Quantifying Information Asymmetry in Corporate Bond Markets*

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Abstract

We develop a structural credit-risk model to study how information asymmetry impacts corporate bond pricing. In the model, the presence of informed trading in the secondary market causes endogenous adverse selection and generates an informational discount in the equilibrium bond price. We calibrate the model to match the non-monotonic empirical relationship between yield spread and trading volume. We find that information asymmetry depresses bond prices by 0.5%-1% for investment-grade bonds and by 2%-7.5% for speculative-grade bonds. We provide testable predictions and policy implications regarding the informational illiquidity in corporate bond markets.

Keywords: corporate bonds, liquidity, information asymmetry, turnover rates

JEL Classifications: G33, G14, G12

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1 Introduction

As we have witnessed during the 2008 financial crisis and the 2020 COVID-19 crisis, liquidity plays a significant role in determining corporate bond prices. For instance, Dick-Nielsen et al. (2012) and Haddad et al. (2021) find a drastic increase in the liquidity component in corporate yield spreads at the onsets of the 2008 financial crisis and the 2020 COVID-19 crisis. Friewald et al. (2012), Falato et al. (2021), Kargar et al. (2021), and O'Hara and Zhou (2021) also provide empirical evidence to demonstrate how fragile corporate bond markets can be due to liquidity, especially during crisis periods. Given the importance of bond market liquidity, several papers have attempted to assess the effect of illiquidity on corporate bond pricing. Huang and Huang (2012) and Huang et al. (2023b) show that a broad class of standard structural credit-risk models without a liquidity channel largely underestimate credit spreads not only in the US but also in other countries. He and Xiong (2012), He and Milbradt (2014), Chen et al. (2018), and Huang et al. (2023a) develop structural models to quantify the distinct effects of credit risk and liquidity risk on yield spreads, particularly highlighting the rollover channel of short-term debt.

However, most of these structure models focus on non-informational frictions, such as search frictions and inventory costs, and do not explicitly consider informational frictions. As such, our understanding of bond market illiquidity is still limited because informational frictions are important sources of market illiquidity. For instance, Han and Zhou (2014) find significant contributions of asymmetric information to corporate bond yields using market-microstructure measures. Therefore, a structural model with both informational and non-informational frictions is warranted to quantify the effect of information asymmetry on corporate bond trading and to analyze the interaction between different types of trading frictions in corporate bond markets.

Our paper develops a structural credit-risk model in which the secondary bond market suffers from information asymmetry between sellers and buyers. In the model, the presence of informed trading in the secondary market causes endogenous adverse selection and generates an informational discount in the equilibrium bond price. The model predicts a non-monotonic relationship between credit risks and turnover rates of corporate bonds, which is consistent with empirical data. Calibrating the model to match this relationship, we show that the price discounts caused by information asymmetry are non-negligible (0.5%-1%) for investment-grade bonds but are sizable (2%-7.5%) for high-yield bonds. The model also generates testable predictions and policy implications about how the size of informational liquidity costs interacts with non-informational trading costs, investors' liquidity needs, and the degree of information asymmetry in determining bond market liquidity.

Our model considers a firm that generates stochastic cash flows over time. The firm has a fixed amount of bonds diversely held by bond investors. The firm's bonds are traded in a secondary market with information asymmetry. Specifically, the firm's liquidation value in bankruptcy depends on its intrinsic type, which can be either high or low. We assume that bond sellers are generally better informed of the firm's liquidation value than bond buyers: all current bondholders (sellers) are perfectly informed of their firm's liquidation value, while all but a few outside bond investors (buyers) are uninformed.

In the model, bondholders sell their bonds for two distinct reasons. First, each bondholder is exposed to an idiosyncratic liquidity shock. Upon being hit by a liquidity shock, the affected bondholder immediately sells her bond position due to substantially high bond-holding costs. Second, non-liquidity-shocked bondholders of low-type firms may have incentives to sell their bonds to exploit their informational advantage against potential bond buyers, causing endogenous adverse selection in the secondary market. In addition to this informational illiquidity, we assume each bond seller faces additional trading costs, which we can broadly interpret as search costs, inventory costs, monopoly power of dealers, and so on.

Notably, we assume each bond seller has an option to reveal her liquidity status at some costs before selling her bond. This liquidity-status revealing option can be interpreted as a bond seller's costly effort to search for potential bond buyers or dealers who can correctly identify the seller's trading motive based on her balance sheet or trading record. Due to this option, those liquidity-shocked bond sellers who reveal their liquidity status can avoid adverse selection by differentiating themselves against non-liquidity-shocked bond sellers of low-type firms, who sell their bonds for informational motives. The anecdotal evidence documented by Da et al. (2011) suggests that the funds managed by Dimensional Fund Advisors consistently generate value by providing liquidity to institutional investors seeking to offload small-cap stocks for non-informational reasons. This particular type of transaction observed in practice can be considered supportive evidence of our assumption regarding the liquidity-status revealing channel. Given this assumption, only those trades made by bond sellers who do not reveal their liquidity status, which we refer to as anonymous trades, are subject to adverse selection and informational illiquidity.

Our model generates a non-monotonic relationship between credit risk and the size of informed bond selling. When a firm's credit risk is low, the private information about the firm's liquidation value in bankruptcy has little value. Then, due to the presence of trading costs, bondholders of low-type firms have no incentives to sell their bonds for informational motives, and the size of informed bond selling is unaffected by a change in credit risk. When the credit risk is at an intermediate level, the non-liquidity-shocked bondholders of low-type firms have some incentives to exploit their private information. In this case, an increase in credit risk induces more informed trading. However, when the firm's credit risk is substantially high, liquidity-shocked bondholders will reveal their liquidity status aggressively to avoid adverse selection. Then, even a small number of informed bond sellers can cause a large price impact, reducing the incentives of other bondholders to conduct informed trading. In that case, the size of informed bond selling can decrease with credit risk.

We show that the non-monotonic relationship between turnover rates and credit risks is consistent with the data. Specifically, using the US corporate bond data, we demonstrate that monthly weighted-average yield spreads and turnover rates of corporate bonds indeed exhibit a non-monotonic relationship. We then calibrate the model to quantify the effect of information asymmetry on corporate bond prices. In calibration, we match the empirically observed turnover rates across different yield-spread groups as closely as possible because the non-monotonic relationship between these two variables is one of the unique predictions of our model. Our model performs well in reproducing these cross-sectional empirical moments.

According to the calibrated model, the effects of information asymmetry on corporate bond prices are non-negligible for investment-grade bonds and are sizable for speculative-grade bonds. Specifically, we measure the effect of information asymmetry by the size of informational liquidity costs, defined as the scaled difference between the bond price of anonymous trades in the benchmark model and the bond price in an alternative model without information asymmetry. We show that the size of informational liquidity costs is equal to 0.47%, 0.54%, 0.70%, and 1.07% for bonds whose yield spreads are equal to the weighted average yield spreads of AAA, AA, A, and BBB rated bonds, respectively. While our model predicts that most investment-grade bonds do not directly suffer from adverse selection in the secondary market, the equilibrium prices of these low-risk bonds still contain positive informational discounts due to the expectation of potential adverse selection in the future.

The size of informational liquidity costs becomes much larger when the bond enters the speculative-grade region. In the calibrated model, the size of informational liquidity costs is 2.10%, 2.51%, 4.44% and 7.48% for bonds whose yield spreads are equal to the weighted average yield spreads of BB, B, CCC, and CC/C rated bonds, respectively. For these speculative-grade bonds, the size of informational liquidity costs can be close to the size of non-informational liquidity costs, suggesting severe adverse selection in the secondary bond market.

Furthermore, our model provides several policy implications through comparative statics analysis. We find that an increase in the size of non-informational trading costs or the investors' liquidity-shock intensity has the largest negative effect on market liquidity for bonds with intermediate levels of credit risk. These results suggest that the effect of the Volcker rule, which tends to increase trading costs through reducing market-making activities, can be overestimated when we focus only on its effect on bonds that are recently downgraded to junk status Bao et al. (2018). In addition, our model predicts that forced bond liquidation caused by performance-driven mutual fund redemptions (Goldstein et al., 2017) would have the largest adverse effects on prices of high-yield bonds with BB ratings. In addition, our model suggests that an improvement in accounting transparency or credit-rating informativeness can reduce yield spread by lowering informational liquidity costs, but its effect on trading volume is ambiguous and varies across bonds with different credit risks.

This paper contributes to the quantitative credit-risk literature by developing a structural credit-risk model with information asymmetry in a secondary bond market. In the literature, Ericsson and Renault (2006), He and Xiong (2012), Huang and Huang (2012), He and Milbradt (2014), and Chen et al. (2018) develop structural models to study the impact of liquidity on bond prices. In particular, Ericsson and Renault (2006) investigates the effects of liquidity on the negotiation outcome between equityholders and bondholders. He and Xiong (2012) study the feedback effect between default risk and liquidity risk through a short-term debt rollover channel. He and Milbradt (2014) endogenizes the liquidity risk in He and Xiong (2012), using search frictions. Chen et al. (2018) further extend this model by considering the effects of the business cycle. Our paper contributes to this literature by developing a structural model that enables us to quantitatively examine the effects of information asymmetry among bond investors on corporate bond prices. In the literature, Duffie and Lando (2001) study the effects of informational frictions on the term structures of yield spreads. Their paper assumes that all bond investors possess the same information, while ours focuses on information asymmetry between bond investors.

In this regard, our paper is also related to the theoretical literature examining the implications of information asymmetry in financial markets. A selective list of seminal contributions in this area includes Grossman and Stiglitz (1980), Kyle (1985), Glosten and Milgrom (1985), Eisfeldt (2004), Daley and Green (2012) Malherbe (2014), Biais et al. (2015), Collin-Dufresne and Fos (2016), Daley and Green (2016), and Albagli et al. (2023), among others. Extending this literature, which mainly focuses on stock markets, we embed an information-based model into a structural credit-risk model in an analytically tractable way to quantify the effects of information asymmetry on corporate bond pricing.

Several papers attempt to estimate the adverse selection component in asset prices using the conceptual frameworks developed by the above papers. For instance, Glosten and Harris (1988) presents the empirical evidence on the existence of adverse selection in stock markets by decomposing the bid-ask spread into an adverse-selection component and a transitory component. Stoll (1989) finds that the quoted bid-ask spread of stocks contains a statistically significant information-asymmetry component, whereas George et al. (1991) and Huang and Stoll (1997) show that the economic effect of information asymmetry is smaller, albeit significant, than that of order-processing costs. Our paper extends the strand of this literature by quantifying the effect of information asymmetry in corporate bond markets. In this regard, our paper is close to Han and Zhou (2014), which estimates the contribution of asymmetric information to corporate bond yields using reduced-form models. However, the structural approach in our paper allows us to better capture the equilibrium relation between informed trading and bond pricing. For instance, the methodology in their paper takes the trade size as an exogenous variable when modeling the relationship between the trade size and the informational liquidity component in bond prices. Yet, these two variables are simultaneously determined in our model and affected by common factors such as firm fundamentals, trading costs, and investors' liquidity needs.

Besides these papers backing out information asymmetry from bid-ask spreads, some other papers show evidence of information asymmetry from price movement, trading volume, and other measures of trading activities in stock and option markets; see, for instance, Hasbrouck (1988), Hasbrouck (1991), Lin et al. (1995), Chan et al. (2002), Collin-Dufresne and Fos (2015), and Kacperczyk and Pagnotta (2019). We show that informational frictions can explain the empirically observed non-monotonic relationship between trading volume and yield spread in the bond market. So, our paper suggests that trading volume may not be a good measure of liquidity in markets that suffer from information frictions.

The rest of the paper is organized as follows. Section 2 develops the model. Section 3 analyzes the model. Section 4 presents the quantitative results. Section 5 provides the concluding remarks.

2 Model

We develop a structural credit-risk model with information asymmetry in the secondary bond market, building on Leland (1994). Time is continuous and is indexed by $t \in [0, \infty)$. All agents in the model are risk-neutral and discount future cash flows at a constant risk-free rate of r.

2.1 Firm Assets

Consider a firm whose existing assets produce a stochastic after-tax cash flow $x_t dt$ over each instantaneous time interval $[t, t + dt)$. The cash flow x_t evolves according to

$$\frac{dx_t}{x_t} = \mu dt + \sigma dZ_t,$$

where μ is a growth rate, $\sigma > 0$ is a volatility, and Z_t is a standard Brownian motion. The first-best value of the assets at time t is then given by

$$V(x_t) = E_t\left[\int_t^\infty e^{-r(s-t)} x_s ds\right] = \frac{x_t}{r-\mu}.$$

To ensure that this first-best value is finite, we assume $r - \mu > 0$. The realized cash flow x_t is publicly observable. We will also call x_t the firm's fundamental at time t interchangeably.

2.2 Defaultable Bonds

The firm's capital structure is exogenously given. Specifically, the firm has a fixed amount of perpetual bonds diversely held by a unit mass of investors, whom we call bondholders. To make the model tractable, we assume that any bond investor can hold either 0 or 1 unit of a bond.

Each unit of bond pays a constant coupon of c per unit of time. The corporate tax rate is τ. Debt payment is tax deductible, meaning that the net cash flow to equityholders equals $x_t - (1-\tau)c$ at each time t. The net cash flow to equity can be negative, in which case, equityholders should inject additional capital to cover the temporary loss to avoid default. But when injecting more capital is no longer profitable, equityholders choose to default as in Leland (1994). We postulate that the default event occurs when the firm's cash flow hits x_D, which is endogenously determined.

When the firm defaults, its bondholders take over the firm's assets and immediately liquidate them. From liquidation, the bondholders recover only a fraction of the first-best value of the assets due to bankruptcy costs. The key feature of the model is that the recovery rate of a firm depends on the firm's intrinsic type, which can be either high (H) or low (L). Denote the recovery rate of a high-type firm as α_H and that of a low-type firm as α_L. Then the recovery value of a k-type firm will be $\frac{\alpha_k x_D}{r-\mu}$ in default for each type $k \in \{H, L\}$. We assume $0 \leq \alpha_L < \alpha_H \leq 1$, so high-type firms will experience lower bankruptcy costs than low-type firms. The chance that a given firm is of high type is $\pi \in (0,1)$. We can equivalently say that the fraction of high-type firms among all existing firms is π. For clarification, a firm's type is predetermined at date 0 and does not change over time.

A common assumption in structural credit-risk models is that sellers and buyers of bonds have symmetric information. But this assumption is inconsistent with the empirical findings of Han and Zhou (2014) and Benmelech and Bergman (2018) that secondary bond markets suffer from information asymmetry. To reflect this empirical fact in a tractable way, we assume that current bondholders (sellers) can observe their firm's type precisely, but not all new bond investors (buyers) are informed about the firm's type. We will describe this assumption in detail later. As pointed out by Han and Zhou (2014), the assumption that existing bondholders are relatively better informed than outside bond investors is reasonable because of the institutional feature of corporate bond markets. For instance, a firm's institutional bondholders are generally entitled to participate in regular meetings organized by the firm's management and request key information from the firm. For tractability, we assume that a new bond investor becomes informed right after purchasing a bond. This simplifying assumption is also imposed in Daley and Green (2016).

For clarification, note that whether equityholders are informed of their firm's type or not does not play any role in our model because equityholders are supposed to be wiped out in default. Also, one may argue that, in the real world, information asymmetry may arise around some other factors beyond the recovery rate, such as the growth potential or the uncertainty level of a firm's fundamentals, which generally affects the firm's default probability. However, those factors can be possibly learned from a firm's realized cash flows reported in its financial statements. Thus, the degree of information asymmetry regarding those factors may not be as severe as that regarding a firm's future recovery value. Even if we assume that bond investors have asymmetric information about the default probability, adverse selection will still particularly matter when credit risk is high and bond value becomes informationally sensitive (Hölmstrom, 2015), which is qualitatively similar as in the case where information asymmetry arises around the recovery value. In this regard, we parsimoniously assume that information asymmetry arises only around the recovery value in the model.

2.3 Secondary Bond Market

We now describe bond trades in the secondary market. In this model, bondholders sell their bonds for two motives: one for liquidity needs and the other for informational reasons.

Liquidity-driven selling: Each bondholder is subject to an uninsurable idiosyncratic liquidity shock that arrives with Poisson intensity $\xi > 0$. Similar to Eisfeldt (2004) and He and Xiong (2012), when hit by a liquidity shock, the affected bondholder will face substantially high bond-holding costs and thus decides to sell her bond holdings immediately.

In addition, the liquidity status of a bond seller is not publicly known to bond buyers, as in Eisfeldt (2004), who also consider the adverse selection problem in asset markets. To make our model more realistic, we further assume that each bond seller has the option to reveal her liquidity status at costs. Specifically, each bond seller can credibly reveal her liquidity status with probability $\theta \in [0, 1]$, if she incurs costs amounting to $\frac{\delta\theta^2}{2}$. Here, the parameter δ affects the scale of liquidity-status revealing costs and the parameter θ can be interpreted as a bond seller's effort in revealing her liquidity status. We assume that the effort level θ is not publicly observable to bond buyers. Due to this costly liquidity-status revealing option, any liquidity-shocked bond seller can differentiate herself from other bond sellers who attempt to sell their bonds for the informational motive, which will be discussed in more detail later.

In practice, the costly liquidity-status revealing effort can be interpreted as a bond seller's attempt to search for dealers or liquidity providers, who can successfully identify the seller's liquidity status based on her balance sheet and trading records. Once a seller's liquidity status is revealed, the buyer does not need to worry about adverse selection because none of the non-liquidity-shocked bondholders will choose to reveal their liquidity status at costs. As anecdotal evidence, Da et al. (2011) document that Dimensional Fund Advisors frequently provided liquidity to institutional stock investors who tried to sell their small-cap stocks for non-informational reasons, supporting the validity of our assumption about the liquidity-status revealing option. From now on, we will refer to trades made by those bondholders who do not reveal their liquidity status as anonymous trades.

For simplicity, we do not explicitly consider other types of options that allow bond sellers to reveal the information about their firm's type itself either directly or indirectly. Even if we consider these alternative types of options, the model would produce qualitatively similar outcomes because regardless of whether a bond seller can reveal her liquidity status or the borrowing firm's type itself, she would reveal such information when the firm's fundamental x is low. In this regard, although we consider only the liquidity-status revealing option for simplicity in this paper, we can broadly interpret this option as other types of options such as a direct disclosure of a firm's type or indirect information signaling.

To proceed further, note that because the effort level θ is not publicly observable, we can postulate that any liquidity-shocked bondholder's effort level for revealing her liquidity status is independent of the borrowing firm's type, which we will verify later. As such, we can simply denote θ as $\theta(x)$ to indicate that θ depends only on the firm's current fundamental, not on its type. As for off-equilibrium beliefs, if a non-liquidity-shocked bondholder reveals her liquidity status, she would be regarded as a bondholder of a low-type firm. So, none of the non-liquidity-shocked bondholders would have incentives to reveal their liquidity status in equilibrium.

Information-driven selling: In the presence of information asymmetry, non-liquidity-shocked bondholders may have incentives to sell their bonds to exploit their informational advantages. Such an incentive to conduct informed selling only happens when the underlying firm is of low type. As such, we postulate that each non-liquidity-shocked bondholder of a low-type firm sells her bond with an infinitesimal probability $m(x_t)dt$ at each time t, where the bond-selling strategy $m(x) \in [0, \infty)$ is endogenously determined. Here, bondholders sell their bonds with an infinitesimally small probability because only such a behavior can be sustained in equilibrium, given that the measure of liquidity-shocked bondholders is also of dt order.

Throughout, we assume that any aggregate trading data, such as the trading volume of an individual firm, is not publicly observable. This assumption, which is also adopted in Grossman and Stiglitz (1980), Bolton et al. (2011), Malherbe (2014), and Zou (2019), rules out the possibility that bond investors can infer the firm's type from the aggregate trading data. This assumption is reasonable in our setting because not all trading data of corporate bonds, which are mostly traded in over-the-counter markets, are instantly disseminated. Even after Trade Reporting and Compliance Engine (TRACE) was introduced, some information about bond trades, such as the uncapped trading volume, is publicized with several months of delay.[1] Or, we may assume that trading data are observed with some noises, so that bond investors cannot perfectly infer the firm's type from that data.

Bond Buyers: The secondary bond market is populated with infinitely many potential bond buyers all the time. Potential bond buyers are either informed or uninformed about the firm's type. Specifically, a measure νdt of informed bond investors enters the market per dt unit of time, while all other bond investors in the secondary market are uninformed. Assuming that some bond buyers are informed is not only realistic but also helps us obtain better calibration results.

We consider the following simple trading mechanism between sellers and buyers within each dt period. First, each informed buyer can preemptively reach out to one bond seller before uninformed bond investors move. Upon the meeting, an informed buyer makes a take-it-or-leave-it offer to the seller. The price of this offer is set to a level that makes the seller indifferent between accepting and rejecting the offer. In equilibrium, informed buyers will only approach bond sellers when the underlying firm is of high type. We assume $\nu < \pi\xi$ to rule out a trivial symmetric-information outcome in which all liquidity-shocked sellers of high-type firms can sell their bond holdings to informed buyers.[2]

Then, the remaining bond sellers are matched to uninformed bond buyers. Here, we do not explicitly model search frictions. Upon the meeting, each bond seller decides whether to reveal her liquidity status or not. After this decision is made, a bond is traded at a price that makes the bond buyer break even, assuming that the outside option value of all bond buyers is 0. Note that in each bond trade, the price certainly depends on whether the seller has revealed her liquidity status or not.

Non-informational trading costs: Besides information asymmetry, bond sellers face non-informational trading frictions, which we model in reduced form. Specifically, we assume that each bond seller has to bear additional trading costs of $\kappa(x_t)$ when she sells her bond. This additional trading cost can be broadly considered search frictions, monopoly power of dealers, inventory costs, and so on. While all qualitative results of our model will continue

[1]Financial Industry Regulatory Authority (FINRA) makes historical data available 6 months after the transaction date for corporate and agency transactions and 18 months for securitized product transactions.

[2]Here, we have implicitly assumed that the total number of firms in the economy is normalized to 1.

to hold as long as $\kappa(x)$ is weakly decreasing in x, we assume that $\kappa(x)$ is a constant κ to provide a closed-form solution for the model.

2.4 Timing

The timing of the events over each time interval $[t, t + dt)$ is as follows: (i) the firm's cash flow x_t is realized, (ii) the firm's equityholders make a default decision, (iii) if the firm does not default, some bondholders are hit by idiosyncratic liquidity shocks, (iv) informed buyers preemptively approach bond sellers and make take-it-or-leave-it offers, (v) the remaining bond sellers are matched with uninformed bond buyers, (vi) those bond sellers decide whether to reveal their liquidity status before selling their bonds, and (vii) bonds are traded at prices that make buyers break even.

3 Equilibrium Analysis

In this section, we characterize an equilibrium of the model and discuss the qualitative properties of the model.

3.1 Bond Prices

To characterize an equilibrium, we first let (i) $P^I(x)$ denote the price offered by informed buyers to bond sellers of high-type firms, (ii) $P^R(x)$ denote the price at which the bondholders, who were not approached by informed buyers, can sell their bonds by revealing their liquidity status, (iii) $P^A(x)$ denote the price at which those bondholders can sell their bonds without revealing their liquidity status, and (iv) $D^k(x)$ denote the true value of bonds of a k-type firm for each type $k \in \{H, L\}$. Below, we first explain how the prices $P^R(x)$ and $P^A(x)$ are determined and then discuss how $P^I(x)$ is determined.

Recall that we have postulated (i) each liquidity-shocked bondholder reveals her liquidity status with a probability $\theta(x)$ regardless of a firm's type and (ii) each non-liquidity-shocked bondholder of low-type firms sells her bond with a probability $m(x)dt$. Thus, the bond prices

$P^R(x)$ and $P^A(x)$ should be respectively equal to

$$P^R(x) = \frac{(\pi\xi - \nu)\theta(x)D^H(x) + (1-\pi)\xi\theta(x)D^L(x)}{(\pi\xi - \nu)\theta(x) + (1-\pi)\xi\theta(x)} = \lambda D^H(x) + (1-\lambda)D^L(x) \tag{1}$$

and

$$P^A(x) = \frac{(\pi\xi - \nu)(1-\theta(x))D^H(x) + (1-\pi)(\xi(1-\theta(x)) + m(x))D^L(x)}{(\pi\xi - \nu)(1-\theta(x)) + (1-\pi)(\xi(1-\theta(x)) + m(x))}, \tag{2}$$

where $\lambda = \frac{\pi\xi-\nu}{\xi-\nu}$. Specifically, the expression for $P^R(x)$ denotes the average value of bonds sold by liquidity-shocked bond sellers who reveal their liquidity status. Here, we have used the fact that a measure ν of informed buyers have already absorbed some bonds from bond sellers of high-type firms. The expression for $P^A(x)$ denotes the average value of bonds sold by bondholders who do not reveal their liquidity status. In this expression, we have used the fact that those bond sellers include a measure $(1-\pi)m(x)$ of non-liquidity-shocked bondholders of low-type firms who sell their bonds for informational reasons. The above two expressions immediately imply that $P^A(x) \leq P^R(x)$, meaning that informed bond selling causes a negative price impact.

The price that is offered by informed buyers preemptively to bond sellers of high-type firms should be equal to

$$P^I(x) = \theta(x)P^R(x) + (1-\theta(x))P^A(x) - \frac{\delta}{2}\theta(x)^2, \tag{3}$$

because an informed buyer sets the price to a level at which a bond seller is indifferent between accepting and rejecting the offer. Here, informed buyers set this price by rationally anticipating the equilibrium effort level for liquidity status revealing, $\theta(x)$, which we pin down in the next section. By offering this price, each informed buyer earns a positive profit of $D^H(x) - P^I(x)$.

3.2 Optimal Strategies and Valuation

In this section, we pin down the optimal default strategy, liquidity-status revealing strategy, and informed bond-selling strategy. We also discuss how to calculate the true debt value of each type of firm.

Default Strategy: The equityholders in our model face the same problem as those equityholders in Leland (1994) because equityholders in both models are not concerned about the recovery value of their assets in default. Thus, the default threshold x_D is given by

$$x_D = \frac{-\eta_2(r-\mu)(1-\tau)c}{(1-\eta_2)r}, \tag{4}$$

where

$$\eta_1, \eta_2 = \frac{-\mu + \frac{\sigma^2}{2} \pm \sqrt{\left(\mu - \frac{\sigma^2}{2}\right)^2 + 2\sigma^2 r}}{\sigma^2}. \tag{5}$$

The constant η_1 will be used later.

Liquidity-Status Revealing Strategy: Now, consider the liquidity-shocked bondholders who were not contacted by informed buyers. Regardless of the borrowing firm's type, each of these remaining liquidity-shocked bondholders chooses the effort level $\theta(x_t)$ for liquidity-status revealing to maximize her expected profits:

$$\max_{\theta(x_t)\in[0,1]} \theta(x_t)P^R(x_t) + (1-\theta(x_t))P^A(x_t) - \frac{\delta}{2}\theta(x_t)^2 - \kappa.$$

The sum of the first two terms indicates the expected bond price she would receive, the third term denotes the effort costs, and the last term is the non-informational trading costs, which are not affected by $\theta(x)$. Here, as briefly mentioned above, a firm's type does not enter into this problem because the effort level $\theta(x)$ is not observable to the bond buyers and thereby the prices $P^R(x)$ and $P^A(x)$ do not depend on such an effort level.

The solution to the above problem is

$$\theta(x) = \min\left\{\frac{P^R(x) - P^A(x)}{\delta}, 1\right\}. \tag{6}$$

That is, a liquidity-shocked bond seller is more willing to reveal her liquidity status if (i) the price impact caused by informed bond selling, that is, $P^R(x) - P^A(x)$, is larger or (ii) the liquidity-status revealing cost, δ, is lower. Under the above optimal strategy $\theta(x)$, the expected profits to each liquidity-shocked bond seller are equal to

$$\begin{cases} P^R(x) - \frac{\delta}{2} - \kappa, & \text{if } P^R(x) - P^A(x) > \delta \\ P^A(x) + \frac{(P^R(x)-P^A(x))^2}{2\delta} - \kappa, & \text{otherwise.} \end{cases} \tag{7}$$

We will use this expression when calculating the true value of debt of each type of firm.

Informed Bond-Selling Strategy: Regarding the informed bond-selling strategy, note first that if a non-liquidity-shocked bondholder of a low-type firm sells her bond holdings today, she would earn $P^A(x) - \kappa$. But if she keeps her bond, her valuation is given by $D^L(x)$. Hence, the informed bond-selling strategy $m(x)$ must satisfy

$$\begin{cases} m(x) \in [0, \infty), & \text{if } P^A(x) - \kappa = D^L(x) \\ m(x) = 0, & \text{if } P^A(x) - \kappa < D^L(x). \end{cases} \tag{8}$$

Specifically, the first line indicates the case where the bond seller is indifferent between selling or keeping her bond, and thus, $m(x)$ can be any number. The second line indicates the case where keeping the bond is strictly more profitable and so, $m(x)$ is set to 0. For clarification, note that the case of $P^A(x) - \kappa > D^L(x)$ never arises in equilibrium because if that case occurs, all non-liquidity-shocked bondholders of low-type firms will sell their bond holdings, which would then push down the bond price $P^A(x)$ to $D^L(x)$, a contradiction because $\kappa > 0$.

Valuation: We now discuss how to calculate the true value of debt of each type of firm. Under the risk-neutrality assumption, the standard continuous-time method implies that the value functions $D^H(x)$ and $D^L(x)$ must satisfy the following Hamilton-Jacobi-Bellman (HJB) equations:

$$\begin{aligned} rD^H = c + \xi \Bigg[\frac{\nu}{\pi\xi} \cdot P^I(x) + \left(1 - \frac{\nu}{\pi\xi}\right) \max_{\theta(x)\in[0,1]} \{\theta(x)P^R(x) + (1-\theta(x))P^A(x) - \frac{\delta}{2}\theta(x)^2\} - \kappa \\ -D^H(x)\Bigg] + \mathcal{A}D^H, \end{aligned} \tag{9}$$

$$rD^L = c + \xi \left[\max_{\theta(x)\in[0,1]} \theta(x)P^R(x) + (1-\theta(x))P^A(x) - \frac{\delta}{2}\theta(x)^2 - \kappa - D^L(x) \right] + \max_{m(x)\geq 0} m(x)(P^A(x) - \kappa - D^L(x)) + \mathcal{A}D^L, \quad (10)$$

subject to

$$D^H(x_D) = \frac{\alpha_H x_D}{r-\mu} \quad \text{and} \quad D^L(x_D) = \frac{\alpha_L x_D}{r-\mu},$$

where $\mathcal{A}U(x)$ denotes $\mu x U_x(x) + \frac{\sigma^2 x^2}{2} U_{xx}(x)$ for any value function U. The term on the left-hand side of (9) is the expected return on a high-type firm's debt. The first term on the right-hand side of (9) is the coupon payment. The second term describes the expected profits that will be obtained when hit by an idiosyncratic liquidity shock. Inside the bracket, the first term denotes the case where a bond is sold to an informed buyer; the second term describes the presence of the liquidity-status revealing option for those bondholders who were not approached by informed buyers; and the third term denotes non-informational trading costs. The remaining term $\mathcal{A}D^H$ indicates the expected changes in the debt value due to changes in the fundamental.

We can similarly understand the equation for $D^L(x)$ in (10) except the term, $m(x)(P^A(x) - \kappa - D^L(x))$. This term represents the expected incremental profits that a non-liquidity-shocked bondholder of a low-type firm can earn by selling her bond with a probability $m(x)dt$ rather than keeping her bond.

3.3 Equilibrium

An equilibrium of this model is defined as a collection of $\{x_D, \theta(x), m(x), P^I(x), P^R(x), P^A(x), D^H(x), D^L(x)\}$ such that (i) the default threshold is given by (4), (ii) the liquidity-status revealing strategy $\theta(x)$ satisfies (6), (iii) the informed bond-selling strategy $m(x)$ satisfies (8), (iv) the bond price offered by informed buyers, $P^I(x)$, satisfies (3), (v) the bond price $P^R(x)$ at which bondholders can sell their bonds by revealing their liquidity status satisfies (1), (vi) the bond price $P^A(x)$ at which bondholders can sell their bonds without revealing their liquidity status satisfies (2), (vii) the true value of a high-type bond satisfies (9), and (viii) the true value of a low-type bond satisfies (10).

Equilibrium Thresholds: To pin down an equilibrium, we first conjecture that the liquidity-status revealing strategy $\theta(x)$ increases as a firm's fundamental x decreases. We will certainly verify this conjecture later. Specifically, note that information asymmetry in our model arises around the firm's recovery rate. Thus, the asymmetric information problem becomes more severe as the firm's fundamental deteriorates. Hence, the conjecture that a liquidity-shocked bondholder would have more incentives to avoid the asymmetric information problem as the firm's fundamental falls is reasonable.

Under this conjecture, let x_L denote the threshold, if exists, such that $\theta(x) = 1$ if and only if $x \leq x_L$. That is, x_L is the point under which the asymmetric information problem is so severe that all liquidity-shocked bondholders choose to reveal their liquidity status at full capacity. When there is no such threshold, that is, when $\theta(x) < 1$ for all $x \geq x_D$, we just set $x_L = x_D$ for notational convenience.

Regarding the informed bond-selling strategy $m(x)$, first note that when $x_D < x_L$, $m(x)$ must be 0 for all $x \leq x_L$. The reason is that when all liquidity-shocked bondholders reveal their liquidity status, there would be no bond sellers whom the non-liquidity-shocked bondholders of low-type firms can mimic, thereby leading to $m(x) = 0$ for all $x \leq x_L$. To be more formal, in this case, as off-equilibrium beliefs, if any bond seller tries to sell her bond without revealing her liquidity status, we assume that she would be believed to be a bondholder of a low-type firm. Under this off-equilibrium belief, the non-liquidity-shocked bondholders of low-type firms will indeed never sell their bonds for informational reasons when $x \leq x_L$.

Now, we also conjecture that there is another threshold x_S such that $x_L < x_S$ and $m(x)$ is 0 for all $x \geq x_S$. That is, in equilibrium, $m(x)$ should be 0 not only for sufficiently small x but also for sufficiently large x. This conjecture makes sense because when the firm's fundamental is sufficiently high, the debt values of a low-type firm and a high-type firm would be almost indistinguishable and therefore, the non-liquidity-shocked bondholders of low-type firms would have no incentives to sell their bonds for the informational motive due to the presence of the additional trading costs κ.

Further, when $x > x_S$, the liquidity-status revealing strategy $\theta(x)$ should also be 0. Intuitively, when the market is not plagued with adverse selection, liquidity-shocked bondholders

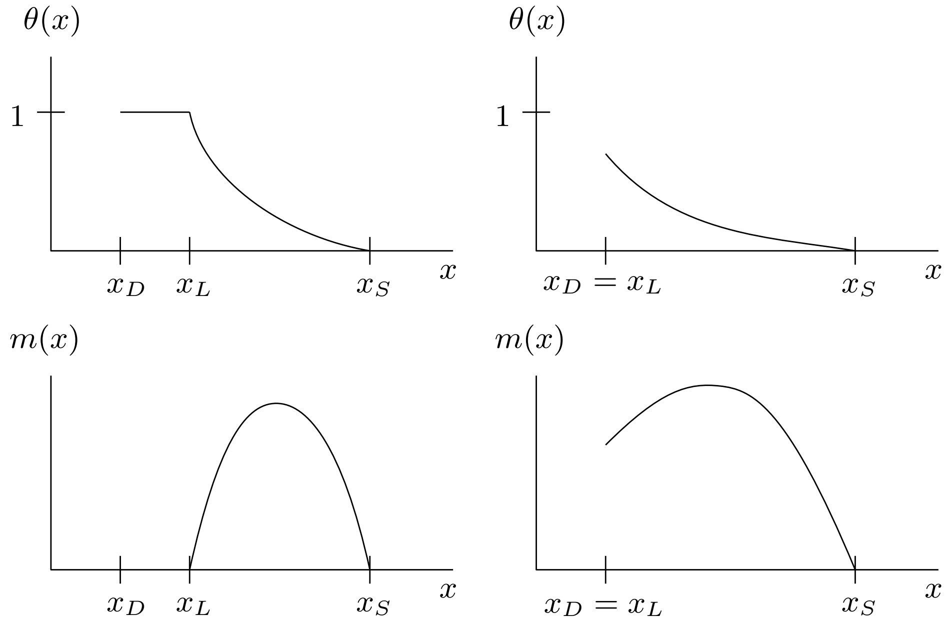

Figure 1: The left two graphs plot the liquidity-status revealing strategy $\theta(x)$ and the informed bond-selling strategy, respectively, in the case of $x_D < x_L$. The right two graphs plot the liquidity-status revealing strategy $\theta(x)$ and the informed bond-selling strategy, respectively, in the case of $x_D = x_L$.

would not have any incentives to reveal their liquidity status at costs.

In sum, Figure 1 describes the general shapes of $\theta(x)$ and $m(x)$. The graph on the left describes the case of $x_D < x_L$, while the graph on the right depicts the case of $x_D = x_L$. We later show that the second case, that is, the case of $x_D = x_L$, arises under reasonably calibrated parameter values. In the first case, information asymmetry disappears for bonds that are close to default as all liquidity-shocked bondholders reveal their liquidity status at full capacity, which we think is highly unlikely in the real world.

Key Equilibrium Conditions: We now describe the procedure to find the equilibrium thresholds x_L and x_S. To this aim, note first that in equilibrium, the bond price at which bondholders can sell their bonds anonymously should be given as follows:

$$\begin{cases} P^A(x) = D^L(x), & \text{if } x \in (x_D, x_L] \\ P^A(x) = D^L(x) + \kappa, & \text{if } x \in (x_L, x_S) \\ P^A(x) = \lambda D^H(x) + (1-\lambda) D^L(x), & \text{if } x \in [x_S, \infty). \end{cases} \tag{11}$$

Specifically, under our postulation, when $x \geq x_S$, the market does not suffer from adverse selection. So, in this case, all liquidity-shocked bondholders can simply sell their bonds at the price equal to $P^R(x) = \lambda D^H(x) + (1-\lambda)D^L(x)$, leading to the third line in (11). In other words, when $x \geq x_S$, the bond price is not discounted due to informed selling.

When $x \in (x_L, x_S)$, we have postulated that the non-liquidity-shocked bondholders of low-type firms sell their bonds with a positive probability, that is, $m(x) > 0$. For this outcome to occur, those bondholders should be indifferent between selling and keeping their bonds, leading to $P^A(x) - \kappa = D^L(x)$.

When $x \in (x_D, x_L]$, we have postulated that all liquidity-shocked bondholders reveal their liquidity status at full capacity. Hence, in this case, no bondholders sell their bonds for informational reasons. To be more formal, as the off-equilibrium price, $P^A(x)$ is set to $D^L(x)$ because we have already mentioned that any bond seller who sells her bond without revealing her liquidity status will be believed to be a bondholder of a low-type firm in this case.

Next, note that the results in (6) and (8) respectively imply

$$\begin{cases} \lim_{x \downarrow x_L} P^R(x) - P^A(x) = \delta, & \text{if } x_D < x_L \\ P^R(x_L) - P^A(x_L) < \delta, & \text{if } x_D = x_L \end{cases} \quad \text{and} \quad P^A(x_S) - \kappa = D^L(x_S).$$

Then, using the second and third conditions in (11), we can rewrite these conditions as

$$\begin{cases} \lambda J(x_L) = \kappa + \delta, & \text{if } x_D < x_L \\ \lambda J(x_L) < \kappa + \delta, & \text{if } x_D = x_L \end{cases} \quad \text{and} \quad \lambda J(x_S) = \kappa, \tag{12}$$

where $J(x) := D^H(x) - D^L(x)$. The conditions in (12) are the key conditions that we use to pin down the equilibrium thresholds x_L and x_S. In Proposition 3.1, we show that $J(x)$ is strictly decreasing in x, thereby showing that there is a unique pair of (x_L, x_S) that satisfies $x_L < x_S$ and the conditions in (12). Intuitively, this property makes sense because as the chance of default increases, the future recovery value of assets matters more for debt valuation and therefore, the gap between the values of high-type bonds and low-type bonds must increase. In the proof of Proposition 3.1, we verify all other equilibrium conditions described above and also provide the closed-form solution of our model up to a system of

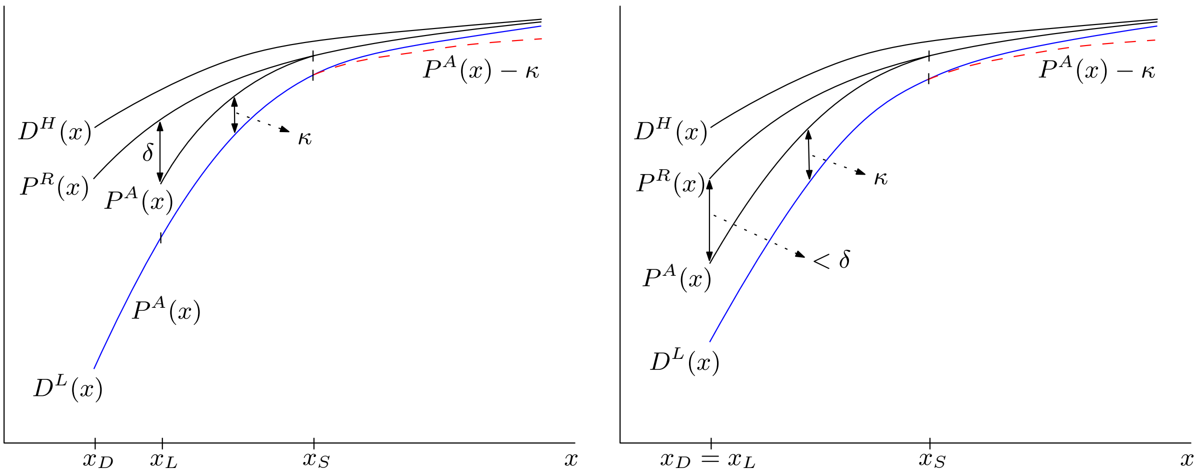

Figure 2: This figure describes the value functions $D^H(x)$ and $D^L(x)$ and the bond prices $P^R(x)$ and $P^A(x)$ in equilibrium. The left graph describes the case of $x_D < x_L$ and the right graph depicts the case of $x_D = x_L$.

highly tractable equations to complete equilibrium characterization.

Proposition 3.1. Our model has a unique equilibrium, provided that we focus on a threshold-type equilibrium that is represented by a pair of thresholds (x_L, x_S).

Proof. See Appendix A.1. □

Figure 2 depicts the general shapes of $D^H(x)$, $D^L(x)$, $P^R(x)$, and $P^A(x)$ in equilibrium. The left panel describes the case of $x_D < x_L$ and the right panel depicts the case of $x_D = x_L$. Let us first consider the case of $x_D < x_L$. In this case, for each $x \geq x_S$, the figure shows that $P^R(x) = P^A(x)$ and $P^A(x) - \kappa \leq D^L(x)$, consistent with the postulation that $\theta(x) = 0$ and $m(x) = 0$ for all such x. When $x_L < x < x_S$, the figure shows that $0 < P^R(x) - P^A(x) < \delta$ and $P^A(x) - \kappa = D^L(x)$, consistent with the postulation that $0 < \theta(x) < 1$ and $m(x) > 0$ for all such x. When $x \leq x_L$, the figure shows that $P^R(x) - P^A(x) > \delta$ and $P^A(x) - \kappa < D^L(x)$, consistent with the postulation that $\theta(x) = 1$ and $m(x) = 0$ for all such x. In the case of $x_D = x_L$, the only difference is that $P^R(x) - P^R(x) < \delta$ at $x = x_D$ as shown in the right panel.

3.4 Turnover Rates and Informational Illiquidity

This section discusses the main qualitative properties of our model regarding bond turnover rates and illiquidity caused by information asymmetry. Specifically, we show that when credit risk increases, the average turnover rate of bonds tends to exhibit a hump-shaped pattern, while informational liquidity costs, which we define later, monotonically increase.

Regarding turnover rates, recall that the informed trading strategy, $m(x)$, tends to exhibit a hump-shaped pattern as credit risk increases, as shown in the bottom two panels in Figure 1. Intuitively, when a firm's fundamental is higher than x_S, the non-liquidity-shocked bondholders of low-type firms have no incentives to exploit their private information due to the additional non-informational trading costs. But when the firm's fundamental falls below x_S, the informed bond-selling strategy $m(x)$ starts increasing because the benefit of exploiting the private information starts to justify the non-informational trading costs. However, in the case of $x_D < x_L$, if the firm's fundamental falls further below the threshold x_L, all liquidity-shocked bondholders reveal their liquidity status at full capacity (with probability 1) and no bondholders of low-type firms are willing to sell their bonds for informational reasons. Hence, the informed bond-selling strategy exhibits a hump-shaped pattern. Similarly, such a humped-shape relation can also arise in the case of $x_D = x_L$, although in that case $m(x)$ will not entirely fall to 0 at x_D.

This result immediately implies that the average turnover rate of bonds with the same fundamental across two different types of firms, that is, $\xi + (1 - \pi)m(x)$, also exhibits a hump-shaped pattern as credit risk increases. When we calibrate our model using data in a later section, we will use this non-monotonicity property regarding the average turnover rate rather than examining the turnover rate of only low-type firms. The reason is that, as econometricians, we cannot directly distinguish between different types of firms in the data. We summarize this hump-shaped relation below.

Proposition 3.2. The average turnover rate of bonds, $\xi + (1 - \pi)m(x)$, tends to exhibit a hump-shaped relationship with the firm's fundamental x.

Now we show that the size of informational liquidity costs monotonically increases with credit risk. In this section, we define informational liquidity costs as $\bar{D}(x) - P^A(x)$, where

$$\bar{D}(x) := \pi D^H(x) + (1-\pi)D^L(x)$$

denotes the unconditional expected value of debt from the perspective of a bond seller who believes that the informational friction will temporarily disappear today but will reemerge from tomorrow. In this regard, $\bar{D}(x) - P^A(x)$ captures the costs of information asymmetry in the current bond market. Nevertheless, when we quantify the overall costs of information asymmetry in corporate bond markets in Section 4.4, this definition may not be appropriate because $\bar{D}(x)$ also includes the present value of informational liquidity costs in future bond markets. In that section, we will define informational liquidity costs in a slightly different way, considering a hypothetical model in which information asymmetry is completely absent. The details will be discussed later.

To show the above claim, first recall that when a firm's fundamental x is above x_S, the bond price for anonymous trades, $P^A(x)$, is equal to $\lambda D^H(x) + (1-\lambda)D^L(x)$. Hence, in this case, $\bar{D}(x) - P^A(x)$ is equal to $(\pi - \lambda)J(x)$. Then, as we have seen that $J(x)$ is increasing with credit risk, $\bar{D}(x) - P^A(x)$ also increases with credit risk when x is higher than x_S.

When a firm's fundamental x lies between x_L and x_S, we have seen that $P^A(x)$ is equal to $D^L(x) + \kappa$. Hence, in this case, $\bar{D}(x) - P^A(x) = \pi J(x) - \kappa$ and thus, for the same reason, $\bar{D}(x) - P^A(x)$ increases with credit risk within the interval $[x_L, x_S]$. Over the extended interval $[x_L, \infty)$, $\bar{D}(x) - P^A(x)$ must still increase with credit risk due to continuity. To be more concrete, because $\lambda J(x_S)$ is equal to κ in equilibrium as described in (12), we have $\pi J(x_S) - \kappa = (\pi - \lambda)J(x_S)$. In the case of $x_D < x_L$, we can further extend the above property to the whole interval, $[x_D, \infty)$, because $P^A(x)$ is set to $D^L(x)$ for each $x < x_L$ as the off-equilibrium price so that $\bar{D}(x) - P^A(x)$ is equal to $\pi J(x)$. We summarize this monotonicity property below.

Proposition 3.3. The size of informational liquidity costs, defined as $\bar{D}(x) - P^A(x)$, increases with the firm's fundamental x.

Intuitively, the monotonic relationship between credit risk and informational liquidity costs is not hard to understand because bond prices generally become informationally more sensitive when credit risk increases, as highlighted by Hölmstrom (2015). However, this result may seem inconsistent with the non-monotonic relation between credit risk and turnover rates, which we have derived above, if we try to understand these two results from the reduced-form framework proposed by Han and Zhou (2014). In their paper, a trade size is taken as an exogenous variable and the adverse-selection component of yield spread is assumed to be linearly dependent on the trade size. As such, the non-monotonic relation between turnover rates and the informational liquidity costs does not arise in their framework.

Meanwhile, in our model, turnover rates and informational liquidity costs are simultaneously determined from the two-way causal effects between those two variables. Hence, when the credit risk or some other common factors change, the turnover rate and the size of informational liquidity costs can move in the opposite direction. To reconcile these two seemingly inconsistent outcomes, note that the expression (2) implies that the price impact caused by a unit increment in informed bond selling increases when the number of liquidity-shocked bond sellers who do not reveal their liquidity status is reduced, all else being equal. Therefore, when credit risk increases, the size of informed trades may fall but the price impact of informed trades rises, causing an increase in the size of informational liquidity costs. A similar result is also obtained in Collin-Dufresne and Fos (2016), who extend the model of Kyle (1985) by considering a stochastic volatility of noise trades. In their paper, the price impact caused by a unit increment in the size of informed trades increases when the volume of uninformed investors declines, which is aligned with our result.

4 Results and Implications

In this section, we first show that the model's prediction regarding the relationship between yield spreads and turnover rates is consistent with US corporate bond trading data. We then calibrate the model to measure the effects of the informational frictions in corporate bond markets. We also conduct comparative statics analysis to examine the effects of several key model parameters on bond market liquidity.

4.1 Data and Summary Statistics

We obtain the monthly trading volume, yields, credit ratings, and other characteristics of corporate bonds from the WRDS Bond Return Database, which is based on bond transactions from FINRA's TRACE data and bond characteristics from Mergent FISD. The data period is from July 2002 to September 2022. Following the literature on corporate bond markets, we focus on bonds issued by non-government US issuers and denominated in US dollars. Further, to focus on plain-vanilla corporate bonds that have better fits with the model, we exclude bonds with zero or variable-rate coupon bonds as well as bonds that are credit-enhanced, convertibles, asset-backed, callable, putable, exchangeable, fungible, preferred, tendered, or a part of a unit deal. We only keep the bonds that are traded on at least 2 distinct months in the sample. This gives us 259,575 bond-month observations for 4,531 bonds.

From this dataset, we compute the yield spread and the annualized turnover rate of each bond-month observation as follows. The yield spread of a bond-month observation is the difference between the bond's yield in that month minus the same-month yield of a treasury bond with the same maturity as the corporate bond.[3] If there is no trade in that month, we use the bond's yield spread in the most recent month with active trading. The annualized turnover rate of a bond-month observation is computed by the bond's par-value trading volume in that month, obtained from the WRDS Bond Return Database, multiplied by 12, and divided by the bond's par-value outstanding amounts obtained from the same database. In addition, we exclude the first-month and last-month trading data of all corporate bonds, where the last trading month is defined as the earlier of the month when the bond matures and the month when the bond defaults. We winsorize yield spreads and turnover rates of the whole sample at the 1% level. Throughout the paper, we use S&P ratings to classify corporate bonds.

To use the empirical relationship between yield spreads and turnover rates for calibration, we group all bond-month observations in 20 bins by yield spread. As in Table 1, the bin width is 50 basis points when the yield spread is below 6% and is 100 basis points otherwise.

[3]The time-series data of treasury yields are obtained from St. Louis's FRED Economic data. Because FRED provides the yields of treasuries with only specific maturities, we use linear interpolation to construct the yield curve.

Table 1: Cross-Sectional Statistics for the Yield Spreads and Turnover Rates

Yield spread bins	$(-\infty$,0.5)	[0.5,1)	[1,1.5)	[1.5,2)	[2,2.5)	[2.5,3)	[3,3.5)	[3.5,4)	[4,4.5)	[4.5,5)
Yield spread (%)	0.27	0.73	1.24	1.73	2.22	2.73	3.23	3.74	4.24	4.74
Turnover rate	0.79	0.68	0.65	0.70	0.71	0.66	0.69	0.74	0.82	0.90
Number of Obs.	39,667	50,681	39,035	30,188	20,110	14,153	10,605	8,597	6,587	4,892
Yield spread bins	[5,5.5)	[5.5,6)	[6,7)	[7,8)	[8,9)	[9,10)	[10,11)	[11,12)	[12,13)	[13,14)
Yield spread (%)	5.24	5.74	6.44	7.47	8.49	9.45	10.50	11.52	12.53	13.55
Turnover rate	0.86	0.87	0.99	1.11	1.23	1.33	1.57	1.33	1.34	1.30
Number of Obs.	3,552	2,786	3,564	2,272	1,476	973	676	464	410	344

Notes: The table contains numbers of observations, weighted averages of yield spreads, and weighted averages of annualized turnover rates for bond-month observations in different yield-spread bins.

We widen the bin interval because the number of observations is much smaller for bonds with higher yield spreads. We exclude observations with yield spreads higher than 14% as those observations are in the default region in our calibrated model. For each bin, we compute the weighted average of yield spreads and the weighted average of annualized turnover rates, where we weight each bond-month observation by the bond's par-value outstanding amount in that month to rely more on data from bonds with larger outstanding amounts.

Figure 3 plots the weighted averages of yield spreads and annualized turnover rates for bond-month observations in different yield-spread bins. The relationship between yield spreads and turnover rates in these yield-spread bins is generally consistent with the model's prediction. The turnover rate does not vary much with the yield spread for bins whose yield spreads are below 400 bps. Yet, the turnover rate becomes a hump-shaped function of the yield spread for bins whose yield spreads are above 400 bps. In Figure 3, we exclude the lowest-yield-spread bin, which contains observations with yield spreads below 50 bps. The turnover rate of that bin is 0.79, which is slightly higher than the average turnover rate of adjacent bins with higher yield spreads. This result, which our model does not predict, can arise in reality because of the clientele effect (Amihud and Mendelson, 1986). That is, bonds with lower yield spreads are more likely to be held by investors with shorter investment horizons and are thus traded more frequently. We will discuss the clientele effect in more detail in Section 4.5.2.

To ensure that the non-monotonic relationship between yield spreads and turnover rates

Table 2: Regressions of Turnover Rates on Yield Spreads

	(1) Turnover Rate (yield spread $\leq$ 400 bps)	(2) Turnover Rate (yield spread $>$ 400 bps)
Yield Spread	-0.0307**	0.0773**
	(0.0077)	(0.0211)
Yield Spread^2		-0.0032**
		(0.0012)
Month FE	Yes	Yes
Bond FE	Yes	Yes
Observations	213,036	30,735

Standard errors in parentheses are double clustered. * $p < 0.05$, ** $p < 0.01$.

is not solely driven by bond-level characteristics or time-varying market conditions, we run a panel regression of turnover rates on yield spreads (in percentage terms) controlling for bond fixed effects and year-month fixed effects. Table 2 presents the regression results. For the sub-sample of observations whose yield spreads are below 400 bps, the regression coefficient is statistically significant: an increase of yield spread by 100 bps (a one-unit increase of the variable Yield Spread) is associated with a decrease of the annualized turnover rate by 3%. In addition, we find that the regression coefficient is statistically insignificant when we focus on the subsample of bonds whose yield spreads are between 100 and 400 bps. This result suggests that the downward-sloping relationship in Table 2, which is not captured by our model, is primarily driven by bonds with very low credit risks and thus can be explained by the clientele effect as discussed above.

For the sub-sample of observations whose yield spreads are above 400 bps, the regression result suggests a hump-shaped relationship between yield spreads and turnover rates, even after controlling for bond fixed effects and month fixed effects. Specifically, the coefficient on the squared yield-spread term is negative and statistically significant, suggesting a downward-sloping relationship between yield spreads and turnover rates for bonds with very high credit risks. According to the estimated regression parameters, an increase in the yield spread is correlated with an increase in turnover rate when the yield spread is below 1200 bps and the correlation turns negative when the yield spread is above 1200 bps. This result is generally consistent with the model's qualitative prediction and the dot plot in Figure 3.

4.2 Model Calibration

In this section, we calibrate the model parameters. The baseline parameter values are summarized in Table 3. We set the risk-free rate r to 4% because the average US Treasury rate generally lies between 3% and 5%. Given that the US corporate tax rate is 35%, we set the tax rate π to 27% by following the arguments by He and Xiong (2012) and He and Milbradt (2014), who take into account the tax exemptions applied to institutional bond investors. The average asset payout ratio estimated by Zhang et al. (2009) and Huang et al. (2020) is about 2%. So, we set the asset growth rate μ to 2% because the asset growth rate is equal to the risk-free rate minus the asset payout ratio in the risk-neutral world. We set the asset volatility σ to 20% because the average asset volatility of corporate bonds estimated by Zhang et al. (2009) is about 20%. According to our data, the average yield spread of BBB-rated bonds is 173 bps, which is also documented as the benchmark case in Table 4. Thus, normalizing the average price of BBB-rated bonds to 100, we set the coupon payment c to 5.73, where we use the fact that the yield spread of any bond with a price P is given by $\frac{c}{P} - r$. For clarification, in our model, the average bond price of firms with a fundamental equal to x is given by

$$P_{avg}(x) = \frac{\nu P^I(x) + (\xi - \nu)\theta(x)P^R(x) + ((\xi - \nu)(1 - \theta(x)) + (1 - \pi)m(x))P^A(x)}{\xi + (1 - \pi)m(x)}.$$

The cash-flow level corresponding to BBB-rated bonds under the calibrated parameter values will be reported later.

Regarding the liquidity-shock intensity ξ, recall that the turnover rate of a bond whose fundamental is higher than x_S is equal to ξ in our model because $m(x) = 0$ when $x \geq x_S$. In other words, the turnover rate of a bond with a low credit risk does not vary with its credit risk. So, based on the observation that the turnover rates of bonds belonging to the second to fifth bins in Table 1 are quite flat as predicted in our model, we set ξ to the average turnover rate of those bonds, which is 0.68. As discussed above, we exclude the first bin because the turnover rate of bonds with yield spreads less than 50 bps is noticeably higher than that of other investment-grade bonds. To explain the relatively higher turnover rate of bonds with substantially low credit risk, we may need to consider other factors such as

Table 3: Baseline Parameter Values

Risk-free rate	$r = 4\%$
Corporate tax rate	$\tau = 27\%$
Asset growth rate	$\mu = 2\%$
Asset volatility	$\sigma = 20\%$
Coupon payment	$c = 5.73$
Liquidity shock intensity	$\xi = 0.68$
Recovery rate of high-type firms	$\alpha_H = 58.9\%$
Recovery rate of low-type firms	$\alpha_L = 49.8\%$
Proportion of high-type firms	$\pi = 57.3\%$
Non-informational trading costs	$\kappa = 0.34$
Liquidity-status revealing costs	$\delta = 2.3$
Measure of informed buyers	$\nu = 0.22$

the clientele effects introduced by Amihud and Mendelson (1986). Exploring these factors together with information asymmetry is beyond the scope of our paper.

We then calibrate the remaining parameters α_H, α_L, π, κ, δ, and ν to jointly match the empirical moments introduced below as closely as possible. First, we match the average recovery rate of assets observed in the data. According to Alderson and Betker (1995), Chen (2010), and Glover (2016), the average asset recovery rate is around 55%. So, we aim to match the average recovery rate in our model, $\pi\alpha_H + (1 - \pi)\alpha_L$, to 55%.

Second, we match the empirically observed total trading costs of BB-rated bonds. According to Edwards et al. (2007), the average trading cost is about 70 bps for junk bonds. This average trading cost corresponds to a trade size of $200,000, which is close to the medium trade size and also used in He and Milbradt (2014). In our model, we use $(\bar{D}(x) - P_{avg}(x) + \kappa)/\bar{D}(x)$ to measure the average total trading costs. As such, we match this model-implied average total trading cost to 70 bps for a bond whose yield spread is at 397 bps, the average yield spread of BB-rated bonds in our sample.

Third, we match the empirically observed turnover rates of bonds across different yield-spread bins as closely as possible, which are summarized in Table 1. In other words, our calibration targets the non-monotonic relationship between yield spreads and turnover rates, which is discussed in detail in 3.4.

The parameter values calibrated from the above approach are as follows: $\alpha_H = 58.9\%$, $\alpha_L = 49.8\%$, $\pi = 57.25\%$, $\kappa = 0.34$, $\delta = 2.3$, and $\nu = 0.22$. Under these calibrated parameter

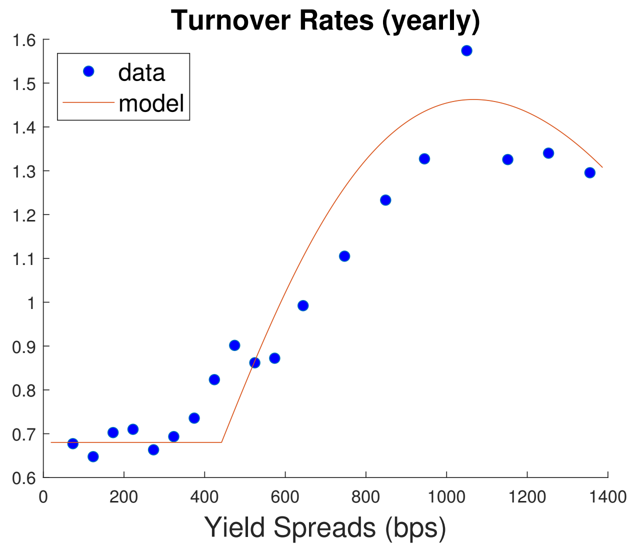

Figure 3: This figure plots both the empirically observed and model-implied turnover rates against the yield spreads of bonds. The cross-sectional empirical moments of the turnover rate are taken from Table 1. For the model-implied result, the baseline parameter values in Table 3 are used.

values, the equilibrium thresholds x_D, x_L, and x_S are 1.23, 1.23, and 1.66, respectively. As briefly mentioned before, the equilibrium thresholds x_D and x_L are the same in the calibrated model, meaning that not all liquidity-shocked bondholders reveal their liquidity status when their firm is close to default. In addition, the cash-flow levels corresponding to BBB- and BB-rated bonds are $x_{BBB} = 2.57$ and $x_{BB} = 1.73$, respectively. This result means that bondholders of low-type firms start to sell their bonds for informational reasons approximately when the credit risk of their bonds is somewhere in between the credit risk of the average BBB bond and that of the average BB bond.

4.3 Turnover Rates and Yield Spreads

Figure 3 plots model-implied and empirically observed turnover rates across different yield-spread bins. The calibrated model predicts a hump-shaped relationship between yield spreads and turnover rates, consistent with empirical data. As shown in Figure 3, (i) when the yield spread is less than 442 bps, the turnover rate is flat, (ii) when the yield spread rises above 442 bps, the turnover rate starts increasing until the yield spread reaches around 1060 bps, and (iii) when the yield spread increases further, the turnover rate tends to decline.[4] These findings are generally consistent with empirical results in the literature. For instance, Namin (2017) shows that the trading volume tends to increase when the credit rating increases from B to CCC and starts decreasing as the credit rating further declines towards CC and C, consistent with our results.

As illustrated in Figure 3, the effect of information asymmetry on trading volume is small for investment-grade bonds. Intuitively, when the bond's credit risk is low, the size of informed bond selling is zero as existing bondholders have no incentives to exploit their informational advantages. In the calibrated model, this no-informed-trading region spans between 0 to 442 bps, which covers most investment-grade bonds (93% of the total investment-grade bond-month observations).

However, informed trading starts to affect trading volume when the yield spread rises above 442 bps, which is in between the average yield spread of BB-rated bonds and that of B-rated bonds. In our sample, 7% of investment-graded bond-month observations and 47% of speculative-grade bond-month observations fall into this informed-trading region.

Moreover, our model shows that the turnover rate decreases with the yield spread for bonds whose yield spreads are larger than 1060 bps. In our sample, this downward-sloping region contains less than 1% of investment-grade bond-month observations and about 10% of speculative-grade bond-month observations. The presence of this downward-sloping region highlights the endogenous determination of adverse selection caused by informed sellers' selling decisions and liquidity-shocked sellers' liquidity-status revealing decisions.

The calibration results raise concerns about using the turnover rate or other volume-based metrics as measures for bond market liquidity. In search-based models such as Duffie et al. (2005) and He and Milbradt (2014), the turnover rate of a bond, which is determined by the searching technology in the bond market, is indeed positively correlated with other price-based-measures of bond market liquidity. However, our model suggests that informational friction complicates the relationship between turnover rate (or other volume-based liquidity measures) and transaction costs (or other price-based liquidity measures). According to

[4] In the calibrated model, note that the turnover rate of bonds with the largest yield spread is higher than the turnover rate of bonds with the smallest yield spread, which explains why the two equilibrium thresholds x_D and x_L are the same under the baseline parameter choice.

our calibration, an increase in the default risk of a bond can cause the turnover rate and the liquidity costs to move in opposite directions, especially for bonds that are traded at relatively large yield spreads (between 442 and 1060 bps in the calibrated model). Therefore, our model suggests that trading volume may not be a good measure of liquidity in markets that suffer from informational frictions.

4.4 Decomposition of Liquidity Costs

In this section, we study the quantitative importance of informational and non-informational liquidity costs in the calibrated model. To this end, we first consider a benchmark model developed by Leland (1994), which does not have any liquidity frictions in the secondary bond market. Let $D^B(x)$ denote the debt value obtained in this benchmark model. We then consider another model that incorporates only non-informational trading costs into Leland (1994) by assuming that a bondholder needs to pay κ to sell her bond when hit by a liquidity shock. That is, this alternative model captures only non-informational trading costs, but not informational trading costs as in our full model. Let $D^N(x)$ denote the debt value obtained in this alternative model. We omit to present the closed-form solutions for this reduced model because the solutions are similar to those obtained in He and Xiong (2012).

Next, we measure the size of non-informational liquidity costs by $\frac{D^B(x)-D^N(x)+\kappa}{D^B(x)}$, where x is the current fundamental of the bond issuer. Here, we set the recovery rate in the model with non-informational trading costs to 55%, which is the average recovery rate in our calibrated model. But, as pointed out by He and Milbradt (2014), if we set the recovery rate in the benchmark model to the same number, the non-informational liquidity costs will approach 0 as the chance of default increases. The reason is that, in such a case, bondholders will no longer face liquidity shocks after default and therefore, the default event is beneficial for bondholders. As such, to measure the size of liquidity costs in secondary asset markets together, He and Milbradt (2014) set the recovery rate in the benchmark model to be higher than that in the model with liquidity frictions. To adopt this point in the simplest way, we use the empirical finding of Acharya et al. (2007) that the recovery rate of firms in financially distressed industries is less than that in financially healthy industries by about 8%, if we exclude utilities and financial service industries. Employing this fact, we set the recovery rate in the benchmark model without any liquidity frictions to $0.55 \times 1.08 = 59.4\%$.

Finally, we measure the size of overall liquidity costs by $\frac{D^B(x)-P^A(x)+\kappa}{D^B(x)}$, where $P^A(x)$ is the bond price (of an anonymous trade) in the calibrated model, and $D^B(x)$ is the bond price in the Leland model with no liquidity costs. This measure of overall liquidity costs can be interpreted as the price discount an uninformed buyer demands in an anonymous trade due to informational and non-informational reasons. Then, we can measure the size of informational liquidity costs by the size difference between overall liquidity costs and non-informational liquidity costs.

Figure 4 plots the decomposition of the overall liquidity costs into informational and non-informational liquidity costs. First of all, we find that the size of informational liquidity costs is non-zero for bonds whose yield spreads are larger than 19 bps, which include most of the no-informed-trading region (between 0 and 442 bps) in Figure 3. To explain this result, note that the size of informational liquidity costs is measured as the percentage difference between the bond price in our calibrated model and that in the alternative Leland model with non-informational costs only. For a bond whose yield spread is in the no-informed-trading region, although there is no information asymmetry in the current bond market, its bondholder may suffer adverse selection in selling her bond in the future when its yield spread moves up to the informed-trading region. In other words, due to the dynamic nature of the model, our measure of informational liquidity costs can take into account the present value of future informational liquidity costs, which is non-zero for most high-quality bonds.

Next, we analyze the size of informational liquidity costs, which can be interpreted as the bond-price discount caused by the negative impact of adverse selection on the secondary bond market. As plotted in Figure 4 and reported in Table 4 (the benchmark case), the sizes of informational liquidity costs are 0.47% 0.54%, 0.70%, and 1.07% for bonds whose yield spreads are equal to the weighted average yield spreads of AAA, AA, A, and BBB rated bonds, respectively. Therefore, for investment-grade bonds with low credit risks, the presence of informational friction generates a positive but relatively small price discount, roughly in the range of $(0.5\%, 1\%)$, when compared to the frictionless benchmark.

However, the size of informational liquidity costs is increasing in the bond's yield spread.

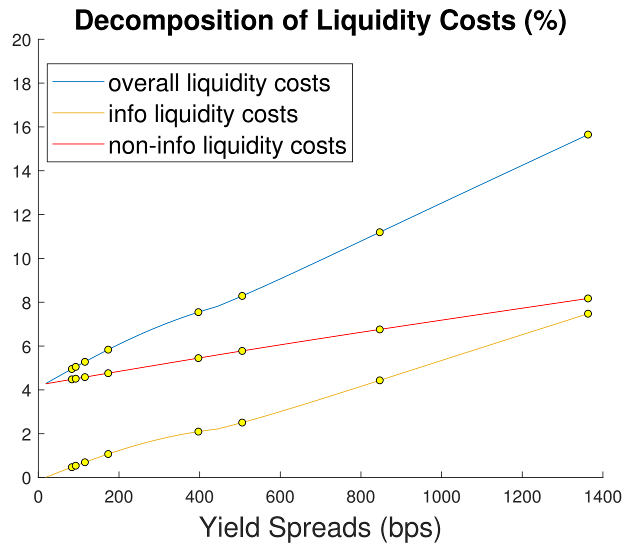

Figure 4: This figure plots how the overall liquidity costs are decomposed into the informational and non-informational parts. The blue curve plots the overall liquidity costs. The orange curve plots the informational liquidity costs. The red curve plots the non-informational liquidity costs. The eight yellow dots on each curve correspond to the weighted average yield spreads of AAA, AA, A, BBB, BB, B, CCC, and CC/C, respectively, from the left to the right.

According to the calibration, the sizes of informational liquidity costs are 2.10%, 2.51%, 4.44% and 7.48% for bonds whose yield spreads are equal to the weighted average yield spreads of BB, B, CCC, and CC/C rated bonds, respectively. For high-yield bonds with high credit risks, informational liquidity costs have much larger effects on bond pricing. The corresponding price discount is about 2% to 2.5% for junk bonds with BB or B ratings and can exceed 5% for junk bonds in the C category.

In sum, our calibrated model shows that adverse selection negatively affects market liquidity not only for high-risk bonds that are currently subject to informed trading but also for low-risk bonds due to the expectation of future informational illiquidity. In the empirical literature, Benmelech and Bergman (2018) finds that the effect of information asymmetry on market liquidity exhibits a hockey-stick pattern and is sizable only for bonds with significant default risks. Our calibration result is consistent with this hockey-stick pattern in the sense that the amount of informed trading is zero for bonds with yield spreads below 442 bps. Nevertheless, we show that when the presence value of future informational liquidity costs is considered, the size of informational liquidity costs corresponds roughly to a price discount of 0.5% to 1% for investment-grade bonds, which is economically significant.

Before discussing the model's comparative statics results, we compare the relative magnitude of informational and non-informational liquidity costs for bonds with different yield spreads. For average investment-grade bonds at different rating classes, their informational liquidity costs take up 9.5%-18.3% of the overall liquidity costs. However, for average speculative-grade bonds at different rating classes, their information liquidity costs take up 27.8%-47.8% of the overall liquidity costs. These results show that both the absolute size and relative importance of informational liquidity costs in determining bond market liquidity are higher for bonds with higher credit risks.

4.5 Comparative Statics Analysis

4.5.1 Effects of Non-Informational Trading Costs

Now we analyze the effect of the non-informational trading costs on yield spread and informational liquidity. The results are summarized in Table 4, which plots yield spreads, turnover rates, informational and non-informational liquidity costs of four investment-grade representative bonds and four speculative-grade representative bonds for three different levels of non-informational trading costs κ. These representative bonds are chosen so that the yield spread of each representative bond corresponds to the weighted average yield spread for each rating class in the calibrated model.

As shown in Table 4, reducing non-informational trading costs κ weakly increases turnover rates for bonds at all rating classes (from AAA to CC/C). For the four investment-grade representative bonds, the turnover rate is not sensitive even for a large decrease of κ from 0.6 to 0.1. In contrast, for the four speculative-grade representative bonds, a decrease in κ significantly increases their trading volume. For instance, when κ decreases from the benchmark case 0.34 to 0.1, the turnover rate of a bond would increase by more than 100% if its yield spread is close to the average yield spread of BB or B rated bonds. This increase in yield spread is primarily driven by more informed trading. Specifically, when facing lower non-information trading costs, informed bondholders have higher incentives to exploit their informational advantage, resulting in more informed trading and higher trading volume.

Although a decrease in the size of non-informational trading costs raises the amount of

Table 4: The Effects of the Non-Informational Trading Costs

		AAA	AA	A	BBB	BB	B	CCC	CC/C
$\kappa = 0.1$	Yield spreads	70	79	101	158	381	493	842	1381
	Turnover rate	0.68	0.68	0.68	0.68	1.39	2.06	3.29	2.27
	Overall liquidity costs	2.03	2.15	2.41	3.04	5.40	6.62	10.33	15.57
	Informational part	0.45	0.51	0.66	1.01	2.28	2.99	5.15	8.15
	Non-informational part	1.59	1.63	1.75	2.03	3.12	3.64	5.18	7.42
$\kappa = 0.34$	Yield spreads	83	93	115	173	397	505	847	1363
(benchmark)	Turnover rate	0.68	0.68	0.68	0.68	0.68	0.82	1.37	1.32
	Overall liquidity costs	4.95	5.05	5.28	5.84	7.55	8.29	11.19	15.65
	Informational part	0.47	0.54	0.70	1.07	2.10	2.51	4.44	7.48
	Non-informational part	4.48	4.51	4.58	4.76	5.45	5.78	6.76	8.17
$\kappa = 0.6$	Yield spreads	99	108	132	191	418	526	857	1355
	Turnover rate	0.68	0.68	0.68	0.68	0.68	0.68	0.98	1.11
	Overall liquidity costs	8.13	8.21	8.41	8.89	10.30	10.70	12.37	15.76
	Informational part	0.51	0.59	0.76	1.17	2.32	2.60	3.90	6.77
	Non-informational part	7.62	7.63	7.65	7.72	7.98	8.10	8.47	8.99

Notes: This table shows the effects of the non-informational trading costs κ on yield spreads (bps), turnover rates (yearly), overall liquidity costs (%), informational liquidity costs (%), and non-informational liquidity costs (%) across different rating classes.

informed trading, our calibration results suggest that it has an ambiguous effect on the size of informational liquidity costs. According to Table 4, when κ decreases from the benchmark case 0.34 to 0.1, the informational part of overall liquidity costs slightly decreases for investment-grade representative bonds, but it significantly increases for speculative-grade representative bonds.

Intuitively, reducing non-informational trading costs affects the size of informational liquidity costs through two channels. On the one hand, reducing non-informational trading costs induces more informed trading, resulting in a higher degree of adverse selection problem and a higher informational liquidity discount. We call this the informed-trading channel. On the other hand, it increases bondholders' valuation of their bonds as they expect lower trading costs when liquidating their bonds in the future. As such, the informational liquidity discount, defined by $\frac{D^N(x)-P^A(x)}{D^B(x)}$, shrinks, because both $P^A(x)$, the bond price of an anonymous trade in the benchmark model, and $D^N(x)$, the bond price in the Leland model with non-informational trading costs, increase and become closer to $D^B(x)$, the bond value in the standard Leland model without trading frictions. We call this the bond-valuation channel.

For representative bonds in the investment-grade region, the effect of the informed-trading channel is small: these bonds are not subject to informed trading in the current bond market and are only affected by this channel in the future when their credit risks substantially increase. As such, the bond-valuation channel dominates, so reducing non-informational trading costs causes a decrease in the size of informational liquidity costs. However, for representative bonds in the speculative-grade region, the effect of the informed-trading channel dominates as informed bondholders exploit their informational advantages by trading these high-risk bonds in the secondary market. In this case, reducing non-informational trading costs causes an increase in the size of informational liquidity costs.

Finally, we analyze how a change in non-informational trading costs affects bond pricing by looking at its effect on the yield spread. Note that a change in non-informational trading cost affects the yield spread both by directly reducing non-informational liquidity costs and by changing informational liquidity costs. Our calibrated model shows that the effect of trading costs on yield spread exhibits a significant degree of heterogeneity across different rating classes. For instance, consider a decrease of κ from the benchmark case 0.34 to 0.1 in Table 4. The yield spread decrease is 13 bps for the average AAA rated bond, and the magnitude of the decrease gradually increases as we go down the rating list, with the largest yield-spread decrease occurring for the average BB rated bond. The above results reflect the fact that a decrease in non-informational trading costs (in dollar terms) has larger effects on non-informational liquidity costs (in percentage terms relative to bond market value) for bonds with higher credit risks and lower market values.

However, for bonds rated below BB, such yield-spread decrease shrinks to 12 bps for the average B rated bond, 5 bps for the average CCC rated bond, and turns to negative 18 bps for the average CC/C rated bond. These results are driven by the endogenous adverse selection due to informed trading. For these speculative-grade bonds, a decrease in the size of non-informational trading costs induces more informed trading, resulting in a substantial increase in the size of informational liquidity costs in the secondary market.

In sum, we find that decreasing non-informational trading costs reduces yield spreads for most bonds, yet the magnitude of these decreases is non-monotonic across bonds with different credit risks. Under reasonable parameter values, our calibration results suggest that bonds around the BB rating class are most sensitive to changes in trading costs.

The above comparative-static results concerning non-informational trading costs generate a few interesting policy implications. First, we can interpret the effect of the Volcker rule on the corporate bond market as an increase in the non-informational trading costs in the model. The Volcker Rule, intended to limit bank risk-taking by restricting certain speculative activities, had the unintended consequence of reducing regulated banks' market-making activities, which may cause a decrease in bond market liquidity. For instance, Bao et al. (2018) find empirical evidence that due to the Volcker Rule, bonds have become less liquid during stress when bonds are downgraded to junk status. Consistent with this empirical finding, our model predicts that increasing the trading costs would generally reduce market liquidity and thus increase yield spreads. Yet, generally speaking, our calibrated model suggests that the yield-spread increase would be the highest for bonds in the BB rating class, which generally corresponds to the subgroup of bonds studied in Bao et al. (2018). Therefore, our model suggests that focusing on these fallen angel bonds may overestimate the effect of the Volcker rule on bond market liquidity.

In addition, the comparative-static results can be used to analyze the effect of electronic trading platforms on corporate bonds. In recent years, the usage of electronic venues in corporate bond trading has become more prevalent. Compared to traditional over-the-counter trading, electronic trading platforms can reduce transaction costs by allowing investors to search many bond dealers simultaneously and to obtain pre-trade information more easily. Hendershott and Madhavan (2015) find that controlling for bond rating and trade size, trading costs are substantially lower in electronic trading platforms than in OTC voice-based trading. According to our model, while a decrease in the trading costs in the model reduces yield spreads for bonds at most rating classes, it also induces more informed trading for speculative-grade bonds, which makes informational illiquidity more critical in determining the prices of these bonds.

Facing a higher degree of adverse selection, liquidity-shocked bond sellers tend to pay higher liquidity-status revealing costs to trade at favorable prices. In this regard, our model predicts that a decrease in trading costs caused by the development of electronic trading platforms increases the demand for liquidity-status revealing. We postulate that liquidity-

Table 5: The Effects of Liquidity-Shock Intensity

		AAA	AA	A	BBB	BB	B	CCC	CC/C
$\xi = 0.5$	Yield spreads	78	88	110	168	392	500	844	1380
	Turnover rate	0.50	0.50	0.50	0.50	0.50	0.52	0.80	0.97
	Overall liquidity costs	3.95	4.05	4.30	4.91	6.92	7.75	10.86	15.61
	Informational part	0.48	0.55	0.71	1.09	2.23	2.64	4.51	7.48
	Non-informational part	3.47	3.51	3.60	3.82	4.69	5.11	6.34	8.13
$\xi = 0.68$	Yield spreads	83	93	115	173	397	505	847	1363
(benchmark)	Turnover rate	0.68	0.68	0.68	0.68	0.68	0.82	1.37	1.32
	Overall liquidity costs	4.95	5.05	5.28	5.84	7.55	8.29	11.19	15.65
	Informational part	0.47	0.54	0.70	1.07	2.10	2.51	4.44	7.48
	Non-informational part	4.48	4.51	4.58	4.76	5.45	5.78	6.76	8.17
$\xi = 0.9$	Yield spreads	89	99	122	180	405	513	853	1343
	Turnover rate	0.90	0.90	0.90	0.90	0.90	1.07	1.97	1.47
	Overall liquidity costs	6.19	6.28	6.49	7.00	8.53	9.10	11.68	15.71
	Informational part	0.47	0.54	0.70	1.09	2.16	2.50	4.41	7.48
	Non-informational part	5.72	5.74	5.79	5.91	6.38	6.60	7.27	8.23

Notes: This table shows the effects of the liquidity-shock intensity ξ on yield spreads (bps), turnover rates (yearly), overall liquidity costs (%), informational liquidity costs (%), and non-informational liquidity costs (%) across different rating classes.

status revealing is more likely to happen when an investor trades with her relationship dealer, who is better informed of her trading motive but charges a higher price due to information monopoly. Therefore, our comparative-static results suggest a certain level of segmentation in corporate bond markets, where an investor searches in the electronic trading platform when trading low-risk information-insensitive bonds and would turn to her relationship dealer when trading high-risk bonds that may cause concerns about adverse selection.

4.5.2 Effects of the Intensity of Liquidity Shocks

Table 5 presents the comparative-static results concerning ξ, the Poisson intensity at which a bondholder is hit by a liquidity shock and forced to sell her bond position. First, Table 5 shows that an increase in the liquidity shock intensity leads to increases in turnover rates and non-informational liquidity costs for all rating classes. These two results are not surprising: when bond investors are more likely to liquidate their bonds, the trading volume is higher, and the expected value of potential trading costs due to forced selling in the future becomes larger.

However, the effect of the liquidity shock intensity on the size of informational liquidity costs is ambiguous. Similar to Section 4.5.1, an increase in the liquidity-shock intensity affects informational liquidity through the informed-trading and the bond-valuation channel. On the one hand, when the liquidity-shock intensity increases, there is more liquidity-driven selling in the secondary market. More liquidity-driven selling induces more non-liquidity-shocked bondholders to exploit their informational advantages, resulting in a higher degree of adverse selection and a higher informational liquidity discount.[5]

On the other hand, an increase in the liquidity-shocked intensity also reduces the bond-value difference between a high-type and a low-type firm. Intuitively, when investors have shorter investment horizons, they expect to liquidate their bonds more frequently in the future, so they worry less about information asymmetry with respect to the recovery value in default. So, an increase in the liquidity-shock intensity reduces the degree of adverse selection by making bonds less information-sensitive in the eyes of their investors.

Due to the presence of these two opposite effects, the impact of an increase in liquidity-shock intensity on informational liquidity costs is theoretically ambiguous. Our calibration results suggest that the effect depends not only on the credit risk of the bond but also on the current level of liquidity shock intensity. For instance, an increase in ξ from 0.5 to 0.68 (benchmark case) tends to reduce informational liquidity discounts for the average BBB bond and the average BB bond, but a further increase in ξ from 0.68 to 0.9 raises informational liquidity discounts for these two representative bonds.

Last, we analyze the effect of liquidity shock intensity on yield spread in the calibrated model. According to Table 5, an increase in the liquidity shock intensity leads to increases in yield spreads for all rating classes except for CC/C. When we increase ξ from 0.68 (benchmark case) to 0.9, the yield-spread increase again exhibits a hump-shaped pattern: roughly speaking, the yield-spread increase is the highest for bonds in the BBB, BB and B rating classes.

The liquidity shock in the model corresponds to bond selling for non-informational reasons such as preference changes, leverage constraints, and forced redemptions in bond ETFs

[5]Note that the increase in the degree of adverse selection is partially mitigated by the presence of the liquidity-status revealing option.

or mutual funds. According to the calibrated model, shocks that force bond investors to liquidate, i.e., performance-driven mutual fund redemptions (Goldstein et al., 2017), would have the largest adverse effects on bond prices for high-yield bonds around the BB rating. Nevertheless, expecting higher costs associated with liquidating these high-yield bonds, a bond mutual fund manager with a diverse portfolio of corporate bonds may choose to sell high-quality corporate bonds to minimize liquidation costs (Ma et al., 2022). Incorporating bond investors' endogenous liquidation decisions into our credit-risk model, which is beyond the scope of our paper, can be valuable for understanding the interaction between investors' liquidation decisions and equilibrium bond pricing.

Another factor that affects the liquidity-shock intensity in the model is the liquidity preference of bond investors. For instance, Chen et al. (2020) tests the clientele effect in the corporate bond market and finds that insurers' investment horizons and funding constraints correlate with the illiquidity of their corporate bond portfolio and have pricing implications in the bond market. Suppose we incorporate this clientele effect into our model by assuming that investors differ in their future demands for liquidity. In that case, investors with higher liquidity-shock intensities should trade bonds with lower credit risks (i.e., investment-grade bonds), and investors with higher liquidity-shock intensities should trade bonds with higher credit risks (i.e., high-yield bonds). Such an extension can improve the model's quantitative performance in explaining the high turnover rate for the first yield-spread bin in Table 1.

4.5.3 Effects of the Recovery Rate Difference

Table 6 presents the comparative-static results concerning $\alpha_H - \alpha_L$, the recovery rate difference between a high-type and a low-type firm. When conducting this analysis, we change the recovery rate difference while holding the average recovery rate $\pi\alpha_H + (1-\pi)\alpha_L$ fixed at 55%. Therefore, an increase in the recovery rate difference raises the degree of information asymmetry between bond investors in the model.

As in Table 6, the effect of the recovery rate difference on the turnover rate in the bond market varies across different rating groups. For representative bonds in the investment-grade region, an increase in the recovery rate difference around its calibrated value has little impact on their turnover rates. This is because informed investors find it unprofitable to

Table 6: The Effects of the Recovery Rate Difference

		AAA	AA	A	BBB	BB	B	CCC	CC/C
$\alpha_H = 57\%$	Yield spreads	82	91	114	170	389	495	816	1304
$\alpha_L = 51.3\%$	Turnover rate	0.68	0.68	0.68	0.68	0.68	0.68	0.96	1.33
	Overall liquidity costs	4.75	4.82	4.98	5.38	6.68	7.17	8.73	11.57
	Informational part	0.27	0.31	0.40	0.62	1.23	1.39	1.97	3.40
	Non-informational part	4.48	4.51	4.58	4.76	5.45	5.78	6.76	8.17
$\alpha_H = 58.9\%$	Yield spreads	83	93	115	173	397	505	847	1363
$\alpha_L = 49.8\%$	Turnover rate	0.68	0.68	0.68	0.68	0.68	0.82	1.37	1.32
(benchmark)	Overall liquidity costs	4.95	5.05	5.28	5.84	7.55	8.29	11.19	15.65
	Informational part	0.47	0.54	0.70	1.07	2.10	2.51	4.44	7.48
	Non-informational part	4.48	4.51	4.58	4.76	5.45	5.78	6.76	8.17
$\alpha_H = 63\%$	Yield spreads	86	96	120	180	420	542	921	1393
$\alpha_L = 40.2\%$	Turnover rate	0.68	0.68	0.68	0.68	0.93	1.28	1.12	0.68
	Overall liquidity costs	5.47	5.64	6.04	7.01	10.20	11.99	17.58	24.72
	Informational part	0.99	1.13	1.46	2.24	4.75	6.21	10.82	16.55
	Non-informational part	4.48	4.51	4.58	4.76	5.45	5.78	6.76	8.17

Notes: This table shows the effects of the difference between the recovery rates of high-type firms and low-type firms, that is, $\alpha_H - \alpha_L$, on yield spreads (bps), turnover rates (yearly), overall liquidity costs (%), informational liquidity costs (%), and non-informational liquidity costs (%) across different rating classes.

exploit their informational advantages on these low-risk bonds. For representative bonds in the speculative-grade region, an increase in the recovery rate difference has ambiguous effects on their turnover rates. For instance, consider an increase of $\alpha_H - \alpha_L$ from 9.1% in the benchmark case to 22.8%. Following the increase, turnover rates become higher for BB and B representative bonds. For these two bonds, a higher degree of information asymmetry increases the amount of informed trading. However, the turnover rate becomes lower for the CCC and the CC/C representative bonds. For those two bonds, a higher degree of information asymmetry reduces the amount of informed trading primarily by inducing liquidity-shocked sellers to reveal their liquidity status at higher intensities. Therefore, our model predicts that an increase in the degree of information asymmetry has a non-monotonic effect on trading volume across bonds with different credit risks.

Besides, Table 6 shows that an increase in the recovery rate difference tends to raise the size of informational liquidity costs and the yield spread in the bond market. This result is straightforward: an increase in the recovery rate difference increases the degree of information asymmetry in the bond market, resulting in higher informational liquidity discounts in bond pricing. Further, Table 6 suggests that for most representative bonds (from AAA to CCC), the effects of recovery rate difference on informational illiquidity and yield spreads are higher for bonds with higher credit risks.

Note that a change in the recovery rate difference affects bond pricing by changing the information structure in the bond market. So, we can interpret it more broadly as a shock that changes the degree of information asymmetry between bond investors, such as a regulatory reform that changes the accounting transparency of corporate bonds or a policy shock that affects the informativeness of credit ratings. In this regard, our model predicts that an improvement in accounting transparency or credit-rating informativeness can reduce yield spread by lowering informational liquidity costs. However, its effect on trading volume is ambiguous and varies across bonds with different credit risks.

5 Discussion and Conclusion

In this paper, we develop a structural credit-risk model to study the effect of information asymmetry on yield spreads and trading volume in the corporate bond market. Due to information asymmetry between bond buyers and sellers, the model predicts a hump-shaped relationship between bonds' turnover rates and yield spreads, consistent with US corporate bond trading data. In the calibrated model, we find that the effects of information asymmetry on bond prices are non-negligible for investment-grade bonds and are economically sizable for speculative-grade bonds. According to the model, regulations that increase bond trading costs and shocks that induce forced liquidation have the most significant adverse effect on market liquidity for bonds with intermediate levels of credit risks.

Our paper highlights the critical role of informational frictions in shaping corporate bond trading volume and prices. The model made several simplifying assumptions about the trading mechanism. First, we model the presence of non-informational frictions by introducing a reduced-form transaction cost in an otherwise competitive market. In reality, these non-informational frictions appear as search costs, inventory costs, and dealers' market power. Thus, future works that endogenize these non-informational frictions in our model can provide further insights into the interaction between informational and non-informational frictions in corporate bond markets.

Besides, we allow liquidity-shocked bondholders to reveal their liquidity status with costly efforts. The liquidity-status revealing option captures the process of bond investors searching for trustworthy dealers or trading venues to reduce informational illiquidity. Micro-founding the liquidity-status revealing option, especially by incorporating time delay as a potential source of signaling device and indirect trading costs (Daley and Green, 2012), can deepen our understanding of information-theoretic illiquidity in corporate bond markets.

A Appendix

A.1 Proof of Proposition 3.1 and Closed-Form Solutions

In this section, we prove the existence and uniqueness of equilibrium. At the same time, we provide the closed-form solutions of the model. For clarification, note that we do not rely on closed-form solutions to derive the existence and uniqueness.

To begin, note that

$$m(x)(P^A(x) - \kappa - D^L(x)) = 0, \quad \forall x \geq x_D, \tag{13}$$

because the second condition in (11) implies $P^A(x) - \kappa - D^L(x)$ has to be 0 unless $m(x) = 0$. Due to this property, together with the property described in (3), equations (9) and (10) are reduced to

$$(r + \xi)J(x) = \mathcal{A}J(x) \tag{14}$$

subject to $J(x_D) = \frac{(\alpha_H - \alpha_L)x_D}{r-\mu}$ and $\lim\limits_{x\to\infty} J(x) = 0$. The explicit solution for $J(x)$ is given by

$$J(x) = \frac{(\alpha_H - \alpha_L)x_D}{r - \mu} \left(\frac{x}{x_D}\right)^{\phi}, \tag{15}$$

where $\phi = \frac{-\mu + \frac{\sigma^2}{2} - \sqrt{\left(\mu - \frac{\sigma^2}{2}\right)^2 + 2\sigma^2(r+\xi)}}{\sigma^2} < 0$. Here, there are no non-homogeneous terms. Hence, as $J(x_D) > 0$ and $\lim\limits_{x\to\infty} J(x) = 0$, the probabilistic representation for $J(x)$ implies $J(x)$ must be decreasing in x. Then there must be a unique pair of (x_L, x_S) that satisfies the conditions in (12). In fact, this result continues to hold even if we assume that the non-informational trading cost $\kappa(x)$ increases in x as briefly mentioned before. Further, we can easily see that $x_L < x_S$ because $\delta > 0$. We have therefore constructed the equilibrium thresholds x_L and x_S, which we can compute numerically using the expressions for $J(x)$ and κ.

Having pinned down $J(x)$, x_L, and x_S, we can now solve the HJB equation for $D^L(x)$. Specifically, due to the properties in (7), (11), and (13), the HJB equation (10) can be rewritten as

$$rD^L = c + \xi \left[1_{x \le x_L} \left(\lambda J - \kappa - \frac{\delta}{2} \right) + 1_{x_L < x < x_S} \frac{(\lambda J - \kappa)^2}{2\delta} + 1_{x_S \le x} (\lambda J - \kappa) \right] + \mathcal{A} D^L. \quad (16)$$

The boundary conditions for the low-type firm's bond value are given by

$$D^L(x_D) = \frac{\alpha_L x_D}{r - \mu}, \; \lim_{x \uparrow x_L} D^L(x) = \lim_{x \downarrow x_L} D^L(x), \; \lim_{x \uparrow x_L} D^L_x(x) = \lim_{x \downarrow x_L} D^L_x(x), \quad (17)$$

$$\lim_{x \uparrow x_S} D^L(x) = \lim_{x \downarrow x_S} D^L(x), \; \lim_{x \uparrow x_S} D^L_x(x) = \lim_{x \downarrow x_S} D^L_x(x), \quad (18)$$

which are usual value-matching and smooth-pasting conditions. To provide the closed-form solution of $D^L(x)$, let $J_1 = J(x)/x^\phi$ for notational convenience. Then the closed-form solution of $D^L(x)$ is given by

$$D^L(x) = \begin{cases} \frac{c - \xi\kappa - \frac{\xi\delta}{2}}{r} + \frac{\xi \lambda J_1}{l(\phi)} x^\phi + A_1 x^{\eta_1} + A_2 x^{\eta_2}, & \text{if } x_D \le x < x_L \\ \frac{c + \frac{\xi \kappa^2}{2\delta}}{r} + \frac{\xi}{2\delta} \left(\frac{\lambda^2 J_1^2}{l(2\phi)} x^{2\phi} - \frac{2\lambda J_1 \kappa}{l(\phi)} x^\phi \right) + A_3 x^{\eta_1} + A_4 x^{\eta_2}, & \text{if } x_L \le x < x_S \\ \frac{c - \xi\kappa}{r} + \frac{\xi \lambda J_1}{l(\phi)} x^\phi + A_5 x^{\eta_2}, & \text{if } x_S \le x, \end{cases} \quad (19)$$

where $l(a) := r - a\mu - a(a-1)\sigma^2/2$ for any a. The coefficients A_1, ..., A_5 are determined from the boundary conditions described in (17).

Using the above results, we can now readily pin down the remaining equilibrium objects. That is, $D^H(x)$ is given by $D^L(x) + J(x)$; $P^R(x)$ is given by $\lambda D^H(x) + (1-\lambda) D^L(x)$; $P^A(x)$ is given by (11); $\theta(x)$ and $m(x)$ is given by

$$\begin{cases} \theta(x) = 1, & \text{if } x \in (x_D, x_L] \\ \theta(x) = \frac{\lambda J(x) - \kappa}{\delta}, & \text{if } x \in (x_L, x_S) \\ \theta(x) = 0, & \text{if } x \in [x_S, \infty) \end{cases}$$

and

$$\begin{cases} m(x) = 0, & \text{if } x \in (x_D, x_L] \\ m(x) = \frac{(1-\theta(x))[\pi(\xi-\nu)J(x) - (\xi - \pi\nu)\kappa]}{(1-\pi)\kappa}, & \text{if } x \in (x_L, x_S) \\ m(x) = 0, & \text{if } x \in [x_S, \infty), \end{cases}$$

respectively, due to (2), (6), and (11). This expression confirms that $0 < \theta(x) < 1$ and $m(x) > 0$ for all $x \in (x_L, x_S)$ because $\kappa < \lambda J(x) < \kappa + \delta$ for all such x as shown above.

Lastly, we prove the global optimality conditions that must be satisfied by the liquidity-status revealing strategy $\theta(x)$ and the informed bond-selling strategy $m(x)$. To this aim, we claim the following conditions hold:

$$\begin{cases} P^R(x) - P^A(x) \geq \delta, & \forall x \in [x_D, x_L) \\ P^R(x) - P^A(x) \in [0, \delta], & \forall x \in [x_L, x_S) \\ P^R(x) - P^A(x) = 0, & \forall x \in [x_S, \infty) \end{cases} \tag{20}$$

and

$$\begin{cases} P^A(x) - \kappa = D^L(x), & \forall x \in [x_D, x_S) \\ P^A(x) - \kappa \leq D^L(x), & \forall x \in [x_S, \infty). \end{cases} \tag{21}$$

The first condition in (20) holds because $P^R(x) - P^A(x) = \lambda J(x) > \delta + \kappa > \delta$ for all $x < x_L$. This condition justifies the conjectured solution that $\theta(x) = 1$ for all such x. The second condition in (20) holds because $0 \leq P^R(x) - P^A(x) = \lambda J(x) - \kappa \leq \delta$ for all $x \in [x_L, x_S)$. This condition justifies the conjectured solution that $0 \leq \theta(x) < 1$ for all such x. We have already shown the third condition in (20) in the third line of (11). This condition justifies the conjectured solution that $\theta(x) = 0$ for all $x \geq x_S$. The first condition in (21) holds because $P^A(x) - \kappa = D^L(x) - \kappa < D^L(x)$ for all $x < x_L$. This condition justifies the conjectured solution that $m(x) = 0$ for all such x. We have already shown the second condition in (21) in the second line of (11). This condition justifies the conjectured solution that $m(x) \geq 0$ for all $x \in [x_L, x_S)$. The third condition in (21) holds because $P^A(x) - D^L(x) = \lambda J(x) \leq \kappa$ for all $x \geq x_S$. This condition justifies the conjectured solution that $m(x) = 0$ for all such x. We have therefore completed characterizing an equilibrium of our model, which has to be unique as mentioned above.

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