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Ph.D Thesis

Essays in Institutional Investors and Financial Markets

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To my dear mother and father.

"Science is the most reliable guide in life."

Mustafa Kemal Atatürk

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ABSTRACT

I use empirical methods to study the effect of institutional investors on financial markets. My studies provide novel evidence on the commonality in liquidity of fixed-income securities, the liquidity provision of hedge funds and mutual funds in equity markets, and the information diffusion from credit default swaps to equities.

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Chapter 1

Preface

The primary interest of my doctoral studies is to analyze the effect of institutional investors on different financial markets such as equities, corporate bonds, and credit default swaps. My Ph.D. thesis consists of three articles, split across three chapters, in the field of asset pricing and the preface summarizes the current and broad state of my research. I try to be innovative and inventive when proposing research questions. Using unique datasets and rigorous empirical methodologies, I propose answers with intuitive examples.

Using empirical approaches, alone or with co-authors, I address the following questions: "Does the increased presence of ETFs and mutual funds in the U.S. corporate bond market give rise to co-movement in liquidity across bonds?", "Are all institutions similarly impacted by funding conditions and what characteristics make some institutions more prone to withdrawing liquidity in bad times?", and "Do long-term institutional investors have a role in information diffusion from the credit markets to equities?" The answers lead to several explanations of the effects and implications of institutional investors on financial markets. In the next section, I present a summary of each paper .

1.1 Summary of Papers

Chapter 2, "Do Mutual Funds and ETFs Affect the Commonality in Liquidity of Corporate Bonds?", explores 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 show that investment-grade bonds exhibit similar liquidity characteristics when they are heavily owned by ETFs. This finding 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 document that the differential impact of ETFs and mutual funds sources from their contrasting investor bases and structural differences. Mutual funds managers have discretion in responding to investor flows by buffering cash and trading securities selectively. However, ETFs essentially operate on autopilot to match an index, giving rise to unintended consequences on the underlying securities they hold.

Chapter 3, "What Constrains Liquidity Provision? Evidence From Institutional Trades" (co-authored with Francesco Franzoni and Alberto Plazzi), studies institutional liquidity provision and its dependence on funding conditions. In the U.S. equity market, buy-side institutions such as mutual funds and hedge funds play an essential role in providing liquidity to satisfy other investors' demands for immediate execution of orders. However, some institution types may curtail their liquidity supply during stress periods and harm market stability. We show that the liquidity provision of hedge funds exhibits much stronger sensitivity to funding conditions compared to that of mutual funds. We posit that the exposure of liquidity provision to aggregate conditions is larger for constrained funds, which we identify from a young age, high leverage, an illiquid portfolio, and poor recent performance. We also provide evidence that the reliance on liquidity supplying hedge funds has stock-level resilience implications such as higher trading costs and lower abnormal returns during the global financial crisis.

Chapter 4, "The Term Structure of Credit Spreads and Institutional Equity

Trading", investigates the role of long-term institutional investors in information diffusion from the credit default swap (CDS) market to equities. I empirically show that the term structure of credit default spreads, namely the CDS slope, explain the equity sales of long-term institutions, but not the sales of short-term institutions. I provide evidence that the negative relation between CDS slope and long-term institutions' equity sales entirely arises from the part of the slope that predicts future CDS spread changes. The finding that the CDS slope captures a significant component of long-term institutional trades, but not that of short-term institutions, provides novel evidence that the future financial health of the firm gradually diffuses from CDS to the equity market through the trading of long-term institutions.

1.2 Future Projects

Going forward, I plan to continue exploring the impact of fixed income mutual funds and ETFs on bond markets. It is important to understand the arbitrage mechanism and the roles of authorized participants (APs) in fixed income ETFs. With this understanding, it will be possible to identify potential systemic risks associated with fixed income funds and analyze further observations under stressed market conditions. My research will address gaps in our current understanding related to mutual funds and less liquid holdings, the behavior of fixed income ETF investors in extreme risk situations, and potential for APs to exacerbate a stressed market situation through their actions including simultaneous withdrawal.

The thesis is structured as follows:

Chapter 2 ***Do Mutual Funds and ETFs Affect the Commonality in Liquidity of Corporate Bonds?***, Efe Cötelioglu

Chapter 3 ***What Constrains Liquidity Provision? Evidence From Institutional Trades***, Efe Cötelioglu, Francesco Franzoni, Alberto Plazzi

Chapter 4 ***The Term Structure of Credit Spreads and Institutional Equity Trading***, Efe Cötelioglu.

Chapter 2

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

2.1 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 2.1).[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

[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.

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 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

[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.

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 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

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

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

[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.

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 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

[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.

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 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). 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.

2.1.1 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 and Zeng, 2019).

The rest of the paper is organized as follows. Section 2.2 presents the data and methodology. Section 2.3 provide empirical results on the relation between institutional ownership and commonality in liquidity. Section 2.4 establishes a causal relationship between fund ownership and liquidity commonality. Section 2.5 explores the underlying channels that explain differential impact of ETFs and mutual funds. Section 2.6 concludes the paper.

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

2.2 Data and Methodology

2.2.1 Data Description

2.2.1.1 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.

2.2.1.2 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

[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.

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 the proportional holdings in each bond attributable to the ETF share

[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.

class.

2.2.2 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

$$illiq_{i,d} = \frac{|R_{i,d}|}{DolVol_{i,d}}, \tag{2.1}$$

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.

[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.

2.2.3 Summary Statistics

Panel A of Table 2.1 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 2.1 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 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.

2.2.4 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 (2.1) 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 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

[11] Koch, Ruenzi, and Starks (2016) drop those stocks that have less than 40 days of observations in a quarter. My results are robust against requiring a minimum of 15 or 30 observations in a quarter.

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 (2.2) for ETF ownership

$$\begin{aligned}\Delta illiq_{i,q,d} = \alpha_2 + \beta^{-1}_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d-1} + \beta_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d} \\ + \beta^{+1}_{HI\_ETF,i,q}\Delta illiq_{ETFOWN,q,d+1} + \beta^{-1}_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d-1} \\ + \beta_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT-ETFreg,i,q}\Delta illiq_{MKT,q,d+1} \\ + \beta^{-1}_{mret-ETFreg,i,q}R_{m,q,d-1} + \beta_{mret-ETFreg,i,q}R_{m,q,d} + \beta^{+1}_{mret-ETFreg,i,q}R_{m,q,d+1} \\ + \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{2,i,q,d}, \quad (2.2)\end{aligned}$$

and regression (2.3) for mutual fund ownership

$$\begin{aligned}\Delta illiq_{i,q,d} = \alpha_1 + \beta^{-1}_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d-1} + \beta_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d} \\ + \beta^{+1}_{HI\_MF,i,q}\Delta illiq_{MFOWN,q,d+1} + \beta^{-1}_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d-1} \\ + \beta_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT-MFreg,i,q}\Delta illiq_{MKT,q,d+1} \\ + \beta^{-1}_{mret-MFreg,i,q}R_{m,q,d-1} + \beta_{mret-MFreg,i,q}R_{m,q,d} + \beta^{+1}_{mret-MFreg,i,q}R_{m,q,d+1} \\ + \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{1,i,q,d}, \quad (2.3)\end{aligned}$$

and finally, regression (2.4) for index fund ownership

$$\begin{aligned}\Delta illiq_{i,q,d} = \alpha_3 + \beta^{-1}_{HI\_INDF,i,q}\Delta illiq_{INDFOWN,q,d-1} + \beta_{HI\_INDF,i,q}\Delta illiq_{INDFOWN,q,d} \\ + \beta^{+1}_{HI\_INDF,i,q}\Delta illiq_{INDFOWN,q,d+1} + \beta^{-1}_{MKT-INDFreg,i,q}\Delta illiq_{MKT,q,d-1} \\ + \beta_{MKT-INDFreg,i,q}\Delta illiq_{MKT,q,d} + \beta^{+1}_{MKT-INDFreg,i,q}\Delta illiq_{MKT,q,d+1} \\ + \beta^{-1}_{mret-INDFreg,i,q}R_{m,q,d-1} + \beta_{mret-INDFreg,i,q}R_{m,q,d} + \beta^{+1}_{mret-INDFreg,i,q}R_{m,q,d+1} \\ + \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{3,i,q,d}. \quad (2.4)\end{aligned}$$

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 2.3 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.

2.3 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.

2.3.1 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

2.4.

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 2.2), 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 comprehensive specification is as follows:

$$\beta_{HI\_ETF,i,q} = \gamma_0 + \gamma_1 MFOWN_{i,q-1} + \gamma_2 ETFOWN_{i,q-1} + \gamma_3 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q} \tag{2.5}$$

The results of this regression for investment-grade bonds are presented in Panel A of Table 2.5. 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

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

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 2.1) 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 2.5.

High-yield bonds: The results for portfolio sorts by ETF ownership are shown in the left side of Panel B of Table 2.4 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 (2.5) for high-yield bonds are presented in Panel A of Table 2.6. 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).

2.3.2 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

$$\beta_{HI\_MF,i,q} = \gamma_0 + \gamma_1 MFOWN_{i,q-1} + \gamma_2 ETFOWN_{i,q-1} + \gamma_3 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}. \tag{2.6}$$

Investment-grade bonds: The results for investment-grade bonds are presented in Panel B of Table 2.5. 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, 2016).

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

High-yield bonds: The results for high-yield bonds are presented in Panel B of Table 2.6. 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.

2.3.3 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

$$\beta_{HI\_INDF,i,q} = \gamma_0+\gamma_1 MFOWN_{i,q-1}+\gamma_2 ETFOWN_{i,q-1}+\gamma_3 INDFOWN_{i,q-1}+\gamma_4 Controls_{i,q-1}+\epsilon_{i,q}. \tag{2.7}$$

Investment-grade bonds: The results for investment-grade bonds are presented in Panel C of Table 2.5. In any of the eight models, I don't have a significant relation between index fund ownership ($INDFOWN$) and commonality in liquidity.

2.3.4 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.

$$ETFCOMOWNij, q = \frac{\sum_{f=1}^{F} parval_{i,f,q} + parval_{j,f,q}}{amtout_{i,q} + amtout_{j,q}} \tag{2.8}$$

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

$$\rho_{ij,q} = \lambda_0 + \lambda_1 ETFCOMOWN_{ij,q-1} + \lambda_2 MFCOMOWN_{ij,q-1} + \lambda_3 INDFCOMOWN_{ij,q-1} + \epsilon_{ij,q}. \tag{2.9}$$

In Table 2.7, I report the estimation results of equation (2.9) 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.

2.4 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.

2.4.1 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 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:

$$Treat_i = \alpha + \beta_1 Amihud_i + \beta_2 Rating + \beta_3 Maturity + \beta_4 Spread, \tag{2.10}$$

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

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

[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.

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:

$$SWITCH_{ij,q} = \begin{cases} 1, & Treat_i = 1 \,\&\, Treat_j = 1 \,\&\, q \text{ is a post-event quarter} \\ 1, & Treat_i = 1 \,\&\, Treat_j = 0 \,\&\, q \text{ is a post-event quarter} \\ 1, & Treat_i = 0 \,\&\, Treat_j = 1 \,\&\, q \text{ is a post-event quarter} \\ 0, & \text{otherwise.} \end{cases} \tag{2.11}$$

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

$$\begin{aligned} \rho_{ij,q} = \lambda_0 + \lambda_1 BLETFCOMOWN_{ij} + \lambda_1 BLETFCOMOWN_{ij} \times SWITCHij,q \\ + \lambda_1 MFCOMOWN_{ij} + \lambda_1 MFCOMOWN_{ij} \times SWITCHij,q \\ + \lambda_1 INDFCOMOWN_{ij} + \lambda_1 INDFCOMOWN_{ij} \times SWITCHij,q \\ + SWITCHij,q + \epsilon_{ij,q}, \end{aligned} \tag{2.12}$$

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 2.8 reports the results for the estimation of Equation (2.17). 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.

2.4.2 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 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:

$$\beta_{HI\_MF,i,q} = \gamma_0 + \gamma_1 Treatment_i \times Post + \gamma_2 Treatment_i + \gamma_3 MFOWN_{i,2014Q2} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}. \tag{2.13}$$

[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.

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 2.9, 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 (2.13) in columns 3–6 of Table 2.9. 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.

2.5 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.

2.5.1 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.

2.5.1.1 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:

$$ETFFlows_{i,q} = \frac{\sum_{j=1}^{J} w_{i,j,q} \times Flows_{j,q}}{Volume_{i,q-1}}, \tag{2.14}$$

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 2.10, 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.

2.5.1.2 Voluntary Correlated Trading of Mutual Funds

In Section 2.4.2, 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:

$$\beta_{HI\_TWMF,i,q} = \gamma_0+\gamma_1 TWMFOWN_{i,q-1}+\gamma_2 ETFOWN_{i,q-1}+\gamma_2 INDFOWN_{i,q-1}+\gamma_4 Controls_{i,q-1}+\epsilon_{i,q}. \tag{2.15}$$

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 2.15 in Panel A of Table 2.10. 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 2.5 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.

2.5.2 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 2.11, 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:

$$FlowVol_{f,m} = \beta_1 ETF_f + \beta_2 Controls_{f,m} + \epsilon_{f,m}. \tag{2.16}$$

I run the regression Equation (2.20) 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 2.11, 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.

2.5.3 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 intra-day 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 2.12 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.

2.6 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.

Figure 2.1: Holders of U.S. Corporate Bonds

(Source: Federal Reserve Financial Accounts L.213)

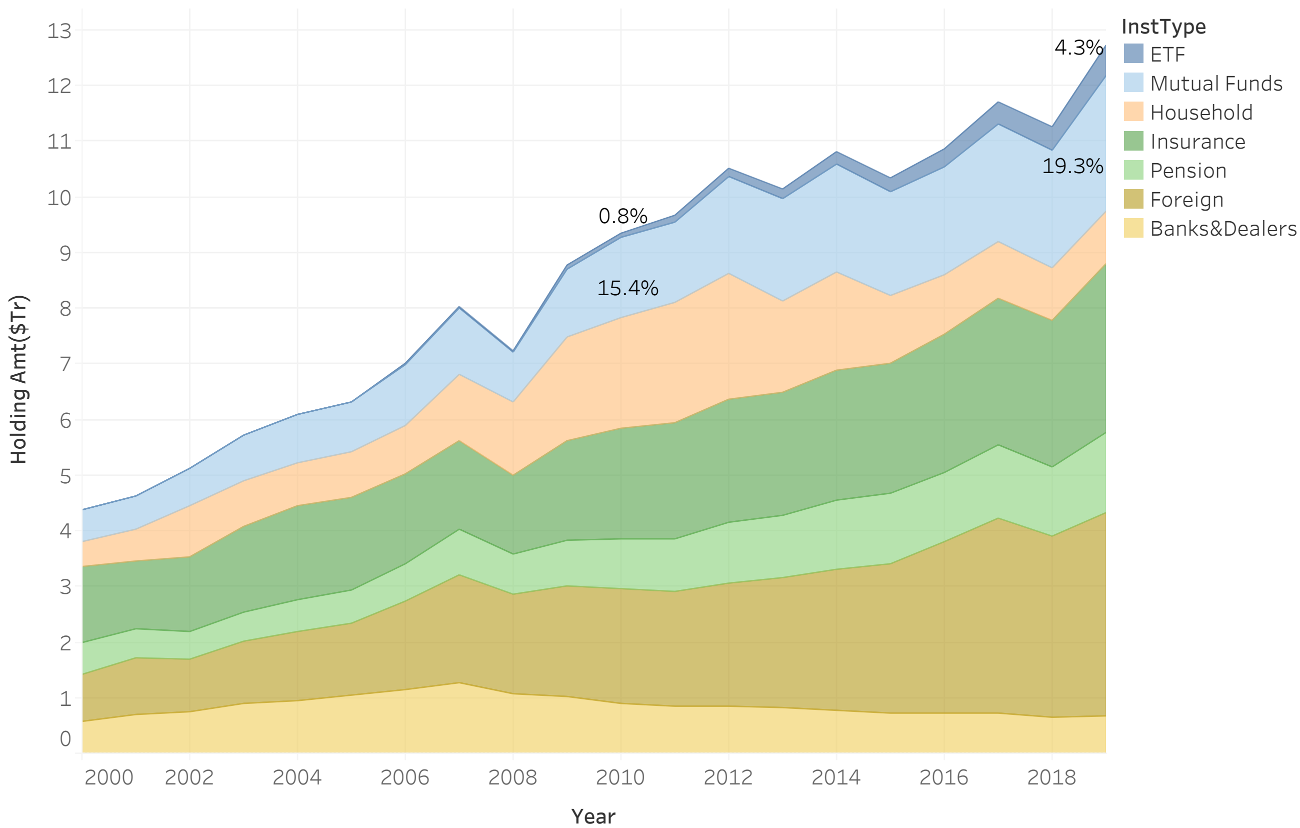


Table 2.1: Summary Statistics

Table 2.1 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 2.2: Correlations

Table 2.2 reports correlations for variables defined in Table 2.1. 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 2.3: Summary for the Time Series Estimates of Commonality Measures

Table 2.3 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 2.4: Average Liquidity Betas Sorted

Table 2.4 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 2.5: Institutional Ownership and Commonality in Liquidity - Investment-grade Bonds

Table 2.5 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 2.6: Institutional Ownership and Commonality in Liquidity - High-yield Bonds

Table 2.5 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 2.7: Pairwise Correlation in Liquidity of Bonds on Institutional Ownership

Table 2.7 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 2.8: Exogeneous Variation in Common ETF Ownership and Commonality in Liquidity

Table 2.8 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:

$$\begin{aligned}\rho_{ij,q} = \lambda_0 + \lambda_1 BLETFCOMOWN_{ij} + \lambda_1 BLETFCOMOWN_{ij} \times SWITCHij,q \\ + \lambda_1 MFCOMOWN_{ij} + \lambda_1 MFCOMOWN_{ij} \times SWITCHij,q \\ + \lambda_1 INDFCOMOWN_{ij} + \lambda_1 INDFCOMOWN_{ij} \times SWITCHij,q \\ + SWITCHij,q + \epsilon_{ij,q}, \end{aligned} \tag{2.17}$$

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 2.9: Exogenous Variation in Mutual Fund Ownership and Commonality in Liqudity

Table 2.9 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 2.10: Correlated Trading of ETFs and Mutual Funds

Panel A of Table 2.10 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:

$$ETFFlows_{i,q} = \frac{\sum_{j=1}^{J} w_{i,j,q} \times Flows_{j,q}}{Volume_{i,q-1}}, \tag{2.18}$$

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

$$\beta_{HI\_TWMF,i,q} = \gamma_0 + \gamma_1 TWMFOWN_{i,q-1} + \gamma_2 ETFOWN_{i,q-1} + \gamma_2 INDFOWN_{i,q-1} + \gamma_4 Controls_{i,q-1} + \epsilon_{i,q}, \tag{2.19}$$

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 2.11: Standard Deviation of Fund Flows and Institution Type

Table 2.11 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:

$$FlowVol_{f,m} = \beta_1 ETF_f + \beta_2 Controls_{f,m} + \epsilon_{f,m}. \tag{2.20}$$

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 2.12: 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	✓	✓	✓	✓

Appendix A: Additional tables

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							✓	✓

Chapter 3

What Constrains Liquidity Provision? Evidence From Institutional Trades

3.1 Introduction

In the theoretical literature, a liquidity provider is a trader that satisfies other investors' demands for immediate execution of orders (e.g., Grossman and Miller, 1988). In real-world financial markets, different classes of investors perform this function. While the typical market makers – i.e., the specialists, the dealers and, more recently, the high-frequency traders – are at the forefront in filling the temporary gap between buyers and sellers, recent empirical evidence points out the importance of long-term suppliers of liquidity in preventing large price fluctuations when the order flow becomes large and persistent (Cella, Ellul, and Giannetti, 2013; Anand et al., 2013). At the same time, the literature shows that liquidity supply by long-term institutions became more scarce during the last financial crisis (Ben-David, Franzoni, and Moussawi, 2012).

The finding that liquidity suppliers curtail their trading of illiquid stocks in bad times contributes to a growing body of work establishing a link between funding conditions and market liquidity (e.g., Comerton-Forde et al., 2010; Hameed, Kang, and Viswanathan, 2010;

Nagel, 2012). The sobering message from this literature is that the re-equilibrating forces in financial markets seem to falter when their contribution is mostly needed. Given its important consequences for market stability, this evidence raises further questions on the behavior of liquidity providing institutions, which we tackle in this paper. Which institutions are more relevant for market liquidity? Are all institutions similarly impacted by funding conditions? What characteristics make some institutions more prone to withdrawing liquidity in bad times?

We use trade-level data to study institutional liquidity provision and its dependence on funding conditions. Our data set contains transactions for different institutions (primarily mutual funds and hedge funds) during the January 1999 to June 2013 period. The data source is Abel Noser Solutions (also called 'Ancerno').[1] Using portfolio managers' names we are able to identify ninety-six distinct hedge-fund management companies. These firms appear to be highly representative of the overall industry along several dimensions. We also have trade-level information covering a large majority of the U.S. mutual fund sector (397 firms in total).

To measure liquidity provision, we exploit the direct visibility that the data gives us on institutions' trading behavior and construct a variable capturing the Trading Style (Anand et al., 2013). Specifically, if the institution trades in the same direction as the price change in the period under consideration, we denote it as a liquidity demander. On the other hand, if the institution's net trading volume opposes the direction of price movements (e.g., it buys when the price is falling), it is deemed a liquidity provider. To validate the inference coming from the Trading Style, we study the reflection of trading behavior on execution prices. Following a long literature, going at least back to Keim and Madhavan (1997), we construct a measure of the price impact of trading as the percentage difference between the execution price and the Price at Market Open for the same stock on the same day, and we

[1] Other recent studies using Ancerno data to investigate the behavior of institutional investors include Chemmanur, He, and Hu (2009), Chen, Goldstein, and Jiang (2010), Chemmanur, Hu, and Huang (2010), Goldstein, Irvine, and Puckett (2011), Puckett and Yan (2011), Anand et al. (2012), Anand et al. (2013), Jame (2018), Barbon et al. (2019), Di Maggio et al. (2019). Also see Hu et al. (2018) for a detailed description of the Ancerno database.

label it execution shortfall. A positive execution shortfall is typically considered an indication of a liquidity demanding trade.

We first ask whether the involvement of institutional investors in liquidity provisions matters for market liquidity contrasting mutual funds to hedge funds. A priori, it is not clear which buy side institutions are more relevant in terms of liquidity provision to the market. On the one hand, mutual funds hold and trade a larger share of the market; therefore, they have a bigger capacity to respond to other investors' liquidity needs. On the other hand, hedge funds adopt more nimble trading strategies that more quickly respond to the market's demand for liquidity and, due to higher restrictions to redemptions, can afford longer investment horizons.

The first result of the paper is that hedge funds' trading behavior is more important for stock-level liquidity, measured by the bid-ask spread and the Amihud (2002) ratio, than that of mutual funds. In particular, hedge funds appear to be the marginal liquidity providers, in that the extent to which they trade in the opposite direction of the market predicts the evolution of stock-level liquidity in the next week.

This finding proves the value added of trade-level data for explaining the high-frequency evolution of market liquidity. Previous work resorts to quarterly portfolio holdings (Ben-David, Franzoni, and Moussawi, 2012) or monthly returns (Jylha, Rinne, and Suominen, 2014) to infer the trading behavior of hedge funds in equity markets during crisis periods. Transaction data has several advantages over lower frequency data. First, liquidity provision is, strictly speaking, a trade-level concept. In this sense, a trade is liquidity providing if it rests on the limit order book until it is hit by an impatient order, notably a market order. The literature sometimes refers to a broader notion of liquidity provision, which is a strategy trading against mispricing (e.g., Brunnermeier and Pedersen, 2009), i.e., a contrarian strategy. While the latter behavior may be detected by a study of quarterly portfolio holdings (e.g., by studying if investors hold value stocks or other mispriced securities), one can only study the strict version of liquidity provision by inspecting trade-level data. Our data source does not separate between market and limit orders. However, trade-level measures of trading style and price impact allow us to separate liquidity providing from liquidity demanding trading behavior. Second, the use of trade-level data allows us to detect shifts in liquidity provision in a timely fashion, that is, at higher frequencies than measures derived from quarterly holdings or monthly returns. Supporting this claim, we find that measures built from monthly returns do not have the same predictive power for the evolution of market liquidity at the weekly frequency as those from trade-level data do.

Next, we investigate the resilience of hedge funds' liquidity provision in response to shocks to aggregate funding conditions. Again, we compare their behavior to that of mutual funds. Mutual funds allow daily redemptions to their investors, while hedge funds often have share restrictions in place that constrain investors' ability to redeem capital at will. This element would suggest that hedge funds are better positioned to provide liquidity when other investors withdraw from the market. On the other hand, hedge funds engage in leveraged strategies and invest in illiquid securities. The first element exposes hedge funds to margin calls, which may force hedge funds to fire sales (e.g., Ben-David, Franzoni, and Moussawi, 2012). The second characteristic exacerbates strategic complementarities (e.g., Chen, Goldstein, and Jiang, 2010), giving hedge fund investors a stronger incentive to run on the fund assets in bad times. It is, therefore, an empirical question which effect prevails in determining mutual and hedge funds' sensitivity to funding conditions.

To study this question, we separately classify institutions into liquidity providers and demanders, and relate their Trading Style and execution shortfall to funding conditions. We find that hedge funds that typically supply liquidity curtail their activity when funding conditions tighten. The effect is statistically and economically strong, and runs opposite to that of mutual funds who respond to the shock by strengthening their liquidity provision. The finding that mutual funds are better able to provide liquidity in stressful times finds an explanation in Goldstein, Jiang, and Ng (2017) who argue that *equity* mutual funds, as opposed to bond funds, are less exposed to redemption risk; a result that also echoes the evidence in Ben-David, Franzoni, and Moussawi (2012) that mutual funds were not exposed to large redemptions during the financial crisis. Notably, the difference is even more pronounced when the classification is based on the whole distribution of institutions in Ancerno, rather than within each group.

The observation that hedge funds withdraw from liquidity provision in bad times is suggestive of a constrained behavior, in line with the theory of limits to arbitrage. To further explore this explanation, we posit that the exposure of liquidity provision to aggregate conditions is likely larger for funds with higher leverage, more illiquid assets, and lower reputational capital (as measured by fund age and past performance). These fund-level characteristics make a fund more sensitive to funding conditions, as they relate to the ability to retain capital in bad times. We combine these characteristics into an indicator that denotes constrained funds. Consistent with the conjecture, we find that, among the liquidity providing hedge funds, only the constrained ones reduce liquidity supply.

We further ask whether the overall behavior of liquidity supplying hedge funds impacts stock-level resiliency. We show that the stocks that were most dependent on these funds, and in particular on constrained funds, at the inception of the last financial crisis later experienced higher trading costs and lower abnormal returns compared to the stocks that were least dependent. Along with prior literature suggesting the importance of hedge funds for stock liquidity (Aragon and Strahan, 2012), this finding furthers qualifies hedge funds as a group of liquidity providers that deserves special attention.

Finally, we focus on the persistence of negative funding shocks to hedge fund trading performance. The goal of this analysis is to establish the duration of the effect of a funding shock on liquidity provision for constrained hedge funds. We find that the impact of a shock on trading performance lasts for at least a month. Especially relevant is the fact that liquidity supplying funds exhibit the largest and longest-lasting effect, which likely reflects the detrimental effect of altering their stance towards liquidity provision. This finding can explain Anand et al.'s (2013) evidence that liquidity providing institutions abstained for several quarters from trading illiquid stocks during the financial crisis. Moreover, the abnormal performance of unconstrained hedge funds is consistent with the result in Grinblatt et al. (2019) that some contrarian hedge funds possess superior investment skills.

Some other literature explores trading activity of institutional investors using Ancerno data. Jame (2018) studies the performance of star hedge fund managers and finds that liquidity provision is an important determinant of this performance. Our paper, instead, is concerned with the constraints to liquidity provision. Gantchev and Jotikasthira (2017) use Ancerno data to show that hedge funds are active in providing liquidity to the market for corporate control when other institutions are selling their stakes.

Other work relies on lower frequency data. Regressing hedge fund returns on returns to a long-short contrarian trading strategy, Jylha, Rinne, and Suominen (2014) find that hedge funds normally supply liquidity in the stock market. Consistent with our evidence, they show that hedge funds decrease liquidity provision in bad times and this is the more likely for funds that are more exposed to redemptions. We complement their evidence by directly measuring liquidity provision at the trade level.[2] Using our direct measure of trading costs, we broaden the perspective by contrasting the exposure to funding conditions of hedge funds to that of mutual funds.

Like our work, the study by Giannetti and Kahraman (2017) points out that the organizational form matters for the exposure to limits of arbitrage. Using quarterly holdings data, they show that closed-end funds, as well as hedge funds with restrictions to redemptions, are better poised to trade against mispricing. Our results are also consistent with those in Cao et al. (2013) and Ben-David, Franzoni, and Moussawi (2012) that hedge funds do not to act as liquidity providers of last resort in bad times. The evidence that their future performance suffers, especially for constrained funds, is suggestive of a forced behavior rather than deliberate market timing ability. Our study further relates to Cella, Ellul, and Giannetti

[2]Suggesting that we capture a different dimension of liquidity provision from their study, we find that the correlation between our trade-level measure of liquidity provision and a measure based on factor loadings from monthly data, while positive, is not perfect, at 40%.

(2013) who link price pressure to investors' preference for the investment horizon. While they focus on the impact of trading horizon on the direction of trading, we document the impact of funding constraints on liquidity provision and expand on their findings by providing trade-level indirect evidence of forced sales. Finally, with respect to the theoretical literature, our results are in line with models that posit time-varying financial constraints for arbitrageurs (Shleifer and Vishny, 1997; Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009).

The paper is organized as follows. Section 3.2 describes the structure of our trade-level dataset, the identification of hedge funds and mutual funds, and the representativeness of our sample. Section 3.3 describes our measures of liquidity provision and funding conditions, and presents the results on predicting stock-level liquidity. Section 3.4 compares the exposure of liquidity provision to funding conditions for hedge funds and mutual funds, and presents the results on trading behavior and stock resiliency. Section 3.5 develops a hedge-fund-level measure of financial constraints that explains the sensitivity of funds' liquidity provision and trading performance to funding shocks. Section 3.6 offers concluding remarks.

3.2 Data Source and Descriptive Statistics

We begin with a description of the institutional trading data that is used in this study. Then, we detail the procedure to identify different institutions. Finally, we discuss sample representativeness.

3.2.1 Institutional Trading Data

Our data on institutional trades spans the January 1, 1999 to June 30, 2013 sample period. The data provider is Abel Noser Solutions, formerly Ancerno Ltd. As customary in the literature, we use the shorter name of 'Ancerno'. Ancerno provides consulting services for transaction cost analysis to institutional investors and makes these data available for academic research with a delay of three quarters under the agreement that the names of the client institutions are not made public. An advantage of Ancerno data is that it contains a record of a manager's trading history since the manager started reporting to Ancerno. While institutions voluntarily report to Ancerno, the fact that clients submit this information to obtain objective evaluations of their trading costs, and not to advertise their performance, suggests that self-reporting should not bias the data.[3] Another appealing feature of Ancerno is the absence of survivorship bias in that it also includes institutions that were reporting in the past but at some point terminated their relationship with Ancerno. Finally, the dataset is devoid of backfill bias, as Ancerno reports only the trades that are dated from the start of the client relationship.

The data are organized on different layers. The lowest-level observational unit is the individual trade. Information at the trade level includes key variables such as: the transaction date and time (at the minute precision); the execution price; the prevailing price when the trade was placed on the market; the number of shares that are traded; the side (buy or sell); the stock CUSIP. Ancerno argues that among the sell trades they also report short sales, which are especially relevant for hedge funds. We cannot, however, separate regular sales from short sales. At the upper level, the trade belongs to a daily broker release which is also called a "ticket". At the daily ticket level, we use the opening price for the traded stock. In the top layer, trades are part of a unique order, which can span several days. Our analysis is carried out at the day-manager level. Hence, we do not use information from the top layer.

3.2.2 Identification of Hedge Funds and Mutual Funds in Ancerno Data

The paper contrasts the trading behavior of hedge funds with that of mutual funds. Thus, we need to describe how we identify these institutions in the Ancerno data. Ancerno obtains the data from either pension funds or money managers. Client names are always anonymized.

[3]Indeed, the characteristics of stocks traded and held by Ancerno institutions and the return performance of the trades have been found to be comparable to those in 13F mandatory filings (Puckett and Yan, 2011; Anand et al., 2012).

However, the names of the companies that are managing the clients' portfolios are visible in our version of the data. This piece of information allows us to identify hedge funds among the different management companies.

An identifier (the variable *managercode*) denotes the trades originating from the same management company. Corresponding to the company identifier, we are given the name of the management company to which the trade pertains (the variable *manager*). This variable is crucial for our identification of hedge funds. We identify hedge funds among Ancerno managers by matching the names of the management companies with two sources. The first source is a list of hedge funds that is based on quarterly 13F mandatory filings. This source is also used in Ben-David, Franzoni, and Moussawi (2012) and is based on the combination of a Thomson Reuters proprietary list of hedge funds, ADV filings, and industry listings. The second source is the combined data from three commercial databases – the Lipper/TASS Hedge Fund Database, Morningstar CISDM, and Hedge Fund Research – which contain hedge-fund-level information at the monthly frequency. In the identification process, we make sure to select exclusively "pure-play" hedge fund management companies, that is, institutions whose core business is managing hedge funds. This is done by applying the same criteria as in Brunnermeier and Nagel (2004) and by manual verification. In Online Appendix A, we provide further discussion of the structure of the Ancerno dataset and details on the matching procedure with these two institutional data sources. In the end, the matching procedure allows us to identify 96 distinct hedge fund management companies that are present in Ancerno at various times throughout the sample.[4]

We single out mutual funds residually as the managers that are not hedge funds or pension funds. To identify pension funds, we use the *Clienttype* variable, as done in e.g., Puckett and Yan (2011). The number of resulting mutual fund management companies in the sample is 397. In some instances, this classification might be incorrect – for example, when the client is

[4]In a recent paper, Jame (2018) also uses Ancerno to identify hedge funds following a procedure that resembles our own. He ends up with a sample of 70 hedge fund management companies, which is comparable albeit smaller to the size of our own sample. As a validation of our matching procedure, in Online Appendix B, we assess the extent to which the hedge fund trades in Ancerno relate to the trades that can be inferred from 13F filings. We find that the trades in the Ancerno dataset capture a fair amount of variation in the quarterly holdings of the institutions that file the 13F form, confirming the evidence in Jame (2018).

a pension fund, but the trades are executed by a mutual fund on its behalf. Therefore, we also perform a manual match of the Ancerno manager name with S12 mandatory filings data. Based on this procedure, we identify 273 distinct mutual fund companies and use this sample to benchmark our results in Section 3.4.1.

As a final note, Ancerno does not provide reliable information on the identity of the individual fund that is executing the trade within a fund management company. For this reason, we work on trades aggregated at the management company level. For simplicity, we will simply refer to hedge funds or mutual funds when talking about the asset management companies.

3.2.3 Sample Selection and Summary Statistics

Following Keim and Madhavan (1997), we filter the data to reduce the impact of outliers and potentially corrupt entries. In detail, we drop transactions with an execution price lower than \$1 and greater than \$1,000. We eliminate trades from orders with an execution time, computed as the difference between the time of first placement and last execution of the order, greater than one month. Together, these filters reduce our initial sample by less than 3%. We also remove observations from the residual/unclassified category with *managercode* equal to zero. The filtered sample consists of nearly 12 million of hedge fund transactions and 241 million mutual fund transactions in U.S. equity.[5] Focusing on hedge funds, Panel A of Table 3.1 contains summary statistics for a number of daily series that are constructed from the final dataset. The first row reports the number of hedge fund management companies that are reporting on a given day. This number is on average 23, and ranges from a minimum of 3 to a maximum of 39 managers. These managers are responsible for an average of 3,265 daily transactions (second row), but the distribution is highly skewed with a maximum of 36,369. The next four rows in the panel provide information on dollar volume. The average

[5]These trades avail us with 858,168 distinct stock-day observations for hedge funds, and 2,577,093 for mutual funds. The intersection of these two samples yields 803,448 observations, which implies that whenever a hedge fund trades on a stock on a given day, we almost always observe also data for mutual funds. Hence, there is a large overlap in the samples.

daily volume is about $500 million. Volume per trade is on average $175 thousand, and varies between $16 thousand and about $2 million. Finally, we look at whether volume per trade differs across buy and sell trades. Interestingly, the volume per sell trades tends to be larger than the volume per buy trade (averages of $186 thousand versus $171 thousand, respectively). Hence, hedge funds appear to be less concerned about reducing the price impact of their trades when it comes to sell trades, possibly reflecting the urgency of fire sales. This is consistent with Keim and Madhavan (1995) who find that institutions tend to split buy trades more than sell trades. On average (median), a hedge fund in our sample trades on 779 (372) distinct stocks and for 904 (636) days.

In Panel B of Table 3.1, similar statistics are displayed for mutual funds that report to Ancerno. There are on average 163 mutual fund managers per day during our sample period. The number of trades and aggregate trading volume are, therefore, much larger than for hedge funds. However, the volume per trade appears directly comparable and varies in a similar range as for hedge funds. This implies that differences in trading costs between the two groups are not mechanically due to systematically different trade sizes.

3.2.4 Is the Sample Representative?

Next, we tackle the important question of whether our sample of institutions is representative of the broader universe. If the companies in our data are selected on the basis of characteristics that correlate with the explanatory variable of interest (funding liquidity), the inference that we make cannot be generalized to the entire hedge fund sector. For example, one may legitimately conjecture that the institutions that turn to Abel Noser Solutions for consulting services are those with lower trading skill. As such, they may be more likely to suffer when aggregate funding conditions deteriorate.

Our first reply to this concern is that the institutions that we study are managers for Ancerno's clients. As such, they are not choosing to use Ancerno's consulting services. Rather, it is the Ancerno clients (e.g., pension funds) that ask the managers to report their trades.

This fact, in our view, goes a long way in addressing the issue of self-selection.

Second, in Internet Appendix C we provide statistical evidence that further dispels the concern of a self-selected sample. In short, we show that the hedge funds in Ancerno load on funding liquidity variables in a similar way to other funds reporting to the commonly used Lipper/TASS database, and are comparable in terms of characteristics.[6] Hence, it appears that our sample is representative of the hedge fund universe as far as the exposure to funding liquidity is concerned.

As far as mutual funds are concerned, our sample is largely representative of the U.S. mutual fund industry. As an example, the top twenty-five management companies of U.S. equity funds account for 84% of the assets in the last year of our sample. Ancerno reports trades for twenty-four out of these twenty-five firms, covering 83% of the total AUM in U.S. equity funds. Of course, we also use information for the remaining mutual fund management companies below the top twenty-five, as our goal is to characterize the behaviour of a typical fund.

3.3 Funding Conditions and Liquidity Provision

In this section, we start from the construction of trade-level measures of institutional liquidity provision. Then, we investigate whether these measures are relevant predictors of stock-level market liquidity. In doing that, we contrast liquidity provision by hedge funds and mutual funds.

3.3.1 Measuring Liquidity Provision and Funding Conditions

The standard approach in the theoretical market microstructure literature is to identify liquidity provision with limit orders and liquidity demand with market orders. However, Ancerno data, like other trade-level datasets (e.g., the Plexus data that is used in Keim and

[6] In addition, we also examine whether the number and risk profile of funds varies systematically over time thus biasing our inference, but find no significant evidence of this.

Madhavan, 1997), does not report the order type. Thus, we follow prior empirical literature and capture liquidity provision via the trading style of an institution, which focuses on the direction of a trade relative to price changes during the same time interval (Anand et al., 2013). We validate this measure by also considering the execution shortfall, which captures the price impact of trades (see Perold, 1988; Wagner and Edwards, 1993; Keim and Madhavan, 1997; Puckett and Yan, 2011).

Specifically, the Trading Style variable (TS) measures an institution's propensity to trade in the direction of the daily stock return. Buy orders are classified as being $Volume\,With$ if they are placed in a day of positive stock return and $Volume\,Against$ if the daily stock return is instead negative. The converse applies to sell orders. Institution i's Trading Style (TS) is finally computed as

$$TS_i = \frac{\sum VolumeWith - \sum VolumeAgainst}{\sum VolumeWith + \sum VolumeAgainst}\,, \tag{3.1}$$

where $Volume$ denotes dollar volume, and the summation is taken over all trades in a reference period, be it a day or a month. We use TS as dependent variable computed at the manager-day level to track fluctuations in a fund's tendency to demand (positive TS) or provide (negative TS) liquidity. We also compute this measure on all trades during the month to categorize institutions into liquidity suppliers (LS) and liquidity demanders (LD), and study their behavior in the following month.

Additionally, a liquidity providing trade typically leans against the main order flow. For this reason, liquidity-providing trades are expected to have limited or negative price impact. We thus measure the economic consequences of liquidity demand through the price impact or execution shortfall. We construct the execution shortfall on day t for manager i as the dollar volume-weighted average of the relative difference between the execution price of trade j, P_j, and a benchmark price, P^*:

$$ES_{i,t} = \sum_j \frac{\$Vol_j}{\sum_j \$Vol_j} \left(\frac{P_j - P^*}{P^*} \right) \times Side_j \tag{3.2}$$

where $Side$ equals 1 for a buy and -1 for a sell trade. Lacking the observation of the bid-ask quote prevailing at the time of the trade, we follow Anand et al. (2013) and rely on Price at Open.[7]

Panels A and B of Table 3.2 contain summary statistics for the TS and for ES expressed in basis points (bps) pooling all fund-day observations. For hedge funds (Panel A), the average TS is positive at 0.13, suggesting that on average they demand liquidity, but with a standard deviation at 0.66 reflecting large cross-sectional heterogeneity and time-series fluctuation in the extent of liquidity provision. Consistent with the view from trading style, the average ES is positive, at about 38bps, with a standard deviation of 178bps. Its distribution is positively skewed, reaching peaks around 750bps. Execution shortfall tends to be on average higher for sell trades (about 44bps) than buy trades (about 29bps), which is arguably a symptom of fire sales. The series are characterized by positive time-series persistence at the day-manager level.[8]

Panel B reports statistics for mutual funds. The average TS is lower at 0.03 compared to hedge funds, but the standard deviation is again quite substantial. The ES of these institutions is instead on average quite smaller than that of hedge funds, averaging about 8.5bps respectively. This evidence is likely due to the different tradeoffs that mutual funds and hedge funds face. Hedge fund strategies are more likely to exploit private, possibly short-lived, signals. For these funds, execution costs may be a smaller concern when confronted with the gain from exploiting the signal, so that they will tend to trade more aggressively. Mutual funds, instead, receiving fewer information signals, must pay more attention to execution

[7] We obtain similar results using other common alternatives, such as Price at Placement (Anand et al., 2012) or the volume-weighted average price (see Berkowitz, Logue, and Noser, 1988; Puckett and Yan, 2011). These results are available from the authors upon request.

[8] The autocorrelations of TS and ES are even higher, in the 0.35 to 0.50 range, when computed at the monthly frequency, which testifies to the persistence in trading style.

costs and may decide to trade more patiently than hedge funds.[9] Internet Appendix D with reference to Figure D.1 discusses the aggregate time-series evolution of ES for the two groups of institutions.

Our analysis studies the evolution of institutional liquidity provision in different states of the market as described by aggregate funding conditions. To measure funding conditions, we draw from prior literature. Based on the findings in Hameed, Kang, and Viswanathan (2010) that liquidity supply by financial intermediaries is positively related to market performance, we select the market return in the prior two weeks as a proxy for an improvement in funding liquidity. Brunnermeier and Pedersen (2009) argue that the margins imposed by brokers to arbitrageurs depend on the volatility of asset prices and Nagel (2012) shows that market liquidity deteriorates when the VIX increases. Garleanu and Pedersen (2011) argue that the interest rate difference between collateralized and uncollateralized loans (or Treasury securities) captures arbitrageurs' shadow costs of funding. Thus, we also use the TED spread (the three-month LIBOR minus the three-month T-bill rate) to proxy for systematic time-series variation in funding liquidity. Finally, Anand et al. (2013) suggest that dealer repos are a close proxy for the availability of capital to market intermediaries. Thus, we use dealer repos, computed as the cumulative difference in short-term lending by U.S. primary dealers (source: Federal Reserve Bank of New York), as another measure of funding conditions. As a catch-all variable, we compute a liquidity factor (LF) by adding the four standardized variables. Since we want the factor to measure a deterioration in funding conditions, the signs of its components are changed where necessary. The liquidity factor therefore equals $LF = -R_M + VIX + TED - Repo$.[10] The factor is also standardized in the time series. Panel C of Table 3.2 collects summary statistics for these variables.

[9]This argument is consistent with the findings in Puckett and Yan (2011), who document that the best performing funds in the Ancerno data set on average demand immediacy. Hedge funds are likely to be among the funds that in their paper display positive alpha from interim activity, as they deliver on average significant abnormal performance compared to other institutions such as mutual funds. See their Table VII and related discussion.

[10]As an alternative, we also experiment taking the first principal component. Results are still qualitatively similar, although generally weaker in economic and statistical magnitude. The reason is that the principal component approach captures only correlated moves, whereas the present approach allows funding conditions to react if any (of just some) of the liquidity proxies is shocked. As a matter of example, during the burst of the Internet bubble the VIX and the market experienced large movements whereas the TED and Repo were not as affected.

3.3.2 Institutions' Liquidity Provision and Stock-Level Liquidity

The first question we address is the role of institutional investors' liquidity provision in affecting the level of liquidity in the market. Importantly, we also analyze how institutional liquidity provision relates to market liquidity in different states of aggregate funding conditions. Motivation for this analysis comes from theories postulating that an asset's liquidity crucially depends on the liquidity provision of the investors that trade the asset (Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009). Institutional investors, being more sophisticated, are the more likely liquidity providers. At the same time, the funding structure of institutions make their ability to provide liquidity dependent on the availability of trading capital, which can dry up during periods of market turmoil. Another question we address is the relevance of the institutional type (i.e., hedge fund or mutual fund) in the provision of liquidity. A priori, hedge funds' more unconstrained and nimble trading strategies qualify them as the most important institutions for market liquidity.

Transaction level data allows a direct and timely measurement of the institutional stance towards liquidity provision. We derive a measure of liquidity supply at the stock level from the trades in Ancerno and study whether this variable predicts the evolution of a stock's liquidity. Specifically, at the stock-week level, we construct a volume-weighted measure of liquidity provision by the institutions that trade in a given stock. In constructing this variable, we are consistent with the Trading Style variable, but we develop it at the stock-level and the weekly frequency. Specifically, we take the difference between institutions' $VolumeWith$ and $VolumeAgainst$ in a given stock-week, over total Ancerno volume in same stock-week, and denote it as $TSLiqDemand$. We stress that we can measure this variable at the weekly frequency for each stock thanks to the resolution of the Ancerno data.[11]

Then, we test whether this measure predicts time variation in stock-level liquidity. We follow the setup in Hameed, Kang, and Viswanathan (2010), who study the determinants of the seasonally-adjusted quoted bid-ask spread ($ASPR$) using panel predictive regressions, i.e.,

[11] We could increase the frequency of measurement, e.g., daily, but that would come at the cost of fewer institutions trading in a stock-period, adding noise to the variable.

we use our variable of institutions' liquidity demand to predict stock-level liquidity in the next week. Like these authors, we include the following controls: *Return* and *STD*, which denote the weekly sum and standard deviation of daily stock returns, respectively; *Turnover*, which is the ratio between the weekly volume, computed as the sum of number of shares traded in each day of the week, to the number of shares outstanding; and the lagged dependent variable. We carry out a similar analysis for the Amihud (2002) ratio, as an alternative measure of stock-level liquidity. We include both the level of *TSLiqDemand* as well as its interaction with the funding liquidity variable *LF* to test whether the predictability in different states of funding conditions.

The corresponding estimates for ASPR and Amihud on the sample of stock-week observations are collected in Table 3.3, Columns 1–5 and 6–10 respectively. We compute *TSLiqDemand* using different groups of institutions reporting to Ancerno. In Columns 1 and 6, we pool hedge funds and mutual funds. The coefficient for *TSLiqDemand* is positive and significant for both ASPR and Amihud, suggesting that a decrease in institutional liquidity supply in a given week predicts a subsequent deterioration in stock-level liquidity. For Amihud, we also note a positive and significant loading on the interaction coefficient, which implies a more important role of institutional liquidity supply as aggregate funding conditions deteriorate.

In Columns 2 and 7, we re-run the previous analysis but now compute *TSLiqDemand* using data on mutual funds only. We find that mutual funds' liquidity provision has a statistically weaker predictive power for ASPR, while it preserves its ability to track future levels of Amihud. In Columns 3 and 8, we use instead hedge fund data to construct *TSLiqDemand*. Compared to mutual funds, we find much stronger evidence of predictability. The baseline coefficient is more statistically significant. Moreover, the interaction term is now significantly positive for both stock liquidity measures, suggesting that hedge funds' liquidity supply is especially relevant at times of scarse capital availability.[12] These estimates

[12] The impact of hedge funds' liquidity provision remains stronger than that of mutual funds when we restrict to the sample of stocks and days for which there are trades by both groups of funds, as shown in Table E.I. Hence, our finding is not an

are not only statistically, but also economically meaningful. Based on the summary statistics in Panel D of Table 3.2, they imply that a one standard deviation increase in hedge funds' $TSLiqDemand$ predicts a rise in ASPR and Amihud by respectively 0.43 and 1.02 when LF equals zero, and by 1.73 and 3.09 respectively (or, about 1% and 23% of the average ASPR and Amihud) when LF is two standard deviations above its mean.

To show that the resolution of the Ancerno data is crucial for predicting liquidity at this high frequency, we also take the alternative route of constructing the hedge funds' liquidity demand measure from low-frequency data. Specifically, we combine 13F institutional data, available quarterly, with the RLP beta from Jylha, Rinne, and Suominen (2014). This variable is computed monthly as the slope from a regression of hedge fund returns on an aggregate factor that measures returns from a contrarian, i.e., liquidity providing, strategy. Specifically, for a given stock week, we define the $RLPLiqDemand$ measure as minus the value-weighted RLP beta, where the beta is the last available as of the previous month, and weights are based on the hedge fund holdings from the 13F filing as of the last quarter. Hence, this variable is constant within a month.[13] In spite of the lower frequency variation in $RLPLiqDemand$, we still run weekly predictive regressions for the stock-level liquidity variables, $ASPR$ and the Amihud ratio, to contrast its predictive power to that of the Ancerno-based variable.

Columns 4 and 9 report the results when using $RLPLiqDemand$ as predictor. The estimates reveal no predictive power of $RLPLiqDemand$ for the adjusted spread, while there is some marginally significant predictability for the Amihud ratio.[14] Finally, in Columns 5 and 10, we run a horse race between the Ancerno based measure and the variable constructed using monthly return data, restricting the sample to the observations for which both variables are available. The $TSLiqDemand$ variable preserves its strong predictive power, thereby

artifact of the two measures being computed over different samples.

[13]Merging the 13F data with the hedge fund commercial databases reduces the sample to 553 funds, out of the original sample of 5560 funds in the commercial databases. This step, however, is necessary to bring the RLP beta, originally at the fund-level, to a stock-level variable by taking the holdings-based average of the RLP betas of the funds that own the stock.

[14]For the analysis on the institutional filings data, we start from the same sample of stock-weeks that is used for the Ancerno-based measure and merge it with the sample in which $RLPLiqDemand$ is available. This operation involves a loss of observations. However, even when we do not condition on the sample of week-stocks that are available but rather use the full sample of observations, $RLPLiqDemand$ displays no predictive power for the ASPR, while its predictive power for the Amihud ratio is somewhat stronger.

indicating that the higher resolution in the Ancerno variable makes it a valid predictor of high-frequency variation in stock-level liquidity.[15]

Overall, the evidence testifies to the importance of hedge funds as marginal investors in the stock market. Additionally, the analysis establishes the merits of the Ancerno data in capturing the high-frequency evolution in liquidity provision. Thus, Ancerno data, although available for a subset of institutions, provides valuable information that is not contained in other datasets. Furthermore, the finding of a significant link between institutional liquidity provision and stock-level liquidity is a novel and important contribution of the paper. Prior literature (Hameed, Kang, and Viswanathan, 2010) shows indirect evidence of a link between liquidity supply and stock-level measures of liquidity, using the prior returns of the stock as a proxy of funding constraints. Thanks to transaction data, we can directly relate the institutional trading behavior to stock-level liquidity and show that the importance of institutional liquidity supply increases when aggregate funding conditions tighten.

3.4 Fund-Level Evidence on Liquidity Provision

Given the evidence from the previous section on the importance of hedge funds for market liquidity, in Section 3.4.1 we study how reliable their liquidity provision is in different states of the market. We also contrast hedge funds' stance towards liquidity provision to that of mutual funds. In Section 3.4.2, we examine the link between funds' liquidity provision and stock resiliency.

[15] An alternative interpretation of the results in Table 3.3 is possible. Hedge funds could reduce their market participation because their investors withdraw capital anticipating a deterioration in liquidity. However, we believe, this alternative explanation of the evidence is implausible for several reasons. First, due to redemption restrictions, hedge funds' investors react at a much lower frequency than the weekly frequency at which our regressions are conducted. Second, our specifications control for the known predictors of future liquidity in the literature (Hameed, Kang, and Viswanathan, 2010), including the contemporaneous liquidity level. Hence, hedge fund investors' foresight would have to be more accurate than the predictive ability of the best models in the literature.

3.4.1 Liquidity Provision: Hedge Funds vs. Mutual Funds

A priori, it is not clear whether funding conditions should matter more for hedge funds than for mutual funds. On the one hand, mutual funds allow daily redemptions, while hedge funds often times have share restrictions in place that constrain investors' ability to redeem capital at will. This element would suggest that hedge funds are better positioned to provide liquidity when other investors withdraw from the market. On the other hand, hedge funds' sophisticated clientele has a higher sensitivity to losses (Ben-David, Franzoni, and Moussawi, 2012). Moreover, hedge funds make intensive use of leverage in the form of borrowed capital, short selling, and derivative positions. As a result, they are under close scrutiny by their prime brokers and trading counterparties, who stand ready to call for additional margins in case of increased risk of the hedge funds' positions, a surge in the cost of capital, and a drop in the value of the collateral. By contrast, mutual funds make very limited use of leverage. These considerations suggest a detailed study of the role of the institution type in determining the sensitivity of liquidity provision to funding conditions.

To study the institutional stance towards liquidity provision, we follow Anand et al. (2013) who categorize institutions into liquidity providers and liquidity demanders based on the Trading Style in the prior month. Specifically, we sort our institutions into terciles based on Trading Style, separately for hedge funds and mutual funds. Managers in the bottom tercile are classified as liquidity suppliers (LS), while the top tercile contains liquidity demanders (LD).

The top plot of Figure 3.1 displays the average execution shortfall (ES) in a quarter for liquidity demanding and providing hedge funds. We note that, as expected, the liquidity demanders experience a positive ES, i.e. they pay a premium for liquidity in terms of positive price impact, while liquidity suppliers' ES is on average negative, i.e., they earn a liquidity premium (also see Internet Appendix E.II).[16] While the two series move in opposite directions

[16] As documented by Anand et al. (2013), a given fund's tendency to provide or demand liquidity is also persistent over time. The rightmost columns of Panel A in Internet Appendix Table E.II show that the average Trading Style is negative for LS hedge funds and positive for LD hedge funds in the formation month, as well as in the following six months. Similar conclusions emerge for mutual funds, whose statistics appear in Panel B.

for most of the sample period, during severely stressed markets (the early 2000, and the last financial crisis), the ES of liquidity providing hedge funds rises significantly above zero and moves in the same direction as for the liquidity demanders. This novel evidence suggests that liquidity supplying hedge funds, which are crucial for market liquidity, curtail their liquidity provision to the point that they mimic the behavior of liquidity demanders in bad times.

The bottom plot of the figure displays the analogous series for the group of mutual funds. Unlike hedge funds, we find that liquidity supplying mutual funds decrease their trading costs during bad times, thereby taking advantage of the high premium for liquidity provision. Their execution shortfall moves systematically in the opposite direction to that of liquidity demanding funds. This graphical evidence adds to the impression that mutual funds are a more reliable source of liquidity provision during bad times than hedge funds.

We next provide a more systematic analysis of these patterns by relating institutional liquidity provision to funding conditions, separately for each LS/LD group. In particular, we ask whether hedge funds' behavior is statistically any different from that of mutual funds through the interacted model

$$TS_{i,t+1} = a + b_1 LF_t + b_2 HF_i + b_3 HF_i \times LF_t + \epsilon_{i,t+1}\,. \tag{3.3}$$

and similarly for ES as dependent variable. The model is estimated on the panel of the available fund-day observations. Since the factor capturing aggregate liquidity conditions (LF) is standardized, the constant term captures the average dependent variable for mutual funds in normal times, while the loading on LF measures the effect of funding conditions on their liquidity provision. The interaction term (b_3) measures instead the additional impact of funding shocks on hedge funds.

We first focus on liquidity supplying funds in Panel A of Table 3.4. In Columns 1 and 4 we observe that the reaction of LS mutual funds to adverse funding shocks is an even more pronounced liquidity provision (slope on LF). The effect for mutual funds is only significant in the regression using ES (t-stat of -7.09), meaning that these institutions earn a higher liquidity premium during bad times. In contrast, the coefficient on HF×LF is positive at 2.249 for TS, with a t-stat of 1.74, and 11.259 for ES, with a t-stat of 3.53. Hence, the reaction of LS hedge funds to funding shocks runs opposite to that of mutual funds, and reveals a peculiar shift towards liquidity demand. Thus, consistent with the impression from Figure 3.1, a tightening in funding conditions pushes liquidity supplying hedge funds towards liquidity consumption.[17]

These findings obtain when classifying hedge funds and mutual funds into LS/LD based on the distribution of Trading Style *within* each group of institution. A natural concern is whether the LS hedge funds in our sample are liquidity suppliers in absolute terms – i.e., with respect to the full cross-section of institutions in the market – or only relative to other hedge funds that tend to consume more liquidity (LD), in which case the comparison with other truly LS institutions would be misleading. A related issue could be that the two funds are trading on different days and stocks. In Columns 2 and 5 (labeled "Joint class. & sample"), we base the LS/LD classification on the Trading Style breakpoints from the *pooled* data of hedge funds and mutual funds and estimate the model on the sample of stocks and days for which there are trades by groups of funds. Thus, we compare institutions with similar attitude towards liquidity provision in absolute rather than relative terms. Notwithstanding the smaller sample size, our evidence becomes slightly stronger under this classification. Namely, hedge funds react more heavily to funding conditions, as the interaction coefficient increases for both ES (from 11.259 to 11.492) and TS (from 2.249 to 2.487), and so does the difference with respect to the coefficient for mutual funds (captured by LF).

We further assess the sensitivity of our results to the use of prior month's Trading Style. This measure has the benefit of tracking month-by-month, and hence short-lived changes in the extent of a fund's liquidity provision. However, since funding conditions are characterized

[17]This finding still holds and becomes even statistically stronger when using the monthly instead of daily TS (Internet Appendix Table E.III) and when including trade-level controls (Internet Appendix Table E.IV). Analogous conclusions also emerge when adding controls and pooling all funds in Internet Appendix Table E.V.

by persistent components, such classification may also potentially underestimate the effect as some LS funds may switch to LD (and remain such) as soon as capital starts being scarce. For this reason, Columns 3 and 6 report estimates for an alternative specification (labelled "Long-term") where the LS/LD classification is based on a fund's Trading Style computed over the past six months, thereby capturing long-term liquidity provision. With this classification, hedge funds' execution liquidity provision appears more sensitive to funding conditions compared to the baseline results, as the interaction term is now larger, in particular in the regression for ES (where it increases to 14.23), and so does its statistical significance. The difference in the sensitivity to funding conditions compared to mutual funds also widens.

Panel B reports the estimates for liquidity demanding funds. We find no differential response of hedge funds' liquidity provision relative to that of mutual funds. The positive and significant coefficient on LF suggests that all funds experience an increase in trading costs during bad times, i.e., they end up paying a higher price for liquidity in bad times, which is not a surprising finding. Hence, it appears that the special behavior of hedge funds is confined to the set of LS funds, who are unable to hold on to their role as funding conditions deteriorate.[18]

3.4.2 Liquidity Provision and Stock Resiliency

We next ask whether the reaction of LS hedge funds to funding shocks has in turn detrimental implications for stock performance and liquidity. To test this conjecture, we explore whether stocks that are more reliant on trading from LS hedge funds experienced a more negative shock during the 2007–2009 financial crisis. To this end, we first compute the fraction of the volume traded by LS hedge funds over the total volume by all liquidity supplying institutions (including hedge funds and other institutions) over the 1-year period

[18] We also re-estimate our baseline specification when replacing the dependent variable with the abnormal ES. Our main conclusions continue to hold, see Internet Appendix Table E.VI. We are thus reassured that our results are not picking up differences in the composition of funds (and the stocks they trade) within the hedge fund sample and compared to mutual funds. Analogous conclusions arise when using the alternative mutual fund classification mentioned in Section 3.2.2, see Internet Appendix Table E.VII.

preceding the crisis (i.e., June, 2006 to May, 2007). Next, we sort each stock based on this fraction into quintiles and focus on the top and bottom quintiles. Stocks in the bottom quintile are the ones for which liquidity provision is least dependent on LS hedge funds. We expect these stocks to recover faster in terms of both performance (as measured by cumulative abnormal returns with respect to the 3-factor Fama and French, 1993 model) and trading costs (as measured by execution shortfall) over the June, 2007 to March, 2009 crisis period.

The left plot of Panel A of Figure 3.2 shows that, although the average execution shortfall for the stocks in the top and bottom quintiles were almost the same prior to the crisis, trading costs are significantly higher in the crisis period for stocks in the top quintile, with differences in the order of 12.5 basis points during the third quarter of 2008. Similarly, the right plot of Panel A documents that stocks in the top quintile (mostly dependent on hedge funds' liquidity provision) indeed experience significantly lower average cumulative abnormal returns and exhibit a slower recovery pattern after the crisis. The difference in cumulative returns hits a maximum of −15%, and is −10% at the end of the crisis period.

In Table 3.5 we cast the analysis in a cross-sectional regression framework with stock-level controls, following the setup in Anand et al. (2013), who use ordered logit regressions due to the discrete nature of the dependent variable. The right-hand-side variables of interest are HF (MF) Liquidity Supply, denoting the fraction of the volume traded by LS hedge funds (resp., LS mutual funds) over the total volume by all institutions over the benchmark period.[19] Panel A of the table reports estimates of an ordered logit cross-sectional estimation where the dependent variable is the fraction of months a stock's trading costs exceed a two-sigma threshold in the crisis period relative to their trading costs in the benchmark period (June 2006-May 2007). We note that the loading on HF Liquidity supply is positive and statistically significant, meaning that everything else controlled for stocks most heavily reliant upon LS liquidity supply experienced higher trading costs. For MF Liquidity supply we do not instead

[19] The controls are: Size, which denotes the market value of equity (B) as of May 2007; Volatility, which denotes the stock's average monthly volatility in the benchmark period; and TED, Repo, and the combined liquidity factor (LF), which denote stock-specific beta coefficients from a regression of a stock's execution shortfall against each variable.

observe a significant effect. In Panel B, we repeat the analysis on the fraction of months during the crisis period when the stock's alpha with respect to the 3-factor Fama and French (1993) model is less than zero. The coefficient on HF Liquidity Supply has the expected negative sign, and is much larger than that of MF; however, it is more noisily estimated than for ES.

As a complementary test, Internet Appendix Section E.8 provides some evidence that LS hedge funds also tilt more strongly their trading towards liquid stocks. Overall, the picture that emerges from these analyses is that hedge funds that normally provide liquidity refrain from doing so in more turbulent times, and this behavior has detrimental effects for stock liquidity.

3.5 Constraints to Hedge Fund Liquidity Provision

In light of the above-documented special behavior of hedge funds' liquidity provision and its role for stock-level liquidity, we now directly focus on hedge funds and study characteristics that make them more exposed to funding shocks. We construct an overall fund-level index capturing financial constraints and the impact of limits to arbitrage. We then show that constrained funds experience a higher sensitivity to funding shocks in their ability to provide liquidity (Section 3.5.1) as well as a more pronounced deterioration in trade performance in periods of low aggregate liquidity (Section 3.5.2).

3.5.1 Liquidity Provision and Hedge Fund Characteristics

A number of hedge fund characteristics are likely to determine different sensitivity of liquidity provision to changes in aggregate funding conditions. For example, higher leverage makes a fund more exposed to changes in the cost of debt and in margin requirements. Then, we expect highly-leveraged hedge funds to withdraw their liquidity provision more strongly in bad times. We measure *Leverage* by the amount of leverage in place.

The extent to which hedge funds can preserve their trading capital when facing adverse conditions also depends on their reputational capital. An established hedge fund can more convincingly negotiate the lending terms with its brokers and prevent investors from leaving the boat than a young fund. For similar reasons, funds with a shining track record are more credible vis-a-vis brokers and investors than poor-performers. Thus, we expect the sensitivity of hedge funds' liquidity provision to aggregate conditions to be higher for young and poor-performing funds.[20] We thus use minus the age of the fund ($Young$) and minus the year-to-date performance (Bad).

Hedge funds with an important component of illiquid assets in their portfolios may be more likely to alter their provision of liquidity in the stock market if funding conditions deteriorate. The logic is that a negative shock to the illiquid part of their portfolio may force them to liquidate their more liquid positions, which qualifies as demand for liquidity.[21] Following Getmansky, Lo, and Makarov (2004), we measure the illiquidity of a fund's portfolio, $Illiquid$, by the first-order autocorrelation in its returns.

We construct an overall fund-level proxy of financial constraints to identify the funds for which limits to arbitrage are more binding. This fund-level score of financial constraints ($Constrained$) is constructed as the sum of the four, standardized variables. The index is then normalized to range between 0 and 1 for ease of interpretation. Given this measure, we test whether the more constrained funds are responsible for the observed withdrawal of hedge funds from liquidity provision in tight funding conditions via the following model:

$$TS_{i,t+1} = a_1 + a_2 Constrained_{i,t} + b_1 LF_t + b_2 Constrained_{i,t} \times LF_t + \delta' Z_{i,t} + \varepsilon_{i,t+1}, \quad (3.4)$$

which is estimated on the panel of the available fund-day observations. The vector $Z_{i,t}$

[20] At a first approximation, share restrictions (i.e., lockup period, redemption notice period, and redemption frequency) represent another legitimate candidate for a fund-measure of constraints. At a closer scrutiny, however, share restrictions are endogenous relative to the funds' clientele. That is, a fund can afford to keep lower restrictions if it expects its clients to be less inclined to redeem. This consideration suggests that the effect of share restrictions is ambiguous. We have tried to include them among our measures of constrains, without a significant improvement of the results. Therefore, we leave them out of our main specifications to focus on a parsimonious set of constraints that appear to be empirically relevant.

[21] Manconi, Massa, and Yasuda (2012) provide evidence for the bond market during the recent financial crisis that is consistent with this story.

denotes a set of controls for trade difficulty.[22] Table 3.6 collects the estimates when using either TS (Columns 1–3) or ES (Columns 4–6) as dependent variable. Columns 1 and 4 use the classification in LS/LD based on prior month' trading, while Columns 2 and 5 rely on the long-term liquidity provision classification described in Section 3.4. In these specifications, we use the subset of 58 funds reporting to Ancerno for which the above-mentioned variables are present in the commercial hedge fund database. In Columns 3 and 6, we compute an alternative *Constrained* fund-level score based on the Ancerno dataset directly, rather than relying on the sparser information from hedge fund datasets.[23] With this approach, the number of available funds is back to 96 (the full set of funds).

We can provide more direct evidence on the role of a fund's portfolio composition in affecting hedge funds' ability to supply liquidity to the market. In particular, an illiquid portfolio prevents a fund from quickly responding to demands for liquidity in the market when they arise. On the other hand, if a fund holds illiquid assets in its portfolio, it means that on average the fund is a liquidity provider. Thus, a priori, it is not clear in which direction portfolio liquidity will affect the fund's ability to respond to liquidity demands, especially at times of market stress. To investigate these issues, we construct two variables focusing on the liquidity risk and the illiquidity level of the stocks in the fund's portfolio using holdings data, as resulting from cumulating the Ancerno trades for each manager over a two-year horizon. Specifically, we compute the value-weighted average of the Pastor and Stambaugh (2003) liquidity betas of the stocks in the portfolio ($Pf.\,LiqBeta$), in order to capture the exposure of the fund's equity portfolio to shocks in aggregate liquidity. The liquidity betas are computed using thirty-six-month rolling-window regressions of stock return

[22] These are: *Buy* is a dummy that equals 1 for buy trades, and 0 otherwise, *Lagged Return* is the stock return on day t, and *Buy*×*Lagged Return* is their interaction; *NYSE* is a dummy that equals 1 for stocks listed at the NYSE, and 0 otherwise; *Inverse Price* is the inverse of day-t stock price; *Relative Volume* is the ratio between the number of shares traded by hedge fund i on day $t+1$ and the average volume in the prior 30 days; *Amihud* is the Amihud illiquidity ratio; *Size* and *Book-to-Market* are the stock market capitalization and book-to-market deciles. All these variables are volume-weighted at the fund level based on the trades on day $t+1$.

[23] Specifically, we construct the *Constrained* fund-level score based on size (as measured by the trading volume quintile in the previous month), illiquidity (the Amihud of the stocks that are traded in the previous month), and performance (the return from interim activity computed as in Puckett and Yan, 2011, over the past year). We then combine these variables (standardized) into a single Constrained index, with constrained funds being those that are smaller in size, more illiquid, and least performing.

on a four-factor model (i.e., the three Fama and French, 1993 plus the traded liquidity factor of Pastor and Stambaugh, 2003). Moreover, we compute the value-weighted average of the Amihud (2002) ratios of the stocks in the portfolio ($Pf. Amihud$), in order to measure the level of illiquidity of the equity portfolio.[24]

Panel A of Table 3.6 reports the results for LS hedge funds. We see that the estimate of the loading on the interaction term (b_2), reported in the first row of the table, is consistently positive throughout all specifications. This finding implies that liquidity provision decreases in bad times for more constrained funds. The coefficient is strongly statistically significant in four out of six cases, and is just marginally insignificant for the TS regression with long-term LS/LD classification. It is also economically sizeable when compared with the baseline $Constrained$ estimate reflecting the extent of liquidity provision of constrained funds in normal times (i.e., when LF equals zero). Notably, we also find that constrained LS funds are mostly impacted by funding conditions when using the alternative Ancerno-based measure of constraints. If anything, the coefficient is more significant than in the other specifications, which is reassuring of the overall validity of our results. Given that $Constrained$ ranges between 0 and 1, the slope on LF captures the effect of funding conditions on the least constrained funds. The negative and significant estimate implies that the relatively unconstrained funds increase their supply of liquidity in bad times (their TS and ES fall), which is consistent with Anand et al.'s (2013) evidence for the set of all institutions in Ancerno. Finally, we find that the loadings on the alternative portfolio measures of liquidity are mostly insignificant, whether in level or interacted with funding conditions. The only exception is $Pf. Amihud$ in specifications 3 and 6, where it enters with a negative sign.

The results for LD hedge funds in Panel B convey a similar picture. The effect of funding shocks are stronger for constrained funds, and is statistically significant when using ES as dependent variable. We also observe a stronger role for the portfolio liquidity measures, in particular for Liquidity Beta, which indicates that funds with a higher level of illiquid assets

[24]Internet Appendix Table E.IX shows that these two variables have very low correlation with the other measures of constraints, suggesting that they can provide independent information on limits to arbitrage.

increase their trading style (i.e., become more demanders) in bad times. Overall, portfolio liquidity appears to matter for hedge funds that demand liquidity while measures of financial constraints are relevant for liquidity supplying hedge funds.

We also explore the importance of constrained and unconstrained funds on stock resiliency during the 2008-9 financial crisis. To this end, we break down the group of stocks that are dependent on LS hedge funds (top quintile) in two groups based on whether they are mostly dependent on Constrained and Unconstrained funds, where the former are funds whose Constrained index is above the median. Panel B of Figure 3.2 plots the average cumulative abnormal returns (right plot) and execution shortfall (left plot) for the two portfolios formed according to the dependence of liquidity provision by constrained and unconstrained liquidity provider hedge funds. We find that stocks that are mostly dependent on constrained LS hedge funds suffer the most during the crisis both in terms of performance and trading costs (i.e., liquidity). Moreover, columns 4–6 of Panel A and B of Table 3.5 show that the effect of Constrained HF Liquidity Supply is large and significant for both ES and Abnormal return, meaning that stocks more heavily held by constrained hedge funds experienced a more severe decrease in liquidity and performance during the crisis, everything else controlled for. These results are consistent with and lend further support to those from the previous analyses.

3.5.2 Trading Performance

Institutional investors' financial performance is a key driver of their ability to provide liquidity (Comerton-Forde et al., 2010). As modeled by Brunnermeier and Pedersen (2009), losses on arbitrageurs' positions can trigger margin calls from brokers which force the arbitrageur to liquidate the losing positions and to experience further losses as a result of price pressure. In this situation, a liquidity supplier turns into a liquidity demander. A related case is that in which arbitrageurs' underperformance causes investors to withdraw their capital, so that profitable positions have to be unwound before convergence (Shleifer and Vishny, 1997). Also in this case, poor performance impairs liquidity provision.

Given the importance of financial performance for liquidity provision, we next study the impact of funding shocks on hedge funds' trading performance. Computing returns over different horizons allows us to measure the duration of negative funding shocks to hedge funds' portfolios. We expect the impact of negative funding conditions to be exacerbated for those institutions that are financially constrained. Further, we expect the sign of the sensitivity to funding conditions to depend on the Trading Style (i.e., liquidity provision vs. liquidity demand) because in bad times the cost of liquidity is higher.

To test these conjectures, we compute hedge funds' trading performance by modifying Puckett and Yan's (2011) methodology to suit our application. First, for each hedge fund trade, we compute the cumulative abnormal non-overlapping return over three different horizons: one week (5 days), two weeks (10 days), and one month (21 days). Stock-level abnormal returns on each day are taken relative to the Fama and French (1993) three-factor model. We then form portfolios of all trades from funds in one of the four subsamples that result from the intersection of the LS vs. LD and the constrained vs. unconstrained splits developed above. When computing total portfolio returns, sell trade returns are subtracted from buy trade returns.[25] The buy and sell portfolios are equally weighted, but using the trade size to construct volume-weighted portfolios gives similar results. We thus obtain daily series of cumulative abnormal returns over three different horizons for the four groups of funds.

We regress the cumulative abnormal returns of portfolios based on day $t+1$ trades on the liquidity factor on day t, separately for LS and LD funds, through the model:

$$r_{i,t+k} = a_1 + a_2 Constrained\,Pf_i + b_1 LF_t + b_2 Constrained\,Pf_i \times LF_t + u_{t+1}. \qquad (3.5)$$

where $Constrained\,Pf_i$ is 1 for if portfolio i is made of constrained funds, and 0 otherwise.

[25] In Ancerno data, buy trades can represent newly initiated long positions as well as the covering of previously opened short positions. Vice versa, sell trades capture liquidations of long positions as well as newly initiated short positions. Then, the returns of our portfolios measure both the performance of new positions and the opportunity cost of unwinding existing positions.

The coefficient b_1 measures the effect of funding conditions on the abnormal performance of unconstrained funds, whereas b_2 captures the additional impact on the group of constrained funds. The horizon k is either 5, 10, or 21 days, so the model is estimated on the sample of horizon-portfolio combinations.

Panel A of Table 3.7 reports the estimates for LS hedge funds, which are economically and statistically relevant. When funding conditions tighten, unconstrained LS funds experience an increase in trading performance up to 3% in the one month after the trade. This result suggests that the subset of hedge funds that are not exposed to financial constraints can take advantage of the profit opportunities that open up in bad times. However, constrained LS funds experience a significant and persistent deterioration in trading performance when funding liquidity dries up. For these funds, the returns on trades that are initiated on a day in which funding conditions worsen by one standard deviation are lower (with respect to unconstrained funds) by about 1.6% after a week, 2.0% after two weeks, and 1.5% after a month. In the rightmost panels, we examine the performance of buy and sell trades separately. The question that we address is which side of the trade is driving our results. The impact of funding shocks on the performance of buy trades is short-lived, as it is no longer significant after the first week and reverses sign after a month. In contrast, the performance of sell trades is progressively worsening for constrained funds, and persists up to a month after the shock in funding conditions. We therefore confirm the evidence in the previous subsection that fund-level constraints interact with aggregate conditions to ultimately affect performance.[26]

The estimates for LD hedge funds in Panel B reveal that unconstrained LD funds earn positive abnormal returns in the order of 1% up to two weeks after the funding shock, but this over-performance vanishes thereafter. The view is more negative for constrained LD funds, as their reaction over the same two-week period tends to be negative, although quite noisily estimated. Unconstrained LD funds gain from buy trades in bad times, but they lose

[26]Analogous conclusions can be drawn from the impulse-response function from a weekly Vector Autoregression (VAR) model on returns, see Internet Appendix Figure E.1. Furthermore, Internet Appendix E.X relates mutual funds trading performance to funding conditions.

from sell trades, consistent with the view that in down markets the main demand for liquidity is on the sell side.

In sum, arbitrageurs' trading performance is sensitive to funding liquidity. The subset of hedge funds that are not subject to financial constraints can take advantage from the widening of mispricing and the increased premium from liquidity provision. On the other hand, the managers that are more exposed to the negative funding shocks because of less stable sources of funding experience a prolonged underperformance. Among these hedge funds, even the liquidity suppliers show signs of financial distress, which probably explains their withdrawal from liquidity provision.

3.6 Conclusion

This paper draws inspiration from the theoretical results and empirical evidence pointing out limits of arbitrage in financial markets. Our goal is to identify more closely the liquidity providing institutions and their behavior in different market environments. The analysis relies on trade-level data that provides a privileged perspective on liquidity supply and trading performance.

First, we document that institutional liquidity provision forecasts stock-level liquidity. In particular, hedge funds' liquidity supply is a powerful predictor compared to that of mutual funds, and such predictive ability strengthens as funding conditions tighten. We also establish the merits of using detailed and timely transaction data, as opposed to low-frequency information, to track institutions' trading behavior.

Next, we show that the liquidity provision of hedge funds – as measured by either trading style or price impact – exhibits much stronger sensitivity to funding conditions compared to that of mutual funds. Importantly, this behavior characterizes hedge funds that are typically liquidity providers, which suggests that these funds are no longer able to perform their role but are forced to switch toward liquidity consumption. We also show that the reliance on liquidity supplying hedge funds has implications for stock resiliency during the financial crisis.

Then, we study the institutional characteristics that make hedge funds' liquidity supply exposed to funding shocks. The ability to steadily provide liquidity varies in the cross-section as a function of attributes relating to the availability and stability of hedge funds' capital. Funding conditions have a stronger impact on constrained funds, which we identify from a young age, high leverage, an illiquid portfolio, and poor recent performance. Such institutions are more prone to margin calls and redemptions at times of market stress. The main result of this analysis is that, among the more financially constrained hedge funds, institutions that provide liquidity in normal times turn into liquidity demanders when funding conditions tighten.

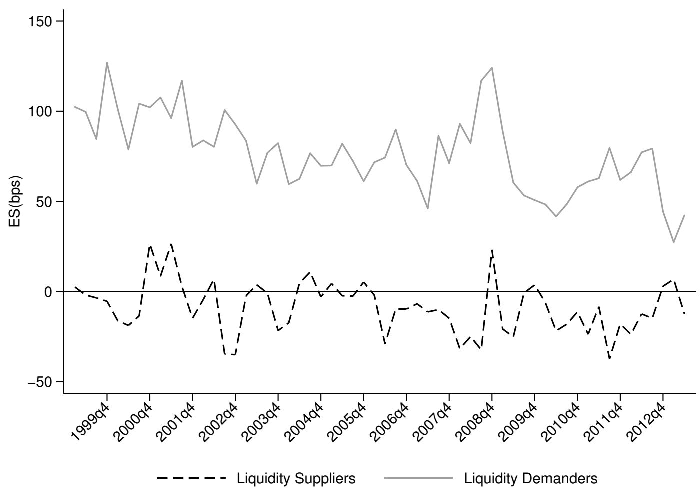
Lastly, we recognize that financial performance is a key determinant of the stability of funding because margin calls and redemptions respond to portfolio returns. Our main finding is that fund-level measures of financial constraints interact with aggregate conditions to generate trading losses in stressed markets, even for institutions that are normally providing liquidity. For these funds, the underperformance persist for at least a month after the initial funding shock, which contributes to explain their withdrawal from liquidity provision.

To conclude, our analysis sheds new light on the behavior of the liquidity providing sector in financial markets. Hedge funds are more important actors in this field than mutual funds. However, their funding structure makes their provision of liquidity exposed to aggregate conditions. When funding dries up, there is a significant increase in liquidity demand coming from this group of institutions. The finding has obvious implications for the evaluation of market stability. Under severe stress, some stabilizing forces in financial markets appear to lose their ability to oppose the main trend and they actually contribute to put further pressure on asset prices. Our result that stocks that were most highly dependent on liquidity supplying hedge funds at the crisis inception later suffered the most is indeed in line with this argument.

Figure 3.1: Execution Shortfall and Trading Style.

Each month, we compute hedge funds' and mutual funds' Trading Style (TS) as in Anand et al. (2013). We label hedge funds in the first tercile Liquidity Suppliers (LS) and those in the third tercile Liquidity Demanders (LD). The figure shows the quarterly averaged execution shortfall (in bps) separately among LS and LD for hedge funds (Panel A) and mutual funds (Panel B) reporting to Ancerno. The sample period is from January, 1999 to June, 2013.

Panel A: Hedge Funds



Panel B: Mutual Funds

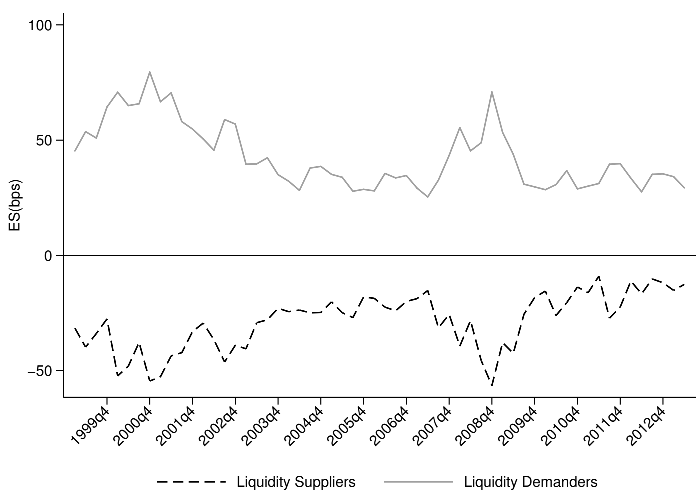
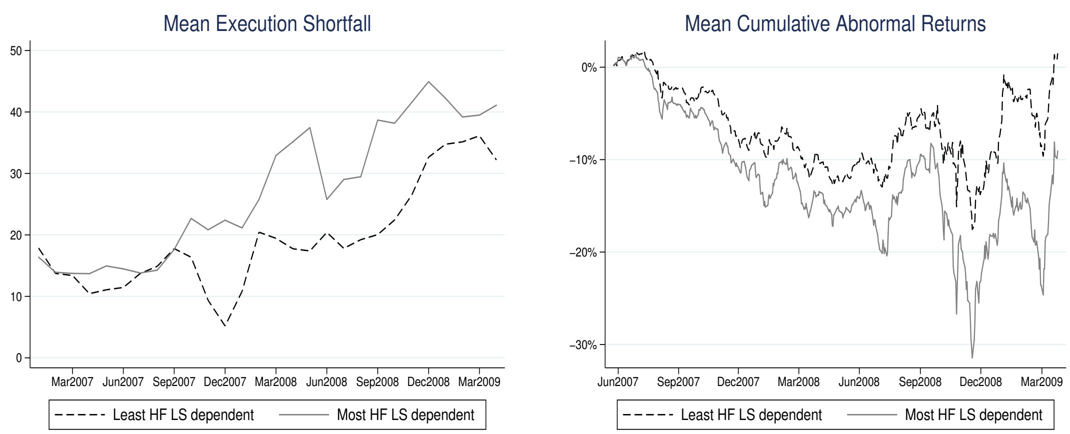


Figure 3.2: Stock Resiliency and Hedge Funds' Liquidity Provision.

We compute the fraction of the volume traded by LS hedge funds over the total volume by all liquidity supplying institutions over June, 2006 to May, 2007 period. Next, we sort each stock based on this fraction into quintiles and focus on the top (most HF LS dependent) and bottom (least LS dependent) quintiles. Panel A reports the execution shortfall (quarterly moving average, left panel) and cumulative abnormal return (right panel) over the June, 2007 to March, 2009 crisis period for the two portfolios of stocks. In Panel B, we provide similar plots when breaking down the stocks that are HF LS dependent in two groups based on whether they are mostly traded by Constrained or Unconstrained hedge funds, defined as funds above (resp. below) the median *Constrained* index from Table 3.6.

Panel A: Hedge Funds vs Other Institutions



Panel B: Constrained vs Unconstrained Hedge Funds

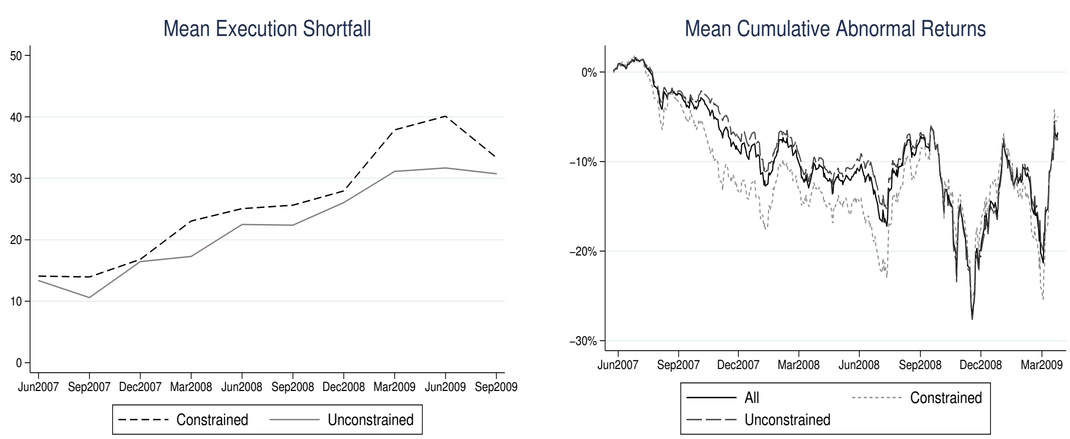


Table 3.1: Summary Statistics for Trade-level Data

The table displays the following statistics: mean; standard deviation; minimum; 25th, 50th, and 75th percentiles; maximum. The variables are: the number of management companies, the daily number of trades, the total daily dollar volume, the daily volume per trade/buy trade/sell trade, the number of distinct stocks a fund trades over the trades it reports, and the number of distinct trading days across funds. The statistics are calculated for trades originating from hedge funds in Panel A and from mutual funds in Panel B. The sample period is from January, 1999 to June, 2013.

Panel A: Hedge funds (HF)

	Mean	Std	Min	p25	p50	p75	Max
Number of management companies	23	5	3	19	22	26	39
Number of trades	3’265	2’643	69	1’018	2’829	4’782	36’639
Volume ($ millions)	501	463	12	164	372	691	9’199
Volume per trade ($ thousands)	175	95	16	111	155	216	1’858
Volume per trade, buy trades ($ thousands)	171	106	20	103	150	210	2’411
Volume per trade, sell trades ($ thousands)	186	108	9	113	160	231	1’335
No. distinct stocks	779	984	13	184	372	926	4’320
No. distinct days	904	897	20	195	636	1’235	3’528

Panel B: Mutual funds (MF)

	Mean	Std	Min	p25	p50	p75	Max
Number of management companies	163	17	85	159	168	175	196
Number of trades	63’004	39’234	7’164	35’096	52’646	80’584	307’484
Volume ($ millions)	10’128	3’946	1’512	7’698	9’769	11’980	117’134
Volume per trade ($ thousands)	211	124	21	117	158	287	758
Volume per trade, buy trades ($ thousands)	200	118	23	111	151	272	780
Volume per trade, sell trades ($ thousands)	227	136	21	125	170	309	827
No. distinct stocks	1406	1405	13	339	891	2138	6693
No. distinct days	1535	1171	10	458.5	1257	2496	3645

Table 3.2: Summary Statistics for Execution Shortfall and Funding Liquidity Determinants

The table reports the following summary statistics: number of observations; mean; standard deviation; first-order autoregressive coefficient; minimum; 25th, 50th, and 75th percentiles; maximum. In Panels A and B, the statistics are for Trading Style, constructed as in Anand et al. (2013), and for the daily execution shortfall (in basis points), constructed as volume-weighted fund-level average across all trades, buy trades only (superscript b), and sell trades only (superscript s). They are computed on the sample of hedge funds in Panel A, and on mutual funds in Panel B. Panel C reports time-series statistics for the following funding liquidity determinants: the two-week return to the CRSP value-weighted index (R_M); the VIX; the TED spread; the volume of dealer Repos (Repo); and the combined liquidity factor (LF) that is obtained by summing the four variables, after having standardized them and changed the signs, where necessary, so that the factor measures deterioration in funding conditions. Finally, Panel D and E report statistics for the week-stock-level data on the adjusted quoted bid-ask spread (ASPR), Amihud ratio, and hedge funds' net liquidity demand measures constructed from either the Ancerno dataset ($TSLiqDemand$) or from institutional holding data ($RLPLiqDemand$) as explained in Section 3.3.2. The sample period is from January, 1999 to June, 2013.

	N	Mean	Std	AR(1)	Min	p25	p50	p75	Max
					Panel A: Hedge funds (HF)				
TS	82'253	0.13	0.66	0.13	−1	−0.34	0.19	0.70	1
ES	82'253	38.21	178.42	0.18	−523.33	−38.76	24.56	102.26	726.69
ES^b	71'203	29.10	197.14	0.15	−615.59	−61.44	19.65	111.66	737.39
ES^s	70'662	44.15	211.27	0.15	−602.38	−52.28	24.52	120.65	877.63
					Panel B: Mutual Funds (MF)				
TS	595'851	0.03	0.62	0.13	−1	−0.41	0.06	0.48	1
ES	595'851	8.47	140.69	0.17	−477.89	−48.23	7.03	62.06	521.49
ES^b	533'070	4.08	162.08	0.13	−557.14	−67.99	4.45	76.61	546.44
ES^s	522'380	17.14	168.85	0.14	−519.58	−58.00	7.51	82.34	665.36
					Panel C: Funding liquidity variables standardized				
R_m	174	0.00	1.00	0.88	−7.36	−0.51	0.10	0.55	5.95
VIX	174	0.00	1.00	0.98	−1.35	−0.69	−0.16	0.39	6.62
TED	174	0.00	1.00	0.99	−0.90	−0.62	−0.31	0.19	8.69
Repo	174	0.00	1.00	0.99	−1.78	−0.72	−0.01	0.58	2.46
LF	174	0.00	1.00	0.96	−1.67	−0.69	−0.24	0.53	8.58
					Panel D: Liquidity measures and hedge funds' liquidity provision				
Amihud	286'338	13.27	47.49	0.87	0.02	0.32	1.25	5.23	371.81
ASPR	298'795	162.78	150.28	0.97	0.00	53.24	121.87	221.36	779.97
TSLiqDemand	298'795	0.02	0.15	0.13	−0.52	−0.01	0.00	0.02	0.80
RLPLiqDemand	179'761	0.06	0.28	0.86	−2.37	−0.05	0.03	0.17	2.37
					Panel E: Liquidity measures and mutual funds' liquidity provision				
Amihud	553'068	51.51	170.39	0.81	0.02	0.79	4.05	22.09	1'287.68
ASPR	583'569	193.85	176.84	0.96	0.00	65.58	144.92	266.26	889.22
TSLiqDemand	583'569	0.09	0.44	0.07	−1	−0.15	0.09	0.35	1

Table 3.3: Stock-level Liquidity and Institutions' Liquidity Provision

The table reports OLS estimates of weekly stock-level predictive regressions of the adjusted quoted bid-ask spread (ASPR, Columns 1–5) and Amihud ratio (columns 6–10) on a set of controls plus institutions' net liquidity demand measures constructed from either the Ancerno dataset, institutional holding data, or both. The variable $TSLiqDemand$ is constructed from Ancerno data by taking the ratio of the difference between the corresponding institutions' $VolumeWith$ and $VolumeAgainst$ (defined as in Section 3.3.1) to total volume. The variable $RLPLiqDemand$ is constructed as minus the weighted average RLP beta from Jylha, Rinne, and Suominen (2014) of hedge funds trading in the stock, where weights are based on stock holdings from quarterly 13F filings. Betas are updated monthly, whereas weights are updated quarterly. The controls are: $Return$ and STD, which denote respectively the weekly sum and standard deviation of daily stock returns; $Turnover$, which is the ratio between the weekly volume, computed as the sum of number of shares traded in each day of the week, to the number of shares outstanding; a constant and a Lag term. All right-hand-side variables are computed based on data as of the week prior to the dependent variable. Below the coefficients, t-statistics based on standard errors clustered at the week and stock level are reported in parentheses. The constant estimate is omitted for brevity. The sample period is January, 1999 to December, 2011.

	Adjusted Quoted Bid-Ask Spread					Amihud measure				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep.Var.	ASPR	ASPR	ASPR	ASPR	ASPR	Amihud	Amihud	Amihud	Amihud	Amihud
Institutions	HF & MF	MF	HF	HF	HF	HF & MF	MF	HF	HF	HF
TSLiqDemand × LF	0.293	0.272	4.323		2.120	2.755	2.641	6.888		3.649
	(1.15)	(1.04)	(4.07)		(3.57)	(4.06)	(3.78)	(10.25)		(8.54)
TSLiqDemand	0.434	0.412	2.888		2.959	4.237	4.126	6.783		4.665
	(2.29)	(1.72)	(3.92)		(4.21)	(7.80)	(7.05)	(9.14)		(9.01)
RLPLiqDemand × LF				−0.108	−0.164				0.423	0.362
				(−0.19)	(−0.29)				(1.96)	(1.73)
RLPLiqDemand				−0.049	−0.065				0.361	0.352
				(−0.07)	(−0.09)				(1.99)	(2.03)
LF	2.205	2.169	1.486	0.532	0.409	8.522	8.101	2.450	0.606	0.401
	(7.94)	(7.73)	(7.92)	(1.37)	(1.05)	(17.09)	(16.97)	(8.40)	(7.10)	(5.97)
Turnover	−1.776	−1.777	−1.310	−1.005	−1.069	−5.435	−5.252	−1.476	−0.508	−0.802
	(−4.42)	(−4.28)	(−4.28)	(−2.29)	(−2.49)	(−3.93)	(−3.87)	(−3.36)	(−1.49)	(−2.28)
Return	−20.738	−20.394	−19.804	−14.792	−14.690	−33.002	−31.373	−7.478	−3.874	−3.789
	(−9.63)	(−10.27)	(−9.33)	(−4.82)	(−4.76)	(−8.46)	(−9.18)	(−5.44)	(−4.59)	(−4.62)
STD	−57.727	−54.161	11.682	−22.806	−24.343	60.073	53.965	26.155	−17.038	−16.401
	(−3.13)	(−3.01)	(0.75)	(−2.17)	(−2.34)	(1.87)	(1.93)	(2.88)	(−3.13)	(−3.05)
Lag	0.947	0.947	0.954	0.977	0.977	0.759	0.759	0.766	0.847	0.828
	(305.35)	(299.80)	(251.35)	(261.35)	(256.49)	(158.31)	(182.08)	(176.55)	(32.00)	(30.76)
Obs.	576,812	572,852	289,776	174,231	174,231	546,126	542,388	277,371	174,231	174,231
R-squared	0.900	0.901	0.914	0.953	0.953	0.591	0.592	0.616	0.742	0.747

Table 3.4: Liquidity Provision and Funding Conditions

We label institutions in the first tercile of the Trading Style variable Liquidity Suppliers (LS) and those in the third tercile Liquidity Demanders (LD). Columns 1–3 in Panel A and B report OLS estimates of the model in equation (3.3) for the group of LS and LD, respectively:

$$TS_{i,t+1} = a + b_1 LF_t + b_2 HF_i + b_3 HF_i \times LF_t + \epsilon_{i,t+1}$$

where: $TS_{i,t+1}$ is institution i's Trading Style on day $t+1$ (multiplied by 100); the dummy HF_i equals 1 if the institution is an hedge fund, and 0 otherwise; and LF is the funding liquidity factor defined in Table 3.2. Columns 4–6 report analogous estimates when the dependent variable is $ES_{i,t+1}$, the volume-weighted execution shortfall on day $t+1$ (in bps). In Columns 2 and 5, the classification in LS/LD is performed pooling hedge funds and mutual funds together and the regression is estimated over the sample of days and stocks for which we observe data for both groups. In Columns 3 and 6, the classification in LS/LD is based on a fund's Trading Style computed over the past six months, thereby capturing long-term liquidity provision. Below the coefficients, t-statistics based on double-clustered standard errors are reported in parentheses. The sample period is from January, 1999 to June, 2013. During this period, we observe on average (total distinct) 23 (96) hedge funds; on average (total distinct) 218 (727) other institutions, of which on average (total distinct) 163 (397) mutual funds.

Panel A: Liquidity Suppliers

	Trading Style			Execution Shortfall		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var.	TS	TS, Joint class. & sample	TS, Long-term	ES	TS, Joint class. & sample	ES, Long-term
HF × LF	2.249	2.487	2.972	11.259	11.492	14.231
	(1.74)	(1.93)	(2.19)	(3.53)	(2.80)	(4.16)
LF	−0.426	−0.277	−0.411	−8.745	−7.939	−10.347
	(−0.98)	(−1.23)	(−0.94)	(−7.09)	(−5.81)	(−8.09)
HF	9.057	−1.980	5.689	20.778	13.564	20.754
	(2.67)	(−0.55)	(1.53)	(2.78)	(1.59)	(2.72)
Constant	−13.015	−4.976	−13.040	−28.865	−29.211	−33.855
	(−9.77)	(−7.84)	(−9.78)	(−10.55)	(−9.81)	(−12.32)
Obs.	195,306	136,030	188,269	195,306	136,030	187,235
R^2	0.002	0.001	0.001	0.005	0.003	0.007

Panel B: Liquidity Demanders

	Trading Style			Execution Shortfall		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var.	TS	TS, Joint class. & sample	TS, Long-term	ES	TS, Joint class. & sample	ES, Long-term
HF × LF	−0.531	−0.412	−0.543	3.554	5.134	5.477
	(−0.52)	(−0.43)	(−0.52)	(0.74)	(0.94)	(1.13)
LF	−0.277	−0.830	−0.191	10.525	10.866	12.236
	(−0.89)	(−4.18)	(−0.60)	(8.20)	(6.75)	(8.70)
HF	10.703	16.783	10.724	33.566	31.053	36.947
	(4.26)	(7.26)	(4.26)	(3.26)	(2.83)	(3.59)
Constant	16.114	9.220	16.302	42.985	48.003	48.294
	(16.10)	(16.91)	(15.86)	(11.15)	(10.25)	(12.88)
Obs.	204,960	155,401	196,326	204,960	155,401	199,722
R^2	0.003	0.018	0.003	0.010	0.008	0.014

Table 3.5: Stock Resiliency, Regression Analysis

This table presents results from an ordered logit cross-sectional estimation. The dependent variable is: in Panel A, the percentage of months a stock's trading costs exceed a two-sigma threshold in the crisis period relative to their trading costs in the benchmark period (June 2006–May 2007); in Panel B, the fraction of months during the crisis period when the stock's alpha with respect to the Fama-French 3-factor model is less than zero. In columns 1–3, we investigate whether stocks that are traded mostly by LS hedge funds in normal times are less resilient in bad times. Columns 4–6 examine the differential effect of constrained and unconstrained hedge funds on the stock resiliency. Size is the market value of equity ($B) as of May 2007. Volatility is the stock's average monthly volatility in the benchmark period. TED, Repo, and the combined liquidity factor (LF) denote stock-specific beta coefficients from a regression of execution shortfall against each variable. In columns 1–3, HF (MF) Liquidity Supply is the fraction of the volume traded by LS hedge funds (LS mutual funds) over the total volume by all institutions over the benchmark period. Columns 4–6 use Constrained HF (Unconstrained HF) Liquidity Supply, which is the fraction of the volume traded by Constrained LS hedge funds (Unconstrained LS hedge funds) over the total volume by all liquidity supplier institutions.

Panel A: Execution Shortfall

	(1)	(2)	(3)	(4)	(5)	(6)
Size	−14.975	−14.915	−14.573	−14.589	−14.520	−14.255
	(−5.51)	(−5.50)	(−5.39)	(−5.44)	(−5.42)	(−5.33)
Volatility	94.632	94.415	95.765	96.202	96.004	97.175
	(16.84)	(16.81)	(17.07)	(17.10)	(17.07)	(17.31)
LF	−0.001			−0.001		
	(−1.09)			(−1.17)		
TED		0.000			0.000	
		(0.42)			(0.42)	
Repo			0.003			0.003
			(5.25)			(5.23)
HF Liquidity Supply	2.471	2.508	2.631			
	(2.04)	(2.07)	(2.17)			
MF Liquidity Supply	−0.060	−0.067	−0.020			
	(−0.17)	(−0.19)	(−0.06)			
Constrained HF Liquidity Supply				1.629	1.631	1.604
				(3.99)	(3.99)	(3.93)
Unconstrained HF Liquidity Supply				0.212	0.201	0.265
				(0.94)	(0.89)	(1.18)
Observations	2,462	2,462	2,462	2,462	2,462	2,462
Pseudo R-squared	0.038	0.038	0.041	0.040	0.039	0.042

Panel B: Abnormal Return

	(1)	(2)	(3)	(4)	(5)	(6)
Size	4.503	4.549	4.613	4.371	4.417	4.478
	(2.49)	(2.52)	(2.55)	(2.44)	(2.46)	(2.49)
Volatility	38.684	38.058	38.420	37.947	37.378	37.741
	(7.06)	(6.96)	(7.04)	(6.95)	(6.86)	(6.93)
LF	−0.002			−0.002		
	(−1.97)			(−1.96)		
TED		−0.001			−0.001	
		(−1.57)			(−1.55)	
Repo			0.001			0.001
			(1.37)			(1.44)
HF Liquidity Supply	−1.433	−1.368	−1.357			
	(−1.18)	(−1.13)	(−1.12)			
MF Liquidity Supply	−0.244	−0.242	−0.244			
	(−0.68)	(−0.68)	(−0.68)			
Constrained HF Liquidity Supply				−1.416	−1.406	−1.424
				(−3.37)	(−3.35)	(−3.40)
Unconstrained HF Liquidity Supply				0.008	0.005	0.008
				(0.04)	(0.02)	(0.04)
Observations	2,380	2,380	2,380	2,380	2,380	2,380
Pseudo R-squared	0.005	0.005	0.005	0.006	0.006	0.006

Table 3.6: Liquidity Provision, Funding Conditions, and Financial Constraints

Columns 1–3 of the table report OLS estimates of equation (3.4):

$$TS_{i,t+1} = a_1 + a_2 Constrained_{i,t} + b_1 LF_t + b_2 Constrained_{i,t} \times LF_t + \delta' Z_{i,t} + \varepsilon_{i,t+1}$$

where $TS_{i,t+1}$ is hedge fund i's Trading Style on day $t+1$; LF is the liquidity factor defined in Table 3.2; *Constrained* is an index of hedge fund financial constraints, constructed as explained in Section 3.5.1, ranging from 0 (=Low) to 1 (=High); $Z_{i,t}$ are the trade-level controls listed in Section 3.5.1; and $Pf.\,LiqBeta$ and $Pf.\,Amihud$ are, respectively, the average liquidity beta from a Pastor and Stambaugh (2003) model and the average Amihud (2002) measure across all the stocks in the portfolio. Columns 4–6 report analogous estimates when the dependent variable is now the volume-weighted execution shortfall $ES_{i,t+1}$. Results are shown for hedge funds classified as Liquidity Suppliers in Panel A, and for Liquidity Demanders in Panel B. Columns 1 and 4 use the classification in LS/LD based on prior month' trading as in Anand et al. (2013), while Columns 2 and 5 rely on the long-term liquidity provision classification described in Section 3.4. In Columns 3 and 6, the *Constrained* index is constructed using trade-level information from the Ancerno database as explained in Section 3.5.1. Below the coefficients, t-statistics based on time-clustered standard errors are reported in parentheses. The constant estimate is omitted for brevity. The sample period is from January, 1999 to June, 2013. During this period, we have on average (total distinct) 10 (58) hedge funds for which we can obtain the Constrained classification, increasing to 23 (96) when we use the classification from Ancerno (columns 3 and 6).

Panel A: Liquidity Suppliers

	Trading Style			Execution Shortfall		
Dep.Var.	(1) TS	(2) TS, Long-Term	(3) TS, Ancerno	(4) ES	(5) ES, Long-Term	(6) ES, Ancerno
Constrained × LF	3.966	11.251	7.801	52.738	64.863	14.791
	(0.70)	(1.61)	(2.87)	(3.47)	(3.52)	(1.82)
Constrained	19.716	22.884	−30.064	50.975	46.009	−62.167
	(3.32)	(3.52)	(−9.04)	(3.70)	(3.12)	(−7.79)
Portf. LiqBeta × LF	0.066	0.284	0.009	−0.203	−0.267	−0.000
	(0.35)	(1.09)	(0.06)	(−0.37)	(−0.40)	(−0.00)
PortLiqBeta	0.289	−0.224	−0.074	0.541	−0.413	−0.118
	(1.21)	(−0.97)	(−0.44)	(0.91)	(−0.71)	(−0.31)
Portf. Amihud × LF	−0.275	−0.220	0.203	0.345	0.326	0.927
	(−1.01)	(−0.80)	(0.76)	(0.50)	(0.47)	(1.36)
portAmihud	0.038	0.008	−0.596	−0.052	−0.054	−1.091
	(0.20)	(0.04)	(−2.95)	(−0.16)	(−0.17)	(−2.85)
LF	−1.673	−3.437	−2.332	−24.318	−33.102	−6.009
	(−0.69)	(−1.16)	(−1.81)	(−3.77)	(−4.35)	(−1.53)
Trade-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,406	6,982	21,478	8,406	6,982	21,478
R-squared	0.013	0.015	0.014	0.026	0.017	0.020

Panel B: Liquidity Demanders

	Trading Style			Execution Shortfall		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep.Var.	TS	TS, Long-Term	TS, Ancerno	ES	ES, Long-Term	ES, Ancerno
Constrained × LF	7.217	1.084	4.266	70.580	67.192	−12.872
	(1.23)	(0.16)	(1.62)	(3.55)	(2.77)	(−1.34)
Constrained	−5.958	7.767	−11.069	47.321	107.251	−27.168
	(−1.09)	(1.29)	(−3.77)	(2.98)	(5.85)	(−3.29)
Portf. LiqBeta × LF	0.284	0.151	0.265	0.018	−0.489	0.475
	(2.23)	(1.24)	(2.58)	(0.04)	(−1.05)	(1.35)
PortLiqBeta	−0.105	−0.053	−0.048	0.052	0.728	0.158
	(−0.85)	(−0.45)	(−0.55)	(0.13)	(1.79)	(0.61)
Portf. Amihud × LF	−1.559	3.311	1.259	−13.482	14.118	4.793
	(−0.59)	(0.60)	(1.29)	(−1.68)	(0.85)	(1.16)
portAmihud	−6.235	−6.496	−2.275	−18.826	−13.201	−7.139
	(−2.76)	(−1.76)	(−1.61)	(−3.12)	(−1.27)	(−1.41)
LF	−3.991	−2.085	−3.176	−11.169	−10.357	19.311
	(−1.75)	(−0.81)	(−2.52)	(−1.47)	(−1.11)	(4.19)
Trade-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,021	11,451	27,478	12,021	11,451	27,478
R-squared	0.011	0.008	0.007	0.045	0.044	0.031

Table 3.7: Trading Performance, Financial Constraints, and Funding Conditions

We separately classify hedge funds as Liquidity Suppliers or Liquidity Demanders based on the Trading Style measure of Anand et al. (2013), and in Constrained (resp. Unconstrained) if their *Constrained* index from Table 3.6 falls above (below) the median. Each day, we form equally-weighted portfolios of the stocks that are traded by the hedge funds in each of these four groups. For these portfolios, we compute non-overlapping cumulative abnormal returns over different horizons (one week, two weeks, and one month). For the two groups of LS/LD funds, the table reports OLS estimates of equation (3.5):

$$r_{i,t+k} = a_1 + a_2 ConstrainedPf_i + b_1 LF_t + b_2 ConstrainedPf_i \times LF_t + u_{t+1}$$

where r is the portfolio abnormal return, $ConstrainedPf_i$ is 1 for the portfolio of constrained funds and 0 otherwise, and LF is the liquidity factor. The horizon k is either 5, 10, or 21. Stock-level abnormal returns on each day are taken relative to the Fama and French (1993) three-factor model. Each panel reports three specifications for all horizons, one where the cumulative abnormal returns are computed from both buy and sell trades, and the other two when buy and sell trades' cumulative returns are examined separately. Sell trades' returns are multiplied by minus one. Below the coefficients, t-statistics based on robust time-clustered standard errors are reported in parentheses. The sample period is from January, 1999 to June, 2013. During this period, we have on average (total distinct) 10 (58) hedge funds for which we can obtain the Constrained classification.

Panel A: Liquidity Suppliers

	All trades			Buy trades			Sell trades		
	(1) 1-week	(2) 2-week	(3) 1-month	(4) 1-week	(5) 2-week	(6) 1-month	(7) 1-week	(8) 2-week	(9) 1-month
Constrained Pf × LF	−0.016	−0.020	−0.015	−0.014	−0.006	0.017	−0.004	−0.018	−0.035
	(−2.75)	(−1.92)	(−0.76)	(−3.31)	(−0.74)	(0.72)	(−0.72)	(−2.01)	(−1.65)
Constrained Pf	−0.011	−0.015	−0.049	−0.008	−0.014	−0.045	−0.004	−0.004	−0.014
	(−2.26)	(−1.69)	(−3.08)	(−2.01)	(−2.03)	(−2.98)	(−1.00)	(−0.50)	(−1.15)
LF	0.012	0.018	0.027	0.013	0.011	0.008	0.001	0.010	0.023
	(3.17)	(3.38)	(2.33)	(3.92)	(2.31)	(0.90)	(0.15)	(2.41)	(2.14)
Constant	0.012	0.017	0.029	0.007	0.015	0.029	0.005	0.004	0.006
	(3.14)	(3.08)	(2.94)	(2.56)	(3.10)	(3.50)	(1.69)	(0.91)	(0.73)
Obs.	763	387	272	656	329	226	661	339	233
R-squared	0.023	0.032	0.051	0.040	0.029	0.043	0.003	0.019	0.038

Panel B: Liquidity Demanders

	All trades			Buy trades			Sell trades		
	(1) 1-week	(2) 2-week	(3) 1-month	(4) 1-week	(5) 2-week	(6) 1-month	(7) 1-week	(8) 2-week	(9) 1-month
Constrained Pf ×LF	−0.005	−0.012	0.002	−0.005	−0.007	−0.008	−0.001	−0.006	0.012
	(−1.14)	(−1.24)	(0.14)	(−1.17)	(−0.89)	(−0.40)	(−0.29)	(−0.62)	(1.15)
Constrained Pf	−0.000	−0.008	−0.004	−0.002	−0.005	−0.002	0.002	−0.004	−0.003
	(−0.04)	(−1.09)	(−0.33)	(−0.71)	(−0.85)	(−0.15)	(0.70)	(−0.64)	(−0.35)
LF	0.006	0.010	−0.003	0.007	0.011	0.012	−0.001	−0.000	−0.017
	(1.93)	(1.63)	(−0.25)	(2.87)	(1.83)	(0.78)	(−0.21)	(−0.10)	(−2.07)
Constant	0.003	0.006	0.000	0.003	0.002	−0.005	−0.000	0.005	0.006
	(0.91)	(1.10)	(0.04)	(1.27)	(0.43)	(−0.55)	(-0.10)	(1.24)	(0.94)
Obs.	1,092	547	308	1,029	521	287	1,004	499	284
R-squared	0.004	0.007	0.001	0.009	0.012	0.007	0.001	0.006	0.020

Chapter 4

The Term Structure of Credit Spreads and Institutional Equity Trading

4.1 Introduction

Over the last few decades, the level of ownership of institutional investors in equity markets has increased dramatically. By the 2010s, over 65% of the average firm is owned by institutional investors (Blume and Keim, 2017). Although institutional investors share some important commonalities, they are far from being homogeneous and may have different investment horizons because of investment objectives, legal restrictions, investor clienteles, and competitive pressure.

Empirical studies argue that stocks held by institutions are more efficiently priced (Boehmer and Kelley, 2009), better governed (Chung and Zhang, 2011; Ferreira and Matos, 2008), and have lower agency costs (Wang and Nanda, 2011) than stocks held by retail investors, suggesting that institutional traders make informed trades. However, institutional investors with different investment horizons might be differentially informed. Yan and Zhang (2009) empirically show that short-term institutions are better informed and they trade actively to exploit their informational advantage. In addition, they find that long-term institutions' trading does not forecast future returns, nor is it related to future earnings news.

The objective of this paper is to investigate the informational content of the trades of institutional investors with different investment horizons. Specifically, I focus on the role of long-term institutional investors in information diffusion from the credit market to equities. There can be informational disparities across derivative securities associated with the same underlying asset. In this case, information needs to attract investor attention before it can be processed and incorporated into asset prices via trading. I argue that long-term institutions in the equity market that trade based on the fundamental value of the firm may be interested in extracting information from the credit default swap market (CDS). A center of interest might be the term structure of the CDS spreads, which is a forward-looking information proxy, that is forecasting future equity returns, future earnings and future creditworthiness of the firm. Accordingly, long-term institutions trade in the equity market in response to the changes in the riskiness of the firm in credit market and contribute to transmission of information from credit market to equities. However, prior literature provides evidence that short-horizon investors specialize on strategies that focus on predicting the short-run trades of other market participants, rather than long-run movements in asset values driven by fundamentals. Therefore, I expect short-term institutions' equity trades not to be affected by the changes in the credit spread slope.

To measure the slope of the credit spread term structure, I use data from the market for credit default swaps, which has grown tremendously and has become increasingly liquid during recent years. CDS contracts trade across different maturities in the credit market. The credit spread slope can be associated with firm's riskiness and future fundamentals. A high CDS slope can indicate that investors expect the firm's credit quality to deteriorate and CDS spreads to increase in the future. Han et al. (2017) empirically show that the CDS slope negatively predicts future stock returns, even after controlling for various measures of risk such as the levels of credit spreads and the loading on a portfolio constructed by sorting on the slope (i.e., a slope factor). These findings indicate that the slope characteristic contains valuable information for the cross section of equity returns that is complementary to traditional risk measures. Consistent with this notion, the credit spread slope also forecasts firm fundamentals such as creditworthiness and earnings.

The equity prices and CDS spreads of a firm are exposed to the same fundamental shocks relating to information about its future cash flows. The creation of CDS has provided the market participants with alternative tools to invest, hedge and speculate. There are two potentially important benefits of CDS. First, CDS can be hedging tools through which investors can manage the risk of their positions in other securities. Second, they can provide informed traders with incentives to trade, facilitating price discovery. CDS markets provide a new venue for traders with private signals about credit risk to trade on their information and improve the informational efficiency of equity prices (Boehmer et al., 2015). Given that bond markets tend to be illiquid, the information-based trades may not occur in the absence of CDS. Acharya and Johnson (2007), Berndt and Ostrovnaya (2007), and Qiu and Yu (2012) document significant credit pricing information flows from CDS to stocks due, in part, to non-public information that informed banks have on borrowers through their lending relationships. In contrast, Norden and Weber (2009) and Hilscher et al. (2015) document credit pricing information unequivocally flows from stocks to CDS, and not vice versa, due to a separating equilibrium where informed traders choose to trade only stocks for transaction cost reasons.

While the existing literature has typically focused on the credit market outcomes of CDS trading, there is little prior work on how CDS trading affects shareholders. To examine the sales behavior of long-term and short-term institutions in response to the changes in the CDS slope, I use institutional ownership data from the first quarter of 2001 until the first quarter of 2013 that was compiled by Thomson-Reuters from U.S. Securities and Exchange Commission (SEC) 13F filings. Equity trades are measured as the quarterly change in holdings of a given stock by a given institution. I use data from CRSP and Compustat to construct other stock-level variables. Given that the main variables from the 13F filings are at the quarterly frequency, I construct all other variables at a quarterly frequency. I obtain the CDS spreads across different maturities from Markit for the years 2001-2013.

Cella et al. (2013) show that during episodes of market turmoil, 13F institutional investors with short trading horizons sell their stock holdings to a larger extent than 13F institutional investors with longer trading horizons. Similar to their methodology, I use panel regressions to explore the relationship between CDS slope and quarterly institutional equity sales. To test my hypotheses, I consider three different institutional ownership variables: All 13F institutions' ownership (total), short-term institutional ownership and long-term institutional ownership. At the individual stock level, I explore the determinants of the net sales of total, short-term and long-term institutions.

The results show that CDS slope is relevant in explaining the net sales of all 13F institutions and long-term institutions, over and above standard controls such as liquidity and momentum. Based on my regression results, a 1-percent increase in CDS slope is associated with 0.303 percentage point increase in the sales of all 13F institutions holding other variables constant. In addition, a 1-percent increase in CDS slope is associated with 0.114 percentage point increase in the sales of the long-term institutions holding other variables constant. Moreover, I find that the CDS slope significantly predicts the equity sales of long-term insitutions belonging to banks, insurance companies, mutual funds, hedge funds and asset management categories. However, the regression results for the short-term institutions show that the coefficient for CDS slope is not significant.

In their empirical analysis, Yan and Zhang (2009) conclude that long-term institutions' holdings or trading does not predict future returns. They also find little evidence that long-term institutional trading is related to either future earnings surprises or earnings announcement abnormal returns. Han et al. (2017) empirically show that the credit spread slope negatively predicts future stock returns. Combining the findings of both papers, one should expect that CDS slope does not forecast the trades of long-term institutions. However, in my study, I find that term structure of CDS spreads, which is a forward-looking information proxy, is relevant in explaining the net sales of long-term institutional investors. One of the most important findings of my paper is that the negative relation between CDS slope and long-term institutions' equity sales entirely arises from the part of the slope that predicts future CDS spread changes. Hence, it can be concluded that long-term institutions react to changes in future firm fundamentals in their equity trades.

The evidence that the CDS slope captures a significant component of long-term institutional trades, but not that of short-term institutions, is consistent information about the future financial health of the firm gradually diffusing from CDS to the equity market. That is, the CDS market acts as a conduit of information through the trading of institutions that rebalance their portfolio based on a firm long-term fundamental value. A competing interpretation is that these institutions are trading on information that is present in both markets, and happens to be correlated with the CDS slope. If that is the case, the CDS slope acts merely as a powerful statistic capturing a firm's long-term prospects. The fact that the CDS slope remains significant after controlling for a relative wide array of control variables makes the case for this alternative hypothesis harder.

The remainder of the paper is structured as follows. In Section 4.2 develops testable hypotheses. Section 4.3 provides a description of the data. Section 4.4 describes the empirical methodology. Section 4.5 presents the empirical results. Section 4.6 presents robustness checks. Section 4.7 discusses why sales by long-term institutions are related to CDS, and Section 4.8 concludes.

4.2 Hypothesis Development

There can be several reasons why one might expect institutions with different investment horizons to be differentially informed. First, if some institutional investors possess superior information and can regularly identify undervalued or overvalued stocks, one would expect these short-term institutions to trade frequently to exploit their informational advantage.

On the other hand, long-term institutional investors possessing limited information would trade more cautiously. Therefore, short-term institutions would be better informed than long-term institutions. Second, one might argue that long-term institutions trade infrequently because they trade only based on information regarding the fundamentals of the firm. On the other hand, short-term institutions might also trade based on noise, perhaps owing to overconfidence (Barber and Odean (2000)). In this case, it would appear on average that long-term institutions are better informed than short-term institutions. Third, it is also possible that both short- and long-term institutions are informed. However, short-term institutions are better at collecting and processing short-term information, while long-term institutions are better at collecting and processing long-term information. Thus, short-term institutions would be better informed in the short run while long-term institutions would be better informed in the long run.

Yan and Zhang (2009) empirically show that short-term institutions are better informed and they trade actively to exploit their informational advantage. In addition, they find that long-term institutions' trading does not forecast future returns, nor is it related to future earnings news. They conduct their analysis between the years 1980 and 2003. I extend the analysis in a different setting and further investigate the informational content of the trades of institutional investors with different investment horizons for the years 2001-2013.

There can be informational disparities across derivative securities associated with the same underlying asset. In this case, information needs to attract investor attention before it can be processed and incorporated into asset prices via trading. As CDS markets are venues for traders with private signals about credit risk to trade on their information and improve the informational efficiency of equity prices (Boehmer et al., 2015), long-term investors that trade based on information regarding the fundamentals of the firm might be interested in extracting information about future fundamentals from the credit default swap market. Specifically, I propose the term structure of credit default spreads, namely CDS slope, as a focus of interest since CDS slope is a forward-looking information proxy, that is forecasting future equity returns, future earnings and future creditworthiness of the firm (Han et al., 2017). Hence, long-term institutions may respond to the changes in the CDS slope and trade accordingly in the equity market. An increase in the CDS slope indicates that investors expect the firm's credit quality to deteriorate and CDS spreads to increase in the future. Accordingly, I expect this change in the credit market to translate into equity sales by long-term institutions. The first hypothesis to be tested is:

H1. Long-term institutions sell their equities when there is an increase in the CDS slope.

Several influential theoretical papers explore the effect of short trading horizons on stock prices (Allen et al., 2006; Dow and Gorton, 1994; Stein, 2005). Gaspar et al. (2005) suggest that short-term institutional investors are weak monitors. There is also evidence that short-term institutional investors pressure managers to maximize short-run profits at the expense of long-run firm value which is called as the short-term pressure hypothesis (Porter, 1992). In particular, Bushee (1998) provides evidence that firms with higher transient institutional ownership are more likely to underinvest in long-term, intangible projects such as R&D to reverse an earnings decline. These papers show that short-horizon investors specialize on strategies that focus on predicting the short-run trades of other market participants, rather than long-run movements in asset values driven by fundamentals. Accordingly, I build my second hypothesis as:

H2. Short-term institutions' equity trades are not affected by changes in the CDS slope.

If CDS slope captures a significant component of long-term institutional trades, but not that of short-term institutions, this might be consistent information about the future financial health of the firm gradually diffusing from CDS to the equity market. That is, the CDS market acts as a conduit of information through the trading of institutions that rebalance their portfolio based on a firm long-term fundamental value. A competing interpretation is that these institutions are trading on information that is present in both markets, and happens to be correlated with the CDS slope. If that is the case, the CDS slope acts merely as a powerful statistic capturing a firm's long-term prospects. This discussion suggests testing the following hypothesis:

H3. The CDS slope contains valuable information about firm fundamentals, which, in turn, is transmitted to the equity market through the trading of long-term institutions.

4.3 Data

My study combines four data sources: Thomson Financial database for quarterly holdings of institutional investors (13F filings), Markit database for CDSs, Center for Research in Securities Prices (CRSP) for stock-related information and CRSP-COMPUSTAT merged database for quarterly balance sheet data. The merged dataset contains 18,901 firm-quarter observations on 626 firms over the period March 2001-March 2013.

4.3.1 Quarterly Holdings of Institutional Investors (13F Filings)

I obtain quarterly institutional holdings from Thomson Financial for all common stocks traded on New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ for the period from the first quarter of 2001 to the first quarter of 2013. The Securities and Exchanges Commission (SEC) requires that all institutions with investment discretion over 13F securities worth $100 million or more report all equity positions greater than 10,000 shares or $200,000 at the end of each quarter. Institutional ownership for each stock is defined as the number of shares held by institutional investors divided by the total number of shares outstanding. The observations with total institutional ownership greater than 100% are excluded.

4.3.2 CDS Data

I use a comprehensive data set of single-name credit default swaps. A single-name CDS is a swap contract that provides protection against adverse credit events of the reference bond. These credit events can be either a downgrade of a bond or a default. The protection buyer makes a periodic payment to the protection seller until the occurrence of a credit event or the maturity date of the contract, whichever is first. This fee, quoted in basis points per $1 notional amount, is called the credit default swap premium, or CDS spread.

I acquire CDS data from the Markit Group, a global financial information services company. Markit constructs a composite CDS spread using input from a variety of market makers and ensures each daily observation passes a rigorous cleaning test to ensure accuracy and reliability. I use US dollar-denominated CDSs written on US entities that are not in the government sector. Since subordinated CDS are a small part of the database, they are excluded. The ”Big Bang” protocol of April 2009 changed the standard for CDS contracts on several dimensions, including a move from Modified Restructuring (MR) to No Restructuring (XR) for North American corporate CDS contracts. Following Lee et al. (2016), my database contains MR contracts prior to the ”Big Bang” and XR contracts afterward.

For each firm in the sample, the data provide CDS spreads across maturities of one, five and ten years. I choose firms that have non-missing quarter-end values for CDS spreads of all maturities. In the empirical analysis, I measure the slope of the term structure of CDS spreads by the difference between the five-year and the one-year CDS spread. As a robustness check, I also employ the difference between the ten-year and the one-year CDS spread.

4.3.3 Institution Classification

I employ two different institution classification data. The first one is the classification of institution types employed in Agarwal et al. (2013), which refines the classification used in the Thomson Reuters database.[1] They divide all institutions into ten categories: (i) banks, (ii) insurance companies, (iii) mutual funds, (iv) hedge funds, (v) asset management firms, (vi) investment banks, (vii) pension funds, (viii) endowment, (ix) corporations and (x) other institutions. The second dataset is from Brian Bushee's website[2], which categorizes institutional investors into three categories: (i) transient, (ii) quasi-indexer and (iii) dedicated.

[1] I thank Baozhong Yang for providing me with the dataset.

[2] https://accounting-faculty.wharton.upenn.edu/bushee/

4.3.4 Stock Related Information

I obtain quarterly stock returns, stock prices, share turnover and shares outstanding from the Center for Research in Security Prices (CRSP). Stock splits and stock dividends are adjusted by using the CRSP price adjustment factor.

4.3.5 Control Variables

A large amount of empirical literature has studied the potential determining factors of institutional ownership and stock sales over a period. To focus on the additional explanatory power of information from the CDS market in the regressions, I include several control variables from the literature. All of my control variables are quarterly measured. I retrieve leverage, market-book ratio, firm size, and return on assets data from the CRSP-Compustat Merged database.

4.3.6 Descriptive Statistics

I winsorize the ownership and control variables, except for dummy variables, at the 1th and 99th percentiles within each quarter to mitigate the effect of outliers. The details of the variable names, definitions and data sources are shown in Table A1.

Table 4.1 reports the summary statistics for CDS spreads and CDS slope, ownership variables and control variables for my sample firms and Table 4.2 presents the correlation matrix. During the sample period, the mean level of CDS spread is 94.42 basis points (bps) for one-year maturity and 155.07 bps for five-year maturity. On average, the CDS slope is positive. During the 2008-2009 financial crisis, CDS spreads experience large spikes, especially for the short maturity, leading to a dramatic drop in the CDS slope. But, by the end of 2009, they bounce back to the levels before the crisis. I illustrate this by Figure 4.1, which shows the quarterly time series of the 20th percentile, the median, and the 80th percentile for the cross-sectional distribution of the CDS slope. The figure also shows that the cross-sectional dispersion of the CDS slope is increasing. The spread between the 80th and the 20th percentiles of the CDS slope increases from about 40 bps in the first one-third of the sample, to about 80 bps in the second one-third of the sample, and to around 140 bps in the last part of the sample.

4.4 Empirical Strategy

4.4.1 Investor Horizons

The empirical literature generally considers horizon as an exogenous characteristic of an investor's trading style, which does not change (or changes rarely) over time. While the trading horizon of an investor is not directly observable, it is revealed through time by the investors' trading behavior. Institutional investors with short trading horizons should buy and sell more frequently than long-horizon investors. Thus, consistent with existing literature, I capture an investor's horizon using a proxy for its portfolio turnover. This measure was formalized by Gaspar et al. (2005) and is similar to measures of investor trading horizon used by Barber and Odean (2000), Yan and Zhang (2009), Cella et al. (2013) and Switzer and Wang (2017). The churn ratio of institutional investor i holding an investment set of firms denoted as Q is calculated as follows:

$$CR_{i,t} = \frac{\sum\limits_{j\epsilon Q} |N_{j,i,t}P_{j,t} - N_{j,i,t-1}P_{j,t-1} - N_{j,i,t-1}\Delta P_{j,t}|}{\frac{\sum\limits_{j\epsilon Q} N_{j,i,t}P_{j,t} + N_{j,i,t-1}P_{j,t-1}}{2}} \tag{4.1}$$

where $P_{j,t}$ and $N_{i,j,t}$ are the price and number of shares of stock j held by institution i in quarter t. Then, I estimate each institution's average churn rate over the past four quarters as:

$$AVG_{CR_{k,t}} = \frac{1}{4}\sum_{j=0}^{3} CR_{k,t-j} \tag{4.2}$$

Given the average churn rate measure, each quarter I sort all institutional investors into three tertile portfolios based on $AVG_{CR_{k,t}}$. Those ranked in the top tertile (with the highest $AVG_{CR_{k,t}}$) are classified as short-term institutional investors and those ranked in the bottom tertile are classified as long-term institutional investors. A higher turnover ratio indicates that the investors will not hold their shares for a long time and are more likely to be short-term investors. Figure 2 shows the time series of the mean and median of the average churn rate for the sample institutions. The median and mean of the time series average churn rate fall in the range of 13.57% to 20.11%, and 17.06% to 24.93%, respectively.

4.4.2 Trading Horizons and Quarterly Sales

I use panel regressions to explore the relationship between CDS slope and quarterly institutional equity sales. To test my hypotheses, I consider three different institutional ownership variables: Aggregate institutional ownership (IO_TOTAL), short-term institutional ownership (IO_ST) and long-term institutional ownership (IO_LT). Table 2 provides summary statistics of the institutional ownership variables for the sample firms. My main measure is the quarterly change in aggregate institutional shareholdings as a percentage of the firm's outstanding shares

$$Net\ Sales_{j,t} = -\frac{\sum_{i\epsilon I} \Delta N_{i,j,t}}{\sum_{i\epsilon I} N_{i,j,t-1}} \tag{4.3}$$

where $P_{j,t}$ and $N_{i,j,t}$ are defined as in Section 4.4.1 and I is the set of institutional investors. All shares are adjusted to splits that occurred during the quarter. Institutional net sales variable is calculated separately for total, short-term and long-term institutions. I estimate the following regression equation:

$$Net\ Sales_{j,t} = \beta_0 + \beta_1 Slope_{j,t-1} + \beta_2 Spread_{j,t-1} + \theta X_{j,t-1} + \eta_j + \nu_t + \epsilon_{j,t} \tag{4.4}$$

The key independent variable, the CDS slope, is measured as the five-year CDS spread minus the one-year CDS spread. CDS slope does not alone capture default risk since CDS slope and default risk do not map on to each other precisely. Hence, as a default risk measure, I add five-year CDS spreads to the regression. In addition to default risk measures, I control for past quarter stock returns (momentum), stock return volatility, stock turnover ratio, past quarter S&P market return, S&P market return volatility over the past quarter, log firm size, book-to-market ratio of equity, leverage and return on assets, which are denoted by the vector $X_{j,t-1}$.

In the panel regressions, I cluster standard errors at firm level to control for cross-correlations in the residuals. I include firm-fixed effects η_j, that control for potential omitted variable bias and year-fixed effects ν_t. Default risk measures and firm control variables are lagged one quarter.

4.5 Estimation Results

4.5.1 CDS Slope and Institutional Sales

I run the regression equation (4.4) separately for three types of institutional ownership: total institutional ownership, long-term institutional ownership and short-term institutional ownership.

4.5.1.1 All 13F Institutional Investors

Table 4.3 shows the results of regression (4.4), the determinants of net sales of all the 13F institutional investors. I find that, when aggregated at the stock level, higher CDS slope in the previous quarter results in higher selling pressure for all 13F institutions. The CDS slope variable is significantly positive at the 1% level. However, the five-year CDS spread is not significant. Based on these estimates, a 1-percent increase in CDS slope is associated with 0.303 percentage point increase in the sales of the all 13F institutions holding other variables constant. The results also show that institutional investors sell more stocks with high market-to-book ratios and larger firm size. In addition, they prefer to buy stocks with higher past stock return, higher stock return volatility, higher leverage and higher return on assets.

4.5.1.2 Long-term Institutional Investors

I report the results of the regression (4.4) for the determinants of net sales of long-term institutional investors in Table 4.4. Similar to the results for all institutional investors, the CDS slope variable is significantly positive at the 1% level. A 1-percent increase in CDS slope is associated with 0.114 percentage point increase in the sales of the long-term institutions holding other variables constant. However, different from my results for all institutions, five-year CDS spread is significantly positive at the 5% level. Hence, an increase in the five-year CDS spreads increases the sales of long-term institutions. The results also show that long-term institutional investors sell more stocks with higher share turnover and larger firm size. They buy stocks with higher past stock volatility. The results for the determinants of sales are consistent with Cella et al. (2013) and Switzer and Wang (2017).

The result for the CDS slope is consistent with my hypothesis for long-term institutional investors. Long-term institutions trade infrequently because they may trade only based on information regarding the fundamentals of the firm. The results mainly show that long-term institutions facilitate the information transmission from the credit default swap market to equity market. I discuss the information content of CDS slopes further in Section ??.

4.5.1.3 Short-term Institutional Investors

Table 4.5 provides the regression results for the determinants of net sales of short-term institutional investors. The coefficient for CDS slope is not significant. This finding is consistent with my hypothesis for short-term institutional investors. Short-term institutions are better at collecting and processing short-term information and they specialize on strategies that focus on predicting the short-run trades of other market participants, rather than long-run movements in asset values driven by fundamentals. In addition, CDS five-year spread variable is not significant. Short-term institutions prefer to sell stocks with high market-to-book ratios and high share turnovers. They also sell their stocks when past market return is high. They rather buy stocks with high past stock return, high past stock return volatility and high leverage.

4.5.2 Selling Pressure During Market Turmoil

In this section, I examine whether long-term and short-term institutional investors exploit the information in the CDS slopes differently during episodes of market turmoil. The main variable of interest is the interaction of the CDS slope with a "Turmoil" dummy variable capturing quarters during which market-wide shocks are experienced. The Turmoil dummy variable takes the value of 1 starting from the Q3 of 2007 (characterized by the Quant crisis) until Q2 of 2009.

Table 4.6 shows the estimation results separately for three types of institutional ownership: all 13F, long-term and short-term. Consistent with Cella et al. (2013), I find that during turmoil periods all institutional investors, long-term institutional investors and short-term institutional investors exert higher selling pressures. When I control for turmoil periods, the CDS slope itself is positively and significantly related to sales of all 13F institutions and long-term institutions. This coefficient is negative for short-term institutions. However, the positive and significant coefficient of the slope-turmoil interaction term in column (3) shows that short-term institutional investors exploit the informational content of the CDS slope during turmoil periods. But, the slope-turmoil interaction term for long-term institutions is not significantly related to sales.

4.5.3 Institution Types and Equity Sales

The relationship between CDS slope and equity sales for long-term institutions may come from some specific institution types. For example, some institution types such as mutual funds and hedge funds may be extracting additional information from the credit market and trade in the equities in the light of this information, whereas the other institution types do not. On the other hand, some short-term institutions belonging to a particular category might also be extracting signals from the credit market and trading in the equity market accordingly. One needs to classify 13F institutions into categories in order to test these hypotheses empirically. The classification of institution types employed in Agarwal et al. (2013) refines the classification used in the Thomson Reuters database. I employ their dataset and divide all institutions into eight categories: (i) banks, (ii) insurance companies, (iii) mutual funds, (iv) hedge funds, (v) asset management firms, (vi) investment banks, (vii) pension funds and (viii) other institutions. For every institution, I keep the long-term and short-term classifications that I computed in the previous sections.

In Table 4.7, I report the regression results for long-term and short-term institutions belonging to different categories. I find that the CDS slope significantly predicts the equity sales of long-term institutions belonging to banks, insurance companies, mutual funds, hedge funds and asset management categories. These are the institution types that facilitate the information transmission from the credit market to the equity market. However, the long-term institutions that are classified as investment banks, pension funds and other institutions do not have an effect in the information transmission process as I document that the slope variable does not significantly explain the equity sales. The results for the short-term institutions show that, except the insurance companies, the CDS slope does not explain the equity sales.

4.6 Robustness Checks

4.6.1 CDS contracts with different maturities

Throughout the study, I calculate the slope of the term structure of CDS spreads as the difference between the five-year and the one-year CDS spread. As an additional analysis, I calculate the CDS slope as ten-year CDS spread minus a one-year CDS spread and estimate the regression equation (4.4) separately for three types of institutional ownership: total institutional ownership, long-term institutional ownership and short-term institutional ownership. I report the regression results in Table 4.8, which verifies that my results in Section 4.5.1 remain strong and significant. The fact that the results are robust to using the ten-year spread to measure slope mitigates the concern that my base results are driven by liquidity in the CDS market, because the five-year CDS (used in my base results) tends to be more liquid than other maturities in the beginning of the sample period.

4.6.2 Alternative definitions for long-term and short-term institutions

In my base empirical analysis, I separate institutions into three tertile portfolios based on average churn ratio. I employ two other methodologies as a robustness check for the separation of long-term and short-term institutions.

As the first method, I sort all institutional investors into two groups each quarter based on the median of their average churn rate after computing the average churn rate for each institution in each quarter, as done by Switzer and Wang (2017). Institutional investors with a churn rate that is above (below) the median are classified as short-term (long-term) institutional investors.

Secondly, I employ Bushee (1998, 2001) classification of institutional investors. Bushee classifies institutions into "transient", "dedicated" and "quasi-indexers" based on their past investment behavior. Specifically, "transient" institutions have high portfolio turnover and highly diversified portfolio holdings. This type of institutions tends to be short-term focused. "Dedicated" institutions have by very low portfolio turnover and large investments in portfolio firms. "Quasi-indexers" are also characterized by low turnover, but they have diversified holdings. Both dedicated and quasi-indexers provide long-term, stable ownership to portfolio firms. Hence, I classify them as long-term institutions and I classify "transient" institutions as short-term investors. In my empirical tests, I use the dataset that I retrieve from their website in order to classify institutions into long-term and short-term.

Table 4.9 presents the regression results based on the two different classification methodologies. The results are consistent with Section 4.5.1 and I provide further evidence that long-term institutions are the driver of the information transmission from the credit market to equity market.

4.7 Why does an increase in CDS slope amplify long-term institutional selling pressure?

In Section 4.5.1, I find that quarterly sales by long-term institutions are significantly related to CDS slopes. However, changes in CDS slopes do not explain the quarterly trades of short-term institutions. As CDS slope captures a significant component of long-term institutional trades, but not that of short-term institutions, this might be consistent information about the future financial health of the firm gradually diffusing from CDS to the equity market. In this subsection, I focus on the information content of the CDS slope and test whether the information transmission from the CDS market to the equity market occurs through the trading of long-term institutions.

If investors expect the financial health of the firm to deteriorate in the future, that firm may have an upward-sloping CDS term structure. This is similar to the expectation hypothesis of the (default-free) term structure of interest rates: A long-term rate that is higher than the short-term rate could indicate that the future short-term rate is expected to be higher. Consistent with the hypothesis about CDS term structure, Han et al. (2017) find that differences between current long-term and short-term CDS spreads positively predict future changes in firm default risk measures. Following them, I test the ability of the CDS slope (the five-year spread minus one-year spread) to forecast changes in one-year CDS spreads. In Table 4.10, I report the results of the regression of changes in one-year CDS spreads on the current CDS slope, controlling for the one-year and five-year CDS spreads. I find that the coefficient on CDS slope is positive and significant in all regressions. In addition, Han et al. (2017) find that the term structure of CDS spreads has significant predictive power for earnings. Firms with a low CDS slope tend to experience more favorable earnings surprises in the next quarter. Similarly, they find that low CDS slope firms tend to have significantly higher profitability in the future than the high slope firms. Hence, the term structure slope of CDS spreads captures valuable information about a firm's fundamentals.

The findings show that the term structure CDS spreads significantly predicts changes in the firm fundamentals such as earnings and creditworthiness. The effect of the information content of CDS slopes on the quarterly trades of long-term institutions can be interpreted in two ways. First, diffusion of information may explain why stocks with a high CDS slope face higher selling pressures by long-term institutions. The information may gradually diffuse from the CDS market to the equity market through the trading of long-term institutions, who trade based on information regarding the fundamentals of the firm. A second interpretation is that there may be no diffusion of information among the markets, but the CDS slope is just a proxy for the long-term information in both equity and credit markets.

I attempt to discern whether the part of the future change in the CDS spread that can be forecasted by the current CDS slope is a significant determinant of the institutional sales. Specifically, I test the hypothesis that the slope contains valuable information about firm fundamentals, which, in turn, affect institutional equity sales. For each firm and in each quarter, I use a rolling window of 24 quarters historical data to estimate a predictive regression of change in one-year CDS spreads on lagged CDS slope. The predicted value and the residual of such a regression are denoted by $\Delta\widehat{CDS(1)}$ and $Res_{\Delta CDS(1)}$, respectively.

The regressions whose results are reported in Table 4.11 are similar to those in Table 4.6, except I replace the key regressor CDS slope by $\Delta\widehat{CDS(1)}$ and $Res_{\Delta CDS(1)}$. In column (2), the results for long-term institutions show that the coefficient for $\Delta\widehat{CDS(1)}$ is significantly positive, whereas the coefficient for $Res_{\Delta CDS(1)}$ is insignificant. Thus, the negative relation between CDS slope and long-term institutions' equity sales entirely arises from the part of the slope that predicts future CDS spread changes. This finding provides evidence that a low CDS slope predicts improved creditworthiness, which in turn, is transmitted to the equity market. That is, the CDS market acts as a conduit of information through the trading of institutions that rebalance their portfolio based on a firm long-term fundamental value.

4.8 Conclusion

This paper examines the informational content of the trades of institutional investors with different investment horizons. In particular, I focus on the role of long-term institutional investors in information diffusion from the credit market to equities. I empirically show that the term structure of credit default spreads, namely CDS slope, explain the equity sales of long-term institutions, over and above standard controls such as liquidity and momentum. A 1-percent increase in CDS slope is associated with 0.114 percentage point increase in the sales of the long-term institutions holding other variables constant. Moreover, I document that the CDS slope significantly predicts the equity sales of long-term institutions belonging to banks, insurance companies, mutual funds, hedge funds and asset management categories.

One of the main contributions of my paper is to document that the negative relation between CDS slope and long-term institutions' equity sales entirely arises from the part of the slope that predicts future CDS spread changes. The finding that the CDS slope captures a significant component of long-term institutional trades, but not that of short-term institutions, provides novel evidence that the future financial health of the firm gradually diffuses from CDS to the equity market through the trading of long-term institutions. These findings provide new insights into the literature on the consequences of long-term institutional ownership. Although long-term institutions trade less frequently on the market, they provide information transmission from the credit market to the equities.

Figure 4.1: Time series plot of CDS slopes of different percentiles

This graph plots the time series of the 20th, 50th, and 80th percentiles of the cross section of individual firm credit default swap (CDS) slopes. I measure the CDS slope of a firm, at the end of each quarter from March 2001 to March 2013, as the difference between the five-year CDS and one-year CDS premiums (in basis points) for that firm.

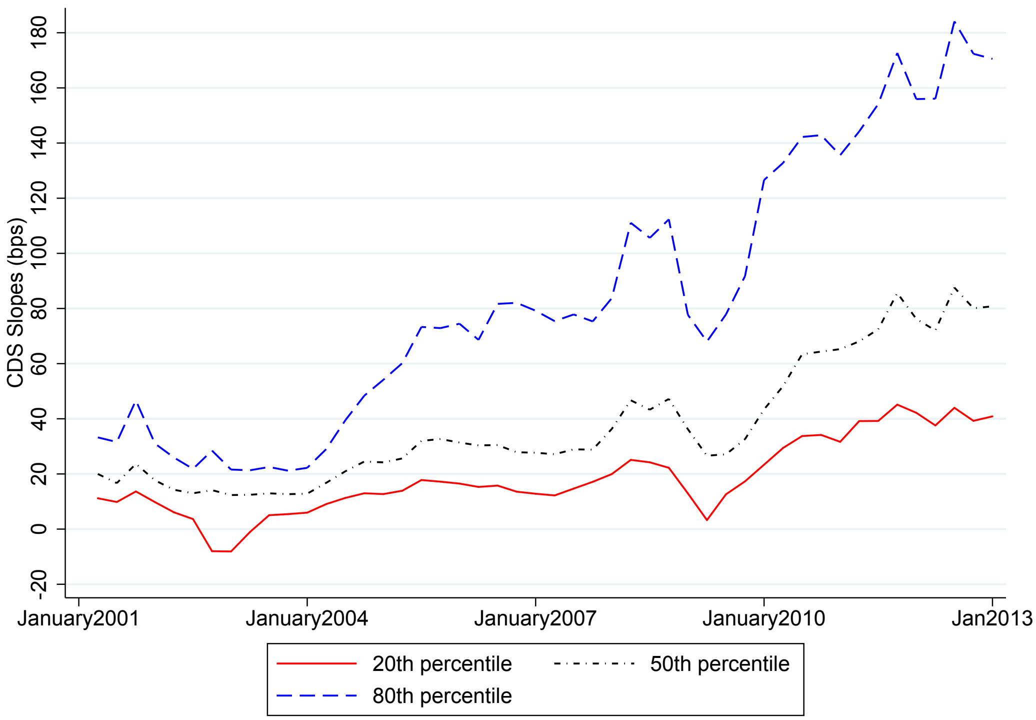


Figure 4.2: Time series mean and median of average churn rate

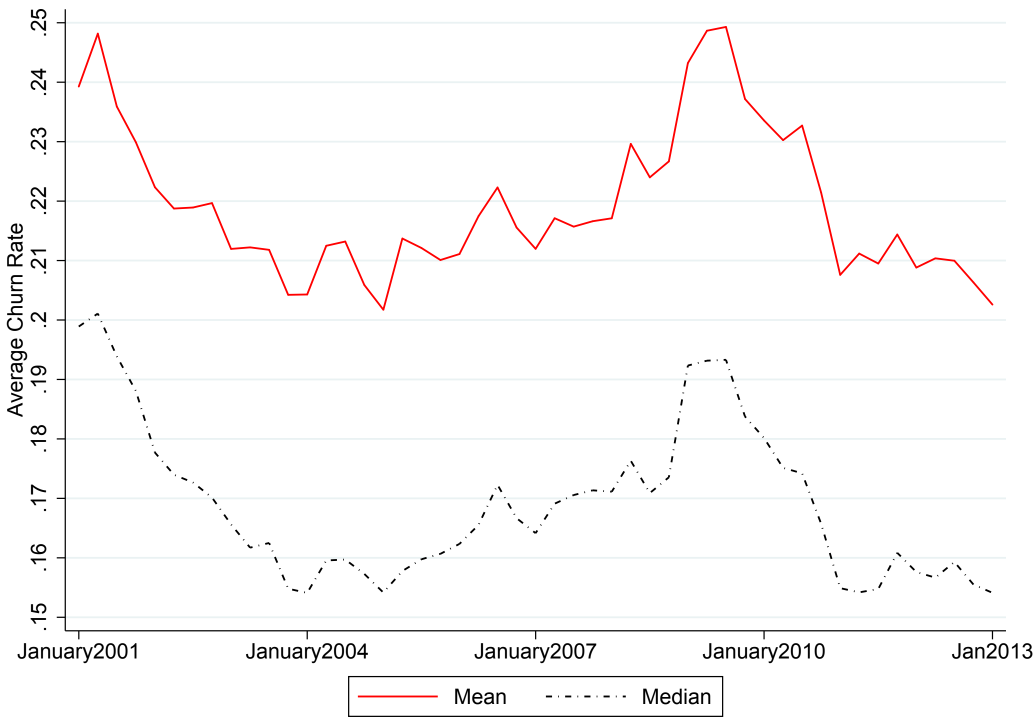


Table 4.1: Summary Statistics

This table presents the summary statistics. It reports mean, standard deviation, median, 5th and 95th percentile values. I winsorize the ownership and control variables, except for dummy variables, at the 1th and 99th percentiles within each quarter to mitigate the effect of outliers.

	N	Mean	SD	P05	Median	P95
% Owned by Institutional Investors	18157	0.692	0.178	0.348	0.723	0.924
% Owned by LT Institutional Investors	18157	0.313	0.116	0.125	0.313	0.497
% Owned by ST Institutional Investors	18157	0.079	0.061	0.019	0.062	0.199
Net Sales Total	18157	-0.002	0.037	-0.064	-0.001	0.056
Net Sales ST	18157	0.001	0.038	-0.065	0.001	0.062
Net Sales LT	18157	-0.003	0.036	-0.061	-0.002	0.056
CDS Spread (1 Year)	18157	0.016	0.020	0.002	0.008	0.054
CDS Spread (5 Years)	18157	0.009	0.019	0.001	0.004	0.038
CDS Slope	18157	0.006	0.007	0.001	0.003	0.021
Past Stock Return	18157	0.024	0.174	-0.256	0.025	0.283
Stock Return Volatility	18157	0.021	0.013	0.009	0.018	0.046
Share Turnover	18157	0.009	0.006	0.003	0.008	0.022
Market Return	18157	0.009	0.087	-0.143	0.016	0.149
Market Return Volatility	18157	0.012	0.007	0.006	0.009	0.022
Market-to-Book	18157	1.570	0.619	0.971	1.366	2.942
Return on Assets	18157	0.012	0.015	-0.008	0.011	0.037
Leverage	18157	0.293	0.151	0.061	0.276	0.586
Firm Size	18157	23.241	1.214	21.416	23.121	25.651

Table 4.2: Pairwise correlation matrix of institutional investor and firm characteristics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) % Owned by Institutional Investors	1.000																	
(2) % Owned by LT Institutional Investors	0.606	1.000																
(3) % Owned by ST Institutional Investors	0.413	-0.107	1.000															
(4) Net Sales Total	-0.093	-0.026	-0.086	1.000														
(5) Net Sales LT	-0.054	-0.126	0.019	0.575	1.000													
(6) Net Sales ST	-0.028	0.019	-0.257	0.328	-0.026	1.000												
(7) CDS Slope	0.049	-0.010	0.145	-0.053	-0.030	-0.014	1.000											
(8) CDS Spread (1Y)	-0.030	-0.064	0.080	0.069	0.035	0.017	-0.736	1.000										
(9) CDS Spread (5Y)	-0.016	-0.088	0.171	0.064	0.031	0.016	-0.483	0.949	1.000									
(10) Past Stock Return	0.014	-0.020	0.084	-0.065	0.018	-0.052	0.065	-0.113	-0.115	1.000								
(11) Stock Return Volatility	0.066	-0.086	0.192	0.009	0.018	-0.042	-0.117	0.397	0.458	-0.126	1.000							
(12) Share Turnover	0.231	0.004	0.335	-0.002	0.022	-0.073	0.015	0.240	0.317	-0.030	0.457	1.000						
(13) Market Return	0.001	0.034	0.027	-0.044	-0.002	-0.034	0.078	-0.118	-0.117	0.522	-0.348	-0.071	1.000					
(14) Market Return Volatility	-0.004	-0.057	-0.046	0.069	0.021	0.001	-0.097	0.187	0.197	-0.307	0.644	0.184	-0.623	1.000				
(15) Market-to-Book	-0.020	0.053	-0.111	0.021	0.027	0.011	-0.052	-0.105	-0.160	0.070	-0.190	-0.118	0.050	-0.128	1.000			
(16) Firm Size	-0.213	0.004	-0.338	-0.004	-0.002	0.005	-0.081	-0.035	-0.083	-0.037	-0.110	-0.071	-0.001	0.017	-0.167	1.000		
(17) Book Leverage	-0.101	-0.146	0.144	-0.018	-0.006	-0.018	0.087	0.155	0.241	-0.006	0.130	0.055	-0.018	0.040	-0.077	-0.117	1.000	
(18) Return on Assets	-0.007	0.042	-0.068	0.002	0.010	0.026	0.018	-0.176	-0.219	0.084	-0.209	-0.128	0.059	-0.106	0.339	-0.032	-0.133	1.000

Table 4.3: Institutional sales by all 13F institutions at the stock level

This table presents regressions for net sales at the firm level. The dependent variable is the total net shares sold (total sales less total purchases) by the institutional investors in firm j during quarter t as a percentage of the shares outstanding of firm j at the end of quarter $t-1$. I aggregate the sales of all 13F institutions. The sample period is 2001-2013. All default risk measures and control variables are measured at the end of quarter $t-1$. All models are estimated by ordinary least squares and include the constant term, but the coefficient is not reported. Standard errors are clustered at firm level. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

	Net Sales by all 13F Institutional Investors at the Stock Level			
	(1)	(2)	(3)	(4)
CDS Slope	0.319***	0.304***	0.256***	0.303***
	(4.70)	(4.53)	(3.55)	(4.21)
CDS Spread (5Y)		-0.046		-0.020
		(-1.63)		(-0.58)
CDS Spread (1Y)			-0.0464*	
			(-1.70)	
Past Stock Return				-0.007***
				(-2.90)
Stock Return Volatility				-0.229***
				(-3.68)
Share Turnover				-0.017
				(-0.16)
Market Return				-0.047***
				(-9.09)
Market Return Volatility				0.010
				(0.10)
Market-to-Book Ratio				0.005***
				(5.45)
Log Firm Size				0.003***
				(2.79)
Leverage				-0.025***
				(-5.35)
Return on Assets				-0.060**
				(-1.99)
N	17,948	17,948	17,948	17,555
R-squared	0.087	0.087	0.087	0.103
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year	Year

Table 4.4: Institutional sales by Long-term 13F institutions at the stock level

This table presents regressions for net sales at the firm level. The dependent variable is the total net shares sold (total sales less total purchases) by the long-term institutional investors in firm j during quarter t as a percentage of the shares outstanding of firm j at the end of quarter $t-1$. I aggregate the sales of long-term 13F institutions. The sample period is 2001-2013. All default risk measures and control variables are measured at the end of quarter $t-1$. All models are estimated by ordinary least squares and include the constant term, but the coefficient is not reported. Standard errors are clustered at firm level. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

	Net Sales by Long-term Institutional Investors at the Stock Level			
	(1)	(2)	(3)	(4)
CDS Slope	0.173***	0.143***	0.052***	0.114***
	(4.88)	(4.32)	(2.78)	(3.32)
CDS Spread (5Y)		-0.093***		-0.023
		(-6.64)		(-1.26)
CDS Spread (1Y)			-0.089***	
			(-6.72)	
Past Stock Return				-0.001
				(-1.04)
Stock Return Volatility				-0.209***
				(-6.25)
Share Turnover				0.156***
				(2.75)
Market Return				0.002
				(0.48)
Market Return Volatility				-0.029
				(-0.53)
Market-to-Book Ratio				0.001**
				(2.16)
Log Firm Size				0.001**
				(2.42)
Leverage				-0.002
				(-0.08)
Return on Assets				-0.019
				(-1.39)
N	17,948	17,948	17,948	17,555
R-squared	0.123	0.126	0.126	0.127
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year	Year

Table 4.5: Institutional sales by Short-term 13F institutions at the stock level

This table presents regressions for net sales at the firm level. The dependent variable is the total net shares sold (total sales less total purchases) by the short-term institutional investors in firm j during quarter t as a percentage of the shares outstanding of firm j at the end of quarter $t-1$. I aggregate the sales of short-term 13F institutions. The sample period is 2001-2013. All default risk measures and control variables are measured at the end of quarter $t-1$. All models are estimated by ordinary least squares and include the constant term, but the coefficient is not reported. Standard errors are clustered at firm level. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

	Net Sales by Short-term Instiutional Investors at the Stock Level			
	(1)	(2)	(3)	(4)
CDS Slope	-0.012	-0.015	-0.026	-0.077
	(-0.23)	(-0.30)	(-0.44)	(-1.44)
CDS Spread (5Y)		-0.012		-0.040
		(-0.59)		(-1.62)
CDS Spread (1Y)			-0.0107	
			(-0.55)	
Past Stock Return				-0.015***
				(-7.31)
Stock Return Volatility				-0.231***
				(-5.19)
Share Turnover				0.431***
				(4.83)
Market Return				-0.041***
				(-8.32)
Market Return Volatility				0.029
				(0.37)
Market-to-Book Ratio				0.004***
				(5.15)
Log Firm Size				0.002**
				(2.07)
Leverage				-0.008**
				(-2.02)
Return on Assets				-0.034
				(-1.43)
N	17,948	17,948	17,948	17,555
R-squared	0.058	0.058	0.058	0.085
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year	Year

Table 4.6: Selling pressure at the stock level during market turmoil periods

This table presents regressions for net sales at the firm level. The dependent variable is the total net shares sold (total sales less total purchases) by institutional investor type i in firm j during quarter t as a percentage of the shares outstanding of firm j at the end of quarter $t-1$. I aggregate the sales of institutional investor type i in each column. The sample include all 13F institutions in column (1), only long-term institutions in column (2) and only short-term institutions in column (3). The sample period is 2001-2013. The Turmoil dummy variable takes the value of 1 starting from the Q3 of 2007 until Q2 of 2009. All default risk measures and control variables are measured at the end of quarter $t-1$. All models are estimated by ordinary least squares and include the constant term, but the coefficient is not reported. Standard errors are clustered at firm level. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

	Net (dollar) Sales at the Stock Level		
	All 13F Institutions	Long-term Institutions	Short-term Institutions
	(1)	(2)	(3)
CDS Slope	0.196***	0.108***	-0.150***
	(2.89)	(3.06)	(-2.79)
Slope x Turmoil	0.289*	-0.072	0.309***
	(1.81)	(-0.93)	(2.81)
Turmoil	0.055***	0.018***	0.019***
	(27.56)	(11.14)	(13.03)
CDS Spread (5Y)	0.041	-0.004	-0.018
	(1.23)	(-0.21)	(-0.73)
Past Stock Return	-0.002	-0.001	-0.013***
	(-0.84)	(-0.05)	(-6.44)
Stock Return Volatility	-0.291***	-0.227***	-0.255***
	(-4.89)	(-6.80)	(-5.91)
Share Turnover	0.086	0.180***	0.477***
	(0.81)	(3.19)	(5.43)
Market Return	-0.071***	-0.006*	-0.049***
	(-14.23)	(-1.77)	(-9.97)
Market Return Volatility	-1.528***	-0.500***	-0.522***
	(-14.06)	(-7.76)	(-6.08)
Market-to-Book Ratio	0.002**	0.001	0.003***
	(2.05)	(0.20)	(3.73)
Log Firm Size	0.002	0.001*	0.001
	(1.38)	(1.70)	(1.27)
Leverage	-0.026***	-0.001	-0.008**
	(-5.67)	(-0.13)	(-2.10)
Return on Assets	-0.002	-0.001	-0.014
	(-0.08)	(-0.08)	(-0.59)
N	17,555	17,555	17,555
R-squared	0.158	0.140	0.097
Firm Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year

Table 4.7: Institution types and equity sales

This table presents regressions for net sales at the firm level . The dependent variable is the total net shares sold (total sales less total purchases) by institutional investor type i in firm j during quarter t as a percentage of the shares outstanding of firm j at the end of quarter $t-1$. I aggregate the sales of institutional investor type i in each column. In odd numbered columns, the total net shares sold is calculated for the sample including long-term institutions of each stated institution category. In even numbered columns, the sample includes short-term institutions of each institution category. The sample period is 2001-2013. All default risk measures and control variables are measured at the end of quarter $t-1$. All models are estimated by ordinary least squares and include the constant term, but the coefficient is not reported. Standard errors are clustered at firm level. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

	Net (dollar) Sales at the Stock Level							
	Bank		Insurance		Mutual Funds		Hedge Funds	
	Long-term (1)	Short-term (2)	Long-term (3)	Short-term (4)	Long-term (5)	Short-term (6)	Long-term (7)	Short-term (8)
CDS Slope	0.0312**	0.00362	0.00367**	-0.00485**	0.0264**	0.00486	0.0252***	0.0109
	(2.16)	(1.44)	(1.99)	(-2.02)	(2.47)	(1.17)	(3.33)	(0.72)
CDS Spread (5Y)	-0.0107	0.00202	-0.000828	-0.00440*	0.0111	0.00111	0.0140***	0.00772
	(-1.44)	(1.22)	(-0.90)	(-1.86)	(1.38)	(0.35)	(2.61)	(0.79)
Past Stock Return	-0.003***	-0.00002	-0.000103	0.00021	0.00316***	0.000260	0.00161***	-0.00152*
	(-3.39)	(-0.12)	(-0.94)	(1.40)	(4.58)	(1.15)	(4.09)	(-1.93)
Stock Return Vol	-0.0422**	0.00284	-0.000283	0.00278	-0.00411	-0.0168***	-0.0106	-0.0480**
	(-2.20)	(1.06)	(-0.08)	(0.73)	(-0.24)	(-2.83)	(-0.93)	(-2.46)
Share Turnover	-0.0390	-0.00604	-0.00207	0.00806	-0.0753***	0.00178	-0.0261	0.0975***
	(-1.31)	(-1.62)	(-0.52)	(1.51)	(-3.19)	(0.25)	(-1.53)	(2.90)
Market Return	-0.00961***	-0.00329***	0.000399	-0.000988**	-0.0264***	-0.00397***	-0.0143***	-0.00135
	(-3.98)	(-7.19)	(1.20)	(-2.09)	(-13.43)	(-5.71)	(-14.71)	(-0.70)
Market Return Vol	-0.721***	-0.0510***	0.0762***	-0.00908	-0.125***	-0.0428***	0.00737	-0.0984***
	(-18.48)	(-7.29)	(12.35)	(-1.39)	(-3.81)	(-4.56)	(0.42)	(-2.88)
Market-to-Book	0.000728**	-0.000137***	-0.0000627	0.000186***	-0.000594*	0.00007	0.0000783	0.000497*
	(2.04)	(-3.62)	(-1.31)	(3.65)	(-1.75)	(0.88)	(0.46)	(1.79)
Firm Size	0.00214***	0.00000477	-0.0000404	0.000228***	-0.000677	-0.000253**	0.000388	0.00101**
	(5.03)	(0.08)	(-0.66)	(2.75)	(-1.57)	(-2.34)	(1.33)	(2.27)
Leverage	-0.00289	-0.000284	-0.0000633	0.0000590	-0.00228	-0.000672	0.000837	-0.00122
	(-1.55)	(-1.33)	(-0.21)	(0.28)	(-1.38)	(-1.31)	(0.68)	(-0.70)
Return on Assets	-0.00563	0.00228*	-0.00295***	0.00117	0.00281	0.00306	0.00499	0.00441
	(-0.88)	(1.84)	(-2.68)	(1.18)	(0.51)	(1.41)	(1.22)	(0.62)
N	18613	18613	18499	18499	18545	18545	18608	18608
R-squared	0.204	0.0225	0.0658	0.0284	0.0992	0.0406	0.149	0.0552
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year

Table 4.7: Institution types and equity sales (continued)

	Asset Management		Investment Banks		Pension Funds		Other	
	Long-term (9)	Short-term (10)	Long-term (11)	Short-term (12)	Long-term (13)	Short-term (14)	Long-term (15)	Short-term (16)
CDS Slope	0.0275**	-0.0131	0.000120	0.00306	0.000826	-0.000683	0.00101	0.00177
	(2.14)	(-1.56)	(0.13)	(0.89)	(0.25)	(-1.05)	(0.91)	(1.33)
CDS Spread (5Y)	0.0183**	-0.00581	-0.00110	0.00170	-0.00256	-0.000271	0.00114	0.00134
	(2.30)	(-1.13)	(-1.43)	(0.71)	(-1.26)	(-0.78)	(0.99)	(0.98)
Past Stock Return	0.00229***	-0.00222***	-0.000297***	-0.000574***	-0.000595***	0.000475	0.0000815	-0.000584
	(3.46)	(-4.18)	(-4.59)	(-2.73)	(-3.79)	(1.22)	(1.28)	(-0.01)
Stock Return Volatility	0.0258	-0.0557***	-0.000545	-0.0122**	0.00916**	-0.00177*	0.00182	0.00366
	(1.60)	(-4.87)	(-0.29)	(-2.54)	(2.36)	(-1.87)	(1.08)	(1.43)
Share Turnover	-0.0802***	0.0751***	0.00442	0.0254***	-0.0209***	0.00461***	-0.00694	-0.00520
	(-3.44)	(4.27)	(1.55)	(3.11)	(-3.22)	(3.60)	(-1.12)	(-1.33)
Market Return	0.00812***	-0.00347**	0.000184	0.00289***	0.000584	-0.000430**	-0.00199***	-0.000707***
	(4.73)	(-2.14)	(1.33)	(4.87)	(1.47)	(-2.56)	(-7.18)	(-9.81)
Market Return Volatility	0.131***	-0.00203	0.00117	0.0942***	0.0115*	0.00650**	-0.0321***	-0.00995***
	(4.12)	(-0.08)	(0.45)	(9.32)	(1.72)	(2.26)	(-5.74)	(-4.08)
Market-to-Book Ratio	-0.000461	0.00138***	0.0000515**	-0.000178***	0.000322***	-0.0000142	0.0000703**	0.0000261
	(-1.61)	(6.90)	(2.37)	(-2.88)	(5.27)	(-1.27)	(2.31)	(1.33)
Firm Size	-0.000259	0.00159***	0.0000890	0.000138	0.000406***	-0.000454	-0.0000269	0.0000420
	(-0.71)	(5.27)	(1.26)	(1.45)	(4.29)	(-0.19)	(-0.59)	(1.51)
Leverage	-0.000185	-0.00320**	-0.0000625	0.000291	-0.000308	0.0000282	0.000224	-0.000380
	(-0.12)	(-2.56)	(-0.35)	(0.80)	(-0.84)	(0.43)	(1.05)	(-0.04)
Return on Assets	-0.00865	0.00863*	-0.000872	0.00611**	-0.00406***	-0.000345	0.000912	-0.000491
	(-1.52)	(1.81)	(-1.38)	(2.49)	(-3.22)	(-1.13)	(0.84)	(-0.78)
N	18662	18662	18604	18604	18324	18324	13630	13630
R-squared	0.0658	0.0369	0.0362	0.0642	0.114	0.0414	0.0531	0.0719
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year

Table 4.8: Robustness check: Slope calculation using CDS contracts with different maturities

This table presents regressions for net sales at the firm level. The sample include all 13F institutions in column (1) and (2), only long-term institutions in column (3) and (4), and only short-term institutions in column (5) and (6). The sample period is 2001-2013. The Turmoil dummy variable takes the value of 1 starting from the Q3 of 2007 until Q2 of 2009. CDS slope is defined as ten-year CDS spread minus a one-year CDS spread. All default risk measures and control variables are measured at the end of quarter $t-1$. All models are estimated by ordinary least squares and include the constant term, but the coefficient is not reported. Standard errors are clustered at firm level. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

	Net (dollar) Sales at the Stock Level					
	All 13F Institutions		Long-term Institutions		Short-term Institutions	
	(1)	(2)	(3)	(4)	(5)	(6)
CDS Slope	0.229***	0.192***	0.103***	0.115***	-0.056	-0.109**
	(3.96)	(3.32)	(3.63)	(3.92)	(-1.30)	(-2.45)
Slope x Turmoil		-0.001		-0.112**		0.194**
		(-0.00)		(-2.02)		(2.36)
Turmoil		0.057***		0.018***		0.019***
		(28.26)		(11.6)		(13.23)
CDS Spread (5Y)	0.007	0.064*	-0.009	0.006	-0.047*	-0.023
	(0.22)	(1.86)	(-0.54)	(0.35)	(-1.80)	(-0.89)
Past Stock Return	-0.007***	-0.002	-0.001	-0.001	-0.015***	-0.013***
	(-2.90)	(-0.96)	(-1.03)	(-0.05)	(-7.31)	(-6.51)
Stock Return Volatility	-0.236***	-0.293***	-0.209***	-0.225***	-0.229***	-0.252***
	(-3.81)	(-4.92)	(-6.27)	(-6.77)	(-5.16)	(-5.83)
Share Turnover	-0.009	0.076	0.152***	0.172***	0.428***	0.469***
	(-0.08)	(0.71)	(2.7)	(3.09)	(4.76)	(5.27)
Market Return	-0.046***	-0.070***	0.002	-0.005*	-0.041***	-0.049***
	(-9.05)	(-14.01)	(0.5)	(-1.72)	(-8.33)	(-9.94)
Market Return Volatility	0.016	-1.524***	-0.029	-0.506***	0.027	-0.514***
	(0.16)	(-13.97)	(-0.54)	(-7.86)	(0.35)	(-6.01)
Market-to-Book Ratio	0.005***	0.002**	0.002**	0.001	0.004***	0.003***
	(5.49)	(2.05)	(2.25)	(0.23)	(5.14)	(3.75)
Log Firm Size	0.003***	0.002	0.002**	0.001*	0.002**	0.001
	(2.71)	(1.43)	(2.42)	(1.75)	(2.11)	(1.35)
Leverage	-0.025***	-0.026***	-0.001	-0.001	-0.007**	-0.007**
	(-5.38)	(-5.68)	(-0.12)	(-0.17)	(-2.01)	(-2.11)
Return on Assets	-0.060**	-0.002	-0.019	0.001	-0.033	-0.017
	(-2.00)	(-0.05)	(-1.40)	(0.08)	(-1.43)	(-0.72)
N	17,555	17,555	17,555	17,555	17,555	17,555
R-squared	0.103	0.158	0.128	0.14	0.085	0.096
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year	Year	Year	Year

Table 4.9: Robustness check: Alternative definitions for long-term and short-term institutions

This table presents regressions for net sales at the firm level for alternative definitions of long-term and short-term institutions. Columns (1) and (2) report the results based on separating the institutions according to the median of their average churn ratio. Column (3) and (4) contains the results for Bushee's classification of short-term and long-term institutions. The sample include only long-term institutions in column (1) and (3), and only short-term institutions in column (2) and (4). The sample period is 2001-2013. All default risk measures and control variables are measured at the end of quarter $t-1$. All models are estimated by ordinary least squares and include the constant term, but the coefficient is not reported. Standard errors are clustered at firm level. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

	Two groups based on median		Bushee's classification	
	Long-term	Short-term	Long-term	Short-term
	(1)	(2)	(3)	(4)
CDS Slope	0.185***	0.071	0.229***	0.001
	(3.45)	(1.01)	(3.28)	(0.03)
CDS Spread (5Y)	0.052**	-0.048	0.063*	-0.012
	(1.99)	(-1.53)	(1.81)	(-0.64)
Past Stock Return	0.004**	-0.012***	0.009***	-0.018***
	(2.17)	(-4.97)	(4.27)	(-11.60)
Stock Return Volatility	-0.001	-0.254***	-0.178***	-0.085**
	(-0.03)	(-4.21)	(-3.16)	(-2.55)
Share Turnover	-0.350***	0.325***	-0.158	0.337***
	(-3.93)	(2.87)	(-1.52)	(4.57)
Market Return	-0.034***	-0.013**	-0.083***	0.041***
	(-6.51)	(-2.26)	(-13.99)	(12.08)
Market Return Volatility	-0.993***	1.004***	-0.864***	0.219***
	(-11.34)	(10.10)	(-8.20)	(4.08)
Market-to-Book Ratio	0.001	0.004***	-0.001	0.004***
	(1.36)	(4.03)	(-0.23)	(6.56)
Log Firm Size	0.002**	0.002	-0.001	0.004***
	(2.5)	(1.35)	(-0.35)	(4.38)
Leverage	-0.008**	-0.018***	-0.020***	-0.013***
	(-2.10)	(-4.10)	(-4.49)	(-4.29)
Return on Assets	-0.01	-0.051*	0.027	-0.041**
	(0.44)	(-1.76)	-0.99	(-2.36)
N	17,555	17,555	17,412	17,412
R-squared	0.123	0.091	0.092	0.072
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year	Year

Table 4.10: CDS slope predicts changes in one-year CDS spread

This table reports the results of monthly Fama-MacBeth regressions of changes in one-year CDS spread from t to $t+i$ on the CDS slope at time t. $\Delta CDS_{t+i} = CDS_{t+i} - CDS_t$. $CDS(1)$ and $CDS(5)$ are one-year and five-year CDS spreads lagged by one quarter. $Ret(1,12)$ is the past one-year stock return in percent. The numbers in parentheses are t-statistics. * , ** , and *** denote significance at the 10%, 5%, and 1% level, respectively.

	ΔCDS_{t+3}	ΔCDS_{t+6}	ΔCDS_{t+9}	ΔCDS_{t+12}
Slope_t	0.149***	0.294**	0.471***	0.476***
	(2.77)	(2.58)	(2.97)	(3.55)
CDS(1)	-0.075*	0.019	0.083	0.009
	(-1.76)	(0.20)	(0.56)	(0.06)
CDS(5)	0.016	-0.089	-0.169	-0.123
	(0.62)	(-1.35)	(-1.51)	(-1.34)
Ret(1,12)	-0.001**	-0.002***	-0.002***	-0.003***
	(-2.37)	(-2.93)	(-4.08)	(-3.86)
R-squared	0.336	0.436	0.464	0.484

Table 4.11: Decomposing the predictive power of CDS slope

This table reports results of panel regressions of which part of credit default swap (CDS) slope predicts institutional sales: the part that predicts changes in credit spreads versus the residual. The dependent variable is the total net shares sold (total sales less total purchases) by institutional investor type i in firm j during quarter t as a percentage of the shares outstanding of firm j at the end of quarter $t-1$. I aggregate the sales of institutional investor type i in each column. The sample include all 13F institutions in column (1), only long-term institutions in column (2) and only short-term institutions in column (3). All independent variables are measured at the end of the previous quarter. $\Delta\widehat{CDS}(1)$ and $Res_{\Delta CDS(1)}$ are the predicted value of $\Delta CDS(1)$ and the residual of the regression of the next period $\Delta CDS(1)$ on $Slope$, respectively, which I acquire by running the regression on the rolling basis for 60 months. All models are estimated by ordinary least squares and include the constant term, but the coefficient is not reported. Standard errors are clustered at firm level. The numbers in parentheses are the t-statistics. ***, ** and * denote statistical significance at the 1, 5 and 10 percent levels respectively.

	Net (dollar) Sales at the Stock Level		
	All 13F Institutions	Long-term Institutions	Short-term Institutions
	(1)	(2)	(3)
$\Delta\widehat{CDS}(1)$	0.970***	0.335***	0.192*
	(5.14)	(3.95)	(1.87)
$Res_{\Delta CDS(1)}$	0.421***	0.051	0.144***
	(5.51)	(1.39)	(3.02)
CDS Spread (5Y)	-0.188**	-0.002	-0.106**
	(-2.58)	(-0.04)	(-2.05)
Past Stock Return	-0.005	-0.001	-0.018***
	(-1.50)	(-0.06)	(-5.81)
Stock Return Volatility	-0.474***	-0.281***	-0.309***
	(-5.25)	(-5.11)	(-4.14)
Share Turnover	-0.007	0.061	0.518***
	(-0.04)	(0.63)	(3.52)
Market Return	-0.063***	0.010**	-0.019***
	(-9.57)	(2.35)	(-3.33)
Market Return Volatility	-0.020	0.103	0.186*
	(-0.16)	(1.40)	(1.83)
Market-to-Book Ratio	0.007***	0.004***	0.006***
	(2.96)	(2.81)	(3.30)
Log Firm Size	0.016***	0.007***	0.006**
	(4.12)	(3.77)	(2.09)
Leverage	-0.035***	-0.010	-0.019*
	(-2.86)	(-1.41)	(-1.88)
Return on Assets	0.049	0.010	-0.018
	(1.06)	(0.47)	(-0.45)
R-squared	0.140	0.191	0.113
Firm Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Year	Year	Year

Appendix A: Additional tables

Table A1: Variable Definitions

Variable	**Description**	**Source**
IO_Total	Ratio of total stock holding percentage by all institutions over the shares outstanding at the end of quarter $t-1$.	Thomson Financial's 13F
IO_ST	Ratio of total stock holdings percentage by short-term institutions over the shares outstanding	Thomson Financial's 13F
IO_LT	Ratio of total stock holdings percentage by long-term institutions over the shares outstanding	Thomson Financial's 13F
Net Sales Total	The total net sales (total sales less total purchases) made by all 13F institutions for each firm during quarter t as a percentage of the market capitalization of the same firm at the end of quarter $t-1$.	Thomson Financial's 13F
Net Sales ST	The total net sales made by short-term institutions for each firm during quarter t as a percentage of the market capitalization of the same firm at the end of quarter $t-1$.	Thomson Financial's 13F
Net Sales LT	The total net sales made by long-term institutions for each firm during quarter t as a percentage of the market capitalization of the same firm at the end of quarter $t-1$.	Thomson Financial's 13F
CDS Spread (5Y)	5-year CDS spread.	Markit
CDS Spread (1Y)	1-year CDS spread.	Markit
CDS Slope	The difference between 5-year CDS spread and 1-year CDS spread	Markit
Past Stock Return	Past 3 month return, which is the stock's 3-month momentum return over the quarter $t-1$.	CRSP
Stock Return Volatility	The standard deviation of daily stock returns during quarter $t-1$.	CRSP
Share Turnover	The quarterly average of the daily turnover in quarter $t-1$.	CRSP
Market Return	The return on the S&P 500 in quarter $t-1$.	CRSP
Market Return Volatility	The standard deviation o the S&P 500 daily returns over the quarter $t-1$.	CRSP
Market-to-Book	The market value of equity divided by book value of common equity.	CRSP, Compustat
Return on Assets	The operating income before depreciation, amortization and taxes (OIBD) divided by total assets.	Compustat
Leverage	Total debt (the sum of long-term and short-term debt) divided by total assets.	Compustat
Firm Size	The natural logarithm of total assets at the end of quarter $t-1$.	Compustat

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