Do Mutual Funds and ETFs Affect the Commonality in Liquidity of Corporate Bonds?

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Abstract

The paper studies the effect of growing mutual fund and ETF ownership on the commonality in liquidity of bonds in their portfolios. Unpredictable liquidity needs of funds may give rise to correlated trading across underlying illiquid bonds. I document a positive and significant relationship between ETF ownership and liquidity commonality of investment-grade bonds, which suggests that ETFs reduce the possibility to diversify liquidity risk. In contrast, and unlike for equities, mutual fund ownership does not affect the co-movement in bond liquidity. I identify three channels that explain the differential impact of ETFs and mutual funds: flow-driven correlated trading, different investor clienteles, and ETF arbitrage activity.

JEL classification: G12, G14, G20

Keywords: Corporate Bonds, Liquidity, Commonality, Exchange-Traded Funds (ETFs), Mutual Funds

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1 Introduction

In the post-2008 period, there has been tremendous growth in the U.S. corporate bond market alongside a significant change in the composition of institutional bondholders. Both exchange-traded funds (ETFs) and mutual funds increased their presence in the market. In the first quarter of 2019, mutual fund holdings account for 20% of the total amount outstanding of corporate bonds and the share of ETF holdings corresponds to almost 5% of the market (see Figure 1).[1] Despite their holdings' illiquidity, fixed-income ETFs and mutual funds allow their investors to redeem their money on a daily basis, which implies that these funds have less predictable liquidity needs and higher turnover than the dominant institutions in the market with long-term liabilities, such as insurance companies and pension funds. Considering the liquidity demand sourcing from increasing ETF and mutual fund activity coupled with the decline in dealer capital for market-making due to the post-crisis regulations (Bao, O'Hara, and Zhou, 2018; Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018; Dick-Nielsen and Rossi, 2019), regulators are concerned that the fragility risk of the corporate bond market has increased (Anand, Jotikasthira, and Venkataraman, 2020).[2]

In this paper, I examine whether the increase in the role of ETFs and mutual funds can give rise to a potential source of market fragility, namely a possible increase in liquidity commonality. As shown in Bao, Pan, and Wang (2011), there is substantial commonality in liquidity across corporate bonds. Co-movement in liquidity reduces the possibility to diversify individual asset's liquidity risk and creates a liquidity risk factor, which is priced in the cross-section of corporate bond returns (Lin, Wang, and Wu, 2011; Bai, Bali, and Wen, 2019). If a group of investors in a set of bonds trades in the same direction with similar timing, these bonds will likely experience large trade imbalances at the same points in time and, as a result, strong co-movements in their liquidity (Koch, Ruenzi, and Starks, 2016). Fixed-income ETFs and mutual funds are potential candidates to exert correlated liquidity demand on their underlying securities, and thus give rise to higher levels of common variation in liquidity across their bonds.

Although ETFs and mutual funds both pool their investors' money, there are key differences

[1] The data are based on aggregating table L.213 from the Federal Reserve Flow of Funds by investor type. The value of the amount outstanding for corporate bonds is $10.4 trillion in 2019 Q1.

[2] U.S Securities and Exchange Commission Fixed Income Market Structure Advisory Committee (FIMSAC) has established "The ETFs and Bond Funds Subcommittee" to consider 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.

in the way they are managed. ETFs provide intraday liquidity for investors, whereas investors can trade mutual funds only at the end-of-day net asset value (NAV). Hence, corporate bond ETFs may attract investors with greater liquidity demands than mutual funds. Furthermore, mutual funds have discretion in responding to investor flows, whereas ETFs translate investor flows by trading in the underlying securities mechanically in the exact same proportions as in the ETF creation or redemption units. This mechanism is referred as the arbitrage process, where Authorized Participants (APs) arbitrage away the deviations between the ETF price and the value of the constituting basket. If the ETF price is lower (higher) than the net asset value of the basket securities, APs long (short) the ETF, short (long) the underlying bonds, and then redeem (create) ETF shares at the end of the day to unwind the intraday arbitrage positions.

Corporate bond ETFs have the potential to affect the commonality in liquidity among their component securities through the arbitrage mechanism. If the ETF price deviates from the net asset value (NAV) of the portfolio holdings because of a demand shock, arbitrageurs trade the underlying securities in the same direction as the initial shock to the ETF price (Ben-David, Franzoni, and Moussawi, 2018; Agarwal, Hanouna, Moussawi, and Stahel, 2018). As a result, the underlying bonds can inherit the shocks that occur in the ETF market and common ETF ownership may lead to simultaneous trading in these bonds. This is associated with correlated demand for the liquidity of these securities, and therefore, greater commonality in liquidity.

At the same time, we should keep in mind that more than 80% of the daily trading activity takes place on exchanges that allow investors to buy and sell ETF shares without actually trading the underlying bonds.[3] This may mitigate the need for the creation and redemption of ETF shares in the primary market. In addition, given their dual role as bond market makers and ETF arbitrageurs (Pan and Zeng, 2019), APs may use their own bond inventory for arbitrage, instead of buying or selling the basket of bonds in the secondary bond market. Such a strategy may cushion the correlated liquidity demand for underlying securities. Therefore, a priori, it is not obvious whether ETFs give rise to commonality in liquidity among the underlying bonds.

It is also not clear whether mutual funds increase commonality in liquidity. Similar to their equity counterparts, bond mutual funds face liquidity shocks in the form of inflows and outflows, which are typically highly correlated across funds. However, unlike equity funds, bond funds tend

[3]See the 2020 Investment Company Fact Book https://www.ici.org/pdf/2020_factbook.pdf

to have higher sensitivity of outflows to bad performance when the overall market illiquidity is high (Goldstein, Jiang, and Ng, 2017). Therefore, in times of stress, bond mutual funds may face larger outflows than equity funds since, for the latter, outflows are not so sensitive to bad performance as inflows are sensitive to good performance. Furthermore, the level of institutional herding in corporate bonds is substantially higher than what is documented for equities, especially on the sell side (Cai, Han, Li, and Li, 2019).

On the one hand, illiquidity combined with the open-ended structure of bond mutual funds can trigger correlated liquidity demand, which may result in excess co-movement in liquidity among bonds, similar to the effect of mutual funds on equities (Koch, Ruenzi, and Starks, 2016). On the other hand, Choi, Hoseinzade, Shin, and Tehranian (2020) find that redemptions from bond mutual funds and the resulting sell-offs do not lead to asset fire sales since bond funds buffer cash against investor redemptions and trade securities selectively to minimize liquidation costs.[4] Such precautionary measures are expected to decrease the correlated demand from funds, which may mitigate the effect of mutual funds on the commonality in liquidity of corporate bonds.

I investigate the effect of ETF, mutual fund, and index fund ownership on the commonality in liquidity of corporate bonds using a two-step process methodology similar to the equity studies (Kamara, Lou, and Sadka, 2008; Koch, Ruenzi, and Starks, 2016; Agarwal, Hanouna, Moussawi, and Stahel, 2018). First, 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 high ETF ownership, high mutual fund ownership, and high index fund ownership, respectively. In the second stage, I relate the commonality measure of each bond to its ETF, mutual fund, and index fund ownership. As individual fund trades are unobservable within a quarter, the analysis employs quarterly institutional ownership at the bond level as a proxy for institutional trading. The underlying assumption is that, if a bond is held more by a group of institutions, it is also traded more by those institutions. As an alternative to the two-step approach, I adapt the methodology in Anton and Polk (2014) to examine the relationship between common fund ownership and co-movements in liquidity on the bond-pair level. However, this approach ignores the correlated liquidity shocks of different funds that own different bonds. As

[4]The literature has found that the opposite is true for equity funds (Coval and Stafford, 2007) showing that funds experiencing large outflows tend to decrease existing positions, which creates price pressure in the securities held in common by distressed funds.

co-movement in liquidity is expected even without the existence of common ownership (Greenwood and Thesmar, 2011), I consider this approach as complementary.

I start my empirical analysis by testing the effect of ETF ownership on liquidity commonality. I show that there is a significant relationship between ETF ownership and liquidity commonality of investment-grade corporate bonds. The relation between ETF ownership and liquidity commonality is distinct from mutual fund and index fund ownership. I obtain similar results when I analyze the relation between common ETF ownership and co-movements in liquidity on the bond-pair level. The findings for the impact of ETF ownership on investment-grade corporate bonds are parallel with the results in Agarwal et al. (2018), who find that ETF ownership significantly increases commonality in liquidity of equities. Contrary to my results for investment-grade bonds, I find that ETF ownership does not generate commonality in liquidity for high-yield corporate bonds. This difference is consistent with the evidence that changes in high-yield bond prices are more often due to changes in firm-specific factors (Schultz, 2001).

Next, I corroborate the hypothesis of a causal relation between ETF ownership and commonality in liquidity. I use the Bloomberg indices rule change, identified by Dathan and Davydenko (2018), as a quasi-natural experiment. On April 1, 2017, Bloomberg, the leading provider of corporate bond indices, increased the investment-grade index size threshold. Therefore, bonds with an amount outstanding less than the new threshold exited the index. Exiting bonds experienced an exogenous decrease in ownership by ETFs tracking Bloomberg indices, and a decline in common ETF ownership at the bond-pair level as well. I show that the liquidity of a bond exiting ETF portfolios co-moves less with the liquidity of other bonds after the index rule change. The results provide evidence that ETF ownership drives the co-movement in liquidity, instead of ETFs' selecting bonds with higher liquidity commonality in their portfolios.

In contrast to the impact of ETF ownership on investment-grade bonds, I find that active mutual fund or index fund ownership does not increase commonality in liquidity of investment-grade or high-yield bonds. The results for the effect of mutual funds are surprising and contrasting with the effect of equity mutual funds on the commonality in liquidity of stocks (Koch, Ruenzi, and Starks, 2016). To establish a causal relationship between mutual fund ownership and liquidity commonality, I use Bill Gross' abrupt resignation from the CIO post of PIMCO as an exogenous source of variation in the flows to PIMCO's bond funds, similar to Zhu (2018). This is a shock to fund flows that affects only a specific management company, thus resulting in cross-sectional variation in ownership that exists for reasons plausibly unrelated to future commonality in liquidity.[5] The event triggered large redemptions from all PIMCO funds. I find that bonds initially owned to a high degree by PIMCO funds experienced significant drops in mutual fund ownership relative to those bonds overweighted by other similar funds. However, results from my difference-in-differences framework show that despite an exogenous reduction in their mutual fund ownership, treated bonds do not experience a decline in their commonality measures.

Next, I investigate the channels that explain the differential impact of ETFs and mutual funds on the commonality in liquidity of underlying bonds. First, I focus on the effect of flow-driven correlated trading on liquidity betas as fund flows can lead to buying or selling pressure on bonds. I define bond-level flows as the weighted average of the quarterly flows in the ETFs and mutual funds that own the bond. I document that, during ETF outflow quarters, bonds have a higher liquidity beta. However, mutual fund flows do not increase commonality in liquidity of underlying bonds in outflow periods.

The differential impact of flow-induced correlated trading on different fund types finds an explanation in active mutual funds' having more discretion in their response to investor flows, compared to ETFs. As mutual funds buffer cash against investor redemptions (Chernenko and Sunderam, 2020) and trade securities selectively to minimize liquidation costs (Jiang, Li, and Wang, 2020), such precautionary measures mitigate the correlated trading of mutual funds during outflow quarters (Choi et al., 2020). However, despite market frictions, ETFs proportionally scale their bond holdings in case of outflows (Dannhauser and Hoseinzade, 2019), which exerts correlated liquidity demand on underlying bonds. In principle, ETFs might be more comparable to index funds. Yet, index fund managers can also exercise some discretion in rebalancing their portfolios in response to changes in the benchmark index as bond index funds have large allocations in liquid securities.

Another type of correlated trading is voluntary trading, as funds may trade on the same information or follow similar investment strategies, giving rise to co-movement in liquidity among securities (Koch, Ruenzi, and Starks, 2016). Voluntary correlated trading is not valid for ETFs as they exactly replicate indices. Since active mutual funds have discretion in tracking their bench-

[5] Pacific Investment Management Company (PIMCO) was the largest fixed-income asset manager in the U.S. when Bill Gross resigned on September 26th, 2014.

marks, they may exert buying or selling pressure on underlying bonds in line with the herding behavior documented for corporate bonds (Cai et al., 2019). To investigate the effect of voluntary fund trading on liquidity commonality, I incorporate mutual funds' turnover ratios into the mutual fund ownership measure. I document that, although the magnitude of the effect on liquidity betas is higher than that of the base ownership measure, the effect of voluntary correlated trading is not statistically significant.

Second, I test whether ETFs attract investors with greater liquidity demands than mutual funds since ETFs trade on an exchange continuously and provide intraday liquidity, whereas mutual funds can be traded only at the end of day NAV. My empirical results confirm the findings in Dannhauser and Hoseinzade (2019) that the flow volatility of ETFs is greater than that of mutual funds. As ETFs translate investor flows directly into underlying bonds by creating and redeeming ETF shares, the high-turnover clientele can expose underlying bonds to new liquidity shocks via arbitrage mechanism (Ben-David, Franzoni, and Moussawi, 2018).

As a third channel explaining the commonality in liquidity and ETF ownership, I investigate the ETF arbitrage mechanism, which differentiates ETFs from their open-end fund counterparts. Correlated demand of the constituent securities in the ETF basket can lead to simultaneous price impact, exacerbating the commonality in liquidity in these securities (Agarwal et al., 2018). To measure the arbitrage activity of ETFs, I employ different proxies such as the deviation between the ETF prices and the NAV of underlying securities, and APs' creation and redemption activities in an ETF. I show that bonds that are owned by high-arbitrage ETFs have higher commonality in liquidity compared to bonds that are held by ETFs with lower arbitrage activity. This finding suggests that the arbitrage mechanism increases the commonality in liquidity among constituent bonds.

1.1 Related Literature

The paper contributes to several 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 supply-side and demand-side sources (Karolyi, Lee, and Van Dijk, 2012). On the supply side, Goldberg and Nozawa (2020) show that liquidity supply shocks are correlated with proxies for dealer financial constraints and lead to persistent changes in corporate bond market liquidity. In addition, Bao, O'Hara, and Zhou (2018) provide evidence that the illiquidity of stressed bonds has increased after the Volcker Rule as the affected dealers curtailed their liquidity supply. My paper contributes to the literature by being the first study to examine the impact demand-side sources on the commonality in liquidity of underlying bonds. Existing studies on the demand-side sources of liquidity commonality have focused on equity markets. Higher mutual fund ownership (Koch, Ruenzi, and Starks, 2016) and ETF ownership (Agarwal et al., 2018) of a stock significantly increase its commonality in liquidity. My results show that there is a significant relationship between ETF ownership and liquidity commonality of investment-grade corporate bonds. However, unlike for equities, mutual fund ownership does not increase commonality in liquidity of corporate bonds.

Second, my paper adds to the literature regarding the effects of mutual fund ownership on corporate bond markets. Cai et al. (2019) examine the extent to which institutional investors herd in the U.S. corporate bond market and the price impact of their herding behavior. Choi et al. (2020) find that bond fund redemptions do not drive fire sale price pressure as they maintain significant liquidity cushions and selectively trade liquid assets, allowing them to absorb investor redemption risk. Jiang, Li, and Wang (2020) show that during tranquil market conditions, bond funds tend to reduce liquid asset holdings such as cash and government bonds to meet investor redemptions. As I provide evidence that flow-driven or voluntary correlated trading of mutual funds does not induce co-movement in liquidity on underlying securities, my paper supports the findings in Choi et al. (2020) and Jiang, Li, and Wang (2020).

Third, my study is closely related to the literature focusing on ETFs. So far, research has found that equity ETFs increase the non-fundamental volatility (Malamud, 2016; Ben-David, Franzoni, and Moussawi, 2018) and increase the co-movement in returns (Da and Shive, 2018) of the underlying stocks they invest in. However, there is no consensus in the literature on the impact of ETFs on the level of liquidity of their underlying securities.[6] In this paper, I examine the impact of fixed-income ETFs on the commonality in liquidity of the underlying bonds in the ETF basket, rather than the level of liquidity. My results contribute to the recent work showing that information linkages and liquidity mismatches between the ETF and the constituent securities can increase market fragility (Bhattacharya and O'Hara, 2018; Dannhauser and Hoseinzade, 2019; Pan

[6]See (Hamm, 2014; Dannhauser, 2017; Israeli, Lee, and Sridharan, 2017; Holden and Nam, 2019; Saglam, Tuzun, and Wermers, 2019; Marta, 2020)

and Zeng, 2019).

The rest of the paper is organized as follows. Section 2 presents the data and methodology. Section 3 provide empirical results on the relation between institutional ownership and commonality in liquidity. Section 4 establishes a causal relationship between fund ownership and liquidity commonality. Section 5 explores the underlying channels that explain differential impact of ETFs and mutual funds. Section 6 concludes the paper.

2 Data and Methodology

2.1 Data Description

2.1.1 Corporate Bond Data

For the data on bond transactions, I use the enhanced version of FINRA's TRACE (Trade Reporting and Compliance Engine) database for the sample period January 2011 to June 2019. TRACE dataset offers over-the-counter (OTC) secondary market transactions of corporate bonds with intraday observations on price, trading volume, and buy and sell indicators. Following the steps in Bai, Bali, and Wen (2019), I filter the intraday data by: (i) removing canceled transactions and adjust records that are corrected or reversed later (Dick-Nielsen, 2009), (ii) using the median and reversal filters introduced by Edwards, Harris, and Piwowar (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 \$1,000.

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

[7] This rule is applied to all 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.

2.1.2 Mutual Fund and ETF Data

My sample consists of U.S. corporate bond ETFs and corporate bond mutual funds from 2010 Q4 through 2019 Q2. Quarterly holdings and fund characteristics data are obtained from the Center for Research in Security Prices (CRSP) survivorship-bias-free mutual fund database.[8] Throughout the study, I consider the implications of ETFs and mutual funds on the investment-grade and high-yield bonds separately to account for differences in the two subclasses.

I classify active mutual funds as corporate bond funds when the Lipper objective code is A, BBB, HY, SII, SID, or IID, or the CRSP objective code starts with 'C'. I exclude index funds, exchange-traded funds, and exchange-traded notes from the sample of active mutual funds, following Choi et al. (2020). Fund total net assets (TNAs) should be at least \$1M and have at least one year of reported holdings. I also require that funds invest at least 20% of their total assets in corporate bonds in the previous quarter. The final sample of active mutual funds includes 935 unique investment-grade and 285 high-yield corporate bond mutual funds. Additionally, I identify index funds investing in investment-grade bonds using both the index fund flag and the fund names in the CRSP Mutual Fund Database. There exist 57 distinct investment-grade index funds in my sample.[9]

Corporate bond ETFs are identified using CRSP Mutual Fund Database summary dataset and the ETF database website. My sample of corporate bond ETFs consists of 70 investment grade and 62 high yield ETFs. Both investment-grade and high-yield segments are highly concentrated. For instance, the top 5 investment-grade ETFs hold 70% of the assets under management of all investment grade ETFs in my sample.

To obtain quarterly bond-level measures of aggregate ETF and mutual fund ownership, I use March, June, September, and December as quarter end dates, and I carry forward each fund's quarterly holdings for 2 months. Then, following the literature, I carry holdings forward an additional quarter if the fund appears to have missed a report date. To handle the special 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 compute

[8] Starting from 2010 Q4, 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. Therefore, I include those in my high-yield mutual funds sample.

the proportional holdings in each bond attributable to the ETF share class.

2.2 Variable Definitions

I create a bond-level proxy for the likelihood of correlated trading based on the percentage of bonds' amount outstanding held by ETFs, active mutual funds, and index funds. The fraction of ownership $ETFOWN_{i,q}$ in bond i by J ETFs at the end of quarter q is

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

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. I update the amount outstanding information for each bond at each quarter using FISD Amount Outstanding File. Similarly, I compute active mutual fund ownership ($MFOWN_{i,q}$) and index fund ownership ($INDFOWN_{i,q}$) separately.

I also employ a turnover-weighted measure of active mutual fund ownership, as in Koch, Ruenzi, and Starks (2016). I weight fund ownership with turnover and then sum weighted ownership across funds,

$$TWMFOWN_{i,q} = \frac{\sum_{j=1}^{J}(turnover_{j,q} \times parval_{i,j,q})}{amtout_{i,q}},$$

where $turnover_{j,q}$ is the turnover (corrected for flow-induced trading) as reported by CRSP for fund j in quarter q.

I use Amihud (2002) illiquidity measure to capture daily bond illiquidity. It relates the price impact of trades, i.e., the price change measured as a return, to the trade volume measured in million dollars. The measure is defined as

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

where $R_{i,d}$ is the daily corporate bond return and $DolVol_{i,d}$ is the million dollar trading volume on day d. I calculate the daily clean price as the trading volume-weighted average of intraday transaction prices to minimize the effect of bid-ask spreads, following Bessembinder et al. (2009) and Dick-Nielsen, Feldhütter, and Lando (2012), and compute the daily corporate bond return accordingly. Since corporate bonds are not as liquid as stocks, some bonds may have no transactions on a given day. In calculating $R_{i,d}$ using daily data, I also consider price changes over multiple days if a bond does not have a transaction on the previous trade day.[10]

In my robustness tests, I employ the bid-ask spread estimator of Corwin and Schultz (2012), which is derived from daily high and low prices. They argue that daily high prices are likely to result from buy orders and low prices correspond to sell orders. Therefore, the ratio between the two reflects both the security's variance and the bid-ask spread. To separate these two components, the authors employ the high-low ratio on consecutive days. The variance component should be proportional to time, whereas the bid-ask spread should be constant.

I also use the quarterly mean of the daily Amihud illiquidity measure as a control variable ($Amihud_{i,q}$) to take into account the potential effect of the bond liquidity level on commonality. $MktVal_{i,q}$ is the log market value of a bond at the end of a quarter. I collect the bond-level rating information from Mergent FISD historical ratings and build the control variable $Rating_{i,q}$. All ratings are assigned a number, e.g. 1 refers to a AAA rating, 2 refers to AA+, . . . , and 21 refers to CCC. High-yield bonds have ratings greater than 10 and a larger number indicates a lower credit quality. I determine a bond's rating as the average of ratings provided by S&P, Moody's and Fitch. The yield spread ($Spread_{i,q}$) of a bond is calculated as the quarterly volume-weighted yield over the maturity-matched risk-free proxy. $Maturity_{i,q}$ is the years to maturity of a given bond.

2.3 Summary Statistics

Panel A of Table 1 reports the sample statistics for investment-grade bonds. The sample covers the period starting from 2011 Q1 until 2019 Q2. 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. I have 8,136 distinct bonds and 1,310 distinct issuers in my investment-grade sample. The median bond has amount outstanding of \$930 millions. On average, 1.44% of the bond par value is held by ETFs, 6.24% by mutual funds, and 2.01% by index funds.

Panel B of Table 1 shows the summary statistics for the high-yield bonds segment. The final sample has 32,648 bond-quarter observations. The high-yield sample consists of 2,613 distinct bonds and 949 distinct issuers. The median high-yield bond has amount outstanding of \$665 million. On average, 16.95% of the bond par value is held by mutual funds and 2.11% is held by ETFs, which

[10] 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.

implies that mutual fund and ETF ownership percentage is higher for high-yield bonds than the investment-grade bonds in the sample.

For comparison, He, Khorrami, and Song (2020) study the commonality in credit spread changes and they have a total of 1,980 distinct investment-grade bonds issued by 383 firms and 900 distinct high-yield bonds issued by 373 firms, with a total of 55,938 observations at the bond-quarter level for the sample period 2005Q1 - 2015Q2.

2.4 Commonality in Liquidity Measure

I construct the commonality in liquidity measure based on the approach used in equity studies. Coughenour and Saad (2004) study how a stock's liquidity co-moves with the liquidity of other stocks handled by the same specialist firm. Kamara, Lou, and Sadka (2008) document that the increase in commonality in liquidity can be attributed to the increasing importance of institutional and index-related trading for these stocks. The co-movement in liquidity of stocks driven by mutual fund ownership, and ETF ownership is studied in Koch, Ruenzi, and Starks (2016) and Agarwal et al. (2018), respectively. The idea behind their commonality measure is that the more a security is owned by a group of institutions, the more its changes in liquidity should co-move with those of other securities that also have high ownership by that group. My measure follows the same intuition with the focus being on corporate bonds instead of stocks.

Following the literature, I employ the Amihud (2002) measure as a proxy for illiquidity. Moreover, consistent with prior studies, I focus on changes as opposed to levels to reduce potential econometric issues such as non-stationarity (Chordia, Roll, and Subrahmanyam, 2000; Karolyi, Lee, and Van Dijk, 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 illiqudity for all the corporate bonds in my sample that have at least 20 observations in a quarter.[11] Koch, Ruenzi, and Starks (2016) keep only the stocks that trade on consecutive

[11] Koch, Ruenzi, and Starks (2016) drop those stocks that have less than 40 days of observations in a quarter. My

days. As many bonds have no transactions at the daily frequency, such a restriction in the corporate bond setting would imply dropping many bonds from the sample. Instead, I limit the difference in days to 5 days though this criteria rarely binds due to my sample selection criteria of requiring a bond to trade on at least 20 days in a quarter.

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, and a market portfolio. Thus, for each trading day in the quarter, I compute changes in the value-weighted illiquidity of 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 amount outstanding of bonds as weights. The daily change in illiquidity of bond i is depicted as $\Delta illiq_{i,q,d}$.

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

$$
\begin{aligned}
\Delta illiq_{i,q,d} = \alpha_2 &+ \beta^{-1}_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d-1} + \beta_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d} \\
&+ \beta^{+1}_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d+1} + \beta^{-1}_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d-1} \\
&+ \beta_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d+1} \\
&+ \beta^{-1}_{mret-ETFreg,i,q}R_{m,q,d-1} + \beta_{mret-ETFreg,i,q}R_{m,q,d} + \beta^{+1}_{mret-ETFreg,i,q}R_{m,q,d+1} \\
&+ \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{2,i,q,d}, \quad (2)
\end{aligned}
$$

and regression (3) for mutual fund ownership

results are robust against requiring a minimum of 15 or 30 observations in a quarter.

$$
\begin{aligned}
\Delta illiq_{i,q,d} = \alpha_1 &+ \beta^{-1}_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d-1} + \beta_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d} \\
&+ \beta^{+1}_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d+1} + \beta^{-1}_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d-1} \\
&+ \beta_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d+1} \\
&+ \beta^{-1}_{mret-MFreg,i,q}R_{m,q,d-1} + \beta_{mret-MFreg,i,q}R_{m,q,d} + \beta^{+1}_{mret-MFreg,i,q}R_{m,q,d+1} \\
&+ \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{1,i,q,d}, \quad (3)
\end{aligned}
$$

and finally, regression (4) for index fund ownership

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

For 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). 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, following the previous studies on equities.

Table 3 presents sample statistics on the market, high mutual fund ownership, and high ETF ownership portfolios used in the time-series regressions, as well as coefficients of interest from the regressions. In Panel A, averages of the quarterly statistics for 1-year periods are reported for investment-grade bonds, whereas Panel B reports the same statistics for high-yield bonds. The yearly averages of β_{HI_ETF}, β_{HI_MF}, and β_{HI_INDF} are positive in every year. The yearly averages of liquidity betas on the market portfolios from ETF regressions, $\beta_{MKT-ETFreg}$, are also positive in every year. The table also reports the number of bonds in the market portfolio. On average, there are 3,244 investment-grade bonds and 914 high-yield bonds in a quarter that have liquidity betas computed.

3 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.

3.1 ETF ownership and commonality in liquidity

If ETFs increase the commonality of liquidity of the underlying basket of securities they hold, then, a security that has higher levels of ETF ownership should exhibit higher commonality in liquidity. As an initial test, I sort individual bonds into quartile portfolios each quarter by the ETF ownership in the previous quarter and report the results in Table 4.

Investment-grade bonds: The left side of Panel A shows the results for investment-grade bonds. The lowest ETF ownership quartile has an average β_{HI_ETF} of 0.08 compared to the top ownership quartile's beta of 0.31. The difference is economically and statistically significant providing evidence that the liquidity of bonds with higher ETF ownership co-moves.

Next, I run OLS regressions of the commonality in liquidity measure (β_{HI_ETF}) on lagged ETF ownership ($ETFOWN$), controlling for the log market value of the bond ($MktVal$), its average illiquidity ($AMIHUD$) in the previous quarter, numerical rating ($Rating$), years to maturity ($Maturity$), and yield spread ($Spread$). The control for average illiquidity aim to address the concern that bond liquidity characteristics determine both commonality and their selection into mutual fund portfolios and ETF baskets. In addition, I use combinations of bond, issuer and time (quarter-year) for adding fixed effects to the models and clustering the standard errors. I use issuer-fixed effects to address changes in the fundamental risk of a firm.

I try to discern whether the relation between β_{HI_ETF} and $ETFOWN$ is a result of ETF ownership or other institutional ownership. Therefore, I add mutual fund ($MFOWN$) and index ownership ($INDFOWN$), which happen to be correlated with ETF ownership (see Table 2), to explanatory variables. Each ownership variable is standardized prior to their inclusion in the model by demeaning the cross-sectional mean and dividing by the standard deviation.[12] The

[12]In untabulated tests, I also employ unstandardized ownership instead of standardized. The results are qualitatively similar.

comprehensive specification is 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 5. Model 1 includes only time-fixed effects and standard errors are clustered by time. I find that bonds with high ETF ownership exhibit stronger co-movement, evidenced by the significant coefficient estimate of 0.071 for the effect of $ETFOWN$. Since this regression includes time-fixed effects, the higher β_{HI_ETF} cannot be caused by the common time trend in ETF ownership levels and liquidity co-movements. In Model 2, standard errors are double-clustered at the bond and quarter levels. Again, the coefficient on ETF ownership is positive and highly significant.

In the third specification, I include both time-fixed and bond-fixed effects and cluster standard errors by bond and time, and obtain similar results. Model 4 controls for the ownership by mutual funds and index funds and also control for $Amihud$ and $MktVal$ which are the main explanatory variables for liquidity commonality in the equity literature. The effect of ETF ownership remains statistically significant with a higher economic magnitude. In contrast, there is a negative relation between mutual fund ownership and β_{HI_ETF}.

In Model 5, I include $Rating$, $Maturity$ and $Spread$ as control variables since these bond-specific variables that have an effect on liquidity are natural candidates to predict liquidity commonality. Since I use standardized measures of ownership, the results imply that a one standard deviation in ETF ownership (1.27%, see Table 1) is associated with a 8.10% increase in the commonality in liquidity, which is economically and statistically significant. Model 6 adds issuer-fixed effects instead of bond-fixed effects and standard errors are double-clustered by issuer and time. The coefficient on $ETFOWN$ is still statistically significant. Model 7 and 8 run Fama and MacBeth (1973) regressions and I have qualitatively similar results with the panel regressions.

Next, I run the same analysis for different periods of time. In each model, I interact institutional ownership variables with subperiod dummies for 2011–2013, 2014–2016, and 2017–2019. The results are reported in Appendix Table A1. Model 1 reports the results for ETF ownership. For the 2011–2013 period, the coefficient on $ETFOWN$ is positive, but not statistically significant. This result is indeed expected since the bond ownership by ETFs is low in the first years of the sample period.

However, the effect becomes economically and statistically significant in the 2014–2016 and 2017–2019 periods.

To assess whether my analysis is robust to alternative measures of bond liquidity, I repeat the analysis using bid-ask spreads instead of Amihud (2002) measure.[13] My results reported in Appendix Table A2 are qualitatively similar to the findings in Panel A of Table 5.

High-yield bonds: The results for portfolio sorts by ETF ownership are shown in the left side of Panel B of Table 4 for high-yield bonds. The difference of average β_{HI_ETF} between the top and bottom quartiles is 0.06 and statistically significant. The results of the regression (5) for high-yield bonds are presented in Panel A of Table 6. The models (1)-(8) are built the same way as explained above for investment-grade tests. Although, the coefficent for $ETFOWN$ is positive in all models, the effect is not statistically significant in any of the models. Specfically, in Model 5, when I add bond-fixed and time-fixed effects and double cluster standard errors by firm and time, ETF ownership does not explain the liquidity beta significantly for high-yield bonds. The results are in line with the view that changes in high-yield bond prices are more often due to changes in firm-specific factors (Schultz, 2001).

3.2 Mutual fund ownership and commonality in liquidity

I investigate the relationship between mutual fund ownership and commonality in liquidity of corporate bonds by running the following regression

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

Investment-grade bonds: The results for investment-grade bonds are presented in Panel B of Table 5. Models 1 and 2 in the table include time-fixed effects. The coefficient estimate on $MFOWN$ is positive and statistically significant in these specifications. However, after adding bond-fixed effects or issuer-fixed effects to the models, I find that that mutual fund ownership does not explain β_{HI_MF}. The results for mutual fund ownership are surprising and contrasting with the effect of mutual funds on the commonality in liquidity of stocks (Koch, Ruenzi, and Starks,

[13] I compute the bid-ask spreads derived from daily high and low prices using the methodology in Corwin and Schultz (2012)

2016).

High-yield bonds: The results for high-yield bonds are presented in Panel B of Table 6. The coefficient estimate on $MFOWN$ is not statistically significant in any specifications. Therefore, I find that mutual fund ownership does not explain β_{HI_MF} also for high-yield bonds.

3.3 Index fund ownership and commonality in liquidity

I investigate the relationship between index fund ownership and commonality in liquidity of corporate bonds by running the following regression

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

Investment-grade bonds: The results for investment-grade bonds are presented in Panel C of Table 5. In any of the eight models, I don't have a significant relation between index fund ownership ($INDFOWN$) and commonality in liquidity.

3.4 Common Ownership and Pairwise Correlation in Liquidity

In the previous sections, I test whether institutional ownership results in commonality in liquidity of corporate bonds using a two-step procedure to estimate liquidity betas. In this section I adapt the methodology in Anton and Polk (2014) to examine the relation between common ownership and co-movements in liquidity on the bond-pair level, in line with Agarwal et al. (2018).

Pairwise correlation methodology has the advantage of not requiring a specific model to estimate the commonality in liquidity. However, this approach ignores the correlated liquidity shocks of different funds that own different bonds. For the equity market, Greenwood and Thesmar (2011) find that co-movement in returns is expected even without the existence of common ownership. Hence, I consider this approach as complementary to the previous two-step approach. In order to establish a causal relation between institutional ownership and liquidity commonality of corporate bonds, I continue to use the two-step approach in the subsequent sections.

To implement this complementary approach, I estimate the pairwise correlation $\rho_{ij,q}$ between the log daily change in the Amihud illiquidity of bond i and bond j over each quarter q. Using this proxy for co-movements in liquidity as the dependent variable, I examine its relation with the common institutional ownership by different types of funds. For ETFs, I compute the common ownership measure $ETFCOMOWN_{ij,q}$ as the total par value held by F common ETFs, scaled by the sum of amount outstanding of the two bonds.

$$ETFCOMOWNij, q = \frac{\sum_{f=1}^{F} parval_{i,f,q} + parval_{j,f,q}}{amtout_{i,q} + amtout_{j,q}} \tag{8}$$

Similarly, I compute $MFCOMOWN$ and $INDFCOMOWN$ for the common ownership by active mutual funds and index mutual funds, respectively. I investigate the relationship between fund ownership and pairwise correlation in liquidity of corporate bonds by running the following regression

$$\rho_{ij,q} = \lambda_0 + \lambda_1 ETFCOMOWN_{ij,q-1} + \lambda_2 MFCOMOWN_{ij,q-1} + \lambda_3 INDFCOMOWN_{ij,q-1} + \epsilon_{ij,q}. \tag{9}$$

In Table 7, I report the estimation results of equation (9) by adding bond-quarter fixed effects for both bonds i and j to control for unobservable time-varying characteristics of each bond in the pair that can affect the pairwise correlation of changes in liquidity. In addition, I triple-cluster the standard errors at the quarter, bond i, and bond j level.

First, I investigate the effect of common ownership separately for each institution type in my sample. In Model 1, I find a positive and significant coefficient of 0.028 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 reports the individual effect of common active mutual fund ownership on the commonality in liquidity. The coefficient 0.015 is statistically significant with a t-stat of 6.73. 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 effect of common ownership by ETFs, active mutual funds and index funds. Although the coefficient for $ETFCOMOWN$ and $MFCOMOWN$ remain positive and statistically significant, I find that the common ownership of index funds do not explain the co-movement in liquidity significantly.

4 Causal Relationship between Institutional Ownership and Commonality in Liquidity of Investment-grade Bonds

Taken together, the results show that there is a significant correlation between ETF ownership and liquidity commonality for investment-grade corporate bonds. The relation between ETF ownership and liquidity commonality is distinct from active mutual fund and index fund ownership. The findings for the impact of ETF ownership on investment-grade corporate bonds are parallel with the results in Agarwal et al. (2018), who find that ETF ownership significantly increases commonality in liquidity of equities. However, I don't find a similar effect for high-yield corporate bonds.

In contrast to the impact of ETF ownership on investment-grade bonds, I find that active mutual fund ownership or index fund ownership does not increase commonality in liquidity of investment-grade or high-yield bonds. The results for mutual fund ownership are surprising and contrasting with the effect of mutual funds on the commonality in liquidity of stocks (Koch, Ruenzi, and Starks, 2016).

However, there is the possibility that investment managers prefer bonds with certain time-varying characteristics that are correlated with co-movements in liquidity and panel regressions may not completely control for endogeneity. To address such endogeneity issues, I employ different identification strategies for ETF and active mutual fund ownership.

4.1 ETF Ownership

To further corroborate the results in OLS regressions for the ETF ownership and commonality in liquidity, I exploit the quasi-natural experiment identified by Dathan and Davydenko (2018).[14] On January 24, 2017, Bloomberg, the leading provider of corporate bond indices, anounced that the minimum amount outstanding for corporate securities in the U.S. Aggregate Index would be raised from $250 million to $300 million, effective April 1, 2017. Therefore, bonds that have amount outstanding less than the new threshold exited the ETFs tracking Bloomberg indices. The rule change provides an ideal experiment to exploit the exogenous decline in ETF ownership, and that in

[14] The experiment is also used by Marta (2020) to examine the impact of ETFs on the liquidity level of corporate bonds.

common ETF ownership among bond pairs, to establish a causal relation between ETF ownership and commonality in liquidity of bonds.

If common ETF ownership drives the co-movement in liquidity, then, the liquidity of a bond exiting ETF portfolios is expected to co-move less with the liquidity of other bonds. To test this hypothesis, I first identify the treatment and control group bonds. The treatment group includes the bonds with an amount outstanding between \$250 to \$299 million and having positive Bloomberg index ETF ownership before the rule change.[15] The selection process yields 65 treatment bonds. My control group candidates include bonds with an amount outstanding above \$300 million. To avoid selection bias, following Dannhauser (2017) and Marta (2020), I use propensity score matching to select control bonds similar to treatment bonds. Using data from 2016 Q4 for bond characteristics, I run the following logit regression:

$$Treat_i = \alpha + \beta_1 Amihud_i + \beta_2 Rating + \beta_3 Maturity + \beta_4 Spread, \tag{10}$$

where the indicator variable $Treat_i$ takes the value of 1 for treated bonds. Next, treatment bonds are matched with their five and ten nearest neighbors based on the p-scores computed. I require the treatment and control bonds to be present in the sample for at least two months both in the pre-event periods (before 2016 Q4) and post-event (after 2017 Q2) periods.

To test my hypothesis, I regress the pairwise correlation of changes in Amihud (2002) liquidity of two bonds i and j on an indicator variable, $SWITCH_{ij,q}$, determining the drop of at least one of the bonds in the pair from Bloomberg indices. Formally, the variable $SWITCH_{ij,q}$ is defined as:

$$SWITCH_{ij,q} = \begin{cases} 1, & Treat_i = 1 \,\&\, Treat_j = 1 \,\&\, q \text{ is a post-event quarter} \\ 1, & Treat_i = 1 \,\&\, Treat_j = 0 \,\&\, q \text{ is a post-event quarter} \\ 1, & Treat_i = 0 \,\&\, Treat_j = 1 \,\&\, q \text{ is a post-event quarter} \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

I interact the $SWITCH$ variable with the common Bloomberg index ETF ownership $BLETFCOMOWN_{ij}$

[15]As a group of exiting bonds continue to be tracked by Bloomberg index ETFs after the effective date, I require that the Bloomberg index ETF ownership of a bond should decrease by at least 50% in the post-event period to be included in the treatment group.

measured in 2016 Q4, which determines the extent to which those two bonds are connected. The idea behind interacting these variables is that if two bonds have higher common ownership before the event, their liquidity co-movement should be affected more in the post-event period.

Specifically, I estimate the following regression over the period starting in 2015 Q1 and ending in 2019 Q1 (excluding the announcement period of 2017 Q1):

$$\begin{aligned}\rho_{ij,q} = \lambda_0 + \lambda_1 BLETFCOMOWN_{ij} + \lambda_1 BLETFCOMOWN_{ij} \times SWITCHij, q \\ + \lambda_1 MFCOMOWN_{ij} + \lambda_1 MFCOMOWN_{ij} \times SWITCHij, q \\ + \lambda_1 INDFCOMOWN_{ij} + \lambda_1 INDFCOMOWN_{ij} \times SWITCHij, q \\ + SWITCHij, q + \epsilon_{ij,q}, \quad (12)\end{aligned}$$

where $\rho_{ij,q}$ is the pairwise correlation between the change in Amihud (2002) liquidity of bond i and that of bond j estimated over each quarter q. The common ownership variables for mutual funds and index funds, $MFCOMOWN_{ij,2016}$ and $INDFCOMOWN_{ij,2016}$, are also measured in 2016 Q4. I add quarter fixed effects and bond fixed effects for both bonds i and j to control for unobservable factors that can potentially affect the correlation in the changes in liquidity of the two bonds. To determine statistical significance, I triple-cluster the standard errors at the quarter, bond i and bond j level.

Table 8 reports the results for the estimation of Equation (17). Models 1–2 report the results when I use five nearest neighbors for matching, and Models 3–4 reports the results for ten nearest neighbors. The results for Model 1 shows that when at least one of the bonds drop out from the Bloomberg indices, the coefficient on the interaction of $BLETFCOMOWN$ with the switch indicator variable, $SWITCH$, is negative and statistically significant at 5% level. This means that, after an exogenous drop in the ETF common ownership, there is a decline in the co-movement of liquidity of two bonds. In Model 2, I include the ownership variables $MFCOMOWN$ and $INDFCOMOWN$ and their interactions with $SWITCH$. The coefficients on these interaction variables are not statistically significant. However, the interaction between $BLETFCOMOWN$ and $SWITCH$ has a negative and statistically significant coefficient. Models 3 and 4 verify the results in the first two models.

Overall, my findings in this section further corroborate my hypothesis of a causal relation between ETF ownership and commonality in liquidity using the Bloomberg indices rule change as a quasi-natural experiment.

4.2 Mutual Fund Ownership

To establish a causal relationship between mutual fund ownership and commonality in liquidity of the bonds they hold, I use a shock to fund flows that affects one specific mutual fund management company, but not the other funds in my sample. This results in cross-sectional variation in ownership that exists for reasons plausibly unrelated to future commonality in liquidity. I use Bill Gross' abrupt resignation from the CIO post of the Pacific Investment Management Company (PIMCO) on September 26th, 2014 as an exogenous source of variation in the flows to PIMCO's bond funds (see Zhu, 2018, for details). PIMCO was the largest fixed-income asset manager in the U.S. when Bill Gross resigned. His departure came as a surprise to the market and triggered large redemptions from all PIMCO funds. In the 12 months following Bill Gross' departure, PIMCO lost 25% of their assets.

Consequently, bonds initially owned to a high degree by PIMCO funds may have experienced serious drops in mutual fund ownership relative to those not owned by these funds. If mutual funds give rise to commonality in liquidity, contrary to my results in panel regressions, I expect a lower subsequent common liquidity for the bonds that were held by PIMCO, as they face an exogenous reduction in their mutual fund ownership.

To examine the effects of a possible decrease in mutual fund ownership on the commonality in liquidity, I estimate a difference-in-differences regression. While selecting treatment and control groups, I require the bonds to have liquidity betas $\beta_{HI\_MF,i,q}$ at least 2 quarters in both the pre-event and the post-event periods. A bond is treated if the fraction of that bond owned by PIMCO funds is high (top quartile or decile) at the end of 2014 Q2. The control group candidates consist of bonds that are held by the Fidelity Management Company. Bonds in Fidelity's portfolio should be suitable as the counterfactual had Bill Gross not left PIMCO as the amount of sample corporate bonds are very similar in PIMCO's and Fidelity's portfolios in 2014 Q2.[16] If the fraction of a bond

[16] Considering only the corporate bonds in my sample, total par value of bonds in PIMCO's portfolio is \$6.7B, whereas it is \$6.8B for Fidelity.

owned by Fidelity funds is high (top quartile or decile) at the end of 2014 Q2, it is included in the control group.

When I use the top quartile classification, I obtain 71 bonds in the treated group and 102 bonds in the control group. In untabulated tests, I find that treated bonds and control bonds are similar in most dimensions (e.g. average rating, amount outstanding, and yield spread). I estimate the following difference-in-differences regression using observations from 2012 Q2 to 2014 Q2 before the pre-event and from 2015 Q3 to 2017 Q3 in the post-event period:

$$\beta_{HI\_MF,i,q} = \gamma_0 + \gamma_1 Treatment_i \times Post + \gamma_2 Treatment_i + \gamma_3 MFOWN_{i,2014Q2} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}. \tag{13}$$

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

With the difference–in–differences approach, I assume that the exogenous shock on ownership in 2014 Q3 is strong enough to have a significant effect on mutual fund ownership levels in the examination period after 2015 Q3. To check whether this is a reasonable assumption, in Table 9, I report results from regressions of the level of mutual fund ownership during the post period as a function of the treatment variable. The results are presented in Columns 1 and 2. The negative and significant coefficient on treatment confirms that bonds owned by PIMCO funds experienced lower levels of mutual fund ownership following the resignation of Bill Gross.

I report the regression results for Equation (13) in columns 3–6 of Table 9. Model 3 and 5 include time-fixed effects, whereas Model 4 and 6 inculude both time-fixed and bond-fixed effects. When the bonds in top ownership quartiles are treated in Models 3 and 4, I find a negative but insignicant coefficient on *treatment* $\times$ *post* indicating that bonds that had a higher ownership by PIMCO before the event do not experience a decrease in commonality in liquidity. When the top ownership decile bonds are treated, the coefficients on *treatment* $\times$ *post* are almost zero in Models 5 and 6. Overall, I find evidence that the exogenous shock on the mutual fund ownership do not affect the co-movement of liquidity in bonds supporting my findings in the previous sections.

5 Institutional Ownership and Liquidity Commonality: Underlying Channels

In the previous sections, I provide evidence that ETF ownership gives rise to commonality in liquidity among underlying bonds, whereas mutual fund or index fund ownership does not exert such an effect. While investigating the relationship between institutional ownership and commonality in liquidity, the underlying assumption is that a bond held more by a group of institutions is also traded more by that group. Further analysis is needed to identify the mechanisms through which high ETF ownership gives rise to commonality. This will also enlighten the reasons behind the differential impact of ETFs and mutual funds on the commonality in liquidity of underlying bonds.

In this section, I investigate three different channels: correlated fund trading, different investor clienteles, and ETF arbitrage mechanism.

5.1 Correlated Fund Trading

I employ two proxies for fund trading that capture different trading motivations: flow-driven (forced) correlated trading and voluntary correlated trading, similar to the methodology in Koch, Ruenzi, and Starks (2016), but with an important distinction in my study. Forced correlated trading is valid for both mutual funds and ETFs as both types face inflows and outflows from their investors, which may give rise to common buying or selling pressure. However, voluntary correlated trading is not valid for ETFs as they must unequivocally translate investor flows into either creating or redeeming ETF shares by trading in the underlying securities.

5.1.1 Flow-driven Correlated Trading of ETFs and Mutual Funds

This section focuses on the relation between flow-induced trading and commonality in liquidity of the bonds that the funds hold. Fund flows can exert buying or selling pressure. Yet, forced mutual fund buying pressure is unlikely in the corporate bond market as inflow mutual funds can purchase new bond issues instead of expanding existing bond positions. Besides, as ETF sponsors use representative sampling, they can also add new bonds to their basket. Hence, I analyze inflow and outflow periods separately as the latter are main candidates that can impact commonality in liquidity.

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

$$ETFFlows_{i,q} = \frac{\sum_{j=1}^{J} w_{i,j,q} \times Flows_{j,q}}{Volume_{i,q-1}}, \tag{14}$$

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

Table 10, Panel A, reports the OLS regressions of institutional liquidity betas on flow variables. Flow variables and liquidity betas are measured in the same quarter, i.e., regressions are not predictive. The analysis is conducted for the full sample, outflow periods, and inflow periods separately. The flow variables are standardized. All specifications include bond-fixed and quarter-fixed effects and standard errors are double-clustered by bond and quarter.

The results show that, on average, ETF flows induces commonality in liquidity. Besides, during ETF outflow quarters, bonds have a higher ETF liquidity beta. However, for inflow quarters, the magnitude of the coefficient on ETF flows is lower and not statistically significant. In addition, Models 4–6 and 7–9 show that neither ETF nor mutual fund flows drive co-movement in liquidity in any of the subperiods.

These results find an explanation in active mutual funds' having more discretion in their response to investor flows, compared to ETFs. The fire-sale literature shows that equity funds experiencing extreme outflows sell almost proportionally across holdings (Coval and Stafford, 2007), while bond funds dynamically trade off price impact against liquidity preservation (Choi et al., 2020). As bond mutual funds buffer cash against investor redemptions (Chernenko and Sunderam, 2020) and trade securities selectively to minimize liquidation costs (Jiang, Li, and Wang, 2020), such precautionary measures mitigate the correlated trading of mutual funds during outflow quarters. However, ETFs must unequivocally translate investor flows into creating or redeeming ETF shares by trading in the underlying securities. Despite market frictions, ETFs proportionally scale their bond holdings in case of outflows (Dannhauser and Hoseinzade, 2019), which exerts correlated liquidity demand on underlying bonds.

5.1.2 Voluntary Correlated Trading of Mutual Funds

In Section 4.2, I find that there is no causal relationship between mutual fund ownership and commonality in liquidity, on average. However, mutual fund ownership may give rise to commonality through voluntary correlated trading as funds may trade on the same information or follow similar investment strategies, giving rise to co-movement in liquidity among securities (Koch, Ruenzi, and Starks, 2016). Since active mutual funds have discretion in tracking their benchmarks, they may exert buying or selling pressure on underlying bonds in line with the herding behavior documented for corporate bonds (Cai et al., 2019).

As active mutual funds may trade on the same information or follow similar investment strategies, they can have correlated trades which can give rise to co-movement in liquidity among corporate bonds. To investigate the effect of voluntary fund trading, I incorporate funds' turnover ratios into the ownership measure, as in Koch, Ruenzi, and Starks (2016). The turnover ratio reported by CRSP is corrected for flow-induced trading. Hence, weighting the mutual fund ownership with turnover ratio yields a proxy for voluntary correlated trading. I estimate the following regression equation:

$$\beta_{HI\_TWMF,i,q} = \gamma_0 + \gamma_1 TWMFOWN_{i,q-1} + \gamma_2 ETFOWN_{i,q-1} + \gamma_2 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}. \tag{15}$$

where I replace the liquidity of a high mutual fund ownership portfolio with that of a high turnover-weighted mutual fund ownership portfolio. To be consistent, I also define the high mutual fund ownership portfolio based on $TWMFOWN$ and calculate the first stage $\beta_{HI\_TWMF,i,q}$ accordingly.

I report the results for the regression 15 in Panel A of Table 10. Model 1 has time-fixed and bond-fixed effects. Model 2 includes time-fixed and issuer-fixed effects, whereas Model 3 reports the results for Fama and MacBeth (1973) regressions. In all models, I find a positive but statistically insignificant coefficient for $TWMFOWN$. However, if the economic magnitude of the coefficients on $TWMFOWN$ are compared with those of $MFOWN$ in columns (5), (6), and (8) of Table 5 Panel B, the magnitudes of the former are higher suggesting that turnover-weighted ownership have a stronger effect on commonality than the unweighted mutual fund ownership.

5.2 ETFs Attracting Customers with Higher Liquidity Demand

ETFs are different from active or index mutual funds since they are traded on a secondary exchange synchronously with the underlying basket of securities they hold, thus providing intraday liquidity to their investors. However, mutual funds can be traded only at the end of day NAV. Thus, ETFs are natural candidates to attract investors with greater liquidity demands than mutual funds. Ben-David, Franzoni, and Moussawi (2018) provide evidence that ETFs attract higher turnover investors than common stocks. Dannhauser and Hoseinzade (2019) provide similar evidence for the corporate bond market, suggesting that ETFs attract higher liquidity demand investors than mutual funds and index funds. In Table 11, I confirm the findings of Dannhauser and Hoseinzade (2019) using my own sample. I investigate the relationship between the volatility of fund flows and the institution type by running the regression:

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

I run the regression Equation (20) both as cross-sectional and panel regressions. The dependent variable $FlowVol$ is the average twelve-month volatility of flows for each fund in my sample. The indicator variable ETF takes the value of one if the fund is an ETF, and zero otherwise. The explanatory variables include fund expense ratio, turnover ratio, log of total assets, log of fund age in years, and the log of fund family assets. In Table 11, the coefficient on the ETF dummy is positive and statistically significant in all specifications suggesting that the monthly volatility of ETF flows are 1.8 to 3.3 percentage points greater than mutual funds, in line with the results from Dannhauser and Hoseinzade (2019).

As ETFs translate investor flows directly into underlying bonds by creating and redeeming ETF shares, the high-turnover clientele can expose underlying bonds to new liquidity shocks via arbitrage mechanism (Ben-David, Franzoni, and Moussawi, 2018). In the next section, I hypothesize that ETF arbitrage process is a source of the relation between ETF ownership and commonality in liquidity and test the hypothesis empirically.

5.3 ETF Arbitrage Activity

As a channel explaining the relation between commonality in liquidity and ETF ownership, I explore the ETF arbitrage mechanism as a source, which differentiates ETFs from open-end mutual funds. The synchronous trading of ETFs and the underlying securities presents the opportunity for market participants to uphold the law of one price. Throughout the trading day, ETF prices are kept in line with the intrinsic value of the underlying securities through a process of arbitrage in which authorized participants (APs) and the other institutional investors participate. If the ETF price is lower (higher) than the net asset value of the basket securities, APs long (short) the ETF, short (long) the underlying bonds, and then redeem (create) ETF shares at the end of the day to unwind the intraday arbitrage positions.

Correlated demand of the underlying securities in the ETF basket can increase the commonality in liquidity in these securities. For equity ETFs, Agarwal et al. (2018) find that arbitrage mechanism contributes to increase the co-movement of liquidity among constituent stocks. As corporate bond ETFs trade on a liquid exchange, but corporate bonds are traded on illiquid over-the-counter (OTC) markets, this liquidity mismatch may even worsen the impact of ETFs on the underlying securities especially at times when liquidity is scarce in the corporate bond market.

To test my hypothesis, I follow a methodology similar to the one in Agarwal et al. (2018). Prior literature has used different proxies of arbitrage activity such as the deviation between the ETF prices and the net asset value (NAV) of underlying securities (Ben-David, Franzoni, and Moussawi, 2018). This measure of mispricing signals arbitrage profitability, which should attract more arbitrageurs to engage in closing out the mispricing. However, it's worth noting that a large deviation can also be due to the existence of limits of arbitrage.

I calculate mispricing as the sum of the absolute value of the daily difference between the ETF's end-of-the-day price and its end-of-the-day NAV (i.e., the ETF's discount or premium), aggregated over each quarter. I use the absolute value of the discount or premium because either a positive or a negative deviation from the NAV will offer opportunities for arbitrage.

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

As a second proxy of arbitrage activities, I use the standard deviation of daily mispricing values in a quarter. The fact that ETF mispricing changes over time suggests that arbitrageurs are actively exploiting it. A drawback of this measure is that the variation of mispricing can be caused by the changes in demand for ETFs relative to their underlying bonds. I calculate this measure by taking the standard deviation of the daily mispricing values over a quarter q for each fund j, and label it as $SDMISPRC_{j,q}$.

Next, I use the average and standard deviation of the creation and redemption activities in an ETF as additional proxies of arbitrage activity, $AVGABSCR$ and $SDABSCR$, as in Agarwal et al. (2018). APs use the creation and redemption processes to maintain the ETF price in line with the price of the underlying basket through the arbitrage mechanism and increase or decrease the shares outstanding of ETFs accordingly. For instance, if a an ETF faces a positive demand shock, the price of the ETF will increase and deviate from the net asset value of the underlying basket. In turn, this mispricing is reduced through the arbitrage mechanism which results in the creation of more 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. I use the absolute value of the flows because net creation or net redemption of ETF units will induce trading in the underlying securities. As a fund is receiving inflows or outflows, it will have to sell or buy the underlying securities and demand liquidity to conduct these operations. Precisely, for each fund j in quarter q, I define:

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

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 $ETFSDCR$ complement the previous two proxies related to mispricing. Contrary to mispricing which we observe at the end of the day, the ETF creation and redemption activities are the outcome of APs conducting arbitrage throughout the day. As suggested by Agarwal et al. (2018), these two proxies have a limitation that arbitrage activities conducted intraday by APs may not necessarily require them to create or redeem at the end of the day, if opposite positions are netted out. Furthermore, APs can carry forward their net short or long positions in ETFs instead of creating or redeeming ETF shares at the end of the day. These two scenarios may lead to an underestimation of the actual arbitrage activities conducted by APs.

In order to classify ETFs with respect to their arbitrage activity levels, first, I form quartiles of ownership to control for the cross-sectional variation in the fund AUMs. Then, separately for each of the four proxies, I divide the funds into quintiles based on their arbitrage activity levels within each ownership quartile. Next, for each of the four proxies, I divide the stocks into two groups, the bottom quintile (lower arbitrage activity) and the remaining (higher arbitrage activity). Finally, for each bond, I define the high-arbitrage (low-arbitrage) ETF ownership as the ratio between the par value held by high-arbitrage (low-arbitrage) ETFs and the amount outstanding of the bond. I use standardized ownership variables in the OLS regressions.

The results in Table 12 consistently show that bonds owned by high-arbitrage ETFs have higher commonality in liquidity compared to the bonds that are held by ETFs with lower arbitrage activity. For instance, Model 1 reports the results for $AVGMISPRC$ proxy. The coefficient on high-arbitrage $ETFOWN$ is 0.072 is higher than the corresponding coefficient of 0.024 for low-arbitrage $ETFOWN$. The difference of 0.048 is significant at the 1% level with an F-statistic of 16.72. Collectively, these findings suggest that the arbitrage mechanism increases the commonality in liquidity among constituent bonds.

6 Conclusion

Increasing fund ownership in the corporate bond market along with the decline in dealer capital have fretted academics and regulators that the fragility risk of the market has increased. Despite the illiquidity of the bonds in their portfolios, ETFs and mutual funds are redeemable on a daily basis. Mutual funds managers have discretion in responding to investor flows by buffering cash and trading securities selectively. However, ETFs essentially operate on autopilot by buying and selling bonds automatically to match an index, which may have unintended consequences on the underlying securities they hold.

The paper studies the effect of ETFs and mutual funds on the commonality in liquidity of underlying corporate bonds. Growing mutual fund and ETF ownership in the bond market may give rise to correlated trading across bonds. My results show that there is a significant relationship between ETF ownership and liquidity commonality of investment-grade corporate bonds. However, I find that mutual fund ownership does not increase commonality in liquidity of corporate bonds, in contrast with the findings for equities. To explain the differential impact of ETFs and mutual funds on liquidity commonality, I provide evidence for three main channels: flow-driven correlated trading of ETFs, different investor clienteles of funds, and ETF arbitrage mechanism.

ETFs have great benefits for investors such as increased access to liquidity and diversification. However, they can have unintended consequences for the securities in the ETF baskets. The paper contributes to the policy debate of widespread implications of ETFs in security markets. I show that higher ETF ownership of investment-grade corporate bonds can reduce the ability of investors to diversify liquidity risk. From the viewpoint of a fixed-income portfolio manager, this may result in facing higher transaction costs and significant impact on bond returns, and even, not being able to trade during stress times.

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Table 1: **Summary Statistics**

Table 1 reports summary statistics for selected variables. The sample consists of 108,906 investment-grade and 32,648 high-yield bond-quarter observations for the period 2011 Q1 to 2019 Q2. The liquidity betas are β_{HI_ETF}, β_{HI_MF}, and β_{HI_INDF}, which measure 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. $ETFOWN(\%)$, $MFOWN(\%)$, and $INDFOWN(\%)$ are the percent ownership in a bond held by ETFs, active mutual funds and index funds, respectively. Control variables include bond-level information on the amount outstanding in $ millions, log market value, quarterly average of daily Amihud (2002) illiquidity measure, numerical rating, years to maturity, and yield spread over the maturity-matched risk-free proxy. Pairwise correlation variables include the pairwise correlation $\rho_{ij,q}$ between the log daily change in the Amihud illiquidity of bond i and bond j over each quarter q, the common ownership measure $ETFCOMOWN_{ij,q}$ as the total par value held by common ETFs, scaled by the sum of amount outstanding of the two bonds, and common ownership measures for open-end funds, $MFCOMOWN$ and $INDFCOMOWN$, respectively. Panel A reports statistics for investment-grade bonds and Panel B include statistics for high-yield bonds.

Panel A: Investment-grade Bonds

				Percentiles				
	N	Mean	Std. Dev.	p1	p25	p50	p75	p99
Commonality in Liquidity Measures								
β_{HI_ETF}	108,906	0.20	2.69	-6.91	-1.34	0.21	1.75	7.12
β_{HI_MF}	108,906	0.12	3.19	-8.18	-1.67	0.13	1.92	8.32
β_{HI_INDF}	108,906	0.13	3.92	-9.32	-1.96	0.13	2.23	9.53
Institutional Ownership Variables								
ETFOWN (%)	108,906	1.44	1.27	0.00	0.44	1.36	2.18	4.31
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	930.00	750.13	30.75	500.00	750.00	1,150.00	3,500.00
Market Value (log)	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
Pairwise Correlation Variables								
$\rho_{\Delta liquidity}$	196,280,847	0.0114	0.2180	-0.5226	-0.1287	0.0129	0.1530	0.5337
ETFCOMOWN	196,290,133	0.0050	0.0073	0.0000	0.0000	0.0011	0.0086	0.0299
MFCOMOWN	196,290,133	0.0043	0.0109	0.0000	0.0000	0.0000	0.0029	0.0513
INDFCOMOWN	196,290,133	0.0126	0.0102	0.0000	0.0023	0.0124	0.0195	0.0395

Panel B: High-yield Bonds

				Percentiles				
	N	Mean	Std. Dev.	p1	p25	p50	p75	p99
Commonality in Liquidity Measures								
β_{HI_ETF}	32,648	0.07	1.46	-3.73	-0.75	0.07	0.91	3.77
β_{HI_MF}	32,648	0.07	1.76	-4.50	-0.91	0.07	1.05	4.65
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
Control Variables								
Amount Outstanding ($M)	32,648	664.60	525.73	46.06	350.00	500.00	800.00	2,805.00
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

Table 2: **Correlations**

Table 2 reports correlations for variables defined in Table 1. The sample consists of 108,906 investment-grade and 32,648 high-yield bond-quarter observations for the period 2011 Q1 to 2019 Q2. Panel A reports statistics for investment-grade bonds and Panel B include statistics for high-yield bonds.

Panel A: Investment-grade Bonds

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_{HI_ETF}	(1)	1.00	0.09	0.12	0.03	0.00	0.01	0.02	0.02	-0.02	0.00	-0.04	-0.03
β_{HI_MF}	(2)	0.09	1.00	0.04	0.01	0.02	0.00	0.00	0.00	-0.01	0.02	-0.03	0.00
β_{HI_INDF}	(3)	0.12	0.04	1.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	-0.01	-0.01
MFOWN (%)	(4)	0.03	0.01	0.01	1.00	0.10	0.39	0.26	0.33	-0.37	-0.11	-0.30	-0.33
ETFOWN (%)	(5)	0.00	0.02	0.01	0.10	1.00	0.09	0.10	0.13	-0.16	0.35	-0.15	0.12
INDFOWN (%)	(6)	0.01	0.00	0.01	0.39	0.09	1.00	0.11	0.22	-0.26	0.02	-0.08	-0.15
Amount Outstanding ($M)	(7)	0.02	0.00	0.00	0.26	0.10	0.11	1.00	0.78	-0.36	-0.21	0.04	-0.05
Log Market Value	(8)	0.02	0.00	0.00	0.33	0.13	0.22	0.78	1.00	-0.57	-0.15	0.01	-0.13
Quarterly Illiquidity (mean)	(9)	-0.02	-0.01	0.00	-0.37	-0.16	-0.26	-0.36	-0.57	1.00	0.07	0.21	0.31
Rating	(10)	0.00	0.02	0.00	-0.11	0.35	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	-0.30	-0.15	-0.08	0.04	0.01	0.21	0.05	1.00	0.41
Spread (%)	(12)	-0.03	0.00	-0.01	-0.33	0.12	-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)
β_{HI_ETF}	(13)	1.00	0.13	0.02	0.01	0.02	0.02	-0.01	-0.01	-0.01	0.00
β_{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 3: **Summary for the Time Series Estimates of Commonality Measures**

Table 3 reports the yearly averages of liquidity betas computed for each bond in each quarter. For bond i in quarter q, I estimate the following regression:

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

where $\Delta illiq_{i,q,d}$ is the change in bond i's illiquidity on day d. For each day d in a quarter q, I compute changes in the value-weighted illiquidity of two portfolios: (i) a market portfolio including all the bonds that have at least one transaction on that day, $\Delta illiq_{MKT,q,d}$, and (ii) 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, $\Delta illiq_{ETFOWN,q,d}$. Similarly, I estimate regressions to compute $\beta_{HI\_MF,i,q}$ and $\beta_{HI\_INDF,i,q}$ for mutual funds and index funds 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.

Panel A: Investment-grade Bonds

	Market	ETFs				Mutual Funds			Index Funds		
	# bonds	R^2_{ETFreg}	β_{HI_ETF}	$\beta_{MKT-ETFreg}$	$ETFOWN(\%)$	R^2_{MFreg}	β_{HI_MF}	$MFOWN(\%)$	$R^2_{INDFreg}$	β_{HI_INDF}	$INDFOWN(\%)$
2011	2,324	0.30	0.06	0.90	0.70	0.30	0.20	6.35	0.30	0.01	1.34
2012	2,580	0.31	0.11	0.84	1.05	0.31	0.09	6.51	0.31	0.17	1.47
2013	2,947	0.30	0.20	0.84	1.19	0.30	0.13	6.50	0.30	0.10	1.56
2014	2,926	0.30	0.26	0.75	1.17	0.31	0.20	6.05	0.31	0.04	1.74
2015	3,160	0.30	0.12	0.93	1.31	0.30	0.08	6.29	0.31	0.07	2.00
2016	3,546	0.30	0.23	0.88	1.46	0.30	0.01	6.37	0.30	0.23	2.10
2017	3,771	0.29	0.22	0.83	1.78	0.29	0.00	6.32	0.29	0.08	2.38
2018	4,035	0.28	0.29	0.63	1.99	0.28	0.21	6.05	0.28	0.26	2.57
2019	3,909	0.29	0.22	0.83	2.03	0.29	0.25	5.59	0.29	0.13	2.59
Full sample	3,244	0.30	0.19	0.82	1.41	0.30	0.13	6.23	0.30	0.12	1.97

Panel B: High-yield Bonds

	Market	ETFs				Mutual Funds		
	# bonds	R^2_{MFreg}	β_{HI_MF}	$\beta_{MKT-MFreg}$	$MFOWN(\%)$	R^2_{ETFreg}	β_{HI_ETF}	$ETFOWN(\%)$
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	1,000	0.29	0.06	0.64	2.15	0.29	-0.06	18.06
2016	1,055	0.29	0.04	0.66	2.06	0.29	0.16	17.42
2017	1,104	0.29	0.10	0.63	2.08	0.28	0.06	16.30
2018	1,008	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	914	0.30	0.07	0.58	2.02	0.29	0.08	16.12

Table 4: **Average Liquidity Betas Sorted**

Table 4 presents ETF, mutual fund, index fund and market liquidity betas sorted by institutional ownership. At the end of each quarter, bonds are sorted into quartiles based on $ETFOWN$, $MFOWN$, and $INDFOWN$. I report the average $\beta_{HI\_ETF,q}$, $\beta_{MKT-ETFreg}$, $\beta_{HI\_MF,q}$, $\beta_{MKT-MFreg}$, $\beta_{HI\_INDF,q}$, and $\beta_{MKT-INDFreg}$ measured over the subsequent quarter. The last two rows in each panel show the difference between average $\beta_{HI\_ETF,q}$, $\beta_{HI\_MF,q}$, and $\beta_{HI\_INDF,q}$, respectively, in the highest and the lowest quartile with respect to the ETF, mutual fund or index fund ownership, as well as the t-statistics indicating statistical significance of the difference. Panel A reports the results for investment-grade bonds and Panel B is for high-yield bonds.

Panel A: Investment-grade Bonds

Sorting variable: ETFOWN

	ETFOWN	$\beta_{HI\_ETF,q}$	$\beta_{MKT-ETFreg}$
Lo	0.25%	0.08	0.69
2	0.97%	0.16	0.87
3	1.72%	0.24	0.89
Hi	2.84%	0.31	0.81
	Hi-Lo	0.23	
	t-stat	(7.64)	

Sorting variable: MFOWN

	MFOWN	$\beta_{HI\_MF,q}$	$\beta_{MKT-MFreg}$
Lo	0.73%	0.06	0.76
2	3.21%	0.10	1.01
3	6.53%	0.13	1.02
Hi	14.49%	0.19	0.92
	Hi-Lo	0.14	
	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

	ETFOWN	$\beta_{HI\_ETF,q}$	$\beta_{MKT-ETFreg}$
Lo	0.03%	0.06	0.42
2	0.91%	0.04	0.56
3	2.67%	0.06	0.69
Hi	4.79%	0.12	0.67
	Hi-Lo	0.06	
	t-stat	(2.52)	

Sorting variable: MFOWN

	MFOWN	$\beta_{HI\_MF,q}$	$\beta_{MKT-MFreg}$
Lo	3.45%	0.04	0.52
2	13.05%	0.10	0.56
3	20.56%	0.07	0.68
Hi	30.30%	0.07	0.59
	Hi-Lo	0.03	
	t-stat	(1.18)	

Table 5: **Institutional Ownership and Commonality in Liquidity - Investment-grade Bonds**

Table 5 reports the relationship between commonality in liquidity and institutional ownership for investment-grade 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 β_{HI_ETF}, β_{HI_MF}, and β_{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 Amihud (2002) illiquidity measure ($Amihud$), 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.

Panel A: ETF Ownership and Commonality in Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var.	β_{HI_ETF} (q)							
ETFOWN $(q-1)$	0.071***	0.071***	0.073***	0.080***	0.081***	0.048***	0.073***	0.036***
	(5.33)	(5.05)	(3.65)	(4.11)	(4.10)	(4.74)	(4.17)	(3.93)
MFOWN $(q-1)$				-0.039*	-0.040*	-0.015	-0.002	-0.009
				(-1.78)	(-1.85)	(-1.21)	(-0.15)	(-1.02)
INDFOWN $(q-1)$				-0.054***	-0.051***	-0.018	-0.020*	-0.014
				(-3.10)	(-2.81)	(-1.66)	(-1.76)	(-1.12)
Amihud $(q-1)$	-0.416**	-0.416**	-0.473***	-0.471***	-0.395**	-0.174	-0.561***	-0.306*
	(-2.64)	(-2.66)	(-2.87)	(-2.83)	(-2.26)	(-1.07)	(-3.29)	(-1.89)
MktVal $(q-1)$	-0.003	-0.003	-0.075*	-0.046	-0.079*	0.031**	-0.004	0.029***
	(-0.19)	(-0.19)	(-1.89)	(-1.22)	(-1.78)	(2.23)	(-0.24)	(2.89)
Rating $(q-1)$					0.020	0.018		-0.002
					(0.98)	(1.26)		(-0.38)
Maturity $(q-1)$					-3.403	-0.010***		-0.008**
					(-1.18)	(-3.99)		(-2.51)
Spread $(q-1)$					-0.043**	-0.008		0.009
					(-2.46)	(-0.58)		(0.99)
Observations	108,906	108,906	108,906	108,906	106,674	106,692	108,906	106,695
R-squared	0.003	0.003	0.087	0.087	0.089	0.020	0.004	0.007
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.				β_{HI_MF} (q)				
ETFOWN $(q-1)$				-0.011	-0.013	-0.008	0.020	-0.004
				(-0.52)	(-0.61)	(-0.58)	(1.29)	(-0.31)
MFOWN $(q-1)$	0.048***	0.048***	0.008	0.008	0.008	0.002	0.048***	0.016
	(3.57)	(3.52)	(0.33)	(0.31)	(0.32)	(0.17)	(4.36)	(1.32)
INDFOWN $(q-1)$				-0.003	-0.004	-0.018	-0.014	-0.011
				(-0.12)	(-0.14)	(-1.30)	(-1.09)	(-0.73)
Amihud $(q-1)$	-0.280*	-0.280*	-0.182	-0.183	-0.136	0.014	-0.162	0.186
	(-1.82)	(-1.89)	(-0.92)	(-0.92)	(-0.64)	(0.09)	(-0.86)	(0.74)
MktVal $(q-1)$	-0.006	-0.006	0.072	0.076	0.072	0.059**	-0.009	0.034
	(-0.40)	(-0.41)	(0.77)	(0.88)	(0.78)	(2.61)	(-0.46)	(1.56)
Rating $(q-1)$					0.039	0.050**		0.020***
					(1.53)	(2.44)		(2.97)
Maturity $(q-1)$					3.447	-0.012***		-0.012***
					(1.28)	(-3.82)		(-4.01)
Spread $(q-1)$					-0.001	0.005		0.033*
					(-0.04)	(0.25)		(1.83)
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							✓	✓

Panel C: Index Fund Ownership and Commonality in Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.				β_{HI_INDF} (q)				
ETFOWN $(q-1)$				0.039**	0.041**	0.013	0.040**	0.024*
				(2.35)	(2.39)	(0.75)	(2.29)	(1.72)
MFOWN $(q-1)$				-0.003	-0.008	0.005	0.010	0.013
				(-0.12)	(-0.28)	(0.31)	(0.79)	(1.05)
INDFOWN $(q-1)$	0.015	0.015	-0.044	-0.053*	-0.048	0.004	0.004	0.005
	(0.91)	(0.90)	(-1.52)	(-1.86)	(-1.60)	(0.26)	(0.33)	(0.34)
Amihud $(q-1)$	-0.212	-0.212	-0.097	-0.089	-0.084	-0.029	-0.270	-0.121
	(-0.91)	(-0.93)	(-0.33)	(-0.31)	(-0.29)	(-0.11)	(-1.51)	(-0.52)
MktVal $(q-1)$	-0.019	-0.019	0.094	0.086	0.073	-0.031	-0.035	-0.021
	(-0.88)	(-0.89)	(0.97)	(0.87)	(0.71)	(-0.91)	(-1.59)	(-1.12)
Rating $(q-1)$					0.014	0.012		0.001
					(0.39)	(0.44)		(0.12)
Maturity $(q-1)$					-1.852	-0.006**		-0.004
					(-0.55)	(-2.61)		(-1.41)
Spread $(q-1)$					-0.011	-0.003		0.005
					(-0.44)	(-0.14)		(0.28)
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	0.004
Time FE	✓	✓	✓	✓	✓	✓		
Bond FE			✓	✓	✓			
Issuer FE						✓		
Time clusters	✓	✓	✓	✓	✓	✓		
Bond clusters		✓	✓	✓	✓			
Issuer clusters						✓		
Fama MacBeth							✓	✓

Table 6: **Institutional Ownership and Commonality in Liquidity - High-yield Bonds**

Table 5 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 β_{HI_ETF} and β_{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.

Panel A: ETF Ownership and Commonality in Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var.				β_{HI_ETF} (q)				
ETFOWN $(q-1)$	0.013	0.013	0.015	0.015	0.018	0.012	0.014	0.012
	(1.40)	(1.40)	(0.87)	(0.85)	(1.07)	(0.94)	(1.47)	(1.13)
MFOWN $(q-1)$				0.011	0.004	0.003	0.002	0.003
				(0.43)	(0.14)	(0.21)	(0.14)	(0.20)
Amihud $(q-1)$	0.109	0.109	0.272**	0.274**	0.224**	0.170	0.138	0.203
	(1.03)	(1.02)	(2.28)	(2.29)	(2.10)	(1.59)	(0.90)	(1.23)
MktVal $(q-1)$	0.041***	0.041***	0.062	0.060	0.066	0.037*	0.043***	0.045***
	(3.27)	(3.10)	(1.62)	(1.53)	(1.45)	(1.93)	(2.91)	(2.82)
Rating $(q-1)$					0.008	0.006		-0.008
					(0.68)	(0.81)		(-1.62)
Maturity $(q-1)$					-2.786	-0.002		-0.003
					(-1.08)	(-1.28)		(-1.51)
Spread $(q-1)$					0.001	0.000		0.001
					(0.34)	(0.07)		(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.				β_{HI_ETF} (q)				
ETFOWN $(q-1)$				0.025	0.034*	0.023	0.015	0.020
				(1.23)	(1.71)	(1.41)	(1.49)	(1.65)
MFOWN $(q-1)$	-0.003	-0.003	0.029	0.028	0.022	0.018	-0.001	0.002
	(-0.23)	(-0.23)	(1.45)	(1.37)	(1.12)	(1.20)	(-0.05)	(0.17)
Amihud $(q-1)$	0.213	0.213	0.207	0.212	0.154	0.194	0.313*	0.348*
	(1.54)	(1.52)	(1.22)	(1.25)	(0.85)	(1.12)	(1.86)	(1.87)
MktVal $(q-1)$	0.050**	0.050**	0.055	0.048	0.033	0.033	0.043**	0.040*
	(2.69)	(2.65)	(1.25)	(1.08)	(0.67)	(1.37)	(2.23)	(1.96)
Rating $(q-1)$					-0.014	-0.023***		-0.007*
					(-1.06)	(-2.99)		(-1.72)
Maturity $(q-1)$					-1.860	-0.000		0.001
					(-0.51)	(-0.09)		(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 7: **Pairwise Correlation in Liquidity of Bonds on Institutional Ownership**

Table 7 reports 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 Amihud (2002) liquidity of bonds i and j estimated in quarter q ($\rho_{ij,q}$). I estimate the following regression equation:

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

All specifications include quarter interacted with bond i and quarter interacted with bond j fixed effects. Standard errors are triple-clustered by quarter, bond i, and bond j. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Dep.Var.		$\rho_{ij,q}$		
$ETFCOMOWN$ $(q-1)$	0.028***			0.023***
	(5.06)			(4.28)
$MFCOMOWN$ $(q-1)$		0.015***		0.013***
		(6.73)		(6.00)
$INDFCOMOWN$ $(q-1)$			0.021***	0.005
			(4.37)	(1.31)
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 8: **Exogeneous Variation in Common ETF Ownership and Commonality in Liquidity**

Table 8 reports the results of the regression of the pairwise correlation of changes in Amihud (2002) liquidity of two bonds i and j, $\rho_{ij,q}$, on an indicator variable, $SWITCH_{ij,q}$, determining the drop of at least one of the bonds in the pair from Bloomberg indices. The common ownership measure $BLETFCOMOWN_{ij,q}$ is the total par value held by F common Bloomberg index ETFs, scaled by the sum of amount outstanding of the two bonds. The common ownership measures are fixed at 2016 Q4 before the Bloomberg rule change. I estimate the following regression equation:

$$\begin{aligned}\rho_{ij,q} = \lambda_0 &+ \lambda_1 BLETFCOMOWN_{ij} + \lambda_1 BLETFCOMOWN_{ij} \times SWITCHij,q \\ &+ \lambda_1 MFCOMOWN_{ij} + \lambda_1 MFCOMOWN_{ij} \times SWITCHij,q \\ &+ \lambda_1 INDFCOMOWN_{ij} + \lambda_1 INDFCOMOWN_{ij} \times SWITCHij,q \\ &+ SWITCHij,q + \epsilon_{ij,q}, \end{aligned} \tag{17}$$

All specifications include quarter interacted with bond i and quarter interacted with bond j fixed effects. Standard errors are triple-clustered by quarter, bond i, and bond j. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Dep.Var.		$\rho_{ij,q}$		
$BLETFCOMOWN \times SWITCH$	-0.0027**	-0.0025**	-0.0017**	-0.0016*
	(-2.76)	(-2.26)	(-2.21)	(-1.95)
$BLETFCOMOWN$	0.0015**	0.0010	0.0006*	0.0003
	(2.19)	(1.31)	(1.92)	(0.69)
$MFCOMOWN \times SWITCH$		-0.0017		-0.0015**
		(-1.55)		(-2.20)
$MFCOMOWN$		0.0009***		0.0005***
		(3.00)		(3.35)
$INDFCOMOWN \times SWITCH$		-0.0002		0.0001
		(-0.13)		(0.12)
$INDFCOMOWN$		0.0017		0.0010
		(1.71)		(1.73)
$SWITCH$	-0.0003	-0.0004	-0.0012	-0.0014
	(-0.23)	(-0.32)	(-0.87)	(-0.98)
Nearest Neighbors	5	5	10	10
Observations	414,979	414,979	1,155,490	1,155,490
R-squared	0.003	0.003	0.002	0.002
FE		Bond i, Bond j, Quarter		
Clusters		Bond i, Bond j, Quarter		

Table 9: **Exogenous Variation in Mutual Fund Ownership and Commonality in Liqudity**

Table 9 reports the results from the difference-in-differences regressions. I use observations from 2012 Q2 to 2014 Q2 before the pre-event and from 2015 Q3 to 2017 Q3 in the post-event period. $Treatment_i$ is an indicator 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 is in the top quartile (Models 1, 3, and 4) or decile (Models 2,5 and 6) $Post$ is a dummy taking value of one after 2015 Q3, and $MFOWN_{i,2014Q2}$ is the overall level of mutual fund ownership in bond i at the end of 2014 Q2. Columns 1 and 2 report the results from a regression of the level of mutual fund ownership in the post period on the treatment indicator and controls. Columns 3–6 report the results of pooled OLS regressions of β_{HI_MF} on treatment and control firms.

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment:	top quartile	top decile	top quartile	top quartile	top decile	top decile
Dep.Var.	MFOWN (q)	MFOWN (q)	β_{HI_MF} (q)	β_{HI_MF} (q)	β_{HI_MF} (q)	β_{HI_MF} (q)
Treatment × Post			0.003	0.059	0.256	0.242
			(0.01)	(0.24)	(0.67)	(0.63)
Treatment	-0.015**	-0.025**	-0.097		-0.299	
	(-3.14)	(-3.12)	(-0.54)		(-0.80)	
MFOWN (2014)	0.829***	0.855***	-2.445**		-3.283*	
	(15.75)	(13.41)	(-2.34)		(-1.94)	
ETFOWN ($q-1$)			7.674	2.814	2.923	-4.744
			(1.22)	(0.38)	(0.22)	(-0.34)
INDFOWN ($q-1$)			-17.970***	-21.439*	-25.113***	-25.144
			(-3.07)	(-2.06)	(-3.58)	(-1.15)
Amihud ($q-1$)	0.039	0.040	0.803	0.972	-0.396	-0.849
	(1.15)	(0.75)	(0.81)	(0.46)	(-0.26)	(-0.32)
MktVal ($q-1$)	0.000	0.001	0.137	0.194	0.097	1.120
	(0.08)	(0.19)	(1.22)	(0.36)	(0.63)	(1.64)
Rating ($q-1$)	0.003	0.005	0.154***	-0.117	-0.056	-0.188
	(1.21)	(1.11)	(3.49)	(-0.88)	(-0.54)	(-0.84)
Maturity ($q-1$)	0.000	-0.000	-0.017*	-27.467	-0.014	-68.503***
	(0.19)	(-0.46)	(-1.86)	(-1.07)	(-1.38)	(-3.06)
Spread ($q-1$)	0.002	0.002	0.094	0.033	0.143	0.094
	(1.08)	(0.54)	(1.61)	(0.34)	(1.41)	(0.69)
Observations	1,295	507	2,519	2,518	996	996
R-squared	0.703	0.710	0.020	0.091	0.047	0.139
Time FE	✓	✓	✓	✓	✓	✓
Bond FE				✓		✓
Time clusters	✓	✓	✓	✓	✓	✓
Bond clusters	✓	✓	✓	✓	✓	✓

Table 10: **Correlated Trading of ETFs and Mutual Funds**

Panel A of 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. I define bond-level ETF flows as the weighted average of the quarterly flows in the ETFs that own the bond:

$$ETFFlows_{i,q} = \frac{\sum_{j=1}^{J} w_{i,j,q} \times Flows_{j,q}}{Volume_{i,q-1}}, \tag{18}$$

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

Panel B reports the results for the voluntary correlated trading of mutual funds. I estimate the regression

$$\beta_{HI\_TWMF,i,q} = \gamma_0 + \gamma_1 TWMFOWN_{i,q-1} + \gamma_2 ETFOWN_{i,q-1} + \gamma_2 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}, \tag{19}$$

where $\beta_{HI\_TWMF,i,q}$ is estimated in a regression in which I replace the liquidity of a high mutual fund ownership portfolio with that of a high turnover-weighted mutual fund ownership portfolio.

Panel A: Flow-induced Correlated Trading of ETFs, Mutual Funds, and Index Funds

	ETF Flows			Mutual Fund Flows			Index Fund Flows		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	Full	Outflow	Inflow	Full	Outflow	Inflow	Full	Outflow	Inflow
Dep.Var.		β_{HI_ETF} (q)			β_{HI_MF} (q)			β_{HI_INDF} (q)	
|ETF flows (q)|	0.074**	0.260**	0.065						
	(2.04)	(2.14)	(1.50)						
|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 $(q-1)$	-0.385**	-1.289**	-0.805***	-0.107	-0.912**	0.016	-0.251	-1.136	-0.317
	(-2.24)	(-2.17)	(-2.86)	(-0.59)	(-2.40)	(0.06)	(-0.92)	(-1.09)	(-0.86)
MktVal $(q-1)$	-0.073	0.065	-0.139**	0.074	0.004	0.126	0.039	-0.117	0.059
	(-1.58)	(0.52)	(-2.12)	(0.82)	(0.04)	(1.10)	(0.44)	(-0.47)	(0.50)
Rating $(q-1)$	0.015	0.092*	0.029	0.031	0.003	-0.004	0.022	0.133	0.026
	(0.76)	(1.93)	(1.10)	(1.26)	(0.05)	(-0.14)	(0.70)	(1.32)	(0.73)
Maturity $(q-1)$	-4.037	-4.545	-3.729	3.378	2.736	7.312**	-1.563	-29.974*	-1.361
	(-1.52)	(-0.66)	(-1.08)	(1.33)	(0.50)	(2.12)	(-0.53)	(-1.79)	(-0.39)
Spread $(q-1)$	-0.041**	-0.028	-0.043*	0.010	-0.002	0.017	-0.022	-0.085	-0.007
	(-2.67)	(-0.47)	(-1.76)	(0.43)	(-0.07)	(0.66)	(-0.77)	(-0.88)	(-0.19)
Observations	106,674	17,560	77,190	106,674	33,589	65,880	106,674	10,461	86,365
R-squared	0.087	0.289	0.108	0.085	0.191	0.125	0.084	0.341	0.095
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bond FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: Voluntary Correlated Mutual Fund Trading

	(1)	(2)	(3)
Dep.Var.		β_{HI_twMF} (q)	
TWMFOWN $(q-1)$	0.021	0.017	0.015
	(0.80)	(0.99)	(1.36)
ETFOWN $(q-1)$	-0.033	-0.016	-0.006
	(-1.39)	(-0.97)	(-0.41)
INDFOWN $(q-1)$	-0.001	-0.005	-0.005
	(-0.05)	(-0.60)	(-0.42)
Amihud $(q-1)$	-0.194	-0.181	-0.149
	(-1.04)	(-1.25)	(-0.98)
MktVal $(q-1)$	0.059	0.048**	0.035**
	(0.91)	(2.59)	(2.25)
Rating $(q-1)$	0.025	0.036**	0.011**
	(1.18)	(2.28)	(2.05)
Maturity $(q-1)$	2.615	-0.007***	-0.007***
	(0.93)	(-2.80)	(-3.27)
Spread $(q-1)$	-0.007	-0.005	0.004
	(-0.33)	(-0.32)	(0.21)
Observations	106,674	106,692	106,695
R-squared	0.086	0.018	0.006
Time FE	✓	✓	
Bond FE	✓		
Issuer FE		✓	
Time clusters	✓	✓	
Bond clusters	✓		
Issuer clusters		✓	
Fama MacBeth			✓

Table 11: **Standard Deviation of Fund Flows and Institution Type**

Table 11 investigates the relationship between the volatility of fund flows and the institution type, following Dannhauser and Hoseinzade (2019). I estimate the following regression equation as cross-sectional and panel regressions:

$$FlowVol_{f,m} = \beta_1 ETF_f + \beta_2 Controls_{f,m} + \epsilon_{f,m}. \tag{20}$$

The dependent variable $FlowVol$ is the average twelve-month volatility of flows for each fund in my sample. The indicator variable ETF takes the value of one if the fund is an ETF, and zero otherwise. The explanatory variables include fund expense ratio, turnover ratio, log of total assets, log of fund age in years, and the log of fund family assets.

Dep.Var.	Std. Dev. Of Fund Flows			
Regressions	Cross-Section		Panel	
	(1)	(2)	(3)	(4)
ETF	3.267***	2.042***	3.237***	1.764***
	(8.14)	(5.53)	(6.58)	(4.21)
Index Fund		0.278		0.119
		(0.74)		(0.47)
Expense Ratio		-9.029		-9.629
		(-0.42)		(-0.65)
Turnover Ratio		0.092		0.107***
		(1.56)		(2.71)
Log(Age)		-0.816***		-1.174***
		(-12.22)		(-18.28)
Log(Assets)		-0.261***		-0.301***
		(-5.19)		(-7.47)
Log(Family Assets)		-0.019		0.067*
		(-0.49)		(1.87)
Observations	1,296	1,296	93,251	92,679
R-squared	0.049	0.256	0.028	0.171
Time Clusters			✓	✓
Month FE			✓	✓

Table 12: **ETF Arbitrage and Commonality in Liquidity**

This table reports results on the effect of ETF ownership ETFOWN on commonality in liquidity for two groups: ownership by low-arbitrage funds and ownership by high-arbitrage funds.$AVGMISPRC$ (Columns 1-3) measures the ETF ownership-weighted average of the sum of the absolute value of the daily difference between the ETF NAV and the ETF end-of-the-day price aggregated over each quarter. $SDMISPRC$ (Columns 4-6) is the standard deviation of that daily difference over the quarter. To classify ETFs with respect to their mispricing levels, first, I form quartiles of ownership to control for the cross-sectional variation in the fund AUMs. Then within each ownership quartile and for each of the proxies, I compute funds' median mispricing ratio. If a fund in a given ownership quartile has a higher (lower) mispricing level than the median value, the fund is classified as a high-arbitrage (low-arbitrage) fund. Finally, for each bond, I define the high-arbitrage (low-arbitrage) ETF ownership as the ratio between the par value held by high-arbitrage (low-arbitrage) ETFs and the amount outstanding of the bond. In all regression models, 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 ($Maturity$).

	(1)	(2)	(3)	(4)
Dep.Var.		β_{HI_ETF} (q)		
$ETFOWN_{HighArbitrage}$ $(q-1)$	0.072***	0.077***	0.079***	0.063***
	(4.09)	(4.30)	(4.29)	(3.35)
$ETFOWN_{LowArbitrage}$ $(q-1)$	0.024	0.022	0.039**	0.053**
	(1.19)	(1.40)	(2.09)	(2.51)
$MFOWN$ $(q-1)$	-0.040*	-0.040*	-0.040*	-0.041*
	(-1.86)	(-1.83)	(-1.85)	(-1.83)
$INDFOWN$ $(q-1)$	-0.050**	-0.052***	-0.052***	-0.053***
	(-2.69)	(-2.81)	(-2.89)	(-2.92)
Amihud $(q-1)$	-0.396**	-0.398**	-0.398**	-0.398**
	(-2.26)	(-2.27)	(-2.27)	(-2.26)
MktVal $(q-1)$	-0.082*	-0.085*	-0.081*	-0.079*
	(-1.84)	(-1.89)	(-1.84)	(-1.76)
Rating $(q-1)$	-3.422	-3.439	-3.375	-3.364
	(-1.18)	(-1.19)	(-1.17)	(-1.17)
Maturity $(q-1)$	-0.044**	-0.045**	-0.043**	-0.043**
	(-2.48)	(-2.54)	(-2.47)	(-2.48)
Spread $(q-1)$	0.020	0.020	0.020	0.021
	(0.96)	(0.96)	(1.00)	(1.02)
Observations	106,674	106,674	106,674	106,674
R-squared	0.089	0.089	0.089	0.089
F - statistic	(16.72)***	(18.47)***	(18.42)***	(11.25)***
Channel	$AVGMISPRC$	$SDMISPRC$	$AVGABSCR$	$SDABSCR$
Time FE	✓	✓	✓	✓
Bond FE	✓	✓	✓	✓
Time clusters	✓	✓	✓	✓
Bond clusters	✓	✓	✓	✓

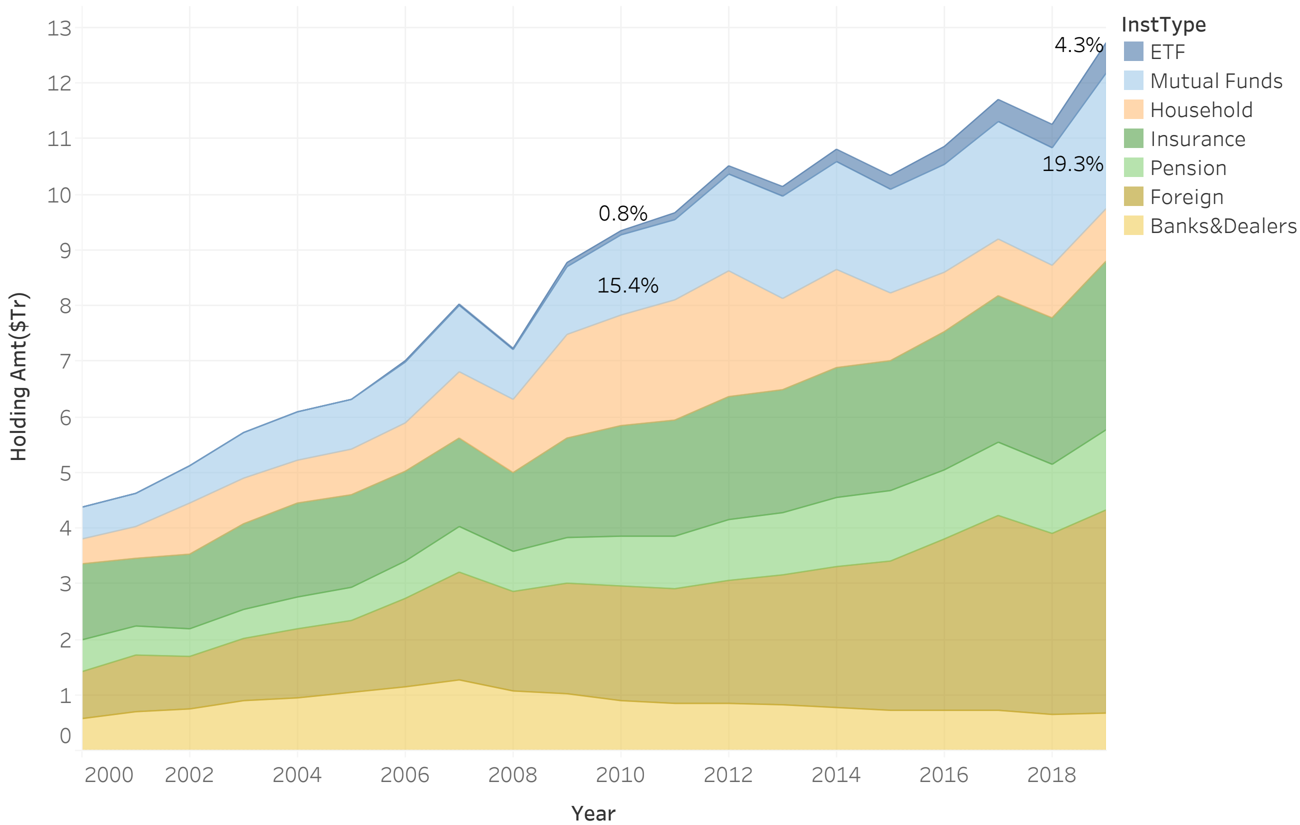

Figure 1: **Holders of U.S. corporate bonds (Source: Federal Reserve Financial Accounts L.213)**

Table A1: **Institutional Ownership and Commonality in Liquidity by Different Periods - Investment-grade Bonds**

Table A1 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 subperiod 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.

	(1)	(2)	(3)
Dep. Var.	β_{HI_ETF} (q)	β_{HI_MF} (q)	β_{HI_INDF} (q)
INSTOWN Var.	ETFOWN	MFOWN	INDFOWN
INSTOWN $(q-1) \times D_{2011-2013}$	0.035	0.003	-0.043
	(1.34)	(0.11)	(-1.04)
INSTOWN $(q-1) \times D_{2014-2016}$	0.084***	0.010	-0.066*
	(3.34)	(0.33)	(-1.90)
INSTOWN $(q-1) \times D_{2017-2019}$	0.118***	0.008	-0.036
	(4.97)	(0.20)	(-0.86)
ETFOWN $(q-1)$		-0.013	0.039**
		(-0.62)	(2.29)
MFOWN $(q-1)$	-0.036		-0.007
	(-1.65)		(-0.26)
INDFOWN $(q-1)$	-0.054***	-0.004	
	(-2.96)	(-0.15)	
Amihud $(q-1)$	-0.417**	-0.137	-0.089
	(-2.42)	(-0.64)	(-0.30)
MktVal $(q-1)$	-0.086*	0.072	0.071
	(-2.02)	(0.79)	(0.67)
Rating $(q-1)$	0.021	0.039	0.015
	(1.02)	(1.49)	(0.40)
Maturity $(q-1)$	-3.321	3.449	-1.863
	(-1.15)	(1.28)	(-0.55)
Spread $(q-1)$	-0.043**	-0.001	-0.011
	(-2.47)	(-0.03)	(-0.44)
Observations	106,674	106,674	106,674
R-squared	0.089	0.086	0.076
Time FE	Y	Y	Y
Bond FE	Y	Y	Y
Time cl	Y	Y	Y
Bond cl	Y	Y	Y

Table A2: **Institutional Ownership and Commonality in Liquidity using Bid-Ask Spreads - Investment-grade Bonds**

Table A2 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 β_{HI_ETF}, β_{HI_MF}, and β_{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.

Panel A: ETF Ownership and Commonality in Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					β_{HI_ETF} (q)			
ETFOWN $(q-1)$	0.133***	0.133**	0.057	0.072*	0.095**	0.059	0.192***	0.075**
	(3.67)	(2.21)	(1.22)	(1.78)	(2.15)	(1.62)	(3.66)	(2.10)
MFOWN $(q-1)$				-0.005	-0.048	-0.042	-0.031	-0.025
				(-0.08)	(-0.65)	(-0.95)	(-0.77)	(-0.55)
INDFOWN $(q-1)$				-0.094	-0.106	-0.025	-0.029	-0.024
				(-1.27)	(-1.42)	(-0.69)	(-0.78)	(-0.70)
Liquidity $(q-1)$	14.066	14.066	1.619	1.952	8.563	28.270***	21.740**	47.141***
	(1.42)	(1.39)	(0.16)	(0.20)	(0.83)	(2.97)	(2.09)	(3.83)
MktVal $(q-1)$	-0.068**	-0.068*	-0.045	-0.006	0.026	0.005	-0.076**	-0.017
	(-2.07)	(-1.90)	(-0.20)	(-0.03)	(0.12)	(0.07)	(-2.44)	(-0.46)
Rating $(q-1)$					0.203***	0.151**		-0.015
					(3.49)	(2.72)		(-1.18)
Maturity $(q-1)$					-5.282	-0.019***		-0.020***
					(-0.70)	(-3.29)		(-3.56)
Spread $(q-1)$					-0.088	-0.120**		-0.105**
					(-1.45)	(-2.14)		(-2.55)
Observations	105,998	105,998	105,998	105,998	103,876	103,890	105,998	103,892
R-squared	0.002	0.002	0.090	0.090	0.091	0.020	0.003	0.005
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)
				β_{HI_MF} (q)				
ETFOWN $(q-1)$				-0.084	-0.077	-0.040	0.017	-0.053
				(-1.67)	(-1.48)	(-1.50)	(0.48)	(-1.35)
MFOWN $(q-1)$	0.061***	0.061***	-0.032	-0.033	-0.050	0.034	0.060***	0.024
	(2.84)	(2.74)	(-0.50)	(-0.52)	(-0.75)	(0.83)	(3.07)	(1.11)
INDFOWN $(q-1)$				0.026	0.015	-0.015	-0.009	-0.008
				(0.32)	(0.19)	(-0.56)	(-0.39)	(-0.37)
Liquidity $(q-1)$	37.004***	37.004***	32.289***	31.856***	24.732**	37.663***	35.800***	49.541***
	(4.62)	(4.61)	(3.27)	(3.23)	(2.27)	(3.76)	(4.58)	(4.46)
MktVal $(q-1)$	0.005	0.005	0.091	0.102	0.142	0.068	-0.008	0.037
	(0.12)	(0.11)	(0.42)	(0.46)	(0.63)	(0.85)	(-0.18)	(0.66)
Rating $(q-1)$					-0.075	-0.041		0.019
					(-0.78)	(-0.52)		(0.90)
Maturity $(q-1)$					3.174	-0.021***		-0.022***
					(0.36)	(-3.60)		(-5.67)
Spread $(q-1)$					0.081	0.005		-0.022
					(1.23)	(0.08)		(-0.40)
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	0.017	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)
				β_{HI_INDF} (q)				
ETFOWN $(q-1)$				0.047	0.041	0.009	0.062*	0.031
				(0.88)	(0.74)	(0.30)	(1.97)	(0.84)
MFOWN $(q-1)$				-0.026	-0.060	-0.046	-0.010	-0.020
				(-0.41)	(-0.90)	(-1.14)	(-0.29)	(-0.49)
INDFOWN $(q-1)$	-0.004	-0.004	-0.040	-0.053	-0.049	-0.036	-0.033	-0.037
	(-0.12)	(-0.12)	(-0.66)	(-0.86)	(-0.79)	(-0.98)	(-0.84)	(-0.88)
Liquidity $(q-1)$	-5.217	-5.217	0.631	0.900	-1.487	-1.196	3.363	10.209
	(-0.64)	(-0.65)	(0.06)	(0.09)	(-0.15)	(-0.14)	(0.41)	(1.10)
MktVal $(q-1)$	-0.014	-0.014	-0.033	-0.035	0.023	-0.067	-0.029	-0.012
	(-0.34)	(-0.37)	(-0.16)	(-0.16)	(0.10)	(-1.21)	(-0.72)	(-0.31)
Rating $(q-1)$					-0.081	-0.019		-0.002
					(-1.19)	(-0.39)		(-0.12)
Maturity $(q-1)$					-7.791	-0.004		-0.004
					(-0.69)	(-0.75)		(-0.68)
Spread $(q-1)$					-0.002	-0.030		-0.055
					(-0.03)	(-0.56)		(-1.32)
Observations	105,998	105,998	105,998	105,998	103,876	103,890	105,998	103,892
R-squared	0.001	0.001	0.083	0.083	0.084	0.016	0.002	0.004
Time FE	✓	✓	✓	✓	✓	✓		
Bond FE			✓	✓	✓			
Issuer FE						✓		
Time clusters	✓	✓	✓	✓	✓	✓		
Bond clusters		✓	✓	✓	✓			
Issuer clusters						✓		
Fama MacBeth							✓	✓