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

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August 2019

Abstract

We propose a model of trading in the over-the-counter corporate bond market where investors buy and sell bonds through dealers, and investors and dealers short bonds by borrowing them in the securities lending market. The model predicts that higher dealer inventory costs are associated with lower short interest for bonds. We construct bond-level proxies for inventory costs and provide empirical evidence in support of the model's prediction. We find that much of the dramatic decline in short interest observed since the Great Financial Crisis (GFC) can be explained by an increase in proxies for inventory costs. We document that implicit short-sale constraints imposed by higher dealer inventory costs have a negative impact on price efficiency in the corporate bond market. Our findings suggest that tighter post-GFC regulation may have had unintended consequences for 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 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. 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]

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)).

[1] For a detailed description of the 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.

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 positions. 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 a model for trading in the 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, the short interest is generated mainly by informed investors who received 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, all else the same, higher inventory costs are associated with lower bid prices. Low bid prices discourage informed investors from trading on negative credit news. When inventory costs are so high that informed investors prefer to abstain from trading on negative news, less precise information is revealed to the market. As a result, uninformed investors trade at prices that tend to be too high given the negative private signal. In that sense, 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 these proxies are higher, short interest tends

[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.

to be lower, even after controlling for the 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 or investor expectations. None of these alternative sources can explain the dramatic decline in short interest observed since 2008. The temporal pattern in short interest is, however, closely matched by that of dealer inventory and other proxies of inventory costs, especially for investment-grade debt.

We further show that the short-sale constraints imposed by high dealer inventory costs have had a negative impact on price efficiency in the corporate bond market. For equity markets, a number of studies have shown that there exists an association between tighter short-sale constraints and lower price efficiency. To the best of our knowledge, however, 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. 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.

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. The data include both pre- and post-GFC periods. This allows us to extend the descriptive analysis of the corporate bond lending market that was initially provided by Asquith, Au, Covert, and Pathak (2013) for the period 2004 to 2007. So far, there are only few additional papers that analyze the market for borrowing corporate bonds (Nashikkar and Pedersen (2007), Kozhan and Raman (2014), Foley-Fisher, Narajabad, and Verani (2016), and Foley-Fisher, Gissler, and Verani (2016)). These authors 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]

[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.

[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

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 (2017), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) and Bao, O'Hara, and Zhou (2018). Our contribution 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 and shows empirically that higher inventory costs are associated with lower short interest. Section 5 shows that higher inventory costs are associated with lower price efficiency, by dampening short interest. Section 6 summarizes our findings and concludes.

2. A Model of Corporate Bond Trading

We establish a theoretical link between dealer inventory costs and trading outcomes 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 at time $t = 0$, is not modeled. We simply assume that it results in a dealer holding I_0 units of the bond, 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 just after the primary market closes, 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.[8] 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

(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.

[8] 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.

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 decide to 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 position in the securities lending market. There are 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.[9] Lenders charge a proportional net lending fee f.

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 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 its creditors 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. The risk-free asset serves as the numeraire and we normalize the risk-free rate to zero.

At time $t = 0$, all agents believe default (i.e., $\tau = 1$) occurs with probability $\pi_0 \in (0, 1)$. When the secondary market opens, I investors observe an updated signal $\pi_I \in (0, 1)$ about the likelihood of default. The log odds ratio of the signal π_I, $Y_I = Y(\pi_I)$, is defined via

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

We assume that Y_I has a normal distribution with mean μ_y and variance σ_y^2. Using $Y_0 = Y(\pi_0)$ to denote beliefs at $t = 0$, the case $Y_I > Y_0$ corresponds to the scenario where I investors learn that the firm has become more risky. If $Y_I < Y_0$, the signal reveals that the financial health of the firm has improved, and if $Y_I = Y_0$, beliefs remain unchanged.

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

[9] In future iterations of the paper, we will extend the model to allow the dealer to lend out his inventory of bonds.

$\widetilde{K} = (1 - \mathrm{R})\, 1_{\{\tau=1\}}$ 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, $X_U = 0$.

After the informed observe the private signals X_I and Y_I, they decide whether or not to contact the dealer with a request to quote (RtQ). I investors make a RtQ only if they anticipate a non-zero chance of positive benefits from trade. The market observes the indicator D_{RtQ}, where $D_{RtQ} = 1$ if the informed request a quote and zero otherwise. Once D_{RtQ} is observed, the dealer publicly posts the unit ask price A^* and the unit bid price B^*. Given quotation (A^*, B^*), each I investor sets their demand $Q_I(A^*, B^*)$ according to the schedule $Q_I(A, B) = Q_I(A, B \big| X_I, Y_I)$. Note that $Q_I(A, B \big| X_I, Y_I) = 0$ for all A and B whenever $D_{RtQ}(X_I, Y_I) = 0$. U investors observe D_{RtQ} and $Q_I(A^*, B^*)$ and set their demand at $Q_U(A^*, B^*)$, where $Q_U(A, B) = Q_U(A, B \big| Q_I(A, B), D_{RtQ})$.

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

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

where, with $q^+ = \max(0, q)$ and $q^- = \max(0, -q)$,

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

is investor i's wealth at $t = 1$, $\delta > 0$ is the absolute risk aversion parameter common to all agents, and $\mathcal{I}_i$ denotes the information available to investors of type i at time $t = 0+$.

Given bid price B and ask price A, the market ask depth α is defined as the total amount of bonds bought by investors and the bid depth β as the total amount sold:

$$\alpha = \sum_{i=I,U} N_i Q_i^+(A, B), \qquad \beta = \sum_{i=I,U} N_i Q_i^-(A, B). \tag{4}$$

The dealer's problem is to choose price levels A^* and B^* to maximize their utility,

$$\max E\left(-e^{-\delta \widetilde{W}_D} \big| \mathcal{I}_D\right), \tag{5}$$

subject to $\widetilde{W}_D = W_D(\widetilde{V})$, where

$$W_D(V) \quad = \quad \alpha(A,B)A - \beta(A,B)B + \text{Inv}(A,B)V - |\text{Inv}(A,B)|c - \text{Inv}(A,B)^- f. \tag{6}$$

Here, $\text{Inv}(A,B) = I_0 + \beta(A,B) - \alpha(A,B)$ denotes the inventory that the dealer holds between $t = 0+$ and $t = 1$. The dealer incurs a proportional cost c on the long or short net inventory they hold. Dealer inventory costs c are at the center of our investigation, which aims to understand how these costs impact equilibrium bond prices and trading volumes.

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

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

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

2. *Given the demand schedules* $Q_I^*(A,B)$ *and* $Q_U^*(A,B)$*, the quoted ask price* A^* *and bid price* B^* *solve the dealer's problem* (5)*. For any* A *and* B*, the dealer's information set is* $\mathcal{I}_D = \{A, B, D_{RtQ}, Q_I^*(A,B)\}$*.*

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

2.1 Equilibrium

We now present investors' optimal demand schedule and describe how equilibrium bid and ask prices depend on the inventory cost c. Although the uninformed cannot observe the private signals, they can extract information about them from observing quoted prices and the trading behavior of the informed.

Proposition 1

(a) Given the private signals X_I and Y_I, $D_{RtQ}(X_I, Y_I) = 1$ and the quotation (A, B), the optimal demand schedule for a type-i investor, $i \in \{I, U\}$, is

$$Q_i^*(A,B) = \begin{cases} Z_i + g(A), & A < P_i^R, \\ 0, & B - f \leq P_i^R \leq A, \\ Z_i + g(B-f), & B - f > P_i^R. \end{cases} \tag{7}$$

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

$$Z_i = X_i - \gamma Y_i. \tag{8}$$

Here, $X_U = 0$ and $Y_U = Y(\pi_U)$ as per (1), where

$$\pi_U = E\left(\pi(Y_I)|\mathcal{I}_U\right). \tag{9}$$

$P_i^R = P^R(Z_i)$, with

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

is investor i's reservation price, i.e., the price at which the investor is indifferent between trading and not trading the bond.

(b) Given $D_{RtQ} = 0$, $Q_I(A, B) = 0$ for each quotation (A, B). The optimal demand schedule for an U investor is as in (7).

Proofs are available in Appendix B.

Proposition 1 implies that as long as I investors request a quote, U investors observe the combined signal Z_I defined in (8). If, however, the informed decide not to request a quote, the uninformed cannot observe Z_I directly. Instead, they only know that $Z_I \in \mathcal{Z}$, where $\mathcal{Z} = \{Z_I | D_{RtQ}(X_I, Y_I) = 0\}$. In

summary,

$$\mathcal{I}_U = \begin{cases} \{A^*, B^*, D_{RtQ}, Z_I\}, & D_{RtQ} = 1 \\ \{A^*, B^*, D_{RtQ}, Z_I \in \mathcal{Z}\}, & D_{RtQ} = 0. \end{cases} \tag{11}$$

The uninformed use the observed information to update their beliefs about the riskiness of the firm to

$$\pi_U \quad = \quad E\left(\pi_I \middle| \mathcal{I}_U\right) = E\left(\frac{1}{1+e^{-Y_I}} \middle| \mathcal{I}_U\right). \tag{12}$$

In equilibrium, the dealer and the uninformed share the same information, meaning $\pi_D = \pi_U$.

With this notation in place, we can formulate trading outcomes in relation to the inventory cost c.[10]

Proposition 2

(a) For a given inventory cost c and private signals X_I and Y_I, $\mathcal{Z} = \{Z_I | Z_I \in [\underline{z}, \overline{z}]\}$, for some $\underline{z} = \underline{z}(X_I, Y_I; c)$ and $\overline{z} = \overline{z}(X_I, Y_I; c)$.

(b) Given X_I and Y_I, the lower boundary $\underline{z}$ is a decreasing function of c, whereas the upper boundary $\overline{z}$ does not depend on c.

(c) As c increases, the bid depth at a given Z_I decreases.

Proposition 2 states that as inventory costs increase, the range of combined signals Z_I for which I investors prefer not to participate in the corporate bond market widens. Specifically, 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 1 shows how the no-RtQ set widens as inventory costs increase.

Figure 2 visualizes the demand by I investors as a function of the combined signal I. As suggested by Figure 1, the range of combined signals Z_I where the informed prefer not to trade widens. And even when $Z_I < \underline{z}$, the short interest generated by I investors is lower when inventory costs are higher.

[10] To date, we have verified Proposition 2 numerically, for a wide range of parameters. In future iterations of the paper, we aim to provide an analytical proof as well.

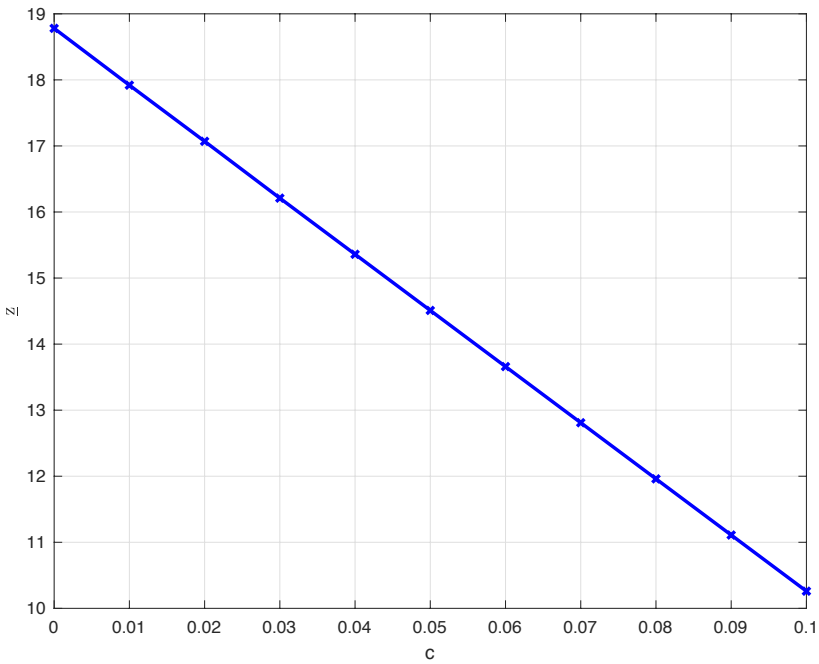

Figure 1: **Lower boundary of non-RtQ set** $\mathcal{Z}$ The figure shows the lower boundary $\underline{z}$, as a function of inventory costs c. The remaining model parameters are set to $\delta = 0.1$, $R = 0.4$, $I_0 = 100$, $N_I = N_U = 10$, $\pi_0 = 0.01$, $\sigma_y = 1$ and $\sigma_x = 10$. The parameter $\mu_y = -5.0789$ is chosen so that $E\left[1/(1+e^{-y})\right] = \pi_0$. The upper boundary, $\overline{z} = 76.51$, does not change with c.

When high inventory costs prevent I investors from taking a short position, the market receives less precise information about the private signals. Depending on D_{RtQ}, the uninformed update their beliefs as follows:

$$\pi_U = \begin{cases} \dfrac{1}{\phi\left(Z_I \middle| \mu_z, \sigma_z\right)} \displaystyle\int_{-\infty}^{\infty} \frac{1}{1+e^{-y}} \phi\left(Z_I + \gamma y \middle| 0, \sigma_x\right) \phi\left(y \middle| \mu_y, \sigma_y\right)\, dy, & D_{RtQ} = 1 \\ \dfrac{1}{\Phi\left(\overline{z} \middle| \mu_z, \sigma_z\right) - \Phi\left(\underline{z} \middle| \mu_z, \sigma_z\right)} & \\ \quad \times \displaystyle\int_{-\infty}^{\infty} \frac{1}{1+e^{-y}} \left[\Phi\left(\overline{z} + \gamma y \middle| 0, \sigma_x\right) - \Phi\left(\underline{z} + \gamma y \middle| 0, \sigma_x\right)\right] \phi\left(y \middle| \mu_y, \sigma_y\right)\, dy, & D_{RtQ} = 0, \end{cases} \tag{13}$$

where $\mu_z = -\gamma\mu_y$ and $\sigma_z = \sqrt{\sigma_x^2 + \gamma^2\sigma_y^2}$ are the mean and standard deviation of Z_I, $\phi(\cdot|\mu,\sigma)$ denotes the probability density function of a normal distribution with mean μ and standard deviation σ and $\Phi(\cdot|\mu,\sigma)$ the associated cumulative density function.

The left plot in Figure 3 shows 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 $Z_I \in \mathcal{Z}$, the uninformed replace π_U estimated based on Z_I with a weighted average across $Z_I \in \mathcal{Z}$. This leads to mis-pricing of the bond relative to the

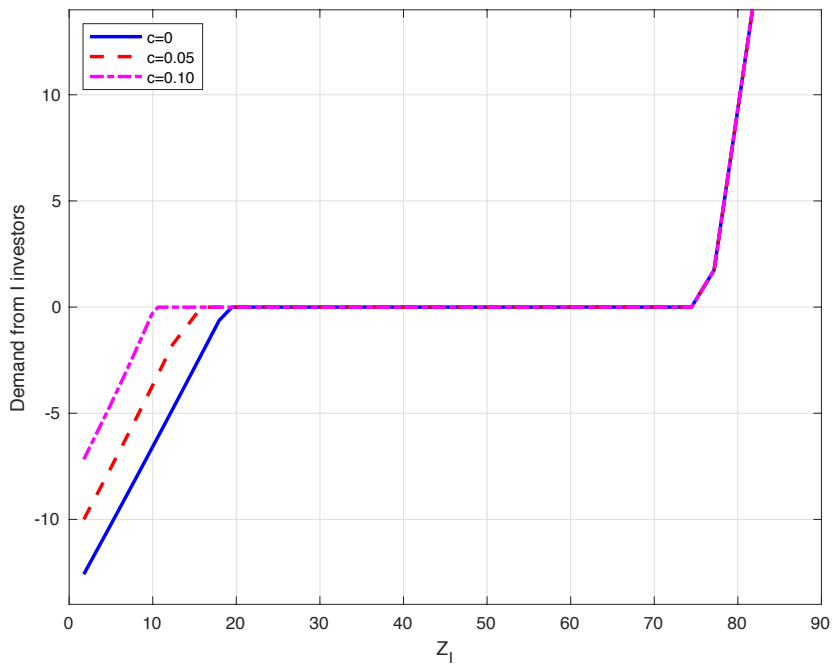

Figure 2: **I investor demand** The figure shows I investor demand $Q_I^*(A^*, B^*)$ as a function of Z_I, for various inventory costs c. The remaining model parameters are set to $\delta = 0.1$, $R = 0.4$, $I_0 = 100$, $N_I = N_U = 10$, $\pi_0 = 0.01$, $\sigma_y = 1$ and $\sigma_x = 10$. The parameter $\mu_y = -5.0789$ is chosen so that $E\left[1/(1+e^{-y})\right] = \pi_0$. The upper boundary, $\overline{z} = 76.51$, does not change with c.

benchmark case where the combined signal Z_I is publicly observed, as shown in the right plot of the figure. As Z_I decreases, the uninformed overprice the bond more and more.

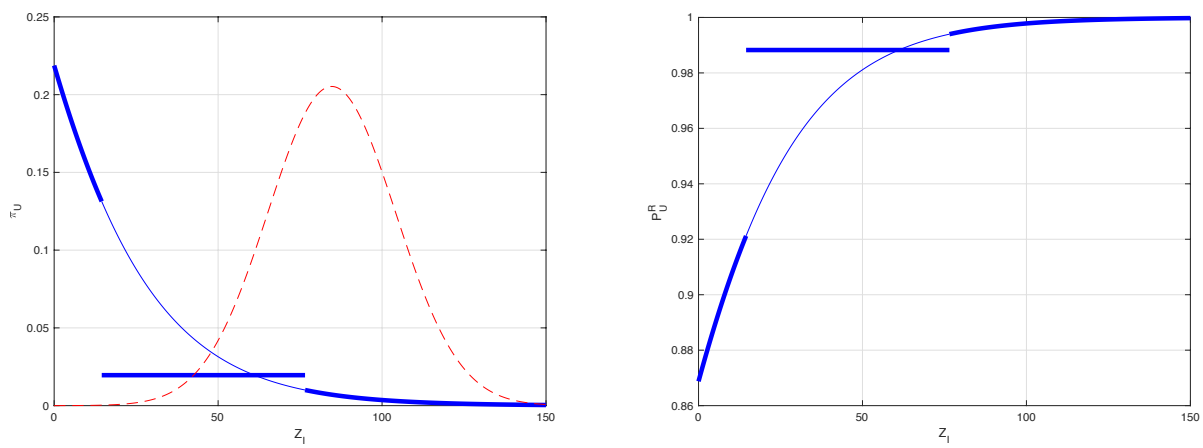

Figure 3: **U investors' updated beliefs** In the left plot, the solid blue line shows U investors' updated beliefs π_U in (12), as a function of Z_I. The inventory cost is fixed at $c = 0.05$. The remaining model parameters are set to $\delta = 0.1$, $R = 0.4$, $I_0 = 100$, $N_I = N_U = 10$, $\pi_0 = 0.01$, $\sigma_y = 1$ 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.

2.2 Testable hypotheses

Our proposed model framework motivates the following two hypotheses:

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

In Section 4, we offer empirical evidence in support of this hypothesis.

Hypothesis 1 states that high inventory costs impose indirect short-sale constraints. 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.

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

Empirical evidence in support of Hypothesis 2 is provided in Section 5.

When testing these hypotheses empirically, we face the challenge that dealer inventory costs are not directly observable. We therefore construct observable proxies for dealer inventory. For example, Figure 4 shows a strong negative link between inventory costs and inventory levels. Thus, we use inventory levels as one proxy for inventory costs.

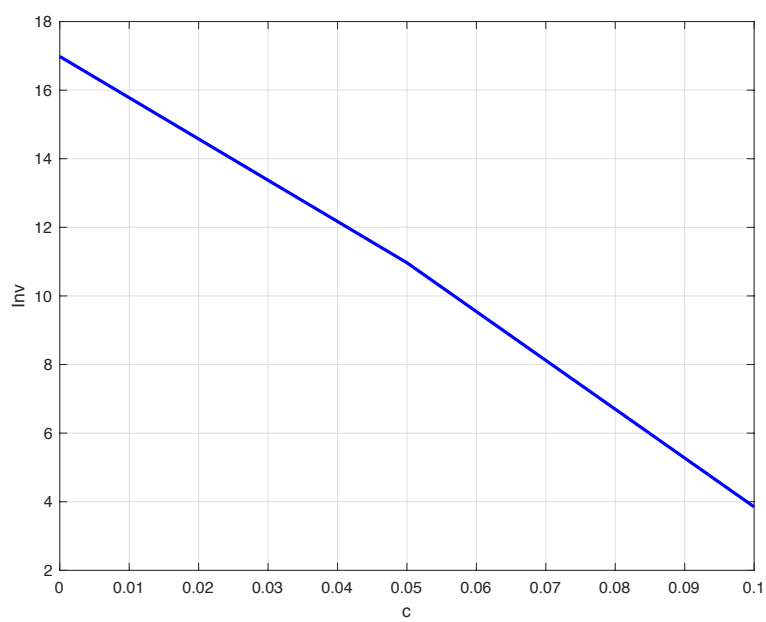

Figure 4: **Dealer inventory** The figure shows the dealer inventory as a function of the inventory costs, c. The combined signal is fixed at Z_I close to 10. The remaining model parameters are set to $\delta = 0.1$, $R = 0.4$, $I_0 = 100$, $N_I = N_U = 10$, $\pi_0 = 0.01$, $\sigma_y = 1$ and $\sigma_x = 10$. The parameter $\mu_y = -5.0789$ is chosen so that $E\left[1/(1+e^{-y})\right] = \pi_0$.

3. Data and Descriptive Statistics

This section describes the bond market and securities lending data used in our study. Additional data—including primary dealer inventory, ETF membership status, CDS availability and expert forecasts—are described in Appendix C.

3.1 Securities lending data

The corporate bond lending data are provided by Markit Financial Securities (MSF). MSF covers about 85 percent of the global securities lending market and more than 90 percent of the U.S 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 that available for lending, the value and quantity of the bond on loan, the on-loan ratio (utilization) computed as bonds on loan divided by bonds available for lending, the total number of transactions outstanding, the transaction-weighted number of days from start date to present for all transactions (tenure), the value on loan against cash collateral as proportion of value on loan (cash), indicative fees and rebate rates, among other variables. We also obtain similar data for the equity market.

The indicative fee variable 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 a borrower 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.

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 (size), 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.[11] We also obtain the bond covenants data and categorize them into four types by the nature of restrictions as discussed in Chava, Kumar, and Warga (2009).[12]

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 TRACE transaction and WRDS bond return data

We obtain corporate bond transaction data from the enhanced Trade Reporting and Compliance Engine (TRACE) database.[13] The main variables include the 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 price outliers (price $< \$50$ or $> \$200$) or trade-size outliers (trade size $< \$1,000$ or $> \$100$ 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.[14]

3.4 Sample construction

We merge the cleaned MSF data with the cleaned FISD and pricing data using 9-digit CUSIPs. We exclude those observations where the lendable value is greater than the bond size. Next, we identify

[11] 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.

[12] The four types of covenants include Investment restrictions, Dividend restrictions, Subsequent financing restrictions and Event-related restrictions. A bond is considered as having a certain type of covenant if the bond indenture includes one or more of the corresponding restrictions.

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

[14] The TRACE manual is available via WRDS.

all bond-date pairs for which Markit reports a five-year CDS rate with modified restructuring for the senior-unsecured debt of the issuing firm. We consider Markit CDS rates as valid quotes if the quality indicators is BB or higher and if a recovery rate estimate is available. If a quote 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.

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 between 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 5,250, or 63%, of bonds in the merged FISD & MSF data are on loan. There is a slight upward trend in the fraction of bonds lent during our sample period.

Table 1: **Descriptive statistics for FISD and MSF data** The first two rows in the top panel 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 FISD & MSF data that are on loan. The first row in the bottom panel shows the daily average of total size at issuance of the bonds in the FISD data. The second row shows the daily average of total size at issuance of the bonds in the merged FISD & MSF data. The third and fourth rows show the daily average of the total lendable value and of the total value on loan for bonds in the merged FISD & MSF 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	5.25	4.08	4.70	4.58	4.21	4.64	4.95	5.22	5.54	5.93	6.27	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	0.07	0.09	0.07	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 comparisons 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 billion in the merged FISD & MSF data. The daily average par value of bond inventory in the merged FISD & MSF data is \$1.0 billion, or 4% of the total par value of bonds issued and listed in FISD. Of this inventory, an average \$50 billion, or 5% of the total par value of the inventory, is on loan. In value terms, the on-loan percentage is decreasing over time, from 10% in 2006 to 5% in 2016, suggesting that although

the 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 dataset covers 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 $820 billion, compared to $197 billion in Asquith, Au, Covert, and Pathak (2013). In addition, the average value on loan is about $70 billion in our sample, compared to $14 billion in their data. The statistics in Table 1 highlight that our corporate bond lending sample is sufficiently large and representative to draw inferences about the entire corporate bond lending market.

3.5 Descriptive statistics

Table C.1 in Appendix C reports descriptive statistics for the bonds in the merged FISD & MSF data. Following Asquith, Au, Covert, and Pathak (2013), we focus on the characteristics that are likely to affect the demand and supply in the corporate bond lending market. These characteristics include the bond size at issue, time since issuance (age), percent floating rate, percent subject to SEC Rule 144a, percent with CDS quotes. We include variables that may impact corporate bond borrowing, such as lender concentration and investor expectations (forecast and momentum). Following Randall (2015), we use TRACE data to construct variables that are likely to reflect dealer inventory cost, including the unpaired trading ratio, average trading size, turnover and the fraction of block trading. We follow Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) to measure dealer capital commitment (time-weighted dealer capital commitment TWDCC and overnight capital commitment OCC). Table C.2 reports descriptive statistics by year, from 2006 to 2017.

3.6 Aggregate demand and short interest in the corporate bond market

Figure 5 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 has recovered

about half of this drop in the post-GFC period. The aggregate quantity of loans tracks the pattern of the aggregate value over time.

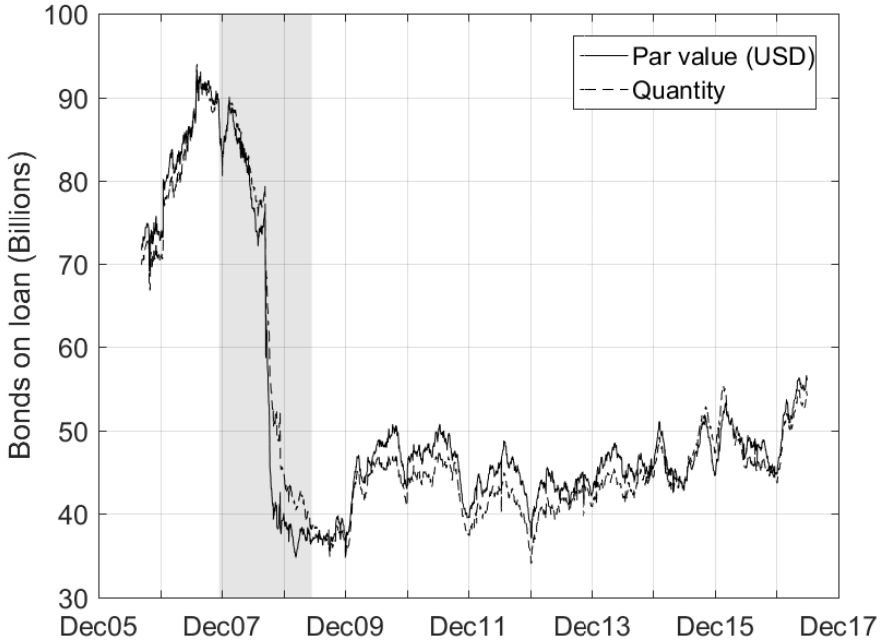

Figure 5: **Aggregate par value and quantity of bonds on loan** The plot shows the daily time series of aggregate demand in the corporate bond borrowing market. The data include all bonds available for lending in the merged FISD & MSF data that have credit rating information, from September 2016 to June 2017.

Figure 6 displays the time series of average short interest, that is, of the average ratio of value on loan to bond size. Average short interest was above 2% prior to the Great Recession, dropped to below 1% during the Great Recession, and remained at or below 1% in the post-GFC period.

The temporal pattern of bond utilization is shown in Figure C.1 in the appendix. It tracks that of short interest.

4. Dealer Inventory and Short Interest

In this section, we provide empirical support for Hypothesis 1 developed in Section 2.

4.1 Visual inspection of the data

Motivated by Figure 4 in Section 2, we first compare the temporal pattern of average short interest in corporate bonds with that for aggregate dealer inventory. Figure 7 shows that the two time series track each other closely. Figure C.2 in the appendix compares short interest patterns to those of other

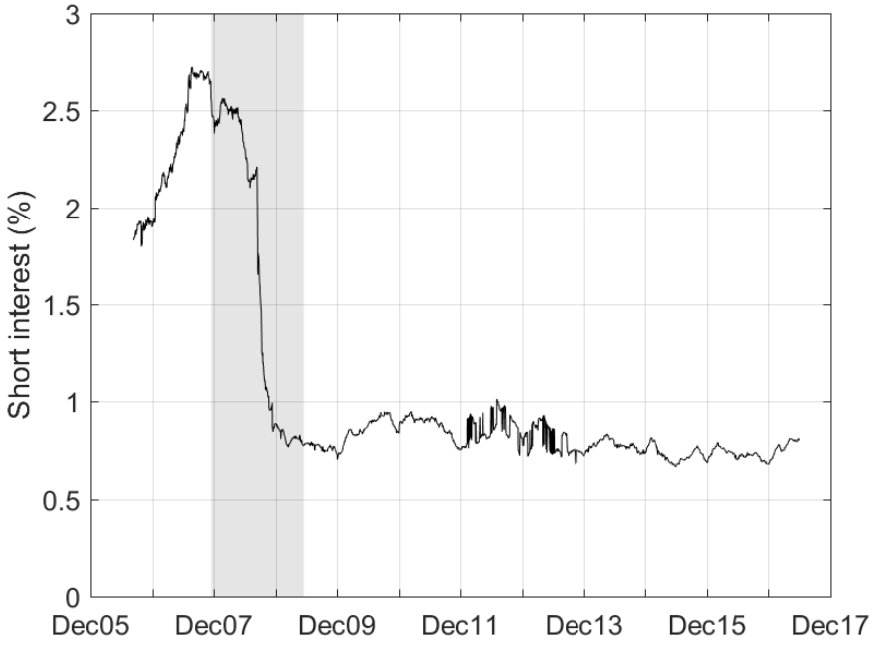

Figure 6: **Short interest** The plot shows the daily time series of average short interest. The data include all bonds available for lending in the merged FISD & MSF data that have credit rating information, from September 20166 to June 2017.

potential drivers—such as investors' expectations, lending fees and lender concentration—and reveals only a weak association.

4.2 Bond-level proxies for dealer inventory

In addition to aggregate dealer inventory, we also compute bond-level inventory proxies. Randall (2015), for example, argues that dealers use paired trades to unwind customer trades immediately in the inter-dealer market, to avoid inventory holding costs. In that sense, a higher fraction of paired trades in the market indicates less willingness by dealers to facilitate the customers' trades using their own inventory. Feldhütter (2011) also state that some trades tend to be part of a pre-matched arrangement by a dealer for a buyer and seller. A trade between the seller and the dealer, and a trade between the buyer and the dealer, are carried out once there is a match. Such a match can reduce the dealer's inventory risk (in addition to earning a "risk-free" bid-ask spread).

We identify paired trades based on the methodologies used in Randall (2015), Zitzewitz (2010) and Feldhütter (2011). Specifically, we label a trade as paired *(i)* if a customer-dealer trades occurs within fifteen minutes of an inter-dealer trade in the same bond and with a quantity difference of no

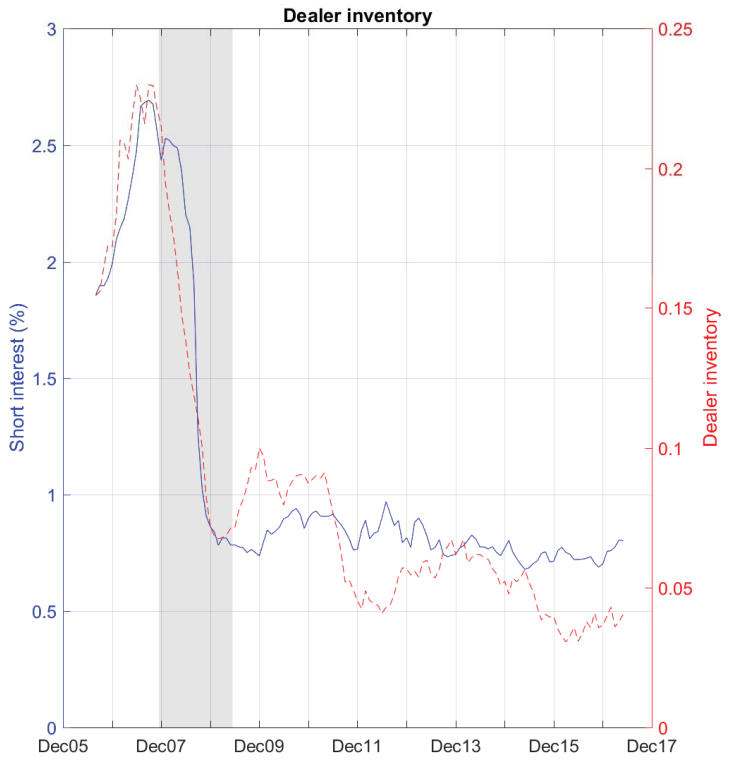

Figure 7: **Short interest and aggregate dealer inventory** This figure shows the monthly time series of average short interest and aggregate dealer inventory. The inventory is measured as the corporate bond inventory of primary dealers, as disseminated by the New York Fed. The shaded area identifies NBER recessions.

more than ±50% (see Randall (2015)), or *(ii)* if 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 ±50% (see Zitzewitz (2010) and Feldhütter (2011)). The fraction of unpaired trading, 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.

Figure 8 shows that a close, albeit not perfect, association between the temporal variation in the Unpair ratio and average short interest, in support of Hypothesis 1. We also plot average short interest against alternative, bond-level proxies of dealer inventory. These include average trade size, turnover, the fraction of block trading, and two measures of dealer capital commitment developed by Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018). For each of these dealer inventory proxies, the data are consistent with Hypothesis 1.

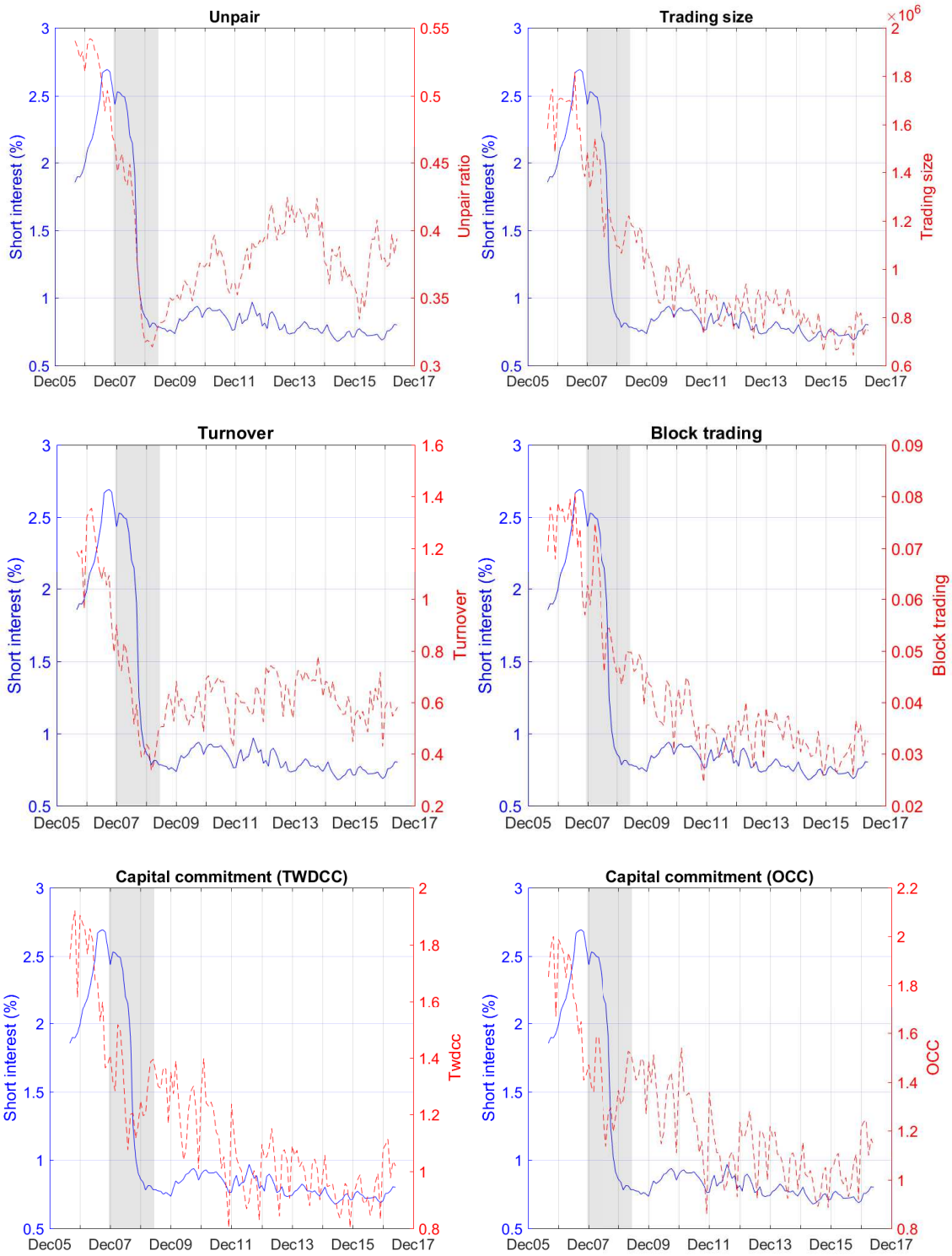

Figure 8: **Short interest and bond-level dealer inventory proxies** The top left (right) plot shows the monthly time series of average short interest and lender unpaired trading ratio (trading size). The middle (right) plot shows the monthly time series of average short interest and lender turnover (fraction of block trading). The bottom (right) plot shows the monthly time series of average short interest and the time weighted daily capital commitment TWDCC (over night capital commitment OCC). The shaded area identifies NBER recessions.

Randall (2015) argues that smaller dealer inventory positions and dealers' higher cost of holding inventory has led to smaller average trade sizes since the crisis. The intuition is that the dealers are more willing to unwind the customer trades immediately in the inter-dealer market when the inventory cost is high, and smaller trade size gives dealers greater ability to pair trades. Hence we consider the average trade size of corporate bonds as a proxy for dealers' inventory. Similar intuition also applies to the turnover and fraction of block trading. We find that the measures of turnover, average trading size and fraction of block trading all decreased significantly after the crisis, indicating less willingness of the dealers to facilitate trades which may incur inventory cost.

Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) measures the time-weighted daily capital commitment (TWDCC) as the time-weighted absolute value of the net cumulative dealer's position in the day for a bond. The overnight capital commitment (OCC) is computed as the change in inventory since the beginning-of-day that is also carried overnight.[15] Due to lack of data on the initial inventory level, we are not able to measure bond-level dealer inventory directly. TWDCC and OCC are two indirect measures as they measure the extent to which dealers are willing to use their own capital to absorb customer order imbalances, rather than simply pairing customers' buy and sell orders to earn a "risk-free" spread.

4.3 Tobit regressions at the bond level

More than 35% of all bond-date pairs in our sample have a short interest of zero.[16] When estimating a predictive model for the demand for corporate bond borrowing, we address this issue as follows. We first present results for a bond-level panel Tobit regression. Afterwards, we sort bonds into 36 different categories based on size, maturity, industry, credit rating and CDS market coverage, and run regressions at the portfolio level.

In the bond-level Tobit regressions, we condition on bond characteristics including indicators for

[15] Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) construct TWDCC and OCC from dealer-level. In the absence of dealer ids in the TRACE data, we assume all dealer-customer trading is facilitated by one representative dealer and construct the measures at the portfolio level directly. We find the overall time-series patterns of TWDCC and OCC are consistent with those in Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018).

[16] 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—that is, bonds that are available for borrowing but have no demand—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 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.

whether taking a short position in the bond could be replicated by buying CDS protection on the issuer, the bond has covenants, or the bond is a constituent of a major bond ETF. We also control for funding liquidity (as proxied by VIX) and condition on investor expectations using momentum and expert forecasts.

The results are reported in Tables 2 and C.3. Independent of the dealer inventory proxy used, our findings are consistent with Hypothesis 1, in that lower dealer inventory is associated with lower short interest. We observe that the effect is particularly pronounced for high-credit-quality firms.

Table 2: **Tobit regression results** The table reports Tobit regression results. Short interest is measured as amount borrowed divided by bond size, and supply is measured as amount lendable divided by bond size. Age of the bond is measured in years. CDS market and ETF membership are dummies 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 returns over past 12 months, separately for IG and HY firms. Forecasts are measured as expected changes in the 3-month T-Bill rate in percent. VIX is scaled by 1/1000. Concentration is a Markit-constructed measure of relative lendable value distribution among lenders. Covenants indicate whether the bond has any type of covenants. A smaller number indicates a large number of lenders with low inventory. Primary dealer inventory of corporate debt is reported by the New York Fed. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information. The sample period is September 2006 to December 2015. The t-statistics are shown in parentheses and are adjusted for clustering of bond CUSIPs.

Inventory cost proxy:	Aggr dealer inv		Unpair ratio	
	Estimate	t-stat	Estimate	t-stat
Constant	-0.63	(-1.9)	-2.15	(-5.4)
IG	-1.16	(-16.0)	-2.41	(-10.0)
Supply	4.09	(24.7)	4.74	(28.3)
Log(size)	0.12	(4.9)	0.13	(5.5)
Age of bond	-0.06	(-25.4)	-0.07	(-31.1)
Coupon	0.95	(1.2)	3.77	(4.5)
CDS quotes	0.22	(7.8)	0.26	(8.9)
Covenants	0.01	(0.3)	-0.07	(-1.7)
ETF membership	0.35	(8.2)	0.21	(4.9)
VIX	-0.61	(-6.6)	1.27	(11.1)
Lender concentration	-0.88	(-12.3)	-0.76	(-10.5)
Forecasts	-0.04	(-1.1)	0.07	(2.2)
Forecasts × IG	-0.02	(-0.5)	-0.18	(-5.2)
Momentum	0.02	(0.5)	0.10	(2.1)
Momentum $\times IG$	-0.90	(-8.8)	-0.81	(-8)
Inventory cost	5.47	(7.7)	2.92	(5.0)
Inventory cost $\times IG$	4.91	(5.7)	3.47	(5.3)
Industry FE	Yes		Yes	
R^2	0.15		0.14	

4.4 Regressions at portfolio level

Next, we 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≥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. Because each proxy alone may only yield a noisy measure of dealer inventory costs, we conduct a principal component analysis at the portfolio level. Specifically, we compute the monthly first principal component of portfolio-level Unpair ratio, trade size, turnover, fraction of block trading, TWDCC and OCC.

Tables 3 and C.5 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.

5. Price Efficiency

In this section, we explore the potential impact of dealer inventory costs on price efficiency in the corporate bond market. The model proposed in Section 2 suggests that one channel through which inventory cost may impact price efficiency is by imposing indirect short sale constraints. According to Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010)—who study equity markets—short sale constraints may be imposed by a low supply of lendable securities and high lending fees, as these would increase the difficulty and cost of short sellers to initiate a short position. We contribute to the existing literature by analyzing price efficiency for corporate bonds instead of stocks, and by identifying 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. In the main part of the paper, results are presented for the case where the Unpair ratio is used to proxy for inventory costs. Robustness checks are described in Appendix C.

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

Table 3: **Portfolio-level regression results** The table reports the results for the portfolio level regression. Short interest is measured as amount borrowed divided by bond size, and supply is measured as amount lendable divided by bond size. Age of the bond is measured in years. CDS market and ETF membership are dummies 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 cumulative returns over the past 12 months at bond level. Forecasts are measured as BlueChip forecast changes in the 3-month TBill rate in percent. 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. Primary dealer inventory of corporate debt is reported by the New York Fed. Unpair is the unpaired trading ratio over a month. Tsize is the average trading size in a month. PCA is the first principal component of the major inventory cost proxies for each portfolio. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information and then merge with TRACE data. The sample period is from September 2006 to June 2017.

Inventory cost proxy:	Aggregate dealer inv	PCA	Unpair
Constant	0.56	-2.04	-4.93
	(0.3)	(-0.8)	(-1.9)
IG	-1.06	-0.39	-1.38
	(-3.7)	(-1.6)	(-2.4)
Supply	1.85	2.64	2.48
	(2.4)	(3.5)	(2.8)
Log(size)	0.04	0.24	0.43
	(0.3)	(1.4)	(2.4)
Age of bond	-0.01	-0.04	-0.05
	(-0.2)	(-0.9)	(-1.1)
Coupon	0.12	0.23	0.32
	(2.4)	(3.6)	(4.7)
ETF membership	-0.17	-1.10	-1.33
	(-0.4)	(-2.4)	(-2.7)
VIX	-0.22	-0.41	-0.59
	(-0.5)	(-0.8)	(-1.1)
Lender concentration	-2.89	-2.68	-2.40
	(-3.9)	(-2.9)	(-2.5)
Forecasts	0.07	0.13	0.15
	(1.1)	(1.5)	(1.7)
Forecasts × IG	-0.04	-0.08	-0.02
	(-0.6)	(-0.8)	(-0.2)
Momentum (ret)	-0.25	-0.29	-0.38
	(-1.6)	(-1.8)	(-2.4)
Momentum (ret) × IG	-0.72	-0.91	-0.97
	(-2.1)	(-2.0)	(-2.2)
Inventory cost	6.72	0.06	0.17
	(4.6)	(1.1)	(0.1)
Inventory cost × IG	6.37	0.43	2.92
	(3.3)	(6.2)	(2.2)
R^2	0.55	0.45	0.40

estimate

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

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 regression of D1 (or D2) as dependent variable on the Unpair ratio, while controlling 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 Unpair ratio—which proxies for lower dealer inventory costs—is associated with less price-response delay. The results are in line with Hypothesis 2, and suggest that high inventory costs—-which impose indirect short-sale constraints— are negatively associated with price efficiency. In Tables C.6 and C.7 in the appendix, we report consistent results for alternative measures of dealer inventory costs.

Next, we control for changes in price efficiency that affect equity markets. The idea is that the association between higher inventory costs and lower price efficiency should only be prevalent in the corporate bond market, hence be robust to the inclusion of controls for changes in equity price efficiency. In this robustness check, we focus on bonds that can be matched to equity data using 6-digit CUSIP, and construct the price delay measures (D1 and D2) for the associated equity data.[17] Table C.8 in the appendix reports the results. We find that the main conclusions remain unchanged—a larger lending

[17] We matched 48% of the observations in our sample with CRSP data by 6-digit CUSIP.

Table 4: **Short-sale constraints and price efficiency** This table reports the panel regression results of corporate bond short-sale constraints and price efficiency. Each firm-month pair needs at least 10 months with non-missing trading data in the past 12 months. The dependent variables D1 and D2 are two measures of price delay as in Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010). The explanatory variables are as follows: Supply is the average lendable value scaled by bond size in a month. Fee is the value-weighted annualized lending fee. Unpair is the fraction of trades that identified as non-paired trading for a bond in a month. Size is the notional value of the bond. BAS is the average value-weighted bid-ask spread of a bond in a month. Turnover is measured as total trading volume scaled by the size of a bond in a month; turnover is scaled by 1/100. IG, Floating, Senior, CDS quotes, and ETF membership show the fraction of observations that are Investment Grade, with floating rate, issued as senior bond, with CDS quotes, and belong to BlackRock's ETF holdings, respectively. Concentration is a Markit-constructed measure of relative lendable value distribution among the lenders. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information from September 2006 to June 2017, and then merge with TRACE data which ends in 2017.

Dependent variable:	D1		D1		D2		D2	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	1.77	34.4	1.74	33.9	1.51	42.6	1.48	42.6
Supply	-0.14	-4.4	-0.17	-5.3	0.00	0.1	-0.01	-0.3
Supply × IG	0.01	0.2	0.04	1.2	-0.05	-2.0	-0.03	-2.4
Fee	0.01	3.0			0.01	1.2		
Fee × IG	-0.01	-2.8			-0.01	-0.6		
Unpair	-0.19	-7.5	-0.18	-7.0	-0.10	-5.5	-0.09	-5.0
Unpair × IG	-0.04	-1.4	-0.03	-1.4	-0.05	-3.2	-0.03	-2.4
Log (Size)	-0.11	-30.4	-0.10	-29.4	-0.07	-30.8	-0.07	-29.8
BAS	-0.24	-0.6	-0.52	-1.2	2.14	5.0	0.03	2.4
Turnover	-0.17	-2.5	-0.14	-2.0	-0.12	-2.5	-0.11	-2.3
Blkpct	-0.44	-3.8	-0.44	-3.6	-0.29	-3.1	0.03	2.4
Tsize	0.06	6.5	0.05	5.7	0.05	6.7	0.04	5.7
IG	0.01	0.7	-0.02	-1.3	0.01	0.9	0.03	2.4
CDS quotes	-0.01	-3.8	-0.01	-3.7	0.00	-1.5	0.00	-1.4
ETF	-0.08	-17.6	-0.08	-18.5	-0.08	-25.7	0.03	2.4
Age	0.29	0.5	0.19	0.3	-0.81	-2.0	-0.85	-2.2
Coupon	7.46	6.0	7.56	6.1	5.45	6.4	0.03	2.4
Concentration	0.20	13.7	0.19	13.5	0.13	13.3	0.12	12.8
Covenants	-0.01	-2.4	-0.01	-2.0	-0.01	-1.6	0.03	2.4
Industry FE	Yes		Yes		Yes		Yes	
R^2	0.18		0.18		0.21		0.21	

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 delay, suggesting that there exist common channels that affect the price efficiency in both stock and bond markets. This result is also consistent with the finding in Hotchkiss and Ronen (2002) that the behavior of bonds is similar to that of the underlying stock in terms of information efficiency.

Finally, we decompose dealer inventory cost variation into a component associated with short interest variation and a residual component unrelated to short interest variation. Table C.9 in the appendix shows that the association with price efficiency is measurably stronger for the former component,

meaning that dealer inventory costs impact price efficiency mainly through the short-sale channel.[18]

6. Concluding Remarks

Our paper sheds light on whether tighter post-GFC regulation may have contributed to a decrease in corporate bond market quality. Both regulators and market participants agree that post-GFC regulatory provisions have resulted in an increase in the cost of providing market-making services. We propose a 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.

We construct bond-level proxies for dealer inventory costs and provide empirical evidence that if these proxies are higher short interest tends to be lower, even after controlling for other sources of short interest variation. We find that neither investor expectations, lending supply nor lending fees can explain the temporal pattern in short interest observed since 2008. The temporal pattern in short interest is, however, closely matched by that of dealer inventory, especially for investment-grade debt.

The model also predicts that because higher inventory costs constrain short selling, they also constrain information revelation. In that sense it predicts that higher inventory costs are associated with lower price efficiency. We present empirical evidence in support of this prediction, using the price efficiency measures proposed by Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010). Specifically, we compute the delay with which corporate bond prices respond to new information and find that for bonds with higher inventory cost proxies this delay tends to be longer.

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. 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.

[18] 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.

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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)).[19] 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.[20]

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

[19] 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.

[20] 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 price P (net of lending fees), endowment X and information $\mathcal{I}$, investors choose the quantity Q of bonds traded to maximize their utility:

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

where $\pi(\mathcal{I}) = E\left(1_{\{\tau=1\}}|\mathcal{I}\right)$. We assume $P \in (R, 1)$ and $\pi(\mathcal{I}) \in (0, 1)$.

(a) For private signals X_I and Y_I, $D_{RtQ}(X_I, Y_I) = 1$ and quotation (A, B), the information sets $\mathcal{I}_I$ and $\mathcal{I}_U$ in Definition 1 are fixed and do not change as a function of Q. Thus, for the purpose of this proof, we can assume that there is no feedback from Q on $\mathcal{I}$, and that the first-order condition for Q is given by

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

Dropping $\mathcal{I}$ from the notation, Equation (B.1) 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), and $\gamma = 1/[\delta(1-R)]$ 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

$$0 = Z + \gamma \log\left(\frac{1-P^R}{P^R-R}\right), \tag{B.2}$$

which can be rewritten as

$$P^R = \frac{1+Re^{-Z/\gamma}}{1+e^{-Z/\gamma}}. \tag{B.3}$$

Note that P^R defined via (B.3) satisfies $P^R \in (R, 1)$, meaning $\log\left(\frac{1-P^R}{P^R-R}\right)$ in (B.2) is well-defined.

(b) Since $D_{RtQ} = 0$ means the informed do not request a quote and abstain from trading the bond, it holds by definition that $Q_I(A, B) = 0$ for each quotation (A, B). Since the information set of the uninformed does not change with Q, the derivations in Part (a) remain valid.

Proof of Proposition 2 To be completed. To date, we have verified the statement numerically for a wide range of parameters.

Proof of Equation (13) If $D_{RtQ} = 1$, then $\mathcal{I}_U$ includes Z_I and

$$\begin{aligned}
\pi_U &= E\left(\frac{1}{1+e^{-Y_I}}\middle| Z_I\right) \\
&= \int_{-\infty}^{\infty} \frac{1}{1+e^{-y}}\, d\text{Prob}\left(X_I = Z_I + \gamma y, Y_I = y \middle| Z_I\right) \\
&= \frac{1}{\phi\left(Z_I \middle| \mu_z, \sigma_z\right)} \int_{-\infty}^{\infty} \frac{1}{1+e^{-y}} \phi\left(Z_I + \gamma y \middle| 0, \sigma_x\right) \phi\left(y \middle| \mu_y, \sigma_y\right)\, dy.
\end{aligned}$$

If $D_{RtQ} = 1$, then $\mathcal{I}_U$ does not include Z_I but only $Z_I \in [\underline{z}, \overline{z}]$. U investors update their beliefs according to

$$\begin{aligned}
\pi_U &= E\left(\frac{1}{1+e^{-Y_I}}\middle| Z_I \in [\underline{z}, \overline{z}]\right) \\
&= \int_{-\infty}^{\infty} \frac{1}{1+e^{-y}}\, d\text{Prob}\left(X_I = Z_I + \gamma y, Y_I = y \middle| Z_I \in [\underline{z}, \overline{z}]\right) \\
&= \frac{1}{\Phi\left(\overline{z} \middle| \mu_z, \sigma_z\right) - \Phi\left(\underline{z} \middle| \mu_z, \sigma_z\right)} \int_{-\infty}^{\infty} \frac{1}{1+e^{-y}} \left[\Phi\left(\overline{z} + \gamma y \middle| 0, \sigma_x\right) - \Phi\left(\underline{z} + \gamma y \middle| 0, \sigma_x\right)\right] \phi\left(y \middle| \mu_y, \sigma_y\right)\, dy.
\end{aligned}$$

C. Additional Tables and Figures

Table C.1: **Summary statistics** This table reports the full sample summary statistics of the main variables at bond-day level. Short interest is measured as the amount borrowed divided by bond size. utilization is measured in percent, Vlent is the value of bond on loan, and Vlendable is the value of bond available for lending. Fee is the annualized lending fee. Concentration is a Markit-constructed measure of relative lendable value distribution among the lenders. Size is the notional value of the bond. Age is measured in years. Bas is the average value-weighted bid-ask spread of a bond in a month. Mom is the cumulative returns over the past 12 months. Tsize is the monthly average trade size of a bond in a month. Unpair is the fraction of trades that identified as non-paired trading for 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. IG, Floating, Rule114a, CDS quotes, ETF membership and Covenants show the fraction of observations that are Investment Grade, with floating rate, issued under Rule 144A, issued as senior bond, with CDS quotes, belong to BlackRock's ETF holdings and having at least one type of covenants, respectively. The column 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
Short interest %	1.08	2.79	0.00	0.00	0.08	0.87	5.52	22.8
Utilization %	5.20	12.34	0.00	0.00	0.41	4.33	26.63	22.8
Vlent (m$)	6.25	17.20	0.00	0.00	0.33	4.83	31.40	22.8
Vlendable (m$)	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
Size (b$)	0.52	0.56	0.05	0.20	0.35	0.60	1.50	22.8
Age (year)	5.80	5.26	0.37	1.84	4.11	8.36	17.21	22.8
Coupon %	5.94	2.32	1.63	4.70	6.00	7.35	9.75	22.7
Bas %	0.69	0.86	0.05	0.22	0.45	0.86	2.11	13.0
Return %	0.59	3.77	-3.44	-0.36	0.39	1.51	4.86	14.4
Mom %	7.15	19.05	-6.31	1.94	5.36	9.93	23.58	12.2
Tsize (m$)	0.98	2.04	0.01	0.12	0.46	1.16	3.32	16.3
Unpair	0.40	0.29	0.00	0.17	0.35	0.58	1.00	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
IG	0.75							22.5
Floating	0.08							22.5
Rule144a	0.12							22.8
CDS quotes	0.39							22.8
ETF membership	0.12							22.8
Covenants	0.68							22.8

Table C.2: **Summary statistics by year** This table reports the annual average values of the main variables in our sample. Short interest is measured as vlent / size. utilization is measured in percent. Vlent is the value of bond on loan. Vlendable is the value of bond available for lending. Fee is the annualized lending fee. Concentration is a Markit-constructed measure of relative lendable value distribution among the lenders. Size is the notional value of the bond. Time to maturity and age are measured in years. Bas is the average value-weighted bid-ask spread of a bond in a month. Mom is the cumulative returns over the past 12 months. Tsize is the monthly average trade size of a bond in a month. Unpair is the fraction of trades that identified as non-paired trading for 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. IG, Floating, Rule114a, CDS quotes, and ETF membership show the fraction of observations that are Investment Grade, with floating rate, issued under Rule 144A, issued as senior bond, with CDS quotes, and belong to BlackRock's ETF holdings, respectively. The column Obs shows the number of non-missing observations for each variable (in thousands). 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
Short interest %	1.90	2.10	2.03	0.79	0.86	0.88	0.86	0.80	0.77	0.73	0.73	0.77
Utilization %	6.91	7.90	7.15	4.32	4.70	4.88	4.93	4.72	4.62	4.69	4.24	4.22
Vlent (m$)	8.75	10.20	8.75	4.80	5.75	5.66	5.66	5.40	5.25	5.15	5.37	5.93
Vlendable (m$)	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
Size (m$)	0.36	0.37	0.42	0.48	0.50	0.52	0.53	0.56	0.56	0.59	0.63	0.65
Age (year)	5.46	5.56	5.82	5.90	5.90	5.83	5.71	5.53	5.70	5.75	6.08	6.32
Coupon %	6.59	6.44	6.35	6.39	6.47	6.35	6.14	5.79	5.53	5.30	5.17	5.05
Bas %	0.52	0.62	1.19	1.18	0.75	0.67	0.59	0.50	0.46	0.59	0.68	0.60
Return %	0.88	0.32	-0.36	2.33	0.83	0.68	0.78	0.14	0.51	-0.06	0.76	0.69
Mom %	6.48	6.50	-1.36	12.06	22.09	7.88	9.82	4.05	5.52	2.20	4.95	8.36
Tsize (m$)	1.64	1.64	1.33	1.13	0.95	0.91	0.84	0.85	0.87	0.77	0.72	0.78
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
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
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
Floating	0.11	0.12	0.12	0.10	0.08	0.07	0.06	0.06	0.06	0.06	0.05	0.05
Rule144a	0.09	0.10	0.10	0.10	0.12	0.13	0.12	0.13	0.12	0.13	0.12	0.13
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

Table C.3: **Tobit regression results using bond-level proxy for inventory cost** The table reports the results for the Tobit regression, using Unpair as a proxy for dealer inventory cost. Unpair is measured as one minus the ratio of the number of paired trades to the number of total trades, for a bond in a month. Short interest is measured as amount borrowed divided by bond size, and supply is measured as amount lendable divided by bond size. Age of the bond is measured in years. CDS market and ETF membership are dummies 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 negative value of past changes in CDS market premia, separately for IG and HY firms. Forecasts are measured as expected changes in the 3-month TBill rate in percent. 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. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information and then merge with TRACE data which ends in 2014 to compute the unpair ratio. The standard errors are adjusted for clustering of bond CUSIPs.

Inventory cost proxy:	Tsize	Blkpct	Turn	TWDCC	OCC
Constant	-0.87	-0.92	-1.06	-0.10	0.19
	(-2.5)	(-2.7)	(-3.1)	(-0.2)	(0.4)
IG	-0.93	-0.92	-0.60	-0.66	-0.64
	(-16.7)	(-16.5)	(-9)	(-10.6)	(-10.5)
Supply	5.17	5.18	5.16	5.09	5.07
	(29.2)	(29.3)	(29.9)	(28.6)	(28.6)
Log(size)	0.13	0.14	0.10	0.05	0.03
	(5.3)	(5.5)	(4.2)	(1.5)	(0.8)
Age of bond	-0.08	-0.08	-0.06	-0.08	-0.08
	(-36.1)	(-36.7)	(-28.9)	(-34.6)	(-34.3)
Coupon	5.91	5.97	5.07	5.71	5.73
	(6.9)	(6.9)	(6.1)	(6.6)	(6.7)
CDS quotes	0.29	0.29	0.27	0.28	0.28
	(9.8)	(9.9)	(9.6)	(9.6)	(9.5)
Covenants	-0.09	-0.09	-0.05	-0.07	-0.06
	(-2.3)	(-2.3)	(-1.4)	(-1.7)	(-1.5)
ETF membership	0.12	0.11	0.08	0.11	0.10
	(2.6)	(2.5)	(1.9)	(2.5)	(2.4)
VIX	-0.25	-0.26	-0.30	-0.28	-0.30
	(-2.6)	(-2.7)	(-3.2)	(-3)	(-3.1)
Lender concentration	-0.64	-0.63	-0.51	-0.69	-0.70
	(-8.5)	(-8.4)	(-6.9)	(-9.1)	(-9.2)
Forecasts	0.11	0.11	0.16	0.11	0.12
	(3.2)	(3.1)	(4.5)	(3.2)	(3.3)
Forecasts × IG	0.04	0.05	0.03	0.05	0.05
	(1.1)	(1.2)	(0.8)	(1.2)	(1.2)
Momentum	-0.03	-0.03	-0.01	-0.01	-0.01
	(-0.6)	(-0.6)	(-0.1)	(-0.2)	(-0.2)
Momentum × IG	-0.99	-1.01	-0.81	-0.97	-0.96
	(-8.9)	(-9.1)	(-7.7)	(-8.5)	(-8.4)
Inventory cost	-0.26	-1.20	6.62	0.23	0.24
	(-2.4)	(-10.3)	(9.0)	(9.5)	(10.6)
Inventory cost × IG	0.95	2.03	-1.04	-0.05	-0.06
	(7.3)	(14.5)	(-1.3)	(-2.2)	(-2.1)
Industry FE	Yes	Yes	Yes	Yes	Yes
R^2	0.13	0.13	0.15	0.14	0.14

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. This table reports the annual average values of the main variables in our sample.

Group	0	1	2	3	4	5
Short interest %	0.00	0.04	0.20	0.61	1.57	5.74
Utilization %	0.00	1.01	2.27	4.44	9.04	23.89
Vlent (m$)	0.00	0.21	1.33	4.44	11.39	34.43
Vlendable (m$)	43.00	117.93	146.88	172.29	185.69	182.60
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 (m$)	336.67	627.05	657.12	727.48	730.79	647.55
Time to maturity	6.90	7.48	7.80	8.63	9.42	10.20
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
Bas %	1.12	0.92	0.92	0.89	0.89	0.91
Tsize	1.31	1.15	1.13	1.14	1.18	1.24
Unpair %	0.57	0.60	0.62	0.64	0.65	0.66
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
IG	0.76	0.77	0.77	0.72	0.69	0.64
Floating	0.21	0.08	0.07	0.06	0.04	0.03
Rule144a	0.20	0.07	0.08	0.10	0.09	0.10
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

Table C.5: **Portfolio level short interest regression (additional results)** The table reports the results for the portfolio level regression. Short interest is measured as amount borrowed divided by bond size, and supply is measured as amount lendable divided by bond size. Age of the bond is measured in years. CDS market and ETF membership are dummies 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 cumulative returns over the past 12 months at bond level. Forecasts are measured as BlueChip forecast changes in the 3-month TBill rate in percent. 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. Blockpct is the average fraction of block trading in a month. Turnover is measured as the average ratio of total trade volume over the size of bond. TWDCC and OCC are measures of dealer capital commitment to absorb the customer's order imbalance. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information and then merge with TRACE data. The sample period is from September 2006 to June 2017.

Inventory cost proxy	Tsize	Blkpct	Turn	TWDCC	OCC
Constant	-3.29	-2.80	-2.87	1.13	1.12
	(-1.4)	(-1.2)	(-1.3)	(0.4)	(0.4)
IG	-0.92	-1.02	0.06	-0.42	-0.38
	(-2.7)	(-3.1)	(0.2)	(-1.4)	(-1.3)
Supply	2.86	2.87	2.36	2.52	2.52
	(3.5)	(3.5)	(3.0)	(3.1)	(3.1)
Log(size)	0.29	0.26	0.21	-0.05	-0.04
	(1.8)	(1.5)	(1.3)	(-0.2)	(-0.2)
Age of bond	-0.05	-0.04	-0.02	-0.02	-0.03
	(-1.0)	(-0.8)	(-0.4)	(-0.5)	(-0.6)
Coupon	0.37	0.34	0.32	0.32	0.32
	(5.4)	(5.3)	(5.1)	(4.6)	(4.5)
ETF membership	-1.30	-1.21	-1.26	-1.10	-1.15
	(-2.9)	(-2.7)	(-3.1)	(-2.4)	(-2.5)
VIX	-1.01	-0.93	-0.99	-0.88	-0.92
	(-2.2)	(-2.1)	(-2.4)	(-1.9)	(-2.0)
Lender concentration	-2.55	-2.58	-2.60	-3.20	-3.14
	(-2.6)	(-2.6)	(-2.9)	(-3.0)	(-2.9)
Forecasts	0.12	0.13	0.19	0.11	0.11
	(1.4)	(1.4)	(2.5)	(1.4)	(1.4)
Forecasts × IG	0.04	0.00	0.04	0.05	0.06
	(0.4)	(0.0)	(0.4)	(0.6)	(0.7)
Momentum (ret)	-0.46	-0.42	-0.35	-0.37	-0.38
	(-2.7)	(-2.5)	(-2.4)	(-2.3)	(-2.3)
Momentum (ret) × IG	-1.21	-0.97	-1.53	-1.37	-1.38
	(-2.7)	(-2.2)	(-3.6)	(-3.2)	(-3.2)
Inventory cost	-0.12	-3.87	-0.11	0.20	0.17
	(-1.2)	(-2.1)	(-0.29)	(1.6)	(1.6)
Inventory cost × IG	0.64	15.99	0.32	0.12	0.08
	(3.3)	(4.0)	(1.62)	(0.9)	(0.7)
R^2	0.41	0.43	0.39	0.39	0.39

Table C.6: **TWDCC and price efficiency** This table reports the panel regression results of corporate bond short-sale constraints and price efficiency. Each firm-month pair needs at least 10 months with non-missing trading data in the past 12 months. The dependent variables D1 and D2 are two measures of price delay as in Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010). The explanatory variables are as follows: Supply is the average lendable value scaled by bond size in a month. Fee is the value-weighted annualized lending fee. Unpair is the fraction of trades that identified as non-paired trading for a bond in a month. Size is the notional value of the bond. BAS is the average value-weighted bid-ask spread of a bond in a month. Turnover is measured as total trading volume scaled by the size of a bond in a month; turnover is scaled by 1/100. IG, Floating, Senior, CDS quotes, and ETF membership show the fraction of observations that are Investment Grade, with floating rate, issued as senior bond, with CDS quotes, and belong to BlackRock's ETF holdings, respectively. Concentration is a Markit-constructed measure of relative lendable value distribution among the lenders. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information from September 2006 to June 2017, and then merge with TRACE data which ends in 2017.

Dependent variable:	D1		D1		D2		D2	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	1.88	30.7	1.83	30.6	1.60	38.1	1.54	38.4
Supply	-0.18	-5.9	-0.21	-6.9	-0.01	-0.5	-0.01	-0.7
Supply × IG	0.02	0.5	0.05	1.6	-0.06	-2.6	-0.03	-2.4
Fee	0.01	3.1			0.01	1.3		
Fee × IG	-0.01	-3.0			0.00	0.3		
TWDCC	-0.23	-7.8	-0.22	-7.6	-0.14	-7.1	-0.13	-6.7
TWDCC × IG	0.01	0.3	0.02	0.7	-0.05	-2.1	-0.03	-2.4
Log (Size)	-0.11	-27.5	-0.10	-26.7	-0.08	-28.4	-0.07	-27.6
BAS	0.53	1.6	0.13	0.4	2.66	5.0	0.03	2.4
Turnover	-0.14	-2.2	-0.11	-1.7	-0.10	-2.3	-0.09	-2.1
Blkpct	-0.29	-3.0	-0.31	-3.2	-0.20	-2.7	0.03	2.4
Tsize	0.03	5.4	0.03	4.8	0.03	6.1	0.03	5.3
IG	-0.01	-0.3	-0.04	-1.7	0.02	1.0	0.03	2.4
CDS quotes	-0.01	-2.9	-0.01	-3.0	0.00	-0.7	0.00	-0.7
ETF	-0.08	-18.2	-0.08	-19.2	-0.08	-26.2	0.03	2.4
Age	2.40	4.1	2.24	3.8	0.77	1.9	0.67	1.7
Coupon	6.31	5.0	6.48	5.2	5.13	5.9	0.03	2.4
Concentration	0.22	15.1	0.20	14.8	0.14	14.7	0.13	13.9
Covenants	-0.02	-2.6	-0.01	-2.2	-0.01	-1.8	0.03	2.4
Industry FE	Yes		Yes		Yes		Yes	
R^2	0.17		0.18		0.20		0.20	

Table C.7: **OCC and price efficiency** This table reports the panel regression results of corporate bond short-sale constraints and price efficiency. Each firm-month pair needs at least 10 months with non-missing trading data in the past 12 months. The dependent variables D1 and D2 are two measures of price delay as in Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010). The explanatory variables are as follows: Supply is the average lendable value scaled by bond size in a month. Fee is the value-weighted annualized lending fee. Unpair is the fraction of trades that identified as non-paired trading for a bond in a month. Size is the notional value of the bond. BAS is the average value-weighted bid-ask spread of a bond in a month. Turnover is measured as total trading volume scaled by the size of a bond in a month; turnover is scaled by 1/100. IG, Floating, Senior, CDS quotes, and ETF membership show the fraction of observations that are Investment Grade, with floating rate, issued as senior bond, with CDS quotes, and belong to BlackRock's ETF holdings, respectively. Concentration is a Markit-constructed measure of relative lendable value distribution among the lenders. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information from September 2006 to June 2017, and then merge with TRACE data which ends in 2017.

Dependent variable:	D1		D1		D2		D2	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	1.87	32.6	1.82	32.5	1.59	41.3	1.54	41.4
Supply	-0.18	-5.9	-0.21	-7.0	-0.01	-0.5	-0.01	-0.7
Supply × IG	0.03	0.8	0.06	1.9	-0.06	-2.3	-0.03	-2.4
Fee	0.01	3.2			0.01	1.4		
Fee × IG	-0.01	-3.1			0.00	0.4		
OCC	-0.26	-8.6	-0.24	-8.6	-0.16	-8.1	-0.15	-8.0
OCC × IG	-0.03	-0.7	-0.01	-0.2	-0.08	-3.2	-0.03	-2.4
Log (Size)	-0.10	-28.3	-0.10	-27.4	-0.07	-29.4	-0.07	-28.4
BAS	0.85	2.5	0.41	1.2	2.89	5.0	0.03	2.4
Turnover	-0.13	-2.1	-0.09	-1.5	-0.09	-2.2	-0.08	-2.1
Blkpct	-0.27	-2.9	-0.30	-3.2	-0.19	-2.5	0.03	2.4
Tsize	0.03	5.0	0.03	4.6	0.03	5.8	0.03	5.1
IG	0.02	0.7	-0.02	-0.8	0.04	2.2	0.03	2.4
CDS quotes	-0.01	-2.6	-0.01	-2.7	0.00	-0.4	0.00	
ETF	-0.08	-18.2	-0.08	-19.1	-0.08	-26.2	0.03	2.4
Age	2.41	4.1	2.28	3.9	0.75	1.9	0.68	1.7
Coupon	5.72	4.6	5.87	4.7	4.72	5.4	0.03	2.4
Concentration	0.22	14.8	0.20	14.5	0.14	14.4	0.12	13.5
Covenants	-0.02	-2.6	-0.01	-2.2	-0.01	-1.9	0.03	2.4
Industry FE	Yes		Yes		Yes		Yes	
R^2	0.17		0.18		0.20		0.20	

Table C.8: **Controlling for price delay in stock returns** This table reports the panel regression results of corporate bond short-sale constraints and price efficiency, controlling for the price delay measures for stock returns. Each firm-month pair needs at least 10 months with non-missing trading data in the past 12 months. The dependent variables D1 and D2 are two measures of price delay as in Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010). The explanatory variables are as follows: Supply is the average lendable value scaled by bond size in a month. Fee is the value-weighted annualized lending fee. Unpair is the fraction of trades that identified as non-paired trading for a bond in a month. Size is the notional value of the bond. BAS is the average value-weighted bid-ask spread of a bond in a month. Turnover is measured as total trading volume scaled by the size of a bond in a month; turnover is scaled by 1/100. IG, Floating, Senior, CDS quotes, and ETF membership show the fraction of observations that are Investment Grade, with floating rate, issued as senior bond, with CDS quotes, and belong to BlackRock's ETF holdings, respectively. Concentration is a Markit-constructed measure of relative lendable value distribution among the lenders. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information from September 2006 to December 2015, and then merge with TRACE data which ends in 2014.

Dependent variable:	D1		D1		D2		D2	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	1.85	23.9	1.87	24.4	1.53	28.5	1.52	28.7
Supply	-0.05	-0.9	-0.07	-1.4	0.06	1.7	0.05	1.5
Supply × IG	-0.06	-1.1	-0.03	-0.6	-0.11	-2.9	-0.03	-2.4
Fee	0.02	2.3			0.00	0.9		
Fee × IG	-0.04	-4.6			-0.02	-3.0		
Unpair	-0.22	-5.7	-0.22	-5.7	-0.11	-4.1	-0.11	-4.0
Unpair × IG	-0.01	-0.4	-0.01	-0.2	-0.05	-2.4	-0.03	-2.4
Equity control	0.03	3.3	0.03	3.6	0.02	1.9	0.02	2.0
Log (Size)	-0.11	-22.0	-0.11	-22.2	-0.08	-21.8	-0.08	-21.8
BAS	0.45	0.7	0.22	0.4	3.83	8.9	0.03	2.4
Turnover	-0.25	-2.3	-0.22	-2.2	-0.19	-3.0	-0.19	-3.1
blkpct	-0.26	-1.6	-0.31	-2.1	-0.24	-1.8	0.03	2.4
tsize	0.05	4.4	0.05	4.6	0.06	5.4	0.05	5.8
IG	0.02	1.0	-0.02	-0.9	0.03	2.1	0.03	2.4
CDS quotes	-0.02	-2.4	-0.02	-2.6	-0.01	-1.5	-0.01	-1.5
ETF	-0.06	-11.0	-0.06	-10.8	-0.08	-17.1	0.03	2.4
Age	3.34	3.6	2.98	3.2	1.29	1.9	1.03	1.6
Coupon	6.29	3.3	6.29	3.3	4.81	3.6	0.03	2.4
Concentration	0.15	6.8	0.15	7.1	0.10	6.5	0.09	6.4
Covenants	0.00	0.2	0.00	0.2	0.02	1.5	0.03	2.4
Industry FE	Yes		Yes		Yes		Yes	
R^2	0.18		0.19		0.22		0.22	

Table C.9: **Decomposing dealer inventory proxies** This table reports the panel regression results of corporate bond short-sale constraints and price efficiency, controlling for the price delay measures of the stock returns. Each firm-month pair needs at least 10 months with non-missing trading data in the past 12 months. The dependent variables D1 and D2 are two measures of price delay as in Hou and Moskowitz (2005) and Saffi and Sigurdsson (2010). The explanatory variables are as follows: Supply is the average lendable value scaled by bond size in a month. Fee is the value-weighted annualized lending fee. Unpair is the fraction of trades that identified as non-paired trading for a bond in a month. Size is the notional value of the bond. BAS is the average value-weighted bid-ask spread of a bond in a month. Turnover is measured as total trading volume scaled by the size of a bond in a month; turnover is scaled by 1/100. IG, Floating, Senior, CDS quotes, and ETF membership show the fraction of observations that are Investment Grade, with floating rate, issued as senior bond, with CDS quotes, and belong to BlackRock's ETF holdings, respectively. Concentration is a Markit-constructed measure of relative lendable value distribution among the lenders. The data include all bonds on loan in the merged FISD & MSF data that have credit rating information from September 2006 to December 2015, and then merge with TRACE data which ends in 2014.

Dependent variable:	D1		D1		D2		D2	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	1.66	34.9	1.65	34.7	1.46	45.1	1.45	3.8
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		
Unpair (SI)	-0.98	-12.4	-0.89	-11.8	-0.60	-7.7	-0.47	-6.2
Unpair (Residual)	-0.04	-3.9	-0.04	-3.7	-0.03	-3.2	-0.02	-2.6
Log (Size)	-0.10	-30.1	-0.10	-30.0	-0.07	-30.6	-0.07	-30.6
BAS	-0.09	-0.2	0.04	0.1	2.04	5.2	2.08	5.2
Turnover	-0.11	-1.7	-0.05	-0.8	-0.09	-1.9	-0.07	-1.6
blkpct	-0.45	-3.8	-0.45	-3.9	-0.33	-3.5	-0.33	-3.5
tsize	0.06	6.4	0.06	6.4	0.05	6.6	0.05	6.7
IG	-0.02	-2.9	-0.02	-3.0	-0.04	-9.5	-0.04	-9.6
CDS quotes	-0.01	-3.4	-0.01	-3.4	0.00	-1.4	0.00	-1.4
ETF	-0.08	-18.1	-0.08	-17.9	-0.08	-26.2	-0.08	-26.1
Age	1.70	2.9	1.67	2.9	0.39	1.0	0.38	1.0
Coupon	7.68	6.2	8.13	6.6	5.48	6.5	5.59	6.6
Concentration	0.19	13.3	0.20	14.2	0.12	12.9	0.13	13.3
Covenants	-0.01	-2.4	-0.01	-2.4	-0.01	-1.8	-0.01	-1.8
Industry FE	Yes		Yes		Yes		Yes	
R^2	0.18		0.18		0.21		0.21	

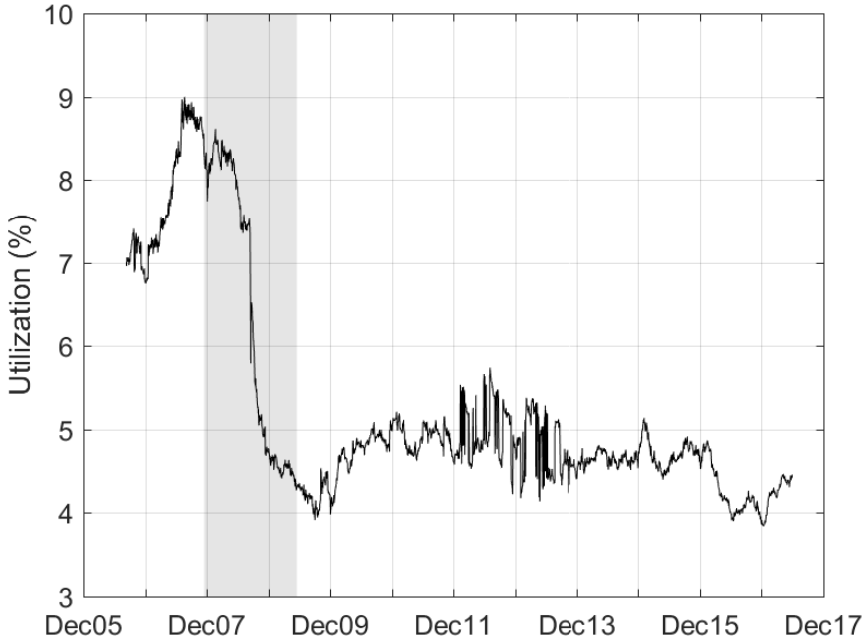

Figure C.1: **Utilization** The plots shows the time series of average utilization. The data include all bonds available for lending in the merged FISD & MSF data that have credit rating information, over September 2006 to June 2017.

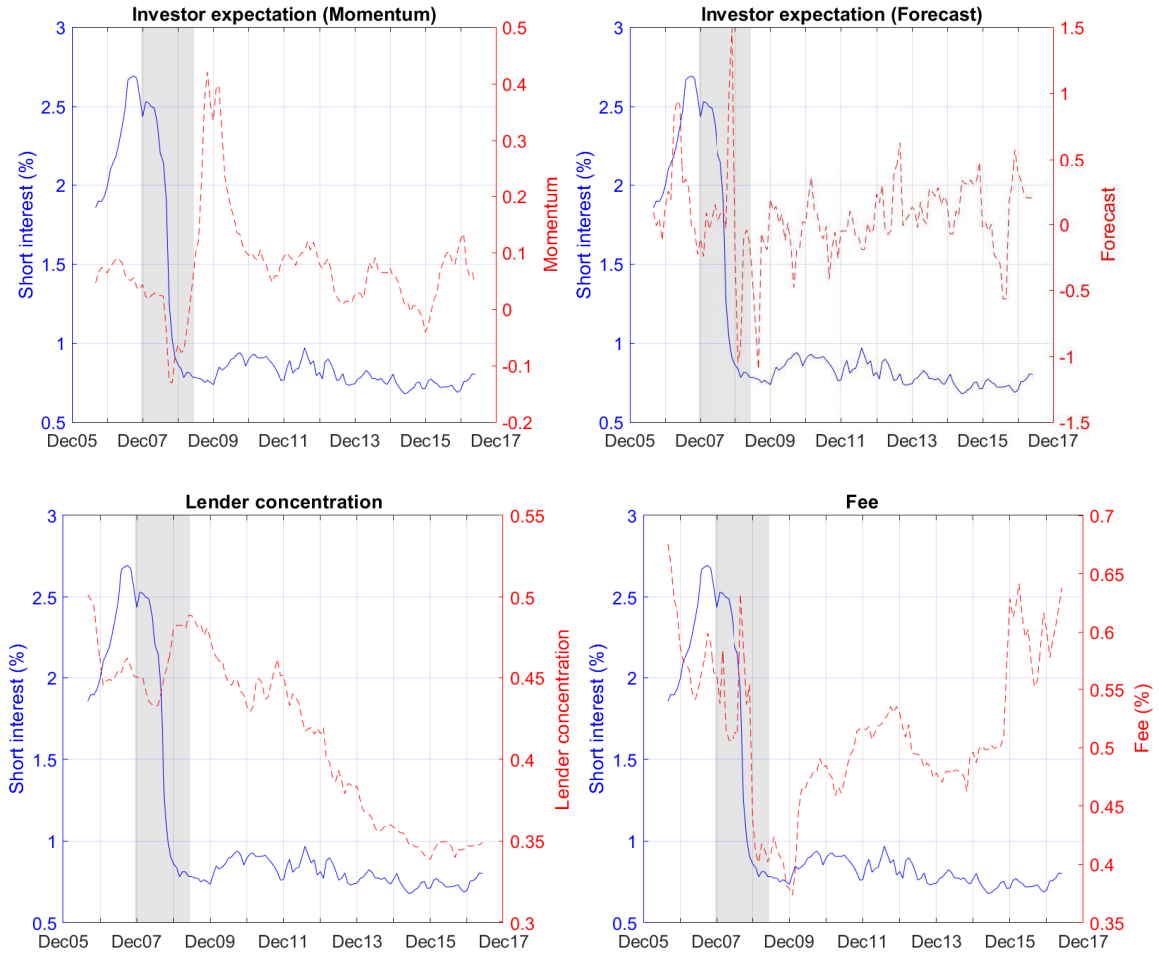

Figure C.2: **Short interest relative to investor expectations and other controls** The top left (right) plot shows the monthly time series of average short interest and momentum (forecast). Momentum is measured as the aggregate returns over the past 12 months. A low past return (past loser) may be associated 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.