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THE IMPORTANCE OF INVESTOR HETEROGENEITY: AN EXAMINATION OF THE CORPORATE BOND MARKET

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ABSTRACT

Corporate bond market participants are increasingly worried about liquidity. However, bid-ask spreads and other standard measures indicate liquidity has not deteriorated significantly. This paper proposes a potential reconciliation. We show the sensitivity of credit yields to bid-ask spreads increased fourfold from 2005 to 2019. We then provide a model that connects this change to the rapid growth of mutual funds in the corporate bond market. The model features heterogeneous investors with different trading needs who choose between a risk-free asset and illiquid bonds. As the risk-free rate declines, more short-term investors reach for yield and enter the bond market. These short-term investors reduce the selling pressure in each sub-market and so the bid-ask spreads. However, their greater trading needs amplify the sensitivity of credit yields to the bid-ask spreads, leading to a larger liquidity component. We next test the model's predictions using detailed data on investor holdings in the U.S. As predicted, we find investor turnover is associated with larger effects of illiquidity on credit yields. Bonds with more short-term investors are traded at lower bid-ask spreads, but their credit yields are more sensitive to the bid-ask spreads. Finally, we look across countries and show that, consistent with the model, larger declines in risk-free rates are associated with higher growth in mutual fund shares. These results highlight the key role that investor heterogeneity plays in determining how liquidity is priced into corporate bond yields and firms' financing conditions.

CHAPTER 1

INTRODUCTION

1.1 Introduction

Corporate bond markets are a crucial financing channel for firms in the U.S. and worldwide. Over the past decade, market participants have grown increasingly worried about liquidity, and have started ongoing discussions with regulators.[1] The corporate bond market disruption in March 2020 certainly seems to suggest that the market has become more fragile. However, proceeding this event, bid-ask spreads and other standard measures implied that liquidity was weakly improving.[2]

Most academic research on bond market liquidity has focused on changes in the level of liquidity (Anderson and Stulz, 2017; Adrian et al., 2017b; Dick-Nielsen and Rossi, 2018). This research is unable to fully rationalize market participants' apparently valid concerns and the trend in liquidity measures. As such, we take a different perspective and study the sensitivity of credit yields to liquidity. We find the sensitivity of credit yields to liquidity has increased fourfold over the past 15 years. Despite the trend in the level of liquidity, small differences in bid-ask spreads are now associated with much larger differences in credit yields. As a result, liquidity components—bid-ask spreads multiplied by the sensitivity—are now a significantly larger fraction of credit yields.

Given the bond market disruption in March 2020, it seems that the market has become more fragile compared to a decade ago. However, ex-ante, it has been difficult to find

1. Wigglesworth, Robin. "Bond market liquidity dominates conversation." *Financial Times*, June 12, 2015; Keohane, David. "People are worried about people being worried about bond market liquidity." *Financial Times*, August 4, 2015; Levine, Matt. "People are worried about bond market liquidity." *Bloomberg*, June 3, 2015.

2. Adrian, Fleming, Shachar and Vogt. "Has U.S. Corporate Bond Market Liquidity Deteriorated?" *Liberty Street Economics*, Oct 5, 2015; Adrian, Fleming, Vogt and Wojtowicz. "Corporate Bond Market Liquidity Redux: More Price-Based Evidence. *Liberty Street Economics*, Fed 9, 2016; Adrian, Fleming, Vogt and Wojtowicz. "Further Analysis of Corporate Bond Market Liquidity. *Liberty Street Economics*, Fed 10, 2016.

any measures indicating such change in the market. Our exercise here can be viewed as proposing a potential leading indicator that measures how sensitive the market is to the secondary market disruptions.

We next present a model that links this change in sensitivity to the other prominent change happening in the corporate bond market — the massive growth in mutual fund share. As shown in Figure A.1, mutual fund share has grown from less than 8% during the early 2000s to more than 20% today. Given the significant difference in trading patterns and the massive change in the market composition, it is interesting to understand how this trend affects the corporate bond market. Our model features heterogeneous investors with different trading needs, choosing between a risk-free asset and illiquid bonds. As the risk-free rate declines,[3] more short-term investors reach for yield and enter the illiquid bond market. While more market participants increase liquidity and lower the bid-ask spreads, the short-term investors amplify the effect of bid-ask spreads on credit yields, due to their higher trading needs.

We then test the model's predictions in the cross-section of bonds using detailed quarterly investor holdings data in the U.S. Consistent with the model, yields of bonds held by short-term investors are more sensitive to differences in bid-ask spreads than bonds held by long-term investors, and countries that experienced larger declines in risk-free rates saw greater growth in mutual fund shares. We conclude by calibrating the model to show it can account for the large changes in the US data and conducting two counterfactual experiments. First, motivated by the Volcker Rule, we find the entry of mutual funds alleviates the impact of dealer regulation changes on the market. Second, we show that prices react more strongly to unexpected aggregate liquidity shocks today compared with the situation in 2005, consistent with the severe disruption in the corporate bond market in March 2020.

We establish our motivating fact by considering a cross-sectional regression of credit

3. We take the decline in the risk-free rate as exogenous to our model.

yields on bid-ask spreads, controlling for firm and bond characteristics. The sensitivity of credit yields to bid-ask spreads (the regression coefficient) has grown four times in the last 15 years. Before the 2008 global financial crisis, a one standard deviation in bid-ask spreads is associated with a 13 bps difference in credit yields. However, in 2019, one standard deviation in bid-ask spreads is associated with more than a 50bps difference in credit yields. We interpret the coefficients as correlations, and not causal estimates. The goal is to replicate these empirical patterns in our heterogeneous-investor model.

We then calculate the change in the median liquidity component – a bond's liquidity component is defined as the sensitivity coefficient multiplied by its bid-ask spreads. Even though bid-ask spreads have been weakly declining since the global financial crisis, as shown in Figure A.2, the median liquidity component as a fraction of credit yields increased from 5% at the beginning of 2005 to more than 25% at the end of 2019, mainly due to the increase in the sensitivity coefficient. Figure A.3a plots the median liquidity component over time for investment-grade bonds and Figure A.3b plots the counterpart for high-yield bonds. Both figures show similar results.

We link this increase in the liquidity component to the rapid growth of mutual fund shares in the corporate bond market. Many papers have documented this increase of mutual funds, particularly in the post-crisis period (Goldstein et al., 2017; Feroli et al., 2014). We show that part of this growth can be attributed to the long-run decline in the risk-free rates. Although there are many institutional differences among corporate bond investors, we choose to focus on one of the most prominent differences — trading frequencies. Mutual funds typically have much higher trading frequencies than the more traditional participants in the corporate bond market, such as insurance companies and pension funds. Insurance companies and pension funds are mainly long-term investors with low turnover rates. We confirm this difference by comparing the average turnover ratio of mutual funds and that of insurance companies in our dataset (see Figure A.4). The quarterly turnover of mutual funds is 0.15-0.2, much higher than the 0.05 turnover rate of insurance companies.

Motivated by the large turnover difference among investors, we build a model with heterogeneous investors choosing between a liquid risk-free asset and illiquid corporate bonds. Investors have heterogeneous trading needs, which we model as differences in their liquidity-shock frequencies. These liquidity shocks generally come from the financial institutions' liability side. For example, insurance companies may need to make large payouts on existing policies; similarly, mutual funds may face sudden inflows and outflows.[4] Bonds are heterogeneous in their maturities and default probabilities. This bond heterogeneity allows us to derive cross-sectional predictions and take the model to data. Investors enter the economy as potential buyers of bonds, and when bond holders are hit by liquidity shocks, they become sellers of bonds in the secondary market. Our model allows for two sources of frictions in the secondary market – search frictions and transaction costs. Sellers decide which type of bond to buy and then engage in a search process to find the buyer. Once a match is found, a fraction of the trade surplus is taken away. This transaction cost captures the bid-ask spreads that dealers in the background charge. We assume bid-ask spreads are increasing in the number of sellers relative to the number of buyers in the market.[5] This corresponds to a direct search setup is more realistic than random search, because in practice, most investors know which types of bonds they want to buy or sell; they then contact dealers to find out about the supply or demand. The occurrence of actual trades may take time and could be uncertain. This waiting time is modeled as search frictions within each sub-market.

We prove the equilibrium features a cutoff strategy: investors with liquidity-shock fre-

4. Although some of the mutual fund flows could be endogenous to bond market conditions, in normal times, the outflows are mostly due to end investors' idiosyncratic liquidity needs. Here, we take a reduced form approach in modeling how the liability sides affect their trading behavior.

5. We do not model dealers explicitly in our baseline model. The bid-ask spreads capture their interaction with the investors. Intuitively, the bid-ask spreads are higher when the imbalance between the number of sellers and buyers is large. For the market and time period that we are studying, we believe it is more likely to be a buyer's market, in which case the bid-ask spread is increasing in the seller-buyer ratio. Appendix C micro-founds this assumption using dealer inventory cost and capacity constraints.

quencies below a certain threshold participate in the bond market and others hold the liquid risk-free asset. As the risk-free rate drops, the cutoff increases and more short-term investors participate in the bond market, reaching for yields. As more short term investors enter, the seller-buyer ratio reduces and that lowers the bid-ask spreads. However, because short-term investors have higher trading needs, the transaction costs are encountered more times before bonds mature, and the credit spreads become more sensitive to the bid-ask spreads.

Furthermore, short-term investors sort into sub-markets with short-term and risky bonds, whereas long-term investors sort into long-term and low-risk bonds. We show that sub-markets with more short-term investors also have lower bid-ask spreads. The mechanism in our model is fundamentally different from that in Amihud and Mendelson (1986), where bid-ask spreads are exogenously fixed and investors choose which sub-market to join based on the bid-ask spreads. In our model, investors sort along bond characteristics such as maturity and default probability. Bid-ask spreads are in turn endogenously determined by the type of investors participating in the sub-markets. Sub-markets with more short-term investors have more buyers relative to sellers, reducing the selling pressure and resulting in lower bid-ask spreads. In addition to the sorting pattern, our model also predicts that the credit yields of bonds with more short-term investors are more sensitive to the bid-ask spreads. The correlation between the sensitivity coefficient and investor composition is partly due to the heightened trading needs, but more importantly, it is because sub-markets with high bid-ask spreads are also sub-markets with high selling pressure. This relationship is built in by assumption in our main model, and we micro-found it via dealers' inventory costs in Appendix C. In the cross-section, both reasons contribute to a positive cross derivative of credit spreads with respect to bid-ask spreads and investor trading frequencies. Lastly, we endogenize firms' choice of debt maturity: firms shorten debt maturity in response to the liquidity needs of their investors.

We test the model implications using detailed quarterly investor holdings data in the U.S.

and find consistent evidence. We obtain investor information from eMaxx special reports, and standard bond information from WRDS, FISD and Trade Reporting and Compliance Engine (TRACE). We measure investor turnover in any given quarter as the lagged average of the net percentage change in its bond holdings over the last four quarters. We then take the value-weighted average and aggregate it to an "investor composition" measure at the bond level.

First, to test the sorting patterns predicted by our model, we group bonds into 50 bins according to their investor-composition measure. We find bins associated with short-term investors have shorter time to maturity and lower average ratings. Second, to investigate whether the sensitivity of credit yields to bid-ask spreads is correlated with investor composition, we sort bonds into five groups according to their average investor composition[6] and regress credit spreads on bid-ask spreads group by group, controlling for bond and firm characteristics. We find that groups in which bonds have more short-term investors have higher coefficients in front of bid-ask spreads, and they also have larger median liquidity components as a fraction of credit spreads. We find similar results using both secondary market yields and offering yields. This is perhaps the strongest evidence demonstrating the importance of investor heterogeneity. In a traditional homogeneous-investor model, the realized difference in turnover is purely due to noise. As a result, if we sort bonds based on investor turnover, we should find no difference in the sensitivity coefficients across bond groups. The positive correlation between the sensitivity coefficient and investor composition is a unique prediction of our heterogeneous-investor model (relative to homogeneous-investor models). Finally, connecting the investor base to firms' issuance decisions, we find that firms tend to issue shorter-maturity bonds when their investor base (measured in the previous four quarters) is composed of more short-term investors. All time-series and cross-section results are robust to alternative measures of liquidity from the literature.[7] We use bid-ask spreads

6. Our findings are robust to the number of groups.

7. In particular, we try the measure from Dick-Nielsen et al. (2012). They measure liquidity as the first

in the main paper because it is a direct empirical counterpart of what is in our model.

On the aggregate level, using data on fixed-income funds from Morningstar, we indeed find higher growth in mutual fund shares in the bond markets is associated with a larger decline in risk-free rates over the same periods, controlling for macroeconomic conditions (GDP, inflation, and unemployment).

We then conduct a simple calibration exercise to confirm our model can match the large changes in the data. We focus on the segment of bonds with maturity between 0.5 and 20 years. Model parameters are calibrated to match the size of the liquidity component in 2005, the average investor turnover rate, the sensitivity coefficient of bid-ask spreads, and the variance of credit spreads and bid-ask spreads in 2005 and 2019.[8] We find that by decreasing the risk-free rate from 4% to 2%,[9] our model can match the growth in the liquidity component and the size of the sensitivity coefficient reasonably well. By the end of 2019, our model generates a sensitivity coefficient of 1.05, versus 1.1 in the data. Models in which bid-ask spreads are exogenous cannot match the size of the sensitivity coefficient quantitatively given the change in investor composition in the data. Our model also predicts the median liquidity component in 2019 should be 21.6%, close to the $\sim 25\%$ estimate from data.[10]

We use the calibrated model to investigate the interactive effect of investor composition

principle of various price measures (Roll's measure, Ahmed's measure, imputed round costs, and standard deviation of each) and quantity measures (days with no trading for the firm and for the bond, bond turnover rate). They argue that the final liquidity measure mostly summarizes the information in price measures and is largely orthogonal to quantity measures. Our bid-ask spread measure is highly correlated with this alternative liquidity measure. Details are explained in Appendix E.

8. We target the liquidity component and sensitivity coefficients because they are the key moments of interest in the data. The average investor turnover is the key driver of other changes in the data; hence, we include it as well. We include variances of credit spreads and bid-ask spreads because they matter for the sensitivity coefficient.

9. These are the 10-year Treasury bond yields in 2005 and at the end of 2019. We take the 10-year Treasury bond yields because Treasury bonds are the liquid risk-free outside options for investors, at least over the time period we are examining.

10. Note the liquidity component in 2019 is not targeted in the calibration.

and recent dealer regulation changes. As part of the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act, the Volcker Rule was intended to limit banks' risk-taking activities. However, an unintended consequence of the rule could be diminished bond market-making activities (Duffie, 2012), because it raises the balance-sheet costs for dealers to hold bonds in inventory. The question we seek to answer is how much this friction transmits to firms' borrowing cost. With more short-term investors participating in the market, two counteracting forces arise: on the one hand, they provide liquidity, relieving the burden on dealer intermediaries. As a result, we should not expect the dealer regulation change to affect the credit yields much. On the other hand, regulations on dealers' balance sheets make intermediating trades costlier for dealers. Higher trading needs from short-term investors amplify the transmission of this cost to credit yields. Hence, we should see a higher increase in credit yields when more short-term investors are present. Using the calibrated model, we find that the former effect dominates and mutual funds entering softens the adverse effect of dealer regulation change on liquidity during normal times.

Lastly, we use the calibration to evaluate changes over time in the market's response to aggregate liquidity shocks.[11] We exogenously raise the seller-buyer ratio in each sub-market by 1%, and examine how credit yields respond in the scenario of 2005 and 2019. Within any time snapshot, sub-markets with more short-term investors experience sharper increases in credit yields, because short term investors with higher trading needs amplify the impact of secondary market frictions on credit yields. Comparing across periods, we find that in 2019's market with more short-term investors (relative to 2005), credit yields are 20%-30% more sensitive to seller-buyer ratios than in 2005. Our results shed light on why the corporate bond market experienced large disruptions in March 2020.

The remainder of the paper is organized as follows. We discuss related literature below.

11. We take our results as suggestive. One can interpret our result as the on-impact impulse responses. To properly conduct these counterfactual exercises, we need to extend the current model to a full dynamic setting. We leave that extension to future research.

Section 2 presents the new fact we identify in detail. Section 3.1 describes the environment of the model. Section 3.2 analyzes the simple one-bond case and the heterogeneous-bond case. Section 4.1 tests the implications from the full model, and Section 4.2 conducts a simple calibration exercise. Section 5 concludes. All tables, figures and proofs are in the respective appendices.

1.2 Related Literature

A growing literature on the corporate bond market has shown that liquidity can explain a significant part of the common component in yield variations (Bao et al., 2011; Friewald et al., 2013; Friewald and Nagler, 2019; Goldstein et al., 2019). In light of the concern from market participants, many papers have studied how the level of liquidity has changed since the global financial crisis. Anderson and Stulz (2017) study the liquidity comparison pre- and post-crisis, and find mixed evidence depending on the exact measure of liquidity. Others argue that the dealer regulation changes altered the market liquidity significantly. Adrian et al. (2017b) show that bonds that are actively traded by constrained institutions are less liquid, and such effect is higher for high-yield bonds. Cost of immediacy may also have increased since the regulatory changes (Dick-Nielsen and Rossi, 2018). On the other hand Adrian et al. (2017a) show limited evidence for deterioration in liquidity in levels. The New York Fed has a series of posts calculating measures of bid-ask spreads and price impact.[12] Those measures indicate liquidity has been weakly improving in the market place. Kargar et al. (2020) examine liquidity during the COVID-19 crisis.

However, we take a different perspective and look at the sensitivity of credit yields to bid-ask spreads. We document the increase in the sensitivity coefficient over time and relate

12. See for example https://libertystreeteconomics.newyorkfed.org/2015/10/has-us-corporate-bond-market-liquidity-deteriorated.html and https://libertystreeteconomics.newyorkfed.org/2016/02/corporate-bond-market-liquidity-redux-more-price-based-evidence.html.

it to the investor-composition change. In a contemporaneous working paper, Wu (2020) documents the same aggregate trend and examines whether this trend is caused by post-crisis changes in dealer regulations. We instead provide a model that explains this trend through observed changes in investor composition.[13] Amihud and Mendelson (1986) is one of the first papers that analyze how investor preference affects the impact of transaction costs in the equity market. They take transaction costs as exogenous and allow investors with different investment horizons to sort into assets with different bid-ask spreads. They show theoretically and empirically that there is a concave relationship between transaction costs and the liquidity premium in the equity market. Subsequent papers have analyzed similar problem with risk-averse agents and time-varying transaction costs (Beber et al., 2020). Apart from the difference in asset class studies, the main difference in our paper is that we take the stance that bid-ask spreads are endogenous to the type of investors who choose to trade that asset. Instead of sorting along transaction costs, investors sort along more exogenous characteristics of assets, namely maturities or default probabilities. This endogeneity turns out to be important for quantitatively matching the sensitivity coefficient in the data.

Due to the increase in the sensitivity coefficient, the liquidity component has also grown significantly. Dick-Nielsen et al. (2012) argue that the liquidity component was small during normal times before the 2008 crisis. Our estimate is consistent with theirs. Although the liquidity component increased sharply during the crisis, it reverted back to a low level at the end of their sample (2009). We use similar analysis but extend the calculation to 2019. We find that the liquidity component increased to more than 25% in 2019, both for investment-grade as well as for high-yield bonds.

An alternative way to measure the liquidity component is to follow Longstaff et al. (2005)

13. In our framework, dealer regulation changes do not directly contribute to the increase in the sensitivity coefficient. That said, dealer regulation changes can have an indirect effect through altering the investor composition.

and calculate the difference between the cash bond yield and the yield of a single-name credit default swap on the same entity (Beber et al., 2009; Oehmke and Zawadowski, 2016; Schwarz, 2018). Choi and Shachar (2014) and Choi et al. (2019) discuss the relationship between the CDS-bond basis and liquidity provision by dealers before and during the financial crisis. A recent paper documents that the CDS-bond basis has become more negative (Bai and Collin-Dufresne, 2019), consistent with our finding that the liquidity component has been growing over time. We do not measure the liquidity component this way for two reasons: the first is that not all firms have an actively traded CDS, which will reduce our sample size by half. The second reason is that the CDS's themselves are not perfectly liquid – their pricing is heavily influenced by the funding situation of dealers.

Our paper emphasizes the importance of investor composition for firms' borrowing cost and issuance decisions. Recent papers have documented empirical clientele effects in other aspects of the corporate bond market. Chen et al. (2020) confirm the concave relation between corporate bond illiquidity and default-adjusted corporate bond yield spreads. They find that among insurance company investors, the different preferences for liquidity affect the credit spread of the bonds that insurance companies hold. We conduct similar analysis but at a larger market-wide scale; we take into account the liquidity preference of not only insurance companies, but more importantly of mutual funds. In addition, the sorting of investors into different bonds is endogenous in our case. Musto et al. (2018) show long-horizon investors take advantage of the liquidity premium. Butler et al. (2019) argue that the decline in bond maturity is due to the decrease of insurance company ownership. We complement the analysis by showing that the decline in bond-issuance maturity is indeed associated with a shorter-term investor base.

In terms of the theoretical framework, our model accounts for both investor and bond heterogeneity. Vayanos and Wang (2007) introduce a model whereby heterogeneous investors with different horizons can invest in two identical assets. They show that there exists a (separating) clientele equilibrium where all short-horizon investors search for the same asset. We study the sorting of heterogeneous investors into heterogeneous-bond types, and in turn look at the role of liquidity in different markets. Hugonnier et al. (2019) allow for arbitrary heterogeneity in dealers' valuations to study the intermediation process in over-the-counter markets. We focus on heterogeneity in trading needs of final investors. Furthermore, different from the papers that use random research techniques to study the over-the-counter markets (Duffie et al., 2005; Lagos and Rocheteau, 2007; Lagos et al., 2011; Hugonnier et al., 2019), we adopt a direct search framework in the full model to capture investors' behaviors more realistically.

The source of illiquidity has attracted a lot of attention in the literature. Many papers have examined the issue of illiquidity from a structural perspective. For example, Ericsson and Renault (2006) link liquidity to bankruptcy renegotiation. He and Xiong (2012) analyze how debt market liquidity affects firms' rollover decisions. He and Milbradt (2014) focus on the interdependence between liquidity and default components in credit yields, and a subsequent paper quantified the relevant channels (Chen et al., 2017). In an environment with search frictions, Feldhütter (2012) shows the difference between prices paid by large and small traders identifies liquidity crises. Our paper focuses on the relationship between liquidity and investor compositions, abstracting away from the interplay between liquidity and default risks.

Another micro-foundation for liquidity is based on dealers facing adverse selection problems when trading (Kyle, 1985; Glosten and Milgrom, 1985; Back and Baruch, 2004; Back and Crotty, 2014). We take the search-based approach because the market structure fits corporate bonds well. We don't model explicitly why dealers charge the bid-ask spreads. For our results, all we need is that the bid-ask spreads increase in the selling pressure. In Appendix C, we provide several potential micro-foundations.

CHAPTER 2

A NEW FACT

We establish the new fact that the sensitivity of credit yields to bid-ask spreads has been increasing since 2005, leading to an increase in the liquidity component from 5% to over 25%. Although the level of bid-ask spreads have been weakly decreasing, it has been playing a much more important role in determining the credit spreads. We show the time trend first by looking at the group of BBB-rated bonds. This group has experienced the most significant growth in the post-crisis period. We then examine the full bond universe with more controls. The rest of this section presents our evidence and methodology in detail.

2.1 Data

For the corporate bond characteristics, we use data from Mergent FISD. Following the literature, we focus on US Corporate Debenture with fixed coupon rate, non-convertible, non-puttable, non-exchangeable. From Mergent, we get information on bond age, rating, offering yield, maturity, and other bond features. In terms of rating, we first use the rating from S&P; if it is missing, we use Moody, and lastly, Fitch. We then merge the bond information with the CRSP for equity price and with Compustat for firm accounting information via the WRDS Bond Link through Permno.

In terms of the transaction data, we use the enhanced Trade Reporting and Compliance Engine (TRACE) maintained by the Financial Industry Regulatory Authority(FINRA). We filter the TRACE data following Dick-Nielsen (2014). Moreover, we also use the price filter to clean the extreme price observations in TRACE. We obtain the reported yield from TRACE, and then calculate the credit spread by subtracting the yield of the corresponding Treasury security. We follow Gürkaynak et al. (2007) in calculating the yield curve. For each bond, we use the average credit spread on the last trading day in each quarter as the dependent variable $CS_{i,t}$. We drop the bonds that have no trades in the last month of the quarter.

We use the bid-ask spreads calculated by WRDS directly for the analysis in this section. The WRDS bid-ask spread is calculated as the difference between the volume-weighted customer sell prices and buy prices, divided by the mean of the two.

Our sample period is from 2005Q2 to 2019Q2 and the sample contains 1,824 firms and 15,567 bonds. Table A.1 and Table A.2 show the summary statistics for the BBB-rated bonds and total bond universe. Within the BBB-rated bonds sample, the average bid-ask spread is about 50 bps and the standard deviation is 50 bps. The average credit spread is 1.7%. For the total bond universe, the average bid-ask spread is also 50 bps. The average credit spread is 2.1% for the broader bond universe, slightly higher than BBB-rated bonds.

2.2 Analysis and Results

The outstanding amount of BBB-rated bonds has almost doubled since the 2008 financial crisis. We run a uni-variate regression of credit spreads on bid-ask spreads quarter by quarter; the coefficients over time are plotted in Figure A.5, and the R-squared of the regression is plotted in Figure A.6. Both the coefficient and the R-squared increased from 2005 to 2019. In 2005, a 100 bps difference in bid-ask spreads is associated with a 25-50 bps difference in credit spreads. In 2019, the same amount of difference in bid-ask spreads is now associated with a 1.75% difference in credit spreads. The increasing trend of regression coefficients implies the transaction cost (bid-ask spreads) or liquidity has a greater impact on bond yields today. This is also evident from the increasing explanatory power of bid-ask spreads.

We then move on to analyze the entire bonds universe and control for other factors that have been shown to affect credit yields. Our baseline regression is shown in equation (2.1), where $CS_{i,t}$ denotes the credit spread for bond i in quarter t and $BA_{i,t}$ denotes bid-ask spread for bond i in quarter t. We run the regression quarter by quarter. The control vector $\mathbf{X_{i,t}}$ includes bond age, time to maturity, couple rate, offering amount, and ratings at the bond level, and firm leverage, size, profitability, equity volatility, and total asset value at the firm level. We also add industry fixed effects at the 4 digit level, and control for the level and slope of the Treasury yield curve.

$$CS_{it} = \alpha_t + \beta_t BA_{it} + bond\ characteristics_{i,t} + \gamma_{\mathbf{t}}^{\top} \mathbf{X_{i,t}} + \epsilon_{i,t} \tag{2.1}$$

The quarterly coefficients in front of the bid-ask spreads β_t are plotted in Figure A.7. The shaded region shows the 95% confidence interval for the estimates over time. Our previous result holds in the general bond universe: the sensitivity coefficient of bid-ask spreads has been increasing in the post-crisis period. More specifically, in 2005-2007, a 100 bps difference in bid-ask spreads is associated with a 20-30 bps difference in credit yields, whereas it is associated with a 1% difference in credit yields in 2019. The increase in the sensitivity coefficient is not caused by changes in the bid-ask spread variation—the same trend holds true if we instead plot the correlation coefficient between credit spreads and bid-ask spreads over time,[1] as shown in Figure A.8. Although our coefficients are not causal estimates of how changes in bid-ask spreads affect credit yields, they are interesting moments that our model will try to match.

There are several concerns regarding the robustness of our result. Although we use the bid-ask spreads reported by WRDS in the main analysis, our results remain qualitatively similar if we use our own calculation of bid-ask spreads[2], implied round trip cost[3] and the illiquidity measure used in Dick-Nielsen et al. (2012). Another concern is that the

1. To calculate the correlation coefficient, we regress credit spreads and bid-ask spreads on bond and firm characteristics respectively, quarter by quarter. We then calculate the correlation coefficient between the two residuals in each quarter.

2. For each day, each bond, we first calculate the daily bid-ask spread —we take the weighted average buy price minus the weighted average sell price divided by the average of the two. We exclude inter-dealer trades, agency trades and retail trades with size smaller than 100K. We then average it over a quarter.

3. We identify matched trades defined as the same bonds traded in the same day of the same size. We then take the weighted average buy price minus the weighted average sell price divided by the average of the two. We then take the average over a quarter.

constitution of bonds may have changed over this time period. To partially address this concern, we also repeat our analysis including bond fixed effect and our results survive the additional test.

This result naturally leads us to compute the liquidity component of the credit spreads. Following the literature, we calculate the liquidity component as

$$\text{liquidity component}_{i,t} = \frac{\beta_t \times BA_{it}}{CS_{it}} \tag{2.2}$$

We plot the cross-sectional median over time, separately for investment-grade and high-yield bonds. The results are shown in Figure A.3a and Figure A.3b, respectively. The main contributing factor for the increase in the liquidity component is the growing β_t coefficient, given that the level of bid-ask spreads has weakly declined. In light of this new finding, the rest of the paper builds a model to explain this fact, linking it to the growth of mutual fun shares in the corporate bond market.

CHAPTER 3

MODEL

3.1 Model Environment

In this section, we describe the model environment in detail. Our model features heterogeneous investors, who are endogenously matched with different assets (bonds). Investors differ in the frequency of liquidity shocks they receive, and bonds differ in their maturities and/or default probabilities. Bonds are illiquid in the secondary market due to search frictions and transaction costs (bid-ask spreads). Once a bond holder receives a liquidity shock, she will try to sell the bond in the secondary market, which involves searching and also paying a bid-ask spread to the dealer intermediating the transaction. We use the model to analyze the endogenous investor composition of different bonds and how the pattern changes as the risk-free rate declines.

3.1.1 Setup

Time is continuous and indexed by $t \geq 0$. There are entrepreneurs and investors. Both types of agents are infinitely lived and risk neutral. Entrepreneurs have discount rate ρ_e and can start projects at $t = 0$. Each project requires one unit of investment initially and generates a perpetual cash flow of $x > 0$.

Corporate Bonds: Entrepreneurs borrow on the corporate bond market to fund their projects. There are N types of bonds, indexed by i, $i = \{1, 2...N\}$. Each bond has face value $F = 1$ with flow coupon payment r_i, which is endogenously determined in equilibrium.[1] Type i bond matures with probability δ_i. So each bond has average maturity $\frac{1}{\delta_i}$. Upon maturity, the firm refinances by issuing bonds with the same characteristics. Default of bond i is modeled as a Poisson process, with intensity d_i. Upon default, investors can recover

1. We assume x is large enough such that $r_i < x$, so firms do not face liquidity issues themselves.

$0 \leq s_i < 1$ from bond i. For most of the analysis, we take δ_i, d_i, and s_i as exogenous, and will endogenize δ_i in the last part. Denote the total bonds outstanding as D_i. Throughout the analysis, the N bonds are ordered such that $\delta_1 + d_1 \leq \delta_2 + d_2 \leq ... \leq \delta_N + d_N$.

Investors: Each period, a measure m_I of investors enters the economy. When investors enter, they are patient with discount rate ρ. Investors can choose which corporate bonds to hold or just hold the risk-free asset. If they choose to hold corporate bonds, they are restricted to holding at most one unit of bond at any time. Because investors are risk-neutral, they choose to either hold one unit or zero unit. Investor j who holds a corporate bond is subject to idiosyncratic liquidity shocks that arrive at Poisson rate θ_j. The liquidity-shock frequency $\theta_j \in [\underline{\theta}, +\infty)$ is heterogeneous among investors, with CDF $F(\cdot)$ and PDF $f(\cdot)$. It is a permanent feature of the investor and is observed by everyone in the marketplace. Once hit by the liquidity shock, patient investors irreversibly become impatient and value the coupon payment Δ units less than before.[2] So the effective flow payment to an impatient bond holder is $r_i - \Delta$.[3] For now, we assume Δ is homogeneous for all bonds, but that assumption can be easily extended to allow for heterogeneity as well.

We view these liquidity shocks as mostly coming from the liability side of the investors and may be exogenous to what is happening in the corporate bond market. In the case of insurance companies, it could come from policy payouts or portfolio adjustments to satisfy the regulatory requirements. For mutual funds, it could come from inflows, outflows, or index weight adjustments. However, for active mutual funds, their trades are often reactions to price adjustments in the market, as some of the inflow/outflows of certain passive mutual funds. Since our trading motive is exogenously specified, we cannot capture this behavior

2. The model can be generalized to the case in which the impatient investors become patient again with some probability. We can view some of the new patient investors here as existing impatient investors reverting back to being patient.

3. This specification follows the over-the-counter literature led by the seminal work of Duffie et al. (2005). Duffie et al. (2007) show this is the limiting case of risk-averse investors as their risk-aversion coefficient approaches 0.

accurately and we acknowledge this is a limitation of the model. Nonetheless, our key mechanism remains valid as long as differences exist in trading frequencies among investors, regardless of what the actual trading motives are.

Bond Markets: Bonds have a primary and a secondary market. In the *primary market*, bonds are placed to investors through an auction in which all investors can participate and bid for the bonds. The primary market is a centralized market and is always open since firms continuously refinance.

In the *secondary market*, bond holders who become impatient (the sellers) search and trade with patient investors who do not have any bond (the buyers). Since the shock is irreversible, once investors are hit by the liquidity shocks, they become homogeneous except for the bonds they hold. So all sellers in the secondary market are heterogeneous only to the extent that they hold different types of bonds. We denote the measure of sellers holding bond i by $\alpha_{s,i}$. Buyers are heterogeneous in their expected liquidity-shock frequencies, and we denote the measure of buyers with θ_j probability of liquidity shock as $\alpha_{b,j}$ or $\alpha_b(\theta_j)$. These measures are determined endogenously in equilibrium. In the searching process, the flow measure of matches is $m(\alpha_{s,i}, \alpha_{b,j})$, where $m_1 \geq 0$, $m_2 \geq 0$, $m(0, \cdot) = 0$, $m(\cdot, 0) = 0$, and continuously differentiable in both arguments.

Each transaction includes a bid-ask spread, denoted as ξ, which captures the surplus taken by dealers during the transactions. Our model focuses on the trading needs of final investors and abstracts away from modeling the intermediate dealers explicitly. However, from the existing literature, we know the intermediary sector matters significantly for how well the bond market functions (He et al., 2020). Having the bid-ask spread ξ_i is our way of capturing the influence of that sector. We endogenize the bid-ask spread for each bond i as a function of the measures of sellers and buyers in that sub-market. The key assumption is laid out in Assumption 1, i.e. the bid-ask spread is increasing in the seller-buyer ratio.

Assumption 1. *The bid-ask spread increases in the seller-buyer ratio*

$$\xi = \xi_0 + \xi_1 g(\frac{\alpha_s}{\alpha_b}) \qquad g' > 0 \quad \xi_0, \xi_1 > 0 \tag{3.1}$$

The validity of this assumption warrants more discussion. We present two ways to justify the bid-ask spreads increasing in the seller-buyer ratio. The first one is that dealers charge bid-ask spreads to cover their inventory costs. If the seller pressure is large, more bonds have to be absorbed by the dealer sector. A large bond inventory on dealers' balance sheet requires the dealers to post a significant amount of capital against the bonds. It also increases the burden of funding these illiquid assets. Part of the bid-ask spreads is charged to cover those costs. The second way to justify this assumption is to assume the dealer capacity is limited in an otherwise standard search mode. Appendix C provides detailed micro-foundations through these two channels.

Earlier work that models dealers' optimal pricing problem has shown that the bid-ask spreads should be symmetric in response to excess supply as well as to excess demand. For example, in Amihud and Mendelson (1980), the bid-ask spread is symmetric around a positive optimal inventory level. However, recent work has shown that dealers' holding of the corporate bonds is a tiny fraction of overall bond outstanding (Dick-Nielsen and Rossi, 2018; He et al., 2020). This is true in particular over the past decade. We take the small inventory of dealers as suggestive evidence that dealers' optimal inventory level is close to zero.

Furthermore, recent empirical work has found significant bid-ask-spread spikes during periods of high selling pressure, both in the global financial crisis and in the ongoing COVID-19 crisis (Dick-Nielsen et al., 2012; Di Maggio et al., 2017; Kargar et al., 2020). On the other hand, the bid-ask spreads during good times do not have any drop that is nearly as close in magnitudes as the spikes in crisis periods. Empirically, the fluctuations of bid-ask spreads are not symmetric.[4]

After a buyer and seller meet, price is determined via a trading mechanism, which differs slightly in different cases that we consider. We defer the discussion to later sections.

Risk-free Asset: As mentioned before, the investors can also at most hold one unit of risk-free liquid asset. In reality, this risk-free asset should be an outside option that mutual funds use as a liquidity buffer. In normal times, this asset could be the Treasury bonds. However, during crises, even Treasury bonds could become illiquid, in which case we should think of this asset as cash or three-month Treasury bills. The return on this asset is what we call the risk-free rate and is denoted by r_f. Many papers have explored factors that affect the risk-free rates, such as international capital flows and demographic changes (Bernanke et al., 2011; Hamilton et al., 2016; Gagnon et al., 2016; Rachel and Smith, 2017). Since most of those factors are outside our model, we take the risk-free rate as exogenous. The value to the investors from holding this liquid asset is simply $V_f = \frac{r_f}{\rho}$.

3.1.2 Investors' Value Functions

Denote $V_{0,i}(\theta)$ as the value of a patient investor θ holding bond i, and $V_{s,i}$ as the value of an impatient investor holding bond i. We use $V_{b,i}(\theta)$ to denote the value that a patient investor θ attaches to searching in bond i's secondary market.

Only when an investor becomes impatient does she start to search for a buyer. When a seller meets a buyer, the surplus for the seller is $P_{s,i} - V_{s,i}$, where $P_{s,i}$ is the price that the seller receives. The surplus for the buyer is $V_{0,i} - P_{b,i} - V_{b,i}$, where $P_{b,i}$ is the price that the buyer pays. Lastly, the bid-ask spread is defined as $\xi_i \equiv P_{b,i} - P_{s,i}$

4. In other models, when dealers' inventory is high, the levels of bid price and ask price both increase by the same amount, such that the bid-ask spread does not change (Ho and Stoll, 1983). The key assumption is that dealers' risk aversion or per-unit inventory cost is constant in the level of inventory. If risk aversion is increasing in the amount of risky bond held, or if the total inventory cost is convex, the bid-ask spreads will be increasing in the level of inventory, consistent with Assumption 1.

The value function of a patient investor θ holding bond i is

$$V_{0,i}(\theta) = E\big[\int_0^{\min\{t_1,t_2,t_3\}} e^{-\rho\tau} r_i d\tau + \mathbf{1}_{t_1 \leq \min\{t_2,t_3\}} e^{-\rho t_1} + \mathbf{1}_{t_3 \leq \min\{t_2,t_1\}} e^{-\rho t_3} s_i + \mathbf{1}_{t_2 < \min\{t_1,t_3\}} e^{-\rho t_2} V_{s,i}\big] \tag{3.2}$$

where t_1 is the time when the bond matures, t_2 is the time when the agent becomes impatient, and t_3 is the time when the bond defaults.

The value of an impatient holder is

$$V_{s,i} = E\big[\int_0^{\min\{t_1,t_3,t_4\}} e^{-\rho\tau} r_i d\tau + \mathbf{1}_{t_1 \leq \min\{t_3,t_4\}} e^{-\rho t_1} + \mathbf{1}_{t_3 \leq \min\{t_1,t_4\}} e^{-\rho t_3} s_i + e^{-\rho t_4} \mathbf{1}_{t_4 < \min\{t_1,t_3\}} P_{s,i}(\theta)\big] \tag{3.3}$$

where t_4 is the time when the seller finds a buyer.

The value of a patient buyer in sub-market i is

$$V_{b,i} = E\big[e^{-\rho t_5}(V_{0,i}(\theta) - P_{b,i})\big] \tag{3.4}$$

where t_5 is the time when the buyer meets a seller.

The Bellman equations for patient debt-holders, sellers and buyers are

$$r_i + \delta_i(1 - V_{0,i}(\theta)) + d_i(s_i - V_{0,i}(\theta)) + \theta(V_{s,i} - V_{0,i}(\theta)) = \rho V_{0,i}(\theta) \tag{3.5}$$

$$r_i + \delta_i(1 - V_{s,i}) + d_i(s_i - V_{s,i}) + \int \mu_s(\alpha_s, \alpha_b(\tilde{\theta}))[P_{s,i}(\tilde{\theta}) - V_{s,i}] dF_B(\tilde{\theta}) = \rho V_{s,i} \tag{3.6}$$

$$\mu_b(\alpha_s, \alpha_b)[V_{0,i}(\theta) - P_{b,i}(\theta) - V_{b,i}(\theta)] = \rho V_{b,i}(\theta) \tag{3.7}$$

where $\mu_s(\alpha_s, \alpha_b(\tilde{\theta}))$ is the probability of meeting a buyer of type $\tilde{\theta}$, from the seller's perspective. μ_b is the probability that a buyer meets a seller, from the buyer's perspective. $F_B(\cdot)$ denotes the distribution of buyer types searching in this sub-market.

Investors choose which bond market to participate in, or to hold the risk-free asset. If they choose to participate in the bond market, they need to decide whether to participate in the primary market or secondary market. The value of participating in bond i's primary market is $V_{0,i} - F$, where F is the value that successful bidders pay the firm. Hence, the investors' problem is summarized as the following,

$$\max\{ \quad \max_{1 \le i \le N} \{V_{0,i} - F, V_{b,i}\}, \quad V_f\} \tag{3.8}$$

Denote the density of bond holders as $h_i(\theta)$. The law of motion of state variables are listed in Appendix B. We study the steady state for most of the analysis. In the next section, we analyze when we have a continuum of heterogeneous-bond types.

3.2 Analysis

We look at the case when $N \to \infty$. This corresponds to a direct search set-up with a continuum of heterogeneous bonds and a continuum of heterogeneous investors. We derive a set of cross-sectional predictions that can be tested further in the data. This extension allows us to look at the exact model counterpart of the variables that we have constructed in the empirical section. We also show this more complicated model is necessary to match the magnitudes of changes in the sensitivity coefficient.

The first result is the equilibrium sorting patterns between investor types and bond types: short-term investors are matched with short-term and high-default-probability bonds. In addition, sub-markets with short-term investors are associated with lower bid-ask spreads. Second, in the cross-section, credit yields of bonds held by short-term investors are more sensitive to bid-ask spreads. We then show that enriching the model does not change the comparative-statics results with respect to the risk-free rates. Finally, we extend the model and endogenize the firms' maturity choice to study the real impact of investor composition on firms' financing decisions.

A continuum of bonds indexed by j differ either by their maturity δ_j or default risk d_j. Investor i chooses which market to participate in. In equilibrium, each sub-market only has one type of investor participating.

For each market, denote the seller-buyer ratio as $\lambda \in [0, \infty]$, which can be interpreted as the queue length. We assume the meeting intensity is only a function of λ. As before, denote $\mu_b(\lambda)$ as the probability that a buyer meets a seller. More sellers means a buyer is more likely to meet a seller, so μ_b is strictly increasing. On the other hand, the probability that a seller meets a buyer μ_s is decreasing in the seller-buyer ratio. We adopt the most commonly used Cobb-Douglas matching function, which implies the meeting intensities take the following form,

$$\mu_b(\lambda) = \eta\lambda^{\gamma} \qquad \mu_s(\lambda) = \eta\lambda^{\gamma-1} \tag{3.9}$$

where $\eta > 0$ and $\gamma \in (0, 1)$.

Price Mechanism: Sellers post prices at which they are willing to sell their bonds. Sellers cannot discriminate against buyers based on their types. Buyers, observing the combination of bond types, prices offered, and queue length, decide which sub-market to participate in. Trades happen at the posted price when a buyer and a seller meet. As before, we assume there is a bid-ask spread (transaction cost) ξ between the price that the seller receives and the price that the buyer pays.

The seller's problem becomes,

$$\rho V_{s,j} = r_j - \Delta + d_j(s_j - V_{s,j}) + \delta_j(1 - V_{s,j}) + \max_{\lambda, p_s} \mu_s(\lambda)(p_s - V_{s,j}) \tag{3.10}$$

subject to the constraint that λ is consistent with the number of buyers choosing to participate in this market. The buyer's problem is

$$\rho V_b(\theta) = \max_{(p_b,\lambda,(\delta,d)_j)\in G} \mu_b(\lambda)(V_{0,j}(\theta) - V_b(\theta) - p_b) \tag{3.11}$$

where G is the support for all the available combinations of $(p_b, \lambda, (\delta, d)_j)$. Furthermore,

$$\rho V_{0,j}(\theta) = r_j + d_j(s_j - V_{0,j}) + \delta_j(1 - V_{0,j}) + \theta(V_{s,j} - V_{0,j}) \tag{3.12}$$

$$p_b - p_s = \xi \tag{3.13}$$

Denote $U(\theta)$ as the maximum value that a buyer of type θ can get across all the sub-markets. Substituting in the prices with $U(\theta)$, we can rewrite the seller's problem as

$$\max_{\theta,\lambda} \quad \frac{\frac{\Delta}{\rho+\delta+d+\theta} - \xi(\lambda) - U(\theta)(1+\frac{\rho}{\mu_b})}{\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta}} \tag{3.14}$$

Sellers take buyers' outside option $U(\theta)$ as given, i.e. they take other sellers' postings as given, and choose which types of buyers to attract, understanding the cost they need to pay to do so. The term $\frac{\Delta}{\rho+\delta+d+\theta} - \xi(\lambda)$ is the total surplus created from the transaction; $U(\theta)(1+\frac{\rho}{\mu_b})$ is the part that buyer type θ gets, in order for her to come to this sub-market. The remaining part is what the seller gets, adjusted for the expected turnover rate.

Note that in this expression, $\delta_j + d_j$ enters as a whole. This implies that $\tilde{\delta}_j = \delta_j + d_j$ is a sufficient statistic for the sorting pattern. In the rest of this subsection, we index each sub-market by bond type $\tilde{\delta}$. We obtain this result because we have assumed all investors are risk neutral and the cost of default is the same for all investors. The value of holding the bond is lower for short-term investors than for long-term investors. Therefore, for a short-term investor, the relative benefit of the bond maturing is higher, and the relative cost of the bond defaulting is lower. Hence, short-term investors are more likely to be sorted into bonds with short maturity and high default probability. In this baseline model, we have not incorporated the fact that different investors have different risk-bearing capacities. Long-term investors, such as insurance companies, often have regulatory restrictions on the risky bonds they hold. As a result, it is more expensive for them to hold risky bonds compared with mutual funds, separately from liquidity considerations. Incorporating this institutional feature would break the linear substitutability between d_j and δ_j. However, it would, in fact, reinforce our current sorting pattern—short-term investors are more likely to hold high-default-probability bonds.[5]

Because a given bond market has only one type of investor. The offering yield is determined by $V_{0,i} - F = V_{b,i}$, i.e. buyers should be indifferent between purchasing from the secondary market vs purchasing from the primary market.

Lemma 1 shows that when the transaction cost is not too large, buyers and sellers do not wait, and trade with the first counterparty they meet. The reason is that investors endogenously choose to enter the bond market, so the buyer's benefit V_0 is ensured to be high enough to make sure that the trade surplus between the seller and any type of buyer is always positive. Lemma 1 also indicates limited heterogeneity among the endogenous group of buyers.

Lemma 1. *When ξ_0 and ξ_1 are small, investors do not wait and always trade with the first counter-party they meet,*

$$V_0 - V_s - V_b - \xi \geq 0 \tag{3.15}$$

Proof: See Appendix B.1.

Although we cannot solve the equilibrium in full closed form, we can still characterize the equilibrium features under special cases. We present our first main result in Proposition 1. The proposition states sufficient conditions for positive assortative matching, i.e in

5. We analyze an extension that incorporates this institutional feature. The derivation is available upon request.

equilibrium, short-term investors buy short-term and high-default-probability bonds.

Proposition 1. *When $\gamma \to 1$, and ξ_0 and ξ_1 are small relative to Δ, the equilibrium features positive assortative matching. Formally,*

$$\theta'(\tilde{\delta}) > 0 \tag{3.16}$$

Short-term investors are matched with short-term and high-default-probability bonds.

Proof: See Appendix B.3.

The conditions in Proposition 1 are sufficient but not necessary. Numerically, we obtain positive assortative matching for a wide set of parameter values away from the sufficient conditions. The intuition is the following: Short-term bonds are valuable because holders are less likely to sell them in the secondary market with discounts. Short-term investors, who have a higher likelihood of having this selling need, value this benefit of short-term bonds more than long-term investors. Hence, in equilibrium, short-term investors are paired with short-term debt. The case for default probability is the other side of the same coin. All investors dislike bonds with high default probability. However, if a bond does not default, a short-term investor is likely to have to sell it on the secondary market at a discount. In this sense, the relative cost of a bond defaulting is smaller for a short-term investors than for a long-term investor. This match-value complementarity implies short term investors sort into bonds with high default probabilities.

Even though that maturity rate and default probability have the same implication for sorting, they do not have the same impact on interest rates. Everything else equal, bonds with higher maturity rates have lower interest rates, whereas the opposite is true for the case of default probabilities.

Empirically, the risk-weighted capital requirement on insurance companies is likely to re-inforce the positive sorting pattern between long-term investors and low-default-probability bonds. It is hard to separate the channel described in our model from the regulatory requirement channel. The fact that our sorting patterns hold within the mutual fund type of investors indicates our mechanism is at least partially at work.

The reason that positive assortative matching is not always true is because search frictions push for the opposite direction – negative assortative matching. All buyers and sellers value trade immediacy, especially the high-type buyers and sellers. A high-type buyer prefer to join a sub-market with a high seller-buyer ratio, but a high seller-buyer ratio would imply long waiting time for the sellers. A low-type seller is more likely to provide this trade security because her opportunity cost for waiting is low. The value for trade immediacy pushes for negative assortative matching. The condition provided in Proposition 1 guarantees the match-value complementarity dominates.

After establishing positive assortative matching, we can characterize the equilibrium in a pair of ODEs. Similar to Eeckhout and Kircher (2010), we are looking for a pair of functions $\lambda(\tilde{\delta})$ and $\theta(\tilde{\delta})$ that solves the sellers' problem and buyers' problem, while respecting the initial distributions of investor types and bond types. For the rest of this subsection, we assume all bonds have one unit of amount outstanding. The equilibrium $\lambda(\tilde{\delta})$ and $\theta(\tilde{\delta})$ can be written as the solution to a pair of boundary value problems. Lemma 2 characterizes the system of ODEs fully.

Lemma 2. *The solution to the problem can be characterized by the following system of ordinary differential equations*

$$\begin{cases} \theta'(\tilde{\delta}) = \frac{\theta m_I f(\theta)\mu_b + \tilde{\delta}\lambda(\mu_s+\tilde{\delta})(\theta+\tilde{\delta})}{(\mu_s+\tilde{\delta})(\tilde{\delta}+\theta)m_I f(\theta)\lambda} \\ \lambda'(\tilde{\delta}) = -\frac{\rho\gamma\lambda U'}{\rho\gamma U - \xi''\eta\lambda^{\gamma} - \xi'\eta\gamma\lambda^{\gamma-1}} + \frac{\frac{1-\gamma}{\theta'}\left[\frac{\Delta}{\mu_s} - U(1+\frac{\rho}{\mu_b}) - \xi\right]}{[\rho\gamma U - \xi''\eta\lambda^{\gamma} - \xi'\eta\gamma\lambda^{\gamma-1}]\left[\frac{\rho+\delta+d+\theta}{\mu_s}+1\right]} \end{cases}$$

with boundary conditions

$$\theta(\underline{\delta} + \underline{d}) = \underline{\theta} \qquad \theta(\overline{\delta} + \overline{d}) = \overline{\theta} \qquad V_b(\overline{\theta}) = V_f$$

Proof: see Appendix B.2.

The decision to enter the corporate bond market features a cutoff strategy. Investors with frequencies of liquidity shocks less than $\overline{\theta}$ enter the corporate bond market, and investors with frequencies of liquidity shocks above that threshold hold risk-free assets.

Our second result concerns the correlation between the investor composition and the liquidity across different sub-markets. Proposition 2 shows that under certain conditions, the bid-ask spreads are lower in the sub-markets populated with short-term investors.

Proposition 2. *When positive assortative matching is true, we have*

$$\lambda'(\tilde{\delta}) < 0 \qquad \xi'(\tilde{\delta}) < 0 \tag{3.17}$$

That is, the bid-ask spreads are lower in markets with more short-term investors.

Proof: See Appendix B.4.

When a buyer chooses which sub-market to join, she trades off value and trade immediacy. Match surplus is higher for long-term-bonds (small $\tilde{\delta}$) sub-markets; both the seller's gain and buyer's gain from trade are larger. γ governs the sensitivity of trading immediacy to the seller-buyer ratio. When γ is close to 1, the waiting time is very sensitive to the seller-buyer ratio, which increases the marginal cost of moving to the long-term-bond sub-markets. Thus, the seller-buyer ratio in the long-term bond market is smaller, leading to higher bid-ask spreads.

The mechanism that generates this correlation between transaction costs and investor composition is fundamentally different from that in Amihud and Mendelson (1986). They assume bid-ask spreads are exogenous, and investors choose sub-markets based on the prespecified bid-ask spreads, whereas in our model, bid-ask spreads are an endogenous outcome given the types of investors in each sub-market. Instead of sorting along transaction costs, in our model, investors sort along features that are relatively exogenous to the secondary market, such as maturity and default probability.

This distinction is important. In our framework, if a certain regulation changes the investor composition for a specific market, the liquidity and transaction cost in *all* markets would change, whereas in Amihud and Mendelson (1986), the transaction costs would be fixed. In Section 4.2, we show investor composition in the sub-markets has an important interactive effect with regulation changes in the dealer sector.

Next, we move to examine what happens when the risk-free rate declines. Proposition 3 shows investor composition in all sub-markets becomes shorter term; liquidity in all sub-markets also improves.

Proposition 3. *As the risk-free rate declines,*

- *More short term investors will be entering the bond market, i.e.* $\frac{d\bar{\theta}}{dr_f} < 0$.
- *Each bond (indexed by* $\tilde{\delta}$*) will be matched with a shorter-term investor; each sub-market will have smaller bid-ask spreads, i.e.* $\frac{d\theta(\tilde{\delta};\bar{\theta})}{d\bar{\theta}} > 0$ *and* $\frac{d\lambda(\tilde{\delta};\bar{\theta})}{d\bar{\theta}} < 0$

Proof: See Appendix B.5.

Investors' outside option decreases as the risk-free rate drops, which induces more short-term investors to participate in the bond market, reaching for higher yields. In this heterogeneous-bond setting, more short-term investors means the cutoff threshold $\bar{\theta}$ increases. As more short-term investors enter the bond market, the bond with the shortest maturity and highest default probability (highest $\tilde{\delta}$) gains more short-term investors. Eventually, it spills over to all the other bonds' sub-markets.

As more short-term investors enter, at any point in time, both the number of sellers and the number of buyers increase. However, the increase of buyers is larger than that of sellers.

The reason is that every new entrant needs to purchase a bond, whereas only bond-holders who are hit by liquidity shocks need to sell. As a result, the entry of more investors relaxes the selling pressure on the secondary market, and hence reduces the bid-ask spreads. On net, the increase of market participants leads to higher liquidity. All sub-markets now have lower seller-buyer ratio and bid-ask spreads. This result is capturing the liquidity-provision role of the mutual fund entrants. Figure A.9 provides a numerical example, illustrating the comparative statics with respect to the risk-free rate.

To analyze the response of credit yields to the entry of short-term investors, we present the equilibrium expression for interest rates in Lemma 3. The first part of the interest rate is to compensate for investors' discount rate; the second part is to compensate for investors' loss in defaults. The last two parts are due to sorting and search frictions across all sub-markets.

Lemma 3. *In equilibrium, the interest rate for firm j is given by*

$$r_j = \underbrace{\rho}_{\text{discount rate}} + \underbrace{d_j(1-s_j)}_{\text{default spread}} + (\rho+\delta_j+d_j)U_j + \frac{\mu_{s,j}\theta_j\left[\frac{\Delta}{\mu_{s,i}} + U_j(1+\frac{\rho}{\mu_{b,j}}) + \xi_j\right]}{\mu_{s,j}+\rho+\delta_j+d_j+\theta_j} \tag{3.18}$$

Proof: See Appendix B.6.

Exogenous liquidity shocks: Our main goal is to analyze the changes in the sensitivity of credit yields to bid-ask-spread changes as the investor composition changes. We first analyze exogenous movement in the bid-ask spreads. Proposition 4 shows the effect of bid-ask spreads on credit spreads increases as there are more short term investors enter the bond market.

Proposition 4. *As $\gamma \to 1$, the sensitivity of credit yield to the bid-ask spread can be simplified to*

$$\frac{dr_j}{d\xi_0} = \frac{\theta\mu_s}{\theta\mu_s+\rho+\delta_j+d_j+\theta} \tag{3.19}$$

In markets with shorter-term investors, credit yields are more sensitive to the bid-ask spreads,

$$\frac{d|\frac{dr_j}{d\xi_0}|}{d\theta} > 0 \tag{3.20}$$

Proof: See Appendix B.7.

Note that ξ_0 is the exogenous component in the bid-ask spreads. The effect works through two channels: the first is that when investors have higher frequencies of liquidity shocks and hence higher trading needs, each bond is traded more times before maturity. Thus, the underlying frictions are amplified more and show up more significantly in prices. This finding is similar to Amihud and Mendelson (1986). The second channel is unique to our framework, which incorporates search frictions. When short-term investors enter, they are also liquidity providers to the market. As a result, the waiting time decreases and trading frequencies increase. This channel also amplifies the effect of transaction costs on credit spreads.

Endogenous liquidity: Both in the data and in our model, bid-ask spreads are endogenous to the type of bonds and the type of investors holding the bonds. To take this endogeneity issue seriously and capture the exact empirical counterpart in the model, we run the same regression using model-simulated data as we do in the actual data. More precisely, we each risk free rate rf_t, we resolve the model, to get the bid-ask spread $BA_{i,t}$ ($\xi_{i,t}$) and credit spread $CS_{i,t}$ for each bond i. We the regress the credit spread on maturity ($\delta_{i,t} = \delta_i$), default probability ($d_{i,t} = d_i$), and bid-ask spread $BA_{i,t}$:

$$CS_{i,t} = \beta_0 + \beta_\xi BA_{i,t} + \beta_1 \delta_{i,t} + \beta_2 d_{i,t} + \epsilon_{i,t} \tag{3.21}$$

We then conduct the following experiment: for each risk-free rate r_f, re-solve the model, run the above the regression, get $\beta_\xi(r_f)$, and compute the liquidity component in the same way as in Section 2. The goal is to see whether the model generates the same pattern as in the data.

Figure A.10 shows how the sensitivity of credit yields to bid-ask spreads changes with risk-free rates. As risk-free rate declines, more short-term investors enter the bond market, amplifying the sensitivity of credit yields to bid-ask spreads for all sub-markets. As a result, we see the coefficient rising as the risk-free rate drops. Correspondingly, even though bid-ask spreads are declining, the whole liquidity component is rising as more short-term investors enter the market. We are able to match qualitatively the aggregate trend that we identify in the data.

Lastly, the same pattern holds true in the cross-section as well – credit spreads are more sensitive to bid-ask spreads for bonds that have more short-term investors. We cannot prove this pattern for a general set of parameters in this mode. Hence, we show this correlation numerically: in Figure A.11, we sort the bonds into five groups with an equal number of bonds in each group, indexed 1 to 5. Group 1 bonds have the longest-term investors and group 5 bonds have the shortest-term investors. We run the same regression group by group and plot the coefficient in Figure A.11. Bonds with more short-term investors have higher-sensitivity coefficients. If we calculate the liquidity component by group, we also see higher liquidity components for groups of bonds with more short-term investors, as shown in Figure A.12. We show later that the empirical data yield similar patterns. This is an important prediction of the model with investor heterogeneity. If all investors are homogeneous, the realized difference in turnover would be purely due to noise. As a result, the sorting of bonds based on investor turnover would be equivalent to a random sort. We should observe no difference in the sensitivity coefficient of credit yields to bid-ask spreads. We show in Section 4.1 that we indeed observe the model-predicted relationship between the sensitivity coefficient and the average investor turnover, confirming the important role of investor heterogeneity.

To unpack what is in the correlation of bond interest rates and bid-ask spreads, we decompose the regression coefficient into two parts (after controlling for default probability and maturity)

$$\begin{aligned}\frac{r(\theta_j,\xi_j)-r(\theta_i,\xi_i)}{\xi_j-\xi_i} &= \frac{r(\theta_j,\xi_j)-r(\theta_j,\xi_i)+r(\theta_j,\xi_i)-r(\theta_i,\xi_i)}{\xi_j-\xi_i} \\ &= \underbrace{\frac{r(\theta_j,\xi_j)-r(\theta_j,\xi_i)}{\xi_j-\xi_i}}_{\phi_1(\theta_j)} + \underbrace{\frac{r(\theta_j,\xi_i)-r(\theta_i,\xi_i)}{\xi_j-\xi_i}}_{\phi_2}\end{aligned}$$

The first part is the direct effect of bid-ask-spread changes on credit yields.

$$\phi_1(\theta) = \frac{\theta\rho\mu_b' - \frac{(\rho+\delta+d)\mu_b}{\rho+\mu_b}(\rho+\delta+d+\theta)(1-\gamma+\frac{\rho\mu_b'\lambda}{(\rho+\mu_b)\mu_b})}{(\rho+\delta+d+\theta)(\rho+\mu_b)(1-\gamma+\frac{\rho\mu_b'}{\rho+\mu_b}(\frac{1}{\rho+\delta+d+\theta}+\frac{\lambda}{\mu_b}))} \tag{3.22}$$

$$< \frac{\theta}{1+\frac{\lambda}{\mu_b}(\rho+\delta+d+\theta)} < \theta \tag{3.23}$$

At the quarterly level, the average realized turnover increased from 0.08 to 0.0925

$$\frac{1}{\theta}+\frac{\lambda}{\mu_b} \geq \frac{1}{0.0925} \Rightarrow \theta < 0.0925 \tag{3.24}$$

This back-of-envelop calculation shows the first direct impact is bounded in size and cannot match the magnitudes that we observe empirically.

The second part ϕ_2 comes from the difference in investor composition across sub-markets and its impact on bid-ask spreads through endogenous seller-buyer ratios. Sub-markets with high bid-ask spreads are also sub-markets with high seller-buyer ratios, which also leads to higher yields. As a result, the second part is positive $\phi_2 > 0$. Due to this endogenous relationship, the cross-sectional correlation between bid-ask spreads and credit yields is much stronger.

As the average investor turnover increases, the first part becomes larger, i.e. $\phi_1' > 0$. It is less obvious how ϕ_2 will change. ϕ_2 is capturing the effect of the seller-buyer ratio on credit yields. As investors become more short termed, the seller-buyer ratio and waiting time becomes more important, which leads to a higher value in ϕ_2. Although both ϕ_1 and ϕ_2 increase with the entrants of more short-term investors, ϕ_2 accounts for the larger portion of the increase, whereas the change on the direct component ϕ_1 is quite limited. We show this in more detail through a calibration exercise in Section 4.2.

Remark 1. *While our model implies higher turnover rates for bonds over time keeping everything else constant, it is no longer true when the amount outstanding for bonds is also increasing. The bond turnover rate is defined as*

$$turnover = \frac{transaction\ volume}{D} \tag{3.25}$$

When D is increasing, turnover decreases for two reasons: (1) More investors acquire bonds from the primary market, so the transaction volume on the secondary market decreases (numerator is decreasing); (2) the total size of bonds is larger (denominator is increasing).[6] *Empirically, we do see higher transaction volume over time, but evidence on bonds' turnover rates has been mixed. Given that the total size of the bond market has been expanding massively over this period, the model implication does not contradict with the facts. Furthermore, if the amount outstanding increases, the model predicts a rising bid-ask spread, which is a counteracting force to the entrance of short-term investors. This force could explain why we are not seeing a sharper decline in bid-ask spreads over time. However, the amount outstanding does not directly affect the sensitivity of credit yields to bid-ask spreads.*

3.2.1 Firms' Maturity Choice

In this section, we endogenize firms' maturity choices. Firms face rollover costs whenever they have to reissue their bonds. We assume this cost is linear in the issuing amount, with the

6. Formal proof is available upon request.

per-unit cost being κ. This cost is capturing any fees related to issuance, for example, fees paid to the investment banks, resources related to negotiation and bargaining with potential investors. These costs are usually larger when the issuance amount is larger. Firms take their investor base and secondary market conditions (search probabilities μ_b, μ_s, and bid-ask spreads ξ_i) as given, and choose maturity of bond δ_i to maximize the entrepreneur's value

$$\max_{\delta_i} E[\int_0^{min\{t_3\}} e^{-\rho_e t}(x - r_i(\delta_i) - \kappa\delta_i)dt] \tag{3.26}$$

where t_3 is the expected default time. As expected, because investors prefer short-term bonds, the interest rate is decreasing in the maturity probability, that is $\frac{dr_i}{d\delta_i} < 0$. For any given set of investors, they demand lower interest rates when the bond has shorter maturity. Hence, firms trade off the lower interest rate of short-term bonds with the higher issuance cost $\kappa\delta$.

We denote the optimal maturity choice as δ_i^* for firm/bond i. Proposition 5 shows that under certain conditions, firms reduce maturity if they face more short-term investors.

Proposition 5. *When $\gamma \to 1$ and $\eta\lambda + \rho + \delta - \theta > 0$, firms reduce the maturity of bonds when more short-term investors are present, i.e.* $\frac{d\delta_i^*}{d\bar{\theta}} > 0$

Proof: See Appendix B.8.

Intuitively, as more short-term investors are entering and when the market is not very liquid, firms cater to the average investors' needs by issuing short-term debt. On the one hand, when there are more short-term investors, there is a greater need for the firms to produce liquidity by issuing short-term bonds. On the other hand, when there are more short-term buyers, a seller can more easily find a buyer, which reduces the need for firms to provide liquidity. When the trading needs relative to the bond maturity rate is high, the first force dominates.

CHAPTER 4

EMPIRICAL TESTS

4.1 Reduced-Form Tests

In this section, we test the model predictions using detailed investor holdings data for the U.S. bonds and international fixed-income funds data. We first look at investor holdings and bond characteristics in the U.S., and then move on to international evidence.

4.1.1 Bond-level Analysis

Our model produces rich cross-sectional predictions. In equilibrium, short-term investors hold shorter-term risky bonds. Those sub-markets endogenously have lower bid-ask spreads. Furthermore, in the sub-markets with more short-term investors, we should see a higher sensitivity of credit yields to bid-ask spreads. We use detailed investor holdings data from eMaxx to test the above predictions. We find sorting patterns between investor types and bond types consistent with model prediction. The interaction term of investor composition and bid-ask spreads on credit yields is highly significant and positive, which implies short-term investors amplify the effect of transaction costs on credit yields. To further validate this, we sort bonds into groups according to their investor composition and find groups with shorter-term investor composition have higher sensitivity coefficients, as our model predicts. Finally, we look at the issuance decision in the primary market, and find that a shorter-term investor base in the previous four quarters is associated with shorter-term debt issued in this quarter. All of our results hold if we use an alternative measure of illiquidity as in Dick-Nielsen et al. (2012).

Data

Same as in Section 2, we use data from Mergent FISD and WRDS for bond characteristics. In addition to the filters in Section 2, we further restrict bonds whose eMaxx coverage exceeds 20%.

We use TRACE to calculate credit spreads and bid-ask spreads. Importantly, we drop the dealer-to-dealer trades, because our model focuses on the transaction costs and liquidity conditions that end investors face. We also drop the retail trades (transactions with face value less then 100,000 USD), because more and more retail trades happen on electronic trading platforms, where trades could happen directly between two customers.[1] Credit spreads are calculated as before. $CS_{i,t}$ denotes the average credit spreads on the last trading day in each quarter. We drop the bonds that have no trades in the last month of the quarter.

To compute the bid-ask spread, we calculate the volume-weighted average customer buy price and customer sell price, for each day and each bond. The bid-ask spread is defined as the difference between the two, normalized by the middle price. We then take the mean for the quarter as the bid-ask spread for that quarter.

Since the measurement of bid-ask spreads may be noisy, we also construct a measure of liquidity following Dick-Nielsen et al. (2012). This alternative measure of liquidity takes into account other price measures such as price impact, imputed round cost, as well as quantity measures such as number of zero-trading days, trading volume etc. We believe this liquidity measure likely has smaller measurement error than empirically estimated bid-ask spreads. All of our results are robust to this alternative liquidity measure, if not stronger. The details are in Appendix E.

Our investor holdings data come from the Lipper eMaxx database of Thomson Reuters.

1. Most electronic trading platforms (e.g., MarketAxess) offer both dealer-to-customer trades, as well as all-to-all trading protocols, where customers trade directly with each other. The frictions on these centralized trading platforms are quite different from the search frictions that we describe in our model; hence, we exclude these trades from our empirical work. Focusing on large trades also partially addresses the concern that bid-ask spreads depend on the size of trades.

It contains the corporate bond CUSIP-level holdings' data for insurance companies, mutual funds, pension funds, and other investors at the quarterly level. Figure A.13a and Figure A.13b plot the coverage of eMaxx for investment-grade and high-yield bonds. For our selected bond space, eMaxx covers 30-40% of bonds' total outstanding amount consistently throughout the sample period. We do not find evidence of increasing coverage over time. Compared with the flow-of-funds data, the missing parties are likely foreign accounts and/or investment banks.

Consistent with the flow-of-funds aggregate data, the share of mutual funds has been increasing over time, especially after 2008, in our dataset. Mutual funds have a larger share in high-yield bonds, whereas life insurance companies have a larger share in investment-grade bonds. Moreover, the growth of mutual fund shares is also more significant in the high-yield bonds than in the investment-grade bonds.

To measure investor composition for each bond, we first create a measure for individual investors, and then aggregate it to the bond level. For individual investors, we use the net changes in bond holdings to approximate the frequencies of their liquidity shocks. The net transaction of a fund j in quarter t is defined as,

$$net\_transaction_{j,t} = \frac{\left| \sum_i holding_{i,j,t} - \sum_i holding_{i,j,t-1} \right|}{\sum_i holding_{i,j,t-1}} \tag{4.1}$$

where $holding_{i,j,t}$ is the par value of bond i held by fund j in quarter t. A higher net transaction indicates the fund experiences inflow and/or outflow more frequently, suggesting the fund is subject to a higher frequency of liquidity shocks.

We then take the average $net\_transaction_{j,t}$ in the past four quarters to capture the persistent component of the fund's trading behavior,

$$NT_{j,t} = \frac{1}{4} \sum_{t'=1}^{4} net\_transaction_{j,t-t'} \tag{4.2}$$

To measure investor composition for a bond i, we take the value-weighted average net transaction of all its bond holders. For bond i in period t,

$$investor\_comp_{i,t} = \frac{\sum_j holding_{i,j,t} \times NT_{j,t}}{\sum_j holding_{i,j,t}} \tag{4.3}$$

Higher $investor\_comp_{i,t}$ means more short-term investors are participating in the sub-market for bond i.

Our final sample contains 1,739 firms and 14,645 bonds, covering 2005Q2 to 2019Q2. Table A.3 shows the summary statistics of our bond-quarter observations. The average bid-ask spread is about 40 bps and the standard deviation of the bid-ask spread is also 40 bps. The average credit spread in the sample is 2.2%, with a standard deviation of 2.5%. It is worth pointing out that there is significant variation in bond maturity; hence, it is reasonable to consider investors sorting along this dimension. Lastly, in terms of ratings, about one third of the bonds are rated AAA-A and a fourth of the bonds are high-yield bonds. The largest component is the BBB-rated bonds, accounting for nearly 40% of all bonds in our sample.

Furthermore, Table A.4 shows the summary statistics of the portfolio information for mutual funds, insurance companies, and P&C insurance companies, which are the most important investor types in our sample. Life insurance companies tend to hold bonds with a longer time to maturity and higher ratings than mutual funds and P&C insurance firms. Mutual funds tend to hold higher shares of high-yield bonds. In terms of the average bid-ask spreads, the bonds held by insurance companies have higher bid-ask spreads, on average, than those held by mutual funds. We test this more formally later.

Analysis and Results

We first test whether the sorting patterns between investor types and bond types match the model predictions. In Figure A.14, we sort bonds into 50 bins according to their investor composition. We then plot the average time to maturity for each bin. Investors with higher turnover rates hold short-term bonds. The relationship is quite strong. To investigate the sorting pattern along default probabilities, we assign numeric values for bonds of different ratings: AAA bonds receive the lowest value, 1, and D-rated bonds receive the highest value, 22. We again sort bonds into 50 bins according to investor composition, and then plot the average numeric rating for each bin. Figure A.15 shows the result — there is a strong increasing relationship between the default probability and investor composition.

We then look at the correlation between investor composition and bonds' time to maturity ($ttm_{i,t}$), controlling for other bond and firm characteristics.

$$ttm_{i,t} = \alpha + \beta_1 investor\_comp_{i,t} + \beta_2 BA_{i,t} + \gamma^\top \mathbf{X_{i,t}} + \epsilon_{i,t} \tag{4.4}$$

The control $\mathbf{X_{i,t}}$ includes time to maturity, coupon rate, offering amount at the bond level, and leverage, profitability, equity volatility and total asset at the firm level. As shown in the first column of Table A.5, short-term investors are more likely to hold short-term bonds, even after controlling for bid-ask spreads.

We also find sub-markets with investors of shorter investment horizons have smaller bid-ask spreads. To establish this correlation, we run the following regression,

$$BA_{i,t} = \alpha + \beta investor\_comp_{i,t} + \gamma^\top \mathbf{X_{i,t}} + \epsilon_{i,t} \tag{4.5}$$

The bond characteristics and firm characteristics are the same as those in regression 4.4. The second column in table A.5 presents the result: long-investment-horizon investors are associated with higher bid-ask spreads. Since both variables are endogenous, we are simply verifying the correlation is the same sign as predicted by the model.

Next, we examine the effect of investor composition on credit spreads. Our benchmark regression is:

$$CS_{i,t} = \alpha + \beta_1 BA_{i,t} + \beta_2 investor\_comp_{i,t} + \beta_3 BA_{i,t} \times investor\_comp_{i,t} + \gamma^\top \mathbf{X_{i,t}} + \epsilon_{i,t} \tag{4.6}$$

The dependent variable $CS_{i,t}$ is the average spread on the last trading day of the bond in each quarter. The controls in $\mathbf{X_{i,t}}$ are the same as in (4.4). We do not use credit default swaps(CDS), because doing so would further restrict our sample to firms that have CDS. Also, CDS itself is not perfectly liquid. We also include the level and slope of the yield curve. We also add industry fixed effects, quarter fixed effects, and rating fixed effects. Since we have a panel data of yield spreads, the standard error is clustered at the quarter and firm level.

Table A.6 reports the benchmark result. First, a higher bid-ask spread is associated with a higher credit spread: a one standard deviation increase in the bid-ask spread leads to an increase in the credit spread of around 38 bps. More importantly, once we add the interaction between investor type and bid-ask spreads into the regression, the sign of bid-ask spreads switches, and the interaction term is highly positive and significant. This result indicates that when the bond-holders are subject to more frequent liquidity shocks, transaction costs have a larger impact on the credit spreads.

We then sort the bonds by investor composition into five groups. Table A.7 reports the summary statistics by investor quintile. Bonds in group 1 have mostly long-term investors (investors subject to less frequent liquidity shocks), whereas bonds in group 5 have mostly short-term investors. We then run the following regression group by group

$$CS_{i,t} = \alpha + \beta_1 BA_{i,t} + \beta_2 investor\_comp_{i,t} + \gamma^\top \mathbf{X_{i,t}} + \epsilon_{i,t} \tag{4.7}$$

Figure A.16 plots the coefficient in front of bid-ask spreads (β_1) and the corresponding confidence intervals for each group. The coefficient is larger as we move to bond groups with more short-term investors. For example, a 1% increase in the bid-ask spread in group 1 indicates an increase in the credit spread of around 25 bps, where as in group 5, the difference is around 1.5%, even after controlling for ratings.[2] This result means bonds with more short-term investors are more affected by the transaction costs or illiquidity in the secondary market, in the sense that differences in bid-ask spreads are mapped into larger differences in credit spreads.

Our results shows the cross derivative of credit spreads with respect to investor trading needs and bid-ask spreads is positive. This finding is direct evidence that investor heterogeneity plays an important role in pricing liquidity into credit spreads of bonds in the cross-section.

Following this analysis, we compute the liquidity component for each group. The liquidity component is calculated as the sensitivity coefficient multiplied by bid-ask spreads. The median liquidity component as a fraction of the credit spreads for each group is plotted in Figure A.17. As expected, bonds with more short-term investors have a larger liquidity component.

Next, we turn to the primary market. We regress offering yields and maturities of new bond issuance on the firms' investor base in the previous four quarters, with the same controls as before. Table A.8 reports our results. When more short-term investors are in the market, the offering yield is higher and the offering maturity is shorter. A one standard deviation increase in investor composition is associated with a 15 bps higher offering yield and 1.4 years less in terms of the offering maturity.

The results for offering yields are more prominent when using the alternative measure of liquidity. We again sort the bonds into five groups based on their investor composition, repeating the exercise in the secondary market. The results are shown in Table E.6; the

2. This is not due to the differences in the standard deviations of bid-ask spreads; in fact, bonds in group 5 have lower bid-ask-spreads standard deviation than those in group 1.

impact of expected illiquidity is higher when more short-term investors are trading the bond. The effect is still weaker than that in the secondary market, partly because we have fewer observations for offering yields.

4.1.2 Cross-country Analysis

Our model predicts that the growth of mutual funds in illiquid asset holdings is due to the decline in the risk-free rate. To investigate the relationship between risk-free rates and mutual fund growth empirically, we conduct a cross-country analysis. We show that countries with a larger decline in risk-free rates have experienced higher growth in mutual fund shares in the bond markets.

Data

From Morningstar, we obtain monthly data on the size of the fixed-income mutual funds across 69 countries from January 2007 to August 2020. To match other controls we have, we average the monthly holdings to the quarter and annual level. We define the growth rate of short-term investor holdings as

$$flow_{i,t+1} = \frac{total\_asset_{i,t+1} - total\_asset_{i,t} - CA_{i,t+1}}{total\_asset_{i,t}}$$

where $total\_asset_{i,t}$ is country i's fixed-income funds' total asset value in period t, and $CA_{i,t+1}$ is the capital appreciation from period t to $t+1$. We subtract the net capital appreciation during the period to capture the net inflow more accurately.

IMF International Financial Statistics database has data on country interest rates and macroeconomic conditions: quarterly GDP growth, the unemployment rate, and inflation. For the risk-free rate, we use the country-specific government bond yields in the baseline analysis. This likely corresponds to the liquid asset that short-term investors would consider holding. Given the difference in capital flow patterns between developed and emerging markets, we include only OECD countries in the baseline case. In an extension, we include all countries available and use"money market rate" or "saving rate" for countries where government bond yields are not available.

Analysis and Results

We run the following regression to examine the relationship between the growth of short-term investors' holdings and the risk-free rate,

$$flow_{i,t} = \beta_0 + \beta_1 \Delta rf_{i,t} + \gamma^\top \mathbf{X_{i,t}} + \epsilon_{i,t} \tag{4.8}$$

The controls $X_{i,t}$ here include macroeconomic conditions — GDP growth, unemployment rate, and inflation— as well as time and country fixed effects. Each period is either a quarter or a year.

The regression results in Table A.9 show a strong cross-country relationship between risk-free rates and fund growth. A larger decline in risk-free rate is associated with a significantly higher fund growth rate in the fixed-income market.[3] This finding is consistent with the time-series pattern observed in the U.S. Moreover, one would expect the effect being larger over a longer time horizon. That is indeed what we find—the effect of the risk-free rate on the fund growth rate at the yearly level is one and half times as large as that at the quarterly level.[4] All our results still hold when we extend the data sample to all countries, as shown in Table A.10.

3. The intuition that more short-term investors enter illiquid asset markets due to the low-risk-free-rate environment should extend to assets other than corporate bonds, which is indeed what we find. The above relationship also holds if we use the growth of all mutual funds, not just fixed-income funds.

4. The reason we are not looking at the growth of mutual fund shares over the full sample period is because the sample periods are different for different countries.

4.2 Calibration

In this section, we conduct a simple calibration exercise and show our full heterogeneous-bond model can account for the significant changes in the data. Using the calibrated model, we investigate how investor-composition change interacts with the recent regulation changes on dealers from the Volcker Rule. We find the liquidity provision role of mutual funds has alleviated the impact of dealer regulations on the market. Lastly, we show that unexpected aggregate liquidity shocks have a much larger impact on the market today than before.

Our calibration is at the quarterly level. We focus on the bonds that are between 0.5 and 20 years of maturity; hence, we set $\underline{\delta} = 0.0125$ and $\overline{\delta} = 0.5$. Furthermore, we assume the ex-ante investor types follow a Pareto distribution with scale parameter $\underline{\theta}$ and shape parameter α. We assume $\xi = \xi_0 + \xi_1 \lambda^{\nu}$.

We calibrate the parameters $(\Delta, \xi_0, \xi_1, \gamma, \eta, \underline{\theta}, \nu, \rho, \alpha)$ to match the size of the liquidity component in 2005, the average investor turnover rate, the sensitivity coefficient of bid-ask spreads, variance of credit spreads, and bid-ask spreads in 2005 and 2019. Table A.11 shows the value of each moment that we are targeting and the model counterparts. We target the liquidity component and sensitivity coefficients because they are the key moments of interest in the data. The average investor turnover is the key driver of all other changes; hence, we include it as well. In the data, we only observed realized turnover; we construct the exact counterpart in the model, taking into account the waiting time.[5] Since the sensitivity coefficients are derived from a cross-section regression, it is influenced by the variances of credit spreads and bid-ask spreads. Thus, we include both as moment targets.

To calculate the average investor turnover rate, we use the definition in Section 4.1. In our eMaxx sample, the average investor turnover rate increased from 0.08 to 0.95 from 2005 to 2019. We use the 10-year Treasury bond rate as our risk-free rate, because it is the main liquid outside option that mutual funds hold. In 2005, the 10-year Treasury rate was around

5. An equivalent way is to target average holding time. In the model, the expected holding time is $\frac{1}{\mu_s} + \frac{1}{\theta}$.

4% annually, and in mid-2019, that rate decreased to around 2%. Table A.12 shows the value of calibrated parameters. Of course, all the parameters are jointly determined.

Even though we have the same number of parameter values and moments, we cannot match all the moments exactly, because the model is quite stylized. However, our model can match the large change in the sensitivity coefficient of credit yields to bid-ask spreads. For this to be true, it is important to endogenize investor sorting behavior, seller-buyer ratio and bid-ask spreads in each sub-market. To see why, consider a model similar to Amihud and Mendelson (1986), in which the bid-ask spreads are exogenous. The average sensitivity coefficient is given by

$$E[\frac{\theta}{1+\rho+\delta+d}] \tag{4.9}$$

Given the value we used for calibration, it is bounded above by 0.1, much lower than what we observe empirically. It cannot generate the observed magnitudes of changes in the impact of bid-ask spreads. The reason our continuum bond model can generate a much higher sensitivity coefficient is that the estimates are upward-biased due to an omitted-variable bias. As we explained before, bid-ask spreads are higher in sub-markets with higher seller-buyer ratios, which also leads to higher interest rates in those sub-markets. Hence, the sensitivity coefficient in the model is much larger and is able to match the empirical counterpart. This implies the waiting time is an important difference across the sub-markets and is priced significantly into the credit spreads.

We then feed in the 10-year Treasury rates, resolving the model for each quarter, to generate a panel dataset. We run the following regression using model-simulated data and compare the coefficients with the empirical data in Table A.13. The model gets the signs of all the coefficients correct, even though the values quantitatively are quite different.[6]

$$
\begin{aligned}
credit\_spread_{i,t} =& \alpha_0 + \beta_1 inv\_comp_{i,t} + \beta_2 bid\_ask_{i,t} + \beta_3 inv\_comp_{i,t} \times bid\_ask_{i,t} \\
&+ controls + \epsilon_{i,t}
\end{aligned} \tag{4.10}
$$

In addition, we calculate the liquidity component in 2019 given the calibrated model parameters. Note this moment is not targeted in the calibration exercise. Our model predicts the liquidity component should be 0.216 given the change in the risk-free rate and investor composition, which closely matches the ∼0.25 empirical counterpart.

Next, using the calibrated parameter values, we perform two exercises. We first look at what happens if ξ_1 increases by 1%. This experiment is motivated by the fact that the implementation of the Volcker Rule has likely raised dealers' cost to hold inventories. We perform the exercise under the market condition of 2005 and that of 2019, respectively. The difference is in the risk-free rate we feed in, and as a result, the equilibrium investor composition in the corporate bond market. Figure A.19 illustrates the comparison of credit-spread changes in response to a 1% increase in dealers' inventory cost, in 2005 and 2019, respectively. The entry of short-term investors could either amplify or alleviate the impact of dealer regulation change on credit conditions. On the one hand, with more short-term investors, credit spreads are more sensitive to secondary market frictions. This channel indicates we should see a larger impact of regulation with more short-term investors. On the other hand, short-term investors provide liquidity. Investors in the secondary market now rely less on the dealer sector to intermediate trades. This channel implies the dealer regulation change should have a smaller impact. In our calibration, we find the latter channel dominates. Compared with 2005, the effect of an increase in ξ_1 on credit spreads is much

6. One important reason our model does not do well quantitatively is that we have assumed investors are risk neutral. As a result, investors have no diversification motives and each bond is held by exactly one type of investor. This striking pattern is unlikely to be true in the real world.

smaller in 2019. Since today's market is populated with more short-term investors, the reliance on dealers to intermediate the trades has decreased. As a result, even if the dealer sector experiences an increase in cost, the effect on credit spreads is quite small. In other words, the entrance of mutual funds has masked the effects of dealer regulation changes to some extent.

In the second exercise, we examine what happens when the selling pressure in all sub-markets increases exogenously. One can think of this experiment as similar to an aggregate liquidity shock hitting all investors, causing more selling needs. In particular, we increase the selling pressure by 1% in all sub-markets using conditions in 2005 and in 2019. The results are illustrated in Figure A.18. Given the situation in 2005, a 1% increase in seller-buyer ratio raises credit spread by 1%-1.6%. The hike in credit spreads is larger for short-term, high-default-probability bonds. However, in 2019, a 1% increase in the sell-buyer ratio would lead to a 1.8%-2.6% increase in credit spreads, higher than those in 2005. The larger impact of selling pressure is due to the change in investor composition and their trading needs. This result potentially explains why market participants are so worried about liquidity.

CHAPTER 5

CONCLUSION

In this paper, we connect two important trends happening in the corporate bond market. The first trend is the massive growth of mutual fund shares, especially in the post-crisis period. The second trend is new—the sensitivity of credit yields to bid-ask spreads increased fourfold in the last 15 years, leading to an increase in liquidity component from 5% in 2005 to around 25% in 2019, both for investment-grade and high-yield bonds.

We then build a model linking the growth of mutual fund share in the bond market with the long-run decline in risk-free rates around the world. Our model is able to match the aggregate trends in the data jointly. In particular, the model predicts that as the risk-free rate declines, more short-term investors enter the bond market, searching for higher yields. This creates more liquidity and lowers the bid-ask spreads. However, due to the higher trading needs and shortened waiting time, the credit yields become more sensitive to bid-ask spreads. As a result, the liquidity component increases. We then test model predictions in the cross-section and find consistent evidence. Finally, we calibrate the model and conduct counterfactual analysis.

Our results indicate secondary market frictions have become a more important factor in pricing liquidity into the credit spreads and ultimately in determining firms' borrowing cost. We contribute to the heated debate about the importance of liquidity in the corporate bond market. Although others have studied how dealer regulations alter the level of liquidity in the secondary market, we point out that the credit yields are more sensitive to underlying frictions today than before, due to the change in investor composition.

Both the current COVID-19 crisis and the 2008 financial crisis have induced high selling pressure in the bond market. Our model implies the disruptive impact of aggregate liquidity shocks is much higher today than before, due to the differences in investor composition. We also find that the entry of mutual funds is potentially masking the negative impact of dealer regulation changes on the corporate bond market.

It would be interesting to apply our framework to evaluate the effectiveness of different quantitative easing (QE) programs. Past QE measures in the U.S. have focused on purchasing long-term government bonds. In the recent COVID-19 crisis, the Fed has started purchasing investment-grade corporate bonds. Our framework can analyze the effectiveness of these two measures in lowering credit spreads, taking into account the difference in the investor base for different bonds.

Finally, different from past crises, investment-grade bonds have suffered larger dislocation than high-yield bonds in the current COVID-19 crisis. Market participants have argued this phenomenon is due to the large outflow of corporate bond mutual funds. Given that the investor composition today is quite different than in the past, it would be interesting to investigate the role of investor heterogeneity in explaining the different behaviors across bonds. One can extend the model to a full dynamic setup, to evaluate the dynamics of investor composition in different bond markets and how the economy's reaction to aggregate shocks depends on the initial distribution of investor composition. We leave this avenue for future research.

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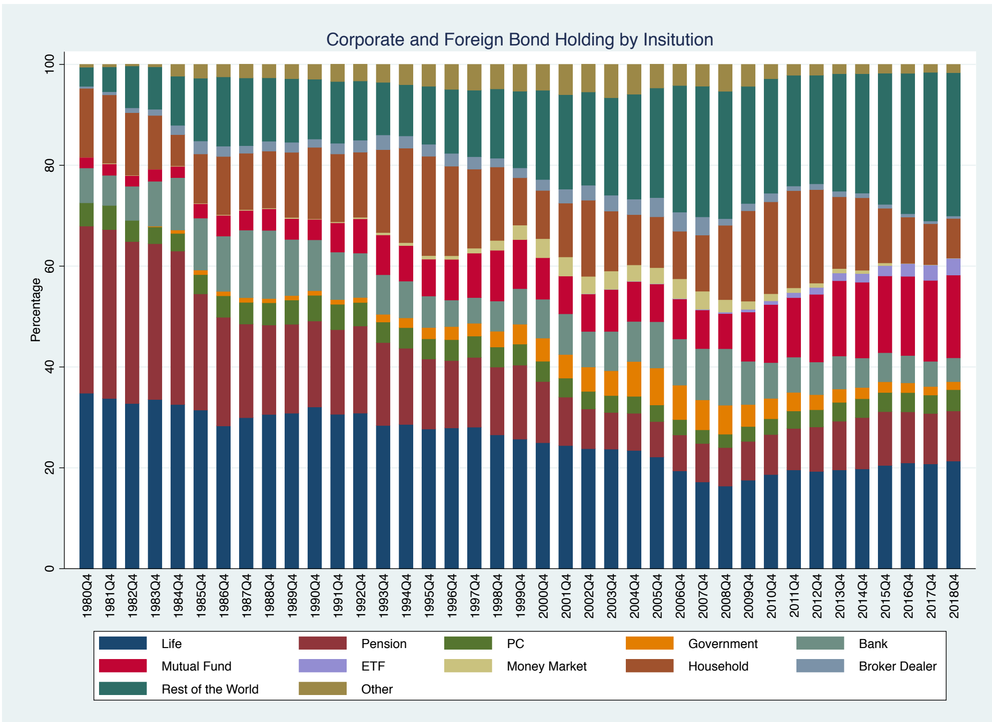
APPENDIX A

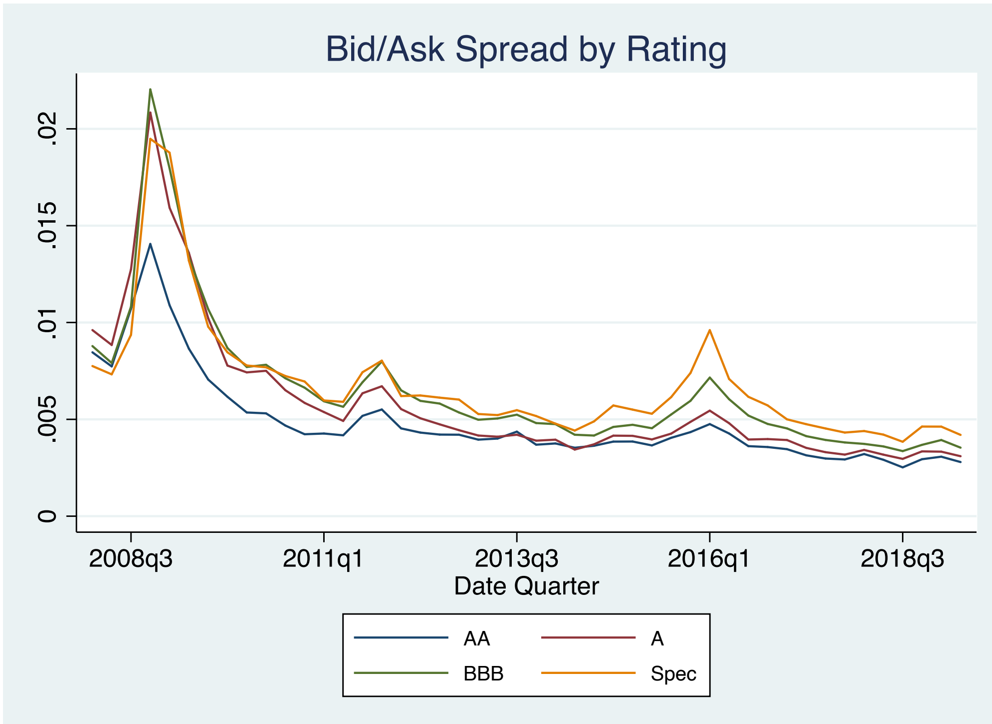
FIGURES AND TABLES TO MAIN PAPER

Figure A.1: Corporate and Foreign Bond Market Breakdowns



This figure plots quarterly share of holding of corporate and foreign bonds by investor type from the flow of funds. The sample period is from 1990Q1 to 2018Q4. "Life" stands for life insurance companies and "PC" stands for property and casualty insurance companies.

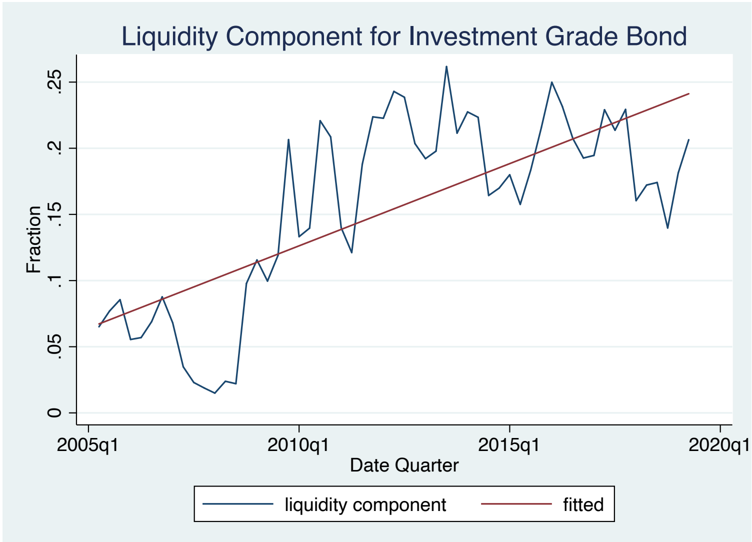
Figure A.2: Bid-ask Spreads by Rating



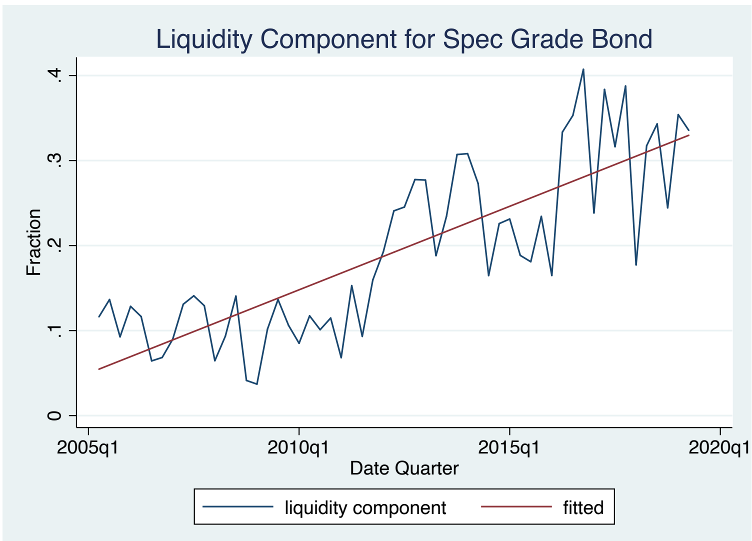
The figure plots the average bid-ask spreads for different ratings. For each bond in each quarter, we first calculate daily bid-ask spread as the average buy price minus average sell price, divided by the average of buy and sell prices. We then take the mean within each quarter. Data comes from TRACE and WRDS Bond Return.

Figure A.3: Liquidity Component as a Fraction of Credit Spreads

(a) Investment-grade Bonds

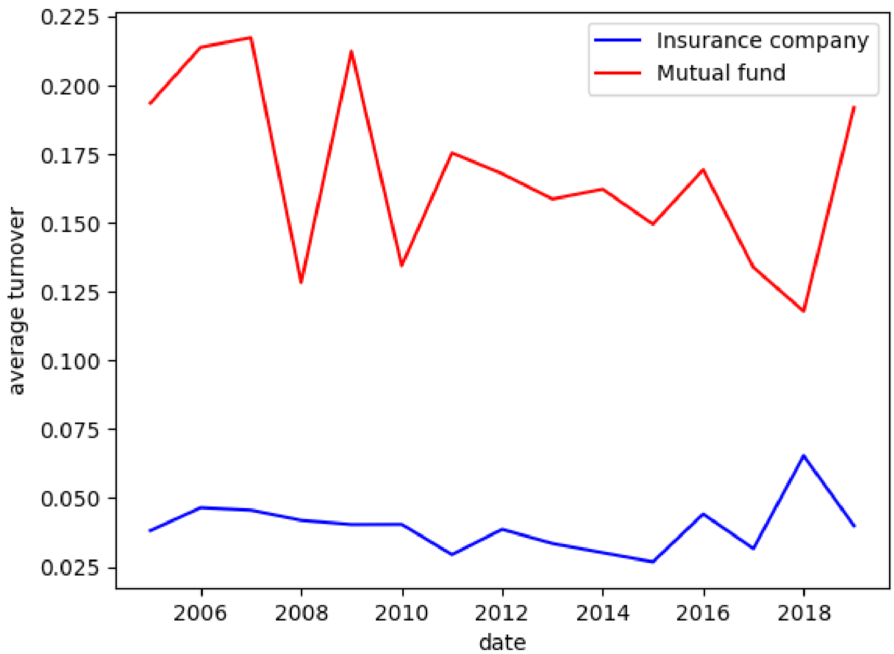


(b) High-Yield Bonds



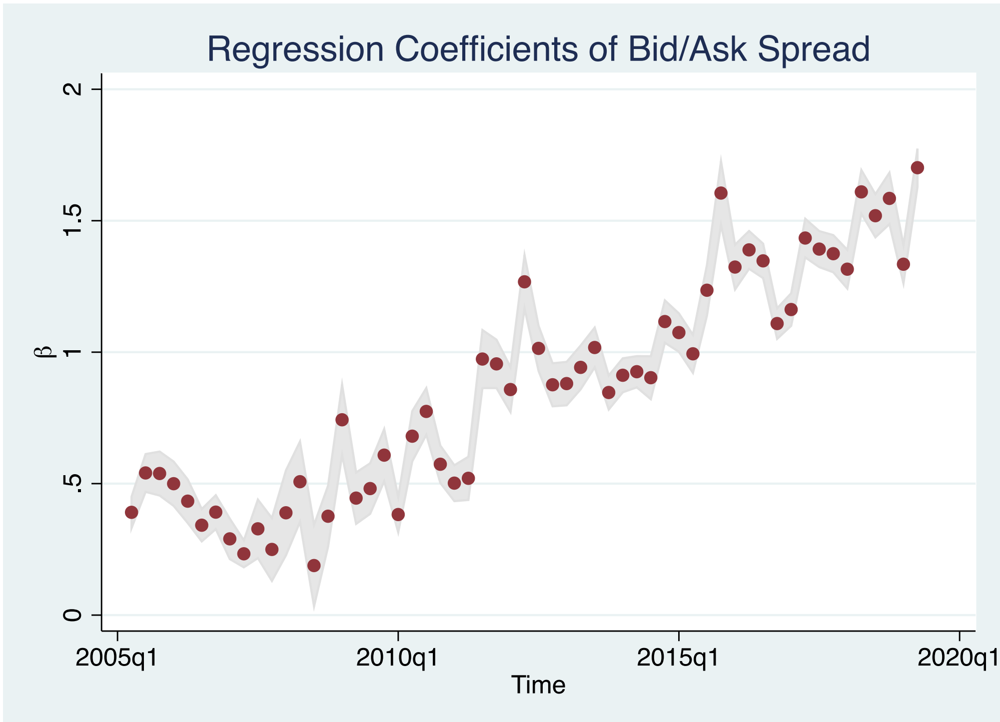
The figure plots the liquidity components of investment-grade bonds and high-yield bonds over time. For each quarter t, we first run 2.1 to get the coefficient of bid-ask spread β. Bond characteristic data is from Mergent FISD and WRDS Bond Returns, the price data is from TRACE. Next for each bond, define $liquidity\_component_{i,t} = \frac{\beta_t \times bid\_ask_{it}}{credit\_spread_{it}}$. The top figure plots the median liquidity component of investment-grade bonds over time and the bottom figure plots the corresponding trend for high-yield bonds. The red line is a fitted linear trend over time.

Figure A.4: Average Turnover of Investors by Type



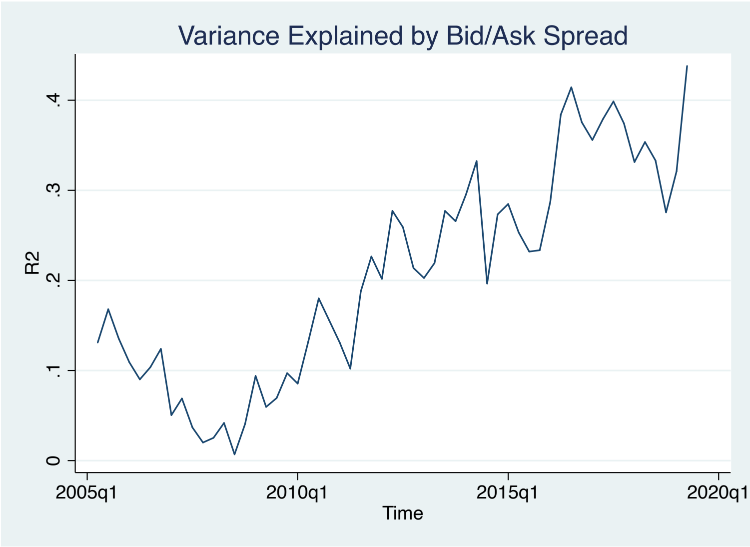
The figure plots the average account level turnover ratio of insurance companies and mutual funds using data from eMaxx. The sample period is from 2005 Q1 to 2019 Q2. Turnover is defined as the net trading from one quarter to the next divided by the total holding in the previous quarter. We then weight this turnover measure by each fund's total holding amount to calculate the average turnover of that investor type at a given quarter. The blue line plots the average turnover of insurance companies, and the red line plots the average turnover of mutual funds.

Figure A.5: Coefficient of the Uni-variate Regression of Credit Spreads on Bid-ask Spreads



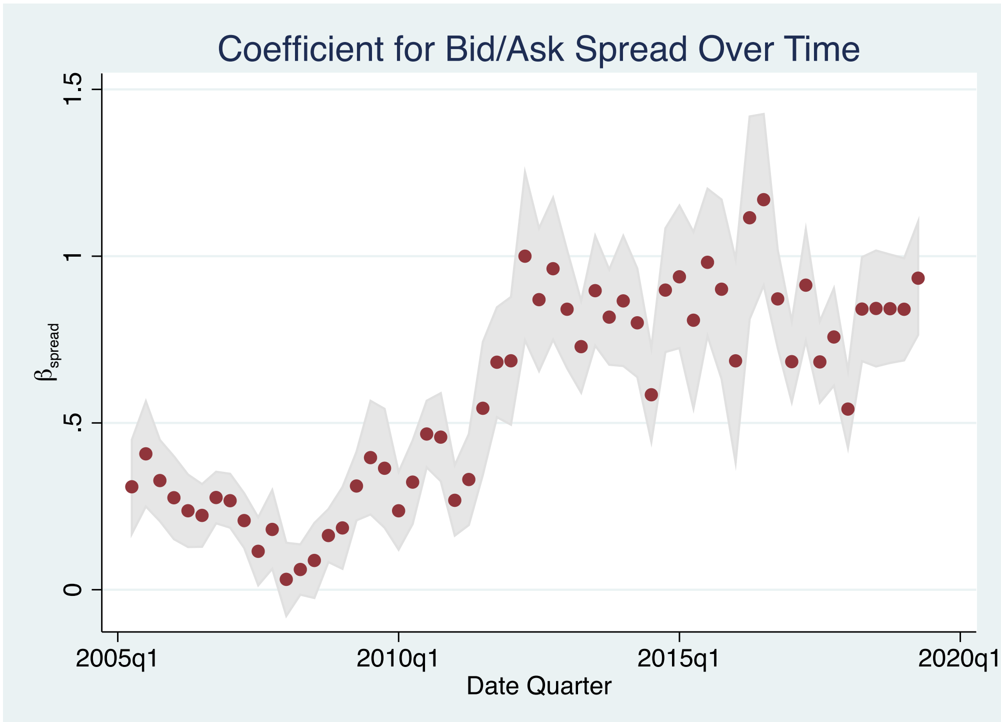
We conduct uni-variate regression $credit\_spread_{i,t} \sim \beta_t bid\_ask_{i,t} + constant$ quarter by quarter for all BBB-rated bonds. We then plot β_t over time in red. The shaded region indicates the 95% confidence interval. Data comes from WRDS Bond Return and Mergent FISD.

Figure A.6: R-squared of the Uni-variate Regression of Credit Spreads on Bid-ask Spreads



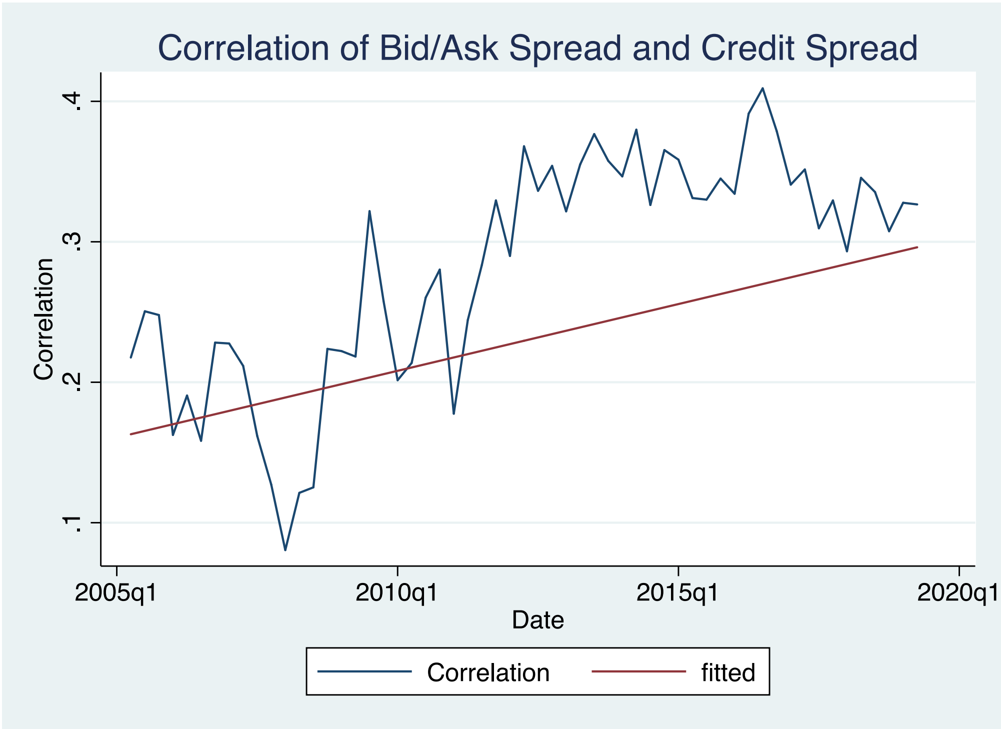
We conduct uni-variate regression $credit\_spread_{i,t} \sim \beta_t bid\_ask_{i,t} + constant$ quarter by quarter. We then plot R-squared over time. The shaded region indicates the 95% confidence interval. Data comes from WRDS Bond Return and Mergent FISD.

Figure A.7: Coefficient of Credit Spread on Bid-ask Spread (All Bonds)



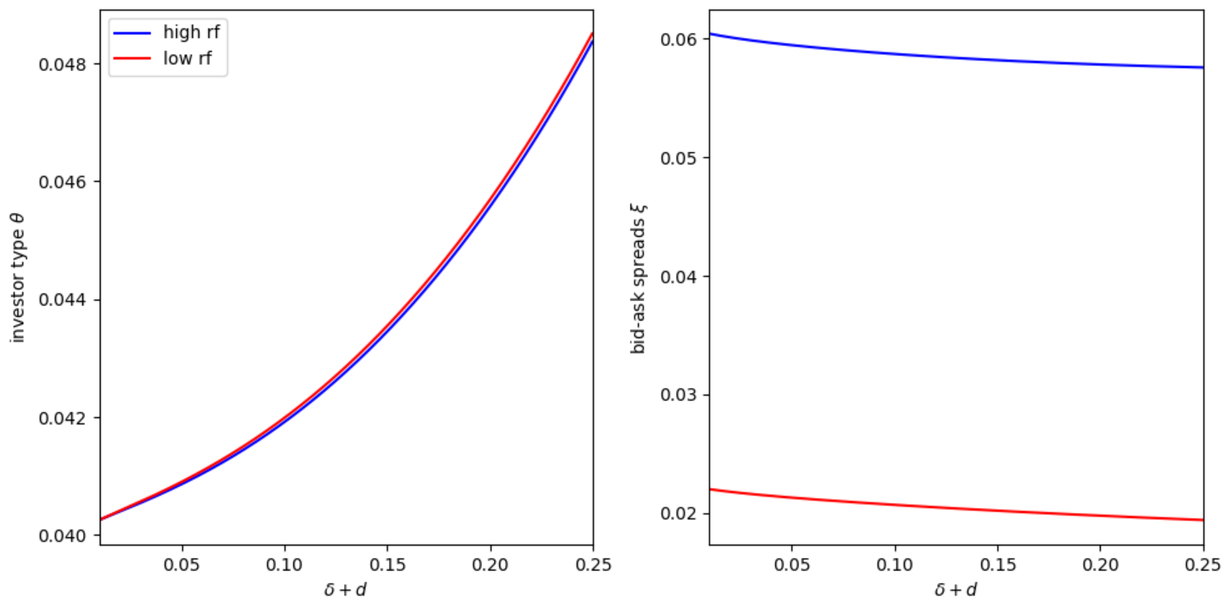
We regress credit spreads on bid-ask spreads quarter by quarter for all bonds, controlling for bond and firm characteristics. We then plot β_t over time in red. The shaded region indicates the 95% confidence interval. Data comes from WRDS Bond Return and Mergent FISD.

Figure A.8: Correlation Coefficient between Credit Spread and Bid-ask Spread (All Bonds)



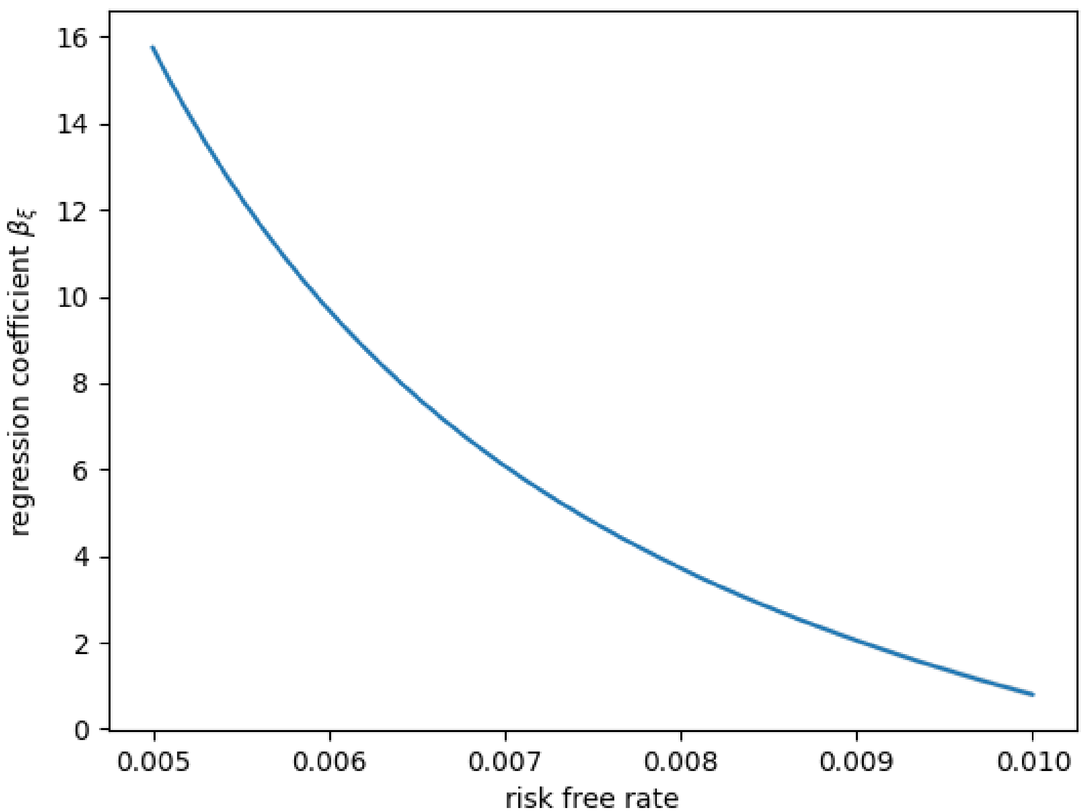
We regress credit spreads and bid-ask spreads on bond and firm characteristics quarter by quarter for all bonds. We then calculate the correlation coefficient for the residuals and plot it over time. The red line is a fitted trend line. Data comes from WRDS Bond Return and Mergent FISD.

Figure A.9: Numerical Example – Sorting and Bid-ask spreads in Equilibrium



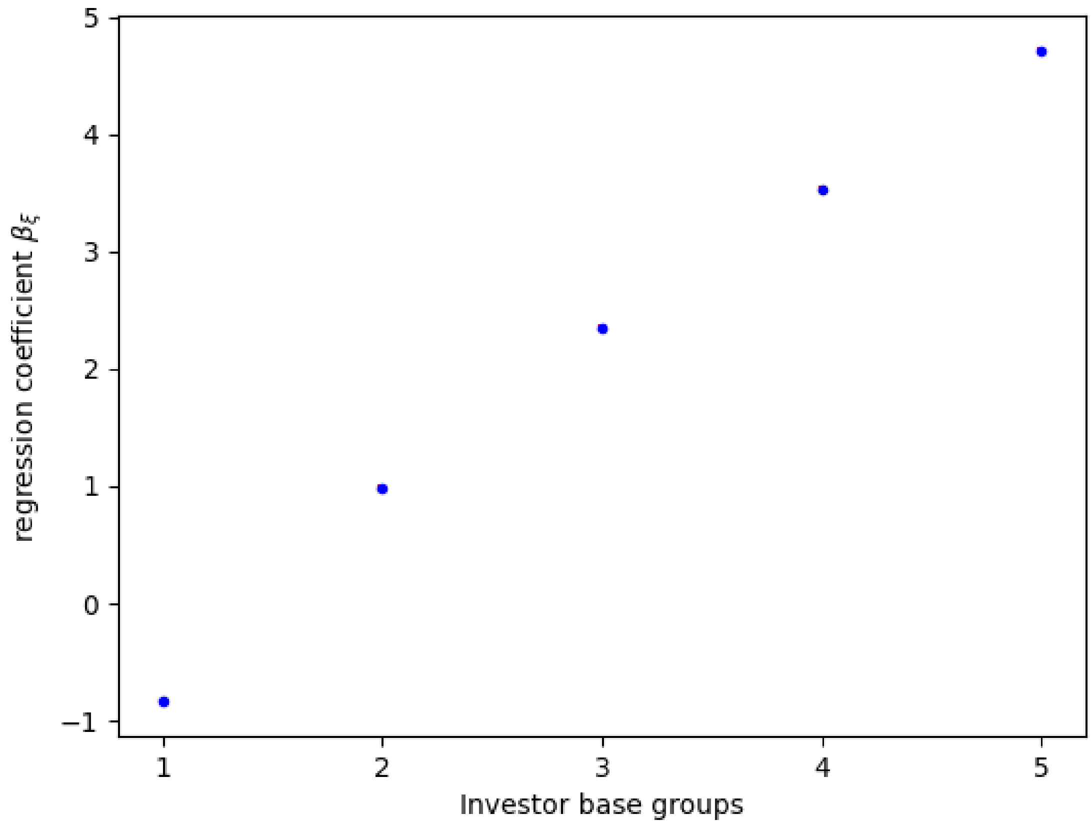
This figure illustrates what happens in equilibrium. The initial distribution of investor types is specified as a Pareto distribution, with the scale parameter equals to 0.0403 and the shape parameter equals to 0.1. For the rest of the parameters: $D = 1$, $m_I = 0.2$, $\Delta = 0.702$, $\rho = 0.009$, $\eta = 0.1135$, $\gamma = 0.9$, $\underline{\delta} + \underline{d} = 0.01$, $\overline{\delta} + \overline{d} = 0.25$. Lastly, the bid-ask spreads $\xi(\lambda) = 0.7145\lambda^2$. The left hand side panel plots the matching between investor type θ and bond type $\tilde{\delta} = \delta + d$. High risk-free rate is specified as 0.01 and low risk-free rate is specified as 0.005. Short-term investors (high θ) are matched with short-term debt (high δ) and high-default-probability debt (high d). The blue line corresponds to the situation when risk-free rate is high and the red line corresponds to the situation when risk-free rate is low. The right hand side panel plots the bid-ask spreads in each sub-market.

Figure A.10: Model Simulated Data– Over-time Regression Results



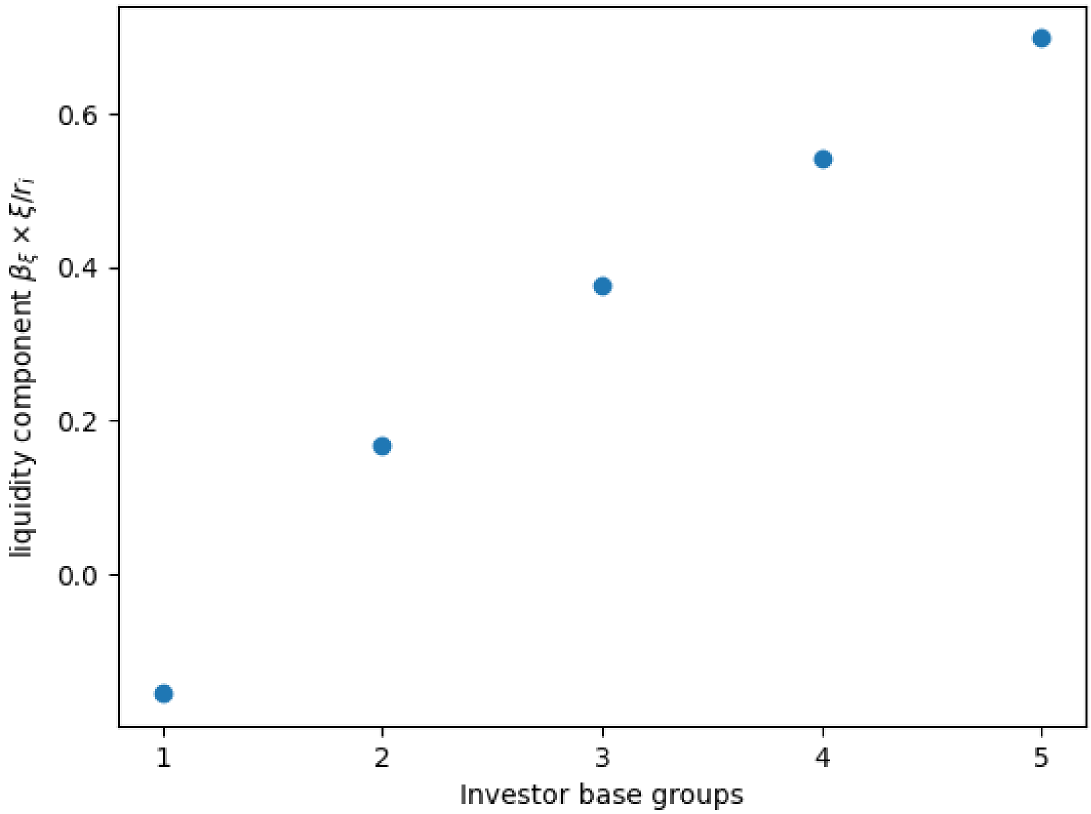
This figure illustrates comparative statics with respect to the risk free rate. The initial distribution of investor types is specified as a Pareto distribution, with the scale parameter equals to 0.0403 and the shape parameter equals to 0.1. For the rest of the parameters: $D = 1$, $m_I = 0.2$, $\Delta = 0.702$, $\rho = 0.009$, $\eta = 0.1135$, $\gamma = 0.9$, $\underline{\delta} + \underline{d} = 0.01$, $\overline{\delta} + \overline{d} = 0.25$. Lastly, the bid-ask spreads $\xi(\lambda) = 0.26 + 0.14\lambda^{1.84}$. The left hand side panel plots the matching between investor type θ and bond type $\tilde{\delta} = \delta + d$. High risk-free rate is specified as 0.01 and low-risk free rate is specified as 0.005. For each given risk-free rate, we solve the model and run the following regression: $r_i \sim constant + \beta_\xi \xi_i + bond\ characteristics$, bond characteristics include maturity and default probability. We then plot β_ξ for each risk-free rate. The shaded region represents 95% confidence interval.

Figure A.11: Model Simulated Data– Cross-sectional Regression Result



This figure reports group regression results from model simulated data described in Section 3.2. The initial distribution of investor types is specified as a Pareto distribution, with the scale parameter equals to 0.0403 and the shape parameter equals to 0.1. For the rest of the parameters: $D = 1$, $m_I = 0.2$, $\Delta = 0.702$, $\rho = 0.009$, $\eta = 0.1135$, $\gamma = 0.9$, $\underline{\delta} + \underline{d} = 0.01$, $\overline{\delta} + \overline{d} = 0.25$. We divide the sub-markets into 5 groups, where group 1 contains bonds with the longest-term investors and group 5 contains bonds with the shortest-term investors. We run the following regression for each group: $credit\_spreads_i \sim \beta_0 + \beta_\xi \xi_i + \beta_1 \delta_i + \beta_2 d_i$ and plot β_ξ. The center point in the figure is the point estimate of the coefficient in front of ξ_i in each group, while the bands around them indicate the 1% confidence interval.

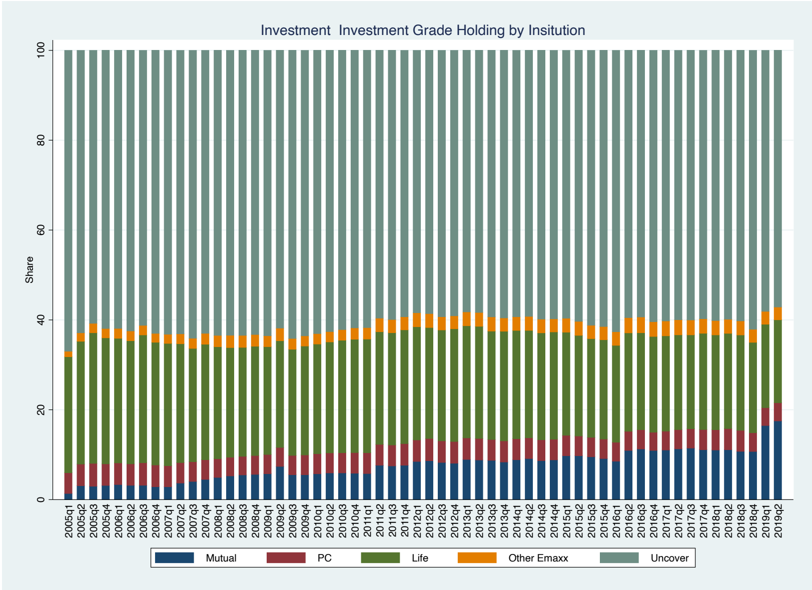
Figure A.12: Model Simulated Data– Liquidity Component by Group



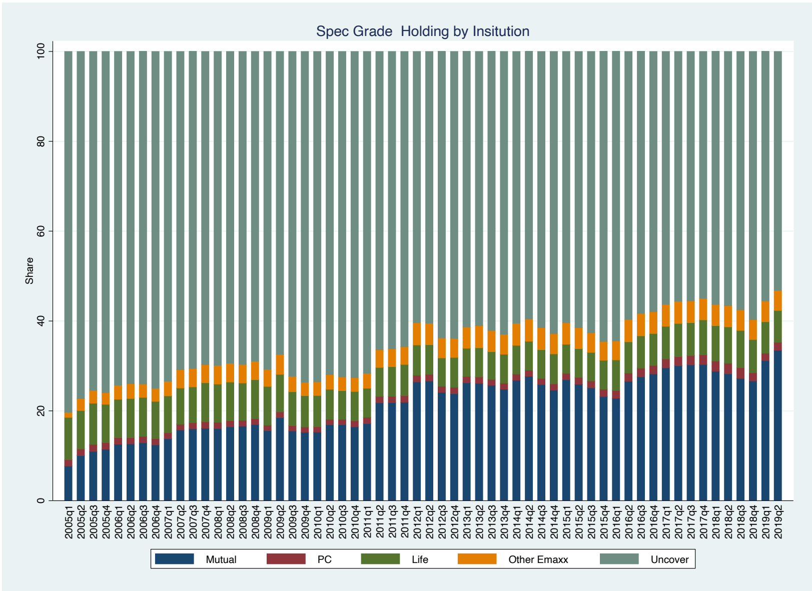
This figure reports group regression results from model simulated data described in Section 3.2. The initial distribution of investor types is specified as a Pareto distribution, with the scale parameter equals to 0.0403 and the shape parameter equals to 0.1. For the rest of the parameters: $D = 1$, $m_I = 0.2$, $\Delta = 0.702$, $\rho = 0.009$, $\eta = 0.1135$, $\gamma = 0.9$, $\underline{\delta} + \underline{d} = 0.01$, $\overline{\delta} + \overline{d} = 0.25$. We divide the sub-markets into 5 groups, where group 1 contains bonds with the longest-term investors and group 5 contains bonds with the shortest-term investors. We run the following regression for each group: $credit\_spreads_i \sim \beta_0 + \beta_\xi \xi_i + \beta_1 \delta_i + \beta_2 d_i$ and plot β_ξ. We then plot the median $\frac{\beta_i \xi_i}{credit\_spread_i}$ for each group.

Figure A.13: eMaxx Bond Coverage

(a) Investment-grade Bonds

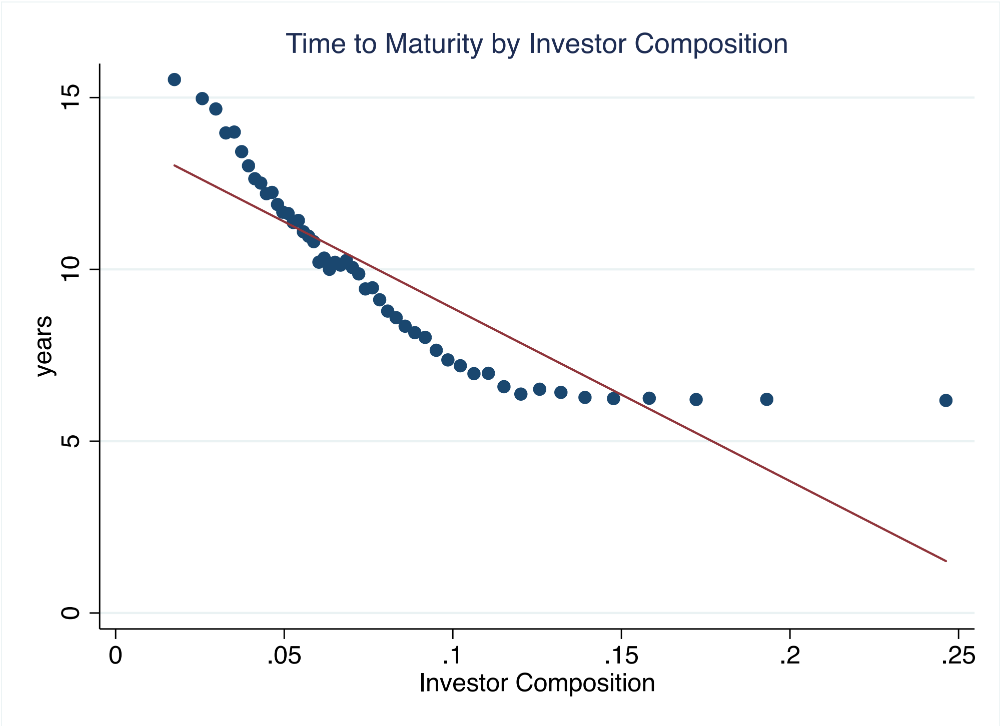


(b) High-yield Bonds



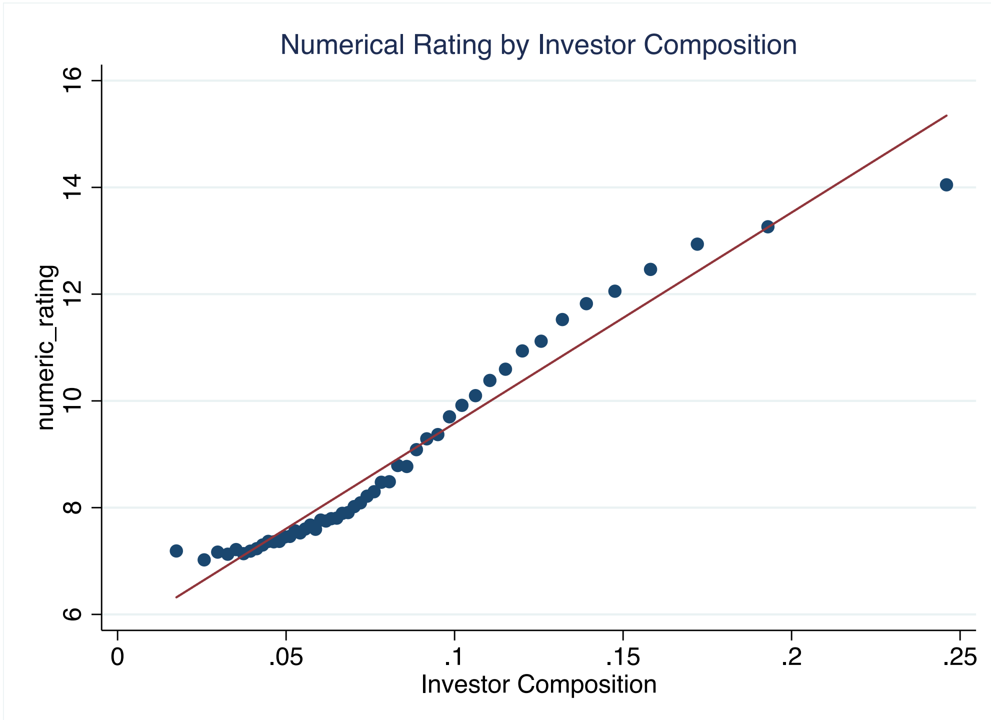
The figure plots quarterly share of holding of investment-grade and high-yield bonds covered by eMaxx from 2005Q2 to 2019Q2. The holding data is from eMaxx; the amount outstanding and rating data are from Mergent FISD. We classify the investors in eMaxx into life insurance company, P&C insurance company, mutual fund and others. The unclassified is calculated using the amount outstanding minus the total amount in eMaxx.

Figure A.14: Correlation between Bond Time to Maturity and Investor Types



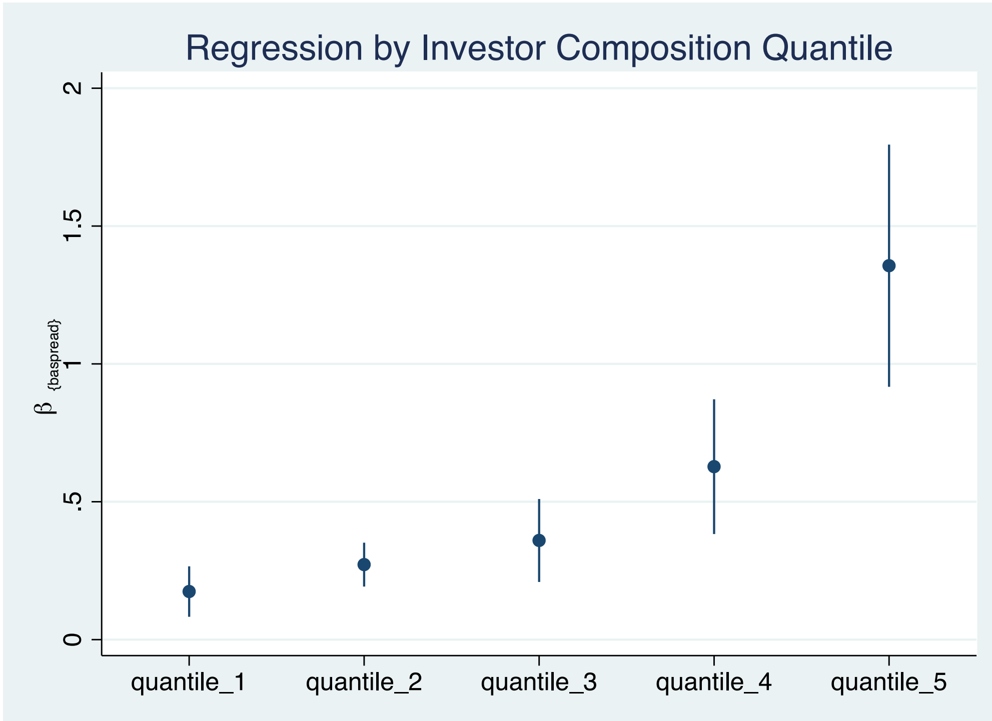
We sort bonds between 2005Q2 to 2019Q2 according to their investor composition, then plot the average time to maturity for each bin. The red line is a linear fitted line. Bond information is obtained from WRDS and investor composition information is constructed from eMaxx.

Figure A.15: Correlation between Bond Ratings and Investor Types



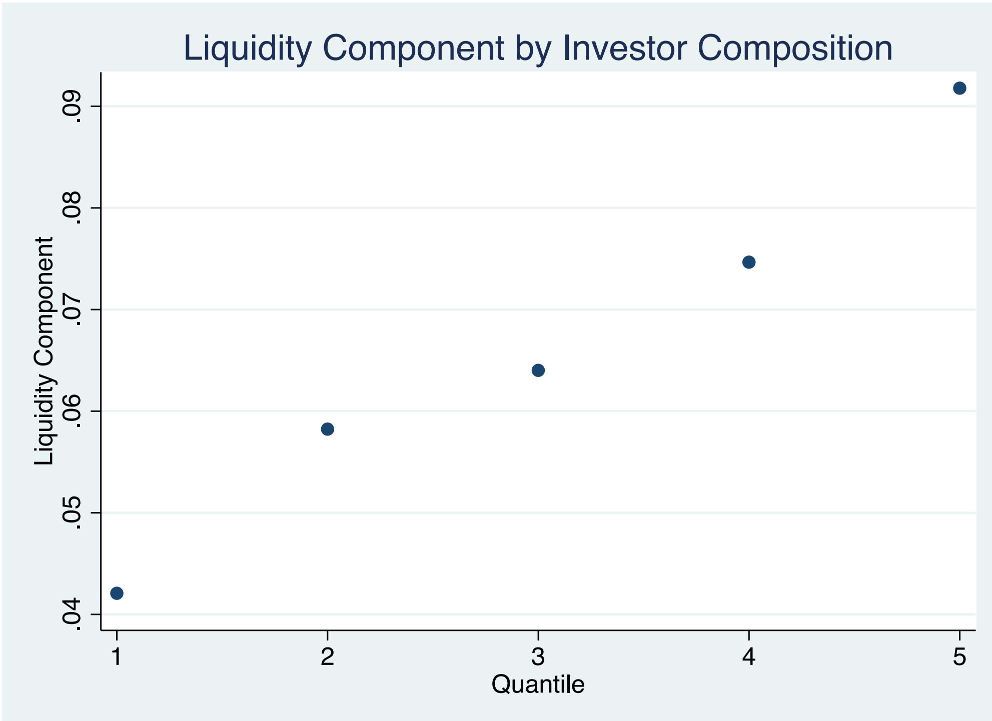
We sort bonds between 2005Q2 to 2019Q2 according to their investor composition, then plot the average numeric rating for each bin. The red line is a linear fitted line. Bond information is obtained from WRDS and investor composition information is constructed from eMaxx.

Figure A.16: Sensitivity of Credit Yields to Bid-Ask Spread by Investor Quantile



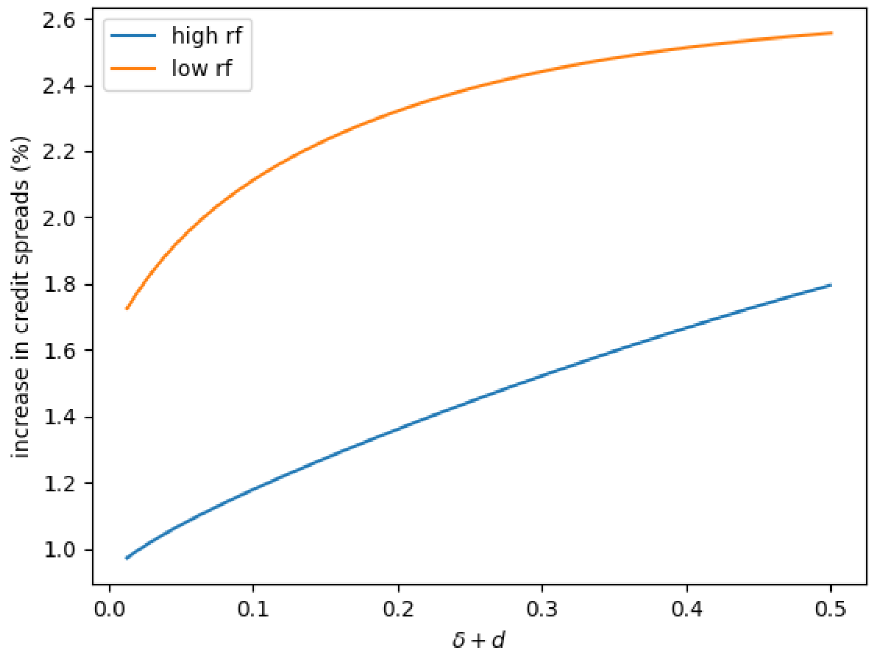
We sort the bonds (in each quarter from 2005Q2 to 2019Q2) into five groups, by investor base turnover. Group 1 contains bonds whose investors have the lowest turnover rate and group 5 contains bonds whose investors have the highest turnover rate. We regression coefficients and 1% confidence interval of credit spread regressed on bid-ask spreads, controlling for bond and firm characteristics, group by group. The exact regression equation is in 4.7.

Figure A.17: Median Liquidity Component as Fraction of Credit Yields, by Investor Quantile



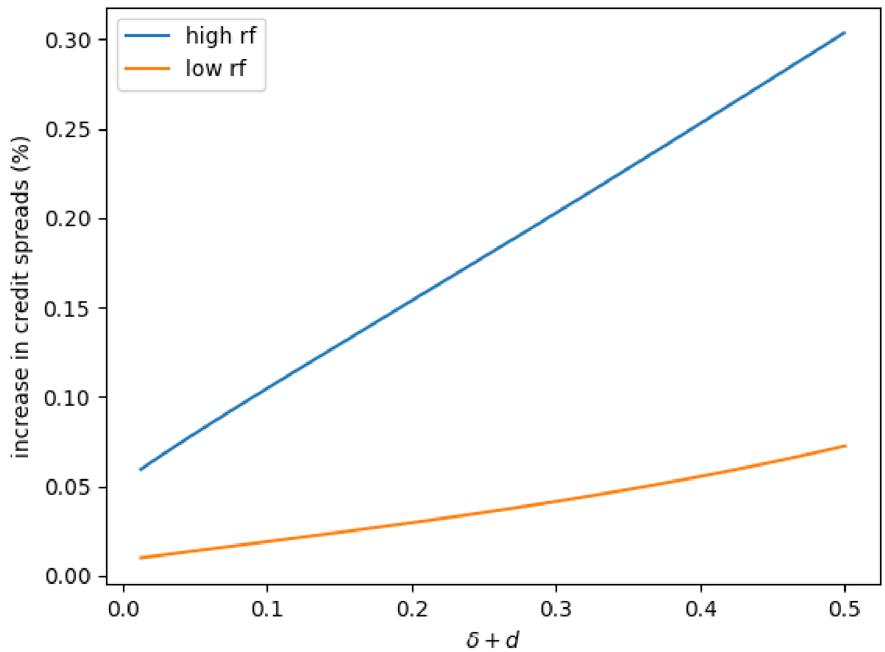
We sort the bonds (in each quarter from 2005Q2 to 2019Q2) into five groups, by investor base turnover. Group 1 contains bonds whose investors have the lowest turnover rate and group 5 contains bonds whose investors have the highest turnover rate. We regress credit spreads on bid-ask spreads group by group, controlling for bond and firm characteristics, group by group. The exact regression equation is in 4.7. For each bond, define $liquidity\_component_{i,t} = \frac{\beta \times bid\_ask_{it}}{credit\_spread_{it}}$, where β is the coefficient in front of bid-ask spreads. The figure plots the median liquidity component over credit spreads for each group.

Figure A.18: Change in Credit Spreads in Response to 1% Selling Pressure Increase



Using calibrated parameter values, we increase the seller-buyer ratio in each sub-market exogenously by 1% and recalculate the interest rates. The figure shows the increase in interest rates for each bond $\delta_i + d_i$. The blue line feeds in market conditions in 2005, and the orange line feeds in the market conditions in 2019.

Figure A.19: Change in Credit Spreads in Response to 1% Increase in ξ_1



Using calibrated parameter values, we increase ξ_1 by 1% and then recalculate the interest rates. We do not allow investors to re-sort. The figure plots the increase in interest rates for each bond $\delta_i + d_i$. The blue line feeds in market conditions in 2005, and the orange line feeds in the market conditions in 2019.

Table A.1: Summary Statistics at Bond-Quarter Level – BBB-rated Bonds

	Mean	Min	Max	Std
Bid-ask spread (WRDS)	.0054158	0	.0965653	.0051473
Credit spread	0.017	0.002	0.182	0.013
Quarterly transaction volume (million USD)	142.8	0.66	10280	260.6
The par value of debt (USD)	651131	6500	15000000	600329
Time to maturity (30/360 Convention)	9.546	0.003	99.962	9.313
Age	4.061	0.008	52.964	3.699
Annual interest rate (%)	5.135	0.700	12.000	1.700
Observations	72511			

This table presents bond-quarter level summary statistics for BBB-rated bonds. Bond data is obtained from WRDS and Mergent FISD. We include only US Corporate debenture with fixed coupon rate, non-convertible, non-puttable, non-exchangeable. Sample period is from 2005Q2 to 2019Q2.

Table A.2: Summary Statistics at Bond-Quarter Level – All Bonds

	Mean	Min	Max	Std
Bid-ask spread (WRDS)	.0053561	0	.0965653	.0050625
Credit spread	0.021	0.002	0.182	0.023
Quarterly transaction volume (million USD)	156.5	0.58	10280	275.4
The par value of debt (USD)	685274	6500	15000000	614380
Time to Maturity (30/360 Convention)	9.131	0.003	99.962	8.991
Age	4.044	0.008	60.518	3.695
Annual interest rate (%)	5.377	0.000	15.000	1.943
Observations	174739			

This table presents bond-quarter level summary statistics. Bond data is obtained from WRDS and Mergent FISD. We include only US Corporate debenture with fixed coupon rate, non-convertible, non-puttable, non-exchangeable. Sample period is from 2005Q2 to 2019Q2.

Table A.3: Summary Statistics at Bond-Quarter Level

	Mean	Min	Max	Std
Investor comp	0.086	0.000	0.679	0.048
Bid-ask spread	0.004	0.000	0.073	0.004
Alternative measure of illiquidity	-0.039	-0.740	10.000	0.666
Credit spread	0.022	0.002	0.182	0.025
Quarterly transaction volume (million USD)	150.1	0.2	1,058	269.1
The par value of debt (USD)	669781.240	6195.000	15000000.000	599798.879
Time to Maturity (30/360 convention)	9.468	0.252	100.153	8.997
Age	4.165	0.000	60.710	3.858
Annual interest rate (%)	5.522	0.000	15.0	1.917
Observations	184125			

This table presents bond-quarter level summary statistics. Bond data is obtained from WRDS and Mergent FISD. We include only US Corporate debenture with fixed coupon rate, non-convertible, non-putable, non-exchangeable. In addition, we only include bonds whose eMaxx coverage exceeds 20%.

Table A.4: Summary Statistics by Investor Type

Investor type	Life insurance	Mutual funds	P&C
Net transaction (%)	0.093	0.203	0.132
Amount (Trillion)	1.88	1.71	0.36
Average bid-ask spreads (bps)	35.5	28.5	25.9
Average yield	2.61	4.33	3.11
Time-to-maturity	12.22	7.56	5.89
Coupon	4.77	5.01	3.99
Number of funds	1091	6498	2014
Fraction of AAA-A	0.432	0.263	0.462
Fraction of BBB	0.465	0.407	0.407
Fraction of high-yield	0.103	0.330	0.131

This table summarizes bond-quarter level statistics by life insurance companies, mutual funds and P&C insurance companies. Data source is WRDS, Mergent FISD and eMaxx. Sample period is from 2015Q1 to 2019Q2.

Table A.5: Sorting of Investors

	(1) Time to maturity	(2) Bid-ask spread
Investor comp	-49.57***	-0.00952***
	(3.884)	(0.000836)
Age	-0.592***	0.000119***
	(0.0591)	(0.0000121)
Coupon	2.126***	-0.0358***
	(0.154)	(0.00471)
Offering amount	-0.000000431	-4.67e-10***
	(0.000000254)	(5.41e-11)
N	179965	151736
adj. R^2	0.200	0.275

Standard errors in parentheses: sym* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents correlation between investor composition and the maturity of bonds they hold, and the bid-ask spreads in each sub-market. "Investor comp" is the measure of investor composition, higher value indicates the investor have higher frequency of liquidity shock, i.e. shorter term investors. We also control for bond age, firm leverage, fraction of long term debt, equity volatility and profitability, where equity volatility is the standard deviation of the equity return of the issuer in that quarter.

Table A.6: Credit Yields Regression on Bid Ask Spreads

	(1) Credit spread	(2) Credit spread	(3) Credit spread
Bid-ask spread	0.405***	0.395***	-0.387***
	(0.0824)	(0.0844)	(0.0889)
Investor comp		-0.0136*	-0.0556***
		(0.00646)	(0.00796)
Bid-ask spread × Investor comp			11.72***
			(1.217)
Time to maturity ($\times 10^{-2}$)	0.0150***	0.0143***	0.0146***
	(0.00176)	(0.00176)	(0.00170)
Coupon ($\times 10^{-2}$)	0.0863***	0.0860***	0.0797***
	(0.0158)	(0.0157)	(0.0157)
Offering amount ($\times 10^{-2}$)	4.25e-08	4.31e-08*	4.13e-08
	(2.18e-08)	(2.14e-08)	(2.08e-08)
N	153831	147242	147242
adj. R^2	0.756	0.760	0.767

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the regression results for equation 4.6. Bid-Ask Spread is the measure of liquidity and "Investor Comp" is the measure of investor composition, higher value indicates the investor have higher frequency of liquidity shock, i.e. shorter term investors. We also control for bond age, firm leverage, fraction of long term debt, equity volatility and profitability, where equity volatility is the standard deviation of the equity return of the issuer in that quarter.

Table A.7: Summary Statistics by Investor Composition Quantile

	(1)		(2)		(3)		(4)		(5)	
	mean	std	mean	std	mean	std	mean	std	mean	std
Investor comp	0.038	0.007	0.052	0.007	0.068	0.010	0.095	0.018	0.154	0.046
Bid-ask Spread	0.005	0.006	0.005	0.005	0.004	0.004	0.004	0.004	0.003	0.003
Alternative measure of illiquidity	0.153	0.839	0.008	0.702	-0.045	0.639	-0.099	0.593	-0.142	0.560
Credit spread	0.016	0.017	0.016	0.017	0.017	0.019	0.023	0.025	0.036	0.032
Quarterly transaction volume (million USD)	47.9	67.68	88.0	124.4	138.9	207.7	207.0	341.4	224.3	360.7
Time to maturity (30/360 Convention)	14.251	10.792	11.168	9.797	9.766	9.305	7.859	7.741	6.189	5.428
Age	6.925	4.774	5.104	3.965	4.006	3.538	3.186	3.127	2.659	2.669
Interest rate (%)	5.618	1.405	5.236	1.478	5.059	1.628	5.254	1.960	6.376	2.396
Fraction of AAA-A bonds	0.546	0.498	0.504	0.500	0.416	0.493	0.259	0.438	0.086	0.280
Fraction of BBB bonds	0.414	0.493	0.456	0.498	0.501	0.500	0.462	0.499	0.261	0.439
Fraction of speculative grade bonds	0.040	0.196	0.040	0.195	0.083	0.276	0.279	0.449	0.653	0.476
Observations	27645		35256		38531		40425		42268	

Bond-Quarter level summary statistics by investor composition quantile. For each quarter, we sort the bond into five groups based on their investor composition. Group 1 are bonds with the shortest-term investor, group 5 are bonds with longest-term investor. A-AAA is a dummy indicating the bond has rating A-AAA. Similar for BBB and Speculative.

Table A.8: Regression of Offering Yields on Bid-ask Spreads

	Offering yield	Offering yield	Offering yield	Bond maturity
Bid-ask spread	0.0697	0.0952	-0.0350	562.3***
	(0.0851)	(0.0771)	(0.121)	(98.80)
Investor comp		0.0297***	0.0258***	-28.56***
		(0.00239)	(0.00439)	(4.308)
Bid-ask spread × Investor comp			1.442	
			(1.316)	
Coupon	0.00637***	0.00662***	0.00660***	4.165***
	(0.000317)	(0.000285)	(0.000289)	(0.255)
Offering amount	-3.70e-13	-1.96e-10	-1.88e-10	-3.84e-08
	(1.08e-10)	(1.24e-10)	(1.24e-10)	(0.000000169)
N	5296	5154	5154	5880
adj. R^2	0.907	0.913	0.913	0.388

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents regression results for equation 4.6 where the left hand side variable is replaced by offering yield. Bid-Ask Spread is the measure of liquidity and "Investor Comp" is the measure of investor composition, higher value indicates the investor have higher frequency of liquidity shock, i.e. shorter term investors. We also control for bond age, firm leverage, fraction of long term debt, equity volatility and profitability, where equity volatility is the standard deviation of the equity return of the issuer in that quarter.

Table A.9: Relationship between Fund Growth and Risk-free Rates (OECD Countries)

	Dependent variable: fixed income fund growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in risk-free rate	-0.046	-0.039*	-0.038*	-0.050**	-0.056***	-0.068***
	(0.029)	(0.022)	(0.021)	(0.020)	(0.020)	(0.021)
GDP growth		-0.011	-0.007		0.008	0.017
		(0.011)	(0.008)		(0.013)	(0.026)
Unemployment		0.002	-0.012		0.003	-0.041
		(0.003)	(0.009)		(0.007)	(0.039)
Inflation		0.043	0.044		0.031	0.038
		(0.033)	(0.030)		(0.050)	(0.101)
Country fixed effect	No	No	Yes	No	No	Yes
Year fixed effect	No	No	Yes	No	No	Yes
Frequency	Quarterly	Quarterly	Quarterly	Yearly	Yearly	Yearly
Observations	671	671	671	188	188	188
R^2	0.005	0.022	0.118	0.012	0.015	0.279
Adjusted R^2	0.004	0.016	0.069	0.006	-0.006	0.101
Residual Std. Error	0.374	0.372	0.362	0.648	0.652	0.616
F Statistic	2.540	1.261	29.544***	6.089**	4.297***	155.570***

Note: *p<0.1; **p<0.05; ***p<0.01

Risk-free rate and macroeconomic data is obtained from IMF statistics. We get aggregate fund size data from Morningstar. Fixed income fund growth is defined as the growth in net flows over the total asset under management in the previous period. Sample period is from January 2007 to August 2020. We include only OECD countries whose fund size data is available.

Table A.10: Relationship between Fund Growth and Risk-free Rates (All Countries)

	Dependent variable: fixed income fund growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in risk-free rate	-0.056***	-0.056***	-0.044**	-0.065***	-0.068***	-0.060***
	(0.016)	(0.017)	(0.018)	(0.015)	(0.015)	(0.019)
GDP growth		0.001	-0.003		0.002	0.030
		(0.003)	(0.004)		(0.006)	(0.024)
Unemployment		-0.006	0.007		-0.010	-0.021
		(0.004)	(0.010)		(0.006)	(0.030)
Inflation		-0.023	-0.041		-0.011	-0.111
		(0.040)	(0.060)		(0.049)	(0.133)
Country fixed effect	No	No	Yes	No	No	Yes
Year fixed effect	No	No	Yes	No	No	Yes
Frequency	Quarterly	Quarterly	Quarterly	Yearly	Yearly	Yearly
Observations	913	913	913	242	242	242
R^2	0.005	0.007	0.086	0.024	0.028	0.423
Adjusted R^2	0.004	0.003	0.036	0.020	0.011	0.280
Residual Std. Error	0.652	0.653	0.642	0.819	0.822	0.701
F Statistic	11.737***	3.351**	68.673***	19.903***	5.264***	484.864***

Note: *p<0.1; **p<0.05; ***p<0.01

Risk-free rate and macroeconomic data is obtained from IMF statistics. We get aggregate fund size data from Morningstar. Fixed income fund growth is defined as the growth in net flows over the total asset under management in the previous period. Sample period is from January 2007 to August 2020. We include all countries whose fund size data is available.

Table A.11: Target Moments and Model Fits

Moment	Empirical	Model simulated value
Ave. inv turnover in 2005	0.08	0.04
Ave. inv turnover in 2019	0.95	0.042
Coeff of BA spreads in 2005	0.25	0.246
Coeff of BA spreads in 2019	1.1	0.835
Liquidity comp in 2005	5%	5.19%
Std in BA spread in 2005	0.0032	0.0034
Std in BA spread in 2019	0.0025	0.00068
Std in credit spread in 2005	0.028	0.104
Std in credit spread in 2019	0.015	0.023

This table presents the targeted empirical moments and model produced moment values. The calibration is at the quarterly level. We focus on the bonds that are between 0.5-20 years of maturity, hence we set $\underline{\delta} = 0.0125$ and $\overline{\delta} = 0.5$. Furthermore, we assume the ex-ante investor types follow a Pareto distribution with scale parameter $\underline{\theta}$ and shape parameter α. We assume $\xi = \xi_0 + \xi_1 \lambda^{\nu}$. We feed in interest rate of 1% in 2005 and 0.5% in 2019, both at the quarterly level. Model parameter values are presented in Table A.12.

Table A.12: Model Parameter Values

Parameter	Value
Liquidity discount Δ	1.39
Time discount ρ	0.0048
Scale parameter of initial distribution $\underline{\theta}$	0.053
Shape parameter of initial distribution α	0.424
Constant in bid-ask spread ξ_0	0.168
Scale parameter in bid-ask spread ξ_1	0.242
Power parameter in bid-ask spread ν	1.86
Scale parameter in matching function η	0.12
Power parameter in matching function γ	0.88

This table presents the calibrated model parameter values. The calibration is at the quarterly level. We focus on the bonds that are between 0.5-20 years of maturity, hence we set $\underline{\delta} = 0.0125$ and $\overline{\delta} = 0.5$. Furthermore, we assume the ex-ante investor types follow a Pareto distribution with scale parameter $\underline{\theta}$ and shape parameter α. We assume $\xi = \xi_0 + \xi_1 \lambda^{\nu}$. We feed in interest rate of 1% in 2005 and 0.5% in 2019, both at the quarterly level. Targeted empirical moments and model produced moment values are presented in Table A.11.

Table A.13: Comparison between Model Simulated and Real Data Regression Coefficients

	Credit spreads	
	Data	Model
Bid-ask spread	-0.39***	-13***
	(0.089)	(0.072)
Investor Comp	-5.561***	-85***
	(0.796)	(0.264)
Bid-ask spread × Investor Comp	11.72***	371***
	(1.21)	(1.217)

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table compares the regression coefficients in real data and model simulated data. The calibration is at the quarterly level. We focus on the bonds that are between 0.5-20 years of maturity, hence we set $\underline{\delta} = 0.0125$ and $\overline{\delta} = 0.5$. Furthermore, we assume the ex-ante investor types follow a Pareto distribution with scale parameter $\underline{\theta}$ and shape parameter α. We assume $\xi = \xi_0 + \xi_1 \lambda^\nu$. The rest of the parameter values are in Table A.12. We feed in the 10-year treasury rate from 2005 to 2019, and resolve the model each period to create a panel dataset.

APPENDIX B

DERIVATIONS AND PROOFS

B.1 Proof for Lemma 1

In this proof, I omit the subscript j in order to present the proof in the simplest way. The proof applies for all j.

$$\rho V_s = r - \Delta + d(s - V_s) + \delta(1 - V_s) + \mu_s(p_s - \xi - V_s)$$

$$\rho V_b = \mu_b(V_0 - V_b - p_b)$$

$$\rho V_0 = r + d(s - V_0) + \delta(1 - V_0) + \theta(V_s - V_0)$$

$$p_b - p_s = \xi$$

from the above four equation, we have

$$V_0 - V_b - V_s - \xi = \frac{\Delta + \mu_s(\frac{\rho V_b}{\mu_b} + \xi)}{\delta + d + \rho + \theta + \mu_s} - \xi$$

when ξ is small, we have $V_0 - V_b - V_s - \xi \geq 0$.

B.2 Proof for Lemma 2

The first differential equation is derived from

$$\theta' = \frac{\alpha_s}{\alpha_b \lambda}$$

where α_s is the measure of sellers and α_b is the measure of buyers. Denote α_h as the measure of patient bond holders. In steady state

$$\theta' m_I f(\theta) - \mu_b \alpha_b - \tilde{\delta} = 0$$
$$- \mu_s \alpha_s - \tilde{\delta}\alpha_s + \theta\alpha_h = 0$$
$$- \theta\alpha_h + \mu_b\alpha_b - \tilde{\delta}\alpha_h + \tilde{\delta} = 0$$

With these conditions, we can derive

$$\frac{\alpha_s}{\alpha_b \lambda} = \frac{\theta m_I f(\theta)\mu_b + \tilde{\delta}\lambda(\mu_s + \tilde{\delta})(\theta + \tilde{\delta})}{(\mu_s + \tilde{\delta})(\tilde{\delta} + \theta) m_I f(\theta)\lambda}$$

To derive the second differential equation, consider the seller's problem,

$$U_s = \max_{\theta,\lambda} \quad \frac{\frac{\Delta}{\rho+\delta+d+\theta} - U(\theta)(1 + \frac{\rho}{\mu_b}) - \xi(\lambda)}{\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta}}$$

Taking first order condition with respect to θ and λ,

$$[\theta]: \qquad -\frac{\left[\frac{\Delta}{\rho+\delta+d+\theta} + U'(\theta)(1+\frac{\rho}{\mu_b})\right](\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta}) + \frac{U(\theta)(1+\frac{\rho}{\mu_b})+\xi}{(\rho+\delta+d+\theta)^2}}{(\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta})^2} = 0 \tag{B.1}$$

$$[\lambda]: \qquad \frac{(\frac{U(\theta)\rho}{\mu_b^2}\mu_b' - \xi')(\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta}) + \frac{1}{\mu_s^2}\mu_s'\left[\frac{\Delta}{\rho+\delta+d+\theta} - U(\theta)(1+\frac{\rho}{\mu_b}) - \xi(\lambda)\right]}{(\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta})^2} = 0 \tag{B.2}$$

from equation B.2,

$$U(\theta) = \frac{\xi'(\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta}) - \frac{\mu_s'}{\mu_s^2}(\frac{\Delta}{\rho+\delta+d+\theta} - \xi)}{\frac{\rho}{\mu_b^2}\mu_b'(\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta}) - \frac{\mu_s'}{\mu_s^2}(1+\frac{\rho}{\mu_b})} \tag{B.3}$$

plug this into equation B.1, we get

$$U'(\theta) = -\frac{\frac{U(\theta)(1+\frac{\rho}{\mu_b})+\xi}{(\rho+\delta+d+\theta)^2(\frac{1}{\mu_s}+\frac{1}{\rho+\delta+d+\theta})} + \frac{\Delta}{\rho+\delta+d+\theta}}{1+\frac{\rho}{\mu_b}} < 0 \tag{B.4}$$

here we can see that long term buyers get higher value from participating in the bond market, which is consistent with our one bond value function.

Next we total-differentiate equation B.2 with respect to θ, and plug in $U'(\theta)$, rearrange terms we get

$$\lambda'(\theta) = -\frac{\rho\gamma\lambda U'\theta'}{\rho\gamma U - \xi''\eta\lambda^{\gamma} - \xi'\eta\gamma\lambda^{\gamma-1}} + \frac{(1-\gamma)\left[\frac{\Delta}{\mu_s} - U(1+\frac{\rho}{\mu_b}) - \xi\right]}{\left[\rho\gamma U - \xi''\eta\lambda^{\gamma} - \xi'\eta\gamma\lambda^{\gamma-1}\right]\left[\frac{\rho+\delta+d+\theta}{\mu_s}+1\right]} \tag{B.5}$$

B.3 Proof for Proposition 1

To satisfy second order condition, denote the hessian as $\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$, where

$$a_{11} = -\frac{\left[-\frac{\Delta}{(\rho+\delta+d+\theta)^2} + U''(\theta)(1+\frac{\rho}{\mu_b})\right](\frac{1}{\mu_s}+\frac{1}{\rho+\delta+d+\theta}) - \frac{\frac{\Delta}{\rho+\delta+d+\theta}+U'(\theta)(1+\frac{\rho}{\mu_b})}{(\rho+\delta+d+\theta)^2} + \frac{U'(\theta)(1+\frac{\rho}{\mu_b})+\xi}{(\rho+\delta+d+\theta)^2} - \frac{U'(\theta)(1+\frac{\rho}{\mu_b})}{(\rho+\delta+d+\theta)^2} - \frac{2U(\theta)(1+\frac{\rho}{\mu_b})+\xi}{(\rho+\delta+d+\theta)^3}}{(\frac{1}{\mu_s}+\frac{1}{\rho+\delta+d+\theta})^2}$$

$$a_{12} = a_{21} = -\frac{-U'(\theta)\frac{\rho}{\mu_b^2}\mu_b'(\frac{1}{\mu_s}+\frac{1}{\rho+\delta+d+\theta}) - \frac{\left[\frac{\Delta}{\rho+\delta+d+\theta}+U'(\theta)(1+\frac{\rho}{\mu_b})\right]}{\mu_s^2}\mu_s' + \frac{U(\theta)\frac{\rho}{\mu_b^2}\mu_b'+\xi'}{(\rho+\delta+d+\theta)^2}}{(\frac{1}{\mu_s}+\frac{1}{\rho+\delta+d+\theta})^2}$$

$$a_{22} = -\frac{\frac{\mu_s'}{\mu_s^2}}{\frac{1}{\mu_s}+\frac{1}{\rho+\delta+d+\theta}}\left[\rho\gamma U - \xi''\eta\lambda^{\gamma} - \xi'\eta\gamma\lambda^{\gamma-1}\right]$$

if SOC is satisfied, $a_{22} < 0$

$$\rho\gamma U - \xi''\eta\lambda^{\gamma} - \xi'\eta\gamma\lambda^{\gamma-1} < 0 \tag{B.6}$$

in addition,

$$a_{11}a_{22} - a_{12}^2 \geq 0$$

totally differentiate equation B.1, to get U'', plug it into a_{11}, we can get

$$a_{11}a_{22} - a_{12}^2 \geq 0 \Leftrightarrow \frac{\frac{\Delta}{\mu_s} - U(\theta)(1 + \frac{\rho}{\mu_b}) - \xi}{\theta'} \geq 0 \tag{B.7}$$

For positive assortative matching to be true, we need

$$\frac{\Delta}{\mu_s} - U(\theta)(1 + \frac{\rho}{\mu_b}) - \xi \geq 0$$

when $\gamma \to 1$ and ξ_0 and ξ_1 are small relative to Δ, this condition is satisfied.

B.4 Proof for Proposition 2

From equation (B.5), we have

$$\lambda'(\theta) = -\frac{\rho\gamma\lambda U'\theta'}{\rho\gamma U - \xi''\eta\lambda^\gamma - \xi'\eta\gamma\lambda^{\gamma-1}} + \frac{(1-\gamma)\left[\frac{\Delta}{\mu_s} - U(1 + \frac{\rho}{\mu_b}) - \xi\right]}{\left[\rho\gamma U - \xi''\eta\lambda^\gamma - \xi'\eta\gamma\lambda^{\gamma-1}\right]\left[\frac{\rho+\delta+d+\theta}{\mu_s} + 1\right]}$$

Given that we have positive assortative matching, we have $\frac{\Delta}{\mu_s} - U(1 + \frac{\rho}{\mu_b}) - \xi \geq 0$ (from equation (B.7)). From the other second order condition equation (B.6), we know

$$\rho\gamma U - \xi''\eta\lambda^\gamma - \xi'\eta\gamma\lambda^{\gamma-1} < 0$$

Lastly, we proved $U' < 0$ in equation (B.4). As a result, both terms in λ' are negative, i.e. $\lambda' < 0$.

B.5 Proof for Proposition 3

As risk-free rate declines, by implicit function theorem, it is straightforward that $\frac{d\bar{\theta}}{dr_f} < 0$. For each bond, we show this using a finite difference method, discretize the two ODEs to

$$\theta_{i+1} - \theta_i + f_1(\theta_{i+1}, \lambda_{i+1})t_\theta = 0$$

$$\lambda_{i+1} - \lambda_i + f_2(\theta_{i+1}, \lambda_{i+1})t_\lambda = 0$$

where t_θ is the grid size of θ and t_λ is the grid size of λ. Order the variables as $X = (\theta_N, \theta_{N-1}, ..., \theta_1, \lambda_N, \lambda_{N-1}, ..., \lambda_2)$. λ_1 can be found using θ_2 and λ_2, I leave it out of the system here. So the system of equation can be defined as

$$GX = \mathbf{0} \tag{B.8}$$

where

$$G = \begin{pmatrix} 1 & 0 & 0 & ... & 0 & 0 & 0 & ... & 0 \\ 1+a & -1 & 0 & ... & 0 & b & 0 & ... & 0 \\ 0 & 1+a & -1 & ... & 0 & 0 & b & ... & 0 \\ & & & ... & & & & ... & \\ 0 & 0 & .... & 1+a & -1 & 0 & 0 & ... & b \\ & & & & & & & & \\ c & 0 & ... & 0 & 0 & 1+d & -1 & ... & 0 \\ 0 & c & ... & 0 & 0 & 0 & 1+d & -1 & ... \\ & & ... & & & & ... & & \\ 0 & 0 & .... & c & 0 & 0 & ... & 0 & 1+d \end{pmatrix} \tag{B.9}$$

where

$$a = -t_\theta \frac{df_1(\theta,\lambda)}{d\theta} \qquad b = -t_\theta \frac{df_1(\theta,\lambda)}{d\lambda} \qquad c = -t_\lambda \frac{df_2(\theta,\lambda)}{d\theta} \qquad d = -t_\lambda \frac{df_2(\theta,\lambda)}{d\lambda}$$

The upper left block is $N \times N$, denote it as A; the upper right block is $N \times (N-1)$, denote is as B; the lower left block is $(N-1) \times N$, denote it as C; the lower right block is D, $(N-1) \times (N-1)$.

r_f increasing, means $\overline{\theta}$ is decreasing

$$\frac{dX}{d\overline{\theta}} = -G^{-1}\begin{pmatrix} -1 \\ 0 \\ ... \\ 0 \end{pmatrix} \tag{B.10}$$

so we just have to show the first column of G is positive. By block inversion, we need to show first columns of $(A - BD^{-1}C)^{-1}$ and $-D^{-1}C(A - BD^{-1}C)^{-1}$ are positive.

$$D^{-1} = \begin{pmatrix} \frac{1}{1+d} & \frac{1}{(1+d)^2} & ... & 0 \\ 0 & \frac{1}{1+d} & ... & 0 \\ & & ... & \\ 0 & 0 & ... & \frac{1}{1+d} \end{pmatrix} \tag{B.11}$$

$$D^{-1}C = \begin{pmatrix} \frac{c}{1+d} & \frac{c}{(1+d)^2} & ... & 0 & 0 \\ 0 & \frac{c}{1+d} & ... & 0 & 0 \\ & & ... & & 0 \\ 0 & 0 & ... & \frac{c}{1+d} & 0 \end{pmatrix} \tag{B.12}$$

$$BD^{-1}C = \begin{pmatrix} 0 & 0 & ... & 0 & 0 \\ \frac{bc}{1+d} & \frac{bc}{(1+d)^2} & ... & 0 & 0 \\ 0 & \frac{bc}{1+d} & ... & 0 & 0 \\ & & ... & & 0 \\ 0 & 0 & ... & \frac{bc}{1+d} & 0 \end{pmatrix} \tag{B.13}$$

$$A - BD^{-1}C = \begin{pmatrix} 1 & 0 & ... & 0 & 0 \\ 1+a-\frac{bc}{1+d} & -1-\frac{bc}{(1+d)^2} & ... & 0 & 0 \\ 0 & 1+a-\frac{bc}{1+d} & ... & 0 & 0 \\ & & ... & & 0 \\ 0 & 0 & ... & 1+a-\frac{bc}{1+d} & -1 \end{pmatrix} \tag{B.14}$$

the first columnn of its inverse is

$$\begin{pmatrix} 1 \\ x_2 \\ x_3 \\ ... \\ x_N \end{pmatrix} \tag{B.15}$$

where

$$
\begin{aligned}
&1 + a - \frac{bc}{1+d} - (1 + \frac{bc}{(1+d)^2})x_2 = 0 \\
&(1 + a - \frac{bc}{1+d})x_i - (1 + \frac{bc}{(1+d)^2})x_{i+1} \qquad \text{for} \quad i = 2..., N-2 \\
&(1 + a - \frac{bc}{1+d})x_{N-1} - x_N = 0
\end{aligned}
$$

a, b, c, d are small, so $x_i > 0$ for $2 \leq i \leq N$.

Next,

$$
-D^{-1}C(A - BD^{-1}C)^{-1} = - \begin{pmatrix} \frac{c}{1+d} & \frac{c}{(1+d)^2} & ... & 0 & 0 \\ 0 & \frac{c}{1+d} & ... & 0 & 0 \\ & & ... & & 0 \\ 0 & 0 & ... & \frac{c}{1+d} & 0 \end{pmatrix} \begin{pmatrix} 1 & ... & ... \\ x_2 & ... & ... \\ & ... & \\ x_N & ... & ... \end{pmatrix} \tag{B.16}
$$

we just need to show $c < 0$,

$$
c = -\frac{df_2(\theta, \lambda)}{d\theta} \tag{B.17}
$$

One can show that when Δ is large, this is indeed the case.

B.6 Proof for Lemma 3

Interest rate is pinned down by $V_b = V_0 - 1$, where $V_b = U(\theta)$ and

$$\rho V_s = r - \Delta + \delta(1 - V_s) + d(s - V_s) + U_s$$

$$\rho V_0 = r + \delta(1 - V_0) + d(s - V_0) + \theta(V_s - V_0)$$

$$r = \rho + d(1 - s) + (\rho + \delta + d)U + \theta \frac{\Delta - U_s}{\rho + \delta + d + \theta}$$

$$= \rho + d(1 - s) + (\rho + \delta + d)U + \frac{\mu_s \theta \left[\frac{\Delta}{\mu_s} + U(1 + \frac{\rho}{\mu_b}) + \xi\right]}{\mu_s + \rho + \delta + d + \theta}$$

B.7 Proof for Proposition 4

To look at $\frac{dr}{d\xi_0}$,

$$\frac{dr}{d\xi_0} = \frac{\mu_s \theta}{\mu_s + \rho + \delta + d + \theta} + \left[\rho + \delta + d + \frac{\mu_s \theta (1 + \frac{\rho}{\mu_b})}{\mu_s + \rho + \delta + d + \theta}\right] \frac{dU}{d\xi_0}$$

$$= \frac{\mu_s \theta}{\mu_s + \rho + \delta + d + \theta} +$$

$$\left[\rho + \delta + d + \frac{\mu_s \theta (1 + \frac{\rho}{\mu_b})}{\mu_s + \rho + \delta + d + \theta}\right] \frac{\frac{\mu_s'}{\mu_s^2}}{\frac{\rho}{\mu_b^2}\mu_b'(\frac{1}{\mu_s} + \frac{1}{\rho+\delta+d+\theta}) - \frac{\mu_s'}{\mu_s^2}(1 + \frac{\rho}{\mu_b})}$$

as $\gamma \to 1$, $\mu_s' \to 0$, $\frac{dr}{d\xi_0} \to \frac{\mu_s \theta}{\mu_s + \rho + \delta + d + \theta}$

B.8 Proof for Proposition 5

The first order condition of δ is proportional to

$$-\frac{dr}{d\delta} - \kappa$$

We analyze $k(\theta, \delta) = -\frac{dr}{d\delta}$,

$$k(\theta,\delta) = -U + \frac{\mu_s\theta[\frac{\Delta}{\mu_s} + U(1+\frac{\rho}{\mu_b}) + \xi]}{(\mu_s+\rho+\delta+d+\theta)^2} - \left[\rho+\delta+d+\frac{\mu_s\theta(1+\frac{\rho}{\mu_b}}{\mu_s+\rho+\delta+d+\theta}\right]\frac{dU}{d\delta}$$

when $\gamma \to 1$, $\frac{dU}{d\delta} \to 0$. By second order condition $\frac{dk(\theta,\delta)}{d\delta} < 0$. To apply implicit function theorem, we look at $\frac{dk(\theta,\delta)}{d\theta}$

$$\frac{dk(\theta,\delta)}{d\theta} = \underbrace{\frac{\partial k}{\partial \lambda}}_{<0}\underbrace{\frac{d\lambda}{d\theta}}_{<0} + \frac{\partial k}{\partial \theta}$$

when $\eta\lambda + \rho + \delta > \theta$, $\frac{\partial k}{\partial \theta} > 0$. So the whole term is positive,

$$\frac{dk(\theta,\delta)}{d\theta} > 0 \qquad \frac{d\delta^*}{d\theta} > 0$$

APPENDIX C

BID-ASK SPREAD AND SELLER-BUYER RATIO

This appendix micro-founds the increasing relationship between bid-ask spreads and the measure of sellers, and the decreasing relationship between bid-ask spreads and measure of buyers. Here we model the dealer sector explicitly: we assume buyers and sellers can only trade with the dealer sector; they cannot trade with each other directly.

Inventory cost

Assume the total measure of dealers is N and each dealer can at most hold 1 unit of bond. N indexes the size of the economy. Denote the probability of a dealer meet a buyer as $\lambda\alpha_b$ and the probability of a dealer meeting a seller as $\lambda\alpha_s$, where α_b and α_s are measures of buyers and sellers. The measure of buyers and sellers are proportional to N: $\alpha_b + \alpha_s = NI$, and I is the ratio of measure of investor over dealers. Denote the measure of dealers holding a bond as d_o and the measure of dealers not holding a bond as d_n. Furthermore, suppose the dealers incur an inventory cost increasing in the total number of bonds they are carrying i.e. $\frac{c}{2}d_o^2$. For simplicity, assume all bonds are perpetual bonds. In steady state, the number of bonds flowing into the dealer sector must equal to the number of bonds flowing out, so

$$-d_o\lambda\alpha_b + d_n\lambda\alpha_s = 0 \tag{C.1}$$

$$-d_o\lambda\alpha_b + (N - d_o)\lambda\alpha_s = 0 \tag{C.2}$$

$$d_o = \frac{N\alpha_s}{\alpha_b + \alpha_s} = \frac{\alpha_s}{I} \tag{C.3}$$

To break even

$$\frac{c}{2}d_o^2 = d_o\lambda\alpha_b\xi \tag{C.4}$$

$$\xi = \frac{c}{2\lambda}\frac{\alpha_s}{I\alpha_b} \tag{C.5}$$

Hence, the bid-ask spread ξ is increasing in the seller-buyer ratio.

Limited Dealer Capacity

Same as before, suppose there is measure N of dealers, d_o of them hold bonds and d_n of them do not. Buyers' valuation of the bond V_b, their value of searching is denoted as V_b^0; sellers' and dealers' valuations are V_s and V_d respectively. Assume with probability θ, bond holders receive a liquidity shock which reduces their valuation of cash flow by Δ. As in Duffie et al. (2005), we assume the investors and dealers engage in Nash bargaining, with bargaining power β and $1-\beta$ respectively. The search technology is also the same as in Duffie et al. (2005), with search intensity λ.

Ask price

$$A = V_d + (1-\beta)(V_b - V_b^0 - V_d) \tag{C.6}$$

Bid price

$$B = V_d - (1-\beta)(V_d - V_s) \tag{C.7}$$

the bid-ask spread is

$$\xi = A - B = (1-\beta)(V_b - V_b^0 - V_s) \tag{C.8}$$

The bellman equations are

$$\rho V_s = r - \Delta + \beta \lambda d_n (V_d - V_s) \tag{C.9}$$

$$\rho V_b = r + \theta (V_s - V_d) \tag{C.10}$$

$$\rho V_b^0 = \lambda d_o \beta (V_b - V_d - V_b^0) \tag{C.11}$$

$$\rho V_d = \lambda \alpha_b (1 - \beta)(V_b - V_b^0 - V_d) \tag{C.12}$$

plug in the value functions from above to the expression for the bid-ask spread, we get

$$\xi = (1 - \beta) \frac{\Delta - r - \frac{\lambda d_n \beta + \rho}{\theta} r}{\lambda d_n \beta + \frac{\frac{\rho}{\theta}(\rho+\theta)[\rho(\rho+\lambda\alpha_b(1-\beta))+\lambda d_o \beta]}{\frac{\rho^2}{\theta}(\rho+\lambda\alpha_b(1-\beta))+\frac{\rho+\theta}{\theta}\lambda d_o \beta}} \tag{C.13}$$

from the previous subsection, we know

$$d_o = \frac{\alpha_s}{\alpha_s + \alpha_b} N \qquad d_n = \frac{\alpha_b}{\alpha_s + \alpha_b} N \tag{C.14}$$

it is easy to show that

$$\frac{d\xi}{d\alpha_s} > 0 \qquad \frac{d\xi}{d\alpha_b} < 0 \tag{C.15}$$

APPENDIX D

CONTINUUM BOND EXTENSION

In this appendix, we analyze an extension of the continuum bond model, taking into account the regulatory restrictions that investors face when holding risky bonds. We show that all the results go through.

To incorporate the fact that long term investors often face higher regulatory cost of holding risky bonds, we assume for investor type θ, there is a flow cost $\kappa(\theta)d$ for holding bonds with default probability d. The HJB for patient type investor θ becomes

$$\rho V_0 = r_i + \delta_i(1 - V_0) + d_i(s_i - V_0) + \theta(V_s - V_0) - \kappa(\theta)d_i \tag{D.1}$$

Furthermore, we assume once the liquidity shock hits, the flow cost no longer applies, since all the investors become the same. If the flow cost applies even after the liquidity shock occurs, then the sellers are heterogeneous along two dimensions – the type of bonds they hold and the level of flow cost from regulatory constraints. This significantly increases the complexity of the sorting problem. To keep it in line with the main model, we assume the flow cost only applies before the liquidity shock occurs.

Empirically, the long term investors (pension funds, insurance companies) have higher risk aversion and/or stricter regulatory constraints in holding risky bonds, hence we assume in the model that $\kappa(\theta)' < 0$. The buyer problem now becomes

$$\max_{\lambda,i} \frac{m}{\rho + m}\left(\frac{\Delta - u - \kappa(\theta)d_i}{\rho + \delta_i + d_i + \theta} - \frac{\lambda}{m}u - \epsilon\right) \tag{D.2}$$

APPENDIX E

ALTERNATIVE MEASURE OF ILLIQUIDITY

In this appendix, we construct an alternative measurement of illiquidity and repeat our empirical analysis in Subsection 4.1.1. We first compute Amihud measure, Roll measure, imputed round-trip cost (IRC), number of zero trading days for the firm and the bond, average bid-ask spreads, standard deviation of Amihud measure, IRC and bid-ask spreads for each bond at the quarterly level. Then we conduct principle component analysis (PCA).

The principle component analysis of Table E.1 indicates that the first component, which mainly consists of the price measures, explains nearly half of the variation in liquidity, while the second and third components are closer to quantity measure, and are almost orthogonal to the first component. Following the literature, we take the first component as the measure of illiquidity for bonds. Moreover, as Table E.2 shows, the price measures are highly correlated. The reason for conducting PCA is to get a more accurate measure of the underlying frictions. Lastly, all the liquidity measures are standardized over time.[1] We denote this measure as $\lambda_{i,t}$. Higher value of $\lambda_{i,t}$ means less liquid. Figure E.1 plots our measure of illiquidity over time, the illiquidity peaks during the financial crisis. Overall, bonds with higher ratings are more liquid.

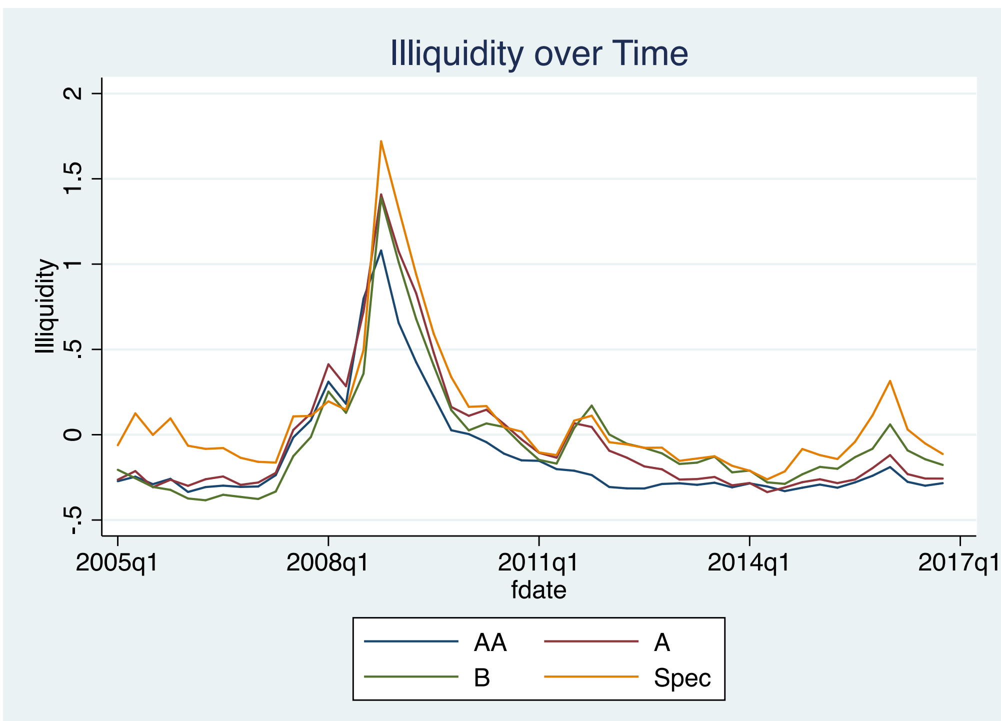
In terms of aggregate trends, Figure E.2 shows the liquidity component for investment grade and speculative grade bonds over time. Despite high volatility, the liquidity components as a fraction of credit spreads have been increasing, at least for the post-crisis period.

Next, we move on to the cross-sectional analysis. First of all, Table E.3 shows the sorting result of investor types and the sub-markets. The column of time to maturity is the same as before. We replace the bid-ask spreads with the new measure of illiquidity. We find the same result as before: sub-markets with more short-term investors have higher liquidity. Figure E.3 is the counterpart of Figure A.16, replacing the bid-ask spread the alternative

1. This means we subtract away the sample mean and divide by the sample standard deviation.

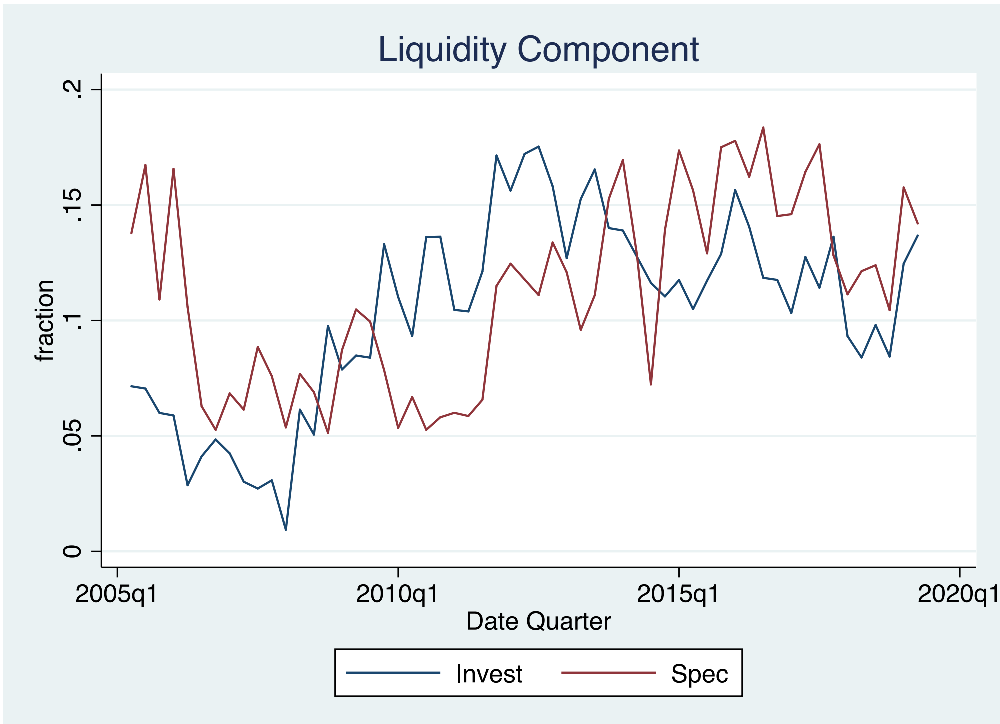
measure of illiquidity. We sort the bonds by their investor composition into five groups, the summary statistics for each group of bonds is shown in Table E.4. We then regress the credit spreads on the new measure of illiquidity group by group, controlling for bond and firm characteristics. We obtain the same result as before, i.e. the sensitivity of credit spreads to illiquidity is higher for bonds with more short-term investors. We present the regression analysis in Table E.5. The key point is that the interaction term of illiquidity and investor composition is highly significant in determining the credit spreads. We repeat the analysis for offering yields in Table E.6.

Figure E.1: Illiquidity by Rating over Time



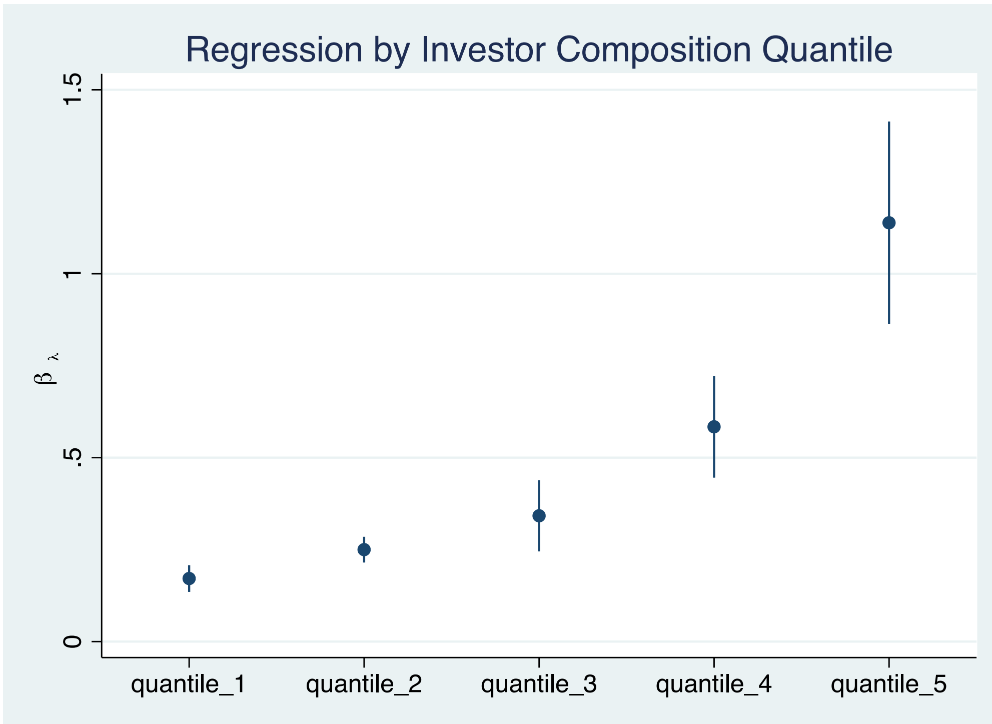
The figure plots quarterly measure of illiquidity from 2005Q1 and 2016Q4. We construct the measure of illiquidity by taking the first principle component of the common liquidity measures in the literature. The corporate bond price data is from TRACE and rating data is from Mergent FISD.

Figure E.2: Liquidity Component as a Fraction of Credit Spreads



The figure plots the liquidity component of investment grade and speculative grade bonds over time. For each quarter t, first run 4.6 to get the coefficient of the alternative illiquidity measure β. Bond characteristic data is from Mergent FISD and WRDS Bond Returns, the price data is from TRACE. Next for each bond, define $liquidity\_component_{i,t} = \frac{\beta_t \times illiquidity_{it}}{credit\_spread_{it}}$. The figure plots the median liquidity component of investment grade and speculative grade bonds over time.

Figure E.3: Sensitivity of Credit Yields to Alternative Measure of Illiquidity by Investor Quantile



We sort the bonds (in each quarter from 2005Q2 to 2019Q2) into five groups, by investor base turnover. Group 1 contains bonds whose investors have the lowest turnover rate and group 5 contains bonds whose investors have the highest turnover rate. The figure plots the regression coefficients and 1% confidence interval of credit spread regressed on the alternative illiquidity measure, controlling for bond and firm characteristics, group by group.

Table E.1: Principle Component Loadings on the Liquidity Variables

	Comp 1	Comp 2	Comp 3
Roll's measure	.306816	.1680553	.1158815
Amihud measure	.3537716	.007733	-.221156
Amihud std	.3772206	-.0198852	-.1215953
IRC	.4141384	.0365575	.2021284
IRC std	.3914108	-.0754453	.1529368
Bid-ask spread	.3995355	.0639768	-.155747
Bid-ask spread std	.388697	-.0459457	-.0664872
Firm with zero trading days	-.007644	.6181877	.3801652
Bond with zero trading days	-.0283332	.6705573	.0729346
Turnover	.0461081	-.35534	.8246865
Cum Explained	0.467	0.644	0.744

The table reports the results of Principle Component Analysis (PCA) of the common liquidity measure used in Dick-Nielsen et al. (2012). We construct each measures at the quarter level using enhanced TRACE then conduct the PCA. The sample period is 2005Q1 to 2015Q4

Table E.2: Correlation of the Iliquidity Measures

	Illiquidity	BA spread	BA spread std	Amihud measure	Amihud measure std	IRC	IRC std	Roll's measure	0 trading days (firm)	0 trading days (bond)	Turnover
Illiquidity	1										
BA spread	0.809***	1									
BA spread std	0.824***	0.783***	1								
Amihud measure	0.720***	0.584***	0.497***	1							
Amihud measure std	0.811***	0.552***	0.600***	0.569***	1						
IRC	0.852***	0.593***	0.582***	0.618***	0.626***	1					
IRC std	0.817***	0.517***	0.580***	0.438***	0.657***	0.853***	1				
Roll's measure	0.607***	0.424***	0.440***	0.315***	0.356***	0.430***	0.386***	1			
0 trading days (firm)	0.0166***	0.0101***	-0.0889***	0.0567***	-0.0556***	0.0780***	-0.0479***	0.0940***	1		
0 trading days (bond)	0.0238***	0.0384***	-0.0964***	0.0934***	-0.0341***	0.0373***	-0.0877***	0.122***	0.573***	1	
Turnover	-0.0263***	-0.0772***	0.0491***	-0.123***	-0.0312***	0.0505***	0.0870***	-0.0522***	-0.217***	-0.484***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table reports the correlation matrix of various illiquidity measures used in Dick-Nielsen et al. (2012). We construct each measures at the quarter level using enhanced TRACE then conduct the PCA. The sample period is 2005Q1 to 2015Q4

Table E.3: Sorting of Investors

	Time to maturity	Illiquidity
Investor comp	-49.57***	-1.666***
	(3.884)	(0.133)
Age	-0.592***	0.0230***
	(0.0591)	(0.00165)
Coupon	2.126***	-0.0358***
	(0.154)	(0.00471)
Offering amount	-0.000000431	-5.14e-08***
	(0.000000254)	(6.58e-09)
N	179965	170957
adj. R^2	0.200	0.345

Standard errors in parentheses: sym* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents correlation between investor composition and the maturity of bonds they hold, and the illiquidity in each sub-market. "Investor comp" is the measure of investor composition, higher value indicates the investor have higher frequency of liquidity shock, i.e. shorter term investors. We also control for bond age, firm leverage, fraction of long-term debt, equity volatility and profitability, where equity volatility is the standard deviation of the equity return of the issuer in that quarter.

Table E.4: Summary Statistics by Illiquidity Quantile

	(1)		(2)		(3)		(4)		(5)	
	mean	std	mean	std	mean	std	mean	std	mean	std
Investor comp	0.091	0.050	0.094	0.050	0.088	0.048	0.081	0.045	0.076	0.044
Bid-ask spread	0.001	0.001	0.002	0.001	0.003	0.002	0.005	0.003	0.009	0.007
Alternative measure of illiquidity	-0.543	0.133	-0.366	0.189	-0.187	0.265	0.081	0.382	0.879	0.902
Credit spread	0.017	0.020	0.021	0.021	0.021	0.021	0.023	0.024	0.031	0.033
Quarterly transaction volume (million USD)	111	202.5	160.7	299.4	180.1	304.2	163.7	265.0	130.7	251.0
Time to Maturity (30/360 Convention)	4.776	4.906	7.351	6.808	10.352	9.207	11.845	9.719	13.110	10.543
Interest rate (%)	5.350	2.171	5.541	2.043	5.507	1.871	5.479	1.759	5.742	1.672
Fraction of AAA-A	0.332	0.471	0.309	0.462	0.366	0.482	0.382	0.486	0.319	0.466
Fraction of BBB	0.458	0.498	0.385	0.487	0.376	0.484	0.412	0.492	0.453	0.498
Fraction of Speculative Grade	0.210	0.407	0.306	0.461	0.257	0.437	0.207	0.405	0.228	0.420
Observations	35870		37942		38262		37647		34404	

Bond-Quarter level summary statistics by illiquidity (λ) quantile. For each quarter, we sort the bond into five groups based on their liquidity. Group 1 are most liquid bonds, group 5 are most illiquid. A-AAA is a dummy indicating the bond has rating A-AAA. Similar for BBB and Speculative.

Table E.5: Credit Spread Regression on Alternative Measure of Illiquidity

	Credit spread	Credit spread	Credit spread
Alternative measure of illiquidity	0.00356***	0.00349***	-0.00202***
	(0.000444)	(0.000457)	(0.000419)
Investor comp		-0.0185*	-0.0138
		(0.00712)	(0.00899)
Illiquidity × Investor comp			0.0804***
			(0.00724)
Time to maturity	0.0000687***	0.0000568**	0.0000616**
	(0.0000190)	(0.0000208)	(0.0000205)
Age	-0.0000108	-0.0000546	-0.0000233
	(0.0000589)	(0.0000487)	(0.0000481)
Coupon	0.000900***	0.000895***	0.000829***
	(0.000173)	(0.000174)	(0.000174)
Offering amount	6.01e-10	6.24e-10	3.76e-10
	(3.17e-10)	(3.13e-10)	(2.84e-10)
N	118058	110060	110060
adj. R^2	0.764	0.768	0.779

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the regression results for equation 4.6. We use the illiquidity measure as in Dick-Nielsen et al. (2012)and "Investor Comp" is the measure of investor composition, higher value indicates the investor have higher frequency of liquidity shock, i.e. shorter term investors. We also control for bond age, firm leverage, fraction of long-term debt, equity volatility and profitability, where equity volatility is the standard deviation of the equity return of the issuer in that quarter.

Table E.6: Regression of Offering Spreads on Alternative Measure of Illiquidity

	Offering yield	Offering yield	Offering yield	Bond maturity
Alternative measure of illiquidity	-0.000252	-0.000114	-0.000898	2.429***
	(0.000445)	(0.000409)	(0.000704)	(0.456)
Investor comp		0.0295***	0.0314***	-28.94***
		(0.00237)	(0.00272)	(4.175)
Illiquidity × Investor comp			0.00872	
			(0.00756)	
Coupon	0.00641***	0.00666***	0.00663***	4.219***
	(0.000323)	(0.000291)	(0.000299)	(0.271)
Offering amount	-5.67e-11	-2.59e-10*	-2.59e-10*	-0.000000195
	(1.10e-10)	(1.26e-10)	(1.25e-10)	(0.000000168)
N	5480	5307	5307	6085
adj. R^2	0.905	0.911	0.911	0.383

Standard errors in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regression results for Equation 4.6 where the left hand variable is replaced by offering spreads. Higher value of investor composition indicates the investor have higher frequency of liquidity shock. Equity volatility is the standard deviation of the equity return of the issuer in that quarter.