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# Do mutual funds and ETFs affect the commonality in liquidity of corporate bonds?☆

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ABSTRACT

This paper explores the influence of increasing ownership in fixed-income ETFs and mutual funds on liquidity commonality among corporate bonds. The unpredictable nature of liquidity demands in these funds may lead to correlated trading in underlying illiquid bonds. The study finds a positive and significant relationship between ETF ownership and liquidity commonality in investment-grade corporate bonds. In contrast, mutual fund or index fund ownership does not exhibit a similar effect, a result that differentiates corporate bonds from equities. This distinction from equities is attributed to different liquidity management strategies employed by equity and corporate bond mutual funds. The paper also highlights factors contributing to the varying impacts of ETFs and mutual funds on corporate bonds, including correlated trading due to fund flows, differences in investor clienteles, and the role of ETF arbitrage activities.

## 1. Introduction

Since the 2008 financial crisis, the U.S. corporate bond market has been notably reshaped, especially in terms of the composition of institutional bondholders. This period witnessed a significant expansion in the participation of fixed-income exchange-traded funds (ETFs) and mutual funds. As of the first quarter of 2019, mutual fund holdings accounted for 20% of the total corporate bonds outstanding, while ETF holdings represented nearly 5% of the market (see Fig. 1).[1] Despite the inherent illiquidity of the corporate bonds in their portfolios, fixed-income ETFs and mutual funds provide investors with the benefit of daily redemptions. Consequently, these funds exhibit higher turnover and face less predictable liquidity needs compared to dominant market institutions with long-term liabilities, such as insurance companies and pension funds. Given the liquidity demands stemming from the increasing activity of ETFs and mutual funds, coupled with the decline in dealer capital for market-making due to post-crisis regulations (Bao

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[1] The estimates are computed by aggregating data from the Federal Reserve's Flow of Funds Table L.213, by investor type. As of Q1 2019, the total amount outstanding in corporate bonds was approximately $10.4 trillion.

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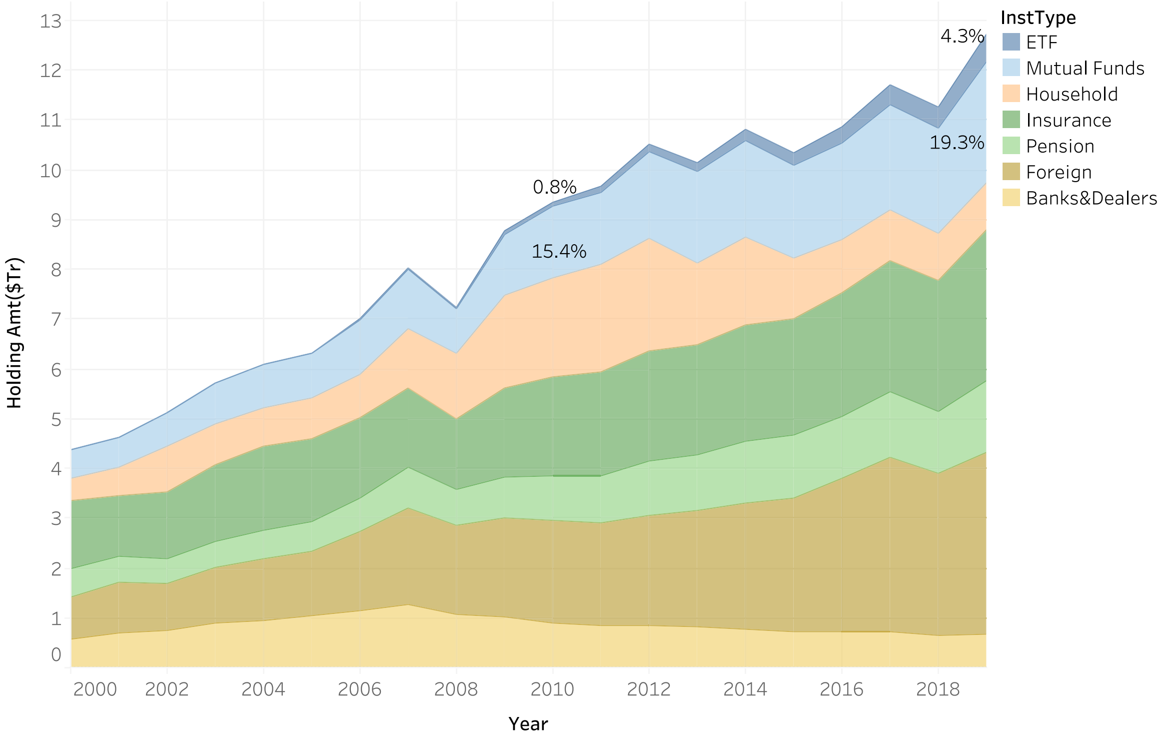


**Fig. 1.** Holders of U.S. corporate bonds. The estimates are computed by aggregating data from the Federal Reserve's Flow of Funds Table L.213, by investor type.

et al., 2018; Bessembinder et al., 2018; Dick-Nielsen and Rossi, 2019), regulators are expressing concerns about the heightened fragility risk in the corporate bond market (Anand et al., 2021).[2]

This paper explores the extent to which the growing activity of ETFs and mutual funds in the corporate bond market contributes to commonality in liquidity, a factor potentially amplifying market fragility. Existing literature has identified institutional holdings as a catalyst for liquidity commonality in equities, demonstrating that higher levels of mutual fund (Koch et al., 2016) and ETF ownership (Agarwal et al., 2018) substantially increase liquidity commonality among stocks. However, there is a lack of similar studies for the corporate bond market. This study seeks to address this gap by examining demand-side factors' impact on liquidity commonality in corporate bonds.

Previous research, notably Bao et al. (2011), has highlighted significant commonality in liquidity among corporate bonds. This commonality typically originates when a cohort of investors consistently engages in the synchronized trading of a specific set of bonds, leading to notable trade imbalances and significant liquidity co-movements (Koch et al., 2016). This scenario becomes particularly problematic during adverse market conditions, as it can trigger widespread liquidity shortages, exacerbating downward price volatility. Given their inherent characteristics, fixed-income ETFs and mutual funds are likely to exert correlated liquidity demand on their underlying bonds and contribute to heightened levels of common liquidity variation across the bonds they hold. However, understanding the influence of these dynamics on bonds is complex, as it is obscured by the differing institutional frameworks that govern equity and corporate bond markets.

I investigate the effect of ETF, mutual fund, and index fund ownership on the commonality in liquidity of corporate bonds by applying a two-step process methodology analogous to that of the equity studies (Kamara et al., 2008; Koch et al., 2016; Agarwal et al., 2018). In the initial step, using the Amihud (2002) price impact measure to capture the daily bond illiquidity, I compute how the liquidity of a bond co-moves with that of three different portfolios consisting of bonds that have ETF ownership, high mutual fund ownership, and high index fund ownership, respectively. Moving to the second stage, I examine the relationship between the commonality measure of each bond and its ownership by ETFs, mutual funds, and index funds. Given the unavailability of individual fund trades within a quarter, I utilize quarterly institutional ownership at the bond level as a proxy for institutional trading activity. The fundamental assumption here is that bonds held to a greater extent by a particular group of institutions are also traded more frequently by those institutions. Complementing the two-step approach, I adapt the methodology put forth by Anton and Polk

[2] The U.S Securities and Exchange Commission Fixed Income Market Structure Advisory Committee (FIMSAC) has established "The ETFs and Bond Funds Subcommittee" to examine the impacts of the growth of registered funds, including both ETFs and open-end mutual funds, as investors in the corporate and municipal bond markets.

(2014) to examine the relationship between common fund ownership and co-movements in liquidity at the bond-pair level. It is essential to recognize that this approach disregards the correlated liquidity shocks experienced by funds holding different bonds. As co-movement in liquidity can occur even without common ownership (Greenwood and Thesmar, 2011), I view this alternative approach as supportive of the primary analysis.

I begin my empirical analysis by examining the impact of ETF ownership on liquidity commonality in the context of investment-grade corporate bonds. The findings suggest an economically and statistically positive relationship between ETF ownership and liquidity commonality in these bonds and highlight a distinct association that sets it apart from mutual fund and index fund ownership. Furthermore, similar findings are obtained when analyzing the relationship between common ETF ownership and liquidity co-movements at the bond-pair level. These outcomes align with the findings of Agarwal et al. (2018), who identify a significant increase in liquidity commonality in equities attributed to ETF ownership.

While my empirical analysis underscores the significant impact of ETF ownership on liquidity commonality in investment-grade bonds, it reveals no similar influence from ownership by either active mutual funds or index funds within the same asset class. This lack of effect is notable given the corporate bond market's inherent illiquidity and contrasts sharply with the established impact of equity mutual funds on liquidity commonality in stock markets, as detailed by Koch et al. (2016). Equity mutual funds typically maintain limited liquidity buffers and liquidate holdings almost dollar-for-dollar in response to investor redemptions (Coval and Stafford, 2007), which exacerbates liquidity commonality across their stock portfolios. In contrast, corporate bond mutual funds typically rely on cash reserves or the sale of other liquid assets rather than immediate bond liquidation to meet redemption demands (Choi et al., 2020).[3] Aligning with the findings of Dannhauser and Hoseinzade (2022), my analysis corroborates that the trading activity in corporate bonds in response to mutual fund outflows is significantly less than one-to-one, diminishing the potential for correlated liquidity demands to influence the liquidity of mutual funds' corporate bond holdings. This divergence in redemption management strategies between equity and corporate bond mutual funds plausibly explains their differing effects on liquidity commonality.

The study also documents no significant linkage between any form of institutional ownership, encompassing ETFs and mutual funds, and liquidity commonality in high-yield corporate bonds. This is noteworthy, given that high-yield bonds possess characteristics of both equities and investment-grade bonds. This absence of relationship could be linked to the more subdued reaction of high-yield bonds to market-wide liquidity shifts, unlike their more responsive investment-grade counterparts. Existing literature, such as the work by Schultz (2001), suggests that trade flows in the high-yield bond market are more influenced by idiosyncratic factors rather than market-wide trends. Additionally, the heightened reactivity of high-yield bonds to firm-specific news, often linked to their increased default risk, is discussed in Dang et al. (2013). To explore further, my analysis differentiates between investment-grade and high-yield segments, assessing the co-movement of individual bond liquidity with the broader market portfolio. The results indicate a higher sensitivity of investment-grade bonds to market liquidity variations, with an average (median) market liquidity beta of 1.03 (1.09) for investment-grade bonds, compared to an average (median) beta of 0.66 (0.74) for high-yield bonds. These findings are consistent with the research of Rhodes and Mason (2023), who report an increased co-movement in returns between an investment-grade bond index and investment-grade bonds with higher ETF ownership levels, but no significant link between ETF ownership and the return co-movement of high-yield bonds with a corresponding high-yield bond index.

I explore the causal relationship between ETF ownership and liquidity commonality in investment-grade corporate bonds, capitalizing on a quasi-natural experiment triggered by a rule change in Bloomberg's investment-grade indices, as identified by Dathan and Davydenko (2018). This pivotal change, implemented on April 1, 2017, raised the minimum amount outstanding for inclusion in the index. Consequently, bonds with an amount outstanding below the new threshold were excluded from the index, leading to an exogenous decrease in ETF ownership at the individual bond level. I document that bonds exiting ETF portfolios due to the rule change exhibited a significant decline in liquidity commonality compared to those that remained. This finding provides compelling evidence that ETF ownership significantly contributes to the liquidity co-movement in corporate bonds, challenging the notion that ETFs only select bonds based on pre-existing liquidity commonality.

To further explore a potential relationship between mutual fund ownership and liquidity commonality, I utilize Bill Gross' abrupt resignation from the Chief Investment Officer (CIO) position at PIMCO as an exogenous source of variation in flows to PIMCO's bond funds, similar to the approach adopted by Zhu (2021). This event represents a shock to fund flows that exclusively affects a specific management company, resulting in cross-sectional variation in ownership that is plausibly unrelated to future liquidity commonality.[4] By examining the event, I find that bonds initially held to a significant degree by PIMCO funds experience substantial decreases in mutual fund ownership compared to bonds that were overweighted by other similar funds. However, the results obtained through the difference-in-differences framework indicate that despite the exogenous reduction in mutual fund ownership, the treated bonds do not exhibit a decline in their measures of liquidity commonality.

In the next stage of the analysis, I explore the mechanisms responsible for the divergent impacts of ETFs and mutual funds on liquidity commonality among bonds. Initially, I examine the impact of flow-driven correlated trading on liquidity betas, given that fund flows can exert buying or selling pressure on bonds. To assess this, I characterize bond-level flows as the weighted average of quarterly flows within both ETFs and mutual funds holding the bond. The analysis reveals that bonds show increased liquidity

[3] Coval and Stafford (2007) document that equity mutual funds experiencing substantial capital outflows create downward price pressures on commonly held stocks. Conversely, Choi et al. (2020) demonstrate that redemptions from bond funds do not result in fire sale pricing and attribute this resilience to funds' liquidity management strategies.

[4] Pacific Investment Management Company (PIMCO) was the largest fixed-income asset manager in the U.S. at the time of Bill Gross's resignation on September 26th, 2014.

betas, signifying heightened sensitivity to liquidity shifts during quarters of ETF outflows. However, no similar rise in liquidity commonality is observed for bonds held by mutual or index funds during outflow periods.

The varying impacts of flow-induced correlated trading across different fund types are mainly due to the distinct liquidity management strategies employed by active mutual funds and index funds in contrast to those of ETFs. A notable disparity is observed in their holdings of cash and Treasuries: the average ETF maintains only 12% in these assets, whereas active mutual fund and index mutual funds allocate 19% and 42%, respectively. In line with Dannhauser and Hoseinzade (2022), my analysis indicates that ETFs' trading activity in response to outflows closely mirrors the outflows themselves, demonstrating proportional scaling. This occurs even though ETFs employ a sampling strategy for portfolio construction and have flexibility in their redemption baskets. In stark contrast, active mutual funds exhibit a trading response significantly less than proportional to outflows. This is consistent with the findings that these funds maintain cash buffers (Chernenko and Sunderam, 2020) and engage in selective trading strategies to reduce liquidation costs (Choi et al., 2020; Jiang et al., 2021). Although index funds may superficially resemble ETFs, they typically track broad fixed-income indices with a higher proportion of liquid assets. Consequently, the trading activity of index funds in corporate bonds in response to outflows is significantly less than one-to-one.

Next, I examine whether ETFs attract investors with greater liquidity demands compared to mutual funds, taking into account that ETFs provide continuous exchange trading and intraday liquidity, whereas mutual funds can only be traded at the end-of-day net asset value (NAV). My results corroborate the findings of Dannhauser and Hoseinzade (2022), indicating that ETFs exhibit higher flow volatility than mutual funds. Since ETFs translate investor flows directly into underlying bonds through the creation and redemption of ETF shares, the high-turnover clientele can expose the underlying bonds to new liquidity shocks via the arbitrage mechanism (Ben-David et al., 2018).

Lastly, I investigate the role of the ETF arbitrage mechanism as a channel explaining the relationship between commonality in liquidity and ETF ownership. This mechanism distinguishes ETFs from their open-end fund counterparts. The correlated demand for constituent securities within the ETF basket can lead to simultaneous price impacts, exacerbating liquidity commonality in these securities (Agarwal et al., 2018). To measure the arbitrage activity of ETFs, I utilize various proxies such as the deviation between ETF prices and the NAV of underlying securities, as well the creation and redemption activities of Authorized Participants (APs) in an ETF. The analysis reveals that bonds held by high-arbitrage ETFs exhibit higher commonality in liquidity compared to bonds held by ETFs with lower arbitrage activity. This outcome suggests that the arbitrage mechanism contributes to the increased liquidity commonality among constituent bonds.

The remainder of the paper is structured as follows: Section 2 summarizes the institutional background and related literature. Section 3 outlines the data and methodology utilized in the study. Section 4 presents the empirical results regarding the relationship between institutional ownership and liquidity commonality. Section 5 establishes a causal link between fund ownership and liquidity commonality. Thereafter, Section 6 investigates the underlying mechanisms that help explain the differential impact of ETFs and mutual funds. Finally, Section 7 concludes the paper, summarizing the pivotal findings and their implications.

## 2. Institutional background and related literature

While ETFs and mutual funds both pool investors' capital, they vary in their approaches to liquidity provision and management. Unlike mutual funds, which are traded only at the end of the day based on their NAV, ETFs offer intraday liquidity and provide investors the convenience to trade throughout the day. This feature makes corporate bond ETFs more appealing to investors with higher liquidity demands in comparison to mutual funds (Dannhauser and Hoseinzade, 2022). Another critical distinction lies in how these funds manage investor flows. Mutual funds exercise discretion in managing these flows, while ETFs utilize a mechanical process known as the arbitrage mechanism. Authorized Participants (APs) participate in this process by trading the underlying securities in precise proportion to the ETF creation or redemption units. This arbitrage process ensures that any deviations between the ETF price and the value of the underlying securities are exploited. The arbitrage process works as follows: if the ETF price is lower than the net asset value of the basket securities, APs go long on the ETF, short the underlying bonds, and subsequently redeem ETF shares at the end of the day to unwind the intraday arbitrage positions. On the other hand, if the ETF price is higher than the net asset value, APs short the ETF, go long on the underlying bonds, and new ETF shares are created to correct the imbalance.

The arbitrage mechanism has the potential to influence liquidity commonality among the constituent securities of the corporate bond ETF. When a demand shock causes the ETF price to deviate from the NAV of the portfolio holdings, arbitrageurs respond by trading the underlying securities in the same direction as the initial shock to the ETF price (Ben-David et al., 2018; Agarwal et al., 2018). As a result, these shocks originating in the ETF market can propagate to the underlying bonds, leading to simultaneous trading in these bonds due to their common ETF ownership. This phenomenon is associated with correlated liquidity demands for these securities, resulting in heightened liquidity commonality.

At the same time, a counterbalancing factor to consider is that more than 80% of the daily trading activity occurs on exchanges, where investors can trade ETF shares without directly engaging in transactions involving the underlying bonds (Investment Company Institute, 2020). This dynamic might alleviate the necessity for creating or redeeming ETF shares in the primary market. Furthermore, Authorized Participants (APs), who serve as both bond market makers and ETF arbitrageurs (Pan and Zeng, 2019), can potentially employ their existing bond inventory for arbitrage purposes instead of relying on buying or selling the basket of bonds in the secondary bond market. Such a strategy has the potential to mitigate the correlated liquidity demand for the underlying securities. Therefore, it is not immediately clear whether ETFs contribute to liquidity commonality among the underlying bonds.

The impact of mutual funds on liquidity commonality is also uncertain. Like equity funds, bond mutual funds are subject to liquidity shocks through correlated inflows and outflows across funds. Nevertheless, bond funds carry unique attributes that distinguish them from their equity counterparts. Particularly, bond funds tend to exhibit a higher sensitivity of outflows to poor performance, especially during periods of elevated market illiquidity (Goldstein et al., 2017; Vivar et al., 2023). Therefore, in times of market stress, bond mutual funds may face larger outflows than equity funds, since equity fund outflows are typically less sensitive to poor performance, while inflows are more sensitive to positive performance. Moreover, institutional herding in corporate bonds is notably higher than what has been observed in equity markets, particularly on the sell side (Cai et al., 2019).

The influence of bond mutual funds on liquidity commonality hinges on several factors. On one hand, the illiquidity of bonds, combined with the open-ended structure of mutual funds, can generate correlated liquidity demands that may lead to excessive co-movements in bond liquidity, similar to the impact of mutual funds on equity markets (Koch et al., 2016). On the other hand, research by Choi et al. (2020) suggests that redemptions from bond mutual funds and resulting sell-offs do not necessarily trigger asset fire sales.[5] Bond funds tend to maintain cash reserves as a precautionary measure against investor redemptions, and they strategically trade securities in a selective manner to minimize liquidation costs. This practice of funds could potentially curb the correlated liquidity demand from funds and consequently attenuate the impact of mutual funds on liquidity commonality in corporate bonds.

This paper contributes to multiple strands of the literature. First, I shed light on the sources of commonality in liquidity of corporate bonds. Explanations for the co-movement in liquidity can be attributed to both supply-side and demand-side sources (Karolyi et al., 2012). From a supply-side perspective, Goldberg and Nozawa (2021) show that liquidity supply shocks are correlated with proxies for dealer financial constraints and lead to persistent changes in corporate bond market liquidity. Additionally, Bao et al. (2018) provide evidence that the illiquidity of stressed bonds has increased after the Volcker Rule, as affected dealers curtailed their liquidity supply. My research enhances the existing literature as the first to investigate the impact of demand-side sources on the commonality in liquidity of underlying bonds. Previous studies on the demand-side sources of liquidity commonality have primarily focused on equity markets. High mutual fund ownership (Koch et al., 2016) and ETF ownership (Agarwal et al., 2018) significantly increase a stock's commonality in liquidity. My findings reveal a significant association between ETF ownership and liquidity commonality in investment-grade corporate bonds, while mutual fund ownership does not amplify liquidity commonality in corporate bonds, contrary to equities.

Secondly, this paper adds to the ongoing discourse on the effects of mutual fund ownership in corporate bond markets. Cai et al. (2019) examine the extent of institutional investor herding in the U.S. corporate bond market and the price implications of this behavior. Choi et al. (2020) find that bond fund redemptions do not trigger fire sale price pressure, as they maintain substantial liquidity cushions and selectively trade liquid assets to absorb investor redemption risk. Jiang et al. (2021) indicate that during tranquil market conditions, bond funds tend to reduce liquid asset holdings such as cash and government bonds to cater to investor redemptions. By providing evidence that flow-driven activities of mutual funds do not induce co-movement in liquidity among underlying securities, my study reinforces the findings of Choi et al. (2020) and Jiang et al. (2021).

Third, this study contributes to the literature on ETFs. Previous research has documented the impact of equity ETFs on the volatility and return co-movement of underlying stocks (Malamud, 2016; Ben-David et al., 2018; Da and Shive, 2018). However, the literature lacks a consensus on the impact of ETFs on the liquidity levels of their underlying securities.[6] This paper shifts the focus to the impact of fixed-income ETFs on the commonality in liquidity of the underlying bonds, rather than the level of liquidity. The findings of this study align with recent work emphasizing the potential market fragility arising from information linkages and liquidity mismatches between ETFs and their constituent securities (Bhattacharya and O'Hara, 2018; Dannhauser and Hoseinzade, 2022; Pan and Zeng, 2019).

## 3. Data and methodology

### 3.1. Data description

#### 3.1.1. Corporate bond data

To gather data on bond transactions, I utilize the enhanced version of FINRA's TRACE (Trade Reporting and Compliance Engine) database for the sample period spanning from January 2011 to June 2019. TRACE provides data on over-the-counter (OTC) secondary market transactions for corporate bonds, including intraday observations on price, trading volume, and buy/sell indicators. The data curation process involves several filtering steps: (i) Removing canceled transactions and adjusting records that are corrected or reversed later (Dick-Nielsen, 2009), (ii) Employing the median and reversal filters introduced by Edwards et al. (2007) to eliminate extreme outliers and erroneous entries, (iii) Removing transactions labeled as when-issued or locked-in, (iv) Removing transaction records that have trade volume less than $10,000, and (v) Removing bonds that trade under $5 or above $1000.

The corporate bond pricing data is merged with the Mergent FISD (Fixed Income Securities Database) to obtain additional bond characteristics such as offering amount, offering date, maturity date, bond type, bond rating, bond option features, and issuer information. The following filtering criteria are applied: (i) Removing bonds that are structured notes, asset backed, agency backed, or equity linked. (ii) Excluding bonds that have less than one year to maturity.[7] (iii) Keeping bonds that are fixed rate or zero-coupon. (iv) Removing convertible bonds and bonds issued under the 144A rule.

[5] This contrasts with equity funds, where large outflows frequently lead to diminished positions, creating price pressure on mutual holdings among distressed funds (Coval and Stafford, 2007).

[6] See Hamm (2014), Dannhauser (2017), Israeli et al. (2017), Holden and Nam (2019), Saglam et al. (2019) and Marta (2020).

[7] This criterion is consistent with major corporate bond indices such as the Barclays Capital Corporate Bond Index, the Bank of America Merrill Lynch Corporate Master Index, and the Citi Fixed Income Indices.

#### 3.1.2. Mutual fund and ETF data

The sample comprises U.S. corporate bond ETFs, mutual funds, and index funds from Q4 2010 through Q2 2019. Quarterly holdings and fund characteristics data are obtained from the Center for Research in Security Prices (CRSP) survivorship-bias-free mutual fund database.[8] Bond funds are identified using the Lipper objective codes (A, BBB, HY, SII, SID, or IID) or the CRSP objective codes (beginning with 'C'). To be included in the sample, funds must have total net assets (TNA) of at least $1 million and at least one year of reported holdings. Furthermore, funds are required to invest at least 20% of their total assets in corporate bonds in the previous quarter. Throughout the study, I examine the implications of ETFs and mutual funds on the investment-grade and high-yield bonds separately to account for distinctions between these subclasses.

Bond ETFs are identified using CRSP's ETF flag. The sample of ETFs consists of 133 investment-grade ETFs and 62 high-yield ETFs. Both investment-grade and high-yield segments exhibit high concentration levels, with a significant portion of assets under management (AUM) held by the top funds. Index funds, exchange-traded funds, and exchange-traded notes are excluded from the sample of active mutual funds, following the methodology of Choi et al. (2020). The final sample of active mutual funds includes 935 unique investment-grade and 285 high-yield corporate bond mutual funds. Index funds are identified using both the index fund flag and the fund names in the CRSP Mutual Fund Database. The sample includes 57 distinct investment-grade index funds.[9]

I use March, June, September, and December as quarter-end dates to calculate quarterly bond-level measures of aggregate ETF and mutual fund ownership. I carry forward each fund's quarterly holdings for 2 months. Additionally, I follow the approach in the literature and carry holdings forward an additional quarter if a fund appears to have missed a report date. In cases where a fund family offers both ETF and open-end index fund share classes (e.g. Vanguard as specified in Dannhauser, 2017), I use the fractional total assets of the ETF share class to determine the proportional holdings in each bond attributable to the ETF share class.

### 3.2. Variable definitions

To capture the likelihood of correlated trading, I construct a bond-level proxy based on the percentage of a bond's outstanding amount held by ETFs, active mutual funds, and index funds. Specifically, I calculate the fraction of ownership $ETFOWN_{i,q}$ in bond $i$ by $J$ ETFs at the end of quarter $q$ using the formula:

$$ETFOWN_{i,q} = \frac{\sum_{j=1}^{J} parval_{i,j,q}}{amtout_{i,q}},$$

where $parval_{i,j,q}$ is the par value amount of bond $i$ owned by ETF $j$ at quarter $q$ and $amtout_{i,q}$ is the amount outstanding for bond $i$ at quarter $q$.[10] Similarly, I compute bond-level active mutual fund ownership ($MFOWN_{i,q}$) and index fund ownership ($INDFOWN_{i,q}$).

To capture the daily bond illiquidity, I employ the illiquidity measure proposed by Amihud (2002). This measure relates the price impact of trades, i.e., the price change measured as a return, to the trade volume measured in million dollars. The formula for the Amihud illiquidity measure is as follows:

$$illiq_{i,d} = \frac{|R_{i,d}|}{DolVol_{i,d}}, \tag{1}$$

where $R_{i,d}$ is the daily corporate bond return and $DolVol_{i,d}$ is the million dollar trading volume on day $d$.

To calculate the daily clean price of the bonds, I use a trading volume-weighted average of the intraday transaction prices. I employ this approach to minimize the impact of bid–ask spreads, following the methodology of Bessembinder et al. (2009) and Dick-Nielsen et al. (2012). By obtaining the daily clean prices, I compute the daily returns of the corporate bonds accordingly. Since corporate bonds are generally less liquid than stocks, it is common for some bonds to have no transactions on a given day. In such cases, I consider price changes over multiple days to calculate daily returns ($R_{i,d}$).[11]

In the robustness tests, I employ the bid–ask spread estimator proposed by Corwin and Schultz (2012), which is derived from daily high and low prices of the bonds. The authors argue that the daily high prices are more likely to result from buy orders, while the low prices correspond to sell orders. As a result, the ratio between the two reflects both the security's variance and the bid–ask spread. By utilizing the high-low ratio over consecutive days, Corwin and Schultz (2012) effectively separate the variance component (which should be proportional to time) from the bid–ask spread component (which should remain relatively constant).

To account for the potential effect of bond liquidity on commonality, I include the quarterly mean of the daily Amihud illiquidity measure as a control variable ($Amihud_{i,q}$). Additionally, I incorporate the log market value of the bond at the end of the quarter ($MktVal_{i,q}$) to account for variations in bond size.

I gather bond-level rating information from the Mergent FISD historical ratings database. I construct a control variable ($Rating_{i,q}$) by assigning a numerical value to each rating category. For example, AAA corresponds to 1, AA+ corresponds to 2, and so on, with CCC assigned a value of 21. High-yield bonds, with ratings greater than 10, indicate lower credit quality. I determine a bond's rating by averaging the ratings provided by S&P, Moody's, and Fitch.

[8] Starting from Q4 2010, CRSP mutual fund database begins to consistently report bond holdings of ETFs.

[9] The number of high-yield index funds and their aggregate ownership is very limited, so they are included in the high-yield mutual funds sample.

[10] To update the amount outstanding information for each bond at each quarter, I utilize the FISD (Fixed Income Securities Database) Amount Outstanding File.

[11] I limit the difference in days to 3 days. However, this criteria rarely binds due to my sample selection criteria and my results are robust against different values of the difference in days.

Furthermore, I calculate the yield spread ($Spread_{i,q}$) of a bond as the quarterly volume-weighted yield over the maturity-matched risk-free proxy. The number of years to maturity of a given bond is denoted by $Maturity_{i,q}$. Incorporating these control variables, I account for factors such as bond liquidity, rating, yield spread, and maturity that may influence liquidity commonality among the bonds.

### 3.3. Summary statistics

Table 1 presents summary statistics for investment-grade and high-yield bonds in the sample period. Panel A reports the sample statistics for investment-grade bonds. The sample covers the period from Q1 2011 to Q2 2019. For investment-grade bonds, the final sample consists of 108,906 bond quarters with both institutional ownership data and trade data sufficient to calculate liquidity betas. There are 8136 distinct bonds and 1310 distinct issuers in the investment-grade sample.[12] The average bond has an outstanding amount of $930 million. On average, 2.05% of the bond par value is held by ETFs, 6.24% by mutual funds, and 2.01% by index funds.

Panel B presents summary statistics for the high-yield bonds segment. The final sample consists of 32,648 bond-quarter observations. There are 2613 distinct high-yield bonds and 949 distinct issuers in the sample. The average high-yield bond has an amount outstanding of $665 million. On average, 16.97% of the bond par value is held by mutual funds and 2.12% is held by ETFs. This indicates that, on average, mutual fund and ETF ownership percentages are higher for high-yield bonds compared to investment-grade bonds in the sample.

### 3.4. Commonality in liquidity measure

To measure the commonality in liquidity among corporate bonds, I adopt an approach similar to previous equity studies. Coughenour and Saad (2004) examine how the liquidity of a stock co-moves with the liquidity of other stocks handled by the same specialist firm, while Kamara et al. (2008) attribute the increase in commonality in liquidity to the growing significance of institutional and index-related trading for stocks. Building on these findings, Koch et al. (2016) explore the co-movement in liquidity of stocks driven by mutual fund ownership, and Agarwal et al. (2018) investigate the same phenomenon for ETF ownership. These studies propose that when a security is owned by a group of institutions, its liquidity changes are more likely to co-move with other securities that also have high ownership by the same group.

I apply a similar approach to the corporate bond market, focusing on the commonality in liquidity among corporate bonds. By examining the extent to which changes in bond liquidity co-move across securities with high ownership by the same group of institutions, I aim to uncover the commonality in liquidity within the corporate bond market. Consistent with previous literature, I use the Amihud (2002) measure as a proxy for bond illiquidity. To address potential econometric issues such as non-stationarity, I focus on changes in liquidity rather than levels, following the methodology of Chordia et al. (2000) and Karolyi et al. (2012).

For bond $i$ on day $d$, I calculate the changes in the Amihud (2002) illiquidity measure (1) as

$$\Delta illiq_{i,d} = log\left[\frac{illiq_{i,d}}{illiq_{i,d-1}}\right]$$

by taking the difference in the logs of the Amihud (2002) between days $d$ and $d-1$.

I calculate the change in bond illiquidity for all the corporate bonds in my sample that have at least 20 observations in a quarter.[13] Koch et al. (2016) keep only the stocks that trade on consecutive days. As many bonds have no transactions at the daily frequency, such a restriction in the corporate bond setting would imply dropping significant number of bonds from the sample. Instead, I limit the difference in days to 5 days, which rarely applies due to my sample selection criteria of requiring a bond to trade on at least 20 days in a quarter. This allows me to capture the changes in bond illiquidity while including a larger number of bonds in the analysis.

To examine the extent to which active mutual fund, ETF, and index fund ownership is related to co-movements in liquidity, I start by estimating how the liquidity of a bond co-moves with the liquidity of three different portfolios consisting of bonds that have high ETF ownership, high mutual fund ownership, and high index fund ownership, respectively, as well as a market portfolio. For each trading day within a quarter, I calculate changes in the value-weighted illiquidity for four portfolios: (i) $\Delta illiq_{MKT,q,d}$, a market portfolio containing all bonds that have at least one transaction on that day, (ii) $\Delta illiq_{ETFOWN,q,d}$, a high ETF ownership portfolio comprised of the bonds in the top quartile of ETF ownership as ranked at the end of the previous quarter, similarly (iii) $\Delta illiq_{MFOWN,q,d}$, a high mutual fund ownership portfolio and, (iv) $\Delta illiq_{INDFOWN,q,d}$, a high index fund ownership portfolio. The portfolios are value weighted using the amount outstanding of bonds as weights. The daily change in illiquidity of bond $i$ is denoted as $\Delta illiq_{i,q,d}$.

[12] For comparison, He et al. (2022) study the commonality in credit spread changes and their sample includes 1980 distinct investment-grade bonds issued by 383 firms, as well as 900 distinct high-yield bonds issued by 373 firms. They have a total of 55,938 observations at the bond-quarter level for the period 2005 Q1 to 2015 Q2.

[13] Koch et al. (2016) drop those stocks that have less than 40 days of observations in a quarter. My results are robust against requiring a minimum of 15 or 30 observations in a quarter.

**Table 1**
Summary statistics.

| Panel A: Investment-grade bonds | N | Mean | Std. Dev. | Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | p1 | p25 | p50 | p75 | p99 |
| *Commonality in liquidity measures* | | | | | | | | |
| $\beta_{HI\_ETF}$ | 108,906 | 0.19 | 2.72 | −6.92 | −1.36 | 0.22 | 1.77 | 7.09 |
| $\beta_{HI\_MF}$ | 108,906 | 0.12 | 3.19 | −8.18 | −1.67 | 0.13 | 1.92 | 8.32 |
| $\beta_{HI\_INDF}$ | 108,906 | 0.13 | 3.92 | −9.32 | −1.96 | 0.13 | 2.23 | 9.53 |
| $\beta_{MKT}$ | 108,906 | 1.03 | 2.36 | −5.51 | −0.27 | 1.09 | 2.40 | 6.95 |
| $\rho_{\Delta liquidity}$ | 196,280,847 | 0.01 | 0.22 | −0.52 | −0.13 | 0.01 | 0.15 | 0.53 |
| *Institutional ownership variables* | | | | | | | | |
| ETFOWN (%) | 108,906 | 2.05 | 1.57 | 0.00 | 0.87 | 1.95 | 3.00 | 5.63 |
| MFOWN (%) | 108,906 | 6.24 | 5.95 | 0.00 | 1.90 | 4.65 | 8.87 | 27.54 |
| INDFOWN (%) | 108,906 | 2.01 | 1.34 | 0.00 | 1.10 | 1.92 | 2.75 | 5.94 |
| *Control variables* | | | | | | | | |
| Amount outstanding ($M) | 108,906 | 931.05 | 750.13 | 30.75 | 500.00 | 750.00 | 1150.00 | 3500.00 |
| Log market value | 108,906 | 20.42 | 0.86 | 17.29 | 20.03 | 20.45 | 20.93 | 22.07 |
| Quarterly illiquidity (mean) | 108,906 | 0.06 | 0.09 | 0.00 | 0.01 | 0.03 | 0.06 | 0.44 |
| Rating | 108,906 | 7.22 | 2.06 | 1.33 | 6.00 | 7.50 | 9.00 | 10.33 |
| Time to maturity (years) | 108,906 | 9.50 | 8.93 | 1.21 | 3.38 | 6.13 | 9.88 | 29.94 |
| Spread (%) | 106,695 | 1.42 | 1.01 | 0.11 | 0.73 | 1.20 | 1.85 | 4.97 |

| Panel B: High-yield bonds | N | Mean | Std. Dev. | Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | p1 | p25 | p50 | p75 | p99 |
| *Commonality in liquidity measures* | | | | | | | | |
| $\beta_{HI\_ETF}$ | 32,648 | 0.07 | 1.46 | −3.73 | −0.75 | 0.07 | 0.91 | 3.77 |
| $\beta_{HI\_MF}$ | 32,648 | 0.07 | 1.76 | −4.50 | −0.91 | 0.07 | 1.05 | 4.65 |
| $\beta_{MKT}$ | 32,648 | 0.66 | 1.83 | −4.36 | −0.33 | 0.74 | 1.71 | 5.20 |
| *Institutional ownership variables* | | | | | | | | |
| ETFOWN (%) | 32,648 | 2.12 | 2.09 | 0.00 | 0.00 | 1.87 | 3.57 | 7.91 |
| MFOWN (%) | 32,648 | 16.97 | 10.52 | 0.00 | 8.73 | 17.07 | 24.36 | 42.04 |
| *Bond characteristics* | | | | | | | | |
| Amount outstanding ($M) | 32,648 | 664.60 | 525.73 | 46.06 | 350.00 | 500.00 | 800.00 | 2805.00 |
| Log market value | 32,648 | 20.01 | 0.85 | 17.48 | 19.59 | 20.06 | 20.51 | 21.70 |
| Quarterly illiquidity (mean) | 32,648 | 0.08 | 0.12 | 0.00 | 0.01 | 0.03 | 0.09 | 0.57 |
| Rating | 32,648 | 13.80 | 2.35 | 10.33 | 12.00 | 13.50 | 15.33 | 20.50 |
| Time to maturity (years) | 32,648 | 6.99 | 5.92 | 1.34 | 4.05 | 5.84 | 7.76 | 26.51 |
| Spread (%) | 31,449 | 5.65 | 9.02 | 0.06 | 2.66 | 3.89 | 5.96 | 38.99 |

| Panel C: Fund-level variables | ETFs | | | Mutual funds | | | Index funds | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | p50 | Mean | Std. Dev. | p50 | Mean | Std. Dev. | p50 |
| Total net assets ($ bln) | 4.31 | 7.85 | 0.51 | 2.02 | 8.04 | 0.41 | 9.06 | 26.43 | 1.24 |
| Flow quarterly (%) | 9.63 | 18.05 | 4.51 | 1.25 | 10.83 | −0.29 | 3.07 | 10.90 | 1.73 |
| % in corporate bonds | 86.50 | 22.11 | 97.98 | 56.85 | 24.94 | 52.14 | 34.19 | 22.33 | 25.46 |
| % in cash | 1.61 | 1.91 | 1.17 | 3.90 | 6.76 | 2.20 | 1.32 | 2.45 | 0.70 |
| % in Treasuries | 10.15 | 19.62 | 0.27 | 15.03 | 15.55 | 10.70 | 41.01 | 18.41 | 43.15 |

Table 1 reports descriptive statistics for selected variables. The sample consists of 108,906 investment-grade and 32,648 high-yield bond-quarter observations from Q1 2011 to Q2 2019. The coefficients $\beta_{HI\_ETF}$, $\beta_{HI\_MF}$, and $\beta_{HI\_INDF}$ denote liquidity betas, capturing the co-movement between a bond's liquidity and the liquidity of portfolios with high ETF, active mutual fund, and index fund ownership, respectively. It also includes the correlation coefficient, $\rho_{ij,q}$, between the log daily changes in Amihud illiquidity for bonds $i$ and $j$ over each quarter $q$. Percent ownership in a bond by ETFs, active mutual funds, and index funds are represented as $ETFOWN(\%)$, $MFOWN(\%)$, and $INDFOWN(\%)$, respectively. Bond characteristics include bond-specific attributes, such as the outstanding amount (in $ million), log market value, daily illiquidity measure following Amihud (2002), numerical rating, years to maturity, and yield spread over the maturity-matched risk-free rate. Panel A provides statistics for investment-grade bonds, while Panel B details high-yield bonds. Panel C denotes summary statistics for corporate bond ETFs, mutual funds, and index funds, including total net assets, quarterly flows, and the composition of corporate bonds, cash, and Treasury holdings within each fund type.

For each bond $i$ in quarter $q$, I estimate the following regression (2) for ETF ownership

$$\begin{aligned}\Delta illiq_{i,q,d} = {} & \alpha_1 + \beta^{-1}_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d-1} + \beta_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d} + \beta^{+1}_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d+1}\\ & + \beta^{-1}_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d-1} + \beta_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d+1}\\ & + \beta^{-1}_{mret-ETFreg,i,q}R_{m,q,d-1} + \beta_{mret-ETFreg,i,q}R_{m,q,d} + \beta^{+1}_{mret-ETFreg,i,q}R_{m,q,d+1} + \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{1,i,q,d},\end{aligned} \tag{2}$$

and regression (3) for mutual fund ownership

$$\begin{aligned}\Delta illiq_{i,q,d} = {} & \alpha_2 + \beta^{-1}_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d-1} + \beta_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d} + \beta^{+1}_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d+1}\\ & + \beta^{-1}_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d-1} + \beta_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d+1}\\ & + \beta^{-1}_{mret-MFreg,i,q}R_{m,q,d-1} + \beta_{mret-MFreg,i,q}R_{m,q,d} + \beta^{+1}_{mret-MFreg,i,q}R_{m,q,d+1} + \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{2,i,q,d},\end{aligned} \tag{3}$$

**Table 2**
Annual averages of quarterly liquidity beta estimates.

Panel A: Investment-grade bonds

| | Market | ETFs | | | | Mutual funds | | | Index funds | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | # bonds | $R^2_{ETFreg}$ | $\beta_{HI\_ETF}$ | $\beta_{MKT-ETFreg}$ | $ETFOWN(\%)$ | $R^2_{MFreg}$ | $\beta_{HI\_MF}$ | $MFOWN(\%)$ | $R^2_{INDFreg}$ | $\beta_{HI\_INDF}$ | $INDFOWN(\%)$ |
| 2011 | 2324 | 0.30 | 0.06 | 0.89 | 0.93% | 0.30 | 0.20 | 6.35 | 0.30 | 0.01 | 1.34 |
| 2012 | 2580 | 0.31 | 0.07 | 0.91 | 1.36% | 0.31 | 0.09 | 6.51 | 0.31 | 0.17 | 1.47 |
| 2013 | 2947 | 0.30 | 0.17 | 0.88 | 1.56% | 0.30 | 0.13 | 6.50 | 0.30 | 0.10 | 1.56 |
| 2014 | 2926 | 0.30 | 0.20 | 0.83 | 1.62% | 0.31 | 0.20 | 6.05 | 0.31 | 0.04 | 1.74 |
| 2015 | 3160 | 0.31 | 0.16 | 0.91 | 1.90% | 0.30 | 0.08 | 6.29 | 0.31 | 0.07 | 2.00 |
| 2016 | 3546 | 0.30 | 0.23 | 0.90 | 2.17% | 0.30 | 0.01 | 6.37 | 0.30 | 0.23 | 2.10 |
| 2017 | 3771 | 0.29 | 0.21 | 0.82 | 2.61% | 0.29 | 0.00 | 6.32 | 0.29 | 0.08 | 2.38 |
| 2018 | 4035 | 0.29 | 0.29 | 0.64 | 2.89% | 0.28 | 0.21 | 6.05 | 0.28 | 0.26 | 2.57 |
| 2019 | 3909 | 0.29 | 0.24 | 0.81 | 2.91% | 0.29 | 0.25 | 5.59 | 0.29 | 0.13 | 2.59 |
| Full sample | 8136 | 0.30 | 0.18 | 0.84 | 1.99% | 0.30 | 0.13 | 6.23 | 0.30 | 0.12 | 1.97 |

Panel B: High-yield bonds

| | Market | ETFs | | | | Mutual funds | | |
|---|---|---|---|---|---|---|---|---|
| | # bonds | $R^2_{ETFreg}$ | $\beta_{HI\_ETF}$ | $\beta_{MKT-ETFreg}$ | $ETFOWN(\%)$ | $R^2_{MFreg}$ | $\beta_{HI\_MF}$ | $MFOWN(\%)$ |
| 2011 | 645 | 0.34 | 0.01 | 0.65 | 1.07 | 0.35 | 0.13 | 8.72 |
| 2012 | 762 | 0.31 | 0.04 | 0.54 | 1.13 | 0.32 | 0.06 | 16.81 |
| 2013 | 844 | 0.32 | 0.06 | 0.53 | 1.96 | 0.31 | 0.06 | 17.75 |
| 2014 | 906 | 0.30 | 0.07 | 0.52 | 2.05 | 0.30 | 0.13 | 17.80 |
| 2015 | 1000 | 0.29 | 0.06 | 0.64 | 2.15 | 0.29 | −0.06 | 18.06 |
| 2016 | 1055 | 0.29 | 0.04 | 0.66 | 2.06 | 0.29 | 0.16 | 17.42 |
| 2017 | 1104 | 0.29 | 0.10 | 0.63 | 2.08 | 0.28 | 0.06 | 16.30 |
| 2018 | 1008 | 0.27 | 0.05 | 0.65 | 2.50 | 0.27 | 0.04 | 16.69 |
| 2019 | 959 | 0.27 | 0.09 | 0.55 | 2.59 | 0.27 | 0.04 | 15.97 |
| Full sample | 2614 | 0.30 | 0.07 | 0.58 | 2.02 | 0.29 | 0.08 | 16.12 |

Table 2 presents the annual averages of quarterly computed liquidity betas for each bond. For bond $i$ in quarter $q$, the regression is as follows:

$$\Delta illiq_{i,q,d} = \alpha_{1,q} + \beta_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d} + \beta_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d} + \gamma_{1,i,q}controls_{q,d} + \epsilon_{1,i,q,d},$$

where $\Delta illiq_{i,q,d}$ refers to the change in the illiquidity of bond $i$ on day $d$ in quarter $q$. On each day $d$ within a quarter $q$, the changes in the value-weighted illiquidity of two distinct portfolios are calculated: (i) a market portfolio encompassing all bonds with at least one transaction that day, denoted as $\Delta illiq_{MKT,q,d}$, and (ii) a high-ETF-ownership portfolio, comprising bonds that ranked in the top quartile for ETF ownership at the end of the preceding quarter, denoted as $\Delta illiq_{ETFOWN,q,d}$. Analogous regressions are utilized to calculate $\beta_{HI\_MF,i,q}$ and $\beta_{HI\_INDF,i,q}$ for mutual funds and index funds, respectively, using $\Delta illiq_{MFOWN,q,d}$ and $\Delta illiq_{INDFOWN,q,d}$ as regressors. Panel A reports the statistics for investment-grade bonds and Panel B corresponds to the statistics fo high-yield bonds.

and finally, regression (4) for index fund ownership

$$\begin{aligned}\Delta illiq_{i,q,d} = {} & \alpha_3 + \beta^{-1}_{HI\_INDF,i,q}\Delta illiq_{INDFOWN,q,d-1} + \beta_{HI\_INDF,i,q}\Delta illiq_{INDFOWN,q,d} + \beta^{+1}_{HI\_INDF,i,q}\Delta illiq_{INDFOWN,q,d+1} \\ & + \beta^{-1}_{MKT-INDFreg,i,q}\Delta illiq_{MKT,q,d-1} + \beta_{MKT-INDFreg,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT-INDFreg,i,q}\Delta illiq_{MKT,q,d+1} \\ & + \beta^{-1}_{mret-INDFreg,i,q}R_{m,q,d-1} + \beta_{mret-INDFreg,i,q}R_{m,q,d} + \beta^{+1}_{mret-INDFreg,i,q}R_{m,q,d+1} + \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{3,i,q,d}.\end{aligned} \tag{4}$$

In each regression, the bond of interest is removed from the market portfolio, as well as from the high ETF, mutual fund, and index fund ownership portfolios (when applicable). To control for potential factors influencing bond illiquidity, I include lead, lag, and contemporaneous market returns ($R_{m,q,d}$), contemporaneous bond return squared ($R^2_{i,q,d}$), and lead and lag changes in the portfolio illiquidity measures as control variables.

Table 2 provides summary statistics for the market, high mutual fund ownership, and high ETF ownership portfolios used in the time-series regressions, along with key regression coefficients. Panel A displays the averages of quarterly statistics for 1-year periods for investment-grade bonds, while Panel B does the same for high-yield bonds. The annual averages of $\beta_{HI\_ETF}$, $\beta_{HI\_MF}$, and $\beta_{HI\_INDF}$ consistently remain positive each year. Similarly, the annual averages of liquidity betas on the market portfolios from ETF regressions, $\beta_{MKT-ETFreg}$, are positive in every year as well. Additionally, the table includes the number of bonds in the market portfolio, averaging 3244 for investment-grade bonds and 914 for high-yield bonds per quarter with computed liquidity betas.

## 4. Commonality in liquidity and institutional ownership

In this section, I examine whether ETFs, mutual funds, and index funds increase the commonality in liquidity of the basket of fixed-income securities they hold by running separate tests for ETFs, mutual funds, and index funds. For instance, in the case of ETFs, the hypothesis posits that if ETFs indeed increase the commonality in liquidity of the securities they own, then securities with a larger proportion of ETF ownership should display increased liquidity commonality. Throughout the investigation, the effects of institutional ownership on investment-grade and high-yield bonds are considered separately to account for their distinctive characteristics within the two subclasses (Dannhauser, 2017).

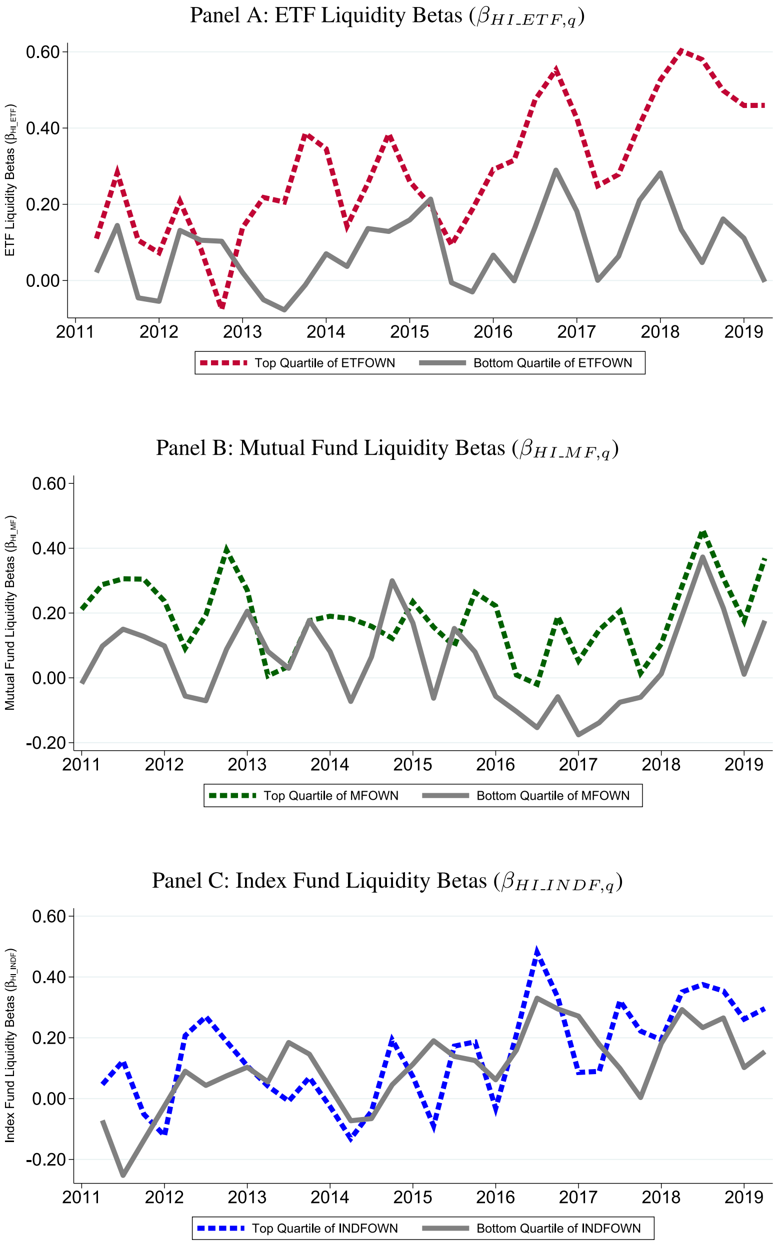


**Fig. 2.** Time series of average quarterly liquidity betas sorted by institutional ownership. Fig. 2 presents the time-series evolution of ETF, mutual fund, and index fund liquidity betas sorted by institutional ownership. Bonds are sorted into quartiles based on their institutional ownership measures ($ETFOWN$, $MFOWN$, and $INDFOWN$) at the end of each quarter. The figure displays the average liquidity betas ($\beta$) for the high ownership quartiles and the lowest ownership quartiles over the subsequent quarter. Specifically, I report the average liquidity betas $\beta_{HI\_ETF,q}$, $\beta_{HI\_MF,q}$, and $\beta_{HI\_INDF,q}$ separately for the top and lowest quartiles of institutional ownership.

### 4.1. *Investment-grade bonds*

#### 4.1.1. *Main analysis*

In the initial stage of analysis, bonds are divided into quartiles based on their institutional ownership measures ($ETFOWN$, $MFOWN$, and $INDFOWN$) at the end of each quarter. Then, average liquidity betas ($\beta_{HI\_ETF,q}$, $\beta_{HI\_MF,q}$, and $\beta_{HI\_INDF,q}$) for both the highest and lowest ownership quartiles are calculated for the subsequent quarter. Panel A of Fig. 2 presents the average liquidity betas for the highest and lowest quartiles of institutional ownership separately. The results show that the top quartile portfolio in terms of ETF ownership consistently exhibits higher ETF liquidity betas than the bottom quartile portfolio throughout the sample period. This is the first piece of evidence suggesting that ETF ownership could potentially induce liquidity commonality.

**Table 3**
Average liquidity betas sorted by institutional ownership.

Panel A: Investment-grade bonds

| Sorting variable: ETFOWN | | | | Sorting variable: MFOWN | | | |
|---|---|---|---|---|---|---|---|
| | ETFOWN | $\beta_{HI\_ETF,q}$ | $\beta_{MKT-ETFreg}$ | | MFOWN | $\beta_{HI\_MF,q}$ | $\beta_{MKT-MFreg}$ |
| Lo | 0.54% | 0.05 | 0.74 | Lo | 0.73% | 0.06 | 0.76 |
| 2 | 1.54% | 0.15 | 0.90 | 2 | 3.21% | 0.10 | 1.01 |
| 3 | 2.42% | 0.27 | 0.87 | 3 | 6.53% | 0.13 | 1.02 |
| Hi | 3.70% | 0.29 | 0.82 | Hi | 14.49% | 0.19 | 0.92 |
| | Hi-Lo | 0.24 | | | Hi-Lo | 0.14 | |
| | t-stat | (8.02) | | | t-stat | (4.34) | |

| Sorting variable: INDFOWN | | | |
|---|---|---|---|
| | INDFOWN | $\beta_{HI\_INDF,q}$ | $\beta_{MKT-INDFreg}$ |
| Lo | 0.55% | 0.12 | 0.69 |
| 2 | 1.60% | 0.11 | 0.98 |
| 3 | 2.28% | 0.12 | 1.07 |
| Hi | 3.62% | 0.16 | 0.94 |
| | Hi-Lo | 0.04 | |
| | t-stat | (1.14) | |

Panel B: High-yield bonds

| Sorting variable: ETFOWN | | | | Sorting variable: MFOWN | | | |
|---|---|---|---|---|---|---|---|
| | ETFOWN | $\beta_{HI\_ETF,q}$ | $\beta_{MKT-ETFreg}$ | | MFOWN | $\beta_{HI\_MF,q}$ | $\beta_{MKT-MFreg}$ |
| Lo | 0.03% | 0.06 | 0.42 | Lo | 3.45% | 0.04 | 0.52 |
| 2 | 0.91% | 0.04 | 0.56 | 2 | 13.05% | 0.10 | 0.56 |
| 3 | 2.67% | 0.06 | 0.69 | 3 | 20.56% | 0.07 | 0.68 |
| Hi | 4.79% | 0.12 | 0.67 | Hi | 30.30% | 0.07 | 0.59 |
| | Hi-Lo | 0.06 | | | Hi-Lo | 0.03 | |
| | t-stat | (2.52) | | | t-stat | (1.18) | |

Table 3 presents average liquidity betas for ETFs, mutual funds, index funds, and the market, sorted by levels of institutional ownership. At the end of each quarter, bonds are sorted into quartiles based on $ETFOWN$, $MFOWN$, and $INDFOWN$. The table reports the subsequent quarter's average values of $\beta_{HI\_ETF,q}$, $\beta_{MKT-ETFreg}$, $\beta_{HI\_MF,q}$, $\beta_{MKT-MFreg}$, $\beta_{HI\_INDF,q}$, and $\beta_{MKT-INDFreg}$. The final two rows in each panel display the difference in average $\beta_{HI\_ETF,q}$, $\beta_{HI\_MF,q}$, and $\beta_{HI\_INDF,q}$ between the highest and lowest quartiles in terms of ETF, mutual fund, and index fund ownership, along with the $t$-statistics reflecting the statistical significance of these differences. Panel A reports the results for investment-grade bonds and Panel B is for high-yield bonds.

Furthermore, Table 3 provides results from the preliminary series of tests using one-dimensional sorts based on quarterly ETF ownership rankings. The quartile portfolio with the lowest ETF ownership has an average liquidity beta ($\beta_{HI\_ETF}$) of 0.05, while the quartile portfolio with the highest ETF ownership has an average liquidity beta of 0.29. This difference is both economically and statistically significant, further supporting the notion that bonds with higher ETF ownership exhibit a higher degree of liquidity commonality.

In the subsequent analysis, I utilize Ordinary Least Squares (OLS) regressions to examine the relationship between the measure of commonality in liquidity ($\beta_{HI\_ETF}$) and lagged ETF ownership ($ETFOWN$). I control for several variables, including the log market value of the bond ($MktVal$), its average illiquidity ($Amihud$) from the preceding quarter, numerical rating ($Rating$), years until maturity ($Maturity$), and yield spread ($Spread$). The inclusion of average illiquidity as a control is designed to mitigate concerns that the liquidity characteristics of a bond could influence both its commonality and its selection into mutual fund portfolios and ETF baskets. To strengthen the robustness of the analysis, I incorporate combinations of bond, issuer, and time (quarter-year) fixed effects into the models, and employ clustering techniques for the standard errors. Issuer-fixed effects are specifically used to account for any changes in the fundamental risk of a firm.

To determine if the relationship between $\beta_{HI\_ETF}$ and $ETFOWN$ is due to ETF ownership or other types of institutional ownership, I extend the model to include mutual fund ($MFOWN$) and index fund ownership ($INDFOWN$). These are both correlated with ETF ownership as indicated in Table A.1. Prior to their incorporation into the model, each ownership variable is standardized by subtracting the cross-sectional mean and then dividing by the standard deviation.[14] The comprehensive model specification is given as follows:

$$\beta_{HI\_ETF,i,q} = \gamma_0 + \gamma_1 MFOWN_{i,q-1} + \gamma_2 ETFOWN_{i,q-1} + \gamma_3 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q} \tag{5}$$

The results of this regression for investment-grade bonds are presented in Panel A of Table 4. Model 1 includes only time-fixed effects, with standard errors clustered by time. The analysis reveals that bonds with high ETF ownership exhibit stronger

[14] In untabulated tests, I employ unstandardized ownership measures as opposed to standardized ones. The outcomes are qualitatively consistent with the main results.

co-movement, as indicated by the significant coefficient estimate of 0.073 for $ETFOWN$. Given that this regression includes time-fixed effects, the elevated $\beta_{HI\_ETF}$ cannot be attributed to the shared time trend in ETF ownership levels and liquidity co-movements. In Model 2, standard errors are double-clustered at both bond and quarter levels. The coefficient for ETF ownership remains positive and highly significant, further reinforcing the initial findings.

In the third specification, I include both time-fixed and bond-fixed effects, and standard errors are clustered by bond and time. I obtain analogous results to the previous models. Model 4 introduces control measures for ownership by mutual funds and index funds, as well as for $Amihud$ and $MktVal$ – the primary explanatory variables for liquidity commonality in equity literature. The impact of ETF ownership continues to be statistically significant, demonstrating an increased economic magnitude.

In Model 5, I incorporate $Rating$, $Maturity$, and $Spread$ as control variables. These bond-specific factors, known to influence liquidity, are logical predictors for liquidity commonality. Given that I use standardized measures of ownership, the results suggest that a one standard deviation increase in ETF ownership (1.57%, as reported in Table 1), corresponds with a 0.068 surge in liquidity commonality, which equates to a 36% increase from its mean of 0.19. This result holds both economic and statistical significance. Model 6 employs issuer-fixed effects in lieu of bond-fixed effects, and standard errors are double-clustered by issuer and time. The coefficient on $ETFOWN$ retains its statistical significance. Models 7 and 8 implement Fama and MacBeth (1973) regressions and produce outcomes that align qualitatively with those from the panel regressions.

Next, I shift my focus towards the interrelation between mutual fund ownership and mutual fund liquidity betas ($\beta_{HI\_MF}$). Specifically, I examine the association between mutual fund ownership and the commonality in liquidity of corporate bonds by executing the following regression:

$$\beta_{HI\_MF,i,q} = \gamma_0 + \gamma_1 MFOWN_{i,q-1} + \gamma_2 ETFOWN_{i,q-1} + \gamma_3 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}. \tag{6}$$

The outcomes for mutual fund ownership are displayed in Panel B of Table 4. Initial models, specifically Models 1 and 2, incorporate time-fixed effects and suggest a positive, statistically significant relationship between mutual fund ownership, $MFOWN$, and mutual fund liquidity betas, $\beta_{HI\_MF}$. However, upon the inclusion of bond-fixed or issuer-fixed effects to the models, the impact of mutual fund ownership on $\beta_{HI\_MF}$ becomes statistically insignificant.

Lastly, I examine the relationship between index fund ownership and index fund liquidity betas ($\beta_{HI\_INDF}$). This relationship is analyzed by implementing the following regression:

$$\beta_{HI\_INDF,i,q} = \gamma_0 + \gamma_1 MFOWN_{i,q-1} + \gamma_2 ETFOWN_{i,q-1} + \gamma_3 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}. \tag{7}$$

The findings pertaining to index fund ownership are outlined in Panel C of Table 4. Across all eight models explored, there is no significant relationship observed between index fund ownership ($INDFOWN$) and commonality in liquidity.

#### *4.1.2. Comparison of results with equities*

The significant effect of ETF ownership on the liquidity commonality of investment-grade bonds parallels Agarwal et al. (2018)'s findings for equities, which document that ETF ownership increases liquidity commonality among stocks. Conversely, the observed effect of mutual fund ownership on liquidity commonality is unanticipated and stands in contrast to the well-established role of equity mutual funds in influencing stock liquidity commonality, as documented by Koch et al. (2016). At first glance, one would expect a similar result for the commonality in liquidity of corporate bonds as they are inherently more illiquid than equities. However, the liquidity management strategies diverge substantially between equity mutual funds and their corporate bond counterparts. Equity mutual funds generally maintain limited cash reserves, as noted by Chernenko and Sunderam (2020), making them prone to large-scale equity liquidations during liquidity shocks. Equity funds exhibit nearly a one-to-one adjustment in their portfolios in response to investor redemptions, thereby inducing negative price pressures on their portfolio securities (Coval and Stafford, 2007).

On the other hand, corporate bond mutual funds adopt different strategies to cushion against the impact of investor redemptions. To investigate how these funds react to investor redemptions, I follow the methodology in Dannhauser and Hoseinzade (2022) and run the Lou (2012) regression:

$$Trade_{i,f,q} = \alpha + \beta_1 Flow_{f,q} + \beta_2 Controls_{i,f,q} + \epsilon_{i,f,q}. \tag{8}$$

The dependent variable, $Trade_{i,f,q}$, quantifies the percentage change in the corporate bond holdings of bond $i$ by fund $f$ from quarter $q-1$ to $q$. The main independent variable is the quarterly flow into the fund, $Flow_{f,q}$, complemented by control variables, which include the prior quarter's Amihud illiquidity proxy of the bond, $Amihud_{i,q-1}$, and percentage of the bond owned by the fund, $Own_{i,f,q-1}$. Additionally, interaction terms are included for flow with both illiquidity and ownership proportions.

The analysis is conducted separately for outflow and inflow periods. The coefficient $\beta_1$ measures a fund's trading response to investor flows. A coefficient of one would suggest that the fund is adjusting its bond holdings in direct proportion to investor

**Table 4**
Institutional ownership and commonality in liquidity - Investment-grade bonds.

| Panel A: ETF ownership and commonality in liquidity | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dep. Var. | $\beta_{HI\_ETF}$ $(q)$ | | | | | | | |
| ETFOWN $(q-1)$ | 0.073*** | 0.073*** | 0.057** | 0.068*** | 0.068*** | 0.038*** | 0.071*** | 0.026** |
| | (5.05) | (3.99) | (2.52) | (2.96) | (2.83) | (3.03) | (3.22) | (2.53) |
| MFOWN $(q-1)$ | | | | −0.038* | −0.037* | −0.015 | −0.002 | −0.013 |
| | | | | (−1.79) | (−1.74) | (−1.19) | (−0.29) | (−1.61) |
| INDFOWN $(q-1)$ | | | | −0.046** | −0.038 | −0.013 | −0.019 | −0.006 |
| | | | | (−2.06) | (−1.68) | (−1.38) | (−1.58) | (−0.57) |
| Amihud $(q-1)$ | −0.426** | −0.426** | −0.416** | −0.417** | −0.343* | −0.267 | −0.591*** | −0.354** |
| | (−2.40) | (−2.42) | (−2.28) | (−2.25) | (−1.77) | (−1.62) | (−3.56) | (−2.22) |
| MktVal $(q-1)$ | 0.007 | 0.007 | −0.048 | −0.024 | −0.066 | 0.041** | 0.005 | 0.039*** |
| | (0.43) | (0.43) | (−0.88) | (−0.45) | (−1.12) | (2.33) | (0.32) | (3.26) |
| Rating $(q-1)$ | | | | | 0.014 | 0.014 | | 0.000 |
| | | | | | (0.62) | (0.95) | | (0.02) |
| Maturity $(q-1)$ | | | | | −2.751 | −0.012*** | | −0.010*** |
| | | | | | (−0.95) | (−4.92) | | (−3.75) |
| Spread $(q-1)$ | | | | | −0.018 | 0.011 | | 0.016 |
| | | | | | (−1.04) | (0.82) | | (1.36) |
| Observations | 108,906 | 108,906 | 108,906 | 108,906 | 106,674 | 106,692 | 108,906 | 106,695 |
| R-squared | 0.003 | 0.003 | 0.088 | 0.088 | 0.090 | 0.021 | 0.003 | 0.006 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond FE | | | ✓ | ✓ | ✓ | | | |
| Issuer FE | | | | | | ✓ | | |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond clusters | | ✓ | ✓ | ✓ | ✓ | | | |
| Issuer clusters | | | | | | ✓ | | |
| Fama MacBeth | | | | | | | ✓ | ✓ |
| **Panel B: Mutual fund ownership and commonality in liquidity** | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dep. Var. | $\beta_{HI\_MF}$ $(q)$ | | | | | | | |
| ETFOWN $(q-1)$ | | | | −0.009 | −0.011 | −0.012 | 0.028 | −0.006 |
| | | | | (−0.39) | (−0.49) | (−0.86) | (1.49) | (−0.40) |
| MFOWN $(q-1)$ | 0.047*** | 0.047*** | 0.011 | 0.010 | 0.011 | 0.003 | 0.045*** | 0.015 |
| | (3.67) | (3.61) | (0.45) | (0.43) | (0.48) | (0.28) | (4.18) | (1.26) |
| INDFOWN $(q-1)$ | | | | −0.003 | −0.004 | −0.017 | −0.018 | −0.010 |
| | | | | (−0.09) | (−0.12) | (−1.04) | (−1.37) | (−0.64) |
| Amihud $(q-1)$ | −0.278* | −0.278* | −0.181 | −0.180 | −0.133 | 0.014 | −0.124 | 0.188 |
| | (−1.81) | (−1.88) | (−0.91) | (−0.90) | (−0.62) | (0.09) | (−0.65) | (0.76) |
| MktVal $(q-1)$ | −0.006 | −0.006 | 0.071 | 0.075 | 0.071 | 0.059** | −0.008 | 0.033 |
| | (−0.41) | (−0.41) | (0.77) | (0.87) | (0.78) | (2.60) | (−0.44) | (1.50) |
| Rating $(q-1)$ | | | | | 0.039 | 0.050** | | 0.020*** |
| | | | | | (1.52) | (2.42) | | (2.96) |
| Maturity $(q-1)$ | | | | | 3.450 | −0.012*** | | −0.012*** |
| | | | | | (1.28) | (−3.78) | | (−3.95) |
| Spread $(q-1)$ | | | | | −0.001 | 0.005 | | 0.032* |
| | | | | | (−0.04) | (0.23) | | (1.81) |
| Observations | 108,906 | 108,906 | 108,906 | 108,906 | 106,674 | 106,692 | 108,906 | 106,695 |
| R-squared | 0.002 | 0.002 | 0.085 | 0.085 | 0.086 | 0.019 | 0.003 | 0.006 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond FE | | | ✓ | ✓ | ✓ | | | |
| Issuer FE | | | | | | ✓ | | |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond clusters | | ✓ | ✓ | ✓ | ✓ | | | |
| Issuer clusters | | | | | | ✓ | | |
| Fama MacBeth | | | | | | | ✓ | ✓ |

(*continued on next page*)

flows. The empirical results, displayed in Table 5, reveal that after factoring in controls, the coefficient associated with mutual fund outflows is 0.377, a value significantly below one. This finding corroborates the results of Dannhauser and Hoseinzade (2022), providing evidence that corporate bond mutual funds, unlike equity mutual funds, do not practice one-to-one selling, opting instead for more sophisticated liquidity management techniques (Choi et al., 2020). These methods effectively decrease the potential for correlated liquidity demands to adversely affect the mutual fund's holdings of corporate bonds. Therefore, the disparate approaches to redemption management between equity and corporate bond mutual funds provide a credible rationale for their divergent effects on liquidity commonality.

**Table 4** (*continued*).

| Panel C: Index fund ownership and commonality in liquidity | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dep. Var. | $\beta_{HI\_INDF}$ $(q)$ | | | | | | | |
| ETFOWN $(q-1)$ | | | | 0.088*** | 0.087*** | 0.025 | 0.056** | 0.027 |
| | | | | (3.88) | (3.64) | (1.05) | (2.58) | (1.61) |
| MFOWN $(q-1)$ | | | | −0.003 | −0.007 | 0.004 | 0.008 | 0.011 |
| | | | | (−0.14) | (−0.29) | (0.28) | (0.69) | (0.92) |
| INDFOWN $(q-1)$ | 0.017 | 0.017 | −0.035 | −0.067** | −0.062** | 0.002 | −0.005 | −0.001 |
| | (1.06) | (1.05) | (−1.22) | (−2.31) | (−2.07) | (0.10) | (−0.36) | (−0.05) |
| Amihud $(q-1)$ | −0.209 | −0.209 | −0.097 | −0.090 | −0.086 | −0.021 | −0.225 | −0.109 |
| | (−0.90) | (−0.92) | (−0.33) | (−0.31) | (−0.29) | (−0.08) | (−1.25) | (−0.47) |
| MktVal $(q-1)$ | −0.020 | −0.020 | 0.091 | 0.077 | 0.067 | −0.033 | −0.034 | −0.021 |
| | (−0.90) | (−0.90) | (0.94) | (0.78) | (0.64) | (−0.96) | (−1.59) | (−1.16) |
| Rating $(q-1)$ | | | | | 0.015 | 0.013 | | 0.001 |
| | | | | | (0.41) | (0.45) | | (0.09) |
| Maturity $(q-1)$ | | | | | −1.804 | −0.006** | | −0.004 |
| | | | | | (−0.53) | (−2.50) | | (−1.35) |
| Spread $(q-1)$ | | | | | −0.009 | −0.002 | | 0.005 |
| | | | | | (−0.36) | (−0.09) | | (0.32) |
| Observations | 108,906 | 108,906 | 108,906 | 108,906 | 106,674 | 106,692 | 108,906 | 106,695 |
| R-squared | 0.001 | 0.001 | 0.076 | 0.076 | 0.076 | 0.016 | 0.003 | 0.005 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond FE | | | ✓ | ✓ | ✓ | | | |
| Issuer FE | | | | | | ✓ | | |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond clusters | | ✓ | ✓ | ✓ | ✓ | | | |
| Issuer clusters | | | | | | ✓ | | |
| Fama MacBeth | | | | | | | ✓ | ✓ |

Table 4 examines the link between commonality in liquidity and institutional ownership for investment-grade bonds, covering the period from Q1 2011 to Q2 2019. The ownership variables, $ETFOWN$, $MFOWN$, and $INDFOWN$, are standardized by subtracting the cross-sectional mean and then dividing by the standard deviation before they are incorporated into the model. The regression is conducted separately for each type of institution:

$$depvar_{i,q} = \gamma_0 + \gamma_1 ETFOWN_{i,q-1} + \gamma_2 MFOWN_{i,q-1} + \gamma_3 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}$$

where $depvar_{i,q}$ represents $\beta_{HI\_ETF}$, $\beta_{HI\_MF}$, and $\beta_{HI\_INDF}$, measuring the commonality in liquidity relative to the illiquidity of bonds in the top quartile of ETF, mutual fund, and index fund ownership, respectively. Bond-level control variables include the quarterly average of the daily Amihud (2002) illiquidity measure ($Amihud$), the log market value of a bond ($MktVal$), the numerical credit rating ($Rating$), the yield spread ($Spread$), and the time to maturity ($Maturity$). Panels A, B, and C present results for ETFs, mutual funds, and index funds, respectively. $t$-statistics are reported in parentheses below the coefficients, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

**Table 5**
Fund trading in response to capital flows.

| | ETF | | | | Mutual fund | | | | Index fund | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Outflow | | Inflow | | Outflow | | Inflow | | Outflow | | Inflow | |
| Flow $(q)$ | 0.832*** | 0.877*** | 0.495*** | 0.502*** | 0.358*** | 0.377*** | 0.168*** | 0.180*** | 0.253*** | 0.302*** | 0.138*** | 0.154*** |
| | (10.12) | (10.09) | (12.62) | (12.28) | (15.94) | (15.54) | (15.61) | (15.70) | (3.46) | (5.19) | (3.35) | (3.39) |
| Amihud $(q-1)$ | | −0.038 | | 0.016 | | −0.034*** | | 0.032*** | | −0.061*** | | −0.004 |
| | | (−1.42) | | (0.75) | | (−5.25) | | (7.22) | | (−4.08) | | (−0.36) |
| Own $(q-1)$ | | 2.067* | | −0.950 | | 0.142* | | 0.028 | | 2.082** | | 0.066 |
| | | (1.94) | | (−1.27) | | (1.95) | | (0.65) | | (2.22) | | (0.12) |
| Amihud $(q-1)$ × Flow $(q-1)$ | | −0.341 | | −1.076*** | | −0.439*** | | −0.231*** | | −1.257** | | −0.576*** |
| | | (−0.92) | | (−4.92) | | (−4.84) | | (−4.51) | | (−2.28) | | (−4.30) |
| Own $(q-1)$ × Flow $(q-1)$ | | −26.897 | | 65.892*** | | 0.518 | | 0.279 | | 3.971 | | 31.112** |
| | | (−1.04) | | (4.74) | | (0.92) | | (0.98) | | (0.18) | | (2.12) |
| Observations | 318,382 | 309,944 | 975,639 | 959,055 | 1,582,957 | 1,533,352 | 1,546,696 | 1,488,986 | 315,218 | 313,188 | 808,235 | 803,028 |
| R-squared | 0.026 | 0.027 | 0.059 | 0.071 | 0.005 | 0.005 | 0.014 | 0.014 | 0.014 | 0.015 | 0.016 | 0.023 |
| $p$-value $[H_0 : \beta_{flow} = 1]$ | 0.05 | 0.14 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Fund clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

This table presents the regression analysis results of fund corporate bond trading in response to capital flows across exchange-traded funds (ETFs), active mutual funds, and index mutual funds, following Dannhauser and Hoseinzade (2022). The flow sample is split into outflows and inflows. The dependent variable for all models is $Trade_{i,f,q}$, which measures the percentage change in the holdings of bond $i$ by fund $f$ from quarter $q-1$ to $q$. The independent variables include the percentage capital flow to the fund ($Flow_{f,q}$), lagged bond illiquidity measure ($Amihud_{i,q-1}$), and the lagged ownership level of the bond by the fund ($Own_{i,f,q-1}$). Interaction terms for the flow with both the illiquidity proxy and ownership levels are also incorporated. All model specifications include quarter fixed effects to control for time-specific variations. $t$-statistics are reported in parentheses below the coefficients, with ***, **, and * indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

### 4.1.3. Robustness analyses

This section presents additional analyses that further confirm the robustness of the findings for investment-grade bonds. The first analysis examines the impact of institutional ownership on liquidity commonality across different time periods. In each model, I interact institutional ownership variables with sub-period dummies for 2011–2013, 2014–2016, and 2017–2019. The results are reported in Table A.2. Model 1 reports the results for ETF ownership. During the 2011–2013 period, the coefficient on $ETFOWN$ is positive but not statistically significance. This outcome is expected, considering the lower levels of bond ownership by ETFs in the early years of the sample period. However, the effect gains both economic and statistical significance in the 2014–2016 and 2017–2019 periods.

In the second analysis, to ensure the robustness of my analysis against alternative measures of bond liquidity, I replicate the study using bid–ask spreads in place of the Amihud (2002) measure.[15] The findings, reported in Table A.3, are qualitatively akin to those found in Table 4. The results in Panel A of Table A.3 suggest that a one standard deviation increase in ETF ownership leads to an increase in ($\beta_{HI\_ETF}$) by 8.7 percentage points. This result, as well as the results in Panels B and C of Table A.3, are similar in magnitude to those obtained when using the Amihud (2002) measure. This reiteration supports the robustness of the previous conclusions.

## 4.2. High-yield bonds

### 4.2.1. Main analysis

In this section, I shift my focus on high-yield corporate bonds. The left side of Panel B in Table 3 presents the results for portfolio sorts based on ETF ownership for these bonds. A statistically significant difference of 0.06 is observed in the average $\beta_{HI\_ETF}$ between the highest and lowest quartiles.

The results from regression (5) applied to high-yield bonds are outlined in Panel A of Table 6. Models (1)–(8) are structured similarly to the previously described tests for investment-grade bonds. Even though the coefficient for $ETFOWN$ is positive in all models, none of these results are statistically significant. In particular, Model 5, which includes both bond-fixed and time-fixed effects and clusters standard errors by firm and time, shows that ETF ownership does not significantly contribute to the explanation of liquidity beta for high-yield bonds. Similarly, the results for mutual fund ownership in Panel B document that the coefficient estimate on $MFOWN$ is not statistically significant in any specifications, showing that mutual fund ownership does not explain $\beta_{HI\_MF}$ also for high-yield bonds.

### 4.2.2. Comparison of results with investment-grade bonds

The results can be attributed to the high-yield bonds' muted response to market-wide liquidity shifts compared to their investment-grade counterparts. The literature indicates that trade flows within the high-yield bond market are more likely swayed by idiosyncratic factors (Schultz, 2001) and the heightened susceptibility of high-yield bonds to firm-specific news is often due to their closer proximity to default (Dang et al., 2013). To explore further, I examine the co-movement of individual bond liquidity with that of the broader market portfolio separately for investment-grade and high-yield segments. For each bond $i$ in quarter $q$, I estimate the following first-step regression detailed in Section 3.4:

$$\Delta illiq_{i,q,d} = \alpha + \beta^{-1}_{MKT,i,q}\Delta illiq_{MKT,q,d-1} + \beta_{MKT,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT,i,q}\Delta illiq_{MKT,q,d+1} + \epsilon_{1,i,q,d}, \quad (9)$$

Due to the granularity of the first-step regressions—where each bond's liquidity beta is calculated quarterly using daily observations—the results for liquidity betas are summarized in Table 1 for investment-grade and high-yield groups separately. The summary statistics for $\beta_{MKT}$ suggest a distinctly greater sensitivity of investment-grade bonds to market liquidity variations, with the average (median) market liquidity beta for investment-grade bonds recorded at 1.03 (1.09), which is notably above the average (median) beta of 0.66 (0.74) identified for high-yield bonds. These statistics provide evidence that high-yield bonds trading is less sensitive to market-wide changes in liquidity. These observations align with the research of Rhodes and Mason (2023), which document increased co-movement in returns between an investment-grade bond index and investment-grade bonds with higher levels of ETF ownership, but no association between ETF ownership and the return co-movement of high-yield bonds with a corresponding high-yield bond index.

## 4.3. Common ownership and pairwise correlation in liquidity

In the preceding sections, I implemented a two-step procedure to assess whether institutional ownership can lead to commonality in the liquidity of corporate bonds. In this section, I adapt the methodology presented by Anton and Polk (2014) to examine the correlation between common ownership and co-movements in liquidity at the bond-pair level, consistent with the approach taken by Agarwal et al. (2018).

The pairwise correlation methodology carries the advantage of not needing a specific model to estimate commonality in liquidity. However, this approach overlooks the potential for correlated liquidity shocks between different funds that hold different bonds. In the context of the equity market, Greenwood and Thesmar (2011) found that co-movement in returns can occur even in the absence of common ownership. Therefore, I view this approach as a complement to the earlier two-step methodology.

In implementing this supplementary method, I calculate the pairwise correlation $\rho_{ij,q}$ between the logarithmic daily changes in the Amihud illiquidity of bond $i$ and bond $j$ over each quarter $q$. Using this proxy for liquidity co-movements as the dependent variable, I investigate its relationship with the common institutional ownership by different types of funds. For ETFs, I derive the

[15] I calculate the bid–ask spreads based on daily high and low prices using the methodology in Corwin and Schultz (2012).

**Table 6**
Institutional ownership and commonality in liquidity - High-yield bonds.

| Panel A: ETF ownership and commonality in liquidity | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dep. Var. | $\beta_{HI\_ETF}$ $(q)$ | | | | | | | |
| ETFOWN $(q-1)$ | 0.013 | 0.013 | 0.013 | 0.013 | 0.019 | 0.013 | 0.016 | 0.012 |
| | (1.12) | (1.13) | (0.61) | (0.60) | (0.95) | (0.98) | (1.66) | (1.17) |
| MFOWN $(q-1)$ | | | | 0.009 | 0.002 | 0.002 | 0.003 | 0.003 |
| | | | | (0.33) | (0.08) | (0.16) | (0.21) | (0.22) |
| Amihud $(q-1)$ | 0.108 | 0.108 | 0.271** | 0.273** | 0.224** | 0.170 | 0.138 | 0.203 |
| | (1.02) | (1.01) | (2.28) | (2.29) | (2.10) | (1.60) | (0.90) | (1.23) |
| MktVal $(q-1)$ | 0.042*** | 0.042*** | 0.063 | 0.061 | 0.067 | 0.036* | 0.043*** | 0.045*** |
| | (3.20) | (3.04) | (1.65) | (1.57) | (1.47) | (1.89) | (2.91) | (2.82) |
| Rating $(q-1)$ | | | | | 0.007 | 0.006 | | −0.008 |
| | | | | | (0.67) | (0.81) | | (−1.61) |
| Maturity $(q-1)$ | | | | | −2.790 | −0.002 | | −0.003 |
| | | | | | (−1.08) | (−1.25) | | (−1.51) |
| Spread $(q-1)$ | | | | | 0.001 | 0.000 | | 0.001 |
| | | | | | (0.34) | (0.06) | | (0.77) |
| Observations | 32,648 | 32,648 | 32,648 | 32,648 | 31,437 | 31,444 | 32,648 | 31,449 |
| R-squared | 0.004 | 0.004 | 0.093 | 0.093 | 0.096 | 0.043 | 0.007 | 0.011 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond FE | | | ✓ | ✓ | ✓ | | | |
| Issuer FE | | | | | | ✓ | | |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond clusters | | ✓ | ✓ | ✓ | ✓ | | | |
| Issuer clusters | | | | | | ✓ | | |
| Fama MacBeth | | | | | | | ✓ | ✓ |
| **Panel B: Mutual fund ownership and commonality in liquidity** | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dep. Var. | $\beta_{HI\_ETF}$ $(q)$ | | | | | | | |
| ETFOWN $(q-1)$ | | | | 0.019 | 0.028 | 0.022 | 0.017 | 0.022 |
| | | | | (1.06) | (1.49) | (1.33) | (1.62) | (1.69) |
| MFOWN $(q-1)$ | −0.003 | −0.003 | 0.030 | 0.029 | 0.024 | 0.019 | −0.001 | 0.001 |
| | (−0.22) | (−0.22) | (1.46) | (1.40) | (1.21) | (1.25) | (−0.11) | (0.08) |
| Amihud $(q-1)$ | 0.213 | 0.213 | 0.207 | 0.210 | 0.153 | 0.193 | 0.313* | 0.348* |
| | (1.54) | (1.52) | (1.22) | (1.24) | (0.84) | (1.11) | (1.86) | (1.87) |
| MktVal $(q-1)$ | 0.050** | 0.050** | 0.056 | 0.050 | 0.034 | 0.034 | 0.043** | 0.040* |
| | (2.69) | (2.64) | (1.25) | (1.12) | (0.70) | (1.40) | (2.23) | (1.96) |
| Rating $(q-1)$ | | | | | −0.014 | −0.023*** | | −0.007* |
| | | | | | (−1.08) | (−2.99) | | (−1.72) |
| Maturity $(q-1)$ | | | | | −1.900 | −0.000 | | 0.001 |
| | | | | | (−0.52) | (−0.14) | | (0.56) |
| Spread $(q-1)$ | | | | | 0.001 | 0.001 | | −0.001 |
| | | | | | (0.24) | (0.35) | | (−0.66) |
| Observations | 32,648 | 32,648 | 32,648 | 32,648 | 31,437 | 31,444 | 32,648 | 31,449 |
| R-squared | 0.005 | 0.005 | 0.094 | 0.094 | 0.095 | 0.041 | 0.007 | 0.011 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond FE | | | ✓ | ✓ | ✓ | | | |
| Issuer FE | | | | | | ✓ | | |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond clusters | | ✓ | ✓ | ✓ | ✓ | | | |
| Issuer clusters | | | | | | ✓ | | |
| Fama MacBeth | | | | | | | ✓ | ✓ |

Table 6 reports the relationship between commonality in liquidity and institutional ownership for high-yield bonds. The sample period is from 2011 Q1 through 2019 Q2. Ownership variables $ETFOWN$, $MFOWN$, and $INDFOWN$ are standardized prior to their inclusion in the model by demeaning the cross-sectional mean and dividing by the standard deviation. I run the following regression separately for each institution type:

$$depvar_{i,q} = \gamma_0 + \gamma_1 ETFOWN_{i,q-1} + \gamma_2 MFOWN_{i,q-1} + \gamma_3 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}$$

where $depvar_{i,q}$ are $\beta_{HI\_ETF}$ and $\beta_{HI\_MF}$, which measure the commonality in liquidity with respect to the illiquidity of bonds that are in the top quartile of ETF, and mutual fund ownership, respectively. Bond-level control variables are the quarterly mean of the daily Amihud illiquidity measure ($Amihud$), log market value of a bond ($MktVal$), numerical rating $Rating$, the yield spread ($Spread$), and time-to-maturity ($Maturity$). Panel A and B present the results for ETFs and mutual funds separately. $t$-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

**Table 7**
Impact of institutional ownership on pairwise liquidity correlation of bonds.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dep. Var. | $\rho_{ij,q}$ | | | |
| $ETFCOMOWN$ $(q-1)$ | 0.023*** | | | 0.017*** |
| | (4.48) | | | (4.02) |
| $MFCOMOWN$ $(q-1)$ | | 0.015*** | | 0.011*** |
| | | (6.73) | | (5.48) |
| $INDFCOMOWN$ $(q-1)$ | | | 0.021*** | 0.004 |
| | | | (4.37) | (1.37) |
| Observations | 196,280,779 | 196,280,779 | 196,280,779 | 196,280,779 |
| R-squared | 0.015 | 0.015 | 0.015 | 0.015 |
| FE | Qtr. × Bond $i$, Qtr. × Bond $j$ | | | |
| Clusters | Qtr., Bond $i$, Bond $j$ | | | |

Table 7 presents the results on the relation between ETF, active mutual fund, and index fund common ownership ($ETFCOMOWN$, $MFCOMOWN$, $INDFCOMOWN$, respectively) in a bond pair $i-j$ and the pairwise correlation of daily log changes in the Amihud (2002) liquidity of bonds $i$ and $j$ computed in quarter $q$ ($\rho_{ij,q}$). The following regression equation is estimated:

$$\rho_{ij,q} = \lambda_0 + \lambda_1 ETFCOMOWN_{ij,q-1} + \lambda_2 MFCOMOWN_{ij,q-1} + \lambda_3 INDFCOMOWN_{ij,q-1} + \epsilon_{ij,q}.$$

All specifications incorporate fixed effects for the interaction of each quarter with bond $i$ and bond $j$. Standard errors are triple-clustered by quarter, bond $i$, and bond $j$. $t$-statistics are provided in parentheses under the coefficients, with ***, **, and * signifying statistical significance at the 1%, 5%, and 10% levels, respectively.

common ownership measure $ETFCOMOWN_{ij,q}$ as the total par value held by $F$ common ETFs, scaled by the sum of the amount outstanding of the two bonds.

$$ETFCOMOWN_{ij,q} = \frac{\sum_{f=1}^{F} parval_{i,f,q} + parval_{j,f,q}}{amtout_{i,q} + amtout_{j,q}} \tag{10}$$

In a similar vein, I compute $MFCOMOWN$ and $INDFCOMOWN$ to represent the common ownership by active mutual funds and index mutual funds, respectively. I then examine the relationship between fund ownership and pairwise correlation in liquidity of corporate bonds by executing the following regression:

$$\rho_{ij,q} = \lambda_0 + \lambda_1 ETFCOMOWN_{ij,q-1} + \lambda_2 MFCOMOWN_{ij,q-1} + \lambda_3 INDFCOMOWN_{ij,q-1} + \epsilon_{ij,q}. \tag{11}$$

In Table 7, I present the estimation results of Eq. (11), incorporating bond-quarter fixed effects for both bonds $i$ and $j$. These adjustments are made to control for unobservable time-varying characteristics of each bond in the pair that could potentially influence the pairwise correlation of liquidity changes. In addition, I triple-cluster the standard errors at the quarter, bond $i$, and bond $j$ levels.

Firstly, I examine the influence of common ownership for each type of institution in my sample individually. In Model 1, I find a positive and significant coefficient of 0.023 on $ETFCOMOWN$ suggesting that an increase in common ETF ownership in a pair of bonds translate into an increase in co-movement of liquidity. Model 2 demonstrates the individual impact of common active mutual fund ownership on liquidity commonality. Here, the coefficient of 0.015 is statistically significant. In Model 3, I investigate the impact of common ownership by index funds and find a positive and statistically significant coefficient of 0.021.

In Model 4, I examine the joint impact of common ownership by ETFs, active mutual funds, and index funds. Even though the coefficients for $ETFCOMOWN$ and $MFCOMOWN$ retain their positive and statistically significant status, I find that the common ownership of index funds does not significantly explain the co-movement in liquidity.

## 5. Establishing a causal relationship between institutional ownership and commonality in liquidity of investment-grade bonds

The evidence gathered so far indicates a significant correlation between ETF ownership and liquidity commonality for investment-grade corporate bonds. This relationship between ETF ownership and liquidity commonality is distinctive from those associated with active mutual fund and index fund ownership. My findings regarding the influence of ETF ownership on investment-grade corporate bonds align with the results of Agarwal et al. (2018), who discern that ETF ownership considerably increases commonality in the liquidity of equities. However, a similar effect for high-yield corporate bonds remains elusive.

In stark contrast to the impact of ETF ownership on investment-grade bonds, I discover that neither active mutual fund ownership nor index fund ownership heighten commonality in the liquidity of investment-grade or high-yield bonds. These results for mutual fund ownership are surprising and directly oppose the established effect of mutual funds on the commonality in liquidity of stocks (Koch et al., 2016).

However, it is essential to consider the possibility that investment managers might have a predilection for bonds with specific time-varying characteristics, which are correlated with liquidity co-movements. This potential preference could introduce endogeneity issues that may not be wholly accounted for by panel regressions. To effectively tackle such endogeneity concerns, I adopt different identification strategies for ETF and active mutual fund ownership.

### 5.1. ETF ownership and liquidity commonality

To further corroborate the relationship between ETF ownership and liquidity commonality observed in OLS regressions, I utilize a quasi-natural experiment as outlined by Dathan and Davydenko (2018) and Marta (2020). On January 24, 2017, Bloomberg announced an increase in the minimum amount outstanding for inclusion in the U.S. Aggregate Index, effective April 1, 2017. This change, which raised the threshold from $250 million to $300 million, led to the exclusion of bonds below this new limit from ETFs tracking Bloomberg indices. This rule change provides a unique opportunity to explore the impact of an exogenous decrease in ETF ownership on bond liquidity commonality.

I hypothesize that bonds exiting ETF portfolios due to this rule change show a decline in liquidity beta. Identifying treatment and control groups, the treatment group includes bonds with an amount outstanding between $250 to $299 million and more than 1% Bloomberg index ETF ownership before the rule change, yielding 63 treatment bonds. Control group candidates include bonds with an amount outstanding above $300 million. Both groups are required to be present in the sample for a minimum of two quarters during both pre-event periods (before Q4 2016) and post-event (after Q2 2017) periods. To prevent selection bias, I use propensity score matching to select control bonds similar to treatment bonds, following the method of Dannhauser (2017). I use bond characteristics data from Q4 2016 and conduct the following logit regression:

$$Treat_i = \alpha + \beta_1 ETFOWN_i + \beta_2 MFOWN_i + \beta_3 INDFOWN_i + \beta_4 Amihud_i + \beta_5 Rating_i + \beta_6 Maturity_i + \beta_7 Spread_i \tag{12}$$

where the indicator variable $Treat_i$ equals 1 for treated bonds. I then match treatment bonds with their five and ten nearest neighbors based on the calculated p-scores. Table A.4, Panel A, provides summary statistics for the treatment and control groups for the last quarter before the rule change. By design, the treatment bonds are smaller with amounts outstanding below $300 million. Panel A also confirms similarity in key bond characteristics between the groups, including liquidity. In Panel B, I test for equality in $\beta_{HI\_ETF}$ changes between the treatment and control groups during quarters prior to the rule change event. The various tests show that pre-event trends in the two groups are almost identical and are not statistically significant in any of the four quarters before the rule change event.

I estimate a difference-in-differences regression for Q1 2015 to Q1 2019, excluding the Q1 2017 announcement period, as follows:

$$\beta_{HI\_ETF,i,q} = \gamma_0 + \gamma_1 Treatment_i \times Post + \gamma_2 Treatment_i + \gamma_3 ETFOWN_{i,2016Q4} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}. \tag{13}$$

$Treatment_i$ is an indicator for treated bonds, and $Post$ is a dummy for the period after Q2 2017. $ETFOWN_{i,2016Q4}$ represents ETF ownership at the end of Q4 2016. A negative coefficient for $Treatment \times Post$ would imply a reduction in liquidity commonality following an exogenous decrease in ETF ownership. Standard errors are double-clustered by bond and quarter.

Employing a difference-in-differences methodology, I assume that the exogenous shock to ownership in Q1 2017 is strong enough to have a significant impact on ETF ownership levels during the subsequent examination period post Q2 2017. To verify the validity of this assumption, I present the results of regressions of ETF ownership levels during the post period as a function of the treatment variable in Table 8, depicted in Columns 1 and 2. The significant negative coefficient on the treatment variable corroborates that bonds held by ETFs tracking Bloomberg indices experienced diminished levels of ETF ownership subsequent to the rule change and indicates the efficacy of the rule change as an exogenous shock.

The main regression results detailed in Table 8, Columns 3 to 6, consistently show negative and statistically significant coefficients for $Treatment \times Post$. This finding is robust across different model specifications, including those with time-fixed effects (Models 3 and 5) and both time-fixed and bond-fixed effects (Models 4 and 6). The negative coefficients indicate that bonds excluded from the Bloomberg indices—and thus experiencing lower ETF ownership—subsequently exhibit lower liquidity commonality compared to bonds that remained in the indices. This pattern is consistent across all models and supports the hypothesis that ETF ownership plays a significant role in influencing liquidity commonality in corporate bonds.

In summary, the results from this quasi-natural experiment provide convincing evidence of a causal relationship between ETF ownership and liquidity commonality in corporate bonds. The findings corroborate the initial observations from OLS regressions and strengthen the argument for the influence of ETFs on market liquidity dynamics.

### 5.2. Mutual fund ownership and liquidity commonality

In an attempt to establish a causal link between mutual fund ownership and the commonality in liquidity of the bonds held by these funds, I exploit an unanticipated shock to fund flows. Specifically, I leverage the unexpected departure of Bill Gross from his Chief Investment Officer position at Pacific Investment Management Company (PIMCO) on September 26, 2014, as an exogenous source of variation in PIMCO's bond fund flows (see Zhu, 2021, for details). This event, which significantly affected PIMCO but not the other funds in my sample, provides an opportunity to analyze the cross-sectional variation in ownership for reasons likely unrelated to future liquidity commonality. At the time of Gross's resignation, PIMCO was the leading fixed-income asset manager in the U.S. His sudden exit took the market by surprise, sparking substantial redemptions across all PIMCO funds. Within the 12 months that followed Bill Gross's departure, PIMCO experienced a 25% loss in their assets.

As a result, bonds initially heavily owned by PIMCO funds may have witnessed substantial declines in mutual fund ownership compared to those not held by these funds. If mutual funds indeed foster commonality in liquidity–a notion contrary to my panel regression results–one should expect to see a subsequent drop in the common liquidity for bonds previously held by PIMCO, given that these bonds have experienced an exogenous decrease in their mutual fund ownership.

**Table 8**
Impact of exogenous variations in ETF ownership on liquidity commonality.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var. | ETFOWN $(q)$ | | $\beta_{HI\_ETF}$ $(q)$ | | | |
| Treatment × Post | | | −0.476** | −0.483** | −0.399** | −0.394* |
| | | | (−2.25) | (−2.03) | (−1.98) | (−1.75) |
| Treatment | −0.012*** | −0.012*** | 0.215 | | 0.210 | |
| | (−8.16) | (−9.16) | (1.15) | | (1.18) | |
| ETFOWN (2016) | 0.793*** | 0.856*** | −5.926 | | −3.380 | |
| | (17.00) | (26.39) | (−1.22) | | (−0.94) | |
| MFOWN $(q-1)$ | | | −0.071 | −0.087 | −0.058* | −0.159* |
| | | | (−1.59) | (−0.85) | (−1.69) | (−1.93) |
| INDFOWN $(q-1)$ | | | 0.035 | 0.047 | 0.017 | 0.067 |
| | | | (0.86) | (0.50) | (0.48) | (0.87) |
| Amihud $(q-1)$ | −0.032*** | −0.033*** | −1.581** | −2.311** | −1.165* | −0.995 |
| | (−5.15) | (−6.16) | (−2.08) | (−2.37) | (−1.81) | (−1.14) |
| MktVal $(q-1)$ | 0.003*** | 0.002*** | 0.145 | −0.462 | 0.048 | −0.199 |
| | (3.40) | (4.32) | (1.60) | (−1.50) | (0.74) | (−0.82) |
| Rating $(q-1)$ | 0.001*** | 0.001*** | −0.036 | 0.060 | 0.013 | 0.046 |
| | (2.84) | (3.46) | (−1.18) | (0.46) | (0.56) | (0.51) |
| Maturity $(q-1)$ | −0.000** | −0.000*** | −0.030*** | −3.876 | −0.012* | −8.003 |
| | (−2.05) | (−3.83) | (−3.24) | (−0.30) | (−1.68) | (−0.81) |
| Spread $(q-1)$ | −0.002*** | −0.002*** | 0.179*** | 0.156 | −0.028 | −0.128* |
| | (−3.03) | (−2.98) | (2.59) | (1.41) | (−0.55) | (−1.72) |
| Observations | 2478 | 3908 | 4866 | 4866 | 7841 | 7841 |
| R-squared | 0.679 | 0.707 | 0.013 | 0.090 | 0.006 | 0.085 |
| Nearest Neighbours | 5 | 10 | 5 | 5 | 10 | 10 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bond FE | | | | ✓ | | ✓ |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bond clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Table 8 presents the findings from the difference-in-differences regression analyses for the ETF quasi-natural experiment. Observations are utilized from the periods 2015 Q1 to 2016 Q4 (pre-event) and 2017 Q2 to 2019 Q1 (post-event). The indicator $Treatment_i$ is set to one for bonds with an amount outstanding between \$250 to \$299 million and more than 1% Bloomberg index ETF ownership before the rule change. Treatment bonds with their five and ten nearest neighbors. The dummy variable $Post$ is set to one for the period after 2017 Q2, while $ETFOWN_{i,2016}$ denotes the total level of ETF ownership in bond $i$ at the end of 2016 Q4. Columns 1 and 2 present the results from a regression of the level of ETF ownership in the post period on the treatment indicator and control variables. Columns 3 to 6 provide the results of pooled OLS regressions of $\beta_{HI\_ETF}$ on both treatment and control groups.

To examine the effects of a possible decrease in mutual fund ownership on the commonality in liquidity, I conduct a difference-in-differences regression analysis. In defining the treatment and control groups, I require bonds to have liquidity betas, denoted as $\beta_{HI\_MF,i,q}$, for at least 2 quarters in both the pre-event and post-event periods. A bond is designated as treated if the share of that bond owned by PIMCO funds ranks high (either in the top quartile or decile) at the end of Q2 2014. The control group comprises bonds held by Fidelity Management Company. Bonds in Fidelity's portfolio present a fitting counterfactual under the hypothetical scenario in which Bill Gross did not leave PIMCO, since the total number of corporate bonds in both PIMCO's and Fidelity's portfolios was strikingly similar in Q2 2014.[16] If the fraction of a bond owned by Fidelity funds is high (in the top quartile or decile) at the end of Q2 2014, it gets included in the control group. When employing the top quartile as a benchmark, I identify 81 bonds in the treated group and 109 bonds in the control group. Using top decile yields 33 treated bonds and 44 control bonds. Table A.5, Panel A, provides summary statistics for the treatment and control groups for the last quarter before the Gross's resignation, confirming the similarity in key bond characteristics between the groups. In Panel B, I test for equality in $\beta_{HI\_MF}$ changes between the treatment and control groups during quarters prior to the event and document that pre-event trends in the two groups are almost identical.

I perform a difference-in-differences regression analysis, using data from Q2 2012 to Q2 2014 for the pre-event period, and Q3 2015 to Q3 2017 for the post-event period, based on the following equation:

$$\beta_{HI\_MF,i,q} = \gamma_0 + \gamma_1 Treatment_i \times Post + \gamma_2 Treatment_i + \gamma_3 MFOWN_{i,2014Q2} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}. \tag{14}$$

In this equation, $Treatment_i$ is a binary indicator set to one if the bond belongs to the treated group. $Post$ is a dummy taking value of 1 after Q3 2015, and $MFOWN_{i,2014Q2}$ represents the overall level of mutual fund ownership of bond $i$ at the end of Q2 2014. If an exogenous reduction in mutual fund ownership translates into a decrease in commonality in liquidity, I would expect the coefficient of $Treatment \times Post$ to be negative. In all specifications, I double-cluster standard errors by bond and quarter.

Employing a difference-in-differences methodology, I posit that the exogenous shock to ownership in Q3 2014 is sufficiently impactful to substantially affect mutual fund ownership levels during the subsequent examination period post Q3 2015. To verify the viability of this assumption, I present the results of regressions of mutual fund ownership levels during the post period as a function of the treatment variable in Table 9, depicted in Columns 1 and 2. The significant negative coefficient on the treatment

[16] Taking into account only the corporate bonds in my sample, the total par value of bonds in PIMCO's portfolio amounts to \$6.7B, while it stands at \$6.8B for Fidelity.

**Table 9**
Impact of exogenous variations in mutual fund ownership on commonality in liquidity.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var. | MFOWN $(q)$ | | $\beta_{HI\_MF}$ $(q)$ | | | |
| Treatment × Post | | | 0.250 | 0.274 | 0.254 | 0.239 |
| | | | (0.77) | (0.84) | (0.67) | (0.61) |
| Treatment | −0.015** | −0.025** | −0.241 | | −0.299 | |
| | (−3.14) | (−3.12) | (−0.78) | | (−0.81) | |
| MFOWN (2014) | 0.829*** | 0.855*** | −2.685** | | −3.275* | |
| | (15.75) | (13.41) | (−2.15) | | (−1.94) | |
| ETFOWN $(q-1)$ | | | 2.180 | 3.495 | 3.096 | 1.759 |
| | | | (0.30) | (0.48) | (0.26) | (0.14) |
| INDFOWN $(q-1)$ | | | −18.406** | −27.673* | −25.686*** | −27.025 |
| | | | (−2.74) | (−1.95) | (−3.09) | (−1.15) |
| Amihud $(q-1)$ | 0.039 | 0.040 | 0.447 | 0.230 | −0.390 | −0.790 |
| | (1.15) | (0.75) | (0.31) | (0.09) | (−0.25) | (−0.29) |
| MktVal $(q-1)$ | 0.000 | 0.001 | 0.122 | 0.188 | 0.095 | 1.114 |
| | (0.08) | (0.19) | (0.99) | (0.27) | (0.63) | (1.62) |
| Rating $(q-1)$ | 0.003 | 0.005 | 0.111* | −0.257* | −0.058 | −0.192 |
| | (1.21) | (1.11) | (2.01) | (−1.75) | (−0.54) | (−0.85) |
| Maturity $(q-1)$ | 0.000 | −0.000 | −0.015 | −58.456** | −0.013 | −68.133*** |
| | (0.19) | (−0.46) | (−1.42) | (−2.30) | (−1.20) | (−3.05) |
| Spread $(q-1)$ | 0.002 | 0.002 | 0.142** | 0.096 | 0.143 | 0.097 |
| | (1.08) | (0.54) | (2.38) | (0.88) | (1.38) | (0.71) |
| Observations | 1295 | 507 | 2519 | 2518 | 996 | 996 |
| R-squared | 0.703 | 0.710 | 0.023 | 0.103 | 0.047 | 0.139 |
| Treatment: | Top quartile | Top decile | Top quartile | | Top decile | |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bond FE | | | | ✓ | | ✓ |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bond clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Table 9 presents the findings from the difference-in-differences regression analyses for the mutual fund quasi-natural experiment. Observations are utilized from the periods 2012 Q2 to 2014 Q2 (pre-event) and 2015 Q3 to 2017 Q3 (post-event). The indicator $Treatment_i$ is set to one if the bond is treated. The treatment identifier is set to one if the shares owned by PIMCO in 2014 Q2, scaled by shares outstanding, fall in the top quartile (Models 1, 3, and 4) or decile (Models 2, 5 and 6). The dummy variable $Post$ is set to one for the period after 2015 Q3, while $MFOWN_{i,2014}$ denotes the total level of mutual fund ownership in bond $i$ at the end of 2014 Q2. Columns 1 and 2 present the results from a regression of the level of mutual fund ownership in the post period on the treatment indicator and control variables. Columns 3 to 6 provide the results of pooled OLS regressions of $\beta_{HI\_MF}$ on both treatment and control groups.

variable corroborates that bonds held by PIMCO funds experienced diminished levels of mutual fund ownership subsequent to Bill Gross's resignation.

I present the regression results for Eq. (14) in columns 3 through 6 of Table 9. Models 3 and 5 incorporate time-fixed effects, while Models 4 and 6 include both time-fixed and bond-fixed effects. When the bonds in the top ownership quartiles are subject to treatment in Models 3 and 4, I observe a negative yet insignificant coefficient on $Treatment \times Post$. This suggests that bonds which had a high level of PIMCO ownership prior to the event do not experience a decline in liquidity commonality in the post-event period. When the top ownership decile bonds are treated, the coefficients on $Treatment \times Post$ are nearly zero in Models 5 and 6. In conclusion, I find no evidence that the exogenous shock to mutual fund ownership impacts the co-movement of liquidity in bonds, reinforcing my findings from earlier sections.

## 6. Institutional ownership and liquidity commonality: Underlying mechanisms

In the preceding sections, I have presented evidence that ETF ownership contributes to liquidity commonality among underlying bonds, whereas mutual fund or index fund ownership does not exert such an effect. When examining the relationship between institutional ownership and liquidity commonality, the underlying premise is that a bond more heavily held by a group of institutions is also traded more frequently by that group. However, further exploration is needed to identify the mechanisms through which high ETF ownership leads to commonality. This investigation will also shed light on why ETFs and mutual funds have different impacts on the liquidity commonality of underlying bonds.

In this section, I explore three distinct mechanisms: correlated fund trading, diverse investor clienteles, and the ETF arbitrage mechanism.

### *6.1. Flow-driven correlated trading of funds*

In this section, I investigate the relationship between flow-induced trading and commonality in liquidity of bonds held by funds. Fund flows can impose buying or selling pressures. However, forced buying pressure from mutual funds is unlikely in the corporate bond market, as these funds can buy new bond issues instead of increasing their positions in existing bonds. Furthermore, since ETF sponsors use a representative sampling approach, they too can incorporate new bonds into their portfolios. As a result, I study inflow and outflow periods separately, with the latter being prime candidates for affecting commonality in liquidity.

**Table 10**
Flow-induced correlated trading of funds.

| | ETF flows | | | Mutual fund flows | | | Index fund flows | | |
|---|---|---|---|---|---|---|---|---|---|
| Sample | (1) Full | (2) Outflow | (3) Inflow | (4) Full | (5) Outflow | (6) Inflow | (7) Full | (8) Outflow | (9) Inflow |
| Dep. Var. | $\beta_{HI\_ETF}$ $(q)$ | | | $\beta_{HI\_MF}$ $(q)$ | | | $\beta_{HI\_INDF}$ $(q)$ | | |
| \|ETF flows $(q)$\| | 0.026 | 0.336** | 0.013 | | | | | | |
| | (0.80) | (2.34) | (0.37) | | | | | | |
| \|MF flows $(q)$\| | | | | −0.008 | −0.025 | 0.017 | | | |
| | | | | (−0.16) | (−0.37) | (0.34) | | | |
| \|INDF flows $(q)$\| | | | | | | | −0.007 | 0.130 | 0.011 |
| | | | | | | | (−0.19) | (0.53) | (0.29) |
| Amihud $(q-1)$ | −0.328* | −0.461 | −0.656** | −0.107 | −0.912** | 0.016 | −0.251 | −1.136 | −0.317 |
| | (−1.87) | (−0.60) | (−2.66) | (−0.59) | (−2.40) | (0.06) | (−0.92) | (−1.09) | (−0.86) |
| MktVal $(q-1)$ | −0.061 | −0.213 | −0.096 | 0.074 | 0.004 | 0.126 | 0.039 | −0.117 | 0.059 |
| | (−1.09) | (−1.05) | (−1.48) | (0.82) | (0.04) | (1.10) | (0.44) | (−0.47) | (0.50) |
| Rating $(q-1)$ | 0.011 | 0.050 | 0.035 | 0.031 | 0.003 | −0.004 | 0.022 | 0.133 | 0.026 |
| | (0.49) | (0.82) | (1.52) | (1.26) | (0.05) | (−0.14) | (0.70) | (1.32) | (0.73) |
| Maturity $(q-1)$ | −2.558 | −6.704 | −1.642 | 3.378 | 2.736 | 7.312** | −1.563 | −29.974* | −1.361 |
| | (−0.99) | (−1.08) | (−0.44) | (1.33) | (0.50) | (2.12) | (−0.53) | (−1.79) | (−0.39) |
| Spread $(q-1)$ | −0.022 | −0.036 | −0.018 | 0.010 | −0.002 | 0.017 | −0.022 | −0.085 | −0.007 |
| | (−1.32) | (−0.64) | (−0.93) | (0.43) | (−0.07) | (0.66) | (−0.77) | (−0.88) | (−0.19) |
| Observations | 106,674 | 13,194 | 83,144 | 106,674 | 33,589 | 65,880 | 106,674 | 10,461 | 86,365 |
| R-squared | 0.088 | 0.308 | 0.103 | 0.085 | 0.191 | 0.125 | 0.084 | 0.341 | 0.095 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bond FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bond clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Table 10 reports the results for the effect of flow-induced correlated trading by ETFs, mutual funds, and index funds on liquidity commonality of bonds. The bond-level ETF flows are defined as the weighted average of the quarterly flows of the ETFs that hold the bond, as given by the equation:

$$ETFFlows_{i,q} = \frac{\sum_{j=1}^{J} w_{i,j,q} \times Flows_{j,q}}{Volume_{i,q-1}}, \tag{17}$$

where $J$ represents the subset of ETFs and $w_{i,j,q}$ denotes the weight of the bond in the portfolio of ETF $j$. $Volume_{i,q}$ is the trading volume of bond $i$ over quarter $q$. The mutual fund flows and index fund flows are calculated similarly. The regressions of liquidity betas on the absolute value of flow variables are run separately for the full sample, outflow periods, and inflow periods. A quarter $q$ is deemed an outflow period for bond $i$ if $Flows_{i,q}$ is negative.

Next, I define bond-level ETF flows as the weighted average of the quarterly flows in the ETFs that own the bond:

$$ETFFlows_{i,q} = \frac{\sum_{j=1}^{J} w_{i,j,q} \times Flows_{j,q}}{Volume_{i,q-1}}, \tag{15}$$

where $J$ is the subset of ETFs and $w_{i,j,q}$ is the weight of the bond in ETF $j$'s portfolio. Quarterly institutional flows are calculated as a fraction of the trading volume over the preceding quarter. Analogously, I compute two additional bond-level flow variables as the weighted average of the quarterly flows of the mutual funds ($MFFlows_{i,q}$) and index funds ($INDFFlows_{i,q}$), separately.

Table 10, Panel A, reports the results from the OLS regressions of institutional liquidity betas on flow variables. Flow variables and liquidity betas are measured in the same quarter, thus the regressions are not predictive. The analysis is performed for the full sample, and separately for outflow and inflow periods. The flow variables are standardized. Each specification incorporates bond-fixed and quarter-fixed effects, with standard errors being double-clustered by bond and quarter. The results indicate that, during ETF outflow quarters, bonds demonstrate a higher ETF liquidity beta. However, for inflow quarters, the coefficient on ETF flows is lower and lacks statistical significance. Moreover, Models 4–6 and 7–9 indicate that flows from mutual funds and index funds do not significantly affect liquidity co-movement.

To understand the mechanisms driving these dynamics, it is crucial to examine the distinct ways in which investor demands are transmitted across different fund types. ETFs manage investor demand through in-kind creations and redemptions facilitated by authorized participants. In contrast, fund managers directly handle flows in active mutual funds and index funds. This leads to diverse impacts of flow-induced correlated trading, largely due to the unique liquidity management strategies of active mutual funds and index funds. There is a significant difference in their holdings of cash and Treasuries, as depicted in Table 1. On average, ETFs hold 1.61% in cash and 10.15% in Treasuries, whereas active mutual funds typically allocate 3.90% in cash and 15.03% in Treasuries. Index funds, which generally track broader fixed-income indices, have higher proportions of liquid assets, with 1.32% in cash and 41.01% in Treasuries.

The substantial 30-percentage-point higher allocation to Treasuries by index funds compared to ETFs underscores their preference for broad-based benchmarks. Conversely, the average 86.50% allocation to corporate bonds in ETFs, compared to 34.19% for index funds, reflects the fact that, unlike index funds, a number of ETFs track corporate bond-only benchmarks. The sizeable liquid holdings of active and index mutual funds imply a cautious approach by managers to mitigate the impact of liquidity demands, as explored in Chernenko and Sunderam (2020) and Choi et al. (2020). On the other hand, ETFs maintain relatively smaller liquidity buffers, indicating a different approach to liquidity management.

In the subsequent analysis, I focus on the trading behavior of funds in reaction to investor flows, following Dannhauser and Hoseinzade (2022). Despite their passive nature, fixed-income funds operating under passive mandates still exercise some level of discretion. They typically choose a representative sample of bonds to replicate the benchmark's characteristics, diverging from the strict sampling approach seen in equity funds. Active fund managers have the advantage of not being confined solely to liquidity buffers. They can use their discretion to effectively manage the impact of investor inflows and outflows. Additionally, it is worth noting that ETF sponsors often cite the role of the secondary market, the discretionary actions of arbitrageurs, and the options for cash redemptions or custom baskets as viable alternatives to traditional liquidity buffers, as noted by Dannhauser and Hoseinzade (2022).

Following the approach detailed in Section 4.1.2, I run the regression Eq. (8). The results in Table 5 show that after including controls, the coefficient ($\beta_1$) associated with ETF outflows is 0.877, a value statistically indistinguishable from one. Despite using a sampling strategy for portfolio construction and the flexibility in creation and redemption baskets, ETFs adjust their bond holdings almost proportionally during outflows.[17] The coefficient for active mutual fund outflows is 0.377 and significantly different than one. This is consistent with findings that these funds maintain cash buffers (Chernenko and Sunderam, 2020) and engage in selective trading strategies to reduce liquidation costs (Choi et al., 2020; Jiang et al., 2021). Similarly, the outflow coefficient for index mutual funds is not statistically significant.

The coefficients for inflow for all fund types are significantly different from one. The difference in ETF inflow and outflow coefficients reflects the structure of corporate bond markets and the decisions of sponsors (Dannhauser and Hoseinzade, 2022).[18] When bonds are considered for passive fund inclusion, any bond in the index universe is potentially eligible to purchase, while for exclusion only portfolio bonds are eligible for sale (Dick-Nielsen and Rossi, 2019). Thus, ETF sponsors offer more flexibility in the composition of creation baskets than redemption baskets. The inflow effects of active mutual funds and index funds are also much lower than the outflow effect, implying managers use cash inflows to build liquidity buffers or to allocate to new positions.

### *6.2. ETFs attracting customers with higher liquidity demand*

ETFs distinguish themselves from active or index mutual funds as they are traded on a secondary exchange in sync with the underlying basket of securities they hold, providing intraday liquidity to their investors. On the other hand, mutual funds can only be traded at the end-of-day NAV. This characteristic of ETFs makes them naturally attractive to investors with greater liquidity needs compared to mutual funds. Dannhauser and Hoseinzade (2022) show that ETFs in the corporate bond market appeal to investors with higher liquidity demands over mutual and index funds. Using my own sample, I validate these findings in Table 11. In order to explore the relationship between the volatility of fund flows and the type of institution, I conduct a regression analysis as follows:

$$FlowVol_{f,m} = \beta_1 ETF_f + \beta_2 Controls_{f,m} + \epsilon_{f,m}. \tag{16}$$

I execute the regression specified by Eq. (16) using both cross-sectional and panel regression methodologies. In this regression, the dependent variable, $FlowVol$, represents the average volatility of flows over twelve months for each fund in my sample. The variable $ETF$ is an indicator that takes a value of one if the fund is an ETF, and zero otherwise. The regression controls for factors such as fund expense ratio, turnover ratio, the natural logarithm of total assets, the natural logarithm of the fund's age in years, and the natural logarithm of fund family assets. The results, presented in Table 11, reveal a positive and statistically significant coefficient on the ETF dummy variable across all specifications. This implies that the monthly volatility of ETF flows is greater by 2.1 to 4.1 percentage points compared to mutual funds, a finding that is consistent with the results from Dannhauser and Hoseinzade (2022).

Insofar as ETFs directly translate investor flows into buying and selling activity in the underlying bonds through the creation and redemption of ETF shares, investors with high turnover rates could expose these underlying bonds to new liquidity shocks via the arbitrage mechanism (Ben-David et al., 2018). In the subsequent section, I advance the hypothesis that the ETF arbitrage process is a driver of the observed relationship between ETF ownership and commonality in liquidity. I will then proceed to test this hypothesis empirically.

### *6.3. ETF arbitrage activity*

As a potential channel explaining the connection between commonality in liquidity and ETF ownership, I explore the unique role of the ETF arbitrage mechanism, a feature that distinguishes ETFs from open-end mutual funds. The concurrent trading of ETFs and their underlying securities presents a ripe environment for market participants to maintain the principle of one price. During the trading day, ETF prices are continually synchronized with the intrinsic value of the underlying securities through an arbitrage process. This process engages authorized participants (APs) and other institutional investors. If the ETF price falls below (rises above) the net asset value of the basket securities, APs will take a long (short) position in the ETF and a short (long) position in the underlying bonds. They will then redeem (create) ETF shares at the end of the day to unwind the intraday arbitrage positions.

The correlated demand for underlying securities in the ETF basket can amplify commonality in liquidity among these securities. For equity ETFs, Agarwal et al. (2018) find that the arbitrage mechanism contributes to an increase in the co-movement of liquidity

[17] BlackRock (2021) reports that the compositions of redemption baskets remain nearly identical in terms of risk characteristics and liquidity, regardless of market conditions, in order to prevent the remaining holdings from becoming disproportionately skewed relative to the fund's benchmark index.

[18] In their letter to the SEC, BlackRock (2018) states that an iterative process is used to determine the components of flexible creation baskets, whereas redemption baskets are generally nonnegotiable because APs do not source securities.

**Table 11**
Standard deviation of fund flows and institution type.

| Dep.Var. | Std. Dev. of fund flows | | | |
|---|---|---|---|---|
| Regressions | Cross-section | | Panel | |
| | (1) | (2) | (3) | (4) |
| ETF | 3.916*** | 2.238*** | 4.140*** | 2.069*** |
| | (16.18) | (9.30) | (13.87) | (7.97) |
| Index fund | | 0.075 | | −0.390 |
| | | (0.19) | | (−1.41) |
| Expense ratio | | 15.870 | | 9.254 |
| | | (0.71) | | (0.66) |
| Turnover ratio | | 0.103* | | 0.114*** |
| | | (1.73) | | (3.09) |
| Log(Age) | | −0.961*** | | −1.417*** |
| | | (−13.72) | | (−22.05) |
| Log(Assets) | | −0.249*** | | −0.303*** |
| | | (−4.92) | | (−7.89) |
| Log(Family Assets) | | −0.037 | | 0.069** |
| | | (−1.01) | | (2.06) |
| Observations | 1355 | 1355 | 98,056 | 97,830 |
| R-squared | 0.154 | 0.349 | 0.092 | 0.268 |
| Time FE | | | ✓ | ✓ |
| Time clusters | | | ✓ | ✓ |

Table 11 explores the correlation between the volatility of fund flows and the type of institution, based on the work of Dannhauser and Hoseinzade (2022). I estimate the following regression equation both as cross-sectional and panel regressions:

$$FlowVol_{f,m} = \beta_1 ETF_f + \beta_2 Controls_{f,m} + \epsilon_{f,m}. \tag{18}$$

In this equation, the dependent variable $FlowVol$ represents the average twelve-month volatility of flows for each fund in my sample. The indicator variable $ETF$ is set to one if the fund is an ETF, and to zero otherwise. The explanatory variables include a dummy variable if the fund is an index fund, the fund expense ratio, turnover ratio, log of total assets, log of fund age in years, and the log of fund family assets.

among constituent stocks. Given that corporate bond ETFs trade on a liquid exchange while corporate bonds are traded on the less liquid OTC markets, this liquidity mismatch could exacerbate the impact of ETFs on the underlying securities, especially during periods when liquidity is scarce in the corporate bond market.

To test this hypothesis, I adopt a methodology akin to the one used by Agarwal et al. (2018). Prior research has employed various proxies for arbitrage activity, such as the discrepancy between ETF prices and the NAV of underlying securities (Ben-David et al., 2018). This measure of mispricing signals arbitrage profitability, which should attract more arbitrageurs to participate in eliminating the mispricing. Nonetheless, it is important to recognize that a large deviation can also be indicative of the existence of limits to arbitrage.

Mispricing is computed as the sum of the absolute values of the daily differences between an ETF's end-of-the-day price and its end-of-the-day NAV (i.e., the ETF's discount or premium), all aggregated on a quarterly basis. I utilize the absolute value of the discount or premium because both positive and negative deviations from the NAV offer arbitrage opportunities.

Precisely, for each fund $j$ in quarter $q$:

$$AVGMISPRC_{j,q} = \frac{1}{D}\sum_{d=1}^{D}\left|\frac{PRC_{j,d} - NAV_{j,d}}{PRC_{j,d}}\right|$$

where $PRC_{j,d}$ and $NAV_{j,d}$ represent the price and NAV of ETF $j$ at the end of day $d$, respectively.

As a second proxy for arbitrage activity, I employ the standard deviation of daily mispricing values within a quarter. The fluctuation of ETF mispricing over time implies that arbitrageurs are actively capitalizing on these discrepancies. A potential limitation of this measure is that the variability in mispricing could be influenced by shifts in ETF demand relative to their underlying bonds. I calculate this measure by computing the standard deviation of daily mispricing values over each quarter $q$ for each fund $j$, which I denote as $SDMISPRC_{j,q}$.

Following this, I use the mean and standard deviation of creation and redemption activities in an ETF as further proxies for arbitrage activity. These are labeled $AVGABSCR$ and $SDABSCR$, respectively, in line with Agarwal et al. (2018). APs utilize the creation and redemption processes to align the ETF price with the value of the underlying basket via the arbitrage mechanism, subsequently adjusting the outstanding shares of ETFs. For instance, if an ETF encounters a positive demand shock, the ETF's price will rise and deviate from the NAV of the underlying basket. This mispricing is subsequently reduced through the arbitrage mechanism, resulting in the creation of additional ETF shares.

Specifically, for both these proxies, I first compute the daily net share creation and redemption for each ETF, which I impute from the change in ETF shares outstanding obtained from Bloomberg. For $AVGABSCR$, I take the sum of the absolute value of the net share creation and redemption for each ETF over each quarter. Precisely, for each fund $j$ in quarter $q$, I define:

$$AVGABSCR_{j,q} = \frac{1}{D}\sum_{d=1}^{D}\left|\frac{SHROUT_{j,d} - SHROUT_{j,d-1}}{SHROUT_{j,d-1}}\right|,$$

**Table 12**
ETF arbitrage and commonality in liquidity.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dep.Var. | $\beta_{HI\_ETF}$ $(q)$ | | | |
| $ETFOWN_{HighArbitrage}$ $(q-1)$ | 0.040** | 0.044** | 0.049*** | 0.032* |
| | (2.30) | (2.44) | (3.17) | (1.87) |
| $ETFOWN_{LowArbitrage}$ $(q-1)$ | 0.015 | 0.020 | 0.023 | 0.024 |
| | (0.89) | (1.41) | (1.25) | (1.42) |
| $MFOWN$ $(q-1)$ | −0.037* | −0.037* | −0.037* | −0.037* |
| | (−1.76) | (−1.75) | (−1.73) | (−1.71) |
| $INDFOWN$ $(q-1)$ | −0.025 | −0.026 | −0.027 | −0.030 |
| | (−1.09) | (−1.16) | (−1.24) | (−1.34) |
| Amihud $(q-1)$ | −0.340* | −0.340* | −0.340* | −0.337* |
| | (−1.77) | (−1.76) | (−1.77) | (−1.75) |
| MktVal $(q-1)$ | −0.066 | −0.067 | −0.066 | −0.065 |
| | (−1.13) | (−1.15) | (−1.13) | (−1.10) |
| Rating $(q-1)$ | −2.784 | −2.786 | −2.753 | −2.718 |
| | (−0.96) | (−0.96) | (−0.95) | (−0.94) |
| Maturity $(q-1)$ | −0.020 | −0.020 | −0.019 | −0.018 |
| | (−1.10) | (−1.11) | (−1.08) | (−1.01) |
| Spread $(q-1)$ | 0.014 | 0.014 | 0.014 | 0.015 |
| | (0.59) | (0.60) | (0.62) | (0.65) |
| Observations | 106,674 | 106,674 | 106,674 | 106,674 |
| R-squared | 0.090 | 0.090 | 0.090 | 0.090 |
| F - statistic | (5.29)** | (5.94)** | (10.05)*** | (3.75)* |
| Channel | $AVGMISPRC$ | $SDMISPRC$ | $AVGABSCR$ | $SDABSCR$ |
| Time FE | ✓ | ✓ | ✓ | ✓ |
| Bond FE | ✓ | ✓ | ✓ | ✓ |
| Time clusters | ✓ | ✓ | ✓ | ✓ |
| Bond clusters | ✓ | ✓ | ✓ | ✓ |

Table 12 presents results on the influence of ETF ownership (ETFOWN) on the commonality in liquidity for two groups: ownership by low-arbitrage funds and ownership by high-arbitrage funds. $AVGMISPRC$ is the average of the absolute value of the daily difference between the ETF NAV and the ETF end-of-the-day price, aggregated over each quarter. $SDMISPRC$ is the standard deviation of that daily difference over the quarter. The mean and standard deviation of daily creation and redemption activities in an ETF, labeled as $AVGABSCR$ and $SDABSCR$ respectively, are used as additional proxies for arbitrage activity over a quarter. To categorize ETFs based on their mispricing levels, I initially form quartiles of ownership to account for the cross-sectional variation in the fund's Assets Under Management (AUMs). Then, within each ownership quartile and for each of the proxies, I compute the median mispricing ratio of the funds. If a fund in a given ownership quartile exhibits a higher (or lower) mispricing level than the median value, it is classified as a high-arbitrage (or low-arbitrage) fund. Subsequently, for each bond, I define the high-arbitrage (or low-arbitrage) ETF ownership as the ratio between the par value held by high-arbitrage (or low-arbitrage) ETFs and the amount outstanding of the bond. All regression models incorporate bond-level control variables including the quarterly mean of the daily Amihud illiquidity measure ($Amihud$), log market value of a bond ($MktVal$), numerical rating $Rating$, the yield spread ($Spread$), and time-to-maturity ($Maturity$).

where $SHROUT_{j,d}$ is the number of shares outstanding of ETF $j$ at the end of day $d$ and $D$ is the number of days in a given quarter $q$. For the other proxy, $ETFSDCR$, I estimate the standard deviation of the daily net share creation and redemption for each ETF over each quarter.

$ETFABSCR$ and $ETFSDCR$ serve as complements to the two earlier proxies related to mispricing. While mispricing is observed at the end of the day, ETF creation and redemption activities arise from APs engaging in arbitrage throughout the day. However, as noted by Agarwal et al. (2018), these measures have an inherent limitation. APs may not need to create or redeem at the end of the day if opposite positions are netted out during the day. Moreover, APs might choose to carry over their net short or long positions in ETFs instead of creating or redeeming ETF shares at day's end. These scenarios could potentially result in an underestimation of actual arbitrage activities conducted by APs.

To categorize ETFs according to their levels of arbitrage activity, I initially form quartiles based on ownership to control for cross-sectional variation in fund AUMs. Then, for each of the four proxies, I distribute the funds into quintiles based on their arbitrage activity levels within each ownership quartile. Subsequently, for each proxy, I segregate the stocks into two groups — the bottom quintile representing lower arbitrage activity, and the top four quintiles signifying higher arbitrage activity. Lastly, for each bond, I define high-arbitrage (or low-arbitrage) ETF ownership as the ratio between the par value held by high-arbitrage (or low-arbitrage) ETFs and the total amount outstanding of the bond. I utilize standardized ownership variables in the OLS regressions.

The results, presented in Table 12, consistently indicate that bonds owned by high-arbitrage ETFs exhibit greater commonality in liquidity relative to bonds held by ETFs with lower arbitrage activity. For example, Model 1 presents the results for the $AVGMISPRC$ proxy, where the coefficient on high-arbitrage $ETFOWN$ is 0.04, which exceeds the corresponding coefficient of 0.015 for low-arbitrage $ETFOWN$. The difference of 0.025 is statistically significant at the 1% level, with an F-statistic of 5.29. Taken together, these findings imply that the arbitrage mechanism heightens the commonality in liquidity among constituent bonds.

## 7. Conclusion

The increasing dominance of fund ownership in the corporate bond market, coupled with a reduction in dealer capital, has raised concerns among scholars and regulators about the potential for heightened fragility in the market. Despite the illiquidity of

**Table A.1**
Correlation matrices.

| Panel A: Investment-grade bonds | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\beta_{HI\_ETF}$ | (1) | 1.00 | 0.09 | 0.21 | 0.01 | 0.04 | 0.01 | 0.02 | 0.02 | −0.03 | 0.00 | −0.04 | −0.03 |
| $\beta_{HI\_MF}$ | (2) | 0.09 | 1.00 | 0.04 | 0.02 | 0.01 | 0.00 | 0.00 | 0.00 | −0.01 | 0.02 | −0.03 | 0.00 |
| $\beta_{HI\_INDF}$ | (3) | 0.21 | 0.04 | 1.00 | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | −0.01 | −0.01 |
| MFOWN (%) | (4) | 0.01 | 0.02 | 0.01 | 1.00 | 0.12 | 0.09 | 0.10 | 0.13 | −0.16 | 0.35 | −0.15 | 0.12 |
| ETFOWN (%) | (5) | 0.04 | 0.01 | 0.01 | 0.12 | 1.00 | 0.50 | 0.23 | 0.32 | −0.39 | −0.07 | −0.33 | −0.34 |
| INDFOWN (%) | (6) | 0.01 | 0.00 | 0.01 | 0.09 | 0.50 | 1.00 | 0.11 | 0.22 | −0.26 | 0.02 | −0.08 | −0.15 |
| Amount Outstanding ($M) | (7) | 0.02 | 0.00 | 0.00 | 0.10 | 0.23 | 0.11 | 1.00 | 0.78 | −0.36 | −0.21 | 0.04 | −0.05 |
| Log market value | (8) | 0.02 | 0.00 | 0.00 | 0.13 | 0.32 | 0.22 | 0.78 | 1.00 | −0.57 | −0.15 | 0.01 | −0.13 |
| Quarterly Illiquidity (mean) | (9) | −0.03 | −0.01 | 0.00 | −0.16 | −0.39 | −0.26 | −0.36 | −0.57 | 1.00 | 0.07 | 0.21 | 0.31 |
| Rating | (10) | 0.00 | 0.02 | 0.00 | 0.35 | −0.07 | 0.02 | −0.21 | −0.15 | 0.07 | 1.00 | 0.05 | 0.43 |
| Time to maturity (years) | (11) | −0.04 | −0.03 | −0.01 | −0.15 | −0.33 | −0.08 | 0.04 | 0.01 | 0.21 | 0.05 | 1.00 | 0.41 |
| Spread (%) | (12) | −0.03 | 0.00 | −0.01 | 0.12 | −0.34 | −0.15 | −0.05 | −0.13 | 0.31 | 0.43 | 0.41 | 1.00 |

| Panel B: High-yield bonds | | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\beta_{HI\_ETF}$ | (13) | 1.00 | 0.13 | 0.02 | 0.01 | 0.02 | 0.02 | −0.01 | −0.01 | −0.01 | 0.00 |
| $\beta_{HI\_MF}$ | (14) | 0.13 | 1.00 | 0.01 | 0.00 | 0.01 | 0.02 | 0.00 | −0.01 | 0.00 | −0.01 |
| MFOWN (%) | (15) | 0.02 | 0.01 | 1.00 | 0.25 | 0.35 | 0.48 | −0.38 | −0.04 | −0.24 | −0.11 |
| ETFOWN (%) | (16) | 0.01 | 0.00 | 0.25 | 1.00 | 0.20 | 0.34 | −0.24 | 0.04 | −0.06 | −0.11 |
| Amount outstanding ($M) | (17) | 0.02 | 0.01 | 0.35 | 0.20 | 1.00 | 0.79 | −0.36 | −0.05 | 0.00 | −0.03 |
| Log market value | (18) | 0.02 | 0.02 | 0.48 | 0.34 | 0.79 | 1.00 | −0.59 | −0.21 | −0.05 | −0.26 |
| Quarterly Illiquidity (mean) | (19) | −0.01 | 0.00 | −0.38 | −0.24 | −0.36 | −0.59 | 1.00 | 0.17 | 0.17 | 0.29 |
| Rating | (20) | −0.01 | −0.01 | −0.04 | 0.04 | −0.05 | −0.21 | 0.17 | 1.00 | −0.12 | 0.47 |
| Time to maturity (years) | (21) | −0.01 | 0.00 | −0.24 | −0.06 | 0.00 | −0.05 | 0.17 | −0.12 | 1.00 | −0.04 |
| Spread (%) | (22) | 0.00 | −0.01 | −0.11 | −0.11 | −0.03 | −0.26 | 0.29 | 0.47 | −0.04 | 1.00 |

Table A.1 presents the correlations between variables specified in Table 1. The sample comprises 108,906 observations of investment-grade bonds and 32,648 observations of high-yield bonds, reported quarterly from Q1 2011 to Q2 2019. Correlations for investment-grade bonds are provided in Panel A, whereas those for high-yield bonds are given in Panel B.

the bonds they hold, ETFs and mutual funds provide daily redemption benefits to investors. Based on this mismatch, this paper examines the effect of ETFs and mutual funds on the commonality in liquidity of underlying corporate bonds.

The findings suggest a positive and significant relationship between ETF ownership and liquidity commonality of investment-grade corporate bonds. However, I do not find any evidence that mutual fund ownership increases commonality in liquidity of corporate bonds, which is contrary to findings observed in equities. I attribute this difference to the distinct liquidity management strategies by equity and corporate bond mutual funds during the outflow periods. Additionally, the study documents that institutional ownership does not impact liquidity commonality in high-yield corporate bonds, likely due to their muted response to market-wide liquidity shifts. The disparate effects of ETFs and mutual funds on investment-grade bond liquidity commonality are explained through three mechanisms: correlated trading driven by ETF flows, differences in investor clienteles, and the unique ETF arbitrage process.

This research contributes to the ongoing policy debate regarding the broader implications of ETFs in security markets. While ETFs provide investors with benefits like improved liquidity access and diversification, they may also inadvertently affect the liquidity risk of the securities within their baskets. The study demonstrates that increased ETF ownership of investment-grade corporate bonds can limit investors' ability to diversify liquidity risks. For fixed-income portfolio managers, this could translate into higher transaction costs and notable impacts on bond returns, particularly in high-stress scenarios where trading might become challenging.

To mitigate such risks, ETF sponsors could consider excluding bonds with higher systematic liquidity risk, focusing instead on less commonly held bonds. This approach is feasible, given that fixed-income ETF sponsors often select a representative bond sample, differing from the strict sampling strategy of equity funds. Future research should explore whether regulatory limitations on specific fund types are necessary and whether a premium should be demanded by investors holding corporate bonds predominantly owned by ETFs.

## CRediT authorship contribution statement

**Efe Cotelioglu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization.

## Appendix

See Tables A.1–A.5.

**Table A.2**
Institutional ownership and commonality in liquidity by different time periods - Investment-grade bonds.

| | (1) | (2) | (3) |
|---|---|---|---|
| Dep. Var. | $\beta_{HI\_ETF}$ $(q)$ | $\beta_{HI\_MF}$ $(q)$ | $\beta_{HI\_INDF}$ $(q)$ |
| INSTOWN Var. | ETFOWN | MFOWN | INDFOWN |
| INSTOWN $(q-1) \times D_{2011-2013}$ | 0.034 | 0.006 | −0.056 |
| | (1.22) | (0.23) | (−1.24) |
| INSTOWN $(q-1) \times D_{2014-2016}$ | 0.053** | 0.014 | −0.079** |
| | (2.05) | (0.49) | (−2.28) |
| INSTOWN $(q-1) \times D_{2017-2019}$ | 0.107*** | 0.012 | −0.054 |
| | (4.23) | (0.29) | (−1.37) |
| ETFOWN $(q-1)$ | | −0.011 | 0.086*** |
| | | (−0.50) | (3.53) |
| MFOWN $(q-1)$ | −0.033 | | −0.007 |
| | (−1.60) | | (−0.28) |
| INDFOWN $(q-1)$ | −0.043* | −0.004 | |
| | (−1.85) | (−0.13) | |
| Amihud $(q-1)$ | −0.369* | −0.134 | −0.089 |
| | (−1.92) | (−0.62) | (−0.30) |
| MktVal $(q-1)$ | −0.071 | 0.071 | 0.065 |
| | (−1.25) | (0.78) | (0.62) |
| Rating $(q-1)$ | 0.016 | 0.039 | 0.015 |
| | (0.69) | (1.47) | (0.42) |
| Maturity $(q-1)$ | −2.685 | 3.454 | −1.814 |
| | (−0.93) | (1.28) | (−0.54) |
| Spread $(q-1)$ | −0.018 | −0.001 | −0.009 |
| | (−1.04) | (−0.03) | (−0.36) |
| Observations | 106,674 | 106,674 | 106,674 |
| R-squared | 0.090 | 0.086 | 0.076 |
| Time FE | ✓ | ✓ | ✓ |
| Bond FE | ✓ | ✓ | ✓ |
| Time clusters | ✓ | ✓ | ✓ |
| Bond clusters | ✓ | ✓ | ✓ |

Table A.2 reports the relationship between commonality in liquidity and institutional ownership by different periods for investment-grade bonds. The sample period is from 2011 Q1 through 2019 Q2. $ETFOWN$, $MFOWN$, and $INDFOWN$ are lagged standardized ownership variables, which are depicted as $INSTOWN$. Each model interacts $INSTOWN$ with sub-period dummies for 2011–2013, 2014–2016, and 2017–2019. Each model presents the results for ETFs, mutual funds, and index funds separately. $t$-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

**Table A.3**
Institutional ownership and commonality in liquidity using bid–ask spreads - Investment-grade bonds.

Panel A: ETF ownership and commonality in liquidity

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dep. Var. | $\beta_{HI\_ETF}$ $(q)$ | | | | | | | |
| ETFOWN $(q-1)$ | 0.161*** | 0.161** | 0.079* | 0.086* | 0.087* | 0.060 | 0.238*** | 0.114*** |
| | (4.40) | (2.36) | (1.82) | (1.90) | (1.93) | (1.22) | (4.93) | (2.91) |
| MFOWN $(q-1)$ | | | | −0.042 | −0.048 | −0.053* | −0.046 | −0.040 |
| | | | | (−0.75) | (−0.83) | (−1.75) | (−1.51) | (−1.33) |
| INDFOWN $(q-1)$ | | | | −0.030 | −0.038 | −0.030 | −0.053* | −0.027 |
| | | | | (−0.47) | (−0.59) | (−1.07) | (−1.79) | (−1.01) |
| Liquidity $(q-1)$ | 28.790*** | 28.790*** | 16.873* | 17.020* | 18.616* | 33.830*** | 35.486*** | 57.345*** |
| | (3.36) | (3.25) | (1.81) | (1.82) | (1.94) | (3.98) | (3.90) | (5.50) |
| MktVal $(q-1)$ | 0.127*** | 0.127*** | 0.194 | 0.213 | 0.210 | 0.195*** | 0.120*** | 0.169*** |
| | (4.17) | (3.32) | (0.92) | (0.99) | (0.99) | (3.43) | (3.48) | (3.92) |
| Rating $(q-1)$ | | | | | 0.062 | 0.051 | | −0.017 |
| | | | | | (1.26) | (1.00) | | (−1.26) |
| Maturity $(q-1)$ | | | | | −9.698 | −0.023*** | | −0.023*** |
| | | | | | (−1.43) | (−4.48) | | (−5.46) |
| Spread $(q-1)$ | | | | | −0.013 | −0.077 | | −0.075 |
| | | | | | (−0.30) | (−1.65) | | (−1.52) |
| Observations | 105,998 | 105,998 | 105,998 | 105,998 | 103,876 | 103,890 | 105,998 | 103,892 |

(continued on next page)

**Table A.3** (*continued*).

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel A: ETF ownership and commonality in liquidity | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dep. Var. | $\beta_{HI\_ETF}$ $(q)$ | | | | | | | |
| R-squared | 0.004 | 0.004 | 0.087 | 0.087 | 0.088 | 0.020 | 0.003 | 0.006 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond FE | | | ✓ | ✓ | ✓ | | | |
| Issuer FE | | | | | | ✓ | | |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond clusters | | ✓ | ✓ | ✓ | ✓ | | | |
| Issuer clusters | | | | | | ✓ | | |
| Fama MacBeth | | | | | | | ✓ | ✓ |
| Panel B: Mutual fund ownership and commonality in liquidity | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dep. Var. | $\beta_{HI\_MF}$ $(q)$ | | | | | | | |
| ETFOWN $(q-1)$ | | | | −0.128** | −0.114* | −0.043* | 0.036 | −0.051 |
| | | | | (−2.24) | (−1.98) | (−1.72) | (0.97) | (−1.32) |
| MFOWN $(q-1)$ | 0.065*** | 0.065*** | −0.027 | −0.028 | −0.052 | 0.026 | 0.063*** | 0.031 |
| | (3.01) | (2.89) | (−0.42) | (−0.44) | (−0.80) | (0.67) | (2.88) | (1.41) |
| INDFOWN $(q-1)$ | | | | 0.057 | 0.028 | −0.022 | −0.017 | −0.004 |
| | | | | (0.72) | (0.35) | (−0.82) | (−0.74) | (−0.17) |
| Liquidity $(q-1)$ | 38.965*** | 38.965*** | 34.666*** | 34.069*** | 25.684** | 36.514*** | 39.118*** | 49.682*** |
| | (4.49) | (4.49) | (3.28) | (3.22) | (2.27) | (3.63) | (4.17) | (4.23) |
| MktVal $(q-1)$ | −0.012 | −0.012 | 0.000 | 0.015 | 0.085 | 0.044 | −0.029 | 0.019 |
| | (−0.30) | (−0.28) | (0.00) | (0.07) | (0.42) | (0.57) | (−0.65) | (0.34) |
| Rating $(q-1)$ | | | | | −0.056 | −0.017 | | 0.011 |
| | | | | | (−0.63) | (−0.26) | | (0.57) |
| Maturity $(q-1)$ | | | | | −1.860 | −0.022*** | | −0.022*** |
| | | | | | (−0.20) | (−3.84) | | (−5.73) |
| Spread $(q-1)$ | | | | | 0.109* | 0.034 | | 0.007 |
| | | | | | (1.72) | (0.57) | | (0.12) |
| Observations | 105,998 | 105,998 | 105,998 | 105,998 | 103,876 | 103,890 | 105,998 | 103,892 |
| R-squared | 0.002 | 0.002 | 0.085 | 0.085 | 0.087 | 0.018 | 0.002 | 0.004 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond FE | | | ✓ | ✓ | ✓ | | | |
| Issuer FE | | | | | | ✓ | | |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond clusters | | ✓ | ✓ | ✓ | ✓ | | | |
| Issuer clusters | | | | | | ✓ | | |
| Fama MacBeth | | | | | | | ✓ | ✓ |
| Panel C: Index fund ownership and commonality in liquidity | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dep. Var. | $\beta_{HI\_INDF}$ $(q)$ | | | | | | | |
| ETFOWN $(q-1)$ | | | | 0.055 | 0.047 | 0.005 | 0.057 | 0.018 |
| | | | | (0.98) | (0.84) | (0.15) | (1.65) | (0.47) |
| MFOWN $(q-1)$ | | | | −0.049 | −0.080 | −0.057 | −0.025 | −0.029 |
| | | | | (−0.73) | (−1.17) | (−1.31) | (−0.61) | (−0.62) |
| INDFOWN $(q-1)$ | 0.010 | 0.010 | −0.006 | −0.028 | −0.015 | −0.023 | −0.029 | −0.024 |
| | (0.30) | (0.31) | (−0.10) | (−0.46) | (−0.23) | (−0.67) | (−0.88) | (−0.69) |
| Liquidity $(q-1)$ | −2.893 | −2.893 | 4.564 | 4.866 | 1.532 | 1.014 | 4.845 | 11.131 |
| | (−0.37) | (−0.37) | (0.43) | (0.45) | (0.15) | (0.11) | (0.62) | (1.28) |
| MktVal $(q-1)$ | −0.014 | −0.014 | −0.057 | −0.054 | 0.005 | −0.095* | −0.024 | −0.011 |
| | (−0.34) | (−0.36) | (−0.26) | (−0.25) | (0.02) | (−1.73) | (−0.56) | (−0.27) |
| Rating $(q-1)$ | | | | | −0.090 | −0.033 | | −0.005 |
| | | | | | (−1.28) | (−0.69) | | (−0.25) |
| Maturity $(q-1)$ | | | | | −6.151 | −0.004 | | −0.003 |
| | | | | | (−0.50) | (−0.79) | | (−0.50) |
| Spread $(q-1)$ | | | | | 0.026 | −0.010 | | −0.057 |
| | | | | | (0.42) | (−0.18) | | (−1.40) |
| Observations | 105,998 | 105,998 | 105,998 | 105,998 | 103,876 | 103,890 | 105,998 | 103,892 |
| R-squared | 0.001 | 0.001 | 0.084 | 0.084 | 0.085 | 0.017 | 0.002 | 0.004 |
| Time FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| Bond FE | | | ✓ | ✓ | ✓ | | | |
| Issuer FE | | | | | | ✓ | | |
| Time clusters | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |

(*continued on next page*)

**Table A.3** (*continued*).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Bond clusters | ✓ | ✓ | ✓ | ✓ | | | |
| Issuer clusters | | | | | ✓ | | |
| Fama MacBeth | | | | | | ✓ | ✓ |

Table A.3 reports the relationship between commonality in liquidity and institutional ownership for investment-grade bonds using Corwin and Schultz's (2012) high-low spread estimator as a measure of liquidity. The sample period is from 2011 Q1 through 2019 Q2. $ETFOWN$, $MFOWN$, and $INDFOWN$ are standardized ownership variables. I run the following regression separately for each institution type:

$$depvar_{i,q} = \gamma_0 + \gamma_1 ETFOWN_{i,q-1} + \gamma_2 MFOWN_{i,q-1} + \gamma_3 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}$$

where $depvar_{i,q}$ are $\beta_{HI\_ETF}$, $\beta_{HI\_MF}$, and $\beta_{HI\_INDF}$, which measure the commonality in liquidity with respect to the illiquidity of bonds that are in the top quartile of ETF, mutual fund and index fund ownership, respectively. Bond-level control variables are the quarterly mean of the daily high-low spread illiquidity measure ($Liquidity$), log market value of a bond ($MktVal$), numerical rating ($Rating$), the yield spread ($Spread$), and time-to-maturity ($Maturity$). Panel A, B, and C present the results for ETFs, mutual funds, and index funds separately. $t$-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

**Table A.4**
ETF quasi-natural experiment: Summary statistics for treated and control bonds.

Panel A: Characteristics of treated and control bonds

| | Summary statistics | | | | | | Test of difference | |
|---|---|---|---|---|---|---|---|---|
| | Treated | | Control | | Control | | Treated vs. Control | |
| Control nearest neighbours: | | | 5 | | 10 | | 5 | 10 |
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | *p*-value | *p*-value |
| ETFOWN | 2.26 | 1.13 | 2.31 | 1.07 | 2.32 | 1.18 | 0.25 | 0.32 |
| MFOWN | 6.71 | 7.05 | 6.90 | 6.15 | 7.16 | 6.10 | 0.37 | 0.20 |
| INDFOWN | 2.94 | 1.82 | 3.01 | 1.67 | 2.58 | 1.62 | 0.67 | 0.23 |
| Amtout ($M) | 253.17 | 8.74 | 676.57 | 723.28 | 736.02 | 508.53 | 0.00 | 0.00 |
| Amihud | 0.10 | 0.09 | 0.08 | 0.08 | 0.08 | 0.08 | 0.29 | 0.22 |
| Rating | 8.17 | 1.47 | 8.25 | 1.64 | 8.30 | 1.60 | 0.46 | 0.32 |
| Maturity (years) | 6.72 | 6.10 | 6.78 | 5.43 | 6.60 | 5.57 | 0.53 | 0.96 |
| Spread | 1.35 | 0.95 | 1.30 | 0.64 | 1.32 | 0.61 | 0.22 | 0.34 |

Panel B: Pre-event trend in $\Delta\beta_{HI\_ETF}$

| | Summary statistics | | | Test of difference | |
|---|---|---|---|---|---|
| | Treated | Control | Control | Treated vs. Control | |
| Control nearest neighbours: | | 5 | 10 | 5 | 10 |
| Quarters prior to event Q(0) | Mean | Mean | Mean | *p*-value | *p*-value |
| Q(−1) | −0.13 | −0.03 | −0.12 | 0.47 | 0.46 |
| Q(−2) | 0.06 | 0.38 | 0.17 | 0.39 | 0.53 |
| Q(−3) | −0.45 | −0.19 | −0.18 | 0.97 | 0.97 |
| Q(−4) | 0.98 | −0.24 | −0.11 | 0.19 | 0.25 |
| Q(−4) through Q(−1) | 0.14 | −0.06 | −0.06 | 0.79 | 0.78 |

This table compares characteristics of treated and control bond groups at the end of the quarter before the Bloomberg index rule change. The treated group consists of bonds affected by the rule change and subsequently removed from the index. The control group includes bonds matched to those in the treated group, selected as either the five or ten nearest neighbors. Panel A presents the mean and standard deviation of bond-level characteristics and the results of mean difference tests, reporting the Wilcoxon rank-sum test results with corresponding p-values. Panel B focuses on the quarterly changes in liquidity betas, $\Delta\beta_{HI\_ETF}$, from four quarters Q(−4) to one quarter Q(−1) prior to the rule change along with test statistics for the average differences.

**Table A.5**
Mutual fund quasi-natural experiment: Summary statistics for treated and control bonds.

Panel A: Characteristics of treated and control bonds

| Treatment: | Top quartile | | | | | Top decile | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Summary statistics | | | | Test of difference | Summary statistics | | | | Test of difference |
| | Treated | | Control | | Treated vs. Control | Treated | | Control | | Treated vs. Control |
| | Mean | Std. Dev. | Mean | Std. Dev. | *p*-value | Mean | Std. Dev. | Mean | Std. Dev. | *p*-value |
| ETFOWN | 1.32 | 0.83 | 1.65 | 0.89 | 0.17 | 1.27 | 0.87 | 1.49 | 0.81 | 0.21 |
| MFOWN | 10.42 | 6.95 | 11.23 | 5.49 | 0.11 | 12.40 | 7.10 | 14.10 | 6.24 | 0.16 |
| INDFOWN | 1.70 | 0.76 | 2.11 | 1.04 | 0.02 | 1.62 | 0.69 | 2.18 | 1.20 | 0.13 |
| Amtout ($M) | 1501.60 | 1212.26 | 1362.13 | 1570.49 | 0.55 | 1594.31 | 1421.30 | 944.79 | 600.91 | 0.17 |
| Amihud | 0.05 | 0.07 | 0.03 | 0.03 | 0.41 | 0.04 | 0.07 | 0.04 | 0.05 | 0.15 |
| Rating | 8.30 | 1.43 | 8.06 | 1.36 | 0.28 | 8.52 | 1.34 | 8.62 | 1.01 | 0.99 |

(*continued on next page*)

**Table A.5** (*continued*).

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Maturity (years) | 13.21 | 10.38 | 10.99 | 7.59 | 0.20 | 10.40 | 8.98 | 9.71 | 8.32 | 0.77 |
| Spread | 1.49 | 0.62 | 1.29 | 0.65 | 0.18 | 1.54 | 0.66 | 1.24 | 0.47 | 0.12 |

Panel B: Pre-event trend in $\Delta\beta_{HI\_MF}$

| | Top quartile | | | Top decile | | |
|---|---|---|---|---|---|---|
| | Treated | Control | Test of difference | Treated | Control | Test of difference |
| Quarters prior to event Q(0) | Mean | Mean | *p*-value | Mean | Mean | *p*-value |
| Q(−1) | −1.28 | −0.08 | 0.39 | −0.54 | 0.22 | 0.20 |
| Q(−2) | −0.81 | −0.10 | 0.43 | −1.28 | 0.43 | 0.36 |
| Q(−3) | 0.52 | −0.01 | 0.42 | −0.81 | −1.02 | 0.94 |
| Q(−4) | −0.47 | 0.31 | 0.21 | 0.52 | 0.76 | 0.99 |
| Q(−4) through Q(−1) | −0.54 | 0.02 | 0.29 | −0.47 | 0.79 | 0.13 |

This table presents a comparative analysis of bond characteristics for treated and control groups as of the end of the quarter preceding Bill Gross's resignation from PIMCO. Bonds in the treated group are those with a high share of ownership by PIMCO funds, specifically in the top quartile or decile as of the end of Q2 2014. The control group consists of bonds similarly held by Fidelity Management Company, also in the top quartile or decile. Panel A presents the mean and standard deviation of bond-level characteristics and the results of mean difference tests, reporting the Wilcoxon rank-sum test results with corresponding p-values. Panel B focuses on the quarterly changes in liquidity betas, $\Delta\beta_{HI\_MF}$, from four quarters Q(−4) to one quarter Q(−1) prior to the event along with test statistics for the average differences.

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