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Dealer Inventory, Short Interest and Price Efficiency in the Corporate Bond Market

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Dealer Inventory, Short Interest and Price Efficiency in the Corporate Bond Market

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Abstract

We propose an equilibrium model of over-the-counter corporate bond trading with short selling, asymmetric information and dealer inventory costs. The model predicts that higher inventory costs impose implicit short-sale constraints and are thus associated with lower price efficiency. We construct bond-level proxies for inventory costs and provide empirical evidence in support of the model's prediction. Our findings suggest that tighter post-GFC regulation may have had unintended consequences for corporate bond market quality.

JEL Classifications: G14, G24, G30

Keywords: Corporate bonds; Securities lending; Dealer inventory; Short selling; Price Efficiency

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1. Introduction

Our work contributes to the ongoing debate between regulators and market participants on whether the Dodd-Frank Act and the Basel 2.5 and III regulatory framework have contributed to a decrease in market quality in the years since the Great Financial Crisis (GFC). These regulatory provisions were designed to make the financial sector more resilient to shocks, by tightening bank capital requirements, introducing leverage ratios and establishing liquidity requirements.[1] Both regulators and market participants agree that these provisions have contributed to an increase in the cost of providing market-making services (Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Adrian, Fleming, Shachar, and Vogt (2017) and Cimon and Garriott (2018)). But the two parties differ in their assessment of the effect that the higher cost of market making has had on market quality.

The cost of providing market-making services is of particular relevance for dealer-intermediated markets, such as the corporate bond market. Market participants have expressed concerns that as a result of higher costs of market making, the corporate bond market has become less liquid.[2] Regulators, on the other hand, claim that there is only limited evidence of a deterioration in corporate bond market liquidity (Adrian, Fleming, Shachar, and Vogt (2017)), and their claims have found support in related academic studies (Trebbi and Xiao (2017)).[3] It appears that both points of view can be supported, mainly because the concept of market liquidity is only loosely defined and the direction of the empirical evidence seems to depend on the choice of the liquidity measure.[4]

[1]For a detailed description of the post-GFC regulatory environment, see Appendix A.

[2]See, for example, "Reduced Liquidity in Bond Markets Concerns Portfolio Managers," Wall Street Journal, August 3, 2014; "What No One Ever Says About Corporate Bond Market Liquidity: It's cornered," Bloomberg News, July 30, 2015; "Corporate bond liquidity struggles to match U.S. market growth," Bloomberg Professional Services, May 31, 2016; "Bond Selloff Highlights Liquidity Shortage, Changing Strategies," Wall Street Journal, November 16, 2016; "Bond Investors Are Worried About Bond Market Liquidity," Bloomberg News, December 4, 2017; and the financial press articles cited in Adrian, Fleming, Shachar, and Vogt (2017).

[3]Trebbi and Xiao (2017) argue that trading costs in the corporate bond market have declined and that liquidity has improved since the post-GFC regulatory provisions were put in place. Mizrach (2015), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) and Anderson and Stulz (2017) compare post-GFC liquidity in the corporate bond market to pre-GFC liquidity, and find mixed results. The direction of the change in liquidity depends on the liquidity measure used and on the group of bonds studied.

[4]Regulators point to a decrease in post-GFC bid-ask spreads to debunk the notion of lower post-GFC liquidity. Market participants, on the other hand, argue that bid-ask spreads are an imperfect measure of market liquidity—in particular immediacy—as they are based only on trades that were realized and ignore bonds that are too expensive to trade. Market participants argue that when inventory costs are higher, dealers buy and sell fewer bonds at their own risk and instead focus more on matching customer trades. The latter involves fewer risks and hence does not require the same level of dealer compensation as keeping risky assets on dealer balance sheets does. As a result, bid-ask spreads of realized trades are tighter post-GFC, but trades will only be realized if dealers can line up a counterparty. See, for example, "Bond Investors Are Worried About Bond Market Liquidity," Bloomberg News, December 4, 2017. In related work, Dick-Nielsen and Rossi (2018) argue that bid-ask spreads are not a suitable measure of the speed of trade execution, and Choi and

Our study centers around a more clearly defined aspect of market quality—price efficiency. Price efficiency is the degree to which prices reflect all available information (Saffi and Sigurdsson (2010)). We focus on the corporate bond market and explore whether the dramatic contraction in dealers' balance sheets since 2008 has had a negative impact on price efficiency. One channel through which such an association could arise are implicit short-sale constraints: When it is more costly for dealers to hold inventory, they may be more reluctant to facilitate investors' sell orders. This in turn may discourage investors from shorting corporate bonds, since investors would have to sell borrowed bonds to a dealer to establish the short position. In that sense, an increase in dealer inventory costs may impose constraints on shorting corporate bonds. If short-sale constraints were to limit the speed or accuracy of information revelation, as the equity-market literature suggests, then higher inventory costs would have a negative impact on price efficiency.

To explore the link between dealer inventory costs and price efficiency, we proceed in two steps. First, we propose an equilibrium model for trading in the secondary corporate bond market that allows us to identify the sources of variation in the degree of information revelation. The corporate bond market is an over-the-counter (OTC) market where dealers intermediate investors' buy and sell orders. We take the simple view that there are three parties involved in trading corporate debt: Informed investors, uninformed investors and a dealer who makes the market. For a given bond, short interest is generated mainly by informed investors who receive a negative signal on the default risk of the bond that they decide to speculate on, or an endowment that exposes them to the bond's default risk that they want to hedge.[5] The bond is supplied to the securities lending market by buy-and-hold investors in exchange for a lending fee.

We show within the framework of our model that when inventory costs are high, the dealer requires a larger spread in investors' beliefs or, equivalently, for credit news to be worse or endowments of credit risk to be higher before facilitating informed investors' orders to sell. In this sense, higher inventory costs discourage informed investors from trading on negative credit news. When inventory costs are so high that informed investors prefer to abstain from taking short positions, less precise information is

Huh (2018) find that when the dealer is trading with their own inventory, customers pay higher spreads after the crisis than before.

[5]Short interest can also stem from the dealer who may want to borrow the bond in the securities lending market to fulfill excess buying orders, or from uninformed investor when bid prices are set sufficiently high by the dealer in response to high buying demand from informed investors.

revealed to the market and price efficiency suffers.

Second, we provide empirical evidence in support of the model's predictions. We construct bond-level proxies for dealer inventory costs and show that when the inventory costs are higher, short interest tends to be lower, even after controlling for other potential sources of short-interest variation identified by the model. Other sources of short-interest variation include supply effects and changes in lending fees, funding liquidity or investor expectations. None of these alternative sources can explain the dramatically lower short interest observed during the post-GFC period. The temporal pattern in short interest is, however, closely matched by that of dealer inventory and other proxies of inventory costs. We conduct an analysis around specific credit events when negative credit news are likely to be revealed and find that the association between high inventory costs and low short interest is more pronounced in the month leading up to rating downgrade events. We also show that the inclusion of a bond into a major exchange-traded fund (ETF) tends to mitigate any pre-existing short-sale constraints by increasing dealers' propensity to warehouse the bond.

We further document a strong association between higher dealer inventory costs and lower price efficiency in the corporate bond market, and show that this association operates mainly through the short-sale channel. While a number of studies have pointed to an association between tighter short-sale constraints and lower price efficiency in equity markets, to the best of our knowledge this issue has not yet been investigated for corporate bonds.[6] To measure price efficiency, we follow Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010) and compute the delay with which corporate bond prices respond to new market information. We find that for bonds with tighter short-sale constraints, this delay tends to be longer. This association is more pronounced at times when negative credit news are likely to be revealed. We analyze bond price changes around ETF inclusion events and find significant downward price adjustments for bonds with high pre-inclusion inventory costs relative to those with low pre-inclusion inventory costs, in line with pre-inclusion short-sale constraints being mitigated by higher dealer propensity to warehouse ETF constituents. Overall, our findings suggest that to the extent that post-GFC regulation has contributed to higher dealer inventory costs, it may have had unintended consequences for bond market quality.

[6] Work by Diamond and Verrecchia (1987), Boehmer, Jones, and Zhang (2008), Bris (2008), Charoenrook and Daouk (2009), Kolasinksi, Reed, and Thornock (2009) and Saffi and Sigurdsson (2010) supports the notion that in the equity market, short-sale restrictions are associated with lower market efficiency.

Our empirical findings are based on data from 2006 to 2017, for all U.S. corporate bonds that can be merged across the FISD, TRACE and Markit Securities Finance (MSF) securities lending databases. There are only a limited number of papers that analyze the market for borrowing corporate bonds (Nashikkar and Pedersen (2007), Asquith, Au, Covert, and Pathak (2013), Kozhan and Raman (2014), Foley-Fisher, Narajabad, and Verani (2016), Foley-Fisher, Gissler, and Verani (2016), and Anderson, Henderson, and Pearson (2018)). These papers focus on explaining borrowing costs, changes in the lending supply and the informational advantage of short sellers. In contrast, we establish a link between dealer inventory costs and price efficiency in the corporate bond market.[7]

Our work is also related to the literature on trading in OTC markets and on dealer behavior and dealer inventory costs, including Duffie, Gârleanu, and Pedersen (2005, 2007), Weill (2007), Lagos, Rocheteau, and Weill (2011), Randall (2015), Hendershott, Li, Livdan, and Schürhoff (2015), Goldstein and Hotchkiss (2019), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Dick-Nielsen and Rossi (2018), Choi and Huh (2018) and Bao, O'Hara, and Zhou (2018). Our contribution to this strand of literature is to establish a theoretical link between dealer inventory cost, short interest and price efficiency, and to provide empirical support for the notion that high inventory costs may have a negative impact on market quality by imposing indirect constraints on short selling, and thus on information revelation.

The remainder of the paper is organized as follows. Section 2 proposes a model of corporate bond trading. It suggests that dealer inventory is one of the main drivers of short interest in corporate debt. Section 3 describes the data and provides descriptive statistics. Section 4 introduces different bond-level proxies for dealer inventory costs. Section 5 shows empirically that higher dealer inventory costs are associated with lower short interest. Section 6 shows empirically that higher inventory costs are associated with lower price efficiency, by dampening short interest. Section 7 summarizes our findings and concludes.

[7] Aggarwal, Bai, and Laeven (2015) study the government bond lending market. The literature on borrowing equity is much more extensive. Studies include Kot (2007), Aggarwal, Saffi, and Sturgess (2015), Blocher and Whaley (2014), Boehmer, Duong, and Huszár (2016), Boehmer, Huszar, Wang, and Zhang (2015), Chen and Zhang (2015), Choi and Huszar (2016), Chuprinin and Ruf (2016), Geraci, Garbaravicius, and David (2016), Huszar, Tan, and Zhang (2014), Karmaziene and Sokolovski (2014), Li and Zhu (2016), Liu, McGuire, and Swanson (2013), Muravyev, Pearson, and Pollet (2016), Patatoukas, Richard Sloan, and Wang (2016), Richardson, Saffi, and Sigurdsson (2014), Beneish, Lee, and Nichols (2015), Engelberg, Reed, and Ringgenberg (2016), Drechsler and Drechsler (2016), Saffi and Sigurdsson (2011), Kolasinski, Reed, and Ringgenberg (2013), Duong, Huszár, and Yamada (2015), and Félix, Kräussl, and Stork (2016), among others. Baklanova and Copeland (2015) offer a general overview over the U.S. repo and securities lending markets, and Baklanova, Caglio, Keane, and Porter (2016) report aggregate statistics on securities lending activity.

2. A Model of Corporate Bond Trading

We establish a theoretical link between dealer inventory costs and price efficiency in the secondary corporate bond market. To do so, we consider a firm who issues a one-period zero-coupon bond with face value F. The primary market, which opens and closes prior to time $t = 0$, is not modeled. We simply assume that it results in a dealer holding $I_0 \geq 0$ units of the bond,[8] with primary market investors holding the remaining $F - I_0$ units. Primary market investors are buy-and-hold (BH) investors who hold the bond until it matures at time $t = 1$.

The secondary market opens at $t = 0$. In addition to the dealer, there are two types of investors involved in trading the bond in the secondary market: Informed investors and uninformed investors.[9] We refer to informed and uninformed investors as I and U investors, respectively. Both types of investors have a one-period investment horizon and facilitate their trades through the dealer. Investors who decide to go long buy the bond from the dealer at $t = 0$ and sell it back to the dealer at $t = 1$. Those who go short borrow the bond in the securities lending market and sell it to the dealer at $t = 0$, before buying the bond back from the dealer at $t = 1$ to close out their short position. There is a mass of N_I identical I investors and N_U identical U investors.

The supply in the securities lending market stems from BH investors who make their holdings available for lending purposes. Lenders charge a proportional net lending fee which is a function of supply and demand in the securities lending market. The fee may differ for investors and the dealer. Borrowers in the securities lending market have to support their short positions with initial and variation margins, and we denote by l any potential costs for short-sellers of accessing funding liquidity.

At the maturity date $t = 1$ of the bond, the firm will either repay its debt in full or declare bankruptcy and pay a recovery value R, as a fraction of notional, to its creditors. To keep things

[8]In this single-dealer set-up, we think of the dealer as being affiliated with the underwriter of the bond issue. Such affiliation may carry contractual obligations to the issuer, such as liquidity provision or price stabilization (Auh, Kim, and Landoni (2018)). Moreover, many corporate bond originations are "firm commitments," or "bought deals," in which the underwriter and affiliated dealer commit to the entire issue and may be left with bonds not sold in the primary market (Manconi, Neretina, and Renneboog (2018), Brealey, Myers, Allen, and Mohanty (2012)). As a result, the underwriter and affiliated dealer may initially hold a positive inventory of the bond. Goldstein and Hotchkiss (2012) and Auh, Kim, and Landoni (2018) refute the notion of positive initial dealer inventory as the result of self-interested trading strategies. In line with this evidence, we treat the initial inventory as exogenous.

[9]Additional agents, such as lending agents and lending brokers, may play a role in facilitating lending and borrowing transactions in the securities lending market. Their actions are subsumed into those of corporate bond lenders and borrowers.

simple, we assume that the firm has no other liabilities due prior to or at maturity of the bond, so that default will not be triggered unless the firm fails to pay the bond's creditors in full at $t = 1$. As a result, one unit notional of the bond has the time-1 payoff $\widetilde{V} = 1_{\{\tau>1\}} + R\,1_{\{\tau=1\}}$, where τ denotes the time of default. Investors can also trade a risk-free asset which is in zero net supply. The risk-free asset serves as the numeraire and we normalize the risk-free rate to zero.

Just before the secondary market opens, at time $t = 0-$, I investors observe a private signal $\pi_I \in (0, 1)$ about the bond's likelihood of default. The log odds ratio of signal π_I, $Y_I = Y(\pi_I)$, is defined via

$$Y(\pi) \quad = \quad \log\left(\frac{\pi}{1-\pi}\right). \tag{1}$$

We assume that Y_I has a normal distribution with mean μ_y and variance σ_y^2. A high value of Y_I reveals to I investors that the firm is risky, whereas a low Y_I indicates that the bond issuer is financially healthy.

To prevent informed investors' private information from being fully revealed in equilibrium, we follow Wang (1997), O'Hara (1997), Vayanos and Wang (2012) and Liu and Wang (2016), among others, and assume that the informed also have a non-information-based trading demand. Specifically, we assume that I investors are subject to a liquidity shock at $t = 0-$ that is modeled as a random endowment of X_I units of a non-tradable synthetic default insurance contract with per-unit payoff $\widetilde{K} = (1 - \mathrm{R})\,1_{\{\tau=1\}}$ at $t = 1$. The distribution of X_I is normal with mean zero and variance σ_x^2. U investors do not receive an endowment, that is, $X_U = 0$.

At time $t = 0$, given the private signals X_I and Y_I, I investors decide whether or not to contact the dealer with a request to quote (RtQ). I investors make a RtQ only if they anticipate positive benefits from trade. We use $D_{RtQ} = D_{RtQ}(X_I, Y_I)$ to denote the indicator function that equals one if the informed request a quote and zero otherwise. The dealer observes D_{RtQ} and then presents the informed and uninformed with a price quote (A, B), where A is the unit ask price at which the dealer is willing to sell and B is the unit bid price at which the dealer is willing to buy. Potential short sellers contact lenders and request a fee quote. Lenders provide a fee quote that reflects their relative bargaining power and bond lending arrangements are made. Afterwards, investors execute their bond trades through the dealer.

When deciding on what prices to post, the dealer takes into account the best response functions, i.e., the fee schedule of the lenders and the demand schedules of the investors. Given quotation (A, B) and lending fee f, investors set their demand $Q_i(A, B, f)$ according to the schedule $Q_i(A, B, f) = Q_i(A, B, f \big| \mathcal{I}_i)$, where $\mathcal{I}_i$ denotes the information available to type-i agents at time $t = 0$. If $D_{RtQ} = 0$, the dealer does not transact with the informed and $Q_I(A, B, f) = 0$ for all A, B and f.

Although the dealer and uninformed cannot directly observe the private default signal π_I, at time $t = 0$ they update their beliefs about the riskiness of the bond to $\pi_i = E\left(\pi_I \big| \mathcal{I}_i\right)$, for $i \in \{D, U\}$. We set $Y_i = Y(\pi_i)$ equal to the log odds ratio of π_i, as per (1).

We assume that each type of investor i, $i \in \{I, U\}$, chooses their demand schedule to maximize their expected constant absolute risk aversion (CARA) utility,

$$\max E\left(-e^{-\delta \widetilde{W}_i} \big| \mathcal{I}_i\right), \tag{2}$$

where $\delta > 0$ is the absolute risk aversion parameter common to all agents and W_i is investor i's wealth at $t = 1$. With $Q^+ = \max(0, Q)$ and $Q^- = \max(0, -Q)$, for a given ask price A, bid price B and lending fee f,

$$\widetilde{W}_i(V) \quad = \quad Q_i(A, B, f)^-(B - f - l) - Q_i(A, B, f)^+ A + Q_i(A, B, f)\widetilde{V} + X_i \widetilde{K}. \tag{3}$$

We denote the total amount of bonds bought and sold by type-i investors by

$$\alpha_i = N_i Q_i(A, B, f)^+ \qquad \text{and} \qquad \beta_i = N_i Q_i(A, B, f)^-. \tag{4}$$

The market ask depth is computed as $\alpha = \alpha_I + \alpha_U$ and the market bid depth is $\beta = \beta_I + \beta_U$. The dealer absorbs deviations between α and β using her own inventory. The adjusted net inventory that the dealer holds between $t = 0$ and $t = 1$ is given by $\text{Inv} = I_0 + \beta - \alpha$. The dealer may derive extra rents k from their net long inventory of corporate bonds, by engaging in repo agreements or bond exchange traded funds (ETFs).

The dealer's ask depth $\alpha_D = (\beta - \alpha)^+$ measures the number of bonds bought by the dealer, and the dealer's bid depth $\beta_D = \text{Inv}^-$ measures the number of bonds borrowed by the dealer in the securities lending market. The short interest SI is defined as the total amount of bonds borrowed, $\mathrm{SI} = \beta + \beta_D$. It is supplied by BH investors who lend out their bond inventory. As a result, SI cannot exceed the total lendable amount of bonds $F - I_0$.

For any realized short interest schedules $\beta(f)$ and $\beta_D(f)$, lender net profits are $(f_R - \underline{f})\beta + (f_W - \underline{f})\beta_D$. Here, $\underline{f} \geq 0$ is the fixed cost associated with lending one unit of the bond, f_R is the retail lending fee charged to investors and f_W is the wholesale lending fee charged to the dealer. We take the simple view that the dealer has significant market power in the lending market, to the extent that she can borrow bonds at cost, that is, at $f_W = \underline{f}$. This implies that lender net profits are $(f_R - \underline{f})\beta$. Let $\overline{f}$ denote the fee that maximizes lender profits, i.e., $\overline{f} = \arg\max_f \{(f - \underline{f})\beta(f)\}$.[10] We assume that the bargaining process between lenders and investors results in the retail lending fee being set equal to the smallest fee f such that

$$(f - \underline{f})\beta(f) \quad = \quad \rho\,(\overline{f} - \underline{f})\beta(\overline{f}). \tag{5}$$

Here, $\rho \in [0, 1]$ denotes the bargaining power of lenders relative to non-dealer short sellers. The scenario $\rho = 0$ reflects a situation where all lending market power is held by investors, and $\rho = 1$ is consistent with all market power being held by lenders. Going forward we drop the subscript R and use f to denote the retail fee, keeping in mind that the wholesale fee is equal to $\underline{f}$.

The dealer can use the initial inventory I_0 to fulfill investors' demand for the bond, but incurs a proportional cost c_β when short selling bonds or c_α when increasing the inventory above its initial level. Thus, total dealer inventory costs are computed as $\alpha_D c_\alpha + \beta_D c_\beta$. Our goal is to understand how the costs c_α and c_β impact equilibrium trading outcomes. We impose $c_\alpha - k \geq 0$ so that the net cost of holding an additional unit of the bond is nonnegative. We further impose $\underline{f} + l - k > 0$, to ensure that even in the absence of inventory costs fees associated with shorting bonds are not outweighed by the extra rents that the dealer can derive from additional inventory.

For any realized fee schedule $f(A, B)$ and demand schedules $Q_I(A, B, f)$ and $Q_U(A, B, f)$, the dealer's problem is to choose an ask price A and bid price B, with $B \leq A$,[11] to maximize their CARA

[10] If there are multiple fee values that maximize lender profits, lenders choose the smallest fee among them.
[11] This condition rules out scenarios where investors can make a certain profit from buying at A and selling at B.

utility,

$$\max E\left(-e^{-\delta W_D(\widetilde{V})}\right), \tag{6}$$

where

$$\begin{aligned} W_D(V) \quad = \quad & \alpha(A,B)A - \beta(A,B)B + \mathrm{Inv}(A,B)V + \mathrm{Inv}(A,B)^{+}k - \mathrm{Inv}(A,B)^{-}(\underline{f}+l) \\ & -\alpha_D(A,B)c_\alpha - \beta_D(A,B)c_\beta. \end{aligned} \tag{7}$$

The dealer's terminal wealth in Equation (7) consists of the revenues from selling α bonds at the ask, buying β bonds at the bid, earning V on the adjusted net inventory, earning rents k from using excess inventory as collateral in the repo market, paying wholesale lending fees $\underline{f}$ and funding liquidity costs l for short positions, and paying inventory costs on dealer trades. We assume the dealer is benevolent in that she chooses the highest bid and lowest ask among prices she is indifferent about.

Generalizing Liu and Wang (2016), we consider Baysian Nash equilibria defined as follows:

Definition 1 *An equilibrium $(Q_I^*(A,B,f), Q_U^*(A,B,f), f^*(A,B), A^*, B^*)$ is such that, given any signals X_I and Y_I, the following holds:*

1. *Given any A, B and f, the demand schedule $Q_i^*(A,B,f)$ solves type-i investors' problem (2), for $i \in \{I, U\}$. The information set of the informed is $\mathcal{I}_I = \{X_I, Y_I, A, B, f\}$, and the information set of the uninformed is $\mathcal{I}_U = \{A, B, f\}$.*

2. *Given the short-interest schedules $\beta^*(f)$ and $\beta_D^*(f)$, the wholesale lending fee is set to $\underline{f}$ and the retail fee f^* is set according to (5). The information set of lenders is $\mathcal{I}_L = \{\beta^*(f),\ \beta_D^*(f)\}$.*

3. *Given the demand schedules $Q_I^*(A,B,f)$ and $Q_U^*(A,B,f)$ and fee schedule $f^*(A,B)$, the quotation (A^*, B^*) solves the dealer's problem (6), where the dealer's information set is $\mathcal{I}_D = \{D_{RtQ}(X_I, Y_I),\ Q_I^*(A,B,f), Q_U^*(A,B,f), f^*(A,B)\}$.*

4. *For every realization of X_I and Y_I, the beliefs of all agents are consistent with the joint conditional probability distribution in equilibrium.*

2.1 Equilibrium

We now present investors' optimal demand schedule and lenders' optimal fee schedule, and describe how equilibrium outcomes depend on the inventory cost c.

Proposition 1 (Demand schedule)

(a) Given $D_{RtQ} = 1$, for each quotation (A, B, f) with $R + f + l < B \leq A < 1$, the optimal demand schedule for an informed investor is

$$Q_i^*(A, B, f) = \begin{cases} Z_i + g(A), & A < P_i^R, \\ 0, & B - f - l \leq P_i^R \leq A, \\ Z_i + g(B - f - l), & B - f - l > P_i^R, \end{cases} \tag{8}$$

where $i = I$, $\gamma = 1/[\delta(1-R)]$, $g(P) = \gamma\left[\log(1-P) - \log(P-R)\right]$ for $P \in (R, 1)$, and

$$Z_i \quad = \quad X_i - \gamma Y_i \tag{9}$$

is a composite signal of X_i and Y_i. $P_i^R = P^R(Z_i)$ defined via

$$P^R(Z) \quad = \quad \frac{1 + Re^{-Z/\gamma}}{1 + e^{-Z/\gamma}} \tag{10}$$

is investor i's reservation price, i.e., the price at which the investor is indifferent between trading and not trading the bond. Given $D_{RtQ} = 0$, $Q_I^*(A, B) = 0$ for each quotation (A, B, f).

(b) Given quotation (A, B, f) with $R + f + l < B \leq A < 1$ and $\pi_U = E(\pi_I|\mathcal{I}_U) \in (0, 1)$, the optimal demand schedule for an uninformed investor is given by (8) through (10), with $i = U$. Note that $X_U = 0$ and thus $Z_U = -\gamma Y_U = -\gamma \log(\pi_U/(1-\pi_U))$.

Proofs are available in Appendix B.

Private signals X_I and Y_I both affect informed investors' demand Q_I^*. For $D_{RtQ} = 1$, Proposition 1 shows that the joint impact of X_I and Y_I on Q_I^* is only through the combined signal Z_I. To simplify exposition and focus on the main forces driving our results, we restrict to equilibria where the RtQ decision itself is a function only of Z_I. Specifically, we assume that

$$D_{RtQ} = \begin{cases} 0, & Z_I \in [\underline{z}, \overline{z}] \\ 1, & Z_I \notin [\underline{z}, \overline{z}]. \end{cases} \tag{11}$$

for some $\underline{z} \leq \overline{z}$. As a result, X_I and Y_I affect I investor demand, and thus equilibrium outcomes, only though Z_I. We further restrict to equilibria where the dealer sets bid and ask prices as monotonic increasing functions of Z_I that are strictly increasing across $Z_I \notin [\underline{z}, \overline{z}]$. As a result, the dealer and uninformed investors share the same information in equilibrium: $\mathcal{I}_D = \mathcal{I}_U = \{Z_I\}$ if $D_{RtQ} = 1$ and $\mathcal{I}_D = \mathcal{I}_U = \{Z_I \in [\underline{z}, \overline{z}]\}$ if $D_{RtQ} = 0$.

When $\mathcal{I}_D = \mathcal{I}_U = \{Z_I\}$, the equilibrium beliefs of the dealer and uninformed about the riskiness of the bond are $\pi_D = \pi_U = \pi(Z_I)$, where

$$\pi(z) \quad = \quad E(\pi_I | Z_I = z) = E\left(\frac{e^{Y_I}}{1 + e^{Y_I}}\middle| Z_I = z\right) = E\left(\frac{1}{1 + e^{\frac{z}{\gamma}\kappa^2 + \xi}}\right). \tag{12}$$

Here, ξ is a normally distributed random variable with mean $-\mu_y(1-\kappa^2)$ and variance $\sigma_y^2(1-\kappa^2)$, with $\kappa = \gamma\sigma_y / \sqrt{\gamma^2\sigma_y^2 + \sigma_x^2}$.[12] Note that $\pi(z)$ is a strictly decreasing function of z, meaning the larger the combined signal Z_I, the lower the inferred default probability. With $Y(z) = \log(\pi(z)/(1 - \pi(z))$ and $Z(z) = -\gamma Y(z)$, it follows that $Z(z)$ satisfies

$$E\left(\frac{1}{1 + e^{\frac{z}{\gamma}\kappa^2 + \xi}}\right) \quad = \quad \frac{1}{1 + e^{\frac{Z(z)}{\gamma}}}. \tag{13}$$

Lemma B.1 in the appendix shows that for $Z(z)$ defined via (13) there exists a unique $\widehat{z}$ such that $Z(\widehat{z}) = \widehat{z}$, $Z(z) < z$ for $z > \widehat{z}$ and $Z(z) > z$ for $z < \widehat{z}$. Since investors' reservation values defined in (10) are strictly increasing in Z, this implies that uninformed investors adjust their reservation value in the same direction as informed investors, but by a smaller magnitude: $P_U^R = P_I^R$ for $Z_I = \widehat{z}$, $P_U^R \in [P^R(\widehat{z}), P_I^R)$ for $Z_I > \widehat{z}$ and $P_U^R \in (P_I^R, P^R(\widehat{z})]$ for $Z_I < \widehat{z}$. Lemma B.3 shows that $\widehat{z} \in [\underline{z}, \overline{z}]$.

[12] Since Y_I and Z_I are jointly normal, conditional on $Z_I = z$, Y_I has a normal distribution with mean $\mu_y(1-\kappa^2) - \frac{z}{\gamma}\kappa^2$ and variance $\sigma_y^2(1-\kappa^2)$. See, for example, Theorem 2.5.1 in Anderson (1984).

When $\mathcal{I}_D = \mathcal{I}_U = \{Z_I \in [\underline{z}, \overline{z}]\}$, the dealer and uninformed update their beliefs to π_{noRtQ}, where

$$\pi_{noRtQ} \quad = \quad E(\pi_I | Z_I \in [\underline{z}, \overline{z}]) = \frac{1}{\text{Prob}(Z_I \in [\underline{z}, \overline{z}])} \int_{\underline{z}}^{\overline{z}} \pi(z)\, d\text{Prob}(Z_I = z). \tag{14}$$

Recall that Z_I is normally distributed with mean $\mu_z = -\gamma\mu_y$ and variance $\sigma_z^2 = \sigma_x^2 + \gamma^2\sigma_y^2$. The left plot in Figure 1 shows the dealer's and U investors' updated beliefs as a function of Z_I. The solid blue line is discontinuous at $Z_I = \underline{z}$ and $Z_I = \overline{z}$. For $Z_I \in [\underline{z}, \overline{z}]$, the uninformed replace π_U estimated based on Z_I with a weighted average across $Z_I \in [\underline{z}, \overline{z}]$. This leads to mis-pricing of the bond relative to the benchmark case where the combined signal Z_I is publicly observed, as shown in the right plot of the figure.

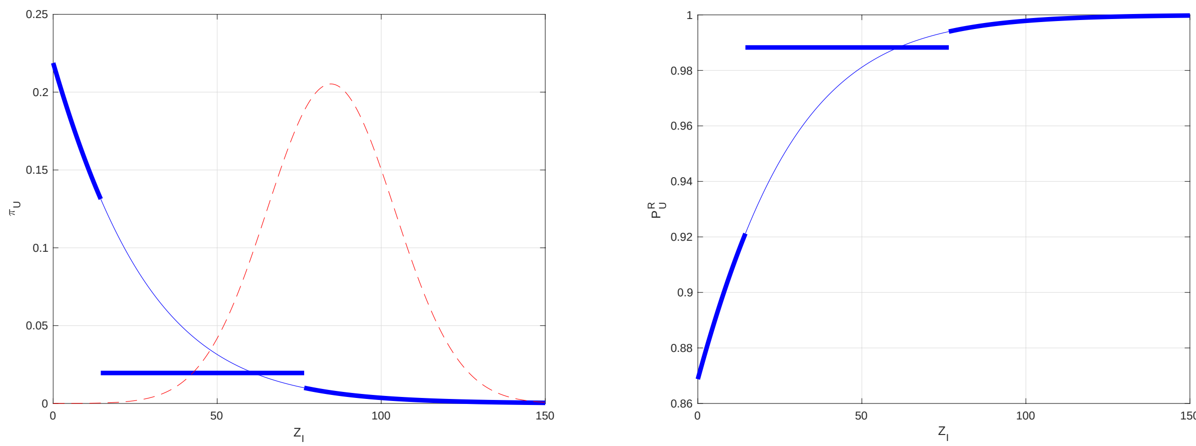

Figure 1: **U investors' updated beliefs** In the left plot, the solid blue line shows U investors' updated beliefs $\pi_D = \pi_U$ in (12), as a function of Z_I. The inventory cost is fixed at $c = 0.05$. The remaining model parameters are set to $\delta = 0.1$, $R = 0.4$, $I_0 = 100$, $N_I = N_U = 10$, $\pi_0 = 0.01$, $\sigma_y = 1$ and $\sigma_x = 10$. The parameter $\mu_y = -5.0789$ is chosen so that $E\left[1/(1+e^{-y})\right] = \pi_0$. We have $\underline{z} = 14.51$ and $\overline{z} = 76.51$. The dashed red line depicts the probability density function of Z_I, multiplied by a factor of 10. The right panel shows the associated reservation value of U investors.

Next, we derive the lenders' optimal retail fee schedule.

Proposition 2 (Fee schedule) *Given the short-interest schedules $\beta(f)$, the maximum retail lending fee $\overline{f}$ satisfies*

$$\overline{f} \quad = \quad \underline{f} + (1-R)\frac{\beta}{\gamma N_i}\frac{e^{-(\frac{\beta}{N_i}+Z_i)/\gamma}}{\left(1+e^{-(\frac{\beta}{N_i}+Z_i)/\gamma}\right)^2}, \quad \beta = -N_i\left[Z_i + g(B - \overline{f} - l)\right],$$

where $i = I$ for $Z_I < \widehat{z}$, $i = U$ for $Z_U > \widehat{z}$ and $\beta = 0$ for $Z_I \in [\underline{z}, \overline{z}]$. Non-monopolist lenders set the retail lending fees as in (5), with $\overline{f}$ as above. Wholesale lending fees are equal to $\underline{f}$.

Given the optimal demand and fee schedules, we can derive the equilibrium price schedule.

Proposition 3 (Price schedule) *Suppose $\mathcal{I}_D = \mathcal{I}_U = \{Z_I = z\}$ for some $z \notin [\underline{z}, \overline{z}]$. Then the equilibrium prices satisfy*

$$I_0 + \beta - \alpha \quad = \quad g(A + \alpha A' + h) + Z(z) = g(B + \beta B' + h) + Z(z). \tag{15}$$

Here, $A' = \partial A/\partial\alpha$, $B' = \partial B/\partial\beta$, $H = \mathrm{Inv}(A,B)^{+}k - \mathrm{Inv}(A,B)^{-}(f(A,B) + l) - \alpha_D(A,B)c_\alpha - \beta_D(A,B)c_\beta$ and $h = \partial H/\partial\alpha = -\partial H(A,B)/\partial\beta$. For $\mathcal{I}_D = \mathcal{I}_U = \{Z_I \in [\underline{z}, \overline{z}]\}$, no trades tale place.

Proposition 3 states that the dealer sets equilibrium bid and ask prices so that her inventory is equal to the amount an equivalent zero-inventory dealer would optimally buy at a unit price equal to the cost of selling one unit less of the bond plus net costs.

Finally, we formulate trading outcomes in relation to the inventory cost c.

Proposition 4 (Price efficiency) *The lower boundary $\underline{z}$ of the non-RtQ set is a decreasing function of c_α, whereas the upper boundary $\overline{z}$ does not depend on inventory costs as long as initial dealer inventory is non-zero. For zero initial dealer inventory, $\overline{z}$ is an increasing function of c_β. As a result, as inventory costs increase, the range of signals for which informed investors do not request a quote widens to the left. For $I_0 = 0$, the range of no-RtQ signals also widens to the right.*

Proposition 4 states that as inventory costs increase, the credit news have to be worse or endowments of credit risk have to be higher for the informed to take a short position. In that sense, higher inventory costs impose indirect short sale constraints. To illustrate this prediction of the model, Figure 2 shows how the no-RtQ set widens as inventory costs increase.

2.2 Testable hypotheses

Our proposed model framework suggests that higher dealer inventory costs impose implicit short-sale constraints on informed investors.

Hypothesis 1 *Higher dealer inventory costs are associated with lower short interest.*

When inventory costs are so high that I investors refrain from taking a short position, the market receives less precise information about the riskiness of the firm. As a result, market quality suffers.

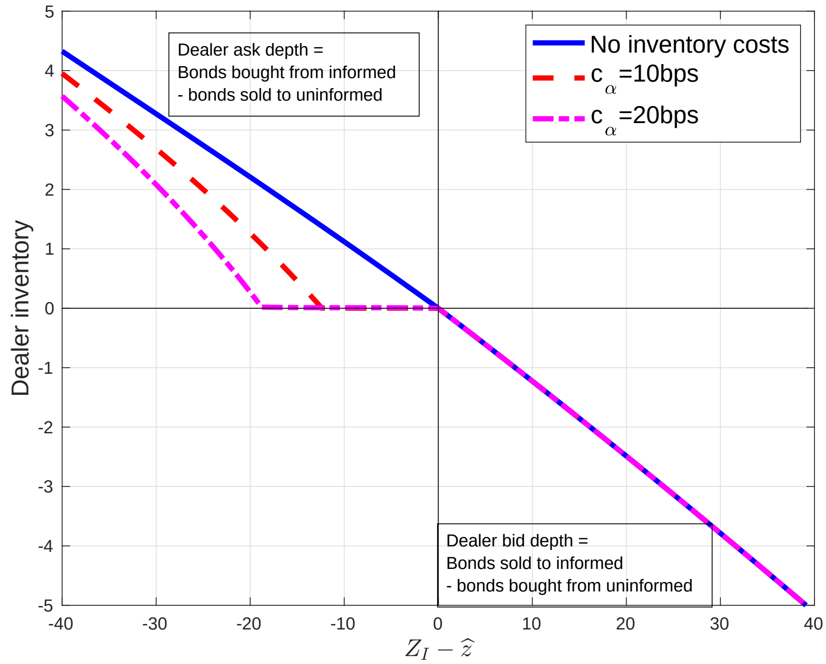

Figure 2: **Dealer inventory** The figure shows the dealer ask depth and bid depth as a function of the combined signal Z_I, for various inventory costs c_α. The remaining model parameters are set to $\delta = 0.1$, $R = 0.4$, $I_0 = 100$, $N_I = N_U = 10$, $\pi_0 = 0.01$, $\sigma_y = 1$ and $\sigma_x = 10$. The parameter $\mu_y = -5.0789$ is chosen so that $E\left[1/(1+e^{-y})\right] = \pi_0$. We set c_β to zero, so the upper boundary equals $\widehat{z}$, meaning $\overline{z} = \widehat{z} = 76.51$.

Hypothesis 2 *Higher dealer inventory costs are associated with lower price efficiency.*

Empirical evidence in support of these hypotheses is provided in Sections 5 and 6.

When testing these hypotheses empirically, we face the challenge that dealer inventory costs are not directly observable. We therefore construct observable proxies for these costs. For example, Figure 2 shows a strong negative link between inventory costs and inventory levels. In addition to inventory levels, we use trade size, the fraction of paired trades, the fraction of block trades and dealer capital commitment measures as proxies for inventory costs.

3. Data and Descriptive Statistics

This section describes the bond market and securities lending data used in our study.

3.1 Securities lending data

Corporate bond lending data are provided by Markit Financial Securities (MSF), which covers more than 90 percent of the U.S. securities lending market (see Foley-Fisher, Narajabad, and Verani

(2016)). The data include daily bond-level identifiers and transaction information, from September 11, 2006 to June 30, 2017. The bond-level data include the value and quantity of the bond available for lending and the value and quantity of the bond on loan. The on-loan values and quantities are reported both including and excluding financing transactions. We focus on the on-loan variables that exclude financing transactions as they offer a cleaner representation of the borrowing demand from investors and dealers.[13] The data further include the on-loan ratio—also known as utilization—which is defined as bonds on loan divided by bonds available for lending, and indicative lending fees.

The indicative fee is Markit's estimate of the borrowing cost. In Markit (2013) it is described as "The expected borrow cost, in fee terms, for a hedge fund on a given day. ... The calculation uses both borrow costs between Agent Lenders and Prime Brokers as well as rates from hedge funds to produce an indication of the current market rate." While not the focus of our study, we interpret these fees as indications of the fees an investor will be charged on a given day for a new loan.

We clean the MSF corporate bond data as follows. First, we exclude daily observations with missing CUSIP or duplicate CUSIP, as well as observations where the value on loan is greater than the inventory. Second, we exclude observations where the computed utilization deviates from the reported utilization by more than than one percent. Third, in cases where MSF reports a positive lendable value and a zero utilization but a missing value in value on loan, we set the value on loan equal to zero. Finally, we repeat the same data collection and cleaning steps for associated equity lending.

3.2 Corporate bond origination data

We obtain origination data for corporate bonds from Mergent's Fixed Income Securities Database (FISD). The FISD contains detailed bond-level information, including the offering amount or size of the bond issue, offering date, maturity date, coupon rate, bond rating, whether the bond is fixed or floating rate, and whether it is issued under U.S. Securities and Exchange Commission (SEC) Rule 144a.[14] We also obtain bond covenants data and categorize them into four groups as in Chava, Kumar,

[13] Anderson, Henderson, and Pearson (2018) point out that a considerable amount of corporate bond loans may represent financing transactions since the associated realized lending fees are negative. We therefore focus on the variable "ShortLoanValue" which reports the on-loan value of a bond after removing financing trades, instead of the variable "ValueOnLoan" which may include financing trades. Our main conclusions, however, are robust to either choice of the on-loan variable.

[14] SEC Rule 144a modifies a two-year holding period requirement on privately placed securities to permit qualified institutional buyers to trade these positions among themselves.

and Warga (2009).[15]

We only retain U.S. dollar-denominated bonds issued by U.S.-domiciled firms. Following Asquith, Au, Covert, and Pathak (2013), we exclude all convertibles, exchangeables, perpetual bonds, unit deals, and bonds with "Equity" in their description. Observations with missing or negative offering amount are also excluded. We apply a rating filter by only keeping bonds with Standard & Poor letter rating of "C" or higher.

3.3 Corporate bond transaction and return data

We obtain corporate bond transaction data from the enhanced Trade Reporting and Compliance Engine (TRACE) database.[16] TRACE data include prices, volumes, trade direction, and the exact date and time of the trade. We follow Dick-Nielsen, Feldhütter, and Lando (2012) and Dick-Nielsen (2014) to clean the data, using the SAS code provided in Dick-Nielsen (2014). We remove all agency transactions and inter-dealer transactions from the sample. We also exclude trades associated with prices of less than \$50 or more than \$200, and with trade sizes of less than \$1,000 or more than \$100 million.

We obtain monthly bond return data from WRDS. These return data are available until June 2016. We extend the return data past that date by following the return computations described in the TRACE manual available via WRDS.

3.4 Other control variables

We identify all bond-date pairs for which Markit reports a valid five-year CDS rate with modified restructuring for senior-unsecured debt of the issuing firm. We consider Markit CDS rates as valid quotes if the quote-quality indicator is BB or higher and if a recovery rate estimate is available. If a quote-quality rating is not available, we require a composite level of "CcyGrp," "DocAd" or "Entity Tier." If on a given date, a firm has a valid Markit CDS quote, then we assume that CDS could be traded for that firm on that date.

We download aggregate primary dealer inventory of corporate debt from the New York Fed's website, identify ETF constituents using Black Rock's monthly holding statements, and obtain expert

[15] The four types of covenants include (i) investment restrictions, (ii) dividend restrictions, (iii) subsequent financing restrictions, and (iv) event-related restrictions. A bond is considered to have a certain type of covenant if the bond indenture includes one or more of the corresponding restrictions.

[16] Enhanced TRACE data are available until June 2017 only, which restricts our sample period to end on that date.

Federal Funds rate forecasts from Blue Chip Financial Forecasts.

3.5 Sample construction and descriptive statistics

We merge across the cleaned data sets using nine-digit CUSIPs. We exclude those observations where the lendable value is greater than the bond size. Table 1 reports the number and par value of bonds in the FISD data and in the merged FISD-MSF data. The top panel shows that between 2006 to 2017, the average number of bonds in the merged data is about 8,380. For an average day, this represents 24.5% of all corporate bonds in the FISD data. The relationship between the number of bonds in the FISD data and in the merged FISD-MSF data is fairly stable over time, and in line with the values report by Asquith, Au, Covert, and Pathak (2013) for 2004 to 2007. On an average day, about 4,880 bonds, or 58% of bonds in the FISD-MSF data, are on loan. There is a slight upward trend in the fraction of bonds on loan during our sample period.

Table 1: **Descriptive statistics for FISD and MSF data** In the top panel, the first two rows show the number of bond CUSIPs in the FISD data and in the merged FISD-MSF data, respectively. The third row reports the number of bond CUSIPs in the merged data that are on loan, with financing trades removed. The first row in the bottom panel shows the daily average of total size at issuance of the bonds in the FISD data, and the second row shows the same statistic for the merged FISD-MSF data. The third and forth rows report the daily average of the total lendable value and of the total on-loan value for bonds in the merged data, respectively.

	All	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
	Daily average number of bonds (thousands)												
FISD	34.2	35.7	36.3	35.7	33.4	32.3	31.9	31.8	32.7	33.6	35.0	36.3	37.9
FISD-MSF	8.38	8.43	8.51	8.11	7.82	8.04	8.29	7.83	7.99	8.72	9.10	9.03	8.85
FISD-MSF, On loan	4.88	3.19	3.61	3.72	3.92	4.43	4.76	5.04	5.35	5.72	6.09	6.22	6.25
	Daily average values (trillion dollars)												
FISD	6.92	5.61	5.88	6.04	6.11	6.28	6.51	6.68	7.10	7.48	7.95	8.45	8.86
FISD-MSF	4.35	3.00	3.18	3.38	3.71	4.01	4.31	4.16	4.43	4.89	5.35	5.66	5.73
FISD-MSF, Supply	0.95	0.82	0.95	0.97	0.84	0.90	0.92	0.88	0.89	0.99	1.03	1.07	1.09
FISD-MSF, On loan	0.05	0.05	0.06	0.04	0.04	0.05	0.05	0.04	0.04	0.05	0.05	0.05	0.05

The bottom panel of Table 1 reports similar statistics using the par value of the bonds. The daily average par value of bonds outstanding is \$6.92 trillion in the FISD data and \$4.35 trillion in the merged FISD-MSF data. The daily average par value of lenders' bond inventory in the merged data is \$0.95 trillion, or 14% of the total par value of bonds issued and listed in FISD. Of this lender inventory, an average \$50 billion, or 5% of the total par value of the lenders' inventory, is on loan. The on-loan percentage is fairly stable over time, suggesting that although investors borrow a larger number of bonds over time, the average size of loans outstanding for each bond is decreasing.

Asquith, Au, Covert, and Pathak (2013) estimate that their proprietary dataset includes close to 20% of all corporate bond loan transactions. Since MSF covers over 90% of the corporate bond lending market, we expect that the daily aggregate value of loans available for lending and of the on-loan value are about four to five times those reported in Asquith, Au, Covert, and Pathak (2013). This is indeed the case. In 2007, for example, the lendable value of bonds in our merged FISD-MSF data is about \$950 billion, compared to \$197 billion in Asquith, Au, Covert, and Pathak (2013). In addition, the average value on loan is about \$60 billion in our sample in 2007, compared to \$14 billion in their data.

At over 90% coverage, our sample is representative of the entire corporate bond lending market. Tables C.1 and C.2 in Appendix C report on the characteristics of the bonds in the merged FISD-MSF data.

The left plot in Figure 3 shows the time series of the aggregate level of bonds on loan, across all loans in our sample. We display both the par value and the quantity of bonds. The aggregate value on loan peaked in mid-2007 and dropped dramatically—by nearly 50%—during the second half of 2008. It recovered about half of this drop in the post-GFC period. The aggregate quantity of loans tracks the temporal pattern of the aggregate value on loan.

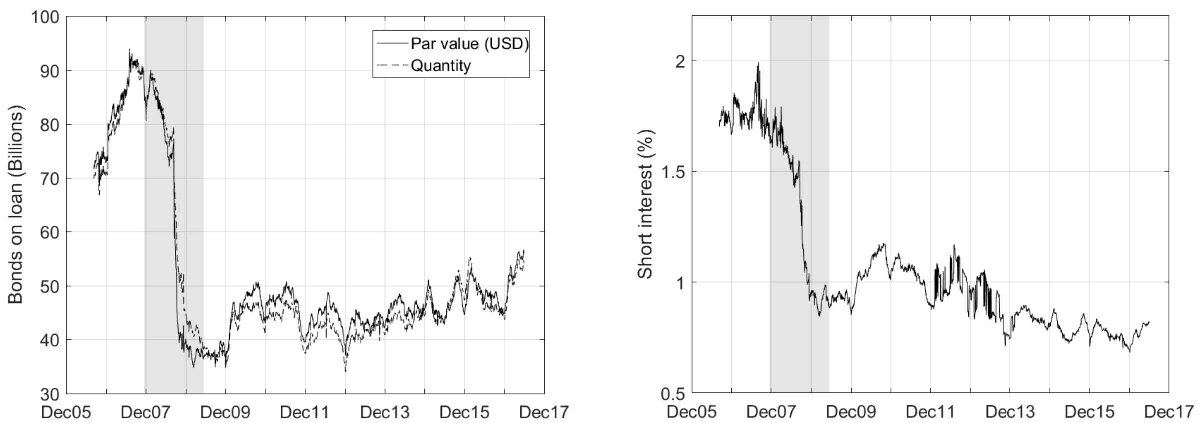

Figure 3: **Demand and short interest in the corporate bond borrowing market** The left plot shows the daily time series of aggregate par value and quantity of bonds on loan. The right plot shows the daily time series of average short interest. Short interest is computed as value on loan divided by bond size. The data include all bonds available for lending in the merged FISD-MSF data that have credit rating information, from September 2016 to June 2017.

The right plot displays the time series of average short interest. Average short interest peaked at around 2% prior to the GFC, dropped to below 1% during the crisis, and remained at or below 1% in the post-GFC period. Figure C.1 in the appendix confirms that the temporal pattern of bond utilization is shown tracks that of short interest, meaning the decline in short interest is not simply due to a decrease in lending supply.

4. Dealer Inventory Cost Proxies

Our model in Section 2 predicts that, all else the same, higher inventory costs are associated with lower short interest. In this section, we describe alternative proxies of dealer inventory costs and visually inspect their co-movement with short interest.

4.1 Aggregate proxy

Our model in Section 2 predicts that higher inventory costs are associated with lower dealer inventory. Figure 4 shows the time series of the corporate bond inventory of primary dealers, as disseminated by the New York Fed. We find a strong time-series association between dealer inventory and short interest.

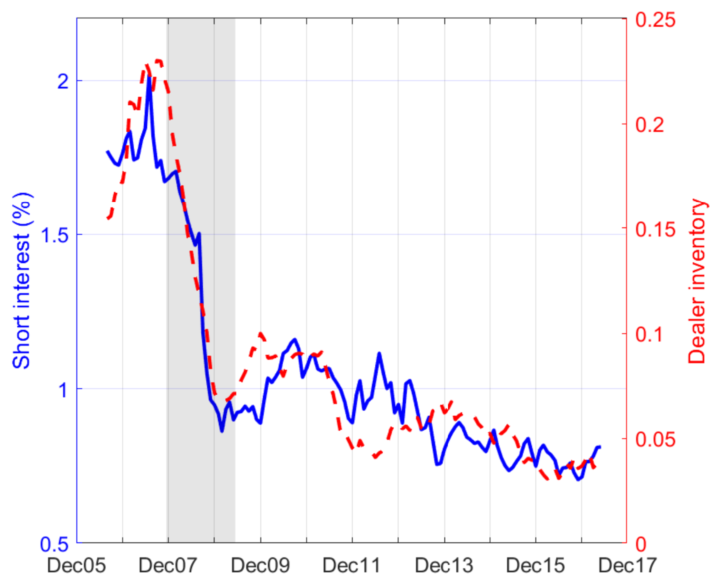

Figure 4: **Aggregate dealer inventory** This figure shows the monthly time series of aggregate dealer inventory. The inventory is measured as the corporate bond inventory of primary dealers, as disseminated by the Federal Reserve Bank of New York. The figure also shows the time series of average short interest.

4.2 Bond-level proxies

Randall (2015) argues that dealers can avoid inventory holding costs by pairing trades, that is, by quickly unwinding customer trades in the inter-dealer market. In that sense, a higher fraction of paired trades indicates less willingness by dealers to facilitate the customers' trades using their own inventory. In addition, Feldhütter (2011) also observes trades that are part of a pre-matched arrangement by a dealer with a buyer and a seller. Pre-matched trades are carried out only once there is a match. They reduce the dealer's inventory risk and inventory holding costs.

We identify paired trades based on the methodologies used in Randall (2015), Zitzewitz (2010) and Feldhütter (2011). Specifically, we label a trade as paired if *(i)* a customer-dealer trade occurs within fifteen minutes of an inter-dealer trade in the same bond and with a quantity difference of no more than $\pm 50\%$ (Randall (2015)), or if *(ii)* a customer-dealer buy trade and a customer-dealer sell trade occur in the same bond within fifteen minutes, and with quantity difference of not more than $\pm 50\%$ (Zitzewitz (2010) and Feldhütter (2011)). The fraction of unpaired trades, labelled Unpair, is measured as one minus the ratio of the number of paired trades to the number of total trades, for a given bond and month. A higher unpair ratio indicates more willingness of the dealer to facilitate the trade with their own inventory. In that sense, it is a proxy for lower inventory costs. Figure 5 shows that a close, albeit not perfect, association between the temporal variation in the unpair ratio and average short interest.

Randall (2015) argues that higher post-crisis dealer inventory costs and smaller dealer inventory positions have led to smaller average trade sizes since the crisis.[17] The intuition is that dealers who face higher inventory costs are more willing to quickly unwind customer trades in the inter-dealer market, and that smaller trade sizes give dealers greater ability to pair trades. Hence we consider the average trade size of corporate bonds as a proxy for inventory costs. Similar intuition also applies to the turnover and fraction of block trading. Figure 5 shows that each proxy is significantly lower in the post-GFC period, indicating less willingness of dealers to facilitate trades which may incur inventory cost. In addition, the temporal variation of trade size, turnover and fraction of block trading tracks that of short interest.

Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) measure dealer time-weighted daily capital commitment (TWDCC) as the time-weighted absolute value of a dealer's net cumulative position in a given bond on a given day. The authors also compute overnight capital commitment (OCC), defined

[17] Randall (2015) focuses on the interplay between trading costs and dealer inventory in the corporate bond market, and does not consider the securities lending market.

Figure 5: **Bond-level dealer inventory cost proxies** The top left and right plots shows the monthly time series of average unpair ratios and trade size. The middle left and right plots show average lender turnover and fraction of block trading. The bottom left and right plots show average time weighted daily capital commitment (TWDCC) and overnight capital commitment (OCC). The figure also shows the time series of average short interest.

as the change in inventory since the beginning-of-day that is also carried overnight.[18] Due to lack of data on dealers' initial inventory levels, TWDCC and OCC are only indirect measures of bond-level dealer inventory. More specifically, they measure the extent to which dealers are willing to use their own capital to absorb customer order imbalances, rather than pairing customers' buy and sell orders.

Note that higher dealer inventory, unpair ratios, trade size, turnover, fraction of block trades and capital commitment all to proxy for lower inventory costs. Thus, going forward, when we refer to inventory cost proxies we refer to the negative of these variables.

Figure C.2 in the appendix displays the time series of a number alternative variables macroeconomic and bond-level variables, including investors' expectations, lending fees and lender concentration. It reveals that variation in these variables is only weakly associated with variation in inventory cost proxies.

5. The Impact of Inventory Costs on Short Interest

The model in Section 2 highlights that the short interest of a bond is a function not only of inventory costs but also of bond characteristics, investors' beliefs and overall market conditions. To offer empirical evidence in support of Hypothesis 1 we have to show that even after holding all else the same, there is less short selling when dealer inventory cost proxies are higher. In our empirical tests, we therefore condition on a wide range of bond characteristics and include controls for investor expectations and overall economic conditions.

5.1 Panel-data regressions

When estimating a predictive model for the demand for corporate bond borrowing, we have to address the issue that there are many zero-short-interest observations, that is, data entries where bonds are available for borrowing but have no demand. Indeed, more than 35% of all bond-date pairs in our sample have zero short interest.[19] We address this issue as follows. First, we present results

[18] Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) construct TWDCC and OCC at the dealer-level. Since the publicly available version of the TRACE data does not include dealer ids, we construct bond-level capital commitment variables by aggregating across dealers. We find that the time-series patterns of our TWDCC and OCC measures are consistent with those in Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018).

[19] In Table C.4 in the appendix, we sort bond-date observations into quintile portfolios based on short interest and report descriptive statistics for each portfolio. We find that zero-short-interest bonds are different from bonds with non-zero borrowing demand. Zero-short-interest bonds tend to be smaller, older, are less likely to be part of major bond ETFs or issued by firms with CDS trading, are less liquid and have fewer lenders. For bonds with non-zero short interest, larger

for a bond-level panel-data Tobit regression. Second, in Appendix D, we sort bonds into 36 different categories based on size, maturity, industry, credit rating and CDS market coverage, and perform OLS regressions at the portfolio level. Both approaches yield the same overall conclusions described below.

The bond-level Tobit regression results are reported in Table 2 and Table C.3 in the appendix. Independent of the specific dealer inventory proxy used, our findings are consistent with Hypothesis 1, in that higher inventory cost proxies are associated with lower short interest.

Table 2: **Short interest panel-data regressions** The table reports Tobit regression results for predicting short interest across firms and over time. Short interest is computed as the on-loan value (excluding financing trades) divided by bond size. Supply is measured as amount lendable divided by bond size. Age of the bond is measured in years. CDS market and ETF membership are dummy variables that equal to one if CDS trade on the firm and if the bond is part of a major corporate bond ETF, respectively. Momentum is measured as the aggregate return over the past 12 months. Forecasts are measured as expected changes in the 3-month T-Bill rate in percent as reported in the Blue Chip Financial Forecasts. VIX is scaled by 1/1000. Concentration is a Markit-constructed measure of relative lendable value distribution among lenders. A smaller number indicates a large number of lenders with low inventory. Covenants indicate whether the bond has any type of covenants. Aggreagte dealer inventory of corporate debt is reported by the New York Fed. Unpair is measured as the one minus the ratio of the number of paired trades to the number of total trades, for a given bond and month. Trade size is the average size of trades for a given bond and month. We take the negative values of aggregate inventory, Unpair and trade size to proxy for inventory cost. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information and TRACE coverage. The sample period is September 2006 to June 2017. The t-statistics are adjusted for clustering of bond CUSIPs.

Inventory cost proxy:	−Aggr dealer inv		−Unpair ratio		−Trade size	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Inventory cost	-5.67	-16.3	-0.95	-9.8	-0.35	-6.2
Supply	3.63	21.5	4.20	24.8	4.30	25.0
Log(size)	0.12	5.3	0.12	5.3	0.12	5.1
Age of bond	-0.07	-25.9	-0.08	-28.4	-0.08	-31.2
Coupon	-1.76	-1.9	-0.32	-0.4	1.38	1.5
CDS quotes	0.28	9.5	0.31	10.4	0.32	10.8
Covenants	-0.03	-0.8	-0.06	-1.7	-0.06	-1.7
ETF membership	0.40	9.2	0.28	6.5	0.24	5.4
VIX	-0.11	-1.4	-0.15	-1.5	-0.17	-1.7
Lender concentration	-0.84	-11.9	-0.78	-10.9	-0.69	-9.5
Forecasts	0.03	2.9	0.04	2.8	0.05	3.9
Momentum	-0.09	-2.0	-0.15	-3.1	-0.23	-4.4
Constant	-0.58	-1.7	-0.83	-2.4	-0.16	-0.4
Industry FE	Yes		Yes		Yes	
Rating FE	Yes		Yes		Yes	
R^2	0.15		0.14		0.14	

Next, we pay particular attention to short selling around credit rating changes. Henry, Kisgen, and Wu (2015), among others, points to considerably higher short selling activities around downgrade events spurred by private information about the forthcoming event. We identify corporate bonds being

size and less time since issuance seem to be indicative of higher demand. In addition, higher bond liquidity (as measured by larger trade size and smaller bid-ask spreads) is associated with more borrowing.

downgraded from investment-grade (IG) to high-yield (HY) status, and those being upgraded from HY to IG. Since short positions are usually built before the downgrade event to take advantage of private information, we set dummy variables DNG and UPG equal to one in a -22 to -1 day time window before the rating change announcement.

We re-run the Tobit panel-data regression after including the DNG and UPG dummies as well as their interaction terms with dealer inventory costs. The results are reported in Table 3. We observe that when there is a downgrade event in the near future, there is a significant increase in short interest. Furthermore, the significant negative sign for the interaction term of DNG with inventory costs suggests that the increase in short selling prior to rating downgrades is dampened when dealer inventory costs are high. An upgrade event, on the other hand, is associated with less short selling, which is consistent with the idea that investors anticipate good news and are closing out short positions and refrain from entering new ones. As expected, inventory costs have little effect on short interest variations around upgrading news.

Table 3: **Short interest around credit rating changes** The table reports Tobit regression results for short interest movements around rating changes. The DNG (UPG) dummy equals one in a -22 to -1 day window prior to a downgrade from investment grade to high yield (an upgrade from high yield to investment grade). All other specifications are as in Table 2.

Inventory cost proxy:	−Unpair ratio		−Trade size	
	Estimate	t-stat	Estimate	t-stat
Inventory cost	-1.31	-13.8	-0.41	-7.8
DNG	0.20	2.6	0.29	2.3
Inventory cost × DNG	-0.16	-2.3	-0.10	-2.0
UPG	-0.24	-2.4	-0.16	-1.6
Inventory cost × UPG	-0.02	-0.4	0.01	0.1
Other controls as in Table 2	Yes		Yes	
R^2	0.14		0.14	

5.2 Event study

To lend further support to Hypothesis 1, we perform a diff-and-diff analysis of dealer inventory proxies and short interest just before and after a bond's inclusion in a major ETF. In general, a bond that is included in an ETF is likely to be more warehoused by dealers for the purpose of market marking and because of the prospect of profitable arbitrage trades associated with ETF creation and redemption (Sushko and Turner (2018)).[20] Dealers' propensity to warehouse particular bonds can be interpreted as dealers associating lower costs with holding the bonds. Thus, our model predicts that constituents of major bond ETFs should be easier to borrow for short-selling purposes. In this sense, ETF inclusion would mitigate any pre-existing implicit short-sale constraints.

In what follows, we focus on inclusions into BlackRock's two major corporate bond ETFs—LQD and HYG—from 2007 to 2017. We identify groups of bonds that were included into an ETF on the same day, have the same credit rating and belong to the same Fama-French five-industry classification. We require at least two bonds in a given group. Our sample includes 2,102 bond-inclusion events that are allocated to 678 distinct groups. Within each group, we further sort bonds into two subgroups by their average inventory cost over the 22 trading days prior to the inclusion event. These two subgroups are named "High IC pre-inclusion" subgroup and "Low IC pre-inclusion" subgroup. We define the post-inclusion period as the inclusion date plus 22 trading days after the inclusion.

Figure 6 compares the average values of inventory costs and short interest for the pre- to post-inclusion period, separately for the High IC pre-inclusion and Low IC pre-inclusion subgroups. The left figure shows that bonds with high inventory costs (low Unpair) prior to the ETF inclusion experienced a significant post-inclusion decrease in inventory costs (an increase in Unpair). Consistent with this finding, the right figure shows that the lower post-inclusion inventory costs are associated with high post-inclusion short interest. In contrast, the subgroup with low pre-inclusion inventory costs exhibits only small changes in costs and short interest.

More formally, we find that the average unpair ratio for the High IC pre-inclusion subgroup increased by 11%, from 18% to 29%, from pre- to post-inclusion. In comparison, the increase was much lower at 2% for the Low IC pre-inclusion subgroup. The difference in these percentage increases is statistically significant with a t-statistics of 8.52. Similarly, the increase in short interest for the IC pre-inclusion subgroups is 0.41%, compared to an increase of 0.14% for the Low IC pre-inclusion subgroup. Further details can be found in Table C.8 in the appendix. Table C.9 and Figure C.3 report consistent results for alternative measure of dealer inventory costs.

[20]Dealers are typically the authorized participants (APs) in an ETF, meaning they facilitate both the primary and secondary market of the ETF. They may benefit from arbitrage profits by exploiting price mismatches between ETF shares and the underlying securities. For example, when the price of ETF shares falls below the value of underlying securities, dealers can purchase ETF shares in the secondary market and then redeem them with the ETF sponsor in exchange for the underlying securities, which the dealers will warehouse and resell in the market, and vice versa.

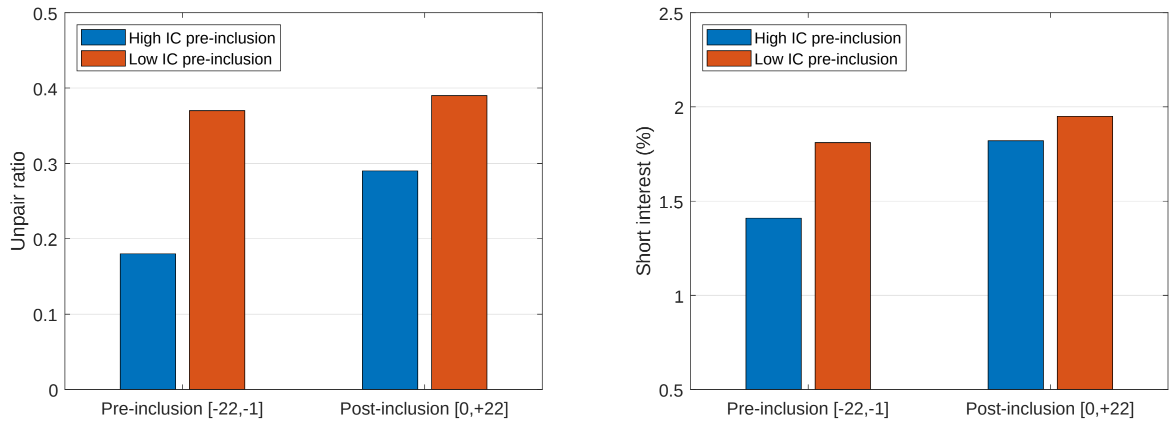

Figure 6: **ETF inclusion effects** The figures show the average value of the unpair ratio and short interest before and after ETF inclusion, for the subgroups with high and low pre-inclusion dealer inventory costs. Groups consist of corporate bonds that were included into major ETFs on the same day, have the same credit rating, and belong to the same Fama-French five-industry classification. The sample includes 2,102 bond-inclusion events belonging to 678 distinct groups. Within each group, we further sort bonds into two subgroups (High and Low) based on average inventory costs over the 22 trading days prior to inclusion. A high unpair ratio represents low inventory costs.

6. The Impact of Inventory Costs on Price Efficiency

We now explore the potential impact of dealer inventory costs on price efficiency in the corporate bond market. Our model in Section 2 suggests that inventory costs may impact price efficiency by imposing indirect short sale constraints. In Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010), who study equity markets, short sale constraints arise when the supply of lendable securities is low or lending fees are high, as these would increase the difficulty and cost of short sellers to initiate a short position. We identify an additional source of short-sale constraints in addition to low supply or high fees—high dealer inventory costs. We show that high inventory costs are associated with low price efficiency, through the short-sale channel.

6.1 Panel-data regressions

We follow Saffi and Sigurdsson (2010) and define price efficiency as the degree to which prices reflect all available information, in terms of speed and accuracy. In particular, we estimate two price-response delay measures. To construct these measures, we use monthly corporate bond return data and estimate a market-model regression with a twelve-month rolling window. In each of the rolling windows, we estimate

$$r_{i,t} \quad = \quad \gamma_i + \sum_{n=0}^{4} \gamma_{i,n} r_{m,t-n} + \varepsilon_{i,t},$$

where $r_{i,t}$ is the return of bond i in month t and $r_{m,t-n}$ is the corresponding value-weighted corporate bond market return relative to month $t-n$. This allows us to the define the first delay measure (D1):

$$\text{D1}_i \quad = \quad 1 - \frac{R^2_{\gamma_{i,n}=0\,\forall\, n=1,\cdots,4}}{R^2}$$

D1 measures the fraction of explained variation in returns that is due to lagged market returns. The larger this measure, the greater the variation in returns captured by lagged market returns, which implies a longer price delay in responding to market information.

The second measure, D2, captures the magnitude of the lagged coefficients relative to the magnitude of all market-return coefficients:

$$\text{D2}_i \quad = \quad \frac{\sum_{n=1}^{4} |\gamma_{i,n}|}{\sum_{n=0}^{4} |\gamma_{i,n}|}.$$

We use the absolute values of each coefficient regardless of their estimated signs because price efficiency is smaller as these measures deviate more from zero.

We estimate a panel-data regression for each price-response delay measure, using inventory cost proxies as the main variables of interest. Our regressions control for lending supply and/or lending fees as proxies for other potential sources of short-sale constraints. The results are reported in Table 4. Consistent with the findings in Saffi and Sigurdsson (2010) for the equity market, we find that in the corporate bond market a larger lending supply and a lower lending fee are associated with less price-response delay. More importantly, however, we also find that a high inventory cost proxy (i.e., low unpair ratio) is associated with a longer price-response delay. The results are in line with Hypothesis 2, and suggest that high inventory costs are negatively associated with price efficiency. In Table C.5 in the appendix, we report consistent results an alternative inventory cost proxy. In Table C.6, we repeat our analysis after replacing returns by changes in yields when constructing the delay measures.

As in Section 5, we pay particular attention to times when negative credit news is likely to be re-

Table 4: **Price efficiency panel regressions** This table reports the results when regressing the price-response delay measures D1 and D2 on an inventory cost proxy (− Unpair). The panel data is at the bond-month level. For a given bond-month pair to be included, we require at least ten months with non-missing data over the past 12 months. We control for lending supply defined as the average lendable value scaled by bond size in a month and indicative lending fees. The remaining variables are defined as in Table 2. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information and TRACE price data.

Dependent variable:	D1		D1		D2		D2	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Inventory cost	0.22	15.9	0.20	14.8	0.17	16.4	0.15	15.1
Supply	-0.12	-8.3	-0.12	-8.2	-0.04	-3.9	-0.04	-3.7
Fee	0.02	2.7			0.01	1.9		
Log (Size)	-0.11	-31.6	-0.11	-30.6	-0.08	-31.5	-0.07	-30.5
BAS	0.45	1.0	0.77	1.6	1.86	4.9	1.51	4.9
Turnover	-2.15	-3.0	-2.16	-3.0	-1.42	-2.9	-1.52	-3.2
Blockpct	-0.36	-3.1	-0.36	-3.0	-0.29	-3.1	-0.28	-2.8
Trade size	0.05	6.2	0.05	5.4	0.05	6.6	0.04	5.6
CDS quotes	-0.01	-3.3	-0.01	-3.3	0.00	-1.3	0.00	-1.2
ETF	-0.07	-17.1	-0.08	-17.8	-0.08	-25.5	-0.09	-26.5
Age	0.25	0.4	0.22	0.4	-0.74	-1.9	-0.74	-1.9
Coupon	8.08	6.5	7.99	6.4	5.47	6.4	5.37	6.3
Concentration	0.18	12.7	0.17	12.3	0.12	12.4	0.10	11.5
Covenants	-0.01	-1.2	-0.01	-1.0	0.00	-1.0	0.00	-0.8
Constant	1.93	37.2	1.90	36.6	1.61	44.9	1.56	44.9
Industry FE	Yes		Yes		Yes		Yes	
Rating FE	Yes		Yes		Yes		Yes	
R^2	0.18		0.18		0.21		0.21	

vealed. Table 5 reports panel-data regression results when interaction terms of inventory costs and rating change dummies are included as control variables. The significant positive sign of $Inventorycost \times DNG$ suggests that prior to a downgrade from IG to HY status, information revelation is slower and less precise for bonds with higher inventory costs.

Next, we control for changes in equity-market price efficiency. While common drivers may impact both equity and bond market price efficiency, the association between higher inventory costs and lower price efficiency should be present in the dealer-intermediated corporate bond market but not for exchange-traded equity. Thus, we expect our result to be robust to the inclusion of controls for changes in equity price efficiency. We focus on bonds that can be matched to equity data using 6-digit CUSIP and construct the associated equity price-response delay measures.[21] Table C.7 in the appendix shows that the main conclusions remain unchanged—a larger lending supply, a lower lending fee and a higher unpair ratio are associated with less price-response delay, even after controlling for stock price efficiency measures. The stock price-response delay is positively related to the bond price-response

[21] We can match 48% of the observations in our sample with CRSP data.

Table 5: **Price efficiency around credit rating changes** This table reports the results when regressing the price-response delay measures D1 and D2 on an inventory cost proxy (− Unpair) and interaction terms between rating change dummies and inventory costs. The DNG (UPG) dummy equals one in a -22 to -1 day window prior to a downgrade from investment grade to high yield (an upgrade from high yield to investment grade). The panel data is at the bond-month level. For a given bond-month pair to be included, we require at least ten months with non-missing data over the past 12 months. We control for lending supply defined as the average lendable value scaled by bond size in a month and indicative lending fees. The remaining variables are as in Table 4. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information and TRACE price data.

Dependent variable:	D1		D1		D2		D2	
	Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat
Inventory cost	0.22	15.9	0.20	14.9	0.17	16.5	0.15	15.2
Inventory cost × DNG	0.04	3.0	0.04	2.8	0.04	4.3	0.04	4.2
Inventory cost × UPG	-0.01	-0.7	-0.01	-0.6	0.00	0.2	0.00	0.3
Supply	-0.12	-8.4	-0.12	-8.3	-0.04	-3.9	-0.04	-3.7
Fee	0.00	0.1			0.01	2.4		
Other controls as in Table 4	Yes		Yes		Yes		Yes	
R^2	0.18		0.19		0.21		0.21	

delay, suggesting that there exist common channels that affect the price efficiency in both markets. Our findings are consistent with and augment those in Hotchkiss and Ronen (2002) which point to a positive relationship between information efficiency in equity and bond markets.

Furthermore, we decompose the variation in dealer inventory costs into a component associated with short interest variation and a residual component unrelated to short interest variation:

$$\mathrm{IC}_{i,t} = \beta_i \mathrm{SI}_{i,t} + \mathrm{Res}_{i,t}. \tag{16}$$

Here, IC is a bond-level inventory cost proxy and Res the residual component. Table 6 shows that the association with price efficiency is much stronger for the short-interest component than the residual component, implying that dealer inventory costs impact price efficiency mainly through the short-sale channel.[22]

6.2 Event study

Finally, we investigate price efficiency around ETF inclusion events. First, we compute the bond-and-event specific change in the average price from the pre- to the post-inclusion period. Second, we average these price changes over all High IC pre-inclusion subgroups and all Low IC pre-inclusion

[22] One standard deviation of the residual component is about ten times that of the short-interest component. Nevertheless, a one-standard-deviation increase in the component of the unpair ratio that is related to short interest variation has twice the impact on price efficiency as a one-standard-deviation increase in the residual component.

Table 6: **Decomposing dealer inventory proxies** This table reports the results when regressing the price-response delay measures D1 and D2 on the short-interest and residual components in Equation (16) of an inventory cost proxy (− Unpair). The panel data is at the bond-month level. For a given bond-month pair to be included, we require at least ten months with non-missing data over the past 12 months. We control for lending supply defined as the average lendable value scaled by bond size in a month and indicative lending fees. The remaining variables are defined as in Table 2. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information and TRACE price data.

Dependent variable:	D1		D1		D2		D2	
	Est	t-stat	Est	t-stat	Est	t-stat	Est	t-stat
Inventory cost (SI)	0.98	12.4	0.89	11.8	0.60	7.7	0.47	6.2
Inventory cost (Residual)	0.04	3.9	0.04	3.7	0.03	3.2	0.02	2.6
Supply	-0.10	-6.5	-0.12	-7.5	-0.02	-2.1	-0.03	-2.5
Fee	0.02	4.7			0.00	1.7		
Other controls as in Table 4	Yes		Yes		Yes		Yes	
R^2	0.18		0.18		0.21		0.21	

subgroups, separately for each year. Third, we compute the difference in price changes between the Low IC and High IC pre-inclusion subgroups. Figure 7 shows this difference in price changes for each year in our sample. We observe that price increases upon ETF inclusion tend to be lower for bonds with high pre-inclusion inventory costs compared to new ETF entrants with low pre-inclusion inventory costs. This result is consistent with the idea that ETF inclusion reduces pre-existing implicit short-sale constraint by increasing dealers' propensity to warehouse the bond. Lifting short sale constraints in turn leads to downward price adjustment.

7. Concluding Remarks

Our paper argues that tighter post-GFC regulation may have contributed to a decrease in corporate bond market quality. We propose an equilibrium model for trading in the secondary corporate bond market that allows us to link the short interest in corporate bonds to dealers' inventory costs, among other variables. The model predicts that, all else the same, higher inventory costs are associated with lower short interest and, through this short-sale channel, with lower price efficiency.

We construct bond-level proxies for dealer inventory costs and provide empirical evidence that if inventory costs are higher short interest tends to be lower, even after controlling for other sources of short interest variation. The association between high inventory costs and low short interest is more pronounced leading up to rating downgrade events when negative credit news are likely to be revealed. We show that the inclusion of a bond into a major ETF tends to mitigate any pre-existing short-sale constraints by increasing dealers' propensity to warehouse the bond.

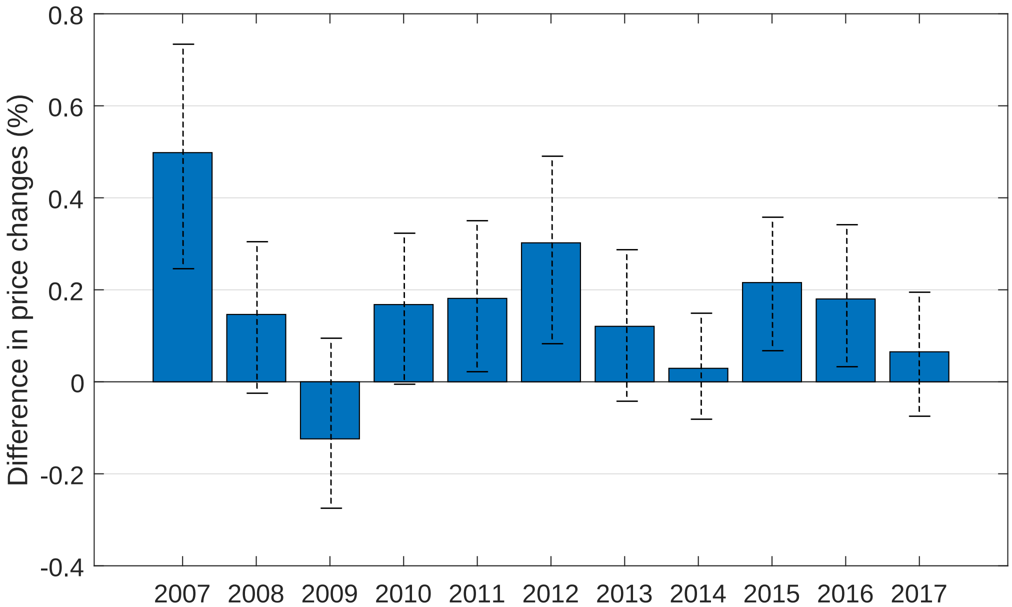

Figure 7: **ETF inclusion effects on bond prices** This plot shows the difference in price changes around ETF inclusion events between the Low IC pre-inclusion group and the High IC pre-inclusion group, as defined in Section 5.2. Bond-event level price changes are computed as the change in average prices from before to after the inclusion, $\Delta P = (P_{post}/P_{pre} - 1)$. Bond-event level price changes are aggregated to the Low IC pre-inclusion and High IC pre-inclusion subgroup level. The difference in price changes is computed as Diff $= \Delta P_{Low} - \Delta P_{High}$. The plot shows the average differences in price changes in each year. The 5% and 95% confidential intervals of the differences are also displayed.

The model shows that higher inventory costs may prevent short sellers from trading on their private information, and thus hinder the timely revelation of negative credit news. We present empirical evidence in support of this prediction. Using the price-response delay measures proposed by Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010), we document that price efficiency is lower for bonds with higher inventory costs, and that this association is more pronounced at times when negative credit news are likely to be revealed. We analyze bond price changes around ETF inclusion events and find significant downward price adjustments for bonds with high pre-inclusion inventory costs relative to those with low pre-inclusion inventory costs, in line with pre-inclusion short-sale constraints being mitigated by higher dealer propensity to warehouse ETF constituents.

We decompose dealer inventory cost variation into a component associated with short interest variation and a residual component unrelated to short interest variation, and show that dealer inventory costs impact price efficiency mainly through the short-sale channel. Regulators and market participants agree that post-GFC regulatory provisions have resulted in an increase in dealer inventory costs. Our findings suggest that this increase in the cost of providing market-making services may have had unintended consequences for bond market quality by lowering price efficiency.

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A. The Regulatory Environment

The regulatory framework for financial markets has changed significantly post-GFC, particularly with the approval of Dodd-Frank Act and the announcement of Basel III. In 2010, the Basel Committee on Banking Supervision announced the Basel III regulatory framework. The framework raised the regulatory capital base qualitatively and quantitatively, and enhanced the risk coverage. Capital requirements for counterparty credit exposures were tightened. In addition, the framework put forth the market risk amendment about incremental risk capital charge and stressed the VaR requirement for credit products. Furthermore, the framework also imposed a leverage ratio requirement to constrain leverage in the banking sector. The framework also proposed the liquidity coverage ratio and the net stable funding ratio to reduce banks' funding risk. A detailed overview over the Basel III framework is provided in Adrian, Fleming, Shachar, and Vogt (2017).

The Dodd-Frank Act was written into law in 2010, with the aim to better regulate financial markets and prevent a repeat of the 2008-09 financial crisis. The Dodd-Frank Act gave the Financial Stability Oversight Council the authority to label certain financial firms as "could pose a threat to the financial stability of the United States" if they failed or engaged in risky regulatory activities, naming them "systemically important financial institution (SIFI)." Any firm designated a SIFI, plus large bank holding companies (BHCs), are subject to stricter oversight from the Federal Reserve, including stress testing, and have to meet stricter capital requirements (WSJ (2016)).[23] In addition, Section 619 of the Dodd-Frank Act (referred to as the Volcker rule), prohibits proprietary trading by banks except for market-making activities.[24]

A.1 Dealers

Securities dealers trade securities on behalf of their customers and for their own account, and use their balance sheets primarily for trading operations, particularly market making. Dealers act as an important intermediary, especially in OTC markets such as corporate bond market. The dealers also

[23] Up to 2016, there are four non-bank SIFIs in the U.S.: insurance giants AIG, Prudential Financial Inc., MetLife Inc. and GE Capital, the financing arm of General Electric Co. Large banks are also considered systemically important, and under Dodd-Frank any U.S. bank holding company (BHCs) with more than $50 billion in assets is automatically subject to stricter rules.

[24] The Volcker rule prohibits insured depository institutions (including those affiliated with an insured depository institution) from engaging in proprietary trading and from acquiring or retaining ownership interests in, sponsoring, or having certain relationships with, a hedge fund or private equity fund.

borrow securities to facilitate buying orders which cannot be fulfilled by their inventory. As documented in Adrian, Fleming, Shachar, and Vogt (2017), the dealer business model has changed rapidly post-crisis, due to the regulatory changes and dealers' voluntary changes in their risk-management practices. The five major independent U.S. dealers either failed (Lehman), were acquired by banking organizations (Bear Stearns and Merrill Lynch), or became bank holding companies (Goldman Sachs and Morgan Stanley). As a result, the major U.S. dealers are now subject to more stringent Basel III rules, as well as the Federal Reserve's stress tests and enhanced capital and liquidity requirements specified in the Dodd-Frank Act.

The new regulations such as requirements on the capital, leverage ratio, incremental risk capital charge and stress tests, significantly increase the dealers' balance sheet costs, as well as the costs to raise market marking assets and the holding costs of corporate bonds. Furthermore, less liquid corporate bonds are ineligible for the liquidity requirement, hence the willingness of banks to hold these assets is further reduced. As a result of the new regulations, many of the largest dealers have shrunk their prime services division and dumped less profitable clients because (FinOps (2015)).

A.2 Borrowers (short-sellers)

Dodd-Frank requires all hedge funds to register with the SEC and provide data about their trades and portfolios, so the SEC can assess overall market risk (SEC (2011)). The regulation impact on the short-sellers is more indirect through the transaction frictions and costs. As stated in JPMorgan (2014), the regulatory changes indirectly impact the traditional hedge fund financing model, almost exclusively, on their prime broker's ability to finance their portfolios as financial intermediary.

A.3 Lenders

Securities lenders are typically mutual funds, ETFs, pension funds, and insurance companies (Baklanova, Copeland, and McCaughrin (2015)). The regulatory framework for security lenders is different for funds and insurance companies, with the main difference being the treatment of the collateral provided by the borrowers.

U.S. regulated mutual funds, ETFs and pension funds are among the most conservative of securities lenders, operating under strict regulatory limits set by the SEC. This regulation was implemented prior to the crisis and restricts the types of collateral that are permissible and how that collateral may be reinvested. A fund may not use an affiliate as its lending agent without approval from the SEC. U.S. regulated funds may invest cash collateral only in highly conservative and liquid investments, in contrast to AIG's risky collateral investments during the financial crisis (ICI (2014)).

For insurance companies, according to NAIC (2011), prior to May 2010, the way insurance companies reported their securities lending activity on their balance sheet and how they reinvested the collateral was not always transparent. To improve transparency regarding collateral investment, NAIC implemented new reporting and accounting requirements in May 2010, and put more defined valuation rules and disclosure requirements on securities lending transactions. As a result, almost all securities lending portfolios are now reported on-balance sheet, and any cash collateral that is recorded on-balance sheet is subject to valuation rules. In addition, the Dodd-Frank Act created a new, national Federal Insurance Office under the Treasury Department to oversee the risk in the insurance industry.

A.4 Lending agents

In securities lending transactions, lending agents typically provide an indemnity guaranteeing lenders the return of their securities. However, regulations and the ensuing capital charges associated with providing indemnification have changed the way the lending agents transact. Davis (2016) state that many agents have suggested that they are no longer willing to do so without additional compensation, and are now requiring a larger share of the lending fee earned from the lending program, effectively reducing the profit to the lenders.

B. Model derivations

Proof of Proposition 1 Given unit bond price $P \in (R, 1)$, where P is net of any potential lending fees $f = f(P)$ and costs l associated with accessing funding liquidity, investors with endowment X and information $\mathcal{I}$ choose the quantity Q of bonds traded to maximize their utility:

$$\begin{aligned} u &= -E\left(e^{-\delta W}|\mathcal{I}\right) \\ &= -e^{-\delta Q(1-P)}E\left(1_{\{\tau>1\}}|\mathcal{I}\right) - e^{-\delta Q(R-P)-\delta(1-R)X}E\left(1_{\{\tau=1\}}|\mathcal{I}\right) \\ &= -e^{-\delta Q(1-P)}\left(1-\pi(\mathcal{I})\right) - e^{-\delta Q(R-P)-\delta(1-R)X}\pi(\mathcal{I}), \end{aligned} \quad \text{(B.1)}$$

where $\pi(\mathcal{I}) = E\left(1_{\{\tau=2\}}|\mathcal{I}\right)$.

The first-order condition (FOC) for u with regard to Q is given by

$$0 = \delta(1-P)e^{-\delta Q(1-P)}(1-\pi(\mathcal{I})) + \delta(R-P)e^{-\delta Q(R-P)-\delta(1-R)X}\pi(\mathcal{I}). \tag{B.2}$$

The derivation of this FOC relies on the assumption that for fixed P, the information set $\mathcal{I}$ and thus the default probability $\pi(\mathcal{I})$ are also fixed and do not change as a function of Q. Since the relevant information sets $\mathcal{I}_I = \{X_I, Y_I, A, B\}$ and $\mathcal{I}_U = \{A, B\}$ are composed of private signals and prices, the "given prices, there is no feedback from the traded quantity Q to $\mathcal{I}$" assumption holds in Proposition 1.

Dropping $\mathcal{I}$ from the notation, Equation (B.2) implies

$$\begin{aligned} Q &= X + \frac{1}{\delta(1-R)} \log\left(\frac{1-P}{P-R}\frac{1-\pi}{\pi}\right) \\ &= X - \gamma Y + \gamma \log\left(\frac{1-P}{P-R}\right) \\ &= Z + g(P), \end{aligned}$$

where $Y = Y(\pi)$ is defined via (1), $\gamma = 1/[\delta(1-R)]$ and $Z = X - \gamma Y$ are as in Proposition 1.

The reservation price P^R is the price where $Q = Z + g(P^R) = 0$. Thus, it solves the equation

$$0 = Z + \gamma \log\left(\frac{1-P^R}{P^R - R}\right), \tag{B.3}$$

which can be rewritten as

$$P^R = \frac{1 + Re^{-Z/\gamma}}{1 + e^{-Z/\gamma}}. \tag{B.4}$$

Note that P^R defined via (B.4) satisfies $P^R \in (R, 1)$, meaning $\log\left(\frac{1-P^R}{P^R-R}\right)$ in (B.3) is well-defined. Further note that $\pi_U \in (0,1)$ as per assumption, meaning $Y_U = \log(\pi_U/(1-\pi_U))$ is also well-defined.

Lemma B.1

(a) For each z, Equation (13) uniquely defines $Z(z)$. $Z(z)$ is a strictly increasing function of z. There exists a unique $\widehat{z}$ such that $Z(\widehat{z}) = \widehat{z}$. We have $Z(z) \in [\widehat{z}, z)$ for $z > \widehat{z}$ and $Z(z) \in (z, \widehat{z}]$ for $z < \widehat{z}$. Also, $\partial(z - Z(z))/\partial z > 1 - \kappa^2$.

(b) $P^R(Z)$ defined in (10) is strictly increasing in Z. As a result, $P^R(Z(z)) \in [P^R(\widehat{z}), P^R(z))$ for $z > \widehat{z}$ and $P^R(Z(z)) \in (P^R(z), P^R(\widehat{z})]$ for $z < \widehat{z}$.

Proof of Lemma B.1 Define $f(z) = E\left[1/\left(1 + e^{\frac{z}{\gamma}\kappa^2 + \xi}\right)\right]$. Then Equation (13) is equivalent to

$$Z(z) \quad = \quad \gamma \log \frac{1 - f(z)}{f(z)}.$$

In that sense, Equation (13) uniquely defines $Z(z)$. Taking derivatives w.r.t. z on both sides yields

$$Z'(z) \quad = \quad -\gamma f'(z) \frac{1}{f(z)(1 - f(z))}. \tag{B.5}$$

Note that $f'(z) = -\frac{\kappa^2}{\gamma} E\left[e^{\frac{z}{\gamma}\kappa^2+\xi} / \left(1 + e^{\frac{z}{\gamma}\kappa^2+\xi}\right)^2\right] < 0$, which implies $Z'(z) > 0$.

Further manipulations yield

$$f'(z) \quad = \quad -\frac{\kappa^2}{\gamma} \left\{ f(z)\left[1 - f(z)\right] - Var\left[\frac{1}{1 + e^{\frac{z}{\gamma}\kappa^2+\xi}}\right] \right\}.$$

Substituting this expression for $f'(z)$ into (B.5), we obtain

$$Z'(z) \quad = \quad \kappa^2 \left\{ f(z)\left[1 - f(z)\right] - Var\left[\frac{1}{1 + e^{\frac{z}{\gamma}\kappa^2+\xi}}\right] \right\} \frac{1}{f(z)\left[1 - f(z)\right]} < \kappa^2, \tag{B.6}$$

which implies $\partial(z - Z(z))/\partial z > 1 - \kappa^2 > 0$. The Jensen inequality applied to Equation (13) states

$$\frac{1}{1 + e^{\frac{Z(z)}{\gamma}}} \quad = \quad E\left(\frac{1}{1 + e^{\frac{z}{\gamma}\kappa^2+\xi}}\right) > \frac{1}{1 + Ee^{\frac{z}{\gamma}\kappa^2+\xi}} = \frac{1}{1 + e^{\frac{z}{\gamma} - \frac{z}{\gamma}(1-\kappa^2) - \mu_y(1-\kappa^2) + \frac{1}{2}\sigma_y^2(1-\kappa^2)}}.$$

As $z \to \infty$, the last term exceeds $1/(1 + e^{\frac{z}{\gamma}})$. Therefore, $z - Z(z) > 0$ as $z \to \infty$. Lastly, Equation (13) implies

$$0 \quad = \quad e^{\frac{Z(z)}{\gamma}} E\left(\frac{1 - e^{\frac{z - Z(z)}{\gamma} - \frac{z}{\gamma}(1-\kappa^2) + \xi}}{1 + e^{\frac{z}{\gamma}\kappa^2+\xi}}\right).$$

Suppose $z - Z(z) \geq 0$ as $z \to -\infty$. Then the term on the right-hand side becomes negative when z is small. Thus, $z - Z(z) < 0$ as $z \to -\infty$ has to hold.

Together, $\partial(z - Z(z))/\partial z > 0$, $z - Z(z) > 0$ as $z \to \infty$ and $z - Z(z) < 0$ as $z \to -\infty$ are sufficient conditions for Part (a) of the Lemma to hold.

For Part (b) to hold, it is sufficient to show that $P^R(Z)$ is increasing in Z. To this end, note that

$$\frac{\partial P^R(Z)}{\partial Z} = \frac{-Re^{-Z/\gamma}}{1+e^{-Z/\gamma}}\frac{1}{\gamma} + \frac{1+Re^{-Z/\gamma}}{(1+e^{-Z/\gamma})^2}\frac{1}{\gamma} = \frac{1}{\gamma}\frac{1-Re^{-2Z/\gamma}}{(1+e^{-Z/\gamma})^2} > 0.$$

The remaining statements in Part (b) then follow from Part (a).

Lemma B.2 *Suppose $Z_I = z$ is observed. Let (A^*, B^*) denote the equilibrium price quotes. If $P_I^R \le P_U^R$, $P_I^R \le B^* \le A^* \le P_U^R$, meaning I investors short the bond and U investors buy it. If $P_U^R \le P_I^R$, $P_U^R \le B^* \le A^* \le P_I^R$, meaning U investors short and I investors buy.*

Proof of Lemma B.2 First, consider the case where $P_I^R \le P_U^R$. Suppose $B > P_U^R$. Then $\alpha = 0$, and the dealer's preferred market bid depth β maximizes her utility

$$u = -e^{-\delta(\beta(1-B)+I_0-(I_0+\beta)(c-k))}(1-\pi_D) - e^{-\delta(\beta(R-B)+I_0R-(I_0+\beta)(c-k))}\pi_D.$$

The FOC w.r.t. β is $0 = (1-B-c+k)(1-\pi_D) + (R-B-c+k)e^{\delta(I_0+\beta)(1-R)}\pi_D$, which implies

$$\beta = -I_0 + \gamma \log\frac{1-(B+c-k)}{(B+c-k)-R} + Z_U \le g(B) + Z_U < g(P_U^R) + Z_U = 0. \tag{B.7}$$

As a result, at price B the dealer would prefer to sell bonds rather than buy them. Therefore, $B \le P_U^R$ has to hold. As $\alpha = 0$ for all $A \ge P_U^R$, the benevolent dealer sets $A \le P_U^R$. Similarly, since $\beta = 0$ for all $B \le P_I^R$, the dealer sets $B \ge P_I^R$. In summary, $P_I^R \le B \le A \le P_U^R$.

Second, consider the case where $P_U^R \le P_I^R$. Suppose $B > P_I^R$. Then $\alpha = 0$, and the dealer's preferred bid depth β is as in (B.7), with P_U^R replaced by P_I^R. As before, it follows that $P_U^R \le B \le A \le P_I^R$ has to hold.

Lemma B.3 *We have $\widehat{z} \in [\underline{z}, \overline{z}]$.*

Proof of Lemma B.3 From Lemma B.1 we know $P^R(\widehat{z}) = P_I^R = P_U^R$. Lemma B.2 then implies $P_I^R = B^* = A^*$, meaning I investors' gains from trade are zero. Therefore, $\widehat{z} \in [\underline{z}, \overline{z}]$.

Lemma B.4 *If $P_I^R \leq P_U^R$, then $\beta_D = \beta_U = 0$ and* SI $= \beta_I$.

Proof of Lemma B.4 If $P_I^R \leq P_U^R$, Lemma B.2 implies $\alpha_I = 0$, $\beta_U = 0$ and SI $= \beta_I + \beta_D$. Suppose $\beta_D > 0$, meaning $I_0 + \beta_I - \alpha_U < 0$. Then the dealer's preferred ask depth α maximizes her utility

$$u = -e^{-\delta[\beta_I(1-B)-\alpha(1-A)+I_0+(I_0+\beta_I-\alpha)(f+l)]}(1-\pi_D) - e^{-\delta[\beta_I(1-B)-\alpha(R-A)+I_0R+(I_0+\beta_I-\alpha)(f+l)]}\pi_D.$$

The FOC w.r.t. α is $0 = [1 - A + (f+l)](1-\pi_D) - [A - (f+l) - R]e^{\delta(I_0+\beta_I-\alpha)(1-R)}\pi_D$, which implies

$$\alpha = I_0 + \beta_I - \left[\gamma \log \frac{1 - [A - (f+l)]}{[A - (f+l)] - R} + Z_U\right] < I_0 + \beta_I - [g(A) + Z_U] = I_0 + \beta_I - \alpha_U < 0.$$

As a result, at price A the dealer would prefer to sell bonds rather than to buy them. Therefore, $I_0 + \beta_I - \alpha_U \geq 0$ has to hold, which implies $\beta_D = 0$ and thus SI $= \beta_I$.

Lemma B.5 *If $\widehat{z} \in [\underline{z}, \overline{z}]$, no trades take place.*

Proof of Lemma B.5 If $\widehat{z} \in [\underline{z}, \overline{z}]$, the informed do not trade. Suppose $\beta_U > 0$. This implies $P_U^R < B - f - l \leq A$, which in turn implies $\alpha_U = 0$. At bid price B, the dealer's marginal utility from decreasing β_U is positive as long as $\frac{\partial u}{\partial \beta_U} < 0$, which is equivalent to

$$[1 - (B + c - k)](1 - \pi_D) - [B + c - k - R]e^{\delta(I_0+\beta_U)(1-R)}\pi_D < 0$$

and $\beta_U > -I_0 + \gamma \log \frac{1-(B+c-k)}{(B+c-k)-R} + Z_U$. Since

$$-I_0 + \gamma \log \frac{1 - (B + c - k)}{(B + c - k) - R} + Z_U \leq g(B + c - k) + Z_U \leq g(B - f - l) + Z_U = -\beta_U/N_U,$$

the dealer's utility increases as β_U decreases as long as $\beta_U > 0$. In other words, the dealer prefers not to trade (by setting $B = P_U^R + f + l$) over buying β_U bonds at B. As a result, $\beta_U = 0$ in equilibrium.

Now suppose $\alpha_U > 0$. This implies $B - f - l \leq A < P_U^R$, meaning $\beta_U = 0$. At ask price A, the dealer's marginal utility from decreasing α_U is positive as long as $\frac{\partial u}{\partial \alpha_U} < 0$, which is equivalent to

$$\begin{aligned} & \left[1 - \left(A - k1_{\{I_0-\alpha_U \geq 0\}} - (c + \underline{f} + l)1_{\{I_0-\alpha_U<0\}}\right)\right](1-\pi_D) \\ & - \left[\left(A - k1_{\{I_0-\alpha_U \geq 0\}} - (c + \underline{f} + l)1_{\{I_0-\alpha_U<0\}}\right) - R\right] e^{\delta(I_0-\alpha_U)(1-R)}\pi_D > 0. \end{aligned} \tag{B.8}$$

Relation (B.8) is equivalent to $\alpha_U > I_0 - \gamma \log \frac{1-(A-k1_{\{I_0-\alpha_U\geq 0\}}-(c+\underline{f}+l)1_{\{I_0-\alpha_U<0\}})}{(A-k1_{\{I_0-\alpha_U\geq 0\}}-(c+\underline{f}+l)1_{\{I_0-\alpha_U<0\}})-R} - Z_U$. Since

$$\begin{aligned} I_0 - \left[\gamma \log \frac{1-(A-k1_{\{I_0-\alpha_U\geq 0\}}-(c+\underline{f}+l)1_{\{I_0-\alpha_U<0\}})}{(A-k1_{\{I_0-\alpha_U\geq 0\}}-(c+\underline{f}+l)1_{\{I_0-\alpha_U<0\}})-R} + Z_U\right] &< I_0 - \left[\gamma \log \frac{1-A}{A-R} + Z_U\right] \\ &= I_0 - [g(A) + Z_U] = I_0 - \frac{\alpha_U}{N_U}, \end{aligned}$$

the dealer's utility increases as α_U decreases as long as $\alpha_U > 0$. In other words, the dealer prefers not to trade (by setting $A = P_U^R$) over selling α_U bonds at A. As a result, $\alpha_U = 0$ in equilibrium.

Proof of Proposition 2 Suppose $z < \underline{z}$. Lemmas B.1 and B.3 imply $P_I^R < P_U^R$, and Lemma B.4 yields SI $= \beta_I$. For a given quotation $B \geq P_I^R + \underline{f} + l$, (4) and (8) imply $\beta_I = -N_I [Z_I + g(B - f - l)]$, and thus

$$f = A - c - l - \frac{1 + Re^{-(\frac{\beta_I}{N_I}+Z_I)/\gamma}}{1 + e^{-(\frac{\beta_I}{N_I}+Z_I)/\gamma}}. \tag{B.9}$$

The monopolist lender chooses f, or equivalently β_I, to maximize $\beta_I(f - \underline{f})$. The FOC w.r.t. β_I is $f = \underline{f} - \beta_I \, \partial f/\partial \beta_I$. In light of (B.9), the FOC can be re-written as

$$f = \underline{f} + (1-R)\frac{\beta_I}{\gamma N_I} \frac{e^{-(\frac{\beta_I}{N_I}+Z_I)/\gamma}}{\left(1 + e^{-(\frac{\beta_I}{N_I}+Z_I)/\gamma}\right)^2}.$$

The proof proceeds along similar steps if $z > \overline{z}$.

Proof of Proposition 3 In equilibrium, $\pi_D = \pi_U = \pi(z)$, where $\pi(z)$ is defined in (12). Holding π_D constant, the dealer chooses (A, B) to maximize

$$u = -e^{-\delta[-\alpha(1-A)+\beta(1-B)+I_0+H(A,B)]}(1-\pi_D) - e^{-\delta[-\alpha(R-A)+\beta(R-B)+I_0 R+H(A,B)]}\pi_D.$$

When $z \leq \widehat{z}$, Lemma B.2 implies $P_I^R \leq B \leq A \leq P_U^R$. I investors short the bond and U investors buy it. We have $\alpha = N_U(g(A) + Z_U)$ and $\beta = -N_I(g(B - f - l) + Z_I)$. If, on the other, $z > \widehat{z}$, we have $P_U^R \leq B \leq A \leq P_I^R$. U investors short the bond and I investors buy it. We have $\alpha = N_I(g(A) + Z_I)$ and $\beta = -N_U(g(B - f - l) + Z_U)$. In either case, finding A and B is equivalent to finding α and β.

The FOC with regard to the ask depth α is given by

$$0 = A + \alpha A' - 1 + h + (1 - R)\frac{e^{\delta(I_0+\beta-\alpha)(1-R)}\frac{\pi_D}{1-\pi_D}}{1 + e^{\delta(I_0+\beta-\alpha)(1-R)}\frac{\pi_D}{1-\pi_D}},$$

where $h = \partial H(A, B)/\partial\alpha$. Using A' to denote $A' = \partial A/\partial\alpha$, we solve for $I_0 + \beta - \alpha$ to obtain

$$I_0 + \beta - \alpha = g(A + \alpha A' + h) + Z(z).$$

Similarly, the FOC with regard to the bid depth β is given by

$$0 = B + \beta B' - 1 + h + (1 - R)\frac{e^{\delta(I_0+\beta-\alpha)(1-R)}\frac{\pi_D}{1-\pi_D}}{1 + e^{\delta(I_0+\beta-\alpha)(1-R)}\frac{\pi_D}{1-\pi_D}},$$

which yields

$$I_0 + \beta - \alpha = g(B + \beta B' + h) + Z(z),$$

with $B' = \partial B/\partial\beta$.

Proof of Proposition 4 Suppose $\mathcal{I}_D = \mathcal{I}_U = \mathcal{I}_L = \{Z_I = z\}$ for some z. In equilibrium, $\pi_D = \pi_U = \pi(z)$, where $\pi(z)$ is defined in (12), and $f = f(z)$. Holding π_D and f constant, the dealer chooses (A, B) to maximize

$$u = -e^{-\delta[-\alpha(1-A)+\beta(1-B)+I_0(1-P_0)+H(A,B)]}(1 - \pi_D) - e^{-\delta[-\alpha(R-A)+\beta(R-B)+I_0(R-P_0)+H(A,B)]}\pi_D,$$

where $H(A,B) = -(I_0+\beta-\alpha)^+(c-k) - (I_0+\beta-\alpha)^-(f+l)$. The FOC with regard to the ask price A is given by

$$0 \;=\; \frac{\alpha}{\alpha'} + A - 1 + h(A,B) + (1-R)\frac{e^{\delta(I_0+\beta-\alpha)(1-R)}\frac{\pi_D}{1-\pi_D}}{1+e^{\delta(I_0+\beta-\alpha)(1-R)}\frac{\pi_D}{1-\pi_D}}, \tag{B.10}$$

where $\alpha' = \partial\alpha/\partial A$ and $h(A,B) = \frac{1}{\alpha'}\partial H(A,B)/\partial A$.[25] Similarly, the dealer's FOC for the bid price B is

$$0 \;=\; \frac{\beta}{\beta'} + B - 1 + h(A,B) + (1-R)\frac{e^{\delta(I_0+\beta-\alpha)(1-R)}\frac{\pi_D}{1-\pi_D}}{1+e^{\delta(I_0+\beta-\alpha)(1-R)}\frac{\pi_D}{1-\pi_D}}, \tag{B.11}$$

where $\beta' = \partial\beta/\partial B$ and we make use of the fact that $\frac{1}{\beta'}\partial H(A,B)/\partial B = -\frac{1}{\alpha'}\partial H(A,B)/\partial A = -h(A,B)$.

In what follows, consider the case where $z = \underline{z}$. As above, $\pi_U = \pi_U(\underline{z})$ and $f = f(\underline{z})$ are held constant. From Lemma B.5 we know that $\underline{z} \leq \widehat{z}$. From Lemma B.1 and B.2 it then follows that $P_I^R \leq B \leq A \leq P_U^R$, meaning $\beta_U = \alpha_I = 0$. Since the informed prefer not to trade and the dealer is benevolent, $B = \max(P_I^R + f + l, A)$ and $\beta_I = 0$. In summary, $\beta = 0$ and $\alpha = \alpha_U$. Combining the two FOCs (B.10) and (B.11), we obtain $\alpha = -\alpha'(A-B)$. With $\alpha' = -\gamma N_U[1/(1-A) + 1/(A-R)]$, α can be expressed as

$$\frac{\alpha}{\gamma N_U} \;=\; \left(\frac{1}{1-A} + \frac{1}{A-R}\right)(A-B), \tag{B.12}$$

with $B = \max(P_I^R + f + l, A)$. Note that (B.12) implies α is zero if $A = B$ and positive if $A \in (B, P_U^R]$. It is straightforward to show that α defined through (B.12) is an increasing function of A:

$$\frac{\partial \frac{\alpha}{\gamma N_U}}{\partial A} = \left(\frac{1}{(1-A)^2} - \frac{1}{(A-R)^2}\right)(A-B) + \left(\frac{1-A}{(1-A)^2} + \frac{A-R}{(A-R)^2}\right) = \frac{1-B}{(1-A)^2} + \frac{B-R}{(A-R)^2} > 0.$$

From Proposition 1 we further know that

$$\frac{\alpha}{\gamma N_U} \;=\; \log\frac{1-A}{A-R} - \log\frac{1-P_U^R}{P_U^R - R}, \tag{B.13}$$

and that $\alpha = 0$ for $A = P_U^R$. Clearly, for α defined through (B.13), $\partial\alpha/\partial A < 0$.

[25] Note that $\partial\alpha/\partial A < 0$ for $A \in (R,1)$ and $\partial\beta/\partial B > 0$ for $B \in (R+f+l,1)$, meaning the inverse of these derivatives are well-defined.

In summary, α as a function of $A \in [B, P_U^R]$ has to satisfy both (B.12) and (B.13). According to (B.12), α is strictly increasing in A and zero at the left boundary. According to (B.13), α is strictly decreasing in A and zero at the right boundary. Thus, there is a unique value $A = A(\underline{z}) \in [B, P_U^R]$ that satisfies both (B.12) and (B.13). This is visualized in Figure B.1.

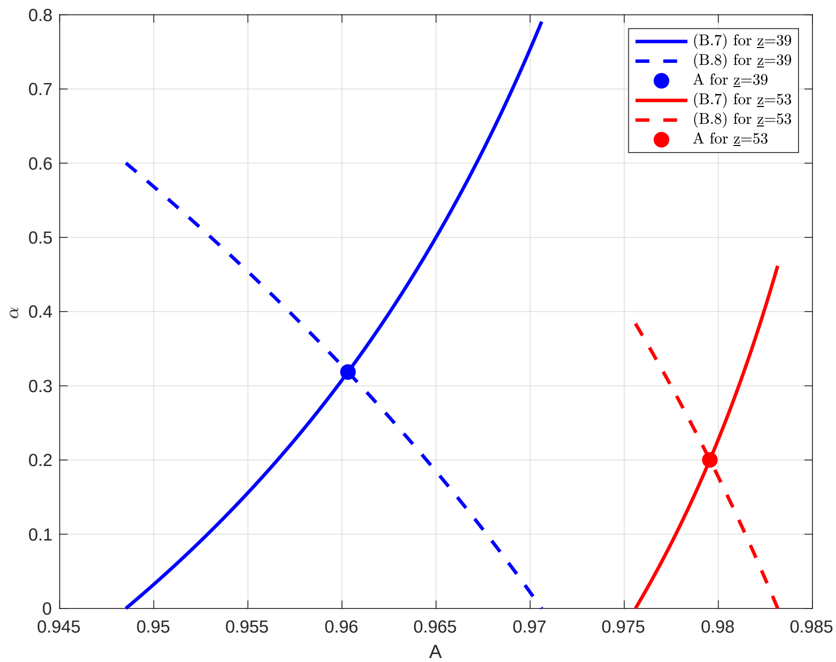

Figure B.1: **Finding A for a given $\underline{z}$** Solid lines show, for a given $Z_I = \underline{z}$, the value of α in (B.12), and dashed lines show the value of α in (B.13). Blue (red) values correspond to a $\underline{z}$ equal to the first (fifth) quantile of the Z_I distribution. The model parameters are $\delta = 0.1$, $R = 0.4$, $I_0 = 100$, $N_I = N_U = 10$, $\pi_0 = 0.01$, $\sigma_y = 1$, $\sigma_x = 10$ and $f = k = 0$. The parameter μ_y is chosen so that $E\left[1/(1+e^{-y})\right] = \pi_0$.

We now show that for any z—and thus, any pair $(P_I^R(z), P_U^R(z))$—the solution $A = A(z)$ to (B.12) and (B.13) is a strictly increasing function of z.[26] Since I investors' reservation value $P_I^R = P^R(z)$ defined in (10) is strictly increasing in z, showing $\partial A/\partial z > 0$ is equivalent to showing $\partial A/\partial P_I^R > 0$. Differentiating both sides of Equation (B.12) w.r.t. P_I^R, we obtain

$$\frac{\partial[\alpha/(\gamma N_U)]}{\partial P_I^R} = \left(\frac{1-B}{(1-A)^2} + \frac{B-R}{(A-R)^2}\right)\frac{\partial A}{\partial P_I^R} - \left(\frac{1}{1-A} + \frac{1}{A-R}\right)\frac{\partial B}{\partial P_I^R}. \tag{B.14}$$

[26]Note that for an arbitrary z, the solution $A = A(z)$ to (B.12) and (B.13) may not yield the equilibrium ask $A^*(z)$. This is because in (B.12), B is forced to be equal to $\max(P_I^R + f + l, A)$.

Differentiating both sides of Equation (B.13) w.r.t. P_I^R yields

$$\frac{\partial[\alpha/(\gamma N_U)]}{\partial P_I^R} = \left(\frac{1}{1-P_U^R}+\frac{1}{P_U^R-R}\right)\frac{\partial P_U^R}{\partial P_I^R}-\left(\frac{1}{1-A}+\frac{1}{A-R}\right)\frac{\partial A}{\partial P_I^R}. \tag{B.15}$$

Lemma B.1 implies $\partial P_U^R/\partial P_I^R > 0$. Suppose $\partial A/\partial P_I^R \leq 0$. Then $\partial[\alpha/(\gamma N_U)]/\partial P_I^R \leq 0$ in (B.14) and $\partial[\alpha/(\gamma N_U)]/\partial P_I^R > 0$ in (B.15). Thus, $\partial A/\partial P_I^R > 0$—and $\partial A/\partial z > 0$—must hold. This is visualized in Figure B.1.

So far with have combined the FOCs for A and B to link A to z. This has been done for z who have the $\underline{z}$ characteristics that $z \leq \widehat{z}$ and $B(z) = \max(P^R(z)+f+l, A)$. Another link between A and z can be derived from the FOC for B alone. We again focus on z with the aforementioned $\underline{z}$ characteristics. Lemma B.4 states $I_0 - \alpha \geq 0$. With this restriction, and $B(z) = \max(P^R(z)+f+l, A)$ and $\beta(\underline{z}) = 0$, Equation (B.11) can be rewritten as

$$\alpha = I_0 - \left(g(B+c-k)+Z_D\right). \tag{B.16}$$

Equation (B.16) states that the amount of debt she wants to sell is equal to the difference between her inventory and the number of bonds she would buy at B. Substituting Equation (B.16) into the definition of α in (4), we obtain the following expression for A:

$$A = \frac{1+Re^{\frac{\alpha}{\gamma N_U}+Y_U}}{1+e^{\frac{\alpha}{\gamma N_U}+Y_U}}. \tag{B.17}$$

The lower boundary $\underline{z}$ of the non-RtQ set $\mathcal{Z}$ is determined by the pair $(\underline{z}, A)$ that lies at the intersection of Equation (B.17) and the solutions to (B.12) and (B.13), as shown in Figure B.2. Since α is an increasing function of c, for any z the ask price A is a decreasing function of c. As inventory costs c increase, $A = A(\underline{z})$ in (B.17) shifts downwards, meaning it intersects the solution $A = A(\underline{z})$ to (B.12) and (B.13) at a lower $\underline{z}$. This is because the solution $A = A(\underline{z})$ to (B.12) and (B.13) is an increasing function of $\underline{z}$. This gives the desired result that $\underline{z}$ is a decreasing function of the inventory cost c.

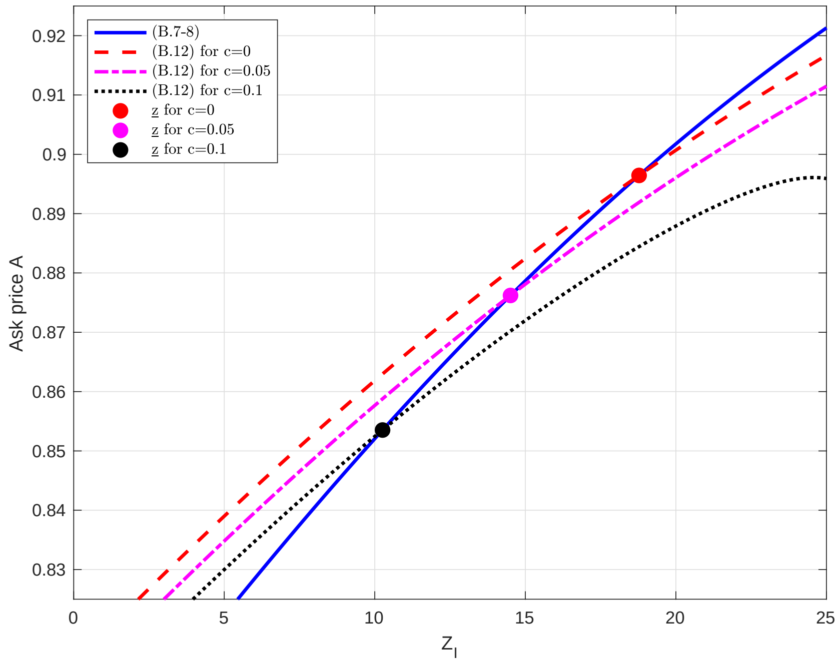

Figure B.2: **Finding the lower boundary of non-RtQ set** $\mathcal{Z}$ The solid blue line shows, for a given Z_I with $P_I^R(Z_I) < P_U^R(Z_I)$, the value for A that satisfies (B.12) and (B.13). The remaining lines show α as per (B.17). The model parameters are $\delta = 0.1$, $R = 0.4$, $I_0 = 100$, $N_I = N_U = 10$, $\pi_0 = 0.01$, $\sigma_y = 1$ and $\sigma_x = 10$. The parameter μ_y is chosen so that $E\left[1/(1+e^{-y})\right] = \pi_0$.

C. Additional Tables and Figures

Table C.1: **Descriptive statistics for merged FISD-MSF data** This table reports summary statistics for the merged FISD-MSF data. The statistics are computed across firms and over time. Size is the notional value of the bond. Age of the bond is measured in years. Coupon is the annualized coupon rate. IG, CDS quotes, ETF membership and Covenants are the fraction of observations that are for investment-grade bonds, for issuers with CDS market coverage, for bonds that are part of a major ETF and for bonds with at least one type of covenants, respectively. ShortLoanValue is the amount of bonds borrowed with financing trades removed. Short interest is measured as ShortLoanValue divided by bond size. Vlendable is the value of bond available for lending. Fee is the annualized indicative lending fee. Concentration is a Markit-constructed measure of relative lendable value distribution among the lenders. A smaller number indicates a large number of lenders with low inventory. Unpair is the fraction of trades identified as non-paired trading for a bond in a month. Tsize is the monthly average trade size of a bond in a month. Turnover is measured as total trading volume scaled by the size of a bond in each day, averaged over a month. Blockpct is the fraction of trades with size above $5 million for a bond in a month. TWDCC and OCC are the average time-weighted dealer capital commitment and overnight capital commitment. BAS is the average value-weighted bid-ask spread of a bond in a month. Forecasts are measured as expected changes in the 3-month T-Bill rate in percent, as reported in the Blue Chip financial forecasts. Momentum is measured as the cumulative bond return over the past 12 months. Obs shows the number of non-missing observations for each variable (in millions). The data include all bonds on loan in the merged FISD-MSF data that have credit rating information from September 2006 to June 2017.

	Mean	Std	P5	P25	P50	P75	P95	Obs
Size (b$)	0.52	0.56	0.05	0.20	0.35	0.60	1.50	22.8
Age (yrs)	5.80	5.26	0.37	1.84	4.11	8.36	17.21	22.8
Coupon (%)	5.94	2.32	1.63	4.70	6.00	7.35	9.75	22.7
IG	0.75							22.5
CDS quotes	0.39							22.8
ETF membership	0.12							22.8
Covenants	0.68							22.8
ShortLoanValue (m$)	6.66	18.03	0.00	0.00	0.56	5.51	32.53	22.8
Short interest (%)	1.03	2.40	0.00	0.00	0.12	0.96	5.06	22.8
Vlendable (m$)	110	150	1	26	71	140	370	22.8
Fee (%)	0.52	0.84	0.25	0.38	0.38	0.38	1.00	13.9
Concentration	0.42	0.27	0.15	0.22	0.32	0.52	1.00	22.8
Unpair	0.40	0.29	0.00	0.17	0.35	0.58	1.00	16.3
Tsize (m$)	0.98	2.04	0.01	0.12	0.46	1.16	3.32	16.3
Turnover (%)	0.68	0.43	0.34	0.54	0.63	0.74	1.23	16.3
Blockpct	0.04	0.11	0.00	0.00	0.00	0.04	0.20	16.3
TWDCC	1.14	2.45	0.01	0.14	0.55	1.39	3.97	16.3
OCC	1.24	2.65	0.01	0.13	0.57	1.50	4.45	16.3
BAS (%)	0.69	0.86	0.05	0.22	0.45	0.86	2.11	13.0
Forecast (%)	0.05	0.33	-0.48	-0.07	0.04	0.21	0.46	22.8
Mom (%)	7.15	19.05	-6.31	1.94	5.36	9.93	23.58	12.2

Table C.2: **Descriptive statistics for merged FISD-MSF data by year** This table reports the annual average statistics for the bonds in the merged FISD-MSF data. For each variable, we first compute daily averages across all bonds and then average within each year. All the variables are defined as in Table C.1. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information from September 2006 to June 2017.

Variables	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Size (b$)	0.36	0.37	0.42	0.48	0.50	0.52	0.53	0.56	0.56	0.59	0.63	0.65
Age (year)	5.46	5.56	5.82	5.90	5.90	5.83	5.71	5.53	5.70	5.75	6.08	6.32
Coupon %	6.59	6.44	6.35	6.39	6.47	6.35	6.14	5.79	5.53	5.30	5.17	5.05
IG	0.74	0.75	0.75	0.73	0.72	0.72	0.74	0.75	0.76	0.78	0.79	0.80
CDS quotes	0.39	0.39	0.40	0.40	0.38	0.37	0.38	0.39	0.39	0.38	0.39	0.38
ETF membership	0.01	0.01	0.02	0.03	0.08	0.11	0.15	0.19	0.19	0.21	0.22	0.21
Covenants	0.61	0.59	0.62	0.66	0.66	0.67	0.71	0.72	0.72	0.72	0.65	0.61
ShortLoanValue (m$)	9.14	9.37	7.92	5.47	6.51	6.23	6.21	5.92	5.62	5.51	5.28	5.83
Short interest %	1.74	1.80	1.46	0.92	1.06	1.04	0.99	0.89	0.84	0.79	0.76	0.77
Vlendable (m$)	97	110	120	110	110	110	110	110	110	110	120	120
Fee %	0.64	0.57	0.55	0.41	0.45	0.48	0.52	0.50	0.48	0.51	0.60	0.61
Concentration	0.51	0.47	0.45	0.49	0.46	0.45	0.43	0.40	0.37	0.35	0.35	0.35
Unpair	0.53	0.52	0.42	0.33	0.36	0.38	0.38	0.41	0.41	0.37	0.37	0.38
Tsize (m$)	1.64	1.64	1.33	1.13	0.95	0.91	0.84	0.85	0.87	0.77	0.72	0.78
Turnover	1.13	1.14	0.64	0.49	0.58	0.62	0.60	0.73	0.70	0.60	0.57	0.58
Blockpct	0.07	0.07	0.06	0.05	0.04	0.04	0.03	0.03	0.04	0.03	0.03	0.03
TWDCC	1.79	1.70	1.29	1.30	1.21	1.14	0.99	1.03	1.00	0.92	0.92	1.05
OCC	1.87	1.77	1.36	1.42	1.33	1.25	1.10	1.14	1.08	1.00	1.02	1.18
BAS (%)	0.52	0.62	1.19	1.18	0.75	0.67	0.59	0.50	0.46	0.59	0.68	0.60
Forecast (%)	-0.01	0.32	0.21	-0.42	-0.05	-0.02	-0.05	0.17	0.15	0.22	-0.09	0.26
Mom (%)	6.48	6.50	-1.36	12.06	22.09	7.88	9.82	4.05	5.52	2.20	4.95	8.36

Table C.3: **Tobit regression results with alternative inventory proxies** The table reports Tobit regression results using alternative inventory proxies. Block trade is the fraction of trades with size above $5 million for a bond in a month. Turnover is measured as the average ratio of total trade volume over the size for a bond in a month. TWDCC and OCC are two measures of dealer capital commitment to absorb the customer's order imbalance as in Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018). We take the negative values of the inventory proxies to proxy for the inventory cost. All other variables are defined as in Table 2. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information and TRACE. The sample period is September 2006 to June 2017. The t-statistics are adjusted for clustering of bond CUSIPs.

Inventory cost proxy:	-Block trade		-Turnover		-TWDCC		-OCC	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Inventory cost	-0.23	-3.7	-6.91	-17.0	-0.11	-2.8	-0.11	-3.4
Constant	-0.17	-0.5	-0.45	-1.3	0.76	1.5	1.07	2.0
Supply	4.32	25.1	4.22	25.5	4.20	23.9	4.19	23.9
Log(size)	0.13	5.3	0.08	3.4	0.04	1.2	0.02	0.4
Age of bond	-0.09	-31.8	-0.06	-24.1	-0.08	-29.2	-0.08	-25.1
Coupon	1.48	1.6	1.55	1.7	1.40	1.5	1.41	1.5
CDS quotes	0.32	10.8	0.30	10.5	0.32	10.8	0.32	10.8
Covenants	-0.06	-1.7	-0.01	-0.3	-0.03	-0.8	-0.02	-0.6
ETF membership	0.24	5.4	0.21	4.8	0.24	5.5	0.24	5.4
VIX	-0.16	-1.6	-0.10	-1.0	-0.17	-1.66	-0.2	-1.5
Lender concentration	-0.69	-9.5	-0.54	-7.7	-0.73	-9.9	-0.75	-10.0
Forecasts	0.06	4.0	0.09	6.5	0.05	4.0	0.06	4.2
Momentum	-0.24	-4.6	-0.12	-2.4	-0.21	-3.9	-0.20	-3.8
Industry FE	Yes		Yes		Yes		Yes	
Rating FE	Yes		Yes		Yes		Yes	
R^2	0.13		0.14		0.14		0.13	

Table C.4: **Portfolio sorts by short interest** This tables the shows the average characteristics bond-date pairs sorted by bond short interest. Each day, we first assign zero-short interest observations to Group 0, and then assign all remaining observations to equally-sized groups of bonds based on their short interest (Groups 1 through 5 from low to high short interest). We compute equally-weighted average values for each portfolio on each day, and then average within portfolios over time. All the variables are defined as in Table C.1. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information from September 2006 to June 2017.

Group	0	1	2	3	4	5
Short interest %	0.00	0.04	0.22	0.62	1.47	5.33
ShortLoan(m$)	0.00	0.24	1.44	4.42	10.58	33.15
Vlendable (m$)	43	117	146	172	185	182
Fee %	1.31	0.53	0.46	0.43	0.43	0.53
Concentration	0.62	0.35	0.32	0.30	0.28	0.27
Size (b$)	0.34	0.63	0.66	0.73	0.73	0.65
Age	4.75	4.16	3.70	3.25	2.90	2.66
Coupon %	5.59	5.73	5.63	5.72	5.81	6.09
IG	0.76	0.77	0.77	0.72	0.69	0.64
CDS quotes	0.15	0.34	0.36	0.38	0.39	0.39
ETF membership	0.01	0.07	0.12	0.18	0.23	0.26
Covenants	0.51	0.76	0.76	0.76	0.76	0.79
Unpair %	0.57	0.60	0.62	0.64	0.65	0.66
Tsize	1.31	1.15	1.13	1.14	1.18	1.24
Blockpct %	0.08	0.08	0.08	0.08	0.09	0.10
Turnover	0.85	0.40	0.38	0.38	0.40	0.48
BAS %	1.12	0.92	0.92	0.89	0.89	0.91
Forecast %	0.05	0.06	0.06	0.06	0.06	0.06
Mom %	6.87	5.80	6.23	6.72	7.51	8.61

Table C.5: **Price efficiency panel regressions using TWDCC** This table reports the results when regressing the price-response delay measures D1 and D2 on an alternative inventory cost proxy (− TWDCC). The panel data is at the bond-month level. For a given bond-month pair to be included, we require at least ten months with non-missing data over the past 12 months. We control for lending supply defined as the average lendable value scaled by bond size in a month and indicative lending fees. The remaining variables are defined as in Table 2. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information and TRACE price data.

Dependent variable:	D1		D1		D2		D2	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Inventory cost	0.23	16.7	0.21	15.6	0.18	17.3	0.16	15.9
Supply	-0.12	-8.4	-0.12	-8.2	-0.03	-2.9	-0.03	-2.7
Fee	0.01	1.2			0.01	1.4		
Log (Size)	-0.11	-31.7	-0.11	-30.6	-0.08	-31.5	-0.07	-30.6
BAS	0.45	1.0	0.77	1.6	1.86	5.0	1.51	5.0
Turnover	-2.15	-3.0	-2.16	-3.0	-1.42	-2.9	-1.52	-3.2
Blkpct	-0.36	-3.1	-0.36	-3.0	-0.29	-3.1	-0.28	-2.8
Tsize	0.05	6.2	0.05	5.5	0.05	6.6	0.04	5.7
CDS quotes	-0.01	-3.3	-0.01	-3.3	0.00	-1.3	0.00	-1.2
ETF	-0.07	-17.1	-0.08	-17.9	-0.08	-25.5	-0.09	-26.6
Age	0.25	0.4	0.22	0.4	-0.74	-1.9	-0.74	-1.9
Coupon	8.08	6.5	7.99	6.4	5.47	6.4	5.37	6.4
Concentration	0.18	12.7	0.17	12.4	0.12	12.4	0.10	11.6
Covenants	-0.01	-1.2	-0.01	-1.0	0.00	-1.0	0.00	-0.8
Constant	1.93	37.3	1.90	36.7	1.61	44.9	1.56	44.9
Industry FE	Yes		Yes		Yes		Yes	
Rating FE	Yes		Yes		Yes		Yes	
R^2	0.18		0.18		0.17		0.17	

Table C.6: **Price efficiency panel regressions using changes in yields** This table reports the results when regressing the alternative measures of price-response delay D1 and D2 on an inventory cost proxy (− Unpair). D1 and D2 are estimated from the changes in bond yields following the same approach as in Table 4. The panel data is at the bond-month level. For a given bond-month pair to be included, we require at least ten months with non-missing data over the past 12 months. We control for lending supply defined as the average lendable value scaled by bond size in a month and indicative lending fees. The remaining variables are defined as in Table 2. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information and TRACE price data.

Dependent variable:	D1		D1		D2		D2	
Inventory cost	0.15	11.7	0.14	11.6	0.10	10.6	0.09	10.6
Supply	-0.13	-8.9	-0.11	-8.2	-0.08	-4.7	-0.06	-4.1
Fee	0.01	2.4			0.01	3.2		
Log (Size)	-0.09	-29.7	-0.09	-27.9	-0.06	-31.4	-0.06	-30.2
BAS	1.37	3.0	1.69	3.6	1.91	6.7	1.76	6.7
Turnover	-2.69	-4.2	-2.91	-4.8	-1.57	-3.7	-1.69	-4.2
Blkpct	-0.28	-2.6	-0.27	-2.7	-0.29	-3.4	-0.27	-3.5
Tsize	0.05	6.6	0.05	6.9	0.05	7.1	0.04	7.5
CDS quotes	-0.01	-2.7	-0.01	-2.8	0.00	-1.4	0.00	-1.5
ETF	-0.09	-18.9	-0.10	-20.2	-0.08	-24.4	-0.08	-25.8
Age	1.39	2.5	1.26	2.3	0.07	0.2	0.02	0.1
Coupon	1.02	0.9	0.65	0.6	-0.79	-1.1	-0.89	-1.2
Concentration	0.22	16.3	0.19	15.2	0.09	10.8	0.07	9.3
Covenants	0.00	0.6	0.01	1.2	0.00	1.1	0.01	1.6
Constant	1.79	38.1	1.72	37.0	1.50	49.4	1.44	49.3
Industry FE	Yes		Yes		Yes		Yes	
Rating FE	Yes		Yes		Yes		Yes	
R^2	0.14		0.14		0.13		0.13	

Table C.7: **Controlling for price delay in stock returns** This table reports the results when regressing the price-response delay measures D1 and D2 on an inventory cost proxy (− Unpair), controlling for the price delay measures for stock returns. The variable Equity control is the price delay of the corresponding stocks, estimated in the same approach as D1 and D2 in Table 4 but using equity returns. The panel data is at the bond-month level. For a given bond-month pair to be included, we require at least ten months with non-missing data over the past 12 months. We control for lending supply defined as the average lendable value scaled by bond size in a month and indicative lending fees. The remaining variables are defined as in Table 2. The data include all bonds on loan in the merged FISD-MSF data that have credit rating information and TRACE price data, and have equity matched by 6-digit CUSIP from CRSP.

Dependent variable:	D1		D1		D2		D2	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Inventory cost	0.24	12.1	0.23	12.1	0.19	13.0	0.18	12.9
Supply	-0.09	-3.9	-0.09	-4.0	-0.02	-1.4	-0.02	-1.3
Fee	0.00	0.2			0.01	2.5		
Equity control	0.03	3.3	0.03	3.6	0.02	2.0	0.02	2.1
Log (Size)	-0.12	-22.7	-0.12	-23.0	-0.08	-21.8	-0.08	-21.8
BAS	0.15	0.3	-0.12	-0.2	3.43	7.9	3.14	7.2
Turnover	-0.28	-2.7	-0.28	-2.8	-0.19	-3.1	-0.21	-3.4
Blkpct	-0.20	-1.2	-0.26	-1.8	-0.28	-2.0	-0.32	-2.6
Tsize	0.50	4.2	0.50	4.6	0.58	5.5	0.58	5.9
CDS quotes	-0.02	-2.7	-0.02	-2.9	-0.01	-1.7	-0.01	-1.7
ETF	-0.06	-10.9	-0.06	-10.7	-0.08	-17.4	-0.08	-17.6
Age	2.72	2.9	2.52	2.7	1.08	1.6	0.91	1.4
Coupon	7.81	4.0	7.70	3.9	5.12	3.8	5.22	3.9
Concentration	0.14	6.4	0.14	6.7	0.09	6.1	0.09	5.8
Covenants	0.01	0.4	0.01	0.4	0.02	1.5	0.02	1.5
Constant	2.02	25.2	2.03	25.8	1.63	28.7	1.61	29.0
Industry FE	Yes		Yes		Yes		Yes	
Rating FE	Yes		Yes		Yes		Yes	
R^2	0.19		0.19		0.22		0.22	

Table C.8: **ETF inclusion and the changes in inventory cost (Unpair) and short interest** This table reports the average values of the unpair ratio and short interest as well as their differences cross-period and cross subgroups. Corporate bonds that were included into the ETFs on the same day, have the same credit rating, in the same Fama-French 5-industry classification are allocated into a same group. The sample includes 2102 bond-inclusion events that are sorted into 678 groups with no less than 2 bonds. Within each group, we further sort bonds into two subgroups by their average inventory cost proxy over 22 trading days before inclusion, namely a *High IC pre-inclusion* in blue and a *Low IC pre-inclusion* in red. A high unpair ratio represents a low inventory cost.

	Unpair ratio			Short interest		
	Pre	Post	Change	Pre	Post	Change
Mean (*High IC pre-inclusion*)	0.18	0.29	0.11	1.41	1.82	0.41
t-stat	35.0	44.1	17.9	33.5	32.0	9.9
Mean (*Low IC pre-inclusion*)	0.37	0.39	0.02	1.81	1.95	0.14
t-stat	50.7	60.6	3.4	27.7	28.2	4.2
Diff	-0.19	-0.10	0.09	-0.39	-0.13	0.27
t-stat	-34.9	-33.7	8.5	-4.0	-3.9	4.8

Table C.9: **ETF inclusion and the changes in inventory cost (TWDCC) and short interest** This table reports the average values of the TWDCC and short interest as well as their differences cross-period and cross subgroups. Corporate bonds that were included into the ETFs on the same day, have the same credit rating, in the same Fama-French 5-industry classification are allocated into a same group. The sample includes 2102 bond-inclusion events that are sorted into 678 groups with no less than 2 bonds. Within each group, we further sort bonds into two subgroups by their average inventory cost proxy over 22 trading days before inclusion, namely a *High IC pre-inclusion* in blue and a *Low IC pre-inclusion* in red. A high TWDCC represents a low inventory cost.

	TWDCC			Short interest		
	Pre	Post	Change	Pre	Post	Change
Mean (*High IC pre-inclusion*)	1.32	1.72	0.40	1.37	1.58	0.21
t-stat	29.5	27.7	11.4	25.7	25.2	4.9
Mean (*Low IC pre-inclusion*)	2.44	2.48	0.05	2.08	2.16	0.08
t-stat	31.8	30.8	3.1	21.0	21.2	2.3
Diff	-1.12	-0.76	0.36	-0.71	-0.58	0.13
t-stat	-12.6	-8.4	5.4	-5.5	-6.3	2.6

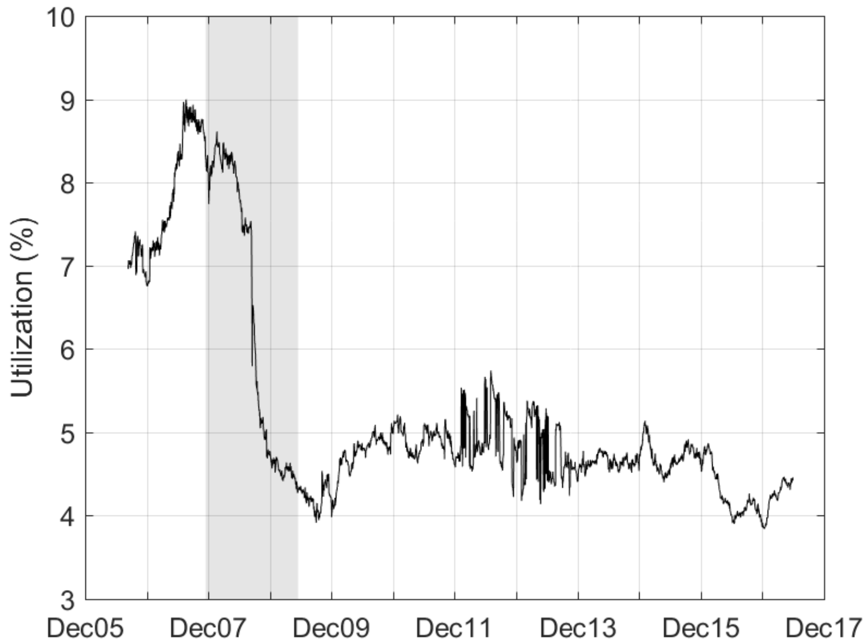

Figure C.1: **Utilization** The plots shows the time series of average utilization. Utilization is measured as the lenders' value on loan divided by the lendable value. The data include all bonds available for lending in the merged FISD & MSF data that have credit rating information, over September 2006 to June 2017.

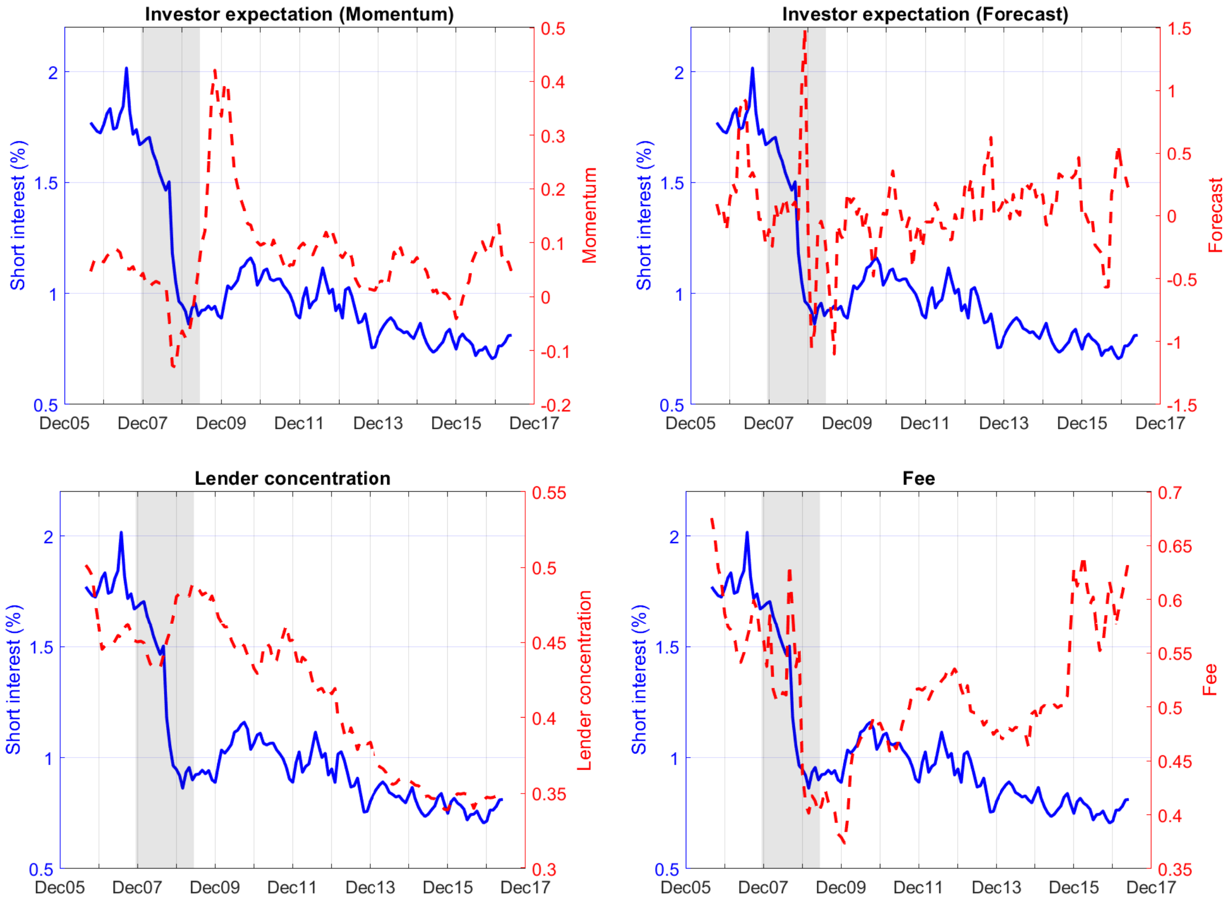

Figure C.2: **Short interest relative to investor expectations and other controls** The top left (right) plot shows the monthly time series of average short interest and momentum (forecast). Momentum is measured as the aggregate returns over the past 12 months. A low past return (past loser) may be associated with low future returns, which speculators may take as a sign of future price decreases which in turn would make a short position in the bond more attractive. Forecast is measured as the 3-month ahead forecast of 3-month T-Bill rates from Blue Chip financial forecast. The bottom left (right) plot shows the monthly time series of average short interest and lender concentration (average indicative lending fees). The measure of lender concentration and indicative lending fees are provided by Markit. The shaded area identifies NBER recessions.

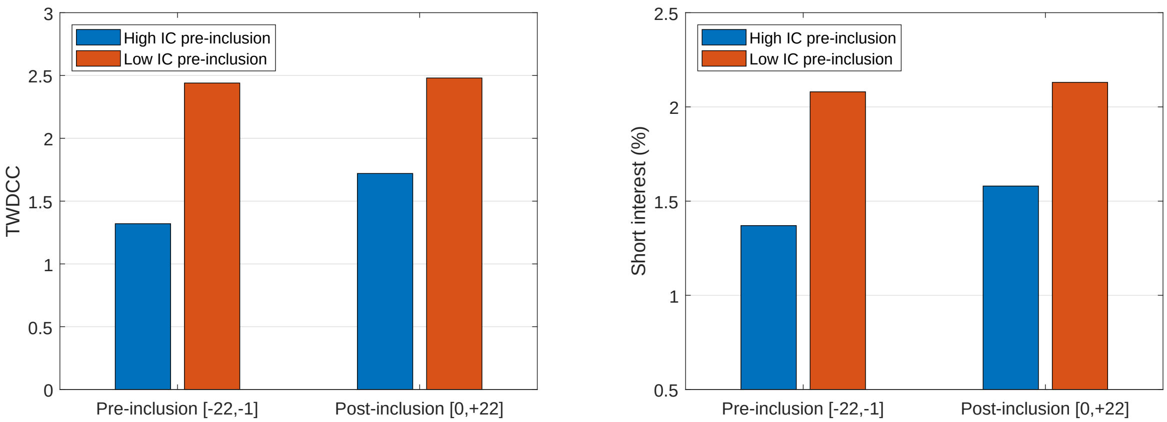

Figure C.3: **ETF inclusion and the changes in inventory cost and short interest** The figures show the average value of TWDCC and short interest (SI) before and after the ETF inclusion for the two subgroups with high and low pre-inclusion average inventory costs. Corporate bonds that were included into the ETFs on the same day, have the same credit rating, in the same Fama-French 5-industry classification are allocated into a same group. The sample includes 2102 bond-inclusion events that are sorted into 678 groups with no less than 2 bonds. Within each group, we further sort bonds into two subgroups by their average inventory cost proxy over 22 trading days before inclusion, namely a *High IC pre-inclusion* in blue and a *Low IC pre-inclusion* in red. A high TWDCC represents a low inventory cost.

D. Regressions at portfolio level

We also use a portfolio approach to address the issue of zero-short-interest bonds. In particular, each bond is assigned to one of 36 portfolios, based on whether the bond's issue size is small (less than \$500 million), medium (between \$500 million and \$1 billion), or large (greater than \$1 billion), whether the bond is rated investment grade (IG) or high yield (HY), whether the issuer belongs to the financial industry or a non-financial sector as defined in Mergent FISD, whether the bond is a long-term bond (maturity$\geq$10 years) or a short/median-term bond (maturity$<$10 years), and whether the issuer has valid CDS quote available.

We reconstruct all the bond characteristics and inventory cost proxies at the portfolio level. Tables D.1 and D.2 reveal that the our portfolio-level findings are largely in line with the bond-level regression results. Consistent with Hypothesis 1, lower dealer inventory is associated with lower short interest, and the effect is particularly pronounced for high-credit-quality firms.

Table D.1: **Portfolio-level regression results** The table reports the regression results for the portfolio level regression. Each bond is assigned to one of 36 portfolios based on size, credit rating, industry and maturity. All the bond characteristics and inventory cost proxies are reconstructed at the portfolio level. We take the negative values of the inventory proxies to proxy for the inventory cost. All variables are defined as in Table 2. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information and TRACE. The sample period is September 2006 to June 2017. The t-statistics are adjusted for clustering of bond CUSIPs.

Inventory cost proxy:	−Aggr dealer inv		−Unpair ratio		−Trade size	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Inventory cost	-8.20	-8.4	-0.64	-2.6	-1.98	-2.3
Supply	1.78	2.0	2.62	2.9	2.46	2.8
Log(size)	0.96	1.3	0.01	0.0	0.08	0.1
Age of bond	-0.17	-2.4	-0.23	-2.8	-0.22	-2.6
Coupon	0.86	2.1	3.22	4.8	2.98	4.7
CDS quotes	-0.36	-0.8	0.06	0.1	0.14	0.3
Covenants	-1.57	-2.7	-1.83	-3.4	-1.77	-3.3
ETF membership	-0.55	-2.3	-1.93	-5.9	-1.82	-5.6
VIX	-0.85	-2.7	-2.05	-4.7	-1.87	-4.6
Lender concentration	-1.85	-2.1	-2.47	-2.6	-2.50	-2.7
Forecasts	0.07	2.1	0.16	3.0	0.14	2.9
Momentum	-0.21	-1.3	-0.37	-2.0	-0.31	-1.7
Constant	-1.01	-1.0	0.34	0.7	0.17	0.9
R^2	0.68		0.64		0.64	

Table D.2: **Portfolio-level regression results with alternative inventory proxies** The table reports the regression results for the portfolio level regression with alternative inventory proxies. Each bond is assigned to one of 36 portfolios based on size, credit rating, industry and maturity. All the bond characteristics and inventory cost proxies are reconstructed at the portfolio level. We take the negative values of the inventory proxies to proxy for the inventory cost. All variables are defined as in Table 2. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information and TRACE. The sample period is September 2006 to June 2017. The t-statistics are adjusted for clustering of bond CUSIPs.

Inventory cost proxy:	−Block trade		-Turnover		−TWDCC		−OCC	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Inventory cost	-4.31	-2.1	-6.36	-3.0	-0.43	-3.9	-0.35	-3.9
Supply	2.46	2.7	2.40	2.9	1.93	2.6	1.98	2.6
Log(size)	0.10	0.1	-0.04	-0.1	-0.68	-1.1	-0.70	-1.1
Age of bond	-0.21	-2.6	-0.19	-2.7	-0.14	-2.0	-0.14	-2.0
Coupon	2.94	4.7	3.13	5.4	2.60	5.1	2.64	5.1
CDS quotes	0.12	0.3	0.29	0.6	0.60	1.2	0.58	1.2
Covenants	-1.76	-3.2	-1.61	-3.3	-1.67	-3.1	-1.70	-3.2
ETF membership	-1.82	-5.4	-1.76	-6.1	-1.51	-5.2	-1.55	-5.3
VIX	-1.84	-4.4	-1.89	-5.4	-1.66	-4.3	-1.73	-4.5
Lender concentration	-2.46	-2.7	-2.59	-3.0	-3.37	-3.5	-3.33	-3.4
Forecasts	0.13	2.7	0.18	3.5	0.12	2.9	0.13	2.9
Momentum	-0.32	-1.8	-0.30	-1.8	-0.29	-1.8	-0.31	-1.9
Constant	0.16	0.9	0.28	0.8	1.14	0.2	1.18	0.2
R^2	0.64		0.64		0.65		0.65	