, Stephen Lenkey, Stefan Lewellen, Jiacui Li, Felix Meschke, David McLean, Raisa Velthuis, Ruijing Yang, Alexei Zhdanov and seminar and conference participants at the Pennsylvania State University, NASMES (Miami), AFR, ESAM, CIRF, SETA, BFGA, and AFBC for valuable comments. All remaining errors are my own.

The Economics of ETF Redemptions

Abstract

This paper investigates the economic incentives underlying the choice of bonds in corporate bond exchange-traded funds (ETFs) redemptions. In the *primary* market between ETF sponsors and authorized participants (APs), sponsors fill baskets with bonds exposed to price pressure, and APs select assets that negatively co-move with illiquidity in their own portfolios. In the *secondary* market, where ETF shares are publicly traded, days with redemptions are associated with lower ETF returns, liquidity, price efficiency, and demand elasticity. APs profit from redemptions by correcting discrepancies between ETF share prices and portfolio values. These results are robust and persistent in exaggerated redemptions throughout the COVID-19 pandemic.

Keywords: Exchange-traded funds (ETFs), corporate bonds, redemption, authorized participant, price pressure, liquidity

JEL: G11, G12, G14, G23

1 Introduction

The exchange-traded fund (ETF) market has grown to become an essential part of the financial markets. Bond ETFs constitute a significant component and have grown substantially over the past 20 years, making up 20% of the assets under management of the ETF industry in 2022. Corporate bond ETFs track corporate bond indices, and share prices are supposed to be close to portfolio values per share (net asset values, NAVs). Whenever share prices are lower than NAVs, ETF sponsors/issuers and market makers trade to alleviate discounts via redemptions. However, at the onset of the COVID-19 pandemic in March 2020, ETF discounts were unprecedentedly and persistently large, implying a broken redemption mechanism. The large discounts reemerged in June 2022, when bonds posted historic losses due to spikes in inflation.[1]

This discrepancy between ETF prices and NAVs has generated broad debate among policymakers and practitioners on the mechanism of ETF redemptions. Todorov (2021) suggests that the discount in corporate bond ETFs is a result of ETFs delivering market makers low-quality securities to prevent more redemptions from these funds. Yet, industry participants such as BlackRock argue that market makers continued to redeem ETF shares throughout the crisis and accept baskets of bonds that did not harm either investors who remained with the fund or those who chose to redeem.[2] Little research has been done to understand the incentives to fulfill redemption requirements and how to select securities into baskets. This paper aims to fill this gap.

To redeem ETF shares, market makers, or authorized participants (APs), return ETF shares in exchange for baskets of securities. These baskets are chosen through negotiation between ETF sponsors and APs (Shim and Todorov, 2022; Koont et al., 2022). In this paper, I first investigate the economic incentives of ETF sponsors and APs in determining bonds in redemption baskets. Then I study the economic impacts of redemptions on ETF investors and the secondary market, including liquidity, efficiency, and demand elasticity.

Redemptions are defined as negative changes in the daily ETF shares outstanding. I

[1] Vanguard Total Bond Market ETF (BND) closed at a 6.2% discount on March 12, 2020, and the discount was persistently larger than average for the whole month. Similarly, BlackRock iShares core US aggregate bond ETF (AGG) closed at a 4.4% discount on the same day. Large discounts also appeared for the US investment-grade corporate bond ETFs and high-yield bond ETFs. In June 2022, iShares iBoxx High Yield Corporate Bond ETF (HYG) and SPDR Bloomberg High Yield Bond ETF (JNK) closed at 1.2% and 1.8% discounts in the biggest divergence since 2021. See Katherine Greifeld, "Credit ETFs are flashing a warning as prices break from assets," Bloomberg, June 14, 2022. See also Petajisto (2017). The *uniqueness* of (liquid) corporate bond ETFs is that sponsors and APs negotiate on the (illiquid) bonds upon redemptions.

[2] For debates between economists and ETF sponsors, see Chris Flood, "Price gap triggers fears for bond ETFs," *Financial Times*, March 29, 2020; Steve Johnson, "BlackRock hits back at BIS theory that it short-changed market makers," *Financial Times*, May 9, 2021; and Dawn Lim, "Bond ETFs Flash Warning Signs of Growing Mismatch," *Wall Street Journal*, March 23, 2020. See also Keshava Shastry, the head of DWS Group, "Structural fundamentals deter potential custom ETF basket conflicts," ETF Stream, July 25, 2022.

separate ETF corporate bond holdings into "baskets" and "remaining portfolios." Baskets include bonds whose number of holdings changes upon redemptions. The remaining portfolios contain bond holding shares that remain the same. The main findings are that, relative to bonds in the remaining portfolios, ETF sponsors choose and put bonds that are highly exposed to price pressure in baskets. APs negotiate basket components to manage the liquidity of their own corporate bond portfolios. Days with redemptions are associated with low future returns, liquidity, price efficiency, and price demand elasticity of ETFs in the secondary market.

To examine the ETF sponsor's incentives for choosing the basket's components, I rely on the corporate bond pricing literature, which identifies downside risk or price pressure as the strongest factor in the cross section of bond returns (Bai, Bali, and Wen, 2019; Falato et al., 2021). Price pressure helps correct the difference between share prices and NAVs and helps minimize tracking errors. Another possible candidate is illiquidity. However, since APs act as market makers in the secondary bond market (Pan and Zeng, 2019), illiquidity is exogenous to the ETF sponsor's choice set. Thus, I hypothesize that the ETF sponsor's incentives are to deliver bonds that are highly exposed to price pressure.

I use two categories of price pressure measures. The holding-based measures use extreme outflow-induced holding changes in active and passive corporate bond mutual funds (Coval and Stafford, 2007; Choi et al., 2020). The flow-based measure is the common flow shock across mutual fund size groups (Aragon and Kim, 2022; Dou, Kogan, and Wu, 2022). I estimate exposure to price pressure at the individual bond level by regressing bond returns on price pressure in a 36-month rolling window. Then, I use a holding-weighted average to aggregate the bond exposure to the ETF level.

The sample average comparison test shows that average exposures in the baskets are significantly higher than those in the remaining portfolios. Specifically, a 1% increase in ETF-level price pressure adds to the value of the baskets in a range of 2.8 to 3.6 basis points (bps), which equals an extra \$23,335 to \$29,860 of the average asset under management (AUM) in the baskets. Meanwhile, the remaining portfolio's values decrease by 2.7 to 3.5 bps, or equivalently, a \$33,593 to \$43,547 decrease for the average AUM in the remaining portfolios. The choice helps narrow the difference between share prices and NAVs, thus attenuating discounts.

To examine how heterogeneity in the negotiation process affects differences in price pressure exposure between the baskets and the remaining portfolios, I conduct a counterfactual experiment. I define a hypothetical ETF that keeps all bonds in redemptions. Then I derive the hypothetical ETF-level exposures using all securities. The intuition is that when ETF sponsors hold baskets with highly exposed corporate bonds, the hypothetical ETF's exposure to price pressure is higher under intense negotiation. To measure the intensity of negotiation, I rely on the relative number of holdings in the two portfolios. Specifically, I calculate the ratio of counts of different corporate bonds in the basket and those in the remaining portfolio. A smaller ratio represents a more intense negotiation between ETF sponsors and APs. I also define a fraction dummy if the ratio is less than 60%.

Then I regress the hypothetical exposures on the ratio or the fraction dummy. The results show that hypothetical ETFs with intense negotiation encounter 0.6% to 5% higher exposures than those with moderate negotiation. The incentive is stronger if the negotiation is more intense. The evidence supports the hypothesis that the ETF sponsor's incentives to choose bonds in the redemption baskets depend on bond price pressure.

Having documented evidence for ETF sponsors' incentive to deliver assets with high exposure to price pressure, I next turn to explore the incentives of APs in the negotiation process. To identify APs, I use the Securities and Exchange Commission's (SEC) N-CEN filings. Management companies with ETF products, such as Goldman Sachs, Citigroup, and J.P. Morgan, must report all incorporated APs. APs simultaneously manage portfolios on behalf of their clients and their own company accounts. I match APs with investment companies on Form 13F by name and calculate AP portfolio-level corporate bond liquidity.

APs are market makers in both the ETF primary and secondary corporate bond markets and are portfolio managers of their own bond portfolios. These multiple functions call for balancing the illiquidity and inventory risks in baskets and their portfolios (Goldstein and Hotchkiss, 2020). Practitioners suggest that APs treat ETF baskets as a substitute for inventory to mitigate relevant risks; hence, I hypothesize that APs' incentives lie in the correlation between the illiquidity of baskets and their own portfolio.

To test this hypothesis, I estimate correlations between percentage changes in the illiquidity of AP portfolios and those of ETF baskets. The result confirms my hypothesis. APs negotiate on components of baskets such that the co-movement between the illiquidity of bonds in the baskets and the illiquidity of bonds in APs' own portfolios is negative. For example, if a basket's illiquidity increases, the AP portfolio's illiquidity decreases, which implies that the liquidity of AP holdings is improved.

The economic magnitude of the co-movement is also significant. A one-standard-deviation increase in the illiquidity of baskets is associated with a 0.4% drop in the AP portfolio's illiquidity, representing 20% of the average AP illiquidity. Thus, the incentive to determine baskets is that APs manage the co-movement between portfolios and baskets to improve liquidity. Basket illiquidity is negatively correlated with AP illiquidity.

Given the negotiation incentives between ETF sponsors and APs in determining redemption baskets, the natural question is, what are the economic impacts of redemptions on investors and APs in the secondary market? To answer this question, I first estimate regressions of various measures of ETF performance on a redemption dummy. The performance measures include daily ETF returns, illiquidity (intraday effective and realized spreads), and inefficiency (intraday variance ratio and order imbalance measure).

ETFs yield lower returns by 2.3 basis points (bps) per day upon redemptions. Given that the unconditional average corporate bond return is 1.3 bps, the decrease upon redemption is economically significant. Investors suffer from 1.3 bps wider effective and realized spreads upon redemptions, implying that they will pay 10% more transaction costs. Finally, I find that order imbalances are, on average, 1.9% greater on redemption days, resulting in a less efficient market.

In light of redemption's adverse effects on investors, I then consider whether APs are able to exploit any arbitrage opportunities arising in this setting. To address this question, I use the rate of short interest and a measure of ETF share price mispricing, defined as the absolute percentage difference between ETF share prices and NAVs. I find that APs benefit from 12.6 bps larger mispricing and a 1.0 bps larger rate of short interest; equivalently, their arbitrage profits are around \$127,660 in a frictionless environment. These effects remain strong for up to a quarter following the redemption day.

Lastly, I study the price elasticities of demand in the corporate bond ETF market on redemption days using the novel approach proposed by Li and Lin (2022). To this end, I estimate the price multiplier, or the inverse of price elasticity, as the coefficient of regressing ETF returns on a measure of demand for ETF shares. The demand measure equals the difference between buyer- and seller-initiated number of trades divided by shares outstanding. The multiplier represents the percentage increase in share prices if trading 1% of shares outstanding.

While normal days exert the typical level of price multiplier for stocks (2.5, similar to micro multipliers summarized by Gabaix and Koijen (2021)), redemption days exhibit dramatically higher price multipliers (10.5). This level of the multiplier is equivalent to the estimates of multipliers for corporate bonds using insurance company holdings (10.0 in Bretscher et al. (2022)). The result is also in line with the aggregate-level factor multipliers in the stock market (7.0 to 9.5 in Li and Lin (2022)), suggesting that investors face less elastic and less competitive ETF markets upon redemptions relative to normal days.

The paper is related to three distinct strands of literature. First, it contributes to the growing literature on the market impacts and the mechanism of ETF redemptions. The literature has mostly focused on equity ETFs. For example, Brown, Davies, and Ringgenberg (2021) find that flows signal non-fundamental demand shocks among equity ETFs and negatively forecast future returns. Similarly, Reilly (2022) shows the underperformance of corporate bond ETFs upon creation. I add to this literature by documenting that redemptions in corporate bond ETFs are also associated with lower returns, contrary to the results for equity ETFs.

A novel contribution of this paper is that I focus on ETF-level liquidity and efficiency upon redemptions. Bae and Kim (2020) argue that ETF-level illiquidity increases tracking errors and return volatilities. ETF competition also affects illiquidity in ETFs and decreases market quality (Box, Davis, and Fuller, 2019). Existing studies also consider the interactions between the ETF ownership and the underlying asset markets (Dannhauser, 2017; Ben-David, Franzoni, and Moussawi, 2018; Agarwal et al., 2018; Glosten, Nallareddy, and Zou, 2021; Dannhauser and Hoseinzade, 2022; Li and Zhu, 2022). My paper provides direct evidence of the effects of redemptions on the ETF markets.

Gorbatikov and Sikorskaya (2022) and Hong, Li, and Subrahmanyam (2022) construct the network relationship between APs and study their effects on ETF mispricing. Focusing on the dual roles of APs as market makers and institutional investors, Pan and Zeng (2019) study the capital constraints among APs to absorb ETF arbitrage opportunities. My paper emphasizes the importance of both ETF sponsors and APs in the negotiation to determine the components of redemption baskets.

Two papers are closely related to this paper. Shim and Todorov (2022) document that bond ETF redemption baskets involve only a small fraction of corporate bond holdings. Meanwhile, sponsors of passive corporate bond ETFs actively manage their portfolios to trade off index tracking against liquidity transformation. Using end-of-month portfolio rebalancing, Koont et al. (2022) show that basket selection depends on the bond illiquidity in their portfolios and the deviations from index holding weights. Since corporate bond ETFs mechanically deviate from indexes upon redemptions, little is known about the incentives of these redemption activities. This paper fills this gap in the literature.

Second, the paper adds to price pressure and run-like fragility studies. In a seminal paper, Coval and Stafford (2007) show that price pressure by equity mutual fund flows and changes in securities holdings significantly affects stock prices. Ellul, Jotikasthira, and Lundblad (2011) and Manconi, Massa, and Yasuda (2012) also document that because of regulatory pressure and illiquidity crises, investment-grade and securitized bonds suffer from severe price pressure. I argue that corporate bond ETF sponsors care about price pressure to maintain stable NAVs and prevent further investor outflows from their funds after redemptions. My finding is also complementary to the spillover effects of fire sales in corporate bond funds with extreme outflows (Falato et al., 2021).

Lastly, I contribute to the literature on liquidity management in financial institutions. Liquidity co-movement is well documented at the individual stock level (Chordia, Roll, and Subrahmanyam, 2000), where changes in stock liquidity are strongly related to market- and industry-level changes in liquidity. Koch, Ruenzi, and Starks (2016) discover that mutual fund ownership is significantly related to stock liquidity co-movement. Koont et al. (2022) discuss basket liquidity management by holding an extra amount of cash and deviating from benchmark indices. I connect liquidity changes in ETF redemption baskets with liquidity changes in APs' portfolios. Moreover, Zeng (2017) argues that mutual funds use cash holding as the buffer to manage liquidity in fund runs. I show that APs manage their portfolio liquidity to improve the overall liquidity condition by negotiating redemption baskets whose liquidity negatively co-moves with their own portfolios.

The paper is organized as follows. Section 2 discusses the institutional background and proposes hypotheses in corporate bond ETFs. Section 3 describes the data used in this paper. I investigate the incentives of ETF sponsors and APs in Section 4. Section 5 presents the results about the impacr of redemption on ETF investors, APs, and demand elasticity. Section 6 provides alternative analyses and robustness tests. Section 7 provides concluding remarks.

2 Institutional Background and Hypotheses

On July 26, 2002, Barclays Global Investors launched the first corporate bond ETFs on the American Stock Exchange, iShares iBoxx $ Investment Grade Corporate Bond ETF (LQD). The year-end assets under management of corporate bond ETFs was $4 billion. Over the past two decades, the market has increased in size and scope. Figure 1 shows that the AUM of bond ETFs increases fast even during the financial and COVID-19 pandemic crises. According to Investment Company Institute, the number reached $1.3 trillion in 2022. It made up one-fifth of the total ETF market (7.2 trillion).

Moreover, a notable pattern is that ETF ownership has flourished in the past two decades. The ownership of ETFs in the corporate bond market has increased to over 5% in recent years (Figure 2), compared to 22% in insurance companies, 17% held by bond mutual funds, 3% by households, and 0.4% by broker-dealers. Still, the ownership in all other institutions is volatile. The ownership of insurance companies and mutual funds is around 10% to 20%, but their number of holdings decreased during the crisis periods. Households and broker-dealers experienced a significant decline after the financial crisis. ETFs are robust investment vehicles in the corporate bond market, whose redemption activities call for more studies.

The ETF product is unique because it combines features of mutual funds and stocks. Figure 3 shows the structure of the ETF primary and secondary markets. Like a stock, ETF shares can be traded intraday in the *secondary* market rather than at the end of the day with NAVs as a mutual fund. The price of the ETF shares is determined in real-time, and the ETF's bid-ask spreads affect transaction costs. Both retail and institutional investors are involved in ETF intraday trading in the secondary market.

Like mutual funds, ETF sponsors continuously offer shares built upon baskets of corporate bonds. However, unlike mutual funds, ETF sponsors do not directly create or redeem shares through specialized entities in the *primary* market. Hence, ETF sponsors do not trade the underlying assets. Creations refer to increasing the supply of ETF shares, and redemptions refer to a decrease in the shares outstanding of the ETFs. The creation/redemption works through arbitrage to keep the price of an ETF close to the intrinsic value of an ETF's holdings.

These specialized entities are authorized participants (APs), who are market makers or liquidity providers, including investment banks, hedge funds, and high-frequency trading companies. For example, the Vanguard total corporate bond ETF (VTC) incorporates with APs such as Barclays Capital Inc., CitiGroup Inc., Goldman Sachs Group Inc., and UBS Group AG. Retail and non-AP institutional investors cannot participate in the primary market. APs create or redeem shares with ETF sponsors in large blocks, known as creation units. Transactions between ETF sponsors and APs are "in-kind," where the AP delivers or receives a basket of securities identical or similar to the ETF's holdings. Then APs provide ETF shares to exchanges.

The creation/redemption process is the core mechanism in the ETF market, aiming to maintain share prices close to NAVs to eliminate share discounts and premiums. APs trade with ETF sponsors in the primary market if there are arbitrage opportunities in the ETF secondary market. For example, when ETF share prices are lower than NAVs, APs profit from correcting these arbitrage opportunities. APs redeem shares with ETF sponsors for baskets of corporate bonds. Since APs also act as market makers in the corporate bond market, they can hold the baskets in their inventory or sell them in the secondary bond market.

The basket is determined as follows. First, an ETF sponsor announces a list of securities for creations or redemptions at the end of each trading day. In this announced basket, at least 80% of corporate bonds are covered (Koont et al., 2022). This fact suggests that ETF sponsors initiate the announced baskets to maintain similar portfolio holdings as the benchmarks to minimize tracking errors.

Second, on the next business day, if an AP identifies an arbitrage opportunity and creates/redeems with the ETF sponsor, the AP is allowed to modify the basket. This realized basket is the result of negotiation between ETF sponsors and APs. The realized basket only includes 20% to 40% corporate bonds, a significant reduction compared with the announced one. One anecdotal reason for negotiation is that ETF sponsors want to maintain long-term relationships with APs. APs negotiate with the ETF sponsor and determine the realized basket based on their bond inventories or balance sheet constraints.

One important question is, what mechanism explains the compromise of realized baskets in the primary market, providing corporate bond ETFs deviate from their benchmarks in the redemption activities? ETF sponsors choose components in redemption baskets, hoping to strengthen the redemption mechanism to amend the discrepancies between share prices and NAVs. Thus, the first hypothesis is about the incentive of ETFs to determine the realized baskets.

Hypothesis 1 (ETF incentive)**.** *ETF sponsors determine the components of baskets such that corporate bonds in baskets are more exposed to price pressure relative to those in the remaining portfolios.*

I study ETF incentives in terms of the price pressure of bonds in the portfolio for the following reasons. First, price pressure is the deterministic factor in the corporate bond market. Second, price pressure inherits the contagion between illiquid bonds and liquid bonds. Third, the recent stress in the Treasury bond and investment-grade corporate bond markets also suggests that price pressure plays a vital role in asset management. Lastly, the extant literature argues that funds carefully select bonds in redemptions to avoid considerable price pressure.[3]

APs negotiate with ETF sponsors to determine the realized baskets, but their incentives to agree on the components of baskets is unclear. I propose a liquidity explanation. To maintain stable liquidity in their bond portfolio and hedge risks across different market conditions, I consider the second moment of liquidity, namely, the liquidity co-movement between baskets and AP bond portfolios. The second hypothesis thus follows

Hypothesis 2 (AP incentives)**.** *APs negotiate with ETF sponsors on the components of baskets if the illiquidity of baskets co-moves negatively with that of the AP's own portfolios.*

Brown, Davies, and Ringgenberg (2021) show that equity ETF returns upon redemptions (negative flows) are significantly higher than during creation. Box, Davis, and Fuller (2019) find that creation/redemption activities decrease effective spreads in equity ETFs. Hong, Li, and Subrahmanyam (2022) use changes in ETF shares to evaluate the balance sheet constraints in APs and suggest that more creation/redemption activities restrict the AP's arbitrage abilities and decrease ETF mispricing. Given the uniqueness of realized baskets in corporate bond ETF redemptions, little is known about the economic impacts on ETF performance and AP arbitrage opportunities in the secondary market.

[3] See the detailed discussion on factors of corporate bond markets in Bai, Bali, and Wen (2019), Falato et al. (2021) and Kargar et al. (2021). Manconi, Massa, and Yasuda (2012) and Falato, Goldstein, and Hortaçsu (2021) investigate price pressure and bond illiquidity. Jiang, Li, and Wang (2021) and Ma, Xiao, and Zeng (2022) study price pressure in the mutual fund industry.

I argue that redemptions in corporate bond ETFs directly affect investors and APs through liquidity, efficiency, and arbitrage opportunities. The third hypothesis discusses the benefits/losses of redemptions.

Hypothesis 3 (Redemption impacts)**.** *When there is a redemption in a corporate bond ETF,*

(a) ETF investors suffer from lower returns in the illiquid and inefficient secondary market.

(b) APs benefit from more arbitrage opportunities regarding ETF mispricing and short interest.

More broadly, redemptions represent the variation in investors' demand for ETF shares, and the trading has different price demand elasticities. The last hypothesis is about price multipliers of the corporate bond ETF market

Hypothesis 4 (Demand elasticity)**.** *The price multiplier, the inverse of price-demand elasticity, of demand for ETF shares in the corporate bond ETF market upon redemption is higher than the multiplier on normal days.*

When investors in the secondary market redeem shares through APs, the price multiplier (the inverse of price elasticity) is presumably large, suggesting that these redemptions are inelastic and have a strong market impact. ETF sponsors also prefer a less elastic secondary market such that increasing demand leads to much higher prices upon redemptions relative to normal days, which helps to reinforce the redemption mechanism and attenuate the differences between share prices and NAVs.

3 Data

This section presents the data and variable definitions. I compile data on corporate bond ETFs, including the daily ETF returns and holdings, intraday ETF illiquidity and inefficiency measures, authorized participants, and data on corporate bond securities, including monthly returns, price pressure measures, and illiquidities.

3.1 Corporate bond ETFs

I gather passive corporate bond ETF information from the ETF Global database, including daily fund returns (in basis points), daily NAVs, daily shares outstanding, daily fund flows, short-selling shares, assets under management (AUM), the size of the creation unit, total expenses, option availability, investment asset classes, category, and investment focus. For each ETF, the number of its daily observations in the first available month should be greater than 10 and its maximum AUM greater than $1 million.

Redemption days for each ETF are identified as the negative changes in daily shares outstanding. Specifically, an ETF i at day t has a redemption activity if its daily shares outstanding decrease by the creation unit size. The final ETF daily return series data include 113 unique corporate bond ETFs from January 3, 2012, to December 31, 2021.

To identify the daily holding basket, I combine the selected corporate bond ETFs with their daily constituents' database from ETF Global. The ETF Global only reports CUSIPs or security names since 2014; thus, the daily holding sample begins in 2014. Then I merge the holding sample with the Mergent FISD database to collect corporate bond information. The daily portfolio recorded in the ETF Global database may lead to or lag by one day. If there is a large number of zero holding changes at day t, I shift holding information by one day to align with the date of share changes. The final holding sample has 104 unique corporate bond ETFs from January 2, 2014, to December 31, 2021.

Figure 4 presents the frequency and percentage absolute changes in shares outstanding of redemption and creation activities for the US corporate bond ETFs. Creations are roughly two times more likely to occur than redemptions (12% versus 5%), but the average changes in shares outstanding of redemptions are larger than creations (4% versus 2%), especially during economic fluctuations such as the COVID-19 pandemic crisis in 2020.

3.1.1 ETF mispricing

For ETF i at day t, p_{it} denotes the logarithm of the daily ETF price and n_{it} the logarithm of the daily NAV. The ETF mispricing ($Misp$) is the absolute difference between log price and log NAV,

$$Misp_{it} = |p_{it} - n_{it}| \times 10^2 ,$$

where $|\cdot|$ is the absolute operator and I scale the measures into percentages. Petajisto (2017) and Lettau and Madhavan (2018) find that the corporate bond market has infrequent transactions and that prices are stale. The mispricing may not promptly reflect the arbitrage profit. Therefore, short selling represents an alternative measure of arbitrage opportunity.

If an investor short sells ETF shares upon redemptions, she can ask the broker to borrow ETF shares directly from brokerage firms. I calculate the short interest rate (SII, in basis points) as the ratio between the number of short-selling shares and AUM. I use AUM instead of shares outstanding because redemptions do not directly affect AUM.

3.1.2 ETF illiquidity and inefficiency

To measure intraday ETF illiquidity in the secondary market, I use the New York Stock Exchange Daily Trade and Quote (DTAQ) database and the WRDS Intraday Indicators to construct the daily ETF effective and realized spread measures. The effective spread of the q^{th} trade of an ETF i at day t is defined as

$$Esprd_{i,q,t} \quad = \quad 2 \times |p_{i,q,t} - m_{i,q,t}| \ ,$$

where $p_{i,q,t}$ is the logarithm of price of the q^{th} trade and $m_{i,q,t}$ is the logarithm of midpoint of the consolidated BBO prevailing at the time of the q^{th} trade. An ETF's $Esprd_{it}$ is the dollar-volume weighted average of $Esprd_{i,q,t}$ computed over all trades everyday in basis points. The realized spread is the temporary component of the effective spread. For a given ETF, the realized spread on the q^{th} trade is defined as

$$Rsprd_{i,q,t} \quad = \quad \begin{cases} 2 \times (p_{i,q,t} - p_{i,q+5,t}) & \text{when the } q^{\text{th}} \text{ is a buy} \\ 2 \times (p_{i,q+5,t} - p_{i,q,t}) & \text{when the } q^{\text{th}} \text{ is a sell ,} \end{cases}$$

where $p_{i,q+5,t}$ is the logarithm of price of trade five minutes after the q^{th} trade. The trades are signed according to the Lee and Ready (1991) algorithm. Aggregating over a day, an ETF's dollar-volume-weighted realized spread ($Rsprd_{it}$) is computed over all trades on day t in basis points.

Intraday inefficiency is measured by the daily 30-minute variance ratio and daily absolute order imbalance. The variance ratio is based on the property of a random walk process such that the variance of its increments must be proportional to the time interval over which the returns are sampled (Lo and MacKinlay, 1988). I use the 30-minute variance ratio (%) as departures from a random walk:

$$VR30_{it} \quad = \quad \left| \frac{15 \times \sigma^2_{i,15\text{ min},t}}{30 \times \sigma^2_{i,30\text{ min},t}} - 1 \right| \ ,$$

where $\sigma^2_{i,15\text{ min},t}$ and $\sigma^2_{i,30\text{ min},t}$ are the return variances measured over 15- and 30-minute intervals of an ETF i at day t. This measure captures the absolute deviations of the ratio of long-term to short-term variance from one, which is the expected value of the ratio under the random walk hypothesis. Greater deviations of the variance ratio from one signal lower price efficiency.

I construct the absolute order imbalance based on the number of orders (OIN, %), defined as the absolute difference between the total number of buys and the total number of sells divided by the sum of buys and sells. By construction, the absolute order imbalance metric is bounded by 100% (when there are no sells or buys) and zero (when buys are equal to sells). A small number of *OIN* represents a more efficient market. Each transaction is designated as either buyer initiated or seller initiated according to the Lee and Ready (1991) algorithm.

3.2 Authorized participants

The SEC From N-CEN is the required form for *annual* reports filed under rule 30a-1 under the Act (17 CFR 270.30a-1) by management companies with ETF products starting from 2018. They must fill out Part E of the form, which captures information about the fund's registered authorized participants (including name, legal entity identifier (LEI), the dollar value of redeemed/purchased fund shares, and so on.). ETFs report all APs with which they have legal agreements, even if an AP is inactive throughout the entire reporting period. Inactive APs are reported to have creation and redemption volumes of zero.[4]

I collect N-CEN and N-CEN/A forms reported by management companies to the SEC Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system from 2018 to 2021. Then, I remove files that cover less than 12 months and keep the last filing in a reporting period (Arora et al., 2020; Gorbatikov and Sikorskaya, 2022). Lastly, I parse all available N-CEN and N-CEN/A forms and collect the identities of APs for each ETF, which yields 2,122 ETFs with reliable AP information. Combining the corporate bond ETF sample with those in the parsed N-CEN forms, I have 104 unique corporate bond ETFs.

Most APs are investment banks and brokers and dealers — for example, Citigroup Inc. and J.P. Morgan Chase & Co. — who can also trade on their accounts and on their clients' behalf. I extract the quarterly portfolio holding amount and values on Form 13F from the WRDS SEC Analytics Suite and manually match AP names with institution names in the 13F database.[5] I remove all corporate bond observations without CUSIP numbers and merge with the Mergent FISD. Lastly, I construct monthly AP portfolio liquidity using quarterly bond holding weights and monthly liquidity measures, defined in the following

[4] For example, Vanguard Scottsdale Funds (CIK=0001021882) reported the authorized participants of all ETFs in the N-CEN form on August 31, 2018, including Vanguard intermediate-term corporate bond index fund (VCIT), Vanguard long-term corporate bond index fund (VCLT), Vanguard total corporate bond ETF (VTC), and so on. The corresponding APs include Barclays Capital Inc., BNY Mellon Capital Markets LLC, CitiGroup Inc., Goldman Sachs Group Inc., J.P.Morgan Chase & Co., BofA Merrill Lynch, Royal Bank of Canada, and UBS Group AG.

[5] There are two caveats to using Form 13F. First, institutional investment managers with investment discretion over $100 million or more in Section 13(f) securities are required to file quarterly reports with the SEC on Form 13F. The SEC publishes the list of Section 13(f) securities, which primarily include US exchange-traded stocks, shares of closed-end investment companies, and shares of ETFs. Certain convertible debt securities, equity options, and warrants are on the official list and may be reported. The second caveat in using Form 13F data to identify institutional corporate bond ownership is that Form 13F covers only a fraction of corporate bond holdings.

section. I then have bond portfolios for 54 APs from 2018 to 2021.

3.3 Corporate bond illiquidity

I use five monthly illiquidity measures in the paper: the Amihud illiquidity measure, the Roll measure, the illiquidity corporate bond measure, the average trade-weighted bid-ask spread, and the imputed roundtrip cost. The detailed variable definitions are described in Appendix A.3.

Illiquidity measures are computed using the intraday bond transactions from the enhanced TRACE database. First, I filter out observations based on Dick-Nielsen, Feldhutter, and Lando (2012). Then I remove bonds with prices lower than \$5 or higher than \$10,000, durations less than one year, and volumes less than 10,000 units. Finally, I exclude bonds with less than 10 observations in the sample.

To construct the common components of liquidity measures, I begin with standardizing measures with zero means and unit standard deviations; then, I take the simple average of non-missing standardized liquidity measures. Thus, the higher the measure's value, the less liquid or more illiquid is the underlying corporate bond. I winsorize the standardized liquidity measure by 1% and 99% levels. The combination of these measures depicts multiple dimensions of illiquidities in the corporate bond market, including market maker costs for facilitating buyers and sellers (Kargar et al., 2021) and price impacts in the secondary market. Illiquidity is assumed exogenous for ETFs but endogenous for APs.

3.4 Price pressure

Price pressure in the corporate bond market is from "emergent" asset sales by institutions with large outflows. I begin with measures at the bond level using mutual fund holdings and flows. Data on active and passive corporate bond mutual funds are from the CRSP Survivorship-bias-free mutual fund database. Fund total net assets (TNA) should be at least \$1 million, with at least one year of holdings data and 10 distinct holdings at each period. I require that funds invest at least 10% of their total assets in corporate bonds. The monthly fund flow is

$$flow_{k,m} = \frac{TNA_{k,m} - TNA_{k,m-1} \times (1 + return_{k,m})}{TNA_{k,m-1}}, \tag{1}$$

where $TNA_{k,m}$ is the TNA for mutual fund k at the end of month m and $return_{k,m}$ is the monthly return for fund k over month m.

I first construct the *holding-based* price pressure measures for each bond. Following Choi et al. (2020), the sell pressure $SellPres$ for bond j in month m is

$$SellPres_{j,m} \quad = \quad \frac{\sum_{k \in \{flow_{k,m} < \text{pctl}(10)_m\}} \max(0, -\Delta Holding_{j,k,m})}{\text{Offering Value}_{j,m}} \, , \tag{2}$$

where k represents the k^{th} mutual fund. $flow_{k,m} < \text{pctl}(10)_m$ requires the monthly flow of fund k below the cross-sectional extreme net outflows (bottom 10^{th} percentile), and *Offering Value*$_{j,m}$ is the initial offering value of bond j available in month m from the Mergent FISD database (Falato et al., 2021). Following Coval and Stafford (2007) and Choi et al. (2020), I combine sells from funds with extreme net outflows and buys from funds with extreme net inflows, and the net sell pressure $NetPres$ for bond j in month m is

$$NetPres_{j,m} \quad = \quad \frac{\textit{Flow Induced Sells}_{j,m} - \textit{Flow Induced Buys}_{j,m}}{\textit{Offering Value}_{j,m}} \, , \tag{3}$$

where $\textit{Flow Induced Sells}_{j,m} = \sum_{k \in \{flow_{k,m} < \text{Percentile}(10)_m\}} \max(0, -\Delta Holding_{j,k,m})$ and $\textit{Flow Induced Buys}_{j,m} = \sum_{k' \in \{flow_{k,m} > \text{Percentile}(90)_m\}} \max(0, \Delta Holding_{j,k',m})$, k (k') represents the k^{th} (k'^{th}) mutual fund, and $flow_{k,m} > \text{pctl}(90)_m$ requires monthly flow of fund k above the cross-sectional extreme net inflows. Coval and Stafford (2007) also construct alternative measures by multiplying changes in holdings by non-negative flows.

Then, I construct the *common-flow-based* pressure for each corporate bond j in month m. Following Aragon and Kim (2022) and Dou, Kogan, and Wu (2022), I start with the definition of *Common flow shock*$_m$, which is the first principal component of the TNA quintile-sorted bond fund net flow shocks. The shock is the residuals, $\eta_{k,m}$, of the following regression:

$$flow_{k,m} \quad = \quad b_0 + \sum_{\tau=1}^{2} b_\tau (return_{k,m-\tau} - return^{mkt}_{m-\tau}) + b_3 flow_{k,m-1} + \xi_m + \eta_{k,m} \, , \tag{4}$$

where $return^{mkt}$ is the CRSP value-weighted market return from Ken French's website and ξ_m is the monthly fixed effect. There are two lags of excess fund returns and one lag of fund flows.

For each price pressure measure defined, the bond-level exposure is the coefficient $Expo$ in the following regression estimated over a 36-month rolling window with a minimum of 10 non-missing observations:

$$BondRet_{j,m} \quad = \quad a + Expo_{j,m} \times \text{price pressure measure}_{j,m-1} + Controls + \varepsilon_{j,m} \, , \tag{5}$$

where $BondRet_{j,m}$ is the end-of-month bond returns from the WRDS Corporate Bond database. I use the one-month lagged price pressure measure to address delayed fund portfolio disclosures. The term *Controls* includes numerical credit ratings, time to maturity, duration, and contemporaneous and lagged standardized illiquidity defined above. These variables control for credit risks, duration risks, interest rate risks, and liquidity risks (Bretscher et al., 2022).

I aggregate over each of the monthly bond level exposures $Expo$ to the ETF level using daily portfolio holding weights $\omega_{i,j,t\in m}$ of bond j held by the i^{th} ETF at day t in month m:

$$Expo_{it} = \sum_{j=1}^{J} \omega_{i,j,t\in m} Expo_{j,m} \,, \tag{6}$$

where J represents the total number of ETFs with bond j in their portfolios. To remove scale differences, I take the standardization of these five exposures to zero means and unit standard errors and winsorize the exposures by 1% and 99% levels.

To further isolate illiquidity effects on exposures, I regress each of five exposures on the standardized illiquidity defined above and use residuals as the final definition of ETF-level exposures, which include holding-based exposures using sell pressure, net sell pressure, and their flow versions, and common-flow-based exposure. The detailed data sources and variable definitions are described in Appendix A.2.

3.5 Summary Statistics

Table 1 summarizes the statistics of variables used in the paper. I report the sample means, standard deviations, median values, and 5^{th}, 25^{th}, 75^{th}, and 95^{th} percentiles. The units of daily fund returns, short interest rate, and effective and realized spreads are in basis points, and the units of mispricing, variance ratio, order imbalance, fund flows, total expenses, price pressure exposures, and illiquidity measures are in percentages.

On average, the daily return on corporate bond ETFs in the sample is 1.34 bps per day. Comparably, the daily return on active managed corporate bond mutual funds is 0.23 bps. ETFs have on average 0.42% mispricing and 4.0 bps short interest of arbitrage opportunities for APs everyday. The average daily effective and realized spreads are 19.1 and 15.0 bps, and the variance ratio and the order imbalance are 29.6% and 30.7%.

Comparably, the average effective and realized spreads of SPDR S&P 500 index ETF (SPY) and Invesco QQQ Trust are 9.2 bps and 8.6 bps, respectively. The variance ratios and order imbalances are 26.5% and 2.8%. I also compare the statistics with common stocks traded in exchanges. The average effective spreads of common stocks are 76.6 bps, and the average variance ratio and order imbalance are similar to bond ETFs at 30.0% and

17.4%.

In terms of price pressure exposure (of hypothetical ETFs), its average is different across different measures. Thus, I standardize the values with zero means and unit standard errors in the empirical analysis. Lastly, the illiquidity percentage changes in ETF baskets, remaining portfolios, and APs are -0.49, 0.12, and 2.15, respectively.

4 Economic Incentives

This section examines the incentives of ETFs and APs on determining the components of baskets in Hypotheses 1 and 2.

4.1 ETF incentives

I begin with sample comparisons of exposures to price pressure between redemption baskets and remaining portfolios on redemption days. To facilitate comparisons across different measures, I standardize exposures with zero means relative to the sample of both the baskets and the remaining portfolios. Figure 5 illustrates the standardized exposure results.

The baskets are exposed to price pressure by 2.8% to 3.6%, and the remaining portfolio exposures range from -3.5% to -2.7%. It turns out that the remaining portfolios are less exposed than baskets on average. For example, the average exposure using $NetPres$ is 3.1% for baskets, whereas the exposure is -3.1% for the remaining portfolios. The differences range from -5.5% to -7.2%. The corresponding t-statistics of differences are -2.9, -11.6, -13.5, -11.9, and -2.6. The results suggest that ETFs prefer to hold bonds with low exposure to price pressure and dispose of those that might suffer from price pressure.

ETF sponsors strengthen the redemption mechanism by choosing baskets with high exposures. Suppose bond mutual funds sell 1% of the offering values for *all* corporate bonds, whose outflows lie below the bottom cross-sectional 10$^{\text{th}}$ percentile of the fund industry. Then the net selling pressure equals 1% for each corporate bond. For bond ETFs, the value of redemption baskets increases by 3.1 bps, and the value of the remaining portfolios decreases by 3.1 bps. Equivalently in dollar value, the baskets increase by \$25,713 (= 3.1bps$\times$average AUM of baskets), and the remaining portfolios reduce by \$38,570 (= -3.1bps$\times$average AUM of remaining portfolios). The redemption mechanism works successfully by correcting the difference between ETF share prices and NAVs to attenuate discounts. Thus, ETF sponsors deliver baskets of corporate bonds exposed to price pressure in redemptions, which is beneficial to reinforcing the redemption mechanism. Since the basket value will be higher, it is also profitable for APs to become involved in the redemption process by absorbing additional risks. Moreover, for corporate bonds, higher price (value) represents lower yield; thus, sponsors keep bonds with high yields in the remaining portfolios.[6]

Then I address heterogeneity in negotiation and include control variables. The question is, under intense negotiation between ETF sponsors and APs, whether sponsors have stronger incentives to fill redemption baskets with more exposed corporate bonds. To evaluate heterogeneous negotiation, I define a ratio between counts of corporate bonds in the baskets and those in the remaining portfolios. The assumption is that a smaller ratio represents a greater deviation from benchmarks after negotiating with APs, implying a more profound negotiation (Shim and Todorov, 2022).

To answer the question, I adopt a counterfactual experiment. First, I assume an ETF does not dispose of any corporate bonds upon redemption. Instead, this hypothetical ETF keeps all bonds, and I calculate its exposures using one-day lagged holding weights. Second, I investigate both the intensive and the extensive margin effects of negotiation. The intensive margin is measured using one minus the ratio such that the higher $1 - ratio$ represents more intense negotiation. The extensive margin is evaluated using a fraction dummy, $D(Fraction)$. The dummy equals one if the ratio is lower than 60% and zero otherwise. I choose the threshold because the average share of components in baskets among corporate bond ETFs is 20% to 40%, as documented in Shim and Todorov (2022) and Koont et al. (2022). The threshold in this paper is sufficiently large, and the results are consistent if I use different levels (from 30% to 90%). The hypothesis is that hypothetical ETFs under more intense negotiation will be associated with larger exposures. The regression is as follows:

$$Expo_{i,t} = \alpha + \beta Fraction_{i,t-1} + \Gamma \mathbf{X}_{i,t-1} + \delta Illiquidity_{i,t-1} + \xi_i + \xi_{obj} \times \xi_t + \varepsilon_{i,t} \,, \tag{7}$$

where $Expo_{i,t}$ is the hypothetical ETF exposure at day t estimated using each of five pressure measures (see Eq. (6)). It is the weighted sum of bond-level exposures ($Expo_{k,m+1}$) in month $m+1$ using one-day lagged holding weights ($\omega_{i,k,t-1 \in m}$). In Eq. (7), $Fraction_{i,t}$ represents both the intensive ($1 - Ratio$) and extensive margins ($D(Fraction)$) defined above; $\boldsymbol{X}$ includes the logarithm of assets under management (log(AUM)), daily fund flow, total expenses, and the standardized illiquidity measure; ξ_i is the individual ETF fixed effect that captures time-invariant heterogeneities among ETFs; $\xi_{obj} \times \xi_t$ is the CRSP investment objective code times the date fixed effect, controlling for time-varying effects across

[6] Moussawi, Shen, and Velthuis (2022) document that in-kind redemption facilitates ETFs to avoid capital gain distribution, contributing to tax efficiency among ETFs. I show that ETF sponsors choose bonds with high exposure to price pressure into baskets, which is consistent with the transaction of offloading assets with capital gains. In the Online Appendix, I further discuss ETFs with annual capital gain distribution and show that exposure to price pressure still works.

investment categories; $\varepsilon_{i,t}$ is the residual; and the standard errors are clustered at the investment category level.

The coefficient of interest is β. The implication of β is to compare the exposures of hypothetical ETFs with intense negotiation relative to those with moderate negotiation on redemption days. Hypothetical ETFs under tough negotiation carry more exposures in redemptions than those under mild negotiation, and sponsors should have filled these bonds in baskets. Therefore, the estimated β should be positive and significant.

Table 2 reports the intensive and extensive margin results using hypothetical ETFs on redemption days. A hypothetical ETF with intense negotiation carries 1.6% to 9.1% higher price pressure exposures using the intensive margin ($1 - ratio$, Panel A) and 0.6% to 2% higher exposures using the extensive margin ($D(Fraction)$, Panel B). This finding implies that the hypothetical ETF under intense negotiation bears extra exposures by keeping baskets. For example, using the net sell pressure measure, the coefficient on the extensive margin, $D(Fraction)$, is 0.64 in Column (1) of Panel B. When the hypothetical ETF negotiates with APs, if the basket contains less than 60% of its total portfolio holding, the exposure would be 0.64% higher than the hypothetical ETFs with moderate negotiation. Similarly, the sell pressure measure coefficient on the extensive margin is 2.5% in Column (3). The flow shock measure also has a significant coefficient on the dummy variable (t-statistic = 2.38).

The coefficients are economically significant. Given that the standard deviation of $1 - ratio$ is 0.72 and $D(Fraction)$ is 0.81, the intensive margin increases net selling pressure, $NetPres$, by 1.15% (=1.59×0.72), and the extensive margin increases $NetPres$ by 0.52% (=0.64×0.81), which represent a 1/10 to 1/5 increase relative to average $NetPres$.

Coefficients on $Illiquidity$ are significant but negative in the regression of net sell pressure ($NetPres$ and $NetPres \times Flow$) and sell pressure ($SellPres$ and $SellPres \times Flow$) measures. The estimates show that illiquidities in the baskets are lower than those in the remaining portfolios under strong negotiation capacity. The results are consistent with the bond characteristics documented in Shim and Todorov (2022) and similar to the liquidity patterns in corporate bond mutual funds documented in Jiang, Li, and Wang (2021) and Ma, Xiao, and Zeng (2022).

The sample comparison test and the counterfactual experiment support Hypothesis 1 and suggest that ETFs dispose of baskets with higher price pressure exposures and hold bonds in remaining portfolios with lower exposures. The incentives of ETFs also show that ETFs do not deliberately deliver APs with low-quality corporate bonds but aim to correct discrepancies between share prices and NAVs. The choice also depends on the intensity of the negotiation. If there is more negotiation between ETFs and APs, then ETFs would prevent bearing price pressure in their remaining portfolios.

4.2 AP incentives

The incentive of ETFs implies that they give baskets exposed to price pressure to APs. The concern is that AP portfolios bear additional risks and may experience a liquidity squeeze after accepting baskets from ETFs. Their companies and clients will absorb the adverse effects. This section reconciles the incentives of APs.

APs are responsible for mitigating the arbitrage via redemptions in the primary market and receiving baskets from ETFs. APs either keep bonds in the inventory for arbitrage or buy and sell bonds in the bond market. Given their dual role as bond investors and ETF arbitrageurs, they carry dual functions: involving redemption activities with ETFs and managing their investment portfolios. Ever since the bankruptcy of Lehman Brothers in 2008, the liquidity provided by investment banks has been under strict scrutiny. Thus, the illiquidities of baskets and investment portfolios are essential to APs.

Liquidity management requires the consideration of the co-movement in illiquidity between baskets and APs' portfolios. I hypothesize that APs negotiate with ETFs to choose components of baskets to reduce the co-movement in illiquidity.

I construct the percentage changes in the illiquidity measure to evaluate the liquidity management in APs upon redemptions. For each ETF-AP pair, I regress the percentage changes in the basket or remaining portfolio illiquidity on the percentage changes in the AP portfolio illiquidity and the percentage changes in the cross-sectional bond market average illiquidity,

$$\begin{aligned}
\Delta Illiq_{AP,i,m\in q} &= \beta_0 + \beta_1 \Delta Illiq^{\text{redemption}}_{\text{Basket},i,t\in m} + \beta_2 \Delta Illiq_{MKT,m} + Controls + \varepsilon_{AP,i,t} \\
\Delta Illiq_{AP,i,m\in q} &= \gamma_0 + \gamma_1 \Delta Illiq^{\text{redemption}}_{\text{Remaining},i,t\in m} + \gamma_2 \Delta Illiq_{MKT,m} + Controls + \varepsilon_{AP,i,t}\ ,
\end{aligned} \tag{8}$$

where $Illiq_{AP,i,m\in q}$ is the ETF i-paired AP's portfolio illiquidity using quarter-end weights and month-end illiquidity measures, and $Illiq^{\text{redemption}}_{\text{Basket},i,t\in m}$ ($Illiq^{\text{redemption}}_{\text{Remaining},i,t\in m}$) represents the paired ETF i's baskets or remaining portfolios in the redemption activity at day t in month m, aggregated over corporate bond illiquidities using daily ETF holding weights. $Illiq_{MKT,m}$ is the cross-sectional average of bond illiquidities in month m. Δ is the percentage change operator. I include the contemporaneous CRSP value-weighted market returns and the contemporaneous ETF portfolio return and its squared. The market returns are included to control for possible correlations between returns and bond illiquidity. The ETF returns squared is included to capture any effects of return volatility that could be related to illiquidity.

I estimate coefficients in a pooled OLS regression with ETF and AP fixed effects to control for heterogeneities in ETFs and APs.[7] I use percentage changes in illiquidities and include various daily series, so I do not include date fixed effects. The standard errors are clustered at the AP level. Since I have around 50 APs in the sample and there is a concentration in the activities of APs with ETFs (Arora et al., 2020), variations are assumed to cluster across APs.

The coefficients of interest are β_1 and γ_1. If the estimated β_1 is significantly negative, APs accept the basket to have negative liquidity co-movement with their portfolio. The magnitude of β_1 is equivalent to the correlation between percentage changes in basket illiquidity and percentage changes in AP portfolio illiquidity, that is, $\beta_1 \propto corr(\Delta Illiq_{AP,i}, \Delta Illiq^{\text{redemption}}_{\text{Basket},i})$. I expect an insignificant γ_1, suggesting APs do not care about illiquidity in the remaining portfolios. The magnitude of γ_1 is assumed to be lower than β_1. The significant difference between β_1 and γ_1 implies that APs have stronger incentives to accept a basket that is helpful in managing liquidity when negotiating with ETFs.

Table 3 presents estimates of percentage changes in baskets (remaining portfolios) and market illiquidities in the panel regressions (Panel A). The negative signs of the two coefficients, β_1 (γ_1) and β_2 (γ_2), show that AP portfolio illiquidity on average co-moves negatively with both the illiquidity of ETF basket and the market portfolio. Moreover, only β_1 on changes in ETF basket illiquidity is significant at the 1% level (t-statistic $=$ -2.11), suggesting that AP portfolio liquidity management focuses on choosing negative co-movement baskets with ETFs.

The magnitudes of β_1 and γ_1 suggest that the negative co-movement in illiquidity between the AP portfolio and redemption basket is stronger than that of the remaining portfolios (F-statistic $= 3.88$ with p-value $= 0.05$), implying that APs choose and negotiate with ETFs on a beneficial basket.

The economic magnitude of β_1 is also significant. Given that the standard deviation of $\Delta Illiq^{Redemption}_{Basket}$ is 14%, then one unit increase in the standard deviation is associated with a 0.42% decrease in AP illiquidities, which is about a 20% drop relative to the sample average of AP illiquidity (2.15%). Yet, the economic value of γ_1 is negligible at 0.06% of average $\Delta Illiq^{AP}$. These results are consistent with Hypothesis 2.

[7] The estimation of illiquidity co-movement is in line with commonality in liquidities. The seminal work of Chordia, Roll, and Subrahmanyam (2000) regresses daily changes in stock liquidities on lead and lag changes of daily market liquidities, market returns, and market return squared for each stock in a month. Then, among estimated coefficients on changes in the contemporaneous market liquidity, they count the percentage of positive and negative ones. They interpret positive coefficients as a more substantial commonality between stock liquidities with market liquidity. However, daily corporate bond liquidity measures are not feasible because of the low trading frequency in the corporate bond market. I modify the method into a panel regression with fixed effects. Since classic methods use daily time-series regressions and take the simple average, I include ETF and AP fixed effects to absorb asset heterogeneity. The estimated coefficients are comparable with the average of the time-series variables in Chordia, Roll, and Subrahmanyam (2000) and are interpreted as co-movement between ETFs and APs.

To further understand the robustness of APs' incentives, I focus on the subsample period with the COVID-19 pandemic. Between March 5 and March 23, 2020, the ICE Bank of America AAA US Corporate Index Option-Adjusted spread increased by about 150 bps. The spread for high-yield bonds increased by over 500 bps. The bond market exerted a positive (negative) shock on corporate bonds' illiquidity (liquidity). Therefore, I test the co-movement using the sample period March 11, 2020 to December 31, 2021. I argue that the incentives of APs to select the negatively co-moved baskets are even stronger than the whole sample results.

The coefficient on $\Delta Illiq_{Basket}^{Redemption}$ in Panel B of Table 3 shows that the co-movement in illiquidity between baskets and AP portfolios is significantly negative, and the magnitude is similar to that of the full sample estimates (-0.043 in the third column). Yet, the coefficient on the remaining portfolios is significantly positive. The result is consistent with the claims by market makers that they kept involved in the redemption process during the COVID-19 pandemic. Meanwhile, the coefficient of remaining portfolio illiquidity is significantly positive, which is consistent with the fact that illiquidities during the crisis are positively correlated across different assets.

The insignificant negative coefficients on ETF returns in baskets (-0.17 and -0.08) suggest that good-performing ETFs marginally contribute to the illiquidity of AP portfolios. For CRSP market returns, in the full sample results, the coefficients are significantly positive (0.13 and *t*-statistic=3.72). Yet, the coefficients are negative in the COVID-19 period (-0.02 and *t*-statistic=-1.46). The average percentage changes in the illiquidity of baskets is 0.69 during the COVID-19 pandemic and -0.80 in other periods, suggesting that in a well-behaved market, APs tend to bear more illiquidity in their own portfolios. During market turbulence, however, APs treat good market returns as a trigger for improving the illiquidity condition of their portfolios.

5 Economic Impacts

This section investigates the economic impacts of redemption on ETF investors, APs, and demand in the secondary market. I compare effects on redemption days with those on normal days, on which shares outstanding do not change. Reilly (2022) suggests that this method is equivalent to a difference-in-differences design. The treatment group includes ETF-day observations on redemption days, and the control group constitutes ETFs on normal days.

5.1 Investors and APs

To examine Hypothesis 3, I estimate the following regression model

$$Outcome_{i,t+1} = \alpha + \beta D(Redemption)_{i,t} + \Gamma \mathbf{X}_{i,t} + \xi_i + \xi_{obj} \times \xi_t + \varepsilon_{i,t+1} , \tag{9}$$

where $Outcome_{i,t+1}$ is one of the seven variables of ETF i at day $t+1$. It includes daily fund returns (Ret), effective spread ($Esprd$), realized spread ($Rsprd$), 30-minute variance ratio ($VR30$), the absolute order imbalance in numbers of transactions (OIN), mispricing ($Misp$), and short interest rate (SII). In Eq. (9), $D(Redemption)_{i,t}$ equals one if there is a redemption in the i^{th} ETF at day t and equals zero if there are no changes in shares outstanding. The coefficient of interest is β, which examines the effect of redemption events on $Outcome$ variables relative to normal days.

The term $\boldsymbol{X}$ is the vector of control variables used in the literature, including the logarithm of assets under management $log(AUM)$, daily fund flow, total expenses, short interest rate, and the dummy for option availability D(Option available). ξ_i is the individual ETF fixed effect that captures time-invariant heterogeneities among ETFs. $\xi_{obj} \times \xi_t$ is the CRSP objective code times date fixed effect, controlling for time-varying effects across investment categories; for example, it accounts for the variations in high-yield and investment-grade corporate bond investment. $\varepsilon_{i,t+1}$ is the residual, and the standard errors are clustered at the investment category level.[8]

Table 4 reports the estimation results. For investors, Column (1) shows that redemption activities are negatively associated with next-day fund returns with coefficients of -2.3 (t-statistic=-3.6). Given that the average daily ETF return is 1.3 bps in Table 1, the impact is economically significant. Columns (2) and (3) document the impact of redemptions on illiquidities, where redemptions escalate the effective and realized spreads by 1.3 bps. The wide spread increases transaction costs in the secondary corporate bond ETF market by 6.8% and 8.7%, where the average effective and realized spreads are 19.1 bps and 15.0 bps. Redemptions reduce price efficiency, as is evident by the large coefficients on variance ratio (0.9%) and order imbalance (1.9%) in Columns (4) and (5). These results imply that investors bear losses in returns and face a worse market condition.

Since ETF investors suffer from redemptions in the secondary market, I examine whether APs gain from exploring arbitrage opportunities upon redemption. In Columns (6) and (7) of Table 4, the coefficients of redemption activities on the mispricing and the rate of short interests are 0.13 and 0.98, respectively (t-statistics = 15.9 and 3.4), suggesting that APs benefit from redemptions with more arbitrage opportunities. For example, in a fric-

[8] In the Online Appendix, I report alternative combinations of fixed effects and clusters. The results are similar to Table 4.

tionless environment, APs explore the 0.13% increase in arbitrage opportunities as the difference between share prices and NAVs. In dollar value, APs' arbitrage profits are \$127,660 (=0.13%×average flows on redemption days).

Control variables are relevant to the analysis. The variable *log(AUM)* addresses the fund size effects on ETF performance. Specifically, a large ETF fund size is related to lower fund returns, implying decreasing returns to scale in corporate bond ETFs. The negative and significant relation between ETF size and illiquidity and inefficiency measures shows that the large-sized ETFs are more liquid in a more efficient market. Fund flows have positive coefficients, and ETFs with more substantial investor demand benefit investors and APs. Yet, ETFs with inflows have large effective and realized spreads and order imbalances. Positive coefficients on total expenses on returns and arbitrage opportunities and negative coefficients on liquidity and efficiency suggest that funds with high expenses are competitive. Lastly, option availability also benefits investors and APs.

In summary, investors suffer from losses in ETF returns, and the secondary market becomes less liquid and less efficient. APs, on the other hand, exploit and gain more arbitrage profits. These results provide supporting evidence for Hypothesis 3.

5.1.1 Longer-horizon impacts

Shim and Todorov (2022) document that the components in baskets of redemptions are not persistent. Still, it is unclear whether gains/losses to investors and APs are persistent. Lettau and Madhavan (2018) also show that corporate bond ETFs might not display arbitrage opportunities through redemption activities because of the infrequent trade in underlying corporate bonds.

I thus calculate *Outcome* variables over the next 20 and 60 days. If the impact of redemption is temporary, the redemption does not affect the longer-horizon variables. Otherwise, even though the components in baskets are short term, redemption events have a longer-horizon market influence. Since the average horizon of bond trading is one month, the longer-horizon tests also illustrate the impact on arbitrage opportunities. The regression and specifications are the same as in Eq. (9), except that the dependent variables are over longer horizons.

Cumulative daily fund returns over the next month and next quarter are 11.3 and 28.9 bps lower (t-statistic = -4.2 and -3.1). The month and quarter averages of illiquidity and inefficiency measures have coefficients similar to those in Table 4. These estimates are economically sizable and persistent, suggesting that my hypothesis is not temporary.

5.2 Price-demand elasticity

Price multipliers (the inverse of price-demand elasticity) lie at the center of understanding how the demand of market participants affects asset prices (Gabaix and Koijen, 2021). The multiplier implies that increasing demand by $1 changes the asset market value by $$M$. I examine Hypothesis 4 using the price multiplier and discuss how redemptions affect demand in the corporate bond ETF market.

Following the novel approach proposed by Li and Lin (2022), I compare the estimated price multipliers on redemption days and normal days. I regress the daily corporate bond ETF returns on the daily demand for ETF shares in the secondary market. The panel regression is

$$Ret_{i,t+1} \quad = \quad a + M \times Demand_{i,t} + Controls_{i,t} + \xi_i + \xi_t + \epsilon_{i,t} \ , \tag{10}$$

where $Ret_{i,t+1}$ is the daily corporate bond ETF i's return at day $t+1$, and $Demand_{i,t}$ is the demand of ETF i at day t, which is defined as

$$Demand_{i,t} \quad = \quad \frac{\text{Number of Buy Shares}_{i,t} - \text{Number of Sell Shares}_{i,t}}{\text{Shares outstanding}_{i,t-1}} \ , \tag{11}$$

where *Number of Buy Shares* and *Number of Sell Shares* are the sums of the total number of shares of ETF i bought and sold at day t, respectively, and the denominator is the lagged number of shares outstanding. The demand definition is similar to the number of order imbalances except for the denominator. The price multiplier (the inverse of price-demand elasticity) is measured by the coefficient $M = \frac{returns}{Demand} = \frac{dP/P}{dQ/Q} = \frac{1}{elasticity}$. *Controls* include four lags of daily ETF returns, the logarithm of AUM, daily fund flows and three-period lagged flows, and total expenses. I add fund (ξ_i) and day (ξ_t) fixed effects and cluster standard errors at the fund and day levels.

Columns (1) and (2) in Table 5 compare the price multipliers on redemption days with those on normal days. On redemption days, the price multiplier is 10.5, implying that on the next day of redemption, a $1 increase in demand for bond ETFs changes the bond ETF market value by $10.5. Equivalently, 1% trade of average shares outstanding in ETFs would affect prices by 10.5%. The level is similar to the price multiplier of insurance companies (an average of around 10) in Bretscher et al. (2022), the aggregate-level price multiplier using size and value factors (around 7.0 to 9.5) in Li and Lin (2022), and the multiplier estimated using high frequent trade data (around 12 to 15) in Frazzini, Israel, and Moskowitz (2018).

On normal days, the price multiplier is 2.5. The level is similar to the micro price multiplier documented by Gabaix and Koijen (2021) and Li and Lin (2022) in the stock market. The high price multiplier on redemption days suggests that the market becomes less elastic and thus less competitive, and investors' welfare worsens relative to normal days. To ensure the effectiveness of the ETF redemption mechanism, ETF sponsors prefer an inelastic market because the ETF share price increases significantly with even a small increase in demand, which narrows discounts. In the Online Appendix, I compare the price multipliers using index-rebalancing-related redemptions (Koont et al., 2022), and the results are similar.

To understand how elasticity works in equilibrium, I describe a basic version of Gabaix and Koijen (2021)'s model. On normal days, investors invest in a mixed fund of corporate bond ETFs and a Treasury bond for simplicity. Whenever the investors collect an extra $1 in cash, they invest it in the mixed fund. The mixed fund must invest this $1 inflow equally in all bond ETFs and the Treasury bond. Hence, this pushes up the prices of ETFs, which causes the mixed fund to allocate more capital into ETFs from the Treasury bond, which pushes ETF share prices up, and so on. In equilibrium, the value of the bond ETF market increases by $2.5. On redemption days, in addition to the ETF investors described above, APs, acting as arbitrageurs, purchase an extra amount of ETF shares and redeem shares with ETFs. This transaction, or demand, further pushes up ETF prices, and the total value of the bond ETF market increases by $10.5.

One possible explanation for the coefficient difference is that the corporate bond market is opaque to investors. When the demand in corporate bond ETFs changes on redemption days, investors do not have direct information on the corporate bond market, which might be associated with subsequent redemptions and large price multipliers, possibly because of risk aversion or portfolio constraints.

I compare retail and institutional demand on redemption and normal days in Columns (3) and (4) of Table 5. It turns out that the magnitude of retail demand (3.9) is less extensive than institutional demand (11.3), and the institutional demand price multiplier is significant. Similarly, the institutional demand price multiplier is significant even on normal days. The levels of institutional demand on redemption and normal days are similar to the aggregate price multipliers. The results show that institutional investors are the primary driver of corporate bond ETF market elasticity. I further separate institutional investors into those with large (above 20,000 shares) and small trading sizes in Columns (5) and (6). The results show that large institutional investors bear the market price elasticity of corporate bond ETFs on redemption days. The evidence is consistent with the situation in which APs are large institutional investors.

Note that the daily fund flow coefficients can be interpreted as the multipliers of supply for ETF shares. Unlike stocks or corporate bonds issued by listed companies, whose supply depends on the level of production, fund flows between ETF sponsors and APs in the primary market directly represent changes in the supply quantity of ETF shares. The coefficient equals the ratio between percentage changes in share prices and percentage changes in supply quantity. The normal-day multipliers are smaller than redemption days, suggesting that the supply curve also becomes less elastic. However, the elasticities of the ETF share supply are larger than one, which implies that the supply is elastic. The results indicate that the redemption activities between ETF sponsors and APs are flexible to correct the discrepancies between share prices and NAVs.

Overall, these results suggest that the bond ETF market price multiplier is more prominent on redemption days than normal days, supporting the prediction of Hypothesis 4.

6 Additional Analyses and Robustness Tests

In this section, I conduct additional analyses to shed light on the endogeneity concerns in the main results, explore the importance of authorized participants in the corporate bond ETF market, and study the balance sheet constraints in APs. I also evaluate the robustness of the hypotheses results.

6.1 Endogeneity concerns

ETFs and APs may prefer bonds with specific time-varying characteristics correlated with the incentives of ETFs and APs, for which there are no controls. For example, credit and interest rate risks may be associated with redemption mechanisms, price pressures, and negotiation. To address the endogeneity concerns, I use shocks to price pressure or negotiations that affect some but not all ETFs, thus resulting in cross-sectional variation in incentives.

6.1.1 ETF incentives: Secondary Market Corporate Credit Facility

On March 11, 2020, the World Health Organization announced that COVID-19 had become a global pandemic. The pandemic became apparent regarding human suffering and turmoil in financial markets by mid-March 2020. For example, fund managers were affected by COVID-19 and the subsequent stay-at-home scheme (Pástor and Vorsatz, 2020; Cao, Simin, and Xiao, 2022). The pandemic also made over-the-counter corporate bond transactions difficult, raising severe bond price pressure concerns (Kargar et al., 2021; Ma, Xiao, and Zeng, 2022).

The Secondary Market Corporate Credit Facility (SMCCF), announced on March 23, 2020, supported market transactions for corporate debt by purchasing bonds and US-listed investment-grade ETFs in the secondary market. On December 31, 2020, SMCCF expired. The Federal Reserve wound down corporate bonds and exchange-traded funds. As of August 31, 2021, the Federal Reserve sold all corporate bonds and ETF shares in the SMCCF program. The unprecedented scope and size of this (exogenous) policy change surprised most investors.

SMCCF was an exogenous shock to relieve price pressure among corporate bonds, thus relaxing the intensity in negotiations between ETFs and APs. Therefore, the treatment group includes non-investment-grade ETFs that consistently bear price pressure and may break redemption mechanisms. The control group constitutes investment-grade corporate bond ETFs. I define $D(Treat)$ as one if an ETF belongs to the treatment group and zero otherwise. The post-period is separated by March 23, 2020, and $D(Post)$ equals one if a day is in the post-period. The difference-in-differences specification is

$$Expo_{i,t} = \alpha + \beta D(Treat)_i \times D(Post)_t + \Gamma \boldsymbol{X}_{i,t} + \delta Illiquidity_{i,t} + \xi_i + \xi_{obj} \times \xi_t + \varepsilon_{i,t} \ , \quad (12)$$

where control vector $\boldsymbol{X}$, $Illiquidity$, and fixed effects are defined as in Section 4. $D(Treat)_i \times D(Post)_t$ captures the shock to negotiation. If an ETF belongs to the non-SMCCF group and operates after the announcement of the SMCCF policy, then the negotiation will be severe between ETFs and APs. The intuition is that non-SMCCF ETFs are excluded by the policy and are confronted with pressure under intense negotiation. The coefficient of interest is β, which is expected to be positive. I report the standard error clustering at the investment objective level. The sample period is January 1, 2019 to December 30, 2020.

Panel A in Table 6 reports the results on net sell pressure and multiplying with flow measures. The coefficients on $D(Treat) \times D(Post)$ are positive and significant, indicating an economically large increase in the price pressure of hypothetical ETFs. For example, the estimated coefficient of 4.9 in Column (1) is large relative to the pre-COVID level of SMCCF-included ETFs. For one unit increase in the standard deviation of the interaction, the exposure to the net sell pressure increases by 3.2 bps, which leads to an increase in NAV by \$66,357 (=3.2 bps$\times$average AUM of ETFs). Column (2) shows that the estimated effect is similar using alternative pressure exposures. The results support Hypothesis 1.

For the difference-in-differences estimator to be valid, the fundamental assumption is that in the absence of the SMCCF, the treated and control groups share similar trends in the hypothetical ETF price pressure. I include additional six-month lags and leads to validate this assumption and estimate the difference-in-differences model above. The results in the Online Appendix show that the coefficients before the policy are (significantly) negative, and the coefficients are strongly positive after March 2020, when the policy was in effect.

6.1.2 AP incentives: SEC Rule 6c-11

SEC Rule 6c-11, which was proposed in September 2019 and came into effect on December 23, 2019, allows ETFs the flexibility to use baskets that differ from a *pro rata* representation of the ETF's portfolio. The rule provides an ETF with flexibility to use "custom baskets" if the ETF has adopted written policies. ETFs hence have more freedom to accept securities disproportionately to their index-tracking commitments.

The concern is that an AP takes advantage of its relationship with an ETF and forces the ETF to construct a basket that favors an authorized participant but hurts the ETF's investors. Therefore, APs can have a stronger incentive to negotiate with ETFs such that the co-movement between the basket and their portfolios is strongly negative and large. [9]

Using this new rule as an exogenous shock, I separate ETFs into treatment and control groups if their tracking errors are higher than the cross-sectional means. A larger tracking error of an ETF represents a greater deviation from the benchmark and leaves more intense negotiation. The post shock dummy $D(\text{6c-11})$ is one if a day is after September 2019 and zero otherwise.[10]

Tracking errors are defined as the standard deviation of the difference between daily ETF returns and underlying index returns over a 20-trading day window with at least 10 non-missing observations. Daily ETF returns are the log differences of share prices from the ETF Global database, the CRSP daily stock file, and the CRSP Survivorship-bias-free mutual fund database. I then hand-collect daily index levels of USD fixed-income indices from Bloomberg and Morningstar. The final sample contains 114 corporate bond ETFs with specified indices.

I define $D(TE)_{it}$ as one if the tracking error of ETF i at day t is higher than its cross-sectional mean, and the dummy equals to zero otherwise. The specification is

$$\begin{aligned} \Delta Illiq_{AP,i,m\in q} &= \beta_0 + \beta_1 \Delta Illiq^{\text{redemption}}_{\text{Basket},i,t\in m} \times D(\text{6c-11})_t \times D(TE)_{it} \\ &\quad + \beta_2 \Delta Illiq_{MKT,m} + Controls + \varepsilon_{AP,i,t} \\ \Delta Illiq_{AP,i,m\in q} &= \gamma_0 + \gamma_1 \Delta Illiq^{\text{redemption}}_{\text{Remaining},i,t\in m} \times D(\text{6c-11})_t \times D(TE)_{it} \\ &\quad + \gamma_2 \Delta Illiq_{MKT,m} + Controls + \varepsilon_{AP,i,t}\ , \end{aligned} \tag{13}$$

[9] For example, the International Organization of Securities Commissions (IOSCO) Consultant Report on ETF Good Practices shows that an AP may take advantage of its relationship with the ETF and pressure the ETF to construct baskets that favor the AP to the detriment of the ETF and its investors.

[10] I use the announcement rather than the implementation date as the introduction of the shock. The first reason is to ensure the policy change is exogenous to APs and ETF investors. The second reason is to have enough post-policy observations. In an alternative test, I define a post-period if a day is after December 23, 2019 and drop the overlapping days from September 1, 2019 to December 22, 2019. The results are similar.

where dependent variable $\Delta Illiq_{AP,i,m\in q}$, independent variables $\Delta Illiq_{i,t\in m}^{\text{redemption}}$, $\Delta Illiq_{MKT,m}$, and $Controls$ are defined as in Section 4. Interactions between $D(TE)_{it}$ and $D(\text{6c-11})_t$ are included in $Controls$. The standard errors are clustered at the AP level. The sample period is from January 1, 2018 to January 31, 2021.

Panel B in Table 6 reports the results on baskets and the remaining portfolios. The coefficient on the basket is significantly negative. Compared with baskets after the new proposed rule and ETFs with large tracking errors, the co-movement is significantly decreasing. The absolute magnitude is greater than that in Table 3 (-0.63 versus -0.03). The result suggests that the negotiation between APs and ETFs is more intense and APs have stronger incentives to select bonds with negative illiquidity co-movement between baskets and AP portfolios.

The estimation of -0.63 in Column (3) is significantly negative. APs negotiate with ETFs and require beneficial baskets for negative co-movement with their portfolios. The coefficient is also more significant than that in Table 3 because ETFs have more flexibility and APs impose more assertive negotiation. Yet, the coefficient of remaining portfolio co-movement is insignificantly negative (-0.136), and the difference between the coefficients of baskets and the remaining portfolios is significant (F-statistic=8.68). The evidence from this natural experiment is consistent with prediction of Hypothesis 2. I also examine whether ETF sponsors and APs negotiate and collude to hurt shareholders' benefits via tracking errors in the later section.

6.2 Contributions of APs to corporate bond ETFs

6.2.1 ETF flows and fragility

In the context of fragility, the effect of redemptions (outflows) is important. For example, since corporate bond mutual funds hold more illiquid assets, the strategic complementarity for redemptions will be stronger (Goldstein, Jiang, and Ng, 2017). The natural question is whether APs are essential in transmitting or preventing financial fragility upon redemptions.

I first regress flows on returns and investigate the sensitivity of outflows (redemptions) on bad performance. Then I study the strategic complementarity of ETF liquidity conditioning on negative returns.

The results are shown in the Online Appendix. First, the sensitivity of outflows of corporate bond ETFs to bad performance is lower than the sensitivity of inflows of those ETFs to good performance, where bad or good performance is indicated by negative or positive ETF returns. Specifically, the estimated coefficient of ETF returns is 0.26, and the coefficient of negative returns is -0.23 and is significant. In other words, the sensitivity of redemptions to negative returns is 0.03 (= 0.26−0.23), which is one-tenth that of the sensitivity of creations to positive returns (0.26). Such a convex flow-performance relation for corporate bond ETFs is different from the concave flow-performance relation documented in the corporate bond mutual funds (Goldstein, Jiang, and Ng, 2017) but is similar to patterns in equity funds (Chen, Goldstein, and Jiang, 2010).

Second, to emphasize the roles of APs, I take a triple interaction using returns, illiquidity, and the dummy of mispricing. The dummy is one if the mispricing is higher than the cross-sectional average and is zero otherwise. The intuition is that APs engage in arbitrage activities and determine the baskets under high mispricing between ETF prices and its NAVs. The results show that APs help attenuate strategic complementarity in ETF redemptions, suggesting that APs migrate fragility.

6.2.2 Comparing with index corporate bond mutual funds

Section 4 discusses the incentives of ETFs and APs in redemptions. One remaining question is whether incentives differ from passive/index corporate bond mutual funds where APs have no intermediation roles. I identify index corporate bond mutual funds from the CRSP Survivorship-bias-free mutual fund database using the non-missing index flag and excluding ETFs. I assume that ETFs are equivalent to index mutual funds only if they do not interact with APs.[11]

Index mutual fund monthly net flow, $flow$, is measured as in Eq. (1). If an index fund has net outflows, (i.e., $flow < 0$), the fund is assumed to encounter investor redemptions. Mutual fund investors do not trade shares in the secondary market but directly redeem shares with mutual funds. The net fund outflow is analogous to ETF redemption activities, except for the participation of APs.

I calculate the month-end changes in holding assets to construct redemption baskets of index mutual funds from the monthly CRSP Holding database. Then I derive the average exposures to price pressure as in Section 3 using monthly mutual fund holding weights.

Similar to the sample average test in Section 4, I compare the average exposures of the index mutual fund baskets and the remaining portfolio. I find that in the baskets of

[11] For example, Vanguard provides an index corporate bond fund and a corporate bond ETF tracking the same index. The index fund, Vanguard Intermediate-Term Bond Index Fund Admiral Shares (VBILX, CUSIP = 921937801), and the bond ETF, Vanguard Intermediate-Term Bond ETF (BIV, CUSIP = 921937819), are designed to track the performance of the Bloomberg US 5-10 Year Government/Credit Float Adjusted Index. This index includes all medium and larger issues of US government, investment-grade corporate, and investment-grade international dollar-denominated bonds that have maturities between 5 and 10 years and are publicly issued. For the index fund VBILX, investors may purchase or redeem shares online through the company website or by mail and telephone. Yet the ETF BIV may only be bought or sold in the secondary market through a brokerage firm. BIV shares cannot be directly purchased from or redeemed with the fund, except by APs.

index funds, the average exposures are not significantly lower than those in the remaining portfolios (t-statistic=-1.1). Even though index funds have investment objectives similar to bond ETFs, they do not share common management priorities.

The results suggest that the negotiation between ETFs and APs provides unique incentives for determining the baskets. The caveat is that the benefit of incorporating with APs is mainly investigated and verified in statistical terms. It would be helpful if there were counterfactual ETF-like financial intermediaries.

6.2.3 Balance sheet constraints in APs

Balance sheet and risk management constraints can limit the provision of arbitrage by APs, particularly in times of stress (Pan and Zeng, 2019; Ma, Xiao, and Zeng, 2022). Yet, market makers may get involved in the redemption process to explore arbitrage opportunities. Balance-sheet-constrained APs might still have provided less capital than they would have otherwise. I investigate whether external and internal balance sheet constraints alter the incentives of APs to select negatively co-moved baskets in redemption.

For external constraints, I use the institution's designation as a Global Systemically Important Bank (G-SIB) as the proxy. For a bank to be classified as G-SIB, the Bank of International Settlements uses a set of indicators from a sample of banks collected by national supervisory authorities. Institutions with G-SIBs face the most stringent external regulation. The systemic risk ($SRISK\%$) in financial institutions measures internal constraints.[12] A financial firm cannot function when the value of its equity falls to a sufficiently small fraction of its outstanding liabilities. $SRISK\%$ is the expected capital shortfall of this firm relative to the financial sector capital shortfall if there is a crisis. This measure is similar to the stress tests of financial firms, but it uses only publicly available information. Thus, a positive $SRISK\%$ represents internal constraints.

I begin with an AP facing internal and external constraints (i.e., G-SIB AP with positive $SRISK\%$). The co-movement between the illiquidity of baskets and the AP's own portfolios is negative but not significant (-0.021 with t-statistic=-1.46). With multiple dimension restrictions on capital, APs bear tight balance sheet constraints, suggesting that balance sheet constraints dent the AP's ability to exploit the arbitrage opportunities.

To isolate the factor contributing to balance sheet constraints, I decompose the regulations into either internal (positive $SRISK\%$) or external (G-SIB AP) sources. The re-

[12] For detailed G-SIB lists and methods, refer to `https://www.bis.org/bcbs/gsib/`. I downloaded the 2021 list of G-SIBs from the Financial Stability Board, `https://www.fsb.org/2021/11/2021-list-of-global-systemically-important-banks-g-sibs/`. The Volatility Laboratory (V-Lab) provides real-time systematic risk measurement constructed in Acharya et al. (2017), and I hand-collected measures for each institution at `https://vlab.stern.nyu.edu/srisk`. See the Online Appendix for more details and estimation results.

sults show that the co-movement is significantly negative under external constraints (-0.09 with t-statistic=-4.33) but not under internal constraints (-0.03 with t-statistic=-0.70). APs subject to external credit regulations can disproportionately increase incentives and reinforce their choice of baskets. However, because of the binding internal balance sheet constraints, APs may not seek baskets to match their incentives. This finding has important implications in the debate about the resilience of market makers in the corporate bond market.

6.3 Robustness

6.3.1 Subsamples

I partition the sample into three subperiods to study whether the results are subject to change policies.

I classify observations from 2012 to 2014 as the period with the Volcker Rule. The Volcker Rule is a federal regulation that prohibits banks from conducting investment activities with their accounts. It could reduce liquidity through a reduction in banks' market-making activities. Thus, liquidity in the financial market might be affected. The second period is the pre-COVID period from 2015 to 2019, and the third is the post-COVID period from 2020 to 2021. The COVID-19 crisis provides an opportunity to inspect the resilience of ETFs in the stress of the crisis and the unprecedented policy actions. I define dummy variables for these subperiods and multiply them with the redemption dummy. In the panel regression, I include all three period dummies.

Table 7 presents the results of these subsample regressions of ETF performance on redemptions. The impacts of redemptions on ETF performance are consistent over time and remain significant during the COVID-19 pandemic. For example, in the Volcker Rule and pre-COVID periods, fund returns decrease by 1.4 bps and 1.5 per redemption. During the COVID-19 pandemic, fund returns decrease by 3.9 bps, whereas the full sample impact is 2.3 bps. It turns out that crises deepen the impact of redemptions on returns. The arbitrage opportunities of mispricing for APs are diminishing during the crisis, but the impacts are still significant. Lastly, impacts on liquidity are low under the Volcker Rule and the pandemic crisis, while the pre-COVID period has higher effects. The market becomes less efficient after the Volcker Rule period, and it has a price efficiency similar to the results in Table 4.

6.3.2 Limits to arbitrage

Limits to arbitrage in the market affect investors' preference for ETF transactions and would change ETFs' and APs' incentives. For example, with high limits to arbitrage, APs might have difficulties disposing of corporate bonds. Investors in the secondary market could be more sensitive to liquidity, making redemption a negative shock to liquidity and efficiency. I show that compared with the period with high and low levels of arbitrage limits, the secondary market's impact is robust. This paper has two measures of limits to arbitrage: negative flows to hedge funds with the fixed-income arbitrage strategy and substantial intermediary distress.

Fixed-income strategy hedge funds aggregate flow Following Cao, Farnsworth, and Zhang (2021), I merge the comprehensive hedge fund data using TASS, HFR, and BarclayHedge databases to identify hedge funds with fixed-income strategies. Then I calculate individual fund flows using their assets under management and net fund returns, and I aggregate fund flows over hedge funds. I provide detailed sample selection filters and variable definitions in the Online Appendix. The assumption is that when there are negative flows among these specific hedge funds, institutional investors face capital constraints on exploring arbitrage opportunities.

Intermediary distress He, Khorrami, and Song (2022) combine the innovation in the leverage factor of intermediaries and the noise measure. Both measures imply a shortage of arbitrage capital in the market. I estimate the first principal component to construct the intermediary distress. The detailed variable definitions and data sources are presented in the Online Appendix. I use the measure to evaluate the limits to arbitrage to corporate bonds. Strong intermediary distress represents high limits to arbitrage.

Thus, I classify periods with negative aggregate flows and intermediary distress as periods with high limits to arbitrage. Table 8 shows the results. Under high limits to arbitrage, redemptions decrease ETF returns significantly while significantly increasing effective and realized spreads and increasing transaction costs by 10%. The positive and significant coefficients on the variance ratio and order imbalance suggest a less efficient market. For APs, the arbitrage opportunities are higher. The results are consistent with those reported in Table 4. Yet, redemptions have adverse or insignificant effects in the secondary market in an environment with low limits to arbitrage.

6.3.3 Tracking errors in ETFs: Do ETF sponsors collude with APs in negotiation?

ETFs are designed to track as closely as the underlying indices, and sponsors are responsible for minimizing the tracking errors. One concern is that transactions and negotiations in the primary market between sponsors and APs sacrifice tracking errors, which hurt ETF shareholders' benefits. It is problematic from a regulatory standpoint. To address this concern, I investigate whether the tracking errors are larger if the transaction between sponsors and APs is larger.

Tracking errors are defined in previous sections: the standard deviation of the difference between daily ETF returns and underlying index returns. The sample contains 114 corporate bond ETFs with index data. I also define the return spreads between ETF and index returns over a 20-day window. I use three variables to evaluate the transaction size in the primary market. These variables are the fund-flow-to-AUM ratio, fund-flow-to-shares outstanding ratio, daily percentage changes in shares outstanding, and redemption size. Redemption size is the integer ratio between daily changes in the number of shares outstanding and the creation unit size. Typically, the creation unit comprises 5,000 ETF shares. A large number of these ratios represent a greater transaction size.

I regress tracking errors or return spreads on the contemporaneous transaction size variables. If ETF sponsors and APs deliberately ignore the tracking errors and shareholder benefits, the significantly positive coefficients cast positive effects on tracking errors. Using return spreads, the coefficients on transaction variables should be significantly negative. The results in Online Appendix shows that the estimates using tracking errors are negative and insignificant. For example, the coefficient on the flow-to-AUM ratio is -0.004 (t-statistic=-1.62). The coefficients using return spreads are positive and insignificant. The results imply that tracking errors do not decrease upon redemptions. Thus, the ETF sponsor and APs do not "collude" to melt down shareholders' benefits.

6.3.4 Municipal and Treasury bond ETFs

The liquidity mismatch between the liquid corporate bond ETF market and the illiquid bond market leads to negotiation in redemptions. APs negotiate with ETFs because of the illiquidity of corporate bonds. The question is whether the liquidity mismatch is a distinguishing characteristic and unique in corporate bond ETFs.

To examine this question, I focus on the impacts of redemptions on municipal and Treasury bond ETFs. The reason is that municipal bonds are illiquid in the secondary market, and Treasury bonds are liquid. Therefore, I hypothesize that municipal bond ETFs have patterns similar to corporate bond ETFs, whereas Treasury bond ETFs differ.

The Online Appendix presents the results. It turns out that municipal bond ETF redemptions have a parallel impact on investors' and APs' profits. Yet, Treasury bond ETFs do not have significant estimations. The results imply that liquidity mismatch and negotiation in redemptions contribute to the unique patterns in bond ETFs.

6.3.5 More robustness checks

Reilly (2022) shows that spreads between ETF and index returns decrease upon creation over a one-month horizon, but spreads are zero upon redemptions. Shim and Todorov (2022) document bond characteristics of creation and redemption baskets are different. Thus, I examine whether ETF share creation has the same effects on ETF performance as redemptions. I conduct an economic impact regression using the creation sample and provide evidence in the Online Appendix. The results show that ETF returns is higher upon creation activities, yet the secondary market is less liquid and less efficient. AP's abitrage gains are marginally negative. The results differ from those in redemptions.

Li (2021) separates ETFs based on their benchmarks into sunshine ETFs and self-indexers. The sunshine ETFs track publicly available indices, and traders know any changes to the index before they are implemented. Self-indexers are ETFs that track internal indices constructed by ETF management companies. I show in the Online Appendix that redemptions among sunshine ETFs and self-indexers are consistent with Li (2021): sunshine ETFs have more substantial effects than self-indexers.

When ETF investors observe corporate bond information, they can reallocate capital from ETFs to other assets, leading to customer facilitation-induced redemptions. Therefore, the alternative channel is bond market learning. Different from equity markets, corporate bonds are opaque and traded in the decentralized over-the-counter market. Hence, investors may have a hard time gathering information on corporate bonds. To isolate the effect, I separate ETFs into "Learn" and "No learn" groups based on whether I can calculate illiquidity from the enhanced TRACE database. The results in the Online Appendix show that the learning difficulty amplifies the economic impacts.

7 Conclusion

When corporate bond ETF share prices are lower than NAVs, the redemption mechanism is designed to narrow the discrepancy, where APs return ETF shares to ETFs and receive a basket of corporate bonds. APs, also acting as market makers in the secondary bond market, sell or keep bonds in inventory. ETF sponsors and APs negotiate to determine the components of redemption baskets. This paper studies how corporate bond ETF sponsors and APs choose the components of redemption baskets in the primary market and discusses the economic impacts of redemptions on ETF investors, AP arbitrage opportunities, and demand in the secondary bond ETF market.

I find that ETF sponsors fill redemption baskets with bonds that are highly exposed to price pressure. On average, the exposure to price pressure that ETF portfolios bear is 6% lower than the exposure of redemption baskets, which is equivalent to the value of ETF portfolios being $64,000 less than the value of redemption baskets. APs agree on the components of redemption baskets such that the illiquidity of baskets negatively co-moves with the illiquidity of their own investment portfolios. A one unit increase in the illiquidity of baskets leads to a 42 bps decrease in the illiquidity of the AP portfolio, which represents 20% of the average level of AP's portfolio illiquidity.

I then show that ETF returns are lower upon redemptions and increase the transaction cost by 10% in terms of effective and realized spreads. Redemptions also lead to a less efficient market. For APs, on the other hand, redemptions increase arbitrage profits by increasing mispricing and short selling rates. In particular, APs gain $13,000 by correcting the differences between share prices and NAVs. I argue that the price multiplier of the corporate bond ETF market is higher on redemption days relative to normal days, implying that investors face a less elastic market.

These results have two limitations. First, I only have access to realized redemption baskets, and negotiation is inferred from the size of the redemption baskets. Second, to uncover the AP portfolio, I collect holding data from Form 13F that includes management companies with more than $100 million in Section 13(f) securities. Future research could dig into proposed baskets and discuss the economic incentives in the negotiation.

Appendix

A Variable construction

The appendix describes the definitions and sources of variables used in this paper.

A.1 ETF performance and control variable definitions

Table A.1. Secondary market ETF performance variable definitions.
I provide the definitions and sources of ETF performance variables in the secondary market and ETF control variables.

Variable	Definition	Source
Fund return (Ret)	Corporate bond ETF daily fund returns in bps	ETF Global
Mispricing ($Misp$)	Daily mispricing measure in percentage, defined as the absolute difference between logarithm of the daily ETF price and the daily ETF net asset value (NAV)	ETF Global, CRSP
Short interest rate (SII)	Daily short interest to assets under management (AUM) ratio in bps	ETF Global
Effective spread ($Esprd$)	Daily dollar-volume-weighted effective spread for each trade in bps, where the spread is the difference between the logarithm of trading price and the mid-point of the trade (i.e., $Esprd_{i,h,t} = p_{i,h,t} - m_{i,h,t}$ for the h^{th} trade of ETF i at day t)	ETF Global, DTAQ, WRDS
Realized spread ($Rsprd$)	Daily dollar-volume-weighted realized spread (bps) for each trade, where the spread is the difference between the logarithm of current and five-minute-later trading price (i.e., $Rsprd_{i,h,t} = p_{i,h,t} - p_{i,h+5,t}$ for the h^{th} buy trade of ETF i at day t)	ETF Global, DTAQ, WRDS
30-minute variance ratio ($VR30$)	Daily variance ratios (%) calculated over a 30-minute interval and defined as the absolute value of one minus the ratio. The ratio is between the 15-minute and 30-minute volatility at day t	ETF Global, DTAQ, WRDS
Order imbalance number (OIN)	Daily order imbalance in percentage, calculated as the ratio of the difference between buyer-initiated and seller-initiated number of trades and the sum of buyer- and seller-initiated number of trades.	ETF Global, DTAQ, WRDS
log(AUM)	Logarithm of AUM	ETF Global
Daily fund flow	Ratio between daily fund flows and AUM in percentage	ETF Global
Total expenses	Total amount of expenses in an ETF in percentage	ETF Global
D(Option available)	Dummy of ETF option availability	ETF Global

A.2 Price pressure measures

I describe the data sources and detailed definitions of the holding- and common-flow-based pressure measures for individual corporate bonds and estimate exposures using monthly bond returns in a rolling window regression. Lastly, I construct the ETF-level exposures using ETF bond holding weights in the ETF Global database.

To identify corporate bond mutual funds, I use CRSP objective code in I, IC, ICQH, ICQM, ICQY, ICDI, ICDS, or IF from the CRSP Survivorship-bias-free mutual fund database. Funds are required to invest at least 10% of total net assets (TNA) into corporate bonds. I aggregate multiple share class assets to the fund level and take the TNA-weighted average of monthly fund net returns. To address incubation bias and backfill bias, I select the earliest offering date as the initial listed date and delete all observations before the listed dates. I drop non-missing mutual fund observations if TNA is lower than \$1 million and keep all observations thereafter. Finally, the total number of observations for each mutual fund is greater than 12. The number of unique bond mutual funds is 1,778 from 2008 to 2021.

I first define the monthly fund flow ratio as

$$flow_{k,m} \quad = \quad \frac{TNA_{k,m} - (1 + returns_{k,m}) \times TNA_{k,m-1}}{TNA_{k,m-1}},$$

where $TNA_{k,m}$ is the monthly TNA for mutual fund k in month m and $returns_{k,m}$ is the monthly fund net returns.

To estimate the price pressure exposures for individual corporate bonds, I collect monthly corporate bond returns from the WRDS Corporate Bond database, and returns are calculated using the last-day prices.

A.2.1 Holding-based price pressure

I identify bond mutual fund holdings using the CRSP Survivorship-bias-free holding database, where I gather the monthly non-missing corporate bond holdings and merge with the Mergent FISD database for their offering values using the eight-digit CUSIP. I require the fund to hold at least 10 bonds and the total percentage of these holdings to be greater than 10%. The sample is from January 2008 to December 2021 with 1,517 unique mutual funds.

Following Choi, Hoseinzade, Shin, and Tehranian (2020), I first define the sell pressure,

$$SellPres_{j,m} \quad = \quad \frac{\sum_{k \in \{flow_{k,m} < \text{pctl}(10)_m\}} \max(0, -\Delta Holding_{j,k,m})}{\text{Offering Value}_{j,m}},$$

where k represents the k^{th} mutual fund. $flow_{k,m} < \text{pctl}(10)_m$ requires the monthly flow of fund k to be below the cross-sectional extreme net outflows (bottom 10$^{\text{th}}$ percentile), and *Offering Value*$_{j,m}$ is the initial offering value of bond j available in month m from the Mergent FISD database (Falato, Hortacsu, Li, and Shin, 2021). The assumption is that a corporate bond experiences sell pressure if mutual fund net outflows are greater than the bottom 10$^{\text{th}}$ percentile of all other mutual funds in month m, $\text{pctl}(10)_m$, suggesting that this mutual fund is supposed to dispose its holding bonds, especially those with large changes in holding shares $\Delta Holding_{j,k,m}$.

I extend the sell pressure measure by multiplying with fund flows (Coval and Stafford, 2007),

$$SellPres \times Flow_{j,m} = \frac{\sum_{k \in \{flow_{k,m} < \text{pctl}(10)_m\}} \max(0, -flow_{k,m}) \times \max(0, -\Delta Holding_{j,k,m})}{\text{Offering Value}_{j,m}} .$$

The net sell pressure measure is combined with extreme outflow-induced selling and extreme inflow-induced buying (Coval and Stafford, 2007; Choi et al., 2020),

$$NetPres_{j,m} = \frac{\textit{Flow Induced Sells}_{j,m} - \textit{Flow Induced Buys}_{j,m}}{\text{Offering Value}_{j,m}} ,$$

where *Flow Induced Sells*$_{j,m} = \sum_{k \in \{flow_{k,m} < \text{Percentile}(10)_m\}} \max(0, -\Delta Holding_{j,k,m})$ and *Flow Induced Buys*$_{j,m} = \sum_{k' \in \{flow_{k,m} > \text{Percentile}(90)_m\}} \max(0, \Delta Holding_{j,k',m})$. k (k') represents the k^{th} (k'^{th}) mutual fund, and $flow_{k,m} > \text{pctl}(90)_m$ requires the monthly flow of fund k to be above the cross-sectional extreme net inflows. I include absolute flows as an alternative net sell pressure measure by multiplying with fund flows,

$$NetPres \times Flow_{j,m} = \frac{\textit{Flow Induced Sells} \times Flow_{j,m} - \textit{Flow Induced Buys} \times Flow_{j,m}}{\text{Offering Value}_{k,m}} ,$$

where *Flow Induced Sells*$\times Flow_{j,m} = \sum_{k \in \{flow_{k,m} < \text{Percentile}(10)_m\}} \max(0, -flow_{k,m}) \times \max(0, -\Delta Holding_{j,k,m})$ and *Flow Induced Buys*$\times Flow_{j,m} = \sum_{k' \in \{flow_{k,m} > \text{Percentile}(90)_m\}} \max(0, flow_{k',m}) \times \max(0, \Delta Holding_{j,k',m})$.

Then I estimate the monthly exposures of individual bonds using a 36-month rolling window and regress monthly bond returns on one-month lagged price pressure measures to address delayed portfolio disclosures,

$$BondRet_{j,m} = a + Expo_{j,m} \times \text{price pressure defined above}_{j,m-1} + Controls + \varepsilon_{k,m} ,$$

where $BondRet_{j,m}$ is the monthly bond returns based on the month-end day prices. *Controls* captures key sources of risks. I include the following four characteristics: (1) To capture credit risk, I follow Bai, Bali, and Wen (2019) and use Standard & Poor credit ratings obtained from the WRDS Bond Return database. I convert bonds' ratings into a numeric scale using the numerical ratings. The numerical ratings range from 1 (AAA) to 21 (C−). (2) I include a bond's time to maturity to capture duration risk (Bretscher et al., 2022). (3) I control for bond duration to address the impact of interest rate risks. (4) Liquidity is an important determinant of corporate bond risks (Dick-Nielsen, Feldhutter, and Lando, 2012). I capture liquidity risk by including the bond's contemporaneous and lagged standardized illiquidity measure. In the Online Appendix, the alternative estimation method adopts the downside risk factor, the liquidity risk factor, and the credit risk factor in Bai, Bali, and Wen (2019) to control for liquidity and credit risks.

I winsorize these measures by 1% and 99% levels and standardize variables with zero means and unit standard errors to isolate the scaling difference in different measures.

A.2.2 Common-flow-based price pressure

Using monthly corporate bond mutual fund flow ratios, I first estimate the innovations in fund flows using the following regression (Dou, Kogan, and Wu, 2022),

$$flow_{k,m} = b_0 + \sum_{\tau=1}^{2} b_\tau (return_{k,m-\tau} - return^{mkt}_{m-\tau}) + b_3 flow_{k,m-1} + \xi_m + \epsilon_{k,m} ,$$

where I include two lags of the difference between fund net returns and the CRSP value-weighted market returns, one lag of fund flow, and monthly fixed effects. The residual $\epsilon_{k,m}$ is the flow shock. Then I sort funds into TNA quintiles and calculate the quintile average flow shocks. I take the first component of these five flow shock sequences using principal component analysis (Aragon and Kim, 2022), and I detrend the component to generate the common flow shock, *Common flow shock*$_m$.

Lastly, I estimate the exposure using common flow shocks,

$$BondRet_{j,m} = a + Expo_{j,m} \times \text{Common flow shock}_m + Controls + \varepsilon_{j,m} ,$$

where $BondRet_{j,m}$ is the monthly bond returns based on the month-end day prices and *Controls* are defined above. The regression is run for each corporate bond over a 36-month rolling window with a minimum of 10 non-missing observations. I winsorize the exposure by 1% and 99% levels and standardize it with zero means and unit standard errors.

A.2.3 Orthogonal exposures

To further isolate the effects of illiquidity on price pressure exposures among ETFs, I regress the ETF level of these five exposure measures on the ETF-level standardized illiquidity and define the residuals as the orthogonal exposures, *Expo*, for these five measures: *NetPres*, $NetPres \times Flow$, *NetPres*, $NetPres \times Flow$, and *Flow shock*.

A.3 Illiquidity measures

I construct four monthly illiquidity measures documented in the literature based on the TRACE database, including the Amihud illiquidity measure, the Roll measure, the Bao-Pan-Wang illiquidity measure, and the imputed roundtrip cost. The common components of illiquidity variables also use the average bid-ask spreads from the WRDS Corporate Bond database.

A.3.1 Amihud measure

Amihud (2002) constructs an illiquidity measure, which measures the price impact of a trade per unit traded. Using the modified Amihud illiquidity measure proposed by Dick-Nielsen, Feldhutter, and Lando (2012), for each corporate bond k at date t, the measure is the daily average of the absolute difference of the logarithm of transaction prices $\log(price_{k,h}) - \log(price_{k,h-1})$ of the h^{th} transaction divided by the trade size $Q_{k,h}$ (in million \$) of consecutive transactions:

$$Amihud_{k,t} \quad = \quad \frac{1}{N_{k,t}} \sum_{j=1}^{N_{k,t}} \frac{|\log(price_{k,h}) - \log(price_{k,h-1})|}{Q_{k,j}} \times 10^6 \,,$$

where $N_{k,t}$ is the number of returns at day t. At least two transactions are required on a given day to calculate the measure, and I define the monthly Amihud measure $Amihud_{k,m}$ by taking the median of daily measures within the month.

A.3.2 Roll measure

Roll (1984) finds that under certain assumptions, the percentage bid–ask spread equals twice the square root of minus the covariance between consecutive returns:

$$Roll_{k,m} \quad = \quad \begin{cases} 2\sqrt{-cov(BondRet_{k,h}, BondRet_{k,h-1})} & \text{if } cov(BondRet_{k,h}, BondRet_{k,h-1}) < 0 \\ 0 & \text{if } cov(BondRet_{k,h}, BondRet_{k,h-1}) \geq 0 \,, \end{cases}$$

where h represents the h^{th} transaction at day t in month m of corporate bond k. The intuition is that the bond price bounces back and forth between the bid and ask price, and higher percentage bid-ask spreads lead to a higher negative covariance between consecutive returns. I define a monthly Roll measure in month m with at least five transactions.

A.3.3 Bao, Pan, and Wang (2011) illiquidity measure

Bao, Pan, and Wang (2011) exploit the transitory component of bond prices. The measure is computed as follows:

$$BPW_{k,m} = -cov(\Delta p_{k,h}, \Delta p_{k,h-1}) ,$$

where h represents the h^{th} transaction at day t in month m of corporate bond k and Δp is the difference between consecutive corporate bond transaction prices. I define a monthly Bao-Pan-Wang (BPW) measure in month m with at least five transactions.

A.3.4 Imputed roundtrip cost

Feldhütter (2012) proposes the measure of transaction costs based on imputed roundtrip trades (IRTs). If two or three trades in a given bond with the same trade size take place on the same day, and there are no other trades with the same size on that day, I define the transactions as part of an IRT. For an IRT, I define the imputed roundtrip cost (IRC) as

$$IRC_{k,m} = \frac{P_{max,k,m} - P_{min,k,m}}{P_{max,k,m}} ,$$

where $P_{max,k,m}$ is the largest price in the IRT and $P_{min,k,m}$ is the smallest price in the IRT of corporate bond k in month m. A daily estimate of roundtrip costs is the average of roundtrip costs on that month for different trade sizes.

A.3.5 Common components of corporate bond illiquidity measures

To remove the impact of scaling of each illiquidity measure, for each bond k in month m, I take the standardization of each illiquidity measure with overall zero means and unit standard deviations. Then I take the simple average of these standardized measures across bonds and months,

$$Illiq_{k,m} = \frac{(Amihud_{k,m} + Roll_{k,m} + BPW_{k,m} + IRC_{k,m} + BAsprd_{k,m} | \text{Non-missing})}{N_{k,m}} ,$$

where I take the simple average conditioning on at least one non-missing illiquidity measure.

References

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson. 2017. Measuring systemic risk. *Review of Financial Studies* 30:2–47.

Agarwal, V., P. Hanouna, R. Moussawi, and C. W. Stahel. 2018. Do ETFs increase the commonality in liquidity of underlying stocks? Working Paper. Georgia State University, Villanova University, and Investment Company Institute.

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5:31–56.

Aragon, G. O., and M. S. Kim. 2022. Fire sale risk and expected stock returns. Working Paper. Arizona State University and Michigan State University.

Arora, R., S. Betermier, G. O. Leblanc, A. Palumbo, and R. Shotlander. 2020. Concentration in the market of authorized participants of US fixed-income exchange-traded funds. Staff Analytical Notes 2020-27, Bank of Canada.

Bae, K., and D. Kim. 2020. Liquidity risk and exchange-traded fund returns, variances, and tracking errors. *Journal of Financial Economics* 138:222–53.

Bai, J., T. G. Bali, and Q. Wen. 2019. Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics* 131:619–42.

Bao, J., J. Pan, and J. Wang. 2011. The illiquidity of corporate bonds. *Journal of Finance* 66:911–46.

Ben-David, I., F. A. Franzoni, and R. Moussawi. 2018. Do ETFs increase volatility? *Journal of Finance* 73:2471–535.

Boehmer, E., C. M. Jones, X. Zhang, and X. Zhang. 2021. Tracking retail investor activity. *Journal of Finance* 76:2249–305.

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

Bretscher, L., L. Schmid, I. Sen, and V. Sharma. 2022. Institutional corporate bond pricing. Working Paper. Swiss Finance Institute.

Brown, D. C., S. W. Davies, and M. C. Ringgenberg. 2021. ETF arbitrage, non-fundamental demand, and return predictability. *Review of Finance* 25:937–72.

Cao, C., G. Farnsworth, and H. Zhang. 2021. The economics of hedge fund startups: Theory and empirical evidence. *Journal of Finance* 76:1427–69.

Cao, C., T. Simin, and H. Xiao. 2022. Do working from home impair mutual fund performance? Working Paper. Pennsylvania State University.

Chen, Q., I. Goldstein, and W. Jiang. 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics* 97:239–62.

Choi, J., S. Hoseinzade, S. S. Shin, and H. Tehranian. 2020. Corporate bond mutual funds and asset fire sales. *Journal of Financial Economics* 138:432–57.

Chordia, T., R. Roll, and A. Subrahmanyam. 2000. Commonality in liquidity. *Journal of Financial Economics* 56:3–28.

Coval, J., and E. Stafford. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86:479–512.

Dannhauser, C. D. 2017. The impact of innovation: Evidence from corporate bond exchange-traded funds (ETFs). *Journal of Financial Economics* 125:537–60.

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

Dick-Nielsen, J., P. Feldhutter, and D. Lando. 2012. Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics* 103:471–49.

Dou, W., L. Kogan, and W. Wu. 2022. Common fund flows: Flow hedging and factor pricing. Working Paper. University of Pennsylvania, MIT Sloan, and Texas A&M University.

Ellul, A., C. Jotikasthira, and C. T. Lundblad. 2011. Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics* 101:596–620.

Falato, A., I. Goldstein, and A. Hortaçsu. 2021. Financial fragility in the covid-19 crisis: The case of investment funds in corporate bond markets. *Journal of Monetary Economics* 123:35–52.

Falato, A., A. Hortacsu, D. Li, and C. Shin. 2021. Fire-sale spillovers in debt markets. *Journal of Finance* 76:3055–102.

Feldhütter, P. 2012. The same bond at different prices: Identifying search frictions and selling pressures. *Review of Financial Studies* 25:1155–206.

Frazzini, A., R. Israel, and T. J. Moskowitz. 2018. Trading costs. Working Paper. AQR Capital Management and Yale University.

Gabaix, X., and R. S. J. Koijen. 2021. In search of the origins of financial fluctuations: The inelastic markets hypothesis. Working Paper. Harvard University and University of Chicago.

Glosten, L., S. Nallareddy, and Y. Zou. 2021. ETF activity and informational efficiency of underlying securities. *Management Science* 67:22–47.

Goldstein, I., H. Jiang, and D. T. Ng. 2017. Investor flows and fragility in corporate bond funds. *Journal of Financial Economics* 126:592–613.

Goldstein, M. A., and E. S. Hotchkiss. 2020. Providing liquidity in an illiquid market: Dealer behavior in US corporate bonds. *Journal of Financial Economics* 135:16–40.

Gorbatikov, E., and T. Sikorskaya. 2022. Two APs are better than one: ETF mispricing and primary market participation. Working Paper. London Business School.

He, Z., P. Khorrami, and Z. Song. 2022. Commonality in credit spread changes: Dealer inventory and intermediary distress. *Review of Financial Studies* in press.

Hong, C. Y., F. W. Li, and A. Subrahmanyam. 2022. Financial intermediaries and contagion in market efficiency: The case of ETFs. Working Paper. Shanghai Jiao Tong University, Singapore Management University, and UCLA.

Jiang, H., D. Li, and A. Wang. 2021. Dynamic liquidity management by corporate bond mutual funds. *Journal of Financial and Quantitative Analysis* 56:1622–52.

Kargar, M., B. Lester, D. Lindsay, S. Liu, P.-O. Weill, and D. Zúñiga. 2021. Corporate bond liquidity during the covid-19 crisis. *Review of Financial Studies* 34:5352–401.

Koch, A., S. Ruenzi, and L. Starks. 2016. Commonality in liquidity: A demand-side explanation. *Review of Financial Studies* 29:1943–74.

Koont, N., Y. Ma, L. Pastor, and Y. Zeng. 2022. Steering a ship in illiquid waters: Active management of passive funds. Working Paper. Columbia University, University of Chicago, and University of Pennsylvania.

Lee, C. M. C., and M. J. Ready. 1991. Inferring trade direction from intraday data. *Journal of Finance* 46:733–46.

Lettau, M., and A. Madhavan. 2018. Exchange-traded funds 101 for economists. *Journal of Economic Perspective* 32:135–54.

Li, F. W., and Q. Zhu. 2022. Short selling ETFs. *Review of Asset Pricing Studies* forthcoming.

Li, J., and Z. Lin. 2022. Prices are less elastic at more aggregate levels. Working Paper. University of Utah and Stanford University.

Li, S. 2021. Should passive investors actively manage their trades? Working Paper. University of Illinois at Urbana-Champaign.

Lo, A. W., and A. C. MacKinlay. 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. *Review of Financial Studies* 1:41–66.

Ma, Y., K. Xiao, and Y. Zeng. 2022. Mutual fund liquidity transformation and reverse flight to liquidity. *Review of Financial Studies* forthcoming.

Manconi, A., M. Massa, and A. Yasuda. 2012. The role of institutional investors in propagating the crisis of 2007 – 2008. *Journal of Financial Economics* 104:491–518.

Moussawi, R., K. Shen, and R. Velthuis. 2022. ETF heartbeat trades, tax efficiencies, and clienteles: The role of taxes in the flow migration from active mutual funds to ETFs. Working Paper. Villanova University and Lehigh University.

Pan, K., and Y. Zeng. 2019. ETF arbitrage under liquidity mismatch. Working Paper. University of Pennsylvania and Goldman Sachs.

Petajisto, A. 2017. Inefficiencies in the pricing of exchange-traded funds. *Financial Analysts Journal* 73:24–54.

Pástor, L., and M. B. Vorsatz. 2020. Mutual fund and performance and flows and during the covid-19 crisis. *Review of Asset Pricing Studies* 10:791–833.

Reilly, C. 2022. The hidden cost of corporate bond ETFs. Working Paper. University of Texas at Dallas.

Roll, R. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39:1127–39.

Shim, J. J., and K. Todorov. 2022. ETFs, illiquid assets, and fire sales. Working Paper. University of Notre Dame and Bank for International Settlements.

Todorov, K. 2021. The anatomy of bond ETF arbitrage. *BIS Quarterly Review* .

Zeng, Y. 2017. A dynamic theory of mutual fund runs and liquidity management. Working Paper. University of Pennsylvania.

Figure 1. Assets under Management of Bond ETFs

The figure shows the assets under management (in billion dollars) of bond ETFs, from 2002 to 2021. The data frequency is annually and collected from the 2022 version of the Investment Company Fact Book. The first corporate bond ETF (iShares iBoxx $ Inv Grade Corporate Bond ETF, LQD) was launched in 2002.

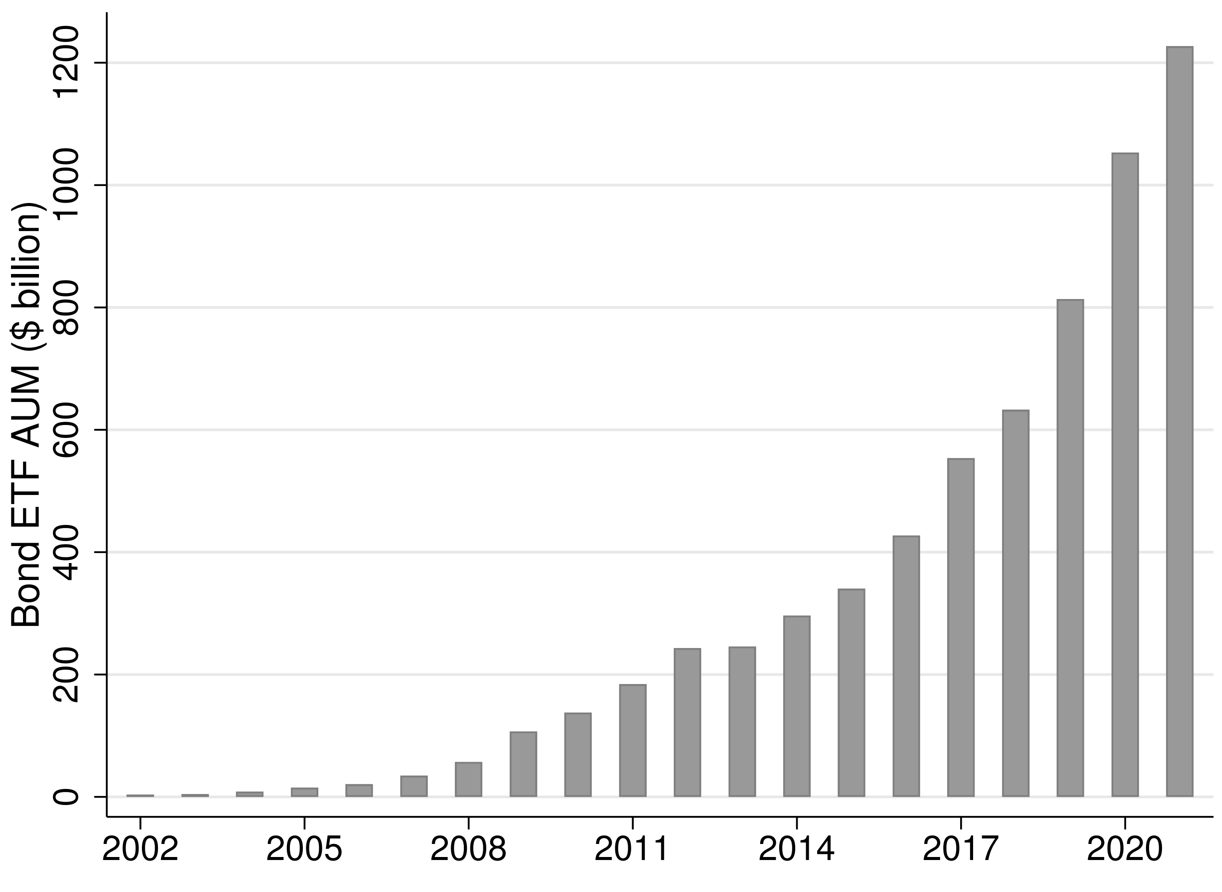

Figure 2. Holding Shares of Corporate Bonds

The figure compares corporate bond holding shares of household and institutional investors (ETFs, mutual funds, insurance companies, and broker-dealers) for the period 2002Q1 to 2021Q4. The data frequency is quarterly and downloaded from the Financial Accounts of the United States from the Board of Governors of the Federal Reserve System. The first non-missing ETF corporate bond holding share observation is in 2002Q3. The shadowed areas are NBER recessions. The total shares of households and institutions range from 38% to 77% with a sample average of 53%.

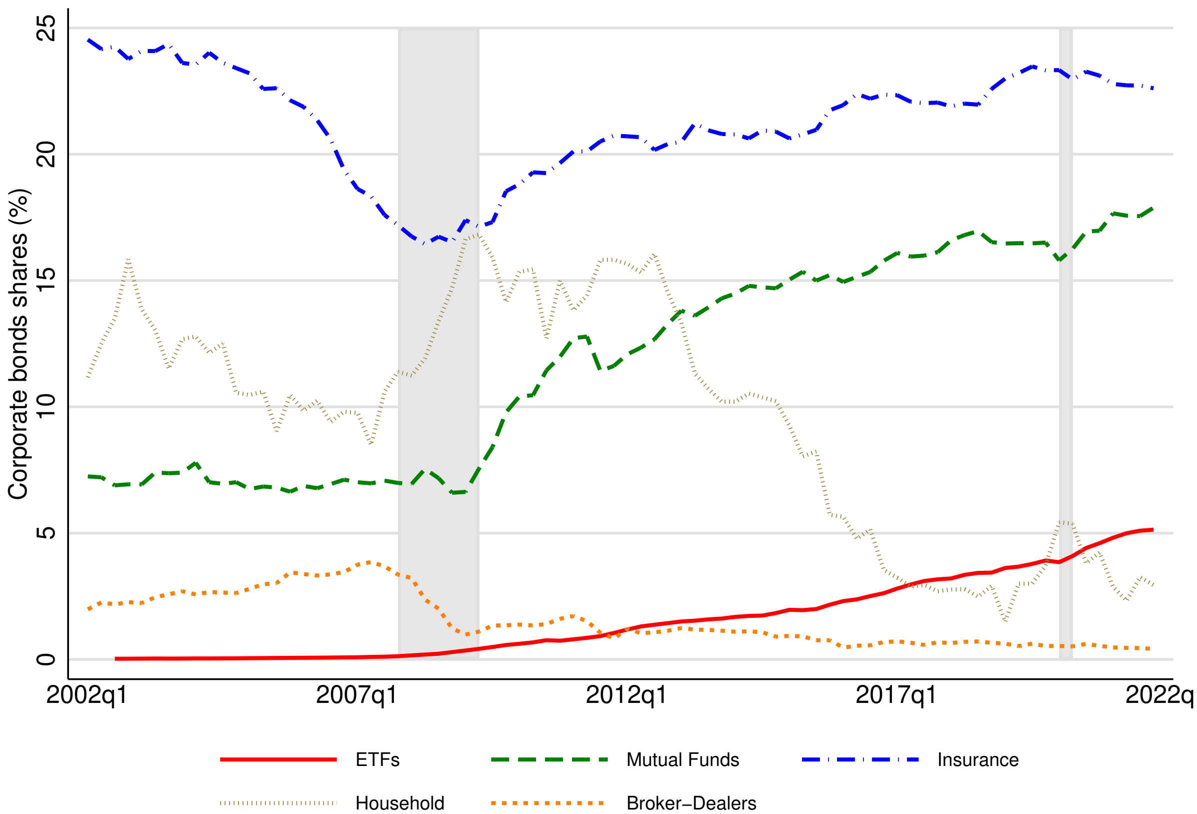

Figure 3. ETF market structure

The figure displays the structure of the ETF market. In the secondary market, retail and institutional investors trade ETFs (for example, Vanguard Total Corporate Bond ETF (VTC) from Vanguard) using cash ($) through exchanges, for example, NYSE. Authorized participants (APs) are market makers or liquidity providers, including investment banks, brokers and dealers, hedge funds, and trading companies (for example, Goldman Sachs). They receive excess buy or sell shares from the exchanges. Creating and redeeming ETF shares with APs involve baskets of corporate bonds in the primary market. Only ETFs and APs trade in the primary market. Creation and redemption depend on the differences between ETF share prices in the secondary market and net asset values (NAVs). For example, when share prices are lower than NAVs (discounts), APs can initiate the redemption process. In "in-kind" creations, APs buy securities from the corporate bond market and deliver these assets to ETFs such that ETFs create new shares. In in-kind redemptions, APs return ETF shares to ETFs and receive the underlying baskets of corporate bonds. They then either sell the bonds in the corporate bond market or hold in the inventory.

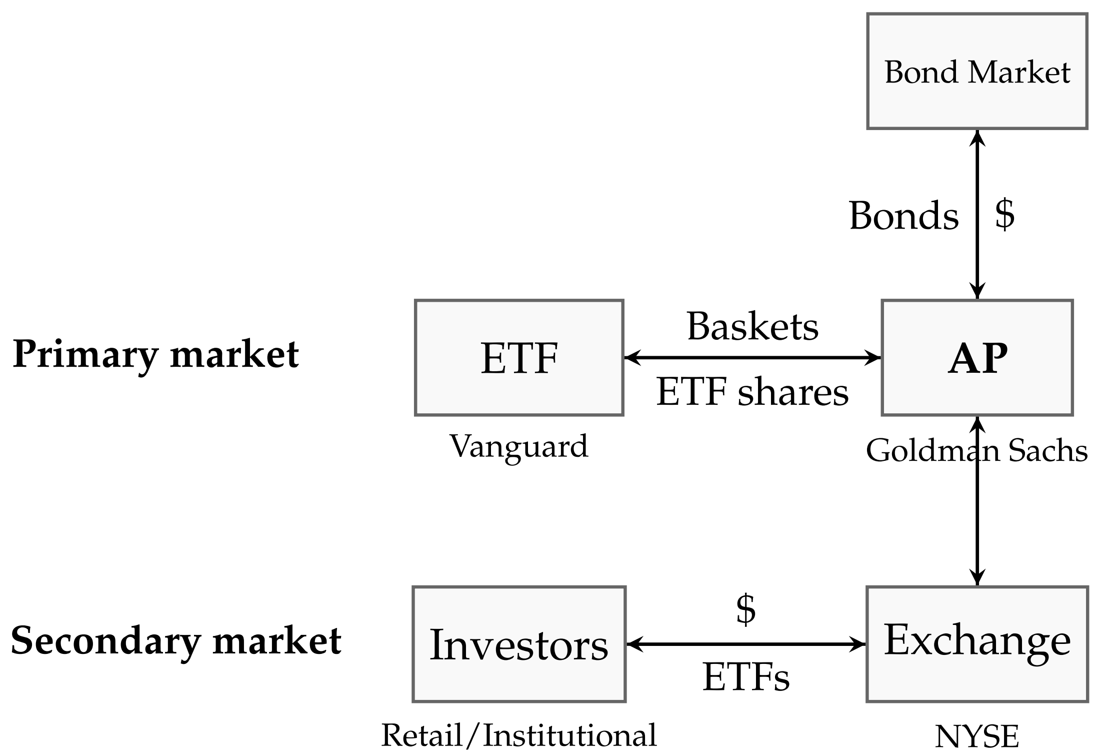

Figure 4. Frequency and size of creation and redemption activities

The figure shows the frequency and size of creation and redemption activities every year. In the upper panel, the frequency of creations and redemptions in an ETF is defined as the ratio of the number of creation or redemption days to total trading days within a year. I take the simple average of all ETFs in the year. In the bottom panel, I calculate the average of daily percentage absolute changes in shares outstanding for creations and redemptions. The sample is from January 4, 2012 to December 31, 2021.

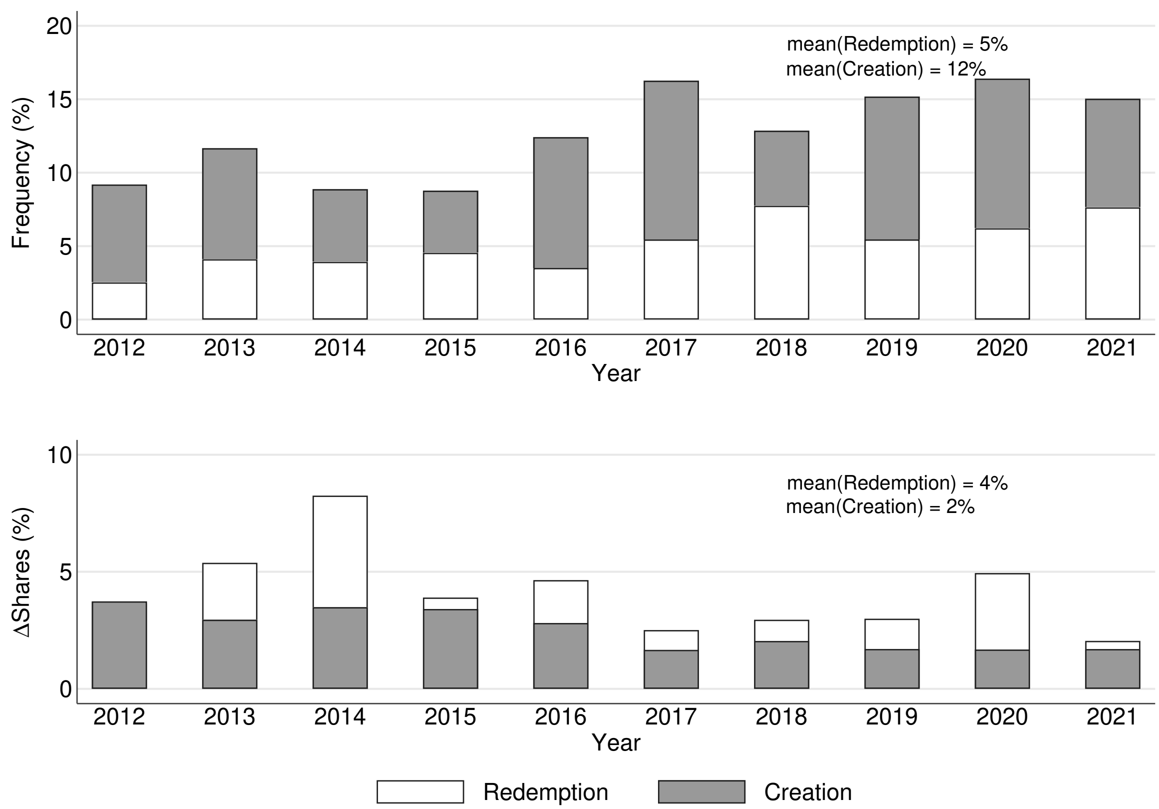

Figure 5. Compare *Expo* of baskets and remaining portfolios on redemption days

The figure compares exposures to price pressure in baskets and remaining portfolios on redemption days. Redemption days are identified if an ETF's daily shares outstanding decrease. Baskets contain bonds with changes in number of holdings, and remaining portfolios contain bonds with no change in number of holdings. The basket and remaining portfolio exposures are aggregated using daily ETF holding weights and then averaged over all ETFs on redemption days. I plot the average exposures using five standardized measures, defined using $NetPres$, $NetPres \times Flow$, $SellPres$, $SellPres \times Flow$, and $Flow\ shock$ (Coval and Stafford, 2007; Choi et al., 2020; Dou, Kogan, and Wu, 2022). The definitions of exposures are in Appendix A.2. The sample difference (Δ) and its t-statistic between baskets and remaining portfolios are reported. The sample is from January 2, 2014 to December 31, 2021.

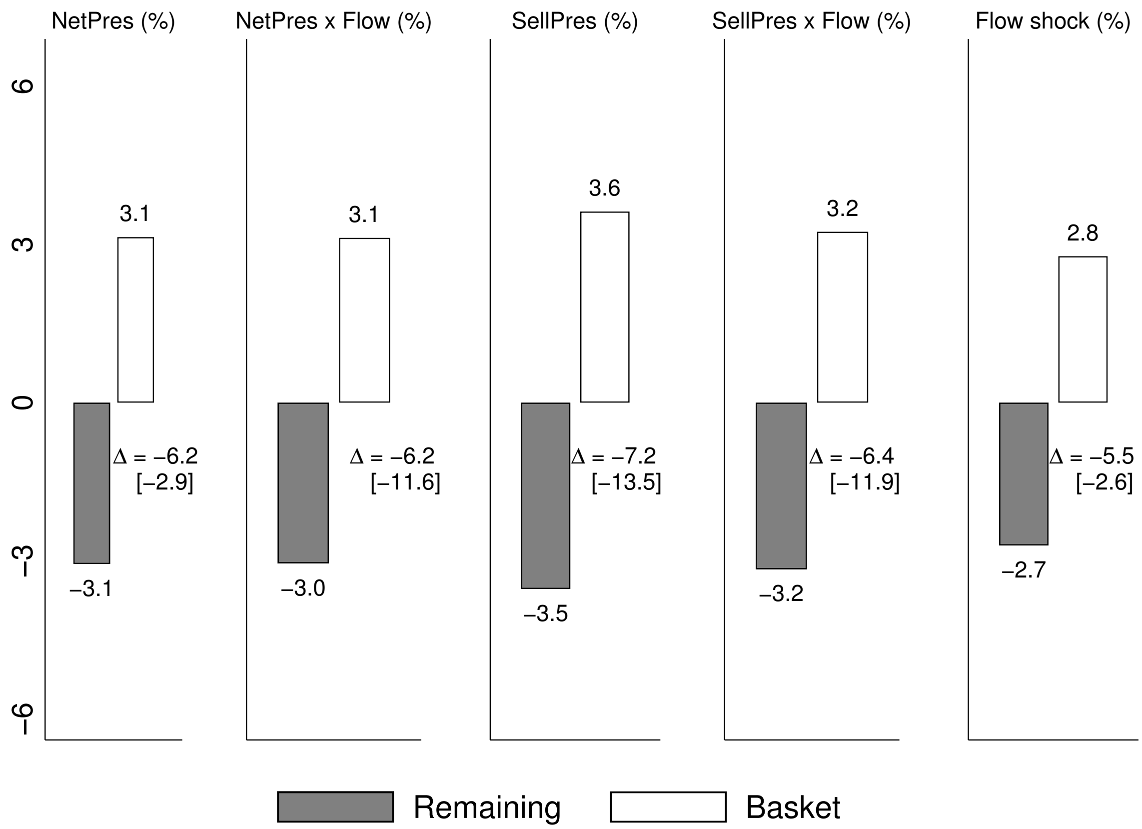

Table 1. Summary Statistics

This table reports the summary statistics of ETF variables, including sample mean (Mean), standard deviation (SD), median (Med), and 5th (p5), 25th (p25), 75th (p75), and 95th (p95) percentile values. Panel A documents ETF variables. The sample period is from January 3, 2012 to December 31, 2021, with 113 unique ETFs. Panel B summarizes the hypothetical ETF price pressure exposures. I use holding-based pressure measures in Coval and Stafford (2007) and Choi et al. (2020) and the common-flow-based measure in Aragon and Kim (2022) and Dou, Kogan, and Wu (2022). The exposures are estimated using individual corporate bond monthly returns in a 36-month rolling window. The sample period is January 2, 2014 to December 31, 2021, with 104 unique ETFs. Panel C includes changes in the illiquidity of ETFs (baskets and remaining portfolios), APs, and the aggregate market. Illiquidities include the Amihud measures, the Roll measure, the Bao-Pan-Wang illiquidity, the imputed roundtrip cost, and the average bid-ask spreads. I take the average of five standardized measures. The sample period is January 2, 2018 to December 31, 2021, with 96 unique ETFs. Appendices A.1, A.2, and A.3 provide detailed definitions.

	Mean	SD	p5	p25	Med	p75	p95
	Panel A: ETFs						
Daily fund returns (bps)	1.34	35.80	-44.77	-7.93	1.16	12.27	47.63
Mispricing (%)	0.42	3.14	0.02	0.10	0.24	0.40	0.86
Short interest rate (bps)	4.03	8.58	0.07	0.59	1.58	3.96	15.33
Effective spread (bps)	19.08	32.36	1.64	4.51	10.34	21.08	65.59
Realized spread (bps)	15.04	24.19	-0.47	2.46	7.04	17.16	62.02
30-min variance ratio (%)	29.61	22.21	2.20	11.19	25.17	43.40	72.41
Order imbalance (%)	30.66	27.34	1.32	9.09	22.08	45.45	100.00
log(AUM)	19.15	2.10	16.02	17.70	18.83	20.61	22.97
Daily fund flow (%)	0.26	5.27	-0.46	0.00	0.00	0.00	1.35
Total expenses (bps)	36.85	48.97	7.00	11.00	24.00	43.00	99.00
D(Option available)	0.28	0.45	–	–	–	–	–
	Panel B: Hypothetical ETF price pressure exposures						
NetPres	-0.05	0.65	-1.50	-0.35	0.00	0.26	1.34
*NetPres*x*Flow*	-0.09	0.49	-0.76	-0.40	-0.19	0.04	1.39
SellPres	0.01	0.91	-2.30	-0.00	0.31	0.40	0.60
*SellPres*x*Flow*	0.02	0.51	-1.64	-0.00	0.17	0.25	0.48
Flow shock	-0.14	0.50	-1.35	-0.23	-0.00	0.06	0.51
	Panel C: Changes in illiquidity						
$\Delta Illiq^{AP}$ (%)	2.15	56.55	-105.48	-23.58	3.71	30.26	98.11
$\Delta Illiq^{ETF}_{Basket}$ (%)	-0.49	13.99	-17.46	-2.53	-0.01	2.34	12.85
$\Delta Illiq^{ETF}_{Remaining}$ (%)	0.12	8.13	-9.00	-0.91	-0.02	0.67	9.36
$\Delta Illiq^{MKT}$ (%)	3.41	7.13	-3.48	-1.15	0.55	3.60	16.57

Table 2. ETF incentives: Hypothetical ETFs hold baskets and remaining portfolios

This table investigates the heterogeneity in negotiation and ETF incentives by constructing hypothetical ETFs, assuming that ETFs hold all bonds rather than dispose of baskets on redemption days,

$$Expo_{i,t} = \alpha + \beta Fraction_{i,t-1} + \Gamma \boldsymbol{X}_{i,t-1} + \delta Illiquidity_{i,t-1} + \xi_i + \xi_{obj} \times \xi_t + \varepsilon_{i,t} \ ,$$

where $Expo_{i,t} \equiv \sum_{k \in i} \omega_{i,k,t-1 \in m} Expo_{k,m+1}$ is each one of five price pressure exposures at day t in month $m+1$, which is the sum of bond-level exposures in month $m+1$ ($Expo_{k,m+1}$) using one-day lagged holding weights ($\omega_{i,k,t-1 \in m}$). $Fraction_{i,t \in m}$ represents both the intensive ($1-$ *ratio*, Panel A) and extensive ($D(Fraction)$, Panel B) margins. The intensive margin is one minus a ratio, which is defined as the ratio between the number of corporate bond names in the baskets and that in the remaining portfolios. The extensive margin is a fraction dummy that equals one if the ratio defined above is less than 60%, and equals zero otherwise. $\boldsymbol{X}$ includes the logarithm of AUM *log(AUM)*, daily fund flow, and total expenses. $Illiquidity_{i,t}$ is the standardized illiquidity. The detailed variable definitions are provided in Appendices A.1, A.2, and A.3. ξ_i and $\xi_{obj} \times \xi_t$ are the individual ETF fixed effect and the investment objective times the date fixed effect. $\varepsilon_{i,t}$ is the residual term, and the standard errors are clustered at the investment objective level. t-statistics are reported in brackets. The sample period is from January 2, 2014 to December 31, 2021.

	$NetPres$	$NetPres \times Flow$	$SellPres$	$SellPres \times Flow$	$Flow\ shocks$
			Panel A: Intensive margin		
$1-$ ratio	1.591	7.439	1.885	2.701	9.127
	[4.52]	[10.00]	[1.89]	[2.65]	[3.99]
log(AUM)	-2.471	-4.596	40.854	22.180	-23.036
	[-0.68]	[-1.27]	[7.29]	[5.30]	[-18.91]
Daily fund flow	0.120	0.064	-0.164	-0.086	0.066
	[65.35]	[13.35]	[-35.08]	[-15.79]	[4.52]
Total expenses	-0.044	0.153	0.223	0.069	0.189
	[-0.55]	[11.29]	[2.69]	[0.85]	[0.88]
Illiquidity	-8.870	-3.455	-6.256	-5.116	11.926
	[-13.68]	[-24.20]	[-11.72]	[-8.69]	[17.27]
N	4,131	4,131	4,131	4,131	4,131
Adj. R^2	0.534	0.573	0.477	0.541	0.379
			Panel B: Extensive margin		
D(Fraction)	0.640	4.505	2.548	2.221	5.027
	[3.49]	[4.96]	[6.22]	[3.04]	[2.38]
log(AUM)	-2.452	-4.580	40.794	22.160	-22.994
	[-0.68]	[-1.25]	[7.31]	[5.30]	[-17.99]
Daily fund flow	0.122	0.069	-0.166	-0.085	0.074
	[58.95]	[13.72]	[-45.98]	[-17.87]	[5.48]
Total expenses	-0.044	0.154	0.228	0.071	0.188
	[-0.56]	[11.91]	[2.66]	[0.87]	[0.86]
Illiquidity	-8.890	-3.547	-6.281	-5.150	11.812
	[-13.57]	[-23.55]	[-11.54]	[-8.55]	[16.20]
N	4,131	4,131	4,131	4,131	4,131
Adj. R^2	0.534	0.572	0.477	0.541	0.378

Table 3. AP incentive: Illiquidity co-movement with AP portfolios

This table estimates the co-movement in illiquidity between ETF and AP portfolios on redemption days. I regress the percentage changes in the ETF portfolio illiquidity (both baskets and remaining portfolios) on the percentage changes in the AP portfolio illiquidity and the percentage changes in the cross-sectional corporate bond market illiquidity,

$$\Delta Illiq_{AP,m\in q} = \alpha + \beta_1 \Delta Illiq^{\text{redemption}}_{\text{Basket}\in i,t\in m} + \beta_2 \Delta Illiq_{MKT,m} + Controls + \varepsilon_{i,t}$$

$$\Delta Illiq_{AP,m\in q} = \alpha + \gamma_1 \Delta Illiq^{\text{redemption}}_{\text{Remaining}\in i,t\in m} + \gamma_2 \Delta Illiq_{MKT,m} + Controls + \varepsilon_{i,t} \ ,$$

where $Illiq_{AP,m\in q}$ is the AP portfolio illiquidity using quarter-end weights and the month-end illiquidity measure. $Illiq^{\text{redemption}}_{\text{Basket}\in i,t\in m}$ and $Illiq^{\text{redemption}}_{\text{Remaining}\in i,t\in m}$ represent illiquidities of baskets and remaining portfolios for ETF i in the redemption at day t in month m. The illiquidity is aggregated over the bond-level liquidities using daily ETF holding weights, $\omega_{i,k,t\in m}$. $Illiq_{MKT,m}$ is the cross-sectional average of the bond illiquidity measure in month m. Δ is the percentage change operator. The regression includes contemporaneous CRSP value-weighted market returns (CRSP market returns) and contemporaneous ETF portfolio returns and the squared (ETF returns and ETF returns^2). I estimate coefficients in a pooled OLS regression with ETF and AP fixed effects, and the standard errors are clustered at the AP level. The sample period in Panel A is from January 2, 2018 to December 31, 2021. Panel B reports the results for the COVID-19 subsample, and the sample period is from March 11, 2020 to December 31, 2021.

	Panel A: Full		Panel B: COVID-19	
	Basket	Remaining	Basket	Remaining
$\Delta Illiq^{\text{redemption}}$	-0.030	-0.000	-0.043	0.035
	[-2.11]	[-0.01]	[-2.24]	[2.08]
$\Delta Illiq_{MKT}$	-0.082	-0.071	-0.449	-0.466
	[-0.21]	[-0.18]	[-0.94]	[-0.97]
ETF returns	-0.169	0.212	-0.078	0.291
	[-0.54]	[0.78]	[-0.96]	[3.24]
ETF returns^2	0.185	0.348	0.115	0.128
	[5.87]	[7.33]	[4.38]	[4.91]
CRSP market returns	0.131	0.095	-0.020	-0.032
	[3.72]	[3.70]	[-1.46]	[-2.81]
N	95,106	110,257	45,658	51,635
Adj. R^2	0.039	0.040	0.072	0.082

Table 4. Redemptions and ETF performance in the secondary market

This table presents the impact of redemptions on ETF performance in the secondary market. The regression is

$$Outcome_{i,t+1} = \alpha + \beta D(Redemption)_{i,t} + \Gamma \mathbf{X}_{i,t} + \xi_i + \xi_{obj} \times \xi_t + \varepsilon_{i,t} ,$$

where $Outcome_{i,t+1}$ is one of the seven variables of the i^{th} ETF at day $t+1$, including daily fund returns (Ret), effective spreads ($Esprd$), realized spreads ($Rsprd$), 30-min variance ratio ($VR30$), the absolute order imbalance in numbers of transactions (OIN), mispricing ($Misp$), and short interest rate (SII). $D(Redemption)_{i,t}$ equals one if there is redemption activity on the i^{th} ETF at day t and equals zero if there are no changes in shares outstanding. Control variables include the logarithm of AUM $log(AUM)$, daily fund flow, total expenses, short interest rate, and the dummy of option availability $D(Option\ available)$. The detailed variable definitions are shown in Appendix A.1. The regression uses the individual ETF fixed effect and the investment objective times the date fixed effect, and the standard errors are clustered at the investment objective level. t-statistics are reported in brackets. The sample period is from January 3, 2012 to December 31, 2021.

	Ret (bps)	$Esprd$ (bps)	$Rsprd$ (bps)	$VR30$ (%)	OIN (%)	$Misp$ (%)	SII (bps)
D(Redemption)	-2.320	1.336	1.311	0.884	1.857	0.126	0.976
	[-3.59]	[3.33]	[2.36]	[3.09]	[7.52]	[15.94]	[3.42]
log(AUM)	-1.118	-4.229	-3.627	-0.675	-7.025	-0.059	-3.603
	[-4.88]	[-5.77]	[-5.62]	[-1.92]	[-7.83]	[-1.25]	[-86.53]
Daily fund flow	0.000	0.012	0.009	-0.002	0.024	0.384	0.011
	[0.03]	[6.84]	[12.90]	[-0.21]	[19.49]	[26.57]	[1.57]
Total expenses	0.041	-0.092	-0.164	-0.071	0.104	0.003	0.024
	[3.05]	[-9.82]	[-16.78]	[-8.92]	[3.57]	[0.22]	[3.25]
Short interest rate	-0.096	-0.233	-0.194	0.010	-0.174	-0.006	–
	[-8.32]	[-13.34]	[-10.69]	[0.72]	[-7.56]	[-1.44]	–
D(Option available)	3.368	0.041	-0.265	1.080	7.620	0.493	7.717
	[2.01]	[0.02]	[-0.14]	[0.73]	[1.64]	[0.83]	[4.73]
N	21,853	21,324	21,318	21,395	21,321	19,582	21,853
Adj. R^2	0.489	0.418	0.476	0.035	0.333	0.706	0.470

Table 5. Price multipliers

This table estimates the price multiplier M, the inverse of price elasticity of demand for ETF shares in the corporate bond ETF market using the following panel regression:

$$Ret_{i,t} = a + M \times Demand_{i,t} + Controls_{i,t} + \xi_i + \xi_t + \epsilon_{i,t},$$

where $Ret_{i,t}$ is the daily bond ETF i's return at day t, and $Demand_{i,t}$ is the demand of ETF i at day t. I decompose $Demand_{i,t}$ into the number of shares traded by retail investors, by above 20,000 trades in institutional investors, and by other institutions using WRDS Intraday Indicator database (Boehmer et al., 2021). *Controls* include four lags of daily ETF returns, the logarithm of AUM *log(AUM)*, the daily fund flows and three lagged flows, and total expenses. ξ_i and ξ_t represent individual ETF and date fixed effects following Li and Lin (2022). I cluster standard errors at the fund and day levels and report t-statistics in brackets. The sample period is from January 2, 2012 to December 31, 2021.

	Redmp Days	Normal Days	Redmp Days	Normal Days	Redmp Days	Normal Days
Demand	10.541	2.548				
	[2.12]	[4.11]				
Retail demand			3.942	2.748	2.356	3.282
			[0.10]	[1.23]	[0.05]	[1.41]
Institutional demand			11.282	2.771		
			[2.28]	[4.51]		
Above 20K inst trades demand					43.747	1.731
					[2.62]	[0.75]
Other inst trades demand					8.836	3.397
					[1.55]	[5.29]
log(AUM)	-0.020	-0.001	-0.021	-0.001	-0.021	-0.000
	[-1.17]	[-0.56]	[-1.18]	[-0.74]	[-1.04]	[-0.34]
Daily fund flow	0.011	0.002	0.011	0.002	0.010	0.002
	[1.99]	[2.31]	[1.95]	[2.19]	[1.82]	[1.98]
Total expenses	0.009	0.014	0.005	0.010	-0.007	0.013
	[0.06]	[0.77]	[0.03]	[0.56]	[-0.05]	[0.66]
Lagged returns	YES	YES	YES	YES	YES	YES
Lagged flows	YES	YES	YES	YES	YES	YES
N	7,364	155,309	7,307	141,724	7,130	117,942
Adj. R^2	0.297	0.312	0.297	0.315	0.300	0.318

Table 6. Addressing endogeneity concerns: Natural experiments

This table addresses the endogeneity concerns in the economic incentive analyses. For ETF incentives, the natural experiment is the Secondary Market Corporate Credit Facility (SMCCF) during the COVID-19 pandemic (Panel A). The difference-in-differences regression is

$$Expo_{i,t} = \alpha + \beta D(Treat)_i \times D(Post)_t + \Gamma \mathbf{X}_{i,t} + \delta Illiquidity_{i,t} + \xi_i + \xi_{obj} \times \xi_t + \varepsilon_{i,t} \ ,$$

where $Expo_{i,t}$ is the price pressure exposure of hypothetical ETF i at day t, using net sell pressure and net sell pressure with flow measures. $D(Treat)$ is the treatment dummy, which equals one if an ETF was not included in the SMCCF program and zero otherwise. $D(Post)$ equals one if a date is after March 23, 2020. Control vector $\boldsymbol{X}$ and $Illiquidity$ and fixed effects ξ_i and $\xi_{obj} \times \xi_t$ are defined as in Table 2. The standard errors are clustered at the investment objective level. t-statistics are reported in brackets. The sample period is from January 1, 2019 to December 31, 2020. For AP incentives, the natural experiment is the SEC rule 6c-11 in Panel B. The regressions are

$$\begin{aligned} \Delta Illiq_{AP,i,m\in q} &= \beta_0 + \beta_1 \Delta Illiq^{\text{redemption}}_{\text{Basket},i,t\in m} \times D(TE)_{it} \times D(\text{6c-11})_t \\ &\quad + \beta_2 \Delta Illiq_{MKT,m} + Controls + \varepsilon_{AP,i,t} \\ \Delta Illiq_{AP,i,m\in q} &= \gamma_0 + \gamma_1 \Delta Illiq^{\text{redemption}}_{\text{Remaining},i,t\in m} \times D(TE)_{it} \times D(\text{6c-11})_t \\ &\quad + \gamma_2 \Delta Illiq_{MKT,m} + Controls + \varepsilon_{AP,i,t} \ , \end{aligned}$$

where $D(TE)_{it}$ is the treatment dummy if an ETF's tracking error is larger than the cross-sectional mean, where the tracking error is the standard deviation of the difference between daily ETF returns and underlying index returns in a 20-trading day window. $D(\text{6c-11})_t$ is the post-announcement of SEC rule 6c-11 dummy, defined as one if a date is after September 2019. Controls and fixed effects are defined as in Table 3. The standard error is clustered at the AP level. t-statistics are reported in brackets. The sample period is from January 1, 2018 to January 31, 2021.

	Panel A: SMCCF		Panel B: 6c-11	
	NetPres	*NetPresxFlow*	Basket	Remaining
D(Treat)×D(Post)	4.944	33.619		
	[16.58]	[186.34]		
$\Delta Illiq^{Redemption}$×D(6c-11)×D(TE)			-0.631	-0.136
			[-6.30]	[-0.81]
Controls	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES
Obj×Date FE	YES	YES		
AP FE			YES	YES
N	1,763	1,763	18,691	20,502
Adj. R^2	0.498	0.793	0.046	0.036

Table 7. Subperiod results

This table presents the impact of redemptions on ETF performance in the secondary market in subperiods. The regression is

$$Outcome_{i,t+1} = \alpha + \beta_1 D(Redemption)_{i,t} \times D(Period) + \beta_2 D(Redemption)_{i,t} + \beta_3 D(Period)$$
$$+\Gamma \mathbf{X}_{i,t} + \xi_i + \xi_{obj} \times \xi_t + \varepsilon_{i,t} \ ,$$

where $Outcome_{i,t+1}$ is one of the seven variables of the i^{th} ETF at day $t+1$, including daily fund returns (Ret), effective spreads ($Esprd$), realized spreads ($Rsprd$), 30-min variance ratio ($VR30$), the number order imbalance of all transactions (OIN), mispricing ($Misp$), and short interest rate (SII). $D(Redemption)_{i,t}$ equals one if there is a redemption on the i^{th} ETF at day t and zero if there are no changes in shares outstanding. $D(Period)$ is the subperiod dummy, where I use three subperiods: Volcker Rule period (2012–2014), pre-COVID period (2015–2019), and post-COVID pandemic period (2020–2021). The logarithm of AUM *log(AUM)*, daily fund flow to AUM ratio, total expenses, short interest rate, and the dummy of option availability *D(Option availability)* are control variables. The detailed variable definitions are shown in Appendix A.1. I use the individual ETF fixed effect and the investment objective times the date fixed effect, and the standard errors are clustered at the investment objective level. t-statistics are reported in brackets. The sample period is from January 3, 2012 to December 31, 2021.

	Ret (bps)	$Esprd$ (bps)	$Rsprd$ (bps)	$VR30$ (%)	OIN (%)	$Misp$ (%)	SII (bps)
D(Redemption)×D(Before 2014)	-1.424	0.536	1.817	-0.842	-7.842	0.130	-0.341
	[-3.33]	[0.31]	[1.00]	[-0.27]	[-19.82]	[1.99]	[-8.16]
D(Redemption)×D(Pre-COVID)	-1.487	2.030	1.901	0.896	2.669	0.183	3.202
	[-7.84]	[5.55]	[4.04]	[3.47]	[45.85]	[442.29]	[13.32]
D(Redemption)×D(Post-COVID)	-3.939	0.247	0.195	1.134	1.975	0.043	-2.781
	[-1.71]	[1.20]	[0.52]	[21.05]	[2.83]	[13.57]	[-3.63]
Controls	YES	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES	YES
Obj×Date FE	YES	YES	YES	YES	YES	YES	YES
N	21,853	21,324	21,318	21,395	21,321	19,582	21,853
Adj. R^2	0.489	0.418	0.476	0.035	0.333	0.706	0.475

Table 8. Limits to arbitrage

This table presents the impact of redemptions on ETF performance in the secondary market in the samples with high and low limits to arbitrage. The panel regression is

$$Outcome_{i,t+1} = \alpha + \beta D(Redemption)_{i,t} + \Gamma \mathbf{X}_{i,t} + \xi_i + \xi_{obj} \times \xi_t + \varepsilon_{i,t} ,$$

where $Outcome_{i,t+1}$ is one of the seven variables of the i^{th} ETF at day $t+1$, including daily fund returns (*Ret*), effective spreads (*Esprd*), realized spreads (*Rsprd*), 30-min variance ratio ($VR30$), the number order imbalance of all transactions (OIN), mispricing (*Misp*), and short interest rate (SII). $D(Redemption)_{i,t}$ equals one if there is a redemption on the i^{th} ETF at day t and equals to zero if there are no changes in shares outstanding. I identify limits to arbitrage using the aggregate fixed-income hedge fund flows and the intermediary distress measure in He, Khorrami, and Song (2022). Negative aggregate fund flows and strong intermediary distress represent high limits to arbitrage. The logarithm of AUM *log(AUM)*, daily fund flow to AUM ratio, total expenses, short interest rate, and the dummy of option availability *D(Option availability)* are control variables. The detailed variable definitions are shown in Appendix A.1. I use the individual ETF fixed effect and the investment objective times the date fixed effect, and the standard errors are clustered at the investment objective level. *t*-statistics are reported in brackets. Because of the limited availability of hedge fund and intermediary leverage ratio data, the sample period is from January 3, 2012 to June 30, 2020.

	Ret (bps)	$Esprd$ (bps)	$Rsprd$ (bps)	$VR30$ (%)	OIN (%)	$Misp$ (%)	SII (bps)
Panel A: Aggregate fixed-income hedge fund flow							
	High limits (negative flows)						
D(Redemption)	-2.369	1.318	1.346	0.524	1.526	0.134	1.302
	[-14.21]	[3.17]	[2.30]	[1.60]	[6.86]	[4.30]	[5.21]
	Low limits (positive flows)						
D(Redemption)	-3.822	1.484	1.799	3.249	-0.199	-0.020	0.650
	[-1.00]	[1.46]	[1.92]	[2.54]	[-0.23]	[-32.92]	[1.25]
Panel B: Intermediary distress							
	High limits (strong distress)						
D(Redemption)	-4.965	1.538	1.521	0.636	1.765	0.154	1.793
	[-14.18]	[4.24]	[3.21]	[1.03]	[12.08]	[3.42]	[4.05]
	Low limits (weak distress)						
D(Redemption)	-0.078	0.347	0.838	1.667	0.328	0.031	0.973
	[-0.12]	[0.62]	[1.11]	[2.06]	[0.85]	[0.98]	[8.40]