Rainy Day Liquidity*

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Abstract

Being the largest stakeholder in the corporate bond market with a cash flow largely independent of capital market conditions, insurance firms can provide liquidity in stressful conditions. This paper models and presents evidence on this distinct role played by insurers. We find that insurers' corporate bond purchases improve bond liquidity while their bond sales do not. Liquidity improvement is stronger in "rainy days", e.g., during the financial crisis, among low-rated and poor-liquidity bonds. Further, insurers' funding and holding horizon positively affect the liquidity of the bonds they purchase, highlighting the link between funding ability and rainy day liquidity provision.

JEL Codes: G11; G22

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1 Introduction

Insurance companies are the largest institutional holders of corporate bonds. The U.S. Flow of Funds Accounts report that life insurers alone held \$2.6 trillion in corporate and foreign bonds in 2018, which is significantly larger than either mutual funds or pension funds did. Given the size of their holdings, insurance companies can conceivably have major impacts on the dynamics of corporate bond liquidity. In particular, given that cash flow in the insurance industry is largely independent of the macroeconomic conditions, insurers arguably can provide liquidity to distressed corporate bonds and thereby play a conditional role — which is referred to as *rainy day liquidity provision* hereafter.[1]

This argument can be based on insights from theoretical literature on financial intermediation. Brunnermeier and Pedersen (2008), for instance, show that bonds' (market) liquidity can be strongly correlated with traders' capital constraints arising from time-varying margins, i.e., funding liquidity. Moreover, as Duffie (2010) notes, during periods of market stress, it is difficult for dealers to offload inventory to potential buyers due to capital scarcity. Consequently, when broker-dealers in the corporate bond market face tightening funding constraints, insurers with well-established relationships with dealers are more likely to provide liquidity than their less established counterparties (Hendershott, Li, Livdan, and Schürhoff, 2017). Notably, the provision of liquidity to the illiquid and risky securities of insurers is also supported by the asset insulator theory of Chodorow-Reich, Ghent, and Haddad (2019) which suggest that insurers actively seek bonds with long-run value above market value.

We present a theoretical model to explain the role of insurers in the corporate bond markets during stressful periods. In our setup, a monopolistic dealer aims to earn a spread by trading with liquidity seekers while keeping his inventory costs at the minimum. Motivated

[1] Insurers' role as active buyers of corporate bonds in stressful periods is consistent with the stylized fact that insurance firms follow a "collect now, pay later" business model (Buffett, 2009). Premiums collected by insurers are independent of capital market fluctuations. In addition, statutory reserve regulation affords insurers the ability to record lower liabilities in a low interest environment (Koijen and Yogo, 2015), hide their liabilities in captive insurance facilities (Koijen and Yogo, 2016), and report historical costs when asset market values are low (Ellul, Jotikasthira, Lundblad, and Wang, 2015). See also Harrington, Niehaus, and Yu (2013) and Berry-Stolzle, Nini, and Wende (2014) on the evidence regarding insurers' operating profitability and financing activities.

by conventional wisdom (that is confirmed by our empirical findings), we assume that orders from insurance companies are positively correlated across time and the magnitude of the correlation is higher for buy orders. Under these market dynamics, buy transactions of insurance firms can induce dealers to provide liquidity to distressed sellers as dealers have lower inventory risk with the higher likelihood to sell these bonds to insurers in a short period of time. Our model gives rise to three testable implications. First, insurers' liquidity provision mainly comes from their buy transactions, and insurers' ability to offer liquidity is stronger under rainy day conditions: financial crisis period, bonds with lower rating, and relatively lower liquidity. Second, because purchases by insurers contain information about their preferences for specific types of bonds, these bond purchases likely have an effect on the liquidity of bonds with similar characteristics. Third, insurers with sufficient cash flow are more likely to purchase distressed securities and provide rainy day liquidity.

Empirically, before examining the above three hypotheses, we analyze the dynamics of the order flow from insurers to support the main assumptions made in our theoretical model. We find that insurer transactions are positively correlated across time and compared to sell orders, buy orders have higher persistence. These findings also hold during crisis periods, supporting the assumptions of our theoretical model. Further, the persistence in buy orders is more pronounced for insurers with stronger cash flow position.

We examine the effect of insurer transactions on the underlying bond's liquidity, and document that, on average, insurers' bond purchases increase liquidity while insurers' bond sales either lower or have no effect on the bond liquidity. Using the *Roll* measure as an example, on average, a 1 percent increase of insurers' bond purchases reduces the median illiquidity (i.e., trading costs) by 0.7 percent. Conversely, a 1 percent increase in insurer bond sales leads to a 0.3 percent increase in the median trading cost measured by *Roll*. Intuitively, this is because, on the buy side, insurers with persistent purchases can be easily matched by market-makers with potential sellers. Insurers' selling transactions, however, are often induced by portfolio rebalancing needs, regulatory requirements, or liquidity concerns, e.g., making unexpected claim payments (see e.g., Ellul, Jotikasthira, and Lundblad, 2011;

Ellul, Jotikasthira, Lundblad, and Wang, 2015). In other words, heterogeneous motives for buying and selling corporate bonds potentially drive asymmetric insurer buy and sell effects on bond liquidity.

We then investigate whether bond liquidity improvement is mainly driven by insurers' corporate bond purchases on "rainy days" — namely, during the financial crisis, among poor-liquidity bonds, or among "threshold bonds".[2] This is supported by our finding. Our estimation shows that, a 1 percent increase in insurer bond purchases should give rise to a 1.6 percent decrease in median illiquidity for illiquid bonds group, a 1.5 percent decrease in median illiquidity for threshold bonds, and a 3 percent decrease in median bond illiquidity during the financial crisis using the *Roll* measure as an example. The magnitude is much greater than the average liquidity effect from insurer bond purchases. Our results imply that as long-horizon investors with relatively stable funding, insurance companies may quieten market shocks. This finding is consistent with Cella, Ellul, and Giannetti (2013), who show that stocks held by long-horizon investors are less susceptible to amplified market shocks compared to stocks held by short-term investors.

Would insurers' bond trading affect the liquidity of bonds not traded by insurers? Prior works document that securities sharing similar characteristics tend to comove in liquidity (e.g., Chordia, Roll, and Subrahmanyam, 2000; Koch, Ruenzi, and Starks, 2016). Applying this to the corporate bond setting, we hypothesize a liquidity spillover effect that insurers' bond purchase potentially contains information on insurers' preference for bonds of that particular type, increasing liquidity of such bonds. To test this hypothesis, we match bonds with the same ratings, same remaining maturity in years, and same liquidity quintile group as bonds purchased by insurers. We find that buy-side cross trading by insurers positively affects bond liquidity on rainy days. Importantly, this finding strengthens our argument for rainy day liquidity provision by insurance firms as it shows that the transactions of insurers not only improve the liquidity of the traded bonds, but also influence the liquidity of other

[2]Threshold bonds are bonds rated around the threshold between investment-grade and high-yield ratings. Studies show that insurers prefer such bonds for their higher yields (see, e.g., Becker and Ivashina, 2015; Chodorow-Reich et al., 2019). Threshold bonds account for a third of corporate bonds while insurers' investments in such bonds account for over 45% of their corporate bond holdings.

bonds potentially appealing to insurers' portfolios.

A primary ingredient for insurers to provide rainy day liquidity is the independence of insurers' cash flow to capital market conditions. We confirm this by showing that insurers' cash flows are uncorrelated with S&P 500 index performance, and complement this finding by showing that insurers with better funding ability are more persistent in their bond purchases. Subsequently, we conduct cross-sectional analysis to test the link between insurers' funding ability and rainy day liquidity provision. We break insurers down into subgroups based on their cash flow or portfolio turnover. We find that insurers with robust cash flows from operations and those with long investment horizons, such as life insurers, purchase more threshold bonds than insurers with weak cash flows or short horizons. The liquidity improvement in threshold bonds purchased by well-funded insurers is higher compared to those purchased by insurers with poor funding ability.

Finally, we use the Dodd-Frank Act implementation as an experiment to test insurers' role in rainy-day liquidity provision, given that the adoption of the Dodd-Frank Act reportedly weakens bank-affiliated dealers' ability to supply liquidity (Bessembinder, Jacobsen, Maxwell, and Venkataraman, 2018). If insurers are able to offer liquidity in rainy conditions, they ought to provide liquidity to bonds sold by bank-affiliated dealers. We perform the analysis by differentiating the liquidity effects of insurer bond purchases around the event between bonds transacted by bank- and nonbank-affiliated dealers. Consistent with our expectation, we find that insurers bond purchase after the Dodd-Frank Act increases the liquidity of bonds executed by bank-affiliated dealers more than those executed by nonbank dealers.

This paper fits into the literature that explores the impact of insurance companies on corporate bond liquidity. There are two related papers to our study in the context of studying insurers' corporate bond transactions. One related study is O'Hara, Wang, and Zhou (2018) which investigate execution quality issues in corporate bond trading. Their key finding is that an insurance company entering into a trade of similar size on the same side and day for the same bond with the same dealer will receive a better price if it is an active investor i.e., this insurer holds more corporate bonds than the median holdings of all insurance companies. In other words, less active investors pay higher execution costs in the corporate bond market. Our paper differs from this study in terms of its research objectives. Namely, we study the active (positive) roles of insurance companies and bond dealers in supplying liquidity, while they uncover cross-sectional differences in trading costs of insurance companies. Another related study is Hendershott et al. (2017) who examine the implications of the network of insurers and dealers in cases where insurers form optimal size dealer networks by trading off increased search intensity against bargaining costs. Larger insurers with higher trading intensity are more likely to form more relations with additional dealers to increase execution speed and enhance their bargaining position to receive better prices. Our paper differs from this study by focusing on insurers' liquidity provision in rainy days.

The role of insurers on bond liquidity contrasts the traditional prior that passive investors often reduce market liquidity. It is also quite different from the role played by other financial intermediaries, such as broker-dealers and hedge funds as insurers offer liquidity when it is really needed by the market. Brunnermeier and Pedersen (2008) theorize that bond (market) liquidity is strongly correlated with traders' capital constraints arising from time-varying margins, i.e., a trader's funding liquidity. While their model is not specific on the funding liquidity of broker-dealers, they focus on the homogeneity of speculators' funding demand. In their framework, margins can lead to sudden liquidity dry-ups when speculators realize small losses. Liquidity provision by such investors is pro-cyclical.[3] Contrarily, we show that insurers improve liquidity in bad times when other intermediaries scale back in their liquidity provision activities. Without insurers' participation, the bond market liquidity could be much worse.

The remainder of the paper is organized as follows. Sections 2 introduces our model that characterizes the role of insurance companies in providing rainy day liquidity. Section 3 discusses testable hypotheses implied from the model. Section 4 describes the data and

[3]Consistent with this view, theoretical models and empirical evidence, e.g., He and Xiong (2012), Dick-Nielsen et al. (2012), and He and Milbradt (2014), suggest that liquidity risk is strongly correlated with credit risk, a phenomenon which could be attributed to the status of capital market.

sample used. Section 5 presents the empirical findings. Section 6 concludes.

2 The Model

In this section, we present a simple theoretical model to introduce the role of insurance companies during stressful periods. Since insurance companies are buy and hold investors, they are typically expected to reduce security liquidity. We, however, formalize this trading behavior of the insurers with persistent buying activity and illustrate that this correlated order flow may incentivize dealers with inventory aversion to provide liquidity to distressed sellers.

2.1 Inventory-averse dealer in the corporate bond market

Our model is inspired from the high-frequency market making model of Aït-Sahalia and Sağlam (2017), with a monopolistic dealer on a single corporate bond. We specifically aim to examine the liquidity of the bond around a distressed state in which there is a net selling trading interest. The dealer in this market acts exclusively as a market maker by maintaining bid and ask prices of the bond. Investors wishing to trade the bond will contact the dealer to transact at these prices. The quantity of each order is fixed at z dollars represented in terms of the face value. For example, the average order size in the corporate bond market is roughly \$1 million.

We assume that the dealer can quote bid and ask prices around the fundamental value of the asset, X_t, which is exogenously available. The minimum price at which the dealer is willing to sell the asset is $X_t + \delta$ with $\delta > 0$ while the minimum price at which he is willing to buy the asset is $X_t - \delta$. We will refer to these prices as the best ask and the best bid prices. Formally, $\ell_t^a = 1$ ($\ell_t^b = 1$) will imply that the dealer is quoting at the best ask (bid) at time t, and similarly, $\ell_t^a = 0$ ($\ell_t^b = 0$) means that the dealer does not want to engage in a transaction at the ask (bid) side. The market will have the highest liquidity when $\ell_t^a = 1$ and $\ell_t^b = 1$ simultaneously.

There are two types of liquidity seekers in the market: non-insurance traders (NITs) and insurance companies (ICs). Both types of the liquidity seekers trade with the dealer, if the dealer has an active quote in the appropriate side of the market. NITs contact the dealer for trade execution at a Poisson intensity of λ. We assume that $y > \frac{1}{2}$ share of NITs would like to sell the corporate bond to dealer whereas $1 - y$ share of them would like to buy the bond. This assumption is due to our interest in studying liquidity dynamics around a distressed state in which the bond is under a strong selling pressure. Finally, we assume that there is no serial dependence between successive order requests of the NITs.

ICs arrive to the market with Poisson intensity μ and the sign of their orders follows a two-state Markov chain. Conditional on a buy order, the next IC order is a buy order with probability $p \geq \frac{1}{2}$. Similarly, conditional on a sell order, the next IC order is a sell order with probability $q \geq \frac{1}{2}$. We obtain the following transition probability matrix:

$$P = \begin{array}{c c} & \begin{array}{cc} \textit{Buy} & \textit{Sell} \end{array} \\ \begin{array}{c} \textit{Buy} \\ \textit{Sell} \end{array} & \begin{bmatrix} p & 1-p \\ 1-q & q \end{bmatrix} \end{array}$$

Note that this transition probability matrix determines the stationary probability of buy and sell orders, π_{buy} and π_{sell}. Letting $\pi = \begin{bmatrix} \pi_{\text{buy}} & \pi_{\text{sell}} \end{bmatrix}$, the stationary probabilities are obtained by solving for $\pi P = \pi$ and $\pi_{\text{buy}} + \pi_{\text{sell}} = 1$. These equations imply that $\pi_{\text{buy}} = \frac{1-q}{2-p-q}$. Therefore, in the long run, the probability of buy orders increases as p increases. We are specifically interested in the parameterization where $1 > p > q > \frac{1}{2}$ as implied by our empirical analysis in Section 5.1. In this setting, $\pi_{\text{buy}} > \frac{1}{2}$, i.e., buy orders from ICs are more likely in the long run. These statistics suggest that in rainy day conditions, insurers' persistent buying activity can induce the dealer to provide liquidity in both sides of the market. Our model will formalize this economic insight in the remainder of this section.

We assume that the dealer's profit is based on the frequency of trades he engages with the liquidity seekers. In each trade, he earns the spread between the fundamental value and the transaction price, δ. He discounts these profits at a rate of $\beta > 0$. The dealer's position in the bond is denoted by x_t which will be an integer multiple of z dollars. This position can be positive or negative. We assume that the dealer penalizes himself for holding excess inventory at a rate of $\Gamma|x_t|$ where Γ is a constant parameter of inventory aversion. In practice, limiting or penalizing inventory is one of the primary sources of risk mitigation by market makers.

The dealer's objective is therefore to maximize his expected discounted rewards earned from the bid-ask spread minus the penalty costs from holding an inventory in a continuous time model. Let ℓ be any feasible policy that chooses ℓ_t^b and ℓ_t^a. Formally, the dealer maximizes

$$\max_{\ell} \mathbb{E}^{\ell}\left[\delta \sum_{i=1}^{\infty} e^{-\beta T_i^{\mathsf{sell}}} \mathbb{1}\left(\ell^b_{T_i^{\mathsf{sell}}} = 1\right) + \delta \sum_{j=1}^{\infty} e^{-\beta T_j^{\mathsf{buy}}} \mathbb{1}\left(\ell^a_{T_j^{\mathsf{buy}}} = 1\right) - \Gamma \int_0^{\infty} e^{-\beta t}|x_t|dt\right] \tag{1}$$

where T_i^{sell} is the ith sell order and T_j^{buy} is the jth buy order from the liquidity seekers.

2.2 Discrete-time representation

The model is set-up in continuous time but there is a key advantage of our model's Poisson-based setup that allows us to represent the model in discrete-time. The reason is that we can merge the two Poisson time clocks λ and μ into a single one arriving at the combined Poisson rate of $\lambda + \mu$, and determine the dealer's actions at the resulting discrete event times. That is, the dealer's maximization problem in continuous-time can be equivalently represented in a discrete-time Markov Decision Process (MDP). We first discuss the state and the action space of the MDP and the resulting value function.

The state space in our model can be represented by the pair of (x, s) where x denotes the current holdings of the dealer with $x \in \{\dots, -2, -1, 0, 1, 2, \dots\}$ and s is the most recent insurance order received by the dealer, with $s \in \{B, S\}$. Here B denotes the buy order and S denotes the sell order submitted buy an IC. The corresponding action taken by the dealer at each state is whether to quote at the best bid and/or best ask, i.e., $\ell_t^b(x, s) \in \{0, 1\}$ and $\ell_t^a(x, s) \in \{0, 1\}$. To focus on the main hypotheses derived from the model, we relegate the detailed construction of the MDP to the Internet Appendix, where we also provide the proofs of the results stated in the remainder of this section. Specifically, we compute the transition probabilities of the system, and the dealer's reward function, as a function of his actions.

2.3 Optimal market making policy

The optimal policy of the dealer internalizes the classical trade-off in inventory-based market making problems, i.e., quoting to capture the spread as often as possible versus the risk of quoting too much and having non-zero inventory. In addition to this, due to the IC's correlated order flow, the dealer should also differentiate his quoting pattern based on the direction of the last order submitted by an IC. We first state the Hamilton-Jacobi-Bellman optimality equations:

Proposition 1. *The dealer's value function $v(x,s)$ derived from holding inventory x when the last insurance order is s satisfies the equations*

$$\begin{aligned}
v(x,B) = -\gamma|x| + \frac{\alpha}{\lambda+\mu}\Big(&\max\Big\{\delta(y\lambda+(1-p)\mu) + v(x+1,B)y\lambda + v(x+1,S)(1-p)\mu, \\
& v(x,B)y\lambda + v(x,S)(1-p)\mu\Big\} + \max\Big\{\delta((1-y)\lambda+p\mu) + v(x-1,B)\left((1-y)\lambda+p\mu\right), \\
& v(x,B)((1-y)\lambda+p\mu)\Big\}\Big) \\
v(x,S) = -\gamma|x| + \frac{\alpha}{\lambda+\mu}\Big(&\max\Big\{\delta(y\lambda+q\mu) + v(x+1,S)(y\lambda+q\mu), v(x,S)(y\lambda+q\mu)\Big\} \\
& + \max\Big\{\delta((1-y)\lambda+(1-q)\mu) + v(x-1,S)(1-y)\lambda + v(x-1,B)(1-q)\mu, \\
& v(x,S)(1-y)\lambda + v(x,B)(1-q)\mu\Big\}
\end{aligned}$$

where

$$\alpha \equiv \frac{\lambda+\mu}{\lambda+\mu+\beta}, \quad \textit{and} \quad \gamma \equiv \frac{\Gamma}{\lambda+\mu+\beta}. \tag{2}$$

This proposition illustrates that the dealer optimally chooses to quote at a particular side of the market by computing the corresponding value functions associated with each action. We solve these value functions using the policy iteration algorithm (see e.g., Puterman, 2014). Further, the following theorem, which we prove in the Internet Appendix, states that the optimal quoting policy of the dealer is based on inventory limits depending on the direction of the last order from an IC:

Theorem 1. *The optimal quoting policy π^* of the dealer aims to quote at the best bid and the best ask according to a threshold policy:*

$$\ell^{b*}(x,B) = \begin{cases} 1 & \textit{when } x < L^*_{bB}, \\ 0 & \textit{when } x \geq L^*_{bB}, \end{cases} \quad \ell^*_a(x,B) = \begin{cases} 1 & x > L^*_{aB}, \\ 0 & x \leq L^*_{aB}. \end{cases}$$
$$\ell^{b*}(x,S) = \begin{cases} 1 & \textit{when } x < L^*_{bS}, \\ 0 & \textit{when } x \geq L^*_{bS}, \end{cases} \quad \ell^*_a(x,S) = \begin{cases} 1 & x > L^*_{aS}, \\ 0 & x \leq L^*_{aS}. \end{cases}$$

Theorem 1 provides the structure of the quoting policy based on inventory limits. The policy iteration algorithm allows us to compute these inventory limits. Intuitively, the dealer does not quote to buy (sell) if his inventory is already too large in the long (short) side. Here, one interesting feature is that the inventory limits depend on the most recent order of the ICs. Given the selling pressure in the market with $y > \frac{1}{2}$, the dealer may not quote at the bid side at an inventory level x, when the state s were S, but he may want to quote to buy at the same inventory level if $s = B$. Further, the inventory limits will not be symmetric across the bid and the ask side due to larger share of sell orders from NITs and the asymmetric correlation of ICs' consecutive buy and sell orders.

2.4 Empirical Predictions of the Model

We analyze the predictions of the model using a realistic calibration. We are specifically interested in the regime where sell orders from NITs are much more likely than buy orders from ICs, i.e., $\lambda y > \mu \pi_{\text{buy}}$. We consider that the dealer makes quoting decisions at the daily level. We assume that the dealer receives 20 orders from NITs and 5 orders from ICs on each trading day, each for \$1 million of the par value. If a transaction occurs, the dealer makes $\delta =$ \$20,000 which amounts to 2% of the par value. We assume that inventory costs of the dealer is $\Gamma =$ \$50,000 per \$1 million inventory which amounts to 5% of the par value. We set $y = 0.75$ implying that 75% of the orders from NITs are sell orders. Our empirical analysis in Section 5.1 finds that $p > q$, thus we use $p = 0.8$ and $q = 0.55$ in our base calibration. Finally, β is taken to be 0.04% which corresponds to an annual rate of 10%. In the Internet Appendix, we show with different calibrations that the main predictions of the model remains the same.

We solve for the optimal limits using this calibration: $L^*_{bB} = 1$, $L^*_{bS} = 0$, $L^*_{aB} = -6$ and $L^*_{aS} = -6$. These limits illustrate that in the presence of selling pressure, the auto-correlation of insurance buy orders are helpful to the dealer in quoting the tightest spread. When the dealer has zero inventory and the last insurance order is a buy order, the dealer is willing to buy from NICs. This willingness disappears if the last insurance order is a sell. If there were no imbalance in the order requests of the NITs, the autocorrelation in the insurance orders would disincentivize the dealer to quote to buy or sell but in the presence of selling pressure, the autocorrelation in the buy orders can induce the dealer to provide liquidity to the distressed sellers if they have recently interacted with an insurance buy order. The persistence in the insurance buy orders can improve the liquidity of the bond in a stressful state.

We also quantify the fraction of observing the tightest spread market in which the dealer is quoting at both sides of the market as a function of p. This probability can be used as a liquidity proxy. Under the dealer's optimal policy, the model is governed by a finite-state Markov Chain. Let P_{opt} be the probability transition matrix defined on this finite state space under the optimal policy. Since the Markov Chain is aperiodic and irreducible, a stationary distribution ν exists for this Markov Chain, which solves $\nu P_{\mathsf{opt}} = \nu$. Using the stationary distribution, we can compute the fraction of the time, the dealer is quoting at both sides of the market.

The left panel in Figure 1 illustrates that as p increases, the fraction of the time the dealer quotes in both directions increases. As p increases, the dealer is more incentivized to provide liquidity to distressed sellers when $s = B$. Further, the long run probability of observing $s = B$ increases as p increases, and the overall liquidity, measured by the fraction of the time the dealer is quoting at both sides, improves in the long run.

We investigate how the dealer responds to an increasing intensity in the arrival of insurance orders. The right panel in Figure 1 illustrates that as μ increases, the fraction of the time the dealer quotes in both directions increases. The increase in the arrival rate of the insurance companies lead the dealer to lower his inventory cost expectations and he ultimately quotes more frequently at the both side of the market, all else equal.

Finally, we study how the improvement in liquidity varies as a function of the persistence in ICs' buy orders and the arrival rate of IC orders when the dealer faces higher selling pressure or higher inventory costs. In both cases of distress, the absolute level of liquidity would drop due to the higher order imbalance and inventory costs. However, in these cases, a small increase in the persistence of IC buy orders or the arrival rate of IC orders can improve the liquidity more compared to the increase in the benchmark case. Figure 2 illustrates this insight numerically. We observe that although the fraction of quoting in both sides drops when the dealer faces higher selling pressure or inventory costs in all four cases, the slope of the liquidity curve is steeper in markets with higher selling pressure and higher inventory costs. Overall, this finding implies that the improvement in liquidity can be much higher in adverse market conditions, such as higher selling pressure or higher inventory costs.

3 Hypotheses

In this section, we introduce three main testable hypotheses that arise from our theoretical model.

First, viewed as buy-and-hold investors, insurers' buy transactions are more persistent than their sell transactions. This results in the following hypothesis:

Hypothesis 1 (Rainy day liquidity)**.** *Insurers' buy (sell) transactions improve (deteriorate) future bond liquidity in times of selling pressure.*

This hypothesis emerges directly from the impact of the state variable s on the optimal quoting policy. In the context of the model, buy transactions can be interpreted as being in state B. In this case, since there is higher likelihood of observing buy orders from insurers in the subsequent periods, the dealers will be incentivized to provide more liquidity to the distressed sellers. Figure 1 illustrates this intuition graphically. When the insurance buy orders have higher auto-correlation in the presence of selling pressure, the dealer can quote in both sides of the market more frequently.

Note that this hypothesis is also supported by two streams of the prior literature. First, Brunnermeier and Pedersen (2008) relate the (market) liquidity of an asset to dealers' funding liquidity and show that bond market liquidity is affected by traders' funding capital and margin constraints. In a distressed market where investors are eager to sell their position, the persistence in insurers' bond purchases eases dealers' capital constraints, making them more likely to post narrower bid-ask spreads. Consistent with Choi and Huh (2017) introducing the notion of customer provided liquidity, our hypothesis focuses on the mechanism for the liquidity provided by insurers. Second, it is also related to the search theory (Duffie, Gârleanu, and Pedersen, 2005, 2007) under which insurers and dealers maintain tight relationships in repeated business, which can minimize search costs under severe market conditions. Aggregate buy transactions of insurance companies signal the dealers their future search costs to identify potential buyers will be lower. Given that insurance companies look for bonds with certain characteristics (e.g., long-term, investment grade), the dealers may be more incentivized to facilitate trading in these types of bonds even under market stress, as they are confident that they can sell these bonds to insurance companies with existing trading relationship.

Next, we conceive that insurers' bond purchases could affect the liquidity of assets not purchased by insurers. As insurers' purchases of a bond potentially reveals their preference of bonds of certain characteristics, we expect that the purchase of a specific bond improves the liquidity of other bonds with similar characteristics under adverse conditions and among unpopular bonds. In other words, there are potential positive cross correlations among bonds purchased by insurers and those with matching characteristics. This hypothesis would be supported directly from our model, if the model were extended to multiple corporate bonds, which are under selling pressure by NITs and there is cross correlation between ICs' buy purchases on these multiple bonds. This extension leads to our second hypothesis on liquidity spillover effect across bonds.

Hypothesis 2 (Cross bond liquidity spillover)**.** *Under rainy conditions, insurers' bond purchases could favorably influence the liquidity of similar bonds that are not directly purchased by insurers.*

This hypothesis is consistent with the literature on commonality in liquidity emanating from Chordia, Roll, and Subrahmanyam (2000)'s finding that liquidity covaries strongly across securities. Brunnermeier and Pedersen (2008) provide a theoretical support by illustrating market liquidity has commonality across securities.

The third hypothesis is related to insurers' funding. An important factor driving insurers' bond purchases is their funding ability. In the context of our model, higher funding ability could be attributed to higher μ. This higher funding ability can also signal larger propensity to purchase corporate bonds in the next period, i.e., higher autocorrelation in ICs' bond purchases, and higher long run probability of buy orders. In both cases, we expect the rainy day liquidity effect to be stronger for insurers with higher cash flows. Thus, our final hypothesis is directly based on the predictions of our model.

Hypothesis 3 (Funding liquidity at the micro level)**.** *Better funded insurers are more likely to supply rainy day liquidity.*

This hypothesis is aligned with the asset insulator theory proposed by Chodorow-Reich et al. (2019) emphasizing insurers' ability, as a group, to target specific assets which have temporarily dropped in value while institutions engaging in such activities benefit from stable sources of funds. It is consistent with the main finding of Ge and Weisbach (2019) that less financially constrained insurers hold riskier and less liquid securities.

4 Data

We use the data from the National Association of Insurance Commissioners (NAIC), the Mergent Fixed Investment Securities Database (FISD), and the enhanced version of Trade Reporting and Compliance Engine (Enhanced TRACE). While the NAIC and FISD data go back to the 1990s, July 2002 is the starting point of the Enhanced TRACE dataset. Our sample period is from July 2002 to December 2014.

State regulations require insurance companies to disclose their annual portfolio holdings and transactions on stocks, bonds and other securities. Such information is included in insurers' Schedule D filings to state insurance departments. We list 15 insurers with the highest corporate bond purchases and sales (in terms of bond par values) during the sample period in the Internet Appendix. Most insurers actively buying or selling corporate bonds are life insurance companies.

Insurers are required to report counterparties involved in their transactions in the Schedule D. In the bond transaction section, the supermajority of reported counterparties are bond dealers. We manually clean-up this data by removing non-trading related observations such as coupon payments, payments to maturing bonds and called bonds, and eliminating direct transactions among insurers (accounting for less than 0.3% of transactions). This results in a total of 896 bond dealers.

4.1 Sample

As summarized in Table 1, we construct the sample in three steps. In the first step, we get insurer daily transactions of corporate bonds from Schedule D of the NAIC database. To do so, we first get the "universe" of insurers' bond transactions; non-trading events (e.g., maturity, redemption, call, sinked fund, and conversion) are excluded. When an insurer has multiple transactions for the same bond in one day, we aggregate par values of these transactions to obtain the insurer's daily transaction amount of that bond. Panel A of Table 1 reports 3,401,354 daily insurer buy transactions and 2,610,027 daily insurer sell observations. As such, insurers engage in buy-side transactions more often than in sell-side transactions. Next, we obtain the full list of corporate bonds from the FISD database, including asset backed securities, convertible bonds, debentures, letter of credit backed bonds, medium-term notes, papers, pass-through trusts, payment-in-kind bonds, strip bonds, zero-coupon bonds, insured debentures, and bank notes for the US corporations.[4] Combining the NAIC bond transactions and the FISD corporate bonds, we have insurer corporate transactions at the daily level.

Subsequently, we apply filters to ensure the quality of the combined data – if for a given bond, an insurer's inferred year-end par value is below 90% or above 110% of the reported year-end par value, we exclude that year's observations on the bond for that insurer from the sample. If more than 10% of observations are excluded for an insurer during a given year for this reason, we exclude all observations in that year for the insurer.[5] As reported in the last row of Panel A, there are 1,588,998 insurer-bond-day observations, including 958,798 insurer-bond purchases and 630,200 insurer-bond sales at the end of the first step.

The second step is to obtain a sample of insurer holding and trading at the bond-insurer level in the monthly frequency. We sum up daily observations in the same month for each insurer to obtain monthly insurer-bond transactions (924,895 buys vs. 603,178 sells as reported in Panel B). The similar numbers of observations in daily and monthly observations provide us information about the frequency of insurer trades. That is, insurers typically do not repeatedly buy or sell the same bond within a month. We merge insurer-bond monthly trades with the TRACE-based bond illiquidity data.[6] We set 0 for an insurer's transaction amount of a bond in a month where bond illiquidity is available but insurer bond transaction data is not available. Alternatively, we drop an insurer-bond-month observation if illiquidity measures are unavailable. Finally, we remove trades within 60 days after initial offerings

[4] Bonds with missing data on key characteristics such as coupon rate, par value, and credit ratings are excluded. We do not consider variable coupon rate bonds, denominated in a foreign currency bonds, or preferred securities. Bonds with less than one year maturity are also not considered because of high pricing errors according to Lin, Wang, and Wu (2011).

[5] To measure inferred insurer's year-end holding on a bond, similar to Chen, Huang, Sun, Yao, and Yu (2018), we start with the par value of its holding of the bond at the beginning of the year, and then add the par value of the insurer's net purchases on this bond from the beginning of the year to the end of the year. The insurer's net purchase of a bond is the aggregate buying amount minus the aggregate selling amount.

[6] Given that our liquidity measures, discussed in Section 4.2, are TRACE based, we follow Dick-Nielsen (2009, 2014) to clean Enhanced TRACE dataset by deleting known errors and double-counted interdealer transactions. We further use the median and the reversal filters from Edwards, Harris, and Piwowar (2007) to smooth extreme observations. Transactions with unreasonable prices and defaulted bond transactions are excluded. In total, these filters remove roughly 38% of transactions originally included in TRACE.

(to focus on trades in the secondary market) and trades for bonds within 1-year remaining maturity (to focus on relatively long-term bonds). There are 1,614,284 insurer-bond-month observations, including 829,967 purchases and 784,317 sales.[7]

Insurers' NAIC data include dates of individual bond transactions, allowing us to aggregate daily transactions to estimate monthly holding and trading for every insurer. We use monthly data instead of daily data for two reasons. First, insurers are low frequency traders. Over 96% of trading days have no trading records from insurers; if daily data were to be used, regression results would be less reliable. By contrast, over 70% of monthly observations are non-zero. Second, daily liquidity measures are highly correlated, especially for the *Roll* measure because it is developed based on historical data, often using the information in the past months or quarters. On the other hand, if we aggregate daily data in a quarterly frequency, the resulting trading measure is potentially contaminated by obsolete information.

In the third step, we aggregate across all insurers to obtain bond level monthly holding and transactions of individual bonds. We only include bonds with coupon, bond age, positive par value, maturity, and available ratings. Shown in Panel C, there are 487,601 observations for all sample bonds from 2002Q3 to 2014Q4. This is the main sample used in our empirical analysis.

4.2 Liquidity Measures

Three widely used corporate bond illiquidity measures are applied in our paper – the Roll (1984) effective spread measure, the Amihud (2002) illiquidity ratio, and the Corwin and Schultz (2012) *Highlow* proxy. Conceptually, *Roll* and *Highlow* are measures of bid-offer spread (considered as the best measure of bond liquidity in Schestag, Schuster, and Uhrig-Homburg (2016), a comprehensive comparative analysis of bond market liquidity measures), whereas *Amihud* is a price impact measure. We estimate liquidity measures in a month when a bond has been traded in 8 different trading days in the month, and to eliminate outliers

[7]Note that we have more monthly insurer-bond observations than daily insurer-bond observations because the monthly dataset additionally include observations that insurers do not trade.

and erroneous entries, the included illiquidity measures are winsorized at 1% and 99% level. Details on constructing these liquidity measures are covered in the Internet Appendix.

We depict the average bond illiquidities over time in Figure 3. All reported numbers are weighted by individual bonds' aggregate par value. Three illiquidity measures share a similar trend though differ in terms of magnitude – *Roll* and *Highlow* are greater than *Amihud*, consistent with the means of respective illiquidity measures reported in Table 2. Illiquidity decreased from July 2002 to June 2007 in the course of before-crisis period. During the credit crunch, they increased sharply and peaked around October 2008, and then dropped to a relatively low level.

4.3 Bond Holding and Trading of Insurers

The fractional holding of insurers on a specific bond i at time t, $Hold_{i,t}$, is defined as:

$$\text{Hold}_{i,t} = \frac{\sum_j \text{Holding}_{i,j,t}}{\text{Par}_{i,t-1}} \tag{3}$$

where $\text{Holding}_{i,j,t}$ is the par value of bond i (or the aggregate par value of bond group i) held by insurer j at period t, and $\text{Par}_{i,t-1}$ is the aggregate par value of bond i (or a bond group i) at the beginning of time t.

Figure 4, the plot for insurer bond holding across different credit ratings, depicts that insurers concentrate their bond investments in relatively risky bonds, i.e., insurers hold a high percentage of investments in low-rated investment grade bonds and high-rated non-investment grade bonds. The peak of their holding occurs at the S&P BBB (holding 34% of these bonds' outstanding value), which far exceeds insurers' holding in AAA bonds (roughly 15%). This indicates that insurers have incentives to invest in risky bonds to achieve high portfolio performance. In Figure 5, we also plot insurer aggregate holding across bond maturities where we put bonds with the same years to maturity to different "year" maturity groups, though there is evidence that insurers' preference leans towards relatively long term bonds.

We further define $\text{Buy}_{i,t}$, for an individual bond i in month t, as the sum of the par value of buy transactions from individual insurer j, $\text{Buy}_{i,j,t}$, across all insurers in our sample scaled by the bond's aggregate par value at the beginning of that month:

$$\text{Buy}_{i,t} = \frac{\sum_j \text{Buy}_{i,j,t}}{\text{Par}_{i,t-1}}, \tag{4}$$

Similarly, $\text{Sell}_{i,t}$ is defined as:

$$\text{Sell}_{i,t} = \frac{\sum_j \text{Sell}_{i,j,t}}{\text{Par}_{i,t-1}}, \tag{5}$$

Figure 4 is a plot of insurers' buys and sales across bond rating groups. The pattern is largely consistent with insurers' holding. BBB is the most preferred rating among all bonds purchased by insurers and BBB-, the lowest investment grade rating assigned by S&P, is the rating of bonds most aggressively sold by insurers. BB appears to be an important rating group since it is the turning point in terms of insurers' bond purchases and sales: insurers' aggregate buy transactions exceed their sell transactions for BB and higher-rated bonds, and their sell transactions exceed buy transactions for bonds with BB- rating and below. We thus choose BB as the lower bound for the group of "threshold" bonds.

In Figure 5, we plot insurers' buys and sales across different maturity groups. We find insurers' sales are evenly distributed in maturities, but they particularly prefer to buy 10-year bonds and 30-year bonds. In an unreported analysis, we find 10-year bonds are mainly purchased by property and casualty insurers, while 30-year bonds are predominately purchased by life insurers.

To understand the insurance trading activities at the broad level, we also examine the determinants of insurers' buy and sell transactions, which is covered in Table A2 of the Internet Appendix and briefly summarize the results here. First, insurers prefer bonds of higher coupon rates, younger age, and longer maturity.[8] Second, compared to highly-rated bonds (A- and above) and liquid bonds, insurers purchase more threshold-rated bonds (between BB and BBB+) and low-liquidity bonds. Third, insurers show less interest in

[8]According to Table A2, insurers appear to buy more small-sized bonds because the dependent variables are scaled by the outstanding par value. After using buy (sell) dummy as dependent variables, we find insurers buy more large-sized bonds.

poorly-rated bonds (BB- and below). The findings are similar across three liquidity measures and robust to different sub-periods of the data such as the financial crisis period.

4.4 Summary Statistics

Panel A of Table 2 provides summary statistics on the sample of plain-vanilla corporate bonds used in our analysis. Bond credit ratings are primarily from S&P. If the S&P rating is missing, we use the rating from Moody's or Fitch, in this order; and bonds without credit ratings are excluded. We assign number 1 to 22 to bond ratings based on their credit ratings, 22 for AAA (best) rated bonds and 1 for D (worst) rated bonds. Bond remaining maturity and bond age are in years. Bond size is the logarithm of bond par value. The distributions include the number of observations, 5th, 25th, 50th, 75th, and 95th percentiles, as well as the mean, and standard deviation. We obtain each statistic in each month and then take the average over time. The means of the three illiquidity measures (*Roll*, *Amihud*, and *Highlow*) are 1.99%, 0.40 (per million), and 0.95% respectively. They are comparable with other studies (e.g., Schestag et al., 2016). The standard deviations of these three measures are 1.73%, 0.57 (per million) and 0.83%, which indicate meaningful illiquidity dispersion. The table further reports the statistics for the aggregate buy and sell transactions by sample insurers, both in terms of the fraction to individual bond par value and unscaled dollar amount. We see that the mean and median insurer buy transactions are slightly higher than those of insurer sell transactions.

Subsequently, in Panel B of Table 2 we report the correlation matrix of key variables. We compute the correlations in each month and then take the averages over time. Correlations among all three illiquidity measures are all positive, ranging from 0.39 to 0.55. The highest correlation is between *Roll* and *Amihud*, and the lowest is between *Amihud* and *Highlow* measure. The reported correlations are consistent with Schestag et al. (2016). Further, bonds with better ratings and larger in size are more liquid; conversely bonds with longer maturity, more aged, and higher coupon rates are less liquid.

5 Results

In this section, we first document the asymmetric persistence in insurers' buy and sell transactions and empirically test the impact of buy and sell transactions on bond liquidity. We examine our hypothesis on rainy day liquidity provision by quantifying the liquidity improvement of buy side transactions under stressful conditions. We then test whether insurers' bond purchases could favorably influence the liquidity of similar bonds under rainy conditions. Finally, we investigate the link between funding ability and rainy day liquidity provision and verify whether insurers provide more liquidity to bank-affiliated dealers after the Dodd-Frank Act which has restricted the banks' proprietary trading activities.

5.1 Persistence in Insurers' Buy and Sell Transactions

In the model section, we postulate a specific form of auto-correlation structure for consecutive buy and sell orders from insurers which ultimately leads to our rainy day liquidity hypothesis. Here, we verify this assumption by computing the degree of persistence in buy and sell transactions of insurers in a panel regression setting:

$$\begin{aligned} \text{Buy}_{i,t+\tau} &= \alpha^b + \beta^b \text{Buy}_{i,t} + \mu_t^b + \varepsilon_{i,t+\tau}^b \\ \text{Sell}_{i,t+\tau} &= \alpha^s + \beta^s \text{Sell}_{i,t} + \mu_t^s + \varepsilon_{i,t+\tau}^s \end{aligned} \tag{6}$$

Regressions are performed independently for insurers buy and sell transactions. The dependent variables are the fractional buy and sell amount of an individual bond by all insurers in our sample in a given month defined in Equations (4) and (5). μ_t represents the month fixed effects in both regressions. To account for potential correlations in error terms across time and assets, we estimate two-way clustered standard errors along time and individual bond dimensions throughout the paper.

Ranging from one month to one year, we consider various values of τ defined as the interval from the most recent buy (sell) transaction to the current buy (sell) transaction. Panel A of Table 3 shows the estimates of the regression for the full sample period. We find that buy transactions are highly persistent and the level of persistence is much stronger for higher values of τ. β^b is estimated to be 0.16 (t-stat=6.96) when τ is set to one month, and the coefficients increase to 0.31 and 0.70, both significant at the 1% level, when τ is extended to a quarterly and annual horizons, respectively. By contrast, the persistence in sell transactions is much weaker. The coefficients on *Sell*, $\hat{\beta}^s$, are respectively 0.05, 0.12, and 0.26 when the dependent variable leads $\text{Sell}_{i,t}$ by a month, a quarter, and a year. The strikingly different persistence levels between buy and sell transactions clearly support our main assumption that the long run probability of observing buy orders is higher than that of sell orders, i.e., $p > q$, in the model.

Next, we separate insurers into firms with a robust and a weak cash flow position and separately measure $\text{Buy}_{i,t}$ ($\text{Sell}_{i,t}$) of these two cash flow groups. We expect the persistence in buy orders to be stronger for insurers with a robust cash flow position. Our model would then imply that rainy day liquidity provision by this group of insurers is also higher, which complements the view that funding sufficiency of dealers and financial intermediaries is critical to securities' market liquidity (Brunnermeier and Pedersen, 2008; He and Krishnamurthy, 2013; He, Kelly, and Manela, 2017).

Specifically, we evaluate an insurer's cash flow relatively using its operations cash flow scaled by its assets,[9] and divide insurers into two groups: the "robust" (R) cash flow group consisting of firms whose cash flow ratios are above the median of the cash flow measure and the "weak" (W) cash flow group consisting of firms whose cash flow ratios are below the median of the cash flow measure in a given year. We run the following panel regressions:

[9]An insurer's cash flow consists of i) operations cash flow, including underwriting cash flow and investment income (stock dividends and bond coupon payments), ii) investment cash flow, mainly the cash flow associated with realized capital gains minus the cash flow of new investments, and iii) financing cash flow. We solely include operations cash flow because operations cash flow is independent of capital market conditions and it is the main component of an insurer's aggregate cash flow. Nevertheless, we also perform the analysis using an all-in measure and obtain consistent results.

$$
\begin{aligned}
\text{Buy}_{i,t+\tau} &= \alpha^b + \beta_1^b \sum_{j\in R} \text{Buy}_{i,j,t} + \beta_2^b \sum_{j\in W} \text{Buy}_{i,j,t} + \mu_t^b + \varepsilon_{i,t+\tau}^b \\
\text{Sell}_{i,t+\tau} &= \alpha^s + \beta_1^s \sum_{j\in R} \text{Sell}_{i,j,t} + \beta_2^s \sum_{j\in W} \text{Sell}_{i,j,t} + \mu_t^s + \varepsilon_{i,t+\tau}^s
\end{aligned} \tag{7}
$$

In Equation (7), the dependent variable $\text{Buy}_{i,t+\tau}$ ($\text{Sell}_{i,t+\tau}$) represent insurers' aggregate purchases (sales) of an individual bond i in a subsequent month. $\text{Buy}_{i,j,t}$ represents insurer j's buy transactions on bond i. β_1^b (β_1^s) quantifies the persistence of robust insurers' buy (sell) transactions; β_2^b (β_2^s) quantifies the persistence of weak insurers' buy (sell) transactions.

As reported in Panel B of Table 3, for the regression of the buy-side transactions, $\hat{\beta}_1^b$ are 0.20 (t-stat=3.64), 0.39 (t-stat=3.15), and 0.80 (t-stat=3.08) when τ corresponds to intervals of one-month, one-quarter, and one-year, respectively. This indicates that insurers' purchases have higher persistency in the long term. Moreover, the economic and statistic magnitude of $\hat{\beta}_2^b$ is much smaller than $\hat{\beta}_1^b$, implying that persistence in buy purchases is higher for robust cash flow group. For insurers' sell transactions, however, persistence is stronger for bonds sold by weak cash flow insurers. For example, in the case of τ equal to 1 month, $\hat{\beta}_1^s$ is 0.03 with a t-statistic of 0.79 while $\hat{\beta}_2^s$ is 0.05 with a t-statistic of 1.97. Clearly, the magnitude of sell side persistence is much weaker than that of insurers' buy-side transactions.

Moreover, reported in Panel C of Table 3, we analyze the persistence in insurers' buy and sell transactions during the crisis period, which is from July 2007 to April 2009.[10] Inferred from the reported results, the persistence in buy and sell transactions during the crisis period is largely consistent with that of the analysis using the full sample. A larger difference between buy and sell persistence in this subsample indicates that insurers are more likely to be persistent buyers during the crisis period.

We subsequently perform a persistence analysis in the financial crisis after separately counting buy and sell transactions with regards to robust and weak cash flow insurers.

[10] There were several major market deterioration events in July 2007. Among them, Bear Stearns liquidated two hedge funds that invested in various types of mortgage-backed securities; Standard and Poor's placed 612 securities backed by subprime mortgages on a credit watch. The span of financial crisis here is consistent with other studies such as Bao, O'Hara, and Zhou (2018).

Shown in Panel D of Table 3, the results show a strong buy-side persistence for robust cash flow insurers (the estimated coefficients, $\hat{\beta}_1^b$, are respectively 0.24, 0.45, and 0.89 in the regressions for the monthly, quarterly and yearly values of τ), and this level of persistence appears to be much higher than that of weak cash flow insurers ($\hat{\beta}_2^b = 0.07$, 0.10, and 0.33, respectively). Moreover, the difference between buy and sell persistence is greater in the crisis period compared to the analysis using the full sample period. As reported in Panel B, for example, in the full sample period β_1 estimates for robust cash flow insurers' buy and sell in the following year are respectively 0.80 (t-stat=3.08) and 0.25 (t-stat=2.38), resulting in a difference of 0.55 in two coefficients; in the financial crisis period, the corresponding estimates are 0.89 (t-stat=3.35) and 0.21 (t-stat=2.29) which produce a difference of 0.68.

Further along, we check whether insurers' bond transactions are correlated across time with the transactions of other bonds with similar characteristics, i.e., persistence in buy or sell transactions across bonds. To conserve space, we cover the empirical findings of cross-bond persistence in buy or sell transactions in the Internet Appendix (Table A3). We identify matching bonds of insurer traded bonds in a particular month if they have the same bond rating, maturity difference within a year and are in the same liquidity quintile group. On average, each bond bought or sold by insurers in a month is matched with 6 bonds not bought or sold in our final sample. Using m to denote a matching bond to a specific bond i purchased by insurers in month t, we estimate the persistence across matching bonds using the following regression:

$$\begin{aligned} \text{Buy}_{m,t+\tau} &= \alpha^b + \beta^b \text{Buy}_{i,t} + \mu_t^b + \varepsilon_{i,t+\tau}^b \\ \text{Sell}_{m,t+\tau} &= \alpha^s + \beta^s \text{Sell}_{i,t} + \mu_t^s + \varepsilon_{i,t+\tau}^s. \end{aligned} \tag{8}$$

Once again, we use the same values of τ: one month, one quarter, and one year. As shown in Panel A of Table A3, insurers' buy transactions lead to an increase in buy transactions of matching bonds. β^b are estimated to be 0.06 (t-stat=5.33), 0.15 (t-stat=6.02) and 0.42 (t-stat=6.19) when τ is taken to be one month, one quarter and one year, respectively. We further separate transactions by insurers with robust and weak cash flows. As reported in Panel B of Table A3, the buy side cross persistence is higher for robust cash flow insurers.

Furthermore, we perform the persistence analysis across bonds during the crisis period and report the results in Panel C of Table A3. Likewise, we find stronger levels of persistence at the buy side. Finally, we examine the role of insurers' cash flow on cross bond trading persistence during the financial crisis period. We find that buy transactions of insurers' with robust cash flow positions have strong influence on the purchase of matching bonds in the subsequent period.

In summary, the analysis indicates that insurers' buy transactions are more persistent than sell transactions, and this persistence is mainly driven by robust cash flow insurers. The effect is also stronger in the crisis period.

5.2 Asymmetric Buy and Sell Effects

We begin the analysis on insurers' rainy day liquidity role by looking at the effect of insurers' buy and sell transactions on bond liquidity in general. Our model predicts that in times of market stress, insurer buy (sell) transactions can improve (reduce) bond liquidity whereas in normal conditions, the autocorrelation in insurance order flow will be detrimental to bond liquidity for both sides of transactions. Thus, the net effect is unclear as it could depend on the magnitude of the effects and the durations of the normal and stressful conditions. This becomes ultimately an empirical question.

We test whether insurers' buy and sell transactions improve bond liquidity using the following regression:

$$\Delta\mathrm{ILQ}_{i,t} = \alpha + \beta_1\mathrm{Buy}_{i,t-1} + \beta_2\mathrm{Sell}_{i,t-1} + \beta_3\mathrm{ILQ}_{i,t-1} + \mathrm{Control}_{i,t-1} + \mu_{t-1} + \varepsilon_{i,t} \tag{9}$$

In Equation (9), the dependent variable is the change of bond illiquidity, measured by *Roll*, *Amihud*, and *Highlow* respectively, in two consecutive months. The key independent variables are the fractional buy and sell amount of an individual bond by all insurers in our sample in a given month. To control for heterogeneity across bonds, we follow Campbell and Taksler (2003) and Dick-Nielsen, Feldhütter, and Lando (2012) to controls for lagged illiquidity, $\mathrm{ILQ}_{i,t-1}$, as well as important bond characteristics including bond coupon rates, bond age, bond size, bond maturity, dummy variables for individual bond ratings,[11] and indicator variables for callable bonds, puttable bonds, exchangeable bonds, convertible bonds, credit enhancements bonds, senior bonds, and secured bonds which are measured at the beginning of that period. μ_{t-1}, the month fixed effects, are included to address time series variations for the change in bond illiquidity.

In Columns (1) through (3) of Table 4, we report the regressions without the inclusion of control variables. Regardless of the use of illiquidity measures, the estimated coefficients on insurers buy transactions, $\hat{\beta}_1$, are all significant at the 1% level – they are respectively -1.53, -0.30, and -0.47 corresponding to the illiquidity measures, *Roll*, *Amihud*, and *Highlow* – insurer purchases help to enhance bond liquidity. By contrast, β_2 are all estimated to be positive and significant, suggesting that insurer sales consume liquidity.

Columns (4) through (6) of Table 4 report the result of regressions specified in Equation (9) with the full set of control variables. The estimated coefficients are similar to those reported in Columns (1) through (3). Using *Roll* as the illiquidity measure, the coefficient on *Buy* is -1.15 significant at the 1% level while the coefficient on *Sell* is 0.48 significant at the 5% level.

We also report the p-values for the Wald test on the hypothesis that coefficients are the same between insurers' buy and sell transactions. This is located in the third last row. A low p-value indicates the asymmetric effect of purchases and sales on bond liquidity. We find that in five out six cases, p-values are less than 0.01, rejecting the null that the coefficients on buy transactions are equal to those on sell transactions. Overall, our findings suggest that insurers' corporate bond purchases improve the bond liquidity in the subsequent period whereas their sales decrease it.

It is worth mentioning that we also conduct regressions of Equation (9) using entire bond transactions covered in TRACE. The coefficients of the market buy and sell, however, are all insignificant when using all three liquidity measures. This finding suggests that insurer trading has an important role in bond trading cost.

[11] Altogether, we include 22 rating dummies associated with different bond ratings based on the S&P schedule.

5.3 Liquidity Provision in Rainy Days

To investigate the rainy day liquidity hypothesis, we break down sample bonds into different liquidity groups, rating groups, crisis and non-crisis periods, and examine whether liquidity improvement of buy side transactions is much stronger under stressful conditions. Panel regressions in form of Equation (9) are performed and reported in Table 5.

In Panel A of Table 5, we report the results of regressions for different liquidity groups. Three liquidity groups are formed: the high liquidity group (HLG) holds bonds with the highest 30 percent liquidity over all bonds in a month; the low liquidity group (LLG) holding bonds with the lowest 30 percent liquidity over all bonds in that month; the rest is placed in the median liquidity group (MLG).

First, we confirm the asymmetric impact of buy and sell transactions on bond liquidity. As shown in Panel A, almost all of the coefficients on insurer purchases, $\hat{\beta}_1$, are significantly negative. By contrast, the coefficients of insurers' bond sells, $\hat{\beta}_2$, are either insignificantly different from zero or even positive for regressions. More importantly, based on different liquidity measures, β_1 is highly negative in the lowest liquidity group. The coefficients on *Buy* for low liquidity bonds are -2.51 (t-stat=-3.37), -0.31 (t-stat=-2.70), and -1.20 (t-stat=-3.03) when bond illiquidity is respectively measured with *Roll*, *Amihud*, and *Highlow*. That is, a 1% increase of insurers' purchase of illiquid bonds in LLG reduces *Roll*, *Amihud*, and *Highlow* measures by approximately a 1.6%, 1.2%, and 1.8% of their respective medians.[12] We also report *LMH*, the difference of β_1 between low and high liquidity groups. They are negative and significant in all cases. *LMH* is -2.05 (t-stat=-2.62) when *Roll* is used as a liquidity measure and it is -0.44 (t-stat=-2.94) when *Amihud* is used.

In addition, according to Panel A, among high liquidity bonds, the estimated β_1 is mostly insignificant. For example, using *Roll* for bond illiquidity, the estimated β_1 is -0.46 with a t-statistic of -1.26. The significant buying effect on bond liquidity reported in Section 5.2 mainly comes from illiquid bonds, a group of rainy bonds. This finding renders additional

[12] A 1% increase in insurers' buy leads to a 2.51% decrease in bond illiquidity. Based on the statistics reported in Table 2, this is a 1.6% decrease in terms of the median of the *Roll* measure (=-2.51*1%/1.56) for example.

support to the rainy liquidity provision hypothesis – insurers' liquidity provision concentrates in stressful conditions.

Next, in Panel B, we look at insurers' liquidity provision across different rating groups. Specifically, bonds in the sample are broken down into three groups based on their ratings: superior (*Sup*), threshold (*Thr*), and inferior (*Inf*). Superior bonds are those whose S&P ratings are A- and above and the threshold group consists of bonds with a S&P rating between BB and BBB+. Bonds in the inferior group are rated BB- or below.

For bonds in the superior bond group, $\hat{\beta}_1$ are 0.37 (t-stat=0.96), 0.08 (t-stat=0.76), and -0.10 (t-stat=-0.70) for *Roll*, *Amihud*, and *Highlow* liquidity measures, implying that insurer purchases do not strongly affect the subsequent liquidity of non-rainy day bonds. However, for bonds in the threshold group, β_1 are -2.35 (t-stat=-6.80), -0.34 (t-stat=-3.86), and -0.77 (t-stat=-5.28). Finally, for bonds in the inferior group, coefficients are also significantly negative, implying insurers' bond purchase improves the liquidity of poor quality junk bonds as well. *TMS* is the difference in coefficients between bonds in the threshold and superior group. We find that for each liquidity measure, the difference between the coefficients is significantly negative. In terms of economic significance, a 1% insurers' purchase leads to approximately a 1.5%, 1.4%, and 1.1% decrease in *Roll*, *Amihud*, and *Highlow* measures, respectively, for bonds in the threshold group.

Finally, in Panel C, we report the results of panel regressions for insurer trading in different subsample periods around the financial crisis. The sample is broken into three periods: before-crisis period (*Before Crisis*), crisis period (*Crisis*), and after-crisis period (*After Crisis*). The before-crisis period is from July 2002 to June 2007. The crisis period is from July 2007 to April 2009. The after-crisis period is from May 2009 to December 2014.

During pre-crisis period, $\hat{\beta}_1$ is -0.33 (t-stat=-1.01), 0.14 (t-stat=1.91), and -0.21 (t-stat=-1.39) for *Roll*, *Amihud*, and *Highlow* measure respectively. This indicates that insurer purchases in the non-crisis period do not positively affect bond liquidity. Conversely, during the financial crisis, $\hat{\beta}_1$ are statistically significant for all three measures of illiquidity. For example, $\hat{\beta}_1$ of the regression in the crisis period is -4.71 (t-stat=-3.86) when *Roll* is the liquidity measure. Economically, a 1% increase of insurers' purchases produce 3% liquidity when *Roll* is the illiquidity measure.

Our untabulated results also support that liquidity enhancement in the crisis is stronger among threshold bonds than bonds of other rating groups. To be specific, we perform regressions to compare the effects of insurers' purchase of threshold bonds before the crisis and in the crisis period. We find that the coefficient on insurers purchase is -6.22 (t-stat=-4.58) in the crisis, and it is -1.87 (t-stat=-2.30) in the pre-crisis period.

Overall, Panel A to Panel C of Table 5 present a strong support to the rainy day liquidity provision hypothesis. These results align with our first hypothesis in the sense that insurers are more likely to offer liquidity under adverse market conditions, on relatively illiquid bonds and threshold rating bonds. Although insurers potentially experience negative shocks during crisis periods, our results suggest that the magnitude of such shocks on insurers' profitability and equity value is milder than that of other financial institutions (e.g., Chodorow-Reich et al., 2019; Koijen and Yogo, 2015, 2016).

5.4 Liquidity Spillover

In this section, we formally test the second hypothesis that insurers' bond purchases could favorably influence the liquidity of similar bonds under rainy conditions. This hypothesis builds on empirical evidence reported in Table A3 included in the Internet Appendix that insurers' buy transactions lead to an increase in buy transactions of matching bonds. It is also consistent with prior studies presenting evidence on the commonality of liquidity across securities i.e., liquidity has been shown to covary strongly across securities (e.g., Chordia et al., 2000; Koch et al., 2016). Alternatively, there is a potential competition/substitution effect, under which insurers' purchase of one bond reduces the liquidity of matching bonds because of the lack of capital after the buy transaction. We differentiate between these effects of insurers' bond trading on the liquidity of other bonds with similar characteristics.

To test the cross-bond liquidity spillover effect, we regress the change of the liquidity of a matching bond onto insurers' buy and sell transactions of a sample bond.

$$\Delta\text{ILQ}_{m_i,t} = \alpha + \beta_1\text{Buy}_{i,t-1} + \beta_2\text{Sell}_{i,t-1} + \beta_3\text{ILQ}_{m_i,t-1} + \text{Control}_{m_i,t-1} + \mu_{t-1} + \varepsilon_{m_i,t} \quad (10)$$

where $\text{ILQ}_{m_i,t}$ is the illiquidity of the bond matched to ith bond, $\text{ILQ}_{m_i,t-1}$ is the illiquidity of matching bond in the previous month, $\text{Buy}_{i,t-1}$ and $\text{Sell}_{i,t-1}$ are the par values of purchases and sales performed by insurance companies on the sample bond, i, in the previous month, scaled by the bond's aggregate par value. The same matching procedure prescribed in Section (sec:persist) is applied. Control variables corresponding to the matching bond are the same as those in Equation (9).

First, we separate sample bonds into three groups based on their illiquidity like what we did in Panel A of Table 5. Panel A of Table 6 reports the results of panel regressions for insurer trading on the illiquidity of the matched bonds for each liquidity group. For all three liquidity measures, the coefficients on insurer purchases for the bonds in low-liquidity (high-liquidity) group are negative (positive). These findings imply that insurers' purchase of sample bonds has a significant contagion effect on the set of matched bonds. The difference in the coefficients for the low-liquidity and high-liquidity group is -0.65 (t-stat=-2.37), -0.26 (t-stat=-3.01), and -0.41 (t-stat=-3.04), respectively. These results imply that the effect of insurer purchases on low liquidity bonds' illiquidity is significantly higher compared to the effect on high liquidity bonds' illiquidity.

Panel B of Table 6 reports the results of panel regressions for the effect of insurer trading on the set of matched bonds within rating groups. The coefficients on insurers' buy transactions are -0.51 (t-stat=-2.66), -0.12 (t-stat=-2.87), and -0.18 (t-stat=-3.02), respectively, for bonds in the threshold group. These estimates are much more negative when compared to the coefficients obtained for superior and inferior bonds. In the superior bonds group, the coefficients on insurers' buy are 0.59 (t-stat=2.40), 0.08 (t-stat=2.03), and 0.11 (t-stat=2.66). The differences in the coefficients between bonds in the threshold and superior group are -1.10 (t-stat=-4.85), -0.20 (t-stat=-3.40), and -0.29 (t-stat=-4.42), respectively. This finding suggests that insurers' bond purchases may have further contagion effects on the set of matched bonds. Namely, we observe that for the bonds in the threshold category, insurers' buy transactions can improve the liquidity of the bonds that have similar characteristics to the traded bond.

Finally, to examine the relationship during the financial crisis, we break down the sample into different subsample periods as we did in Table 5 Panel C. Reported in Table 6 Panel C, we present the regression results on the effect of insurers' trading on matching bonds' subsequent liquidity in alternative subsample periods. In the financial crisis, the coefficients on *Buy* are -1.50 (t-stat=-2.95), -0.37 (t-stat=-3.96), and -0.58 (t-stat=-3.25), respectively. These significant estimates suggest that insurers bond purchases in the crisis period have a spillover effect on the subsequent liquidity of the matched bonds. The differences in the coefficients between crisis and before-crisis periods are -1.52 (t-stat=-2.90), -0.17 (t-stat=-2.26), and -0.69 (t-stat=-3.21), respectively, which echo that insurers' purchases have stronger spillover impact during the financial crisis.

Taken together, when we examine the cross-bond liquidity effects for bonds having lower liquidity, threshold rating, or bonds traded during the crisis period, the buy-side cross trading effect on illiquidity turns out to be negative. This constitutes strong evidence to Hypothesis 2 as rainy day liquidity provision is not only limited to the bonds purchased by insurers—namely, the liquidity of bonds with similar characteristics to the purchased bonds also increases subsequently during stressful periods.

5.5 Effects of Insurer Funding and Holding Horizon on Rainy Day Liquidity

An insurer's ability to supply rainy day liquidity should depend on its funding condition. For this reason, we conjecture that insurers with higher funding ability will engage in stronger rainy day liquidity provision. Insurers' funding liquidity is stronger for those insurers with stable cash flow and with longer holding horizon. We expect that insurers with more robust funding and longer investment horizon will offer more rainy day liquidity.

5.5.1 Role of Insurer Cash Flow

First, we empirically verify the weak correlation between insurers' cash flow and the aggregate market condition. We compute the time-series correlations between individual insurers' cash flow from operations (scaled by total assets) and S&P 500 index returns. Across all insurers, the mean correlation turns out to be 0.003 and the standard deviation is 0.28, implying a p-value of 0.61 for the null hypothesis that the average correlation is zero.[13] This finding confirms that insurer cash flows are not correlated with overall capital market fluctuations.

Next, we perform the cross-sectional analysis to test whether insurers with a strong cash flow position purchase more threshold bonds than insurers with a weak cash flow position. We then test whether the purchases of strong cash flow insurers improve bond liquidity more than the purchases of weak cash flow insurers. Both predictions from the results reported in Section 5.1 show that insurers with robust cash flow positions have more persistence in their bond purchases. Formally, we evaluate an insurer's cash flow position using the three-year average cash flow scaled by the firm's total assets, then break down insurers into a "robust" cash flow group and a "weak" cash flow group based on whether its cash flow ratio is above or below the annual median of the cash flow ratios.

Let k denote an insurer's cash flow type, which equals to R for insurers with robust cash flow and W for insurers with weak cash flow. We then compute $\text{Buy}_{i,t}^{k}$, the purchase of bond i by a robust or weak insurance group k in month t, calculated as $\frac{\sum_{j\in k}\text{Buy}_{i,j,t}}{\text{Par}_{i,t-1}}$.

The following regressions on $\text{Buy}_{i,t}^{k}$, bond purchase of strong and weak insurers, are performed to see their investments in threshold and poorly rated junk bonds.

$$\text{Buy}_{i,t}^{k} = \alpha^{k} + \beta_1^{k}\text{Thr}_{i,t-1} + \beta_2^{k}\text{Inf}_{i,t-1} + \text{Control}_{i,t-1} + \mu_{t-1} + \varepsilon_{i,t} \qquad k = R, W \tag{11}$$

where threshold rating bonds dummy (Thr) equals 1 if bonds are rated between BB and BBB+, inferior rating bonds dummy (Inf) equals 1 for bonds rated BB- and below. Control variables include bond coupon rates, bond age, bond size, bond maturity, indicators for

[13]When performing the similar analysis using operations cash flow of Compustat firms, we find that the average correlation is 0.042, with a p-value of 0.01.

callable bonds, puttable bonds, exchangeable bonds, convertible bonds, credit enhancements bonds, senior bonds, and secured bonds.

Notably, in Equation (11), the intercept of the above regression, α^k, captures the average insurers' purchase of superior bonds after netting the effect of control variables. β_1^R (β_2^R) quantifies the average difference in the purchase of threshold (inferior) bonds and superior bonds among robust insurers and β_1^W (β_2^W) quantifies the average difference in the purchase of threshold (inferior) bonds and superior bonds among weak insurers. We expect β_1^R, β_1^W, and $\beta_1^R - \beta_1^W$ to be positive.

In Table 7, we report the findings of Equation (11) regressions in the first three columns of Panel A. Shown in the first column, $\hat{\beta_1^R}$ is 0.10 (t-stat=4.78), suggesting that robust cash flow insurers purchase more threshold bonds than superiorly rated bonds. In contrast, the estimated $\hat{\beta_1^W}$ reported in the second column is 0.05 (t-stat=2.76), showing weak cash flow insurers also have a purchasing preference on threshold bonds than superior choices. The significantly positive value of the difference, reported in the third column, between $\hat{\beta_1^R}$ and $\hat{\beta_1^W}$, 0.05 (t-stat=3.31), is supportive to the third hypothesis that insurers will be more active in threshold bonds when they have more adequate funding. All $\hat{\beta}_2$ nonetheless are significantly negative. For example, $\hat{\beta_2^R}$ is -0.12 with a t-statistic of -8.39. This indicates that insurers do not aggressively invest in inferior bonds relative to their purchase of superior bonds.

Further, we analyze the net buy measure, defined as insurers' bond purchases net of sales, and check whether well-funded insurers are net buyers of threshold bonds. The net purchase of bond i by a robust or weak insurance group k in month t, $Net_{i,t}^k$, is defined as:

$$\mathrm{Net}_{i,t}^k = \frac{\sum_{j \in k} \mathrm{Buy}_{i,j,t} - \sum_{j \in k} \mathrm{Sell}_{i,j,t}}{\mathrm{Par}_{i,t-1}} \tag{12}$$

Similar to the analysis for $\mathrm{Buy}_{i,t}^k$, we perform the regression analysis on insurers' net bond purchases. The results are reported in the subsequent three columns of Panel A, Table 7. Again, the finding suggests that robust cash flow insurers have higher net purchase of threshold bonds compared to weak cash flow insurers. The estimated β_1 is 0.02, with a t-statistic of 2.03, in the regression for robust insurers' net purchases, suggesting that robust insurers' purchases of threshold bonds exceed their sales by a larger magnitude when compared to the difference in superior bond transactions. We continue to see the difference to be significant and positive (0.02 with a t-statistic of 2.95) in terms of net purchases of threshold bonds between robust and weak insurers.

Subsequently, we run panel regressions of illiquidity changes of individual bonds on insurers' transactions when these transactions are separated into robust and weak transactions based on insurers' cash flow positions. Bond control variables are the same as those in Equation (9).

$$\begin{aligned}\Delta\text{ILQ}_{i,t} &= \alpha + \beta_1 \sum_{j\in R}\text{Buy}_{i,j,t-1} + \beta_2 \sum_{j\in W}\text{Buy}_{i,j,t-1} + \beta_3 \sum_{j\in R}\text{Sell}_{i,j,t-1} + \beta_4 \sum_{j\in W}\text{Sell}_{i,j,t-1} \\ &+ \beta_5\text{ILQ}_{i,t-1} + \text{Control}_{i,t-1} + \mu_{t-1} + \varepsilon_{i,t} \qquad (13)\end{aligned}$$

β_1 and β_2, respectively, measure the purchasing effect of robust cash flow insurers and weak cash flow insurers on bond liquidity. We expect β_1 to be more negative than β_2 for threshold rating bonds according to the third hypothesis. As reported in Table 7 Panel B, for regressions corresponding to the threshold bond group, $\hat{\beta}_1$ are significantly lower than $\hat{\beta}_2$.

5.5.2 Effect of Holding Horizon

Investors are heterogeneous in their holding horizons while long-term investors can better insulate themselves from market fluctuations (Chodorow-Reich et al., 2019). Cella et al. (2013) and Morris and Shin (2004) show that, in stressful markets, short-horizon investors, fearing weak demand from other market participants and possible price declines in the near future, sell their holdings more aggressively compared to long horizon investors who have the possibility of waiting out the storm and hold onto their shares. Chen et al. (2018) show that corporate bonds held by more long-term investors have a lower liquidity premium. In the context of this evidence, we consider holding horizon as an alternative measure for investors' ability to fund "rainy" day liquidity.

We measure insurers' holding horizon based on insurers' portfolio turnovers, which are inversely related to their holding horizons. An insurer's corporate bond portfolio turnover is the minimum of the aggregate market value of securities purchased by an insurer and the aggregate value of securities sold by the insurer in each year, scaled by the aggregate portfolio value at the end of the year. Insurers are divided into two groups based on their holding horizons in each year: the "long" ("short") horizon group includes firms whose holding horizon are above (below) the annual median measure. Consistent with the prior subsection, we first study how insurer holding horizons affect their threshold bond purchase, and we then examine the differential liquidity effects of long and short-horizon insurers' transactions.

Panel A of Table 8 reports the results. The significantly positive value of the difference between $\hat{\beta}_1^L$ and $\hat{\beta}_1^S$ is 0.03 (t-stat=2.86) and 0.02 (t-stat=2.71) when using purchase and net purchase as the dependent variables respectively. These findings align with the third hypothesis in the extent that long holding horizon insurers are be more active in threshold bonds.

Furthermore, we conduct panel regressions of corporate bond illiquidity on insurers' transactions after separating corporate bond transactions based on insurers' holding horizons. As reported in Table 8 Panel B, for threshold bonds, the coefficient on long horizon insurers' purchase, $\hat{\beta}_1$, are respectively -3.10 (t-stat=-6.01), -0.58 (t-stat=-4.46), and -1.04 (t-stat=-4.60) when using *Roll*, *Amihud*, and *Highlow* as liquidity measures, which are significantly lower than the coefficient of short horizon insurers' purchase.

Investment horizon essentially captures investors' ability to hold undervalued assets (Chodorow-Reich et al., 2019). In this sense, life insurers shall share the similar traits as they have more deterministic liability schedule than property and casualty (P&C) companies. We confirm this by finding a high correlation between a dummy variable for life insurers and insurers' investment horizons (0.74). That is, life insurers tend to hold bonds for a longer horizon than P&C insurers do. With the results reported in the Internet Appendix Table A4, we further estimate the regressions specified in Equation (11) and (13) with the trading data corresponding to P&C and life insurers, respectively. The result is consistent with the prior investment horizon analysis. Compared to P&C insurers, life insurers are less likely to sell speculative-grade bonds during the financial crisis, confirming the argument made in Ellul et al. (2015) that, recognizing most speculative bonds using their historical costs, instead of market value, U.S. life insurers utilize market value recognition to a lower extent than P&C insurers do.

Collectively, our finding supports that insurers' funding strongly influences their net purchases of threshold bonds, rendering support to the argument that improvements in rainy day market liquidity are directly linked to insurers' ability to fund the position.

5.6 Dodd-Frank Act and Insurers' Liquidity Provision

Liquidity in the corporate bond market was substantially low in the financial crisis. Despite post-crisis improvement, bond liquidity has remained a serious concern owing to the implementation of the Dodd-Frank Act which restricts banks' proprietary trading activities. Since the crisis, inventories held by bond dealers have shrunk 50%, while bonds outstanding have almost doubled (Dick-Nielsen and Rossi, 2018). Bessembinder et al. (2018) specifically show a decrease in bank-affiliated dealer capital commitment after the implementation of the Dodd-Frank Act in 2012. In this section, we use the implementation of the Dodd-Frank Act as a natural experiment to test insurers' ability to offer liquidity when there is a shortage in bank dealers' liquidity provision.

Noted in the data section, Schedule D not only provides information about transactions insurers engage in but also offer details on the counterparties involved in the transactions. This allows us to test whether or not insurers offer liquidity to bond transactions during the post-crisis regulation period. To do so, we focus on insurers' buy transactions and classify them being from bank-affiliated dealers and nonbank dealers. The top 100 dealers account for nearly 95% bond transactions and thus we focus on this group of bond dealers. 30 of them are identified as commercial bank-affiliated dealers.[14]

[14]Because the Dodd-Frank Act aims to prevent commercial banks from involving in speculative and/or proprietary trading for profit, transactions affected by the Dodd-Frank Act are those executed by commercial banks affiliated dealers. We treat dealers affiliated with Goldman Sachs and Morgan Stanley, as bank-affiliated dealers because both became bank holding companies in 2008, in the same way as Bessembinder et al. (2018).

According to our model, in times of higher selling pressure or dealer inventory costs, an increase in the arrival rate of insurance companies or their persistence in bond purchases can lead to higher liquidity improvements compared to less stressful periods in terms of order imbalance and inventory costs (as illustrated in Figure 2). Motivated by this finding, we expect that insurers' purchases from bank-affiliated dealers (who face higher inventory costs in our model's terminology) will help increase the liquidity of rainy bonds more during the Dodd-Frank period. We test this by comparing illiquidity changes of individual bonds for insurers' transactions with bank-affiliated dealers (B) and with nonbank dealers (N) by running the following regression:

$$\begin{aligned}\Delta \mathrm{ILQ}_{i,t} &= \alpha + \beta_1 \sum_{j\in B} \mathrm{Buy}_{i,j,t-1} + \beta_2 \sum_{j\in N} \mathrm{Buy}_{i,j,t-1} + \beta_3 \sum_{j\in B} \mathrm{Buy}_{i,j,t-1}\mathrm{DF}_t \\ &+ \beta_4 \sum_{j\in N} \mathrm{Buy}_{i,j,t-1}\mathrm{DF}_t + \beta_5 \sum_{j\in B} \mathrm{Sell}_{i,j,t-1} + \beta_6 \sum_{j\in N} \mathrm{Sell}_{i,j,t-1} \\ &+ \beta_7 \sum_{j\in B} \mathrm{Sell}_{i,j,t-1}\mathrm{DF}_t + \beta_8 \sum_{j\in N} \mathrm{Sell}_{i,j,t-1}\mathrm{DF}_t + \mathrm{Control}_{i,t-1} + \mu_{t-1} + \varepsilon_{i,t} \quad (14)\end{aligned}$$

where $\mathrm{Buy}_{i,j,t}$ ($\mathrm{Sell}_{i,j,t}$) is the fraction of insurer j's purchase (sell) in month t in the aggregate par value of the bond i, and DF_t is the indicator for the post-crisis Dodd-Frank regulated period.[15] Bond control variables include the Dodd-Frank period dummy, lagged illiquidity, and the same as those in Equation (11). We exclude data from the financial crisis period (from July 2007 to April 2009) and restrict the sample to threshold bonds in order to focus on the effect of the Dodd-Frank Act on insurers' role in liquidity provision to rainy bonds.[16]

In Equation (14), β_1 and β_2, respectively, measure the effect of insurers' purchase from bank-affiliated dealers and nonbank dealers on bond liquidity during pre-crisis period. Furthermore, β_3 and β_4 measure the difference of purchasing effect on bond liquidity from pre-crisis period to the Dodd-Frank restricted period for bank-affiliated dealers and nonbank dealers, respectively. Because bank-affiliated dealers have higher inventory costs during the

[15]The Dodd-Frank Act was enacted in July 2010 and implemented in January 2011. We thus consider post financial crisis period as the regulated period given the fact that financial institutions face tightened regulations after the financial crisis. We also perform additional analysis to check the effect of Volcker Rule on insurers' purchases. Consistent with Bao et al. (2018), we consider the period after April 2014 as the active Volcker Rule period and find consistent results.

[16]We obtain consistent results when restricting the sample to junk bonds rated BB and above.

Dodd-Frank period, we expect that insurers' buy transactions with bank-affiliated dealers will improve threshold bond liquidity more in the Dodd-Frank period (β_3 is expected to be more negative than β_4). As reported in Table 9, we find that $\hat{\beta}_3$ is smaller than $\hat{\beta}_4$ for all liquidity measures. Further, the low p-value of the Wald test on the equality of $\hat{\beta}_3$ and $\hat{\beta}_4$ suggests that insurers' threshold bond purchases from bank-affiliated dealers improve liquidity more than those from nonbank dealers during the Dodd-Frank period. On the other hand, we also look at the effect of insurers' sells on bond liquidity and do not find a significant difference between insurers' sells to bank-affiliated dealers and nonbank dealers. None of the coefficients of insurers' sells are significant during the pre-crisis period and the Dodd-Frank period.

6 Conclusion

This study examines the important role of insurance firms in the corporate bond market as "rainy day liquidity providers." We theoretically model a dealer's optimal market making policy in times of selling pressure and insurers' auto-correlated trading needs. Motivated by insurers' buy-and-hold investment style, we specifically consider a regime where buy orders are more persistent than the sell orders. In this model, insurers buy transactions can signal the dealer that eliminating a short position in the future can be easier, which then induces the dealer to provide liquidity to distressed sellers.

We empirically test the predictions of the model with regards to rainy day liquidity provision. We show that insurers provide liquidity for illiquid and threshold bonds, and during the financial crisis. We further show that rainy day liquidity provision effect goes beyond bonds purchased by insurers – the liquidity of bonds with similar characteristics as the purchased (sold) bonds also increases in rainy days. Our empirical analysis also establishes the link between insurers' funding ability and their rainy-day liquidity provision. Finally, we show that after the implementation of the Dodd-Frank Act, the liquidity improvement for bonds that insurers purchase from bank-affiliated dealers is greater than the improvement for bonds purchase from nonbank dealers.

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Table 1: Sample Construction

This table outlines the main steps in the construction of final sample using data from the NAIC Schedule D, the FISD, and the TRACE. The sample period is from July 2002 to December 2014.

Panel A: Insurer Bond Daily Observations

	Number of Purchases	Number of Sales
Insurer-bond daily transactions from Schedule D excluding non-trading events, e.g., maturity, payments, redemptions, calls	3,401,354	2,610,027
Corporate bond trades after merging with the FISD	1,125,068	809,541
Applying a discrepancy filter to get clean insurer-bond observations	958,798	630,200

Panel B: Insurer-Bond Monthly Observations

	Number of Purchases	Number of Sales
Insurer-bond monthly trades from daily insurer-bond trades	924,895	603,178
Merge insurer-bond monthly transactions with bond illiquidity data (monthly) generated from TRACE; set 0 for an insurer-bond-month observation does not have a trading amount	1,136,537	872,853
Observations with non-zero trading value	707,153	444,356
Observations with zero trading value	429,384	428,497
Observations at least 60 days after initial offerings and at least 360 days before bond maturity	829,967	784,317

Panel C: Individual Bond Monthly Observations

	Number of Observations
Bond-month observations after summing insurers' trading of the same bond	572,951
Bonds with positive par value, non-missing bond age and remaining maturity	571,700
Bonds with a valid rating from S&P, Moody's, or Fitch	557,018
Deleting negligible no insurer trading	487,601

Table 2: Summary Statistics

Panel A of the table reports the cross-sectional distributions of three illiquidity measures and other key variables for the entire sample. We restrict the sample to the U.S. plain-vanilla corporate bonds which have positive shares outstanding and non-missing credit ratings. The distributions characteristics include the number of observations, 5%, 25%, 75%, 95%, mean, median, and standard deviation. The reported variables are three illiquidity measures including Roll (in percent), Amihud (per million), and Highlow (in percent), Maturity (remaining time to maturity, in years), Rating (the rating score for AAA rated bonds is 22 and that of D rated bonds is 1), Coupon (coupon rate, in percent), BondAge (the age of a bond since its inception, in years), BondSize (the nature logarithm of outstanding par value), buy (the aggregate par value of a bond purchased by insurers in a month scaled by the bond's aggregate par value, in percent), sell (the aggregate par value of a bond sold by insurers in a month scaled by the bond's aggregate par value, in percent). Definitions of the illiquidity measures are provided in the Internet Appendix C. We obtain each statistic in each month and then take the average over time. Panel B reports the correlation matrix of those 10 variables considered in Panel A, where the correlations in each month are estimated and then averaged over time.

Panel A: Summary Statistics of Bond Characteristics

	N	P5	P25	Mean	Median	P75	P95	SD
Roll	448,746	0.01	0.79	1.99	1.56	2.72	5.49	1.73
Amihud	487,601	0.01	0.04	0.40	0.25	0.49	1.98	0.57
Highlow	487,601	0.15	0.37	0.95	0.68	1.26	2.69	0.83
Maturity	487,601	1.65	3.62	8.90	6.13	9.39	27.41	8.27
Rating	487,601	6.47	11.45	13.92	14.26	16.84	19.35	4.04
Coupon	483,438	3.08	5.10	6.21	6.23	7.32	9.36	1.93
BondAge	487,601	0.47	1.58	4.33	3.24	5.95	12.58	3.83
BondSize	487,601	11.93	12.54	13.04	12.99	13.49	14.39	0.77
Buy (%)	487,601	0	0	0.44	0.01	0.22	2.37	1.41
Sell (%)	487,601	0	0	0.41	0.01	0.21	2.29	1.38

Panel B: Correlations among Liquidity and Characteristics

	Roll	Amihud	Highlow	Maturity	Rating	Coupon	BongAge	BondSize	Buy	Sell
Roll	1.00									
Amihud	0.55	1.00								
Highlow	0.51	0.39	1.00							
Maturity	0.25	0.20	0.26	1.00						
Rating	-0.13	-0.05	-0.14	0.06	1.00					
Coupon	0.09	0.06	0.11	0.02	-0.50	1.00				
BondAge	0.26	0.38	0.27	0.06	0.05	0.22	1.00			
BondSize	-0.21	-0.37	-0.17	-0.01	0.24	-0.17	-0.32	1.00		
Buy	0.01	0.02	0.01	0.09	0.05	-0.05	-0.10	-0.02	1.00	
Sell	0.01	-0.02	0.01	0.01	0.01	-0.02	0.02	-0.06	0.12	1.00

Table 3: Persistence of Insurer Buy and Sell Transactions

This table reports the results of the analysis on the persistence in insurers' buy and sell transactions. Panel A reports the results for the full sample period. The dependent variable is the aggregate par value purchased (sold) by all insurance companies in the subsequent month/quarter/year scaled by the par value of the bond in the corresponding month. The independent variable is the aggregate par value purchased (sold) by all insurance companies in a month scaled by the par value of the bond in that month. Panel B reports the effect of insurers' cash flow on their trading persistence. In each year, we break down insurers into two groups based on cash flow, measured as insurers' cash flow from insurance operations cash flow scaled by total assets. Robust cash flow insurers are those whose cash flow above the annual sample median; weak cash flow insurers are those below the annual sample median. R and W represent, respectively, the robust and weak cash flow insurer groups. The dependent variable is the aggregate par value purchased (sold) by all insurance companies in the subsequent month/quarter/year scaled by the par value of the bond. The independent variable is the aggregate par value purchased (sold) by robust insurers and weak insurers in a month scaled by the par value of the bond in that month. Panel C reports the analysis of the persistence in insurers' buy and sell transactions during the financial crisis. Panel D reports the analysis of the persistence in insurers' buy and sell transactions of robust and weak cash flow insurers during the financial crisis. The full sample period is from July 2002 to December 2014. The crisis period is from July 2007 to April 2009. The regressions include the month fixed effects. The t-statistics reported in the parentheses are based on two-way clustered (by time and by bond issuer) standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Persistence in Insurer Bond Transactions: Full Sample

	Following Month		Following Quarter		Following Year	
	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}
Buy	0.16***		0.31***		0.70***	
	(6.96)		(7.41)		(7.84)	
Sell		0.05***		0.12***		0.26***
		(3.46)		(4.84)		(4.28)
Adj R^2	0.05	0.02	0.08	0.03	0.10	0.04
N	487,601	487,601	487,601	487,601	487,601	487,601

Panel B: Insurer Cash Flow and Trading Persistence: Full Sample

	Following Month		Following Quarter		Following Year	
	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}
$\sum_{j \in R} \text{Buy}_j$	0.20***		0.39***		0.80***	
	(3.64)		(3.15)		(3.08)	
$\sum_{j \in W} \text{Buy}_j$	0.10*		0.15**		0.53***	
	(1.94)		(2.01)		(3.08)	
$\sum_{j \in R} \text{Sell}_j$		0.03		0.09		0.25**
		(0.79)		(1.56)		(2.38)
$\sum_{j \in W} \text{Sell}_j$		0.05*		0.13**		0.27***
		(1.97)		(2.34)		(3.23)
Adj R^2	0.04	0.02	0.07	0.04	0.12	0.05
N	487,601	487,601	487,601	487,601	487,601	487,601

Panel C: Persistence in Insurer Bond Transactions: Financial Crisis

	Following Month		Following Quarter		Following Year	
	Buy_{t+1}	$Sell_{t+1}$	Buy_{t+1}	$Sell_{t+1}$	Buy_{t+1}	$Sell_{t+1}$
Buy	0.15***		0.30***		0.68***	
	(6.27)		(6.43)		(7.78)	
Sell		0.04***		0.09***		0.18***
		(2.73)		(3.46)		(2.94)
Adj R^2	0.03	0.02	0.04	0.02	0.07	0.03
N	59,096	59,096	59,096	59,096	59,096	59,096

Panel D: Insurer Cash Flow and Trading Persistence: Financial Crisis

	Following Month		Following Quarter		Following Year	
	Buy_{t+1}	$Sell_{t+1}$	Buy_{t+1}	$Sell_{t+1}$	Buy_{t+1}	$Sell_{t+1}$
$\sum_{j \in R} Buy_j$	0.24***		0.45***		0.89***	
	(3.64)		(3.76)		(3.35)	
$\sum_{j \in W} Buy_j$	0.07*		0.10*		0.33*	
	(1.87)		(1.73)		(1.84)	
$\sum_{j \in R} Sell_j$		0.05**		0.09**		0.21**
		(2.16)		(1.96)		(2.29)
$\sum_{j \in W} Sell_j$		0.04**		0.10**		0.17**
		(2.07)		(2.34)		(2.36)
Adj R^2	0.04	0.03	0.04	0.03	0.08	0.04
N	59,096	59,096	59,096	59,096	59,096	59,096

Table 4: Panel Regressions of Bond Illiquidity Changes

This table reports the results of panel regressions for bond illiquidity changes as:

$$\Delta \text{ILQ}_{i,t} = \alpha + \beta_1 \text{Buy}_{i,t-1} + \beta_2 \text{Sell}_{i,t-1} + \beta_3 \text{ILQ}_{i,t-1} + \mu_{t-1} + \text{Control}_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable is the change of bond illiquidity (*ILQ*), proxied by *Roll* (in percent), *Amihud* (per million), or *Highlow* (in percent). Independent variables include lagged insurer buys, lagged insurer sells, lagged illiquidity, bond coupon rates, bond age, bond size, bond maturity, rating dummies, and indicator variables for callable bonds, puttable bonds, exchangeable bonds, convertible bonds, credit enhancements bonds, senior bonds, and secured bonds which are defined in Section 4.4. *Buy* (*Sell*) is the aggregate par value purchased (sold) by all insurance companies in the sample scaled by the par value of a bond. Lagged illiquidity, lagged insurer buys, and lagged insurer sales are measured in one month before the current. All other independent variables are measured in the beginning of current month. The regressions include the month fixed effects. p-values are for the null hypothesis that coefficients are the same between *Buy* and *Sell* using the Wald test. The t-statistics reported in the parentheses are based on two-way clustered (by time and by bond issuer) standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	$\Delta Roll$	$\Delta Amihud$	$\Delta Highlow$	$\Delta Roll$	$\Delta Amihud$	$\Delta Highlow$
Buy	-1.53***	-0.30***	-0.47***	-1.15***	-0.14**	-0.42***
	(-5.01)	(-3.00)	(-4.41)	(-4.04)	(-1.98)	(-4.01)
Sell	1.04**	0.19**	0.35***	0.48**	0.03	0.25***
	(2.32)	(2.41)	(3.58)	(2.23)	(0.34)	(3.20)
ILQ	-0.60***	-0.47***	-0.36***	-0.71***	-0.59***	-0.45***
	(-24.12)	(-26.81)	(-23.62)	(-26.12)	(-27.04)	(-24.65)
Coupon				-0.04***	-0.01***	-0.01***
				(-6.87)	(-6.10)	(-7.13)
BondAge				0.06***	0.02***	0.02***
				(7.32)	(7.03)	(7.14)
BondSize				-0.18***	-0.12***	-0.03***
				(-7.14)	(-8.43)	(-2.86)
Maturity				0.04***	0.01***	0.01***
				(9.25)	(8.63)	(8.95)
Callable				-0.14***	-0.03***	-0.04***
				(-6.58)	(-4.49)	(-5.63)
Puttable				-0.35***	-0.08***	-0.15***
				(-5.35)	(-3.74)	(-7.15)
Exch				0.03	0.07**	-0.08***
				(0.36)	(1.96)	(-2.64)
Conv				-0.06	0.02	-0.12***
				(-0.95)	(0.96)	(-6.31)
Enhanced				-0.12***	-0.02***	-0.09***
				(-7.90)	(-3.07)	(-7.32)
Senior				0.06**	0.04***	0.01
				(2.36)	(6.08)	(1.46)
Secured				-0.07***	0.01	-0.01
				(-2.81)	(1.46)	(-1.43)
Rating Dummies	No	No	No	Yes	Yes	Yes
p-value on Equality	0.00	0.00	0.00	0.00	0.10	0.00
Adj R^2	0.27	0.24	0.28	0.33	0.30	0.35
N	432,715	434,352	434,391	432,715	434,352	434,391

Table 5: Panel Regressions of Bond Illiquidity: Rainy Day Effect

This table reports the results of panel regressions for bond illiquidity changes across different groups. The dependent variable, change of bond illiquidity, is based on the *Roll*, *Amihud*, and *Highlow* respectively. The independent variables include lagged insurer buys, lagged insurer sales, lagged illiquidity, bond coupon rate, bond age, bond size, bond maturity, bond rating dummy, and indicator variables for callable bonds, puttable bonds, exchangeable bonds, convertible bonds, credit enhancements bonds, senior bonds, and secured bonds. *Buy* (*Sell*) is the aggregate par value purchased (sold) by all insurance companies in the sample scaled by the par value of a bond. Other variables are defined in Table 2. Lagged illiquidity, lagged insurer buys, and lagged insurer sales are measured in one month before the current. Panel A reports the results of panel regressions for insurer tradings by illiquidity groups. Sample bonds are divided into three groups from high liquidity group to low liquidity group. High liquidity group (*HLG*) has bonds with the highest 30 percent liquidity over all bonds in that month. Low liquidity group (*LLG*) has bonds with the lowest 30 percent liquidity over all bonds in that month. Panel B reports the results of panel regressions for insurer tradings by different rating groups. All bonds in the sample are separated into three groups: Superior (*Sup*), Threshold (*Thr*), and Inferior (*Inf*). Superior bonds are rated A- or above. Threshold bonds are rated between BB and BBB+. Inferior bonds are rated BB- or below. Panel C reports the results of panel regressions for insurer tradings in different subsample periods around the financial crisis. The sample is broken into the before-crisis period (*Before Crisis*), crisis period (*Crisis*), and the after-crisis period (*After Crisis*). The before-crisis period is from July 2002 to June 2007. The crisis period is from July 2007 to April 2009. The after-crisis period is from May 2009 to December 2014. All other independent variables are measured in the beginning of current month. "LMH" is the coefficients difference between low liquidity bonds and high liquidity bonds. "TMS" is the coefficients difference between threshold bonds and superior bonds. "CMB" is the coefficients difference between crisis period and before crisis period. The regressions include the month fixed effects. The coefficients on some control variables as well as the regression intercepts are suppressed to preserve space. The t-statistics reported in the parentheses are based on two-way clustered (by time and by bond issuer) standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: By Illiquidity

	ILQ measure: *Roll*				ILQ measure: *Amihud*				ILQ measure: *Highlow*			
	HLG	MLG	LLG	LMH	HLG	MLG	LLG	LMH	HLG	MLG	LLG	LMH
Buy	-0.46	-1.30***	-2.51***	-2.05***	0.06	-0.10**	-0.31***	-0.44***	-0.19*	-0.36**	-1.20***	-1.01**
	(-1.26)	(-3.36)	(-3.37)	(-2.62)	(1.03)	(-2.01)	(-2.70)	(-2.94)	(-1.68)	(-2.04)	(-3.03)	(-2.45)
Sell	0.11	0.88**	0.33	0.22	-0.47**	0.38**	0.45**	0.92***	-0.02	0.32**	0.67***	0.69***
	(0.87)	(2.29)	(1.12)	(0.33)	(-2.00)	(2.32)	(2.42)	(2.86)	(-0.12)	(2.15)	(2.83)	(2.88)
ILQ	-1.68***	-0.66***	-0.79***		1.04***	-0.45***	-0.72***		-0.43***	-0.53***	-0.53***	
	(-21.65)	(-11.43)	(-24.50)		(5.17)	(-6.78)	(-13.26)		(-17.61)	(-9.79)	(-21.31)	
Coupon	-0.03***	-0.04***	-0.08***		-0.00***	0.00	-0.03***		0.00	-0.02***	-0.02**	
	(-4.32)	(-7.06)	(-5.57)		(-3.02)	(0.22)	(-5.30)		(0.44)	(-8.60)	(-2.53)	
BondAge	0.09***	0.05***	0.05***		0.01***	0.01***	0.02***		0.02***	0.02***	0.02***	
	(7.81)	(6.49)	(6.24)		(7.21)	(6.84)	(7.37)		(6.94)	(6.75)	(7.18)	
BondSize	-0.22***	-0.14***	-0.17***		-0.06***	-0.12***	-0.19***		-0.09***	-0.07***	0.08***	
	(-9.26)	(-6.08)	(-3.91)		(-9.11)	(-9.05)	(-7.03)		(-4.36)	(-3.70)	(3.01)	
Maturity	0.04***	0.03***	0.03***		0.00***	0.01***	0.01***		0.01***	0.01***	0.01***	
	(9.51)	(9.25)	(7.52)		(7.85)	(8.65)	(7.91)		(8.65)	(9.12)	(5.57)	
Adj R^2	0.31	0.23	0.31		0.26	0.26	0.32		0.34	0.28	0.33	
N	129,014	173,086	123,615		131,505	173,740	129,107		130,917	173,756	129,718	

Panel B: By Rating

	ILQ measure: *Roll*				ILQ measure: *Amihud*				ILQ measure: *Highlow*			
	Sup	Thr	Inf	TMS	Sup	Thr	Inf	TMS	Sup	Thr	Inf	TMS
Buy	0.37	-2.35***	-2.74**	-2.71***	0.08	-0.34***	-0.81***	-0.43***	-0.10	-0.77***	-0.74**	-0.67***
	(0.96)	(-6.80)	(-2.43)	(-6.04)	(0.76)	(-3.86)	(-4.10)	(-3.00)	(-0.70)	(-5.28)	(-2.48)	(-3.55)
Sell	-0.12	0.67**	1.08***	0.79*	-0.15	0.02	0.03	0.17	0.15	0.51***	0.42**	0.36**
	(-0.28)	(2.00)	(2.96)	(1.74)	(-1.13)	(0.15)	(0.14)	(0.89)	(0.79)	(3.02)	(2.32)	(2.42)
ILQ	-0.74***	-0.73***	-0.71***		-0.65***	-0.61***	-0.54***		-0.48***	-0.46***	-0.43***	
	(-24.98)	(-24.76)	(-27.05)		(-28.80)	(-21.59)	(-11.16)		(-20.70)	(-25.74)	(-27.93)	
Coupon	-0.04***	-0.03***	-0.08***		-0.01***	-0.01***	-0.02***		-0.02***	-0.01***	-0.02***	
	(-3.37)	(-4.11)	(-7.52)		(-2.74)	(-3.86)	(-7.28)		(-5.25)	(-4.21)	(-6.29)	
BondAge	0.06***	0.04***	0.07***		0.02***	0.02***	0.02***		0.02***	0.02***	0.02***	
	(7.25)	(7.02)	(6.97)		(6.87)	(7.12)	(6.89)		(7.42)	(6.85)	(6.83)	
BondSize	-0.14***	-0.25***	-0.20***		-0.13***	-0.14***	-0.10***		-0.02***	-0.05***	-0.02**	
	(-6.87)	(-7.78)	(-6.47)		(-9.01)	(-9.65)	(-6.62)		(-2.95)	(-4.12)	(-2.39)	
Maturity	0.04***	0.03***	0.02***		0.01***	0.01***	0.01***		0.02***	0.01***	0.01***	
	(9.88)	(8.15)	(3.11)		(8.87)	(6.93)	(5.92)		(9.32)	(7.65)	(5.44)	
Adj R^2	0.37	0.37	0.36		0.33	0.32	0.27		0.35	0.33	0.37	
N	177,002	164,516	91,197		177,322	165,144	91,886		177,324	165,175	91,892	

Panel C: Around the Financial Crisis

	ILQ measure: *Roll*				ILQ measure: *Amihud*				ILQ measure: *Highlow*			
	Before Crisis	Crisis	After Crisis	CMB	Before Crisis	Crisis	After Crisis	CMB	Before Crisis	Crisis	After Crisis	CMB
Buy	-0.33	-4.71***	-3.21***	-4.38***	0.14*	-0.78***	-0.60**	-0.92***	-0.21	-1.87***	-0.88***	-1.59***
	(-1.01)	(-3.86)	(-2.68)	(-3.14)	(1.91)	(-2.68)	(-2.54)	(-2.70)	(-1.39)	(-3.52)	(-2.67)	(-2.99)
Sell	1.03**	-0.86	-0.12	-1.89**	0.08	-0.01	-0.36***	-0.10	0.60**	-0.43	0.26	-1.03***
	(2.53)	(-1.10)	(-0.35)	(-2.18)	(0.74)	(-0.02)	(-3.53)	(-0.20)	(2.53)	(-1.00)	(1.57)	(-2.59)
ILQ	-0.70***	-0.69***	-0.70***		-0.64***	-0.60***	-0.60***		-0.42***	-0.56***	-0.44***	
	(-28.48)	(-16.89)	(-28.81)		(-28.19)	(-15.35)	(-28.44)		(-24.11)	(-20.14)	(-25.20)	
Coupon	-0.06***	-0.16***	-0.01**		-0.02***	-0.05***	-0.00**		-0.02***	-0.06***	-0.00**	
	(-6.92)	(-8.16)	(-2.14)		(-4.78)	(-6.70)	(-2.03)		(-7.12)	(-7.92)	(-2.35)	
BondAge	0.08***	0.06***	0.04***		0.03***	0.04***	0.02***		0.03***	0.03***	0.01***	
	(7.16)	(6.29)	(7.47)		(7.20)	(6.46)	(7.24)		(7.15)	(7.04)	(7.15)	
BondSize	-0.15***	-0.21***	-0.20***		-0.13***	-0.18***	-0.12***		-0.03***	0.02	-0.05***	
	(-7.10)	(-6.95)	(-7.74)		(-8.82)	(-6.23)	(-8.74)		(-2.97)	(1.20)	(-4.05)	
Maturity	0.04***	0.06***	0.03***		0.01***	0.02***	0.01***		0.01***	0.02***	0.01***	
	(9.85)	(9.71)	(8.71)		(9.02)	(8.11)	(7.79)		(9.27)	(8.84)	(8.25)	
Adj R^2	0.36	0.40	0.36		0.33	0.31	0.31		0.32	0.38	0.33	
N	162,050	50,453	220,212		162,868	50,837	220,647		162,873	50,855	220,663	

Table 6: Panel Regression on Illiquidity Changes for Matching Bonds

This table reports the results of panel regressions for insurer trading on matching bonds as:

$$\Delta \text{ILQ}_{m,t} = \alpha + \beta_1 \text{Buy}_{i,t-1} + \beta_2 \text{Sell}_{i,t-1} + \beta_3 \text{ILQ}_{m,t-1} + \text{Control}_{m,t-1} + \mu_{t-1} + \varepsilon_{m,t}$$

A matching bond is defined as a bond with the same bond rating, with a maturity difference within a year, and in the same liquidity quintile group. Panel A reports the results of panel regressions for insurer tradings by illiquidity groups: the high liquidity group (*HLG*) is for bonds with the highest 30 percent liquidity over all bonds in that month; the low liquidity group (*LLG*) contains bonds with the lowest 30 percent liquidity over all bonds in that month; the rest are in the median liquidity group (*MLG*). Panel B reports the results of panel regressions for insurer tradings by different rating groups. All bonds in the sample are separated into three groups: Superior (*Sup*), Threshold (*Thr*), and Inferior (*Inf*). Superior bonds are rated A- or above. Threshold bonds are rated between BB and BBB+. Inferior bonds are rated BB- or below. Panel C reports the results of panel regressions for insurer tradings in different subsample periods around the financial crisis. The sample is broken into the before-crisis period (*Before Crisis*), crisis period (*Crisis*), and the after-crisis period (*After Crisis*). The before-crisis period is from July 2002 to June 2007. The crisis period is from July 2007 to April 2009. The after-crisis period is from May 2009 to December 2014. The dependent variable, change of matching bonds' illiquidity, is based on *Roll*, *Amihud*, and *Highlow* respectively. The independent variables include lagged insurer buys of sample bond, lagged insurer sales of sample bond, lagged illiquidity of matching bond, bond coupon rate, bond age, bond size, bond maturity, and bond rating dummy. *Buy* (*Sell*) is the aggregate par value purchased (sold) by all insurance companies in the sample scaled by the par value of a bond. Other variables are defined in Table 2. Lagged illiquidity, lagged insurer buys, and lagged insurer sales are measured in one month before the current. All other independent variables are measured in the beginning of current month. "LMH" is the coefficients difference between low liquidity bonds and high liquidity bonds. "TMS" is the coefficients difference between threshold bonds and superior bonds. "CMB" is the coefficients difference between crisis period and before crisis period. The regressions include the month fixed effects. The coefficients on some control variables and the regression intercepts are suppressed to preserve space. The t-statistics reported in the parentheses are based on bond issuer clustered standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: By Illiquidity

	ILQ measure: *Roll*				ILQ measure: *Amihud*				ILQ measure: *Highlow*			
	HLG	MLG	LLG	LMH	HLG	MLG	LLG	LMH	HLG	MLG	LLG	LMH
Buy	0.22**	0.02	-0.43**	-0.65**	0.10**	-0.11***	-0.15***	-0.26***	0.08*	0.03	-0.34**	-0.41***
	(2.06)	(0.16)	(-2.03)	(-2.37)	(2.19)	(-2.78)	(-2.89)	(-3.01)	(1.77)	(0.25)	(-2.37)	(-3.04)
Sell	0.13	0.18	-0.18*	-0.31**	0.04	-0.01	-0.05	-0.09	0.08*	0.07	-0.09	-0.17**
	(1.10)	(1.54)	(-1.68)	(-2.21)	(0.96)	(-0.28)	(-1.19)	(-1.54)	(1.65)	(1.50)	(-1.31)	(-2.02)
Adj R^2	0.26	0.22	0.23		0.21	0.18	0.23		0.30	0.25	0.27	
N	882,560	1,015,161	640,182		853,842	1,019,298	675,102		871,691	1,019,443	657,436	

Panel B: By Rating

	ILQ measure: *Roll*				ILQ measure: *Amihud*				ILQ measure: *Highlow*			
	Sup	Thr	Inf	TMS	Sup	Thr	Inf	TMS	Sup	Thr	Inf	TMS
Buy	0.59**	-0.51***	-0.11	-1.10***	0.08**	-0.12***	-0.08	-0.20***	0.11***	-0.18***	0.02	-0.29***
	(2.40)	(-2.66)	(-0.40)	(-4.85)	(2.03)	(-2.87)	(-1.00)	(-3.40)	(2.66)	(-3.02)	(0.22)	(-4.42)
Sell	0.21**	-0.19**	-0.45**	-0.40***	0.02	-0.06**	-0.09	-0.08**	0.10***	-0.07**	-0.07	-0.17***
	(2.41)	(-2.31)	(-1.98)	(-3.34)	(0.57)	(-2.42)	(-1.38)	(-2.05)	(2.58)	(-2.25)	(-0.82)	(-3.42)
Adj R^2	0.24	0.21	0.23		0.17	0.19	0.21		0.31	0.26	0.28	
N	1,265,375	976,961	299,387		1,266,851	980,068	301,504		1,266,864	980,304	301,414	

Panel C: Around the Financial Crisis

	ILQ measure: *Roll*				ILQ measure: *Amihud*				ILQ measure: *Highlow*			
	Before Crisis	Crisis	After Crisis	CMB	Before Crisis	Crisis	After Crisis	CMB	Before Crisis	Crisis	After Crisis	CMB
Buy	0.01	-1.50***	-0.47***	-1.52***	-0.19***	-0.37***	-0.15***	-0.17**	0.11**	-0.58***	-0.09**	-0.69***
	(0.15)	(-2.95)	(-2.59)	(-2.90)	(-3.05)	(-3.96)	(-3.22)	(-2.26)	(2.05)	(-3.25)	(-2.04)	(-3.21)
Sell	0.12	-0.80***	-0.03	-0.92***	-0.02	-0.19**	-0.00	-0.17**	0.04	-0.27***	0.01	-0.32***
	(1.37)	(-2.96)	(-0.57)	(-3.27)	(-0.76)	(-2.49)	(-0.15)	(-2.09)	(1.27)	(-2.64)	(0.50)	(-2.93)
Adj R^2	0.21	0.23	0.25		0.22	0.23	0.23		0.27	0.25	0.27	
N	798,506	224,162	1,519,096		801,446	225,586	1,521,413		801,470	225,711	1,521,504	

Table 7: Insurer Cash Flow and Rainy Day Liquidity Provision

This table is on the role of insurers' cash flow on insurers' rainy day liquidity provision. In each year, we break down insurers into two groups based on cash flow, measured as insurers' cash flow from insurance operations cash flow scaled by total assets. Robust cash flow insurers are those whose cash flow above the annual sample median; weak cash flow insurers are those below the annual sample median. Panel A reports the result for the test of how insurer cash flow affects the purchase of threshold and inferior corporate bonds. Two insurer purchase measures are used as the dependent variable: buy (results reported in the first three columns) and net buy (results reported in the subsequent three columns). Independent variables are the threshold bond dummy (*Thr*), the inferior bond dummy (*Inf*), and the same set of bond control variables used in Table 4. *Diff* is the difference in regression coefficients between robust cash flow insurers and weak cash flow insurers. Panel B reports the results for the panel regressions of corporate bond illiquidity on insurers' transactions when we separate corporate bond transactions based on insurers' cash flow positions. In both panels, the regressions include month fixed effects, and the coefficients on some bond control variables as well as the regression intercepts are suppressed to preserve space. *p-value* is for the null hypothesis on the equality between the coefficients on $\sum_{j\in R}\text{Buy}_j$ and on $\sum_{j\in W}\text{Buy}_j$ using the Wald test. The t-statistics reported in the parentheses are based on two-way clustered (by time and by bond issuer) standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Insurers' Threshold Bond Purchase and Net Purchase

	Buy			Net		
	Robust	Weak	Diff	Robust	Weak	Diff
Thr	0.10***	0.05***	0.05***	0.02**	-0.00	0.02***
	(4.78)	(2.76)	(3.31)	(2.03)	(-0.48)	(2.95)
Inf	-0.12***	-0.13***	0.00	-0.10***	-0.12***	0.02**
	(-8.39)	(-8.70)	(0.74)	(-7.61)	(-7.09)	(2.23)
Adj R^2	0.07	0.06		0.06	0.06	

Panel B: High and Low Cash Flow Insurers' Purchases and Liquidity Provision

	ILQ measure: *Roll*			ILQ measure: *Amihud*			ILQ measure: *Highlow*		
	Sup	Thr	Inf	Sup	Thr	Inf	Sup	Thr	Inf
(1) $\sum_{j\in R}\text{Buy}_j$	0.47	-2.38***	-2.83**	0.08	-0.58***	-1.07**	0.03	-0.89***	-1.27**
	(1.07)	(-6.42)	(-2.48)	(0.53)	(-3.24)	(-2.36)	(0.15)	(-3.78)	(-2.55)
(2) $\sum_{j\in W}\text{Buy}_j$	0.13	-1.61**	-1.90	0.05	-0.22**	-0.77**	-0.41	-0.53**	-0.71
	(0.17)	(-2.56)	(-1.59)	(0.21)	(-1.97)	(-2.51)	(-1.49)	(-2.55)	(-1.37)
$\sum_{j\in R}\text{Sell}_j$	0.12	0.92*	1.46**	-0.16	-0.01	0.08	0.09	0.54**	1.16**
	(0.23)	(1.93)	(2.47)	(-0.94)	(-0.09)	(0.27)	(0.36)	(2.38)	(2.53)
$\sum_{j\in W}\text{Sell}_j$	-0.46	0.23	0.94	-0.18	0.08	-0.02	0.23	0.46**	-0.34
	(-0.60)	(0.35)	(0.79)	(-0.63)	(0.35)	(-0.04)	(0.81)	(2.01)	(-0.64)
p-value on (1)=(2)	0.18	0.09	0.14	0.43	0.04	0.18	0.19	0.08	0.17
Adj R^2	0.39	0.38	0.38	0.35	0.35	0.30	0.36	0.35	0.39

Table 8: Investment Horizon and Rainy Day Liquidity Provision

This table is on the effect of insurers' investment horizons on insurers' rainy day liquidity provision. In each year, we break down insurers into two groups based on their holding horizons, the inverse of the turnover ratios of individual insurers' corporate bond portfolios which are measured as the minimum of the aggregate market value of securities purchased by an insurer and the aggregate value of securities sold by the insurer in each year, scaled by the aggregate portfolio value at the end of the year. Panel A reports the test results of how insurers' holding horizon affects their purchases of threshold bonds and inferiorly rated corporate bonds. Two insurer purchase measures are used as the dependent variable: buy (results reported in the first three columns) and net buy (results reported in the subsequent three columns). Independent variables are the threshold bond dummy (*Thr*), the inferior bond dummy (*Inf*), and the same set of bond control variables used in Table 4. *Diff* is the coefficients difference between long horizon insurers and short horizon insurers. Panel B reports the results for the panel regressions of corporate bond illiquidity on insurers' transactions when we separate corporate bond transactions based on insurers' investment horizons. In both panels, the regressions include month fixed effects, and the coefficients on some bond control variables as well as the regression intercepts are suppressed to preserve space. *p-value* is for the null hypothesis on the equality between the coefficients on $\sum_{j\in L}\text{Buy}_j$ and on $\sum_{j\in S}\text{Buy}_j$ using the Wald test. The t-statistics reported in the parentheses are based on two-way clustered (by time and by bond issuer) standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Insurers' Threshold Bond Purchase and Net Purchase

	Buy			Net		
	Long	Short	Diff	Long	Short	Diff
Threshold	0.10***	0.06***	0.03***	0.02***	0.00	0.02***
	(5.38)	(3.54)	(2.86)	(2.82)	(0.32)	(2.71)
Inferior	-0.10***	-0.11***	0.01	-0.11***	-0.13***	0.02**
	(-5.76)	(-6.19)	(0.95)	(-5.10)	(-6.46)	(2.25)
Adj R^2	0.07	0.07		0.06	0.06	

Panel B: Long and Short Horizon Insurers' Purchases and Liquidity Provision

	ILQ measure: *Roll*			ILQ measure: *Amihud*			ILQ measure: *Highlow*		
	Sup	Thr	Inf	Sup	Thr	Inf	Sup	Thr	Inf
(1) $\sum_{j\in L}\text{Buy}_j$	0.42	-3.10***	-3.44***	0.06	-0.58***	-1.14***	-0.26	-1.04***	-1.01**
	(0.94)	(-6.01)	(-3.29)	(0.27)	(-4.46)	(-3.52)	(-1.01)	(-4.60)	(-2.22)
(2) $\sum_{j\in S}\text{Buy}_j$	0.30	-2.14***	-1.83	0.22	-0.25***	-0.68**	-0.06	-0.67***	-0.60
	(0.82)	(-4.35)	(-0.76)	(1.20)	(-2.69)	(-2.21)	(-0.26)	(-2.67)	(-1.56)
$\sum_{j\in L}\text{Sell}_j$	0.35	1.15*	1.05*	-0.06	0.44**	-0.08	0.54*	0.90***	0.38
	(0.44)	(1.69)	(1.88)	(-0.26)	(2.38)	(-0.24)	(1.67)	(3.33)	(0.73)
$\sum_{j\in S}\text{Sell}_j$	-0.84	0.10	1.69*	-0.39**	-0.29	0.62	-0.43*	0.13	0.64
	(-1.43)	(0.16)	(1.85)	(-2.06)	(-1.01)	(1.48)	(-1.82)	(0.45)	(1.56)
p-value on (1)=(2)	0.38	0.07	0.04	0.25	0.04	0.13	0.27	0.06	0.14
Adj R^2	0.39	0.39	0.38	0.34	0.33	0.30	0.36	0.35	0.40

Table 9: Dodd-Frank Act and Insurer Bond Purchase Effect on Bond Liquidity

This table reports the results for the panel regressions to test the liquidity effect of insurers' corporate bond transactions. Corporate bond transactions are classified to those with bank-affiliated dealers and with nonbank dealers. Only threshold rating bonds (bonds are rated between BB and BBB+) during the pre-crisis period (from July 2002 to June 2007) and the Dodd-Frank restricted period (from May 2009 to December 2014) are included in the sample. Independent variables include the aggregate par value purchased (sold) of individual bonds from bank-affiliated dealers (B) and nonbank dealers (N) scaled by their respective par values, the interactions between transactions and the dummy variable for the Dodd-Frank restricted period (DF). The control variables include the dummy variable for the Dodd-Frank restricted period, lagged illiquidity, and the same set of bond control variables used in Table 4. The regressions include the month fix effects. The coefficients on some control variables as well as the regression intercepts are suppressed to preserve space. *p-values* on (1)=(2) is for the null hypothesis on the equality between the coefficients on $\sum_{j\in B}\text{Buy}_j * DF$ and on $\sum_{j\in N}\text{Buy}_j * DF$, *p-values* on (3)=(4) is for the null hypothesis on the equality between the coefficients on $\sum_{j\in B}\text{Sell}_j * DF$ and on $\sum_{j\in N}\text{Sell}_j * DF$. The t-statistics reported in the parentheses are based on two-way clustered (by time and by bond issuer) standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	ILQ measure: *Roll*	ILQ measure: *Amihud*	ILQ measure: *Highlow*
$\sum_{j\in B}\text{Buy}_j$	-1.85***	-0.84**	-0.93***
	(-2.96)	(-2.43)	(-3.02)
$\sum_{j\in N}\text{Buy}_j$	-1.28***	-0.48**	-0.29
	(-2.69)	(-2.40)	(-1.64)
(1) $\sum_{j\in B}\text{Buy}_j * DF$	-0.78***	-0.27***	-0.52**
	(-2.75)	(-2.77)	(-2.02)
(2) $\sum_{j\in N}\text{Buy}_j * DF$	-0.25	-0.13	-0.19
	(-1.24)	(-0.84)	(-0.80)
$\sum_{j\in B}\text{Sell}_j$	0.88	0.24	0.78*
	(1.22)	(0.87)	(1.94)
$\sum_{j\in N}\text{Sell}_j$	0.30	0.11	0.16
	(1.47)	(0.56)	(1.21)
(3) $\sum_{j\in B}\text{Sell}_j * DF$	0.42*	0.11	0.27*
	(1.76)	(0.43)	(1.69)
(4) $\sum_{j\in N}\text{Sell}_j * DF$	0.24	0.04	0.13
	(0.72)	(0.25)	(0.70)
p-value on (1)=(2)	0.03	0.14	0.05
p-value on (3)=(4)	0.39	0.33	0.39
Adj R^2	0.38	0.34	0.32

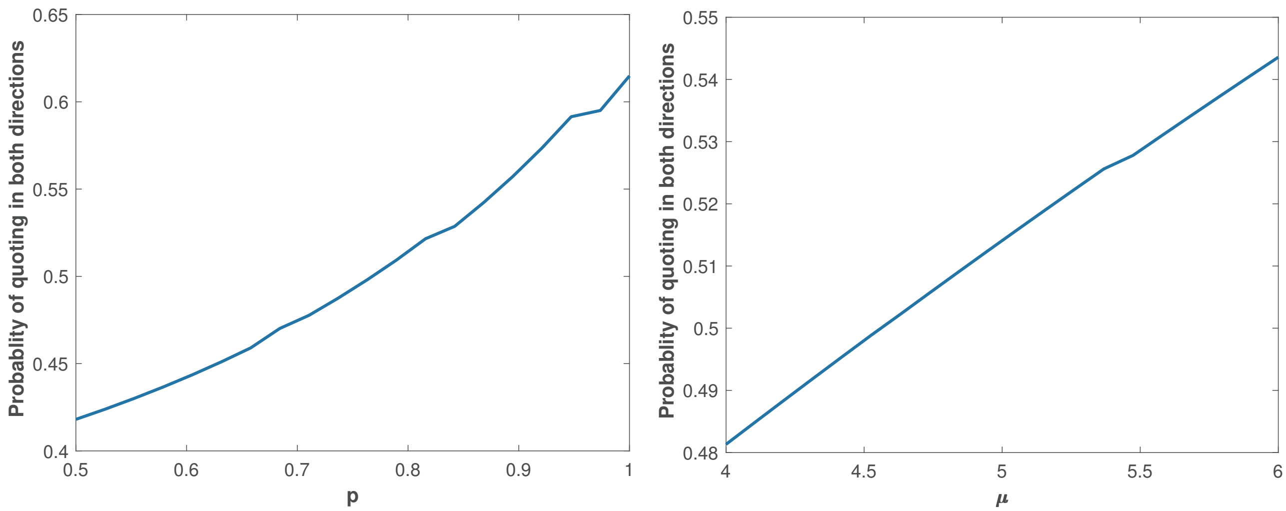

Figure 1: This figure plots the fraction of the time the dealer quotes in both directions as a function of p (left) and the arrival rate of insurance orders, μ (right). μ is the Poisson intensity for insurance companies (ICs) arriving to the market. p is the conditional probability that on a buy order, the next IC order is a buy order.

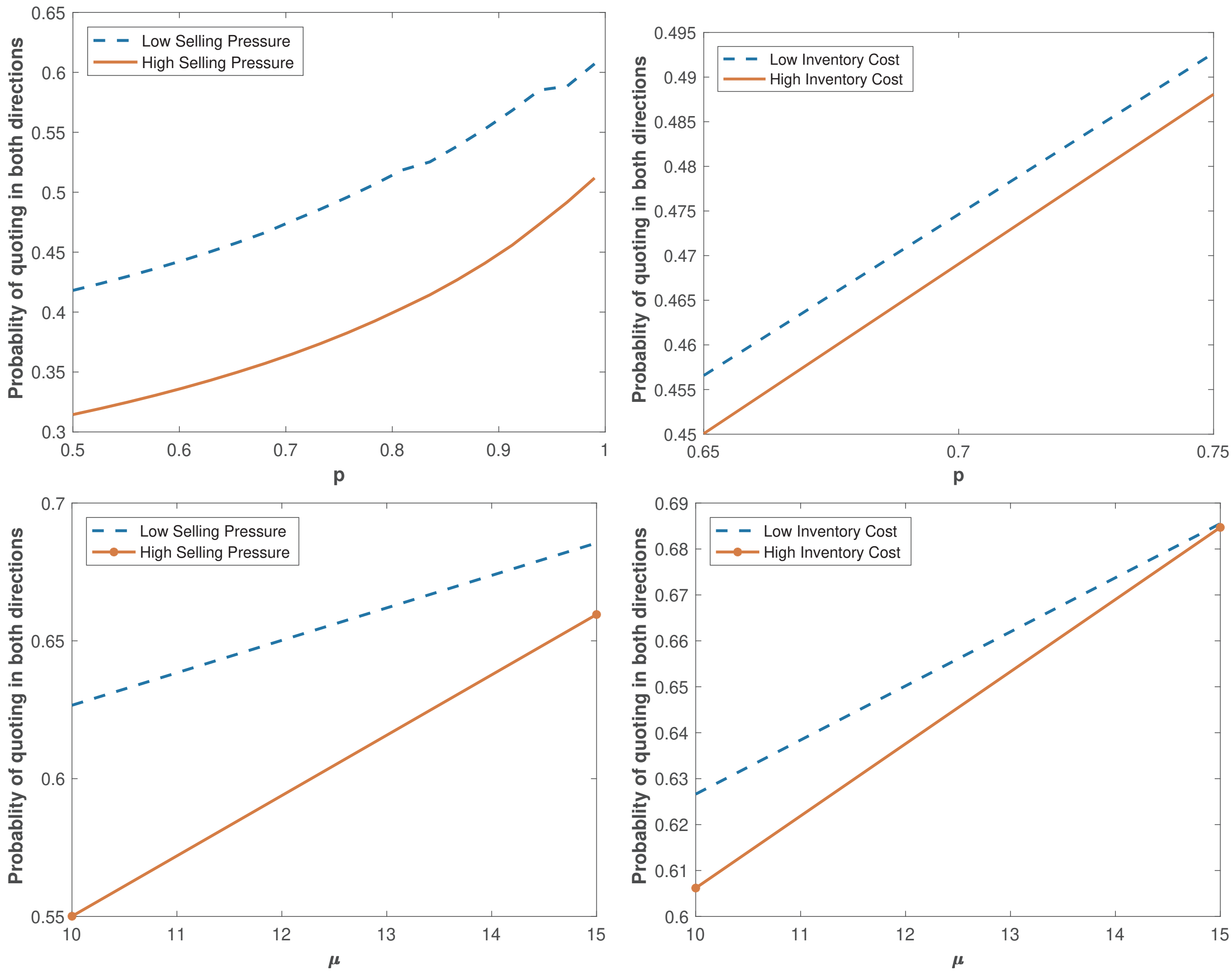

Figure 2: This figure plots the fraction of the time the dealer quotes in both directions as a function of p in periods with low and high selling pressure (top-left) and with low and high inventory cost (top-right) and the fraction of the time the dealer quotes in both directions as a function of μ in periods with low and high selling pressure (bottom-left) and with low and high inventory cost (bottom-right).

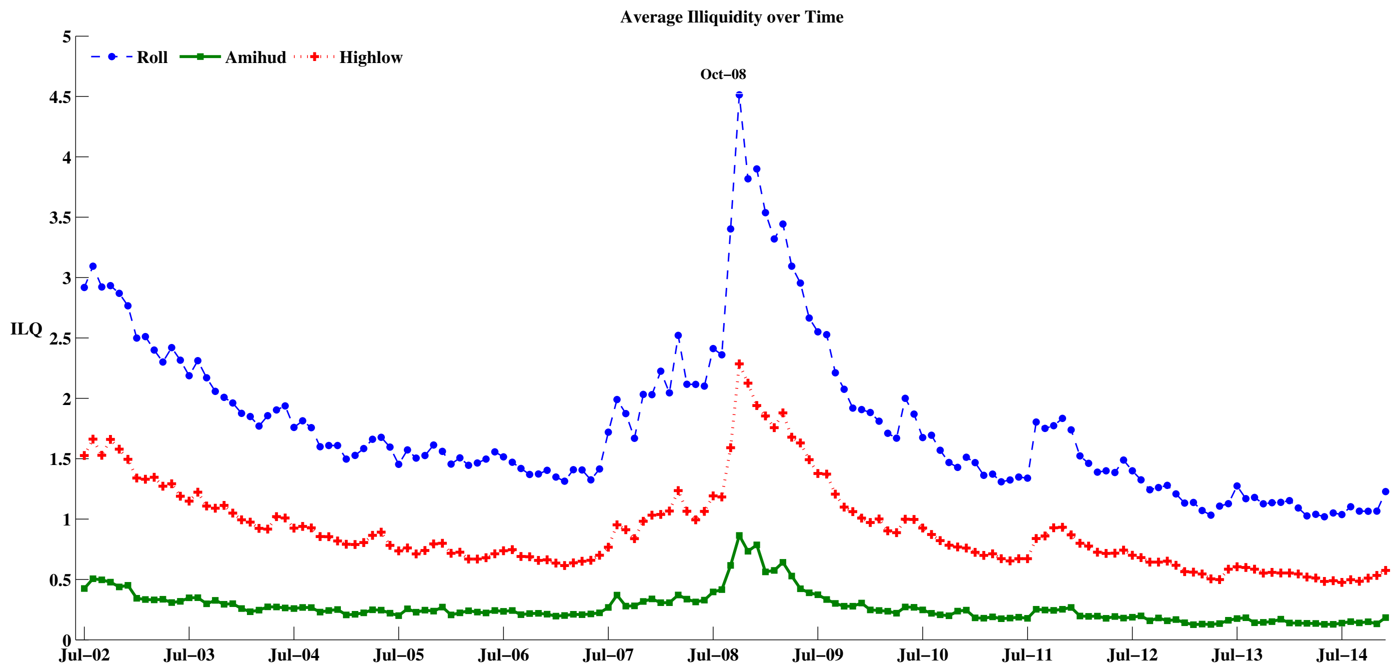

Figure 3: The figure depicts corporate bonds illiquidity over time. The illiquidity measures are i) *Roll*, ii) *Amihud*, and iii) *Highlow*. The reported numbers are weighted by bonds par value.

Figure 4: The figure depicts the average insurers holding, insurer purchases, and sales across bond ratings. Insurers holding is the aggregate par value held by all insurers scaled by the bond par value at the end of each month. Insurers purchase (sale) is the aggregate par value purchased (sold) by all insurers scaled by the bond par value. We compute bonds par value weighted averages across bond ratings in each month and then take the averages over time.

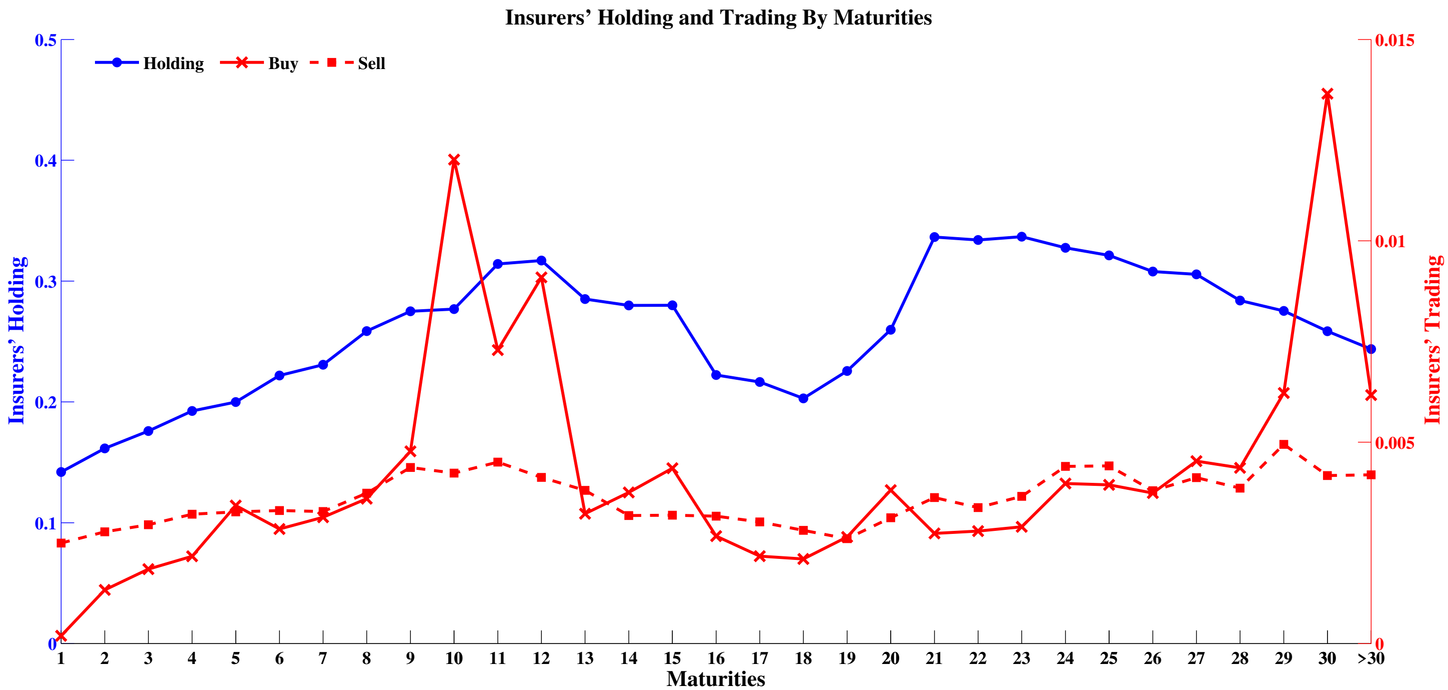

Figure 5: The figure depicts the average insurer holding, insurer purchase, and sales across bond maturity groups. Bond maturities are rounded up to the nearest integers to form maturity groups. Bonds with maturities longer than 30 years are placed in maturity group "> 30". Insurers holding is the aggregate par value held by all insurers scaled by the bond par value at the end of each month. Insurers purchase (sale) is the aggregate par value purchased (sold) by all insurers scaled by the bond par value. We compute bonds par value weighted averages across bond maturities in each month and then take the averages over time.

Rainy Day Liquidity

(Internet Appendix)

A Discrete-time equivalent formulation

We start by recalling the definition of a discounted infinite horizon Markov Decision Process (MDP), before showing that our continuous-time dealer optimization problem can be represented as a MDP. A MDP is defined by a 4-tuple, $(I, A_i, \mathbb{P}(.|i,a), \mathbb{R}(.|i,a))$, in which I is the state space, A_i is the action space, i.e., the set of possible actions that a decision maker can take when the state is $i \in I$, $\mathbb{P}(.|i,a)$ is the probability transition matrix determining the state of the system in the next decision time, and finally $\mathbb{R}(.|i,a)$ is the reward matrix, specifying the reward obtained using action a when the state is in i. The decision maker seeks a policy that maximizes the expected discounted reward

$$v(i) = \max_{\ell} \mathbb{E}\left[\sum_{t=0}^{\infty} \alpha^t \mathbb{R}(i_{t+1}|i_t, \ell(i_t))|i_0 = i\right], \tag{A1}$$

where α is the discount rate. An admissible stationary policy ℓ maps each state $i \in I$ to an action in A_i. Under mild technical conditions, we can guarantee the existence of optimal stationary policies (see Puterman, 2014). Conditioning on the first transition from i to i', we obtain the Hamilton-Jacobi-Bellman optimality equation

$$\begin{aligned} v(i) &= \max_{\ell}\left\{\sum_{i'} \mathbb{P}(i'|i,\ell(i))\left(\mathbb{R}(i'|i,\ell(i)) + \alpha\mathbb{E}\left[\sum_{t=1}^{\infty}\alpha^{t-1}\mathbb{R}(i_{t+1}|i_t,\ell(i_t))|i_1 = i'\right]\right)\right\} \\ &= \max_{\ell}\left\{\sum_{i'} \mathbb{P}(i'|i,\ell(i))\left(\mathbb{R}(i'|i,\ell(i)) + \alpha\mathbb{E}\left[\sum_{k=0}^{\infty}\alpha^{k}\mathbb{R}(i_{k+1}|i_k,\ell(i_k))|i_k = i'\right]\right)\right\} \\ &= \max_{a\in A_i}\left\{\sum_{i'} \mathbb{P}(i'|i,a)\left(\mathbb{R}(i'|i,a) + \alpha v(i')\right)\right\}. \end{aligned} \tag{A2}$$

A.1 Transition Probabilities

We now calculate the transition probabilities at each state of the dealer. First, note that the state transitions occur at a rate of $\lambda + \mu$ and the rate is the same for all states and actions. Let $\mathbb{P}((x', s')|(x, s), (\ell^b, \ell^a))$ be the probability of reaching state (x', s') when the system is in state (x, s) and the trader takes the actions of ℓ^b and ℓ^a.

Suppose that the current state of the dealer is (x, s). Since the inter-arrival times are exponentially distributed, we can use the following property regarding the probability of the event types: If $Z_1, \ldots, Z_n$ are each exponentially distributed with mean $1/z_i$, then $\mathbb{P}\left(Z_k = \min\left\{Z_1, \ldots, Z_n\right\}\right) = z_k/(z_1 + \ldots + z_n)$.

First, if the dealer does not quote, we obtain

$$\mathbb{P}\left((x', s')|(x, s), (0, 0)\right) = \begin{cases} \frac{\lambda + p\mu}{\mu + \lambda} & \text{if } x = x', s = s' = B, \\ \frac{(1-p)\mu}{\mu + \lambda} & \text{if } x = x', s = B, s' = S, \\ \frac{\lambda + q\mu}{\mu + \lambda} & \text{if } x = x', s = s' = S, \\ \frac{(1-q)\mu}{\mu + \lambda} & \text{if } x = x', s = S, s' = B, \\ 0 & \text{otherwise.} \end{cases}$$

If the dealer does not quote, his inventory cannot change. However, if ICs contact the dealer, there may be change in the expected sign of the incoming IC order.

When the dealer takes action $(1, 0)$, we have the following transition probabilities:

$$\mathbb{P}\left((x', s')|(x, s), (1, 0)\right) = \begin{cases} \frac{(1-y)\lambda + p\mu}{\mu + \lambda} & \text{if } x = x', s = s' = B, \\ \frac{y\lambda}{\mu + \lambda} & \text{if } x + 1 = x', s = s' = B, \\ \frac{(1-p)\mu}{\mu + \lambda} & \text{if } x + 1 = x', s = B, s' = S, \\ \frac{y\lambda + q\mu}{\mu + \lambda} & \text{if } x + 1 = x', s = s' = S, \\ \frac{(1-y)\lambda}{\mu + \lambda} & \text{if } x = x', s = s' = S, \\ \frac{(1-q)\mu}{\mu + \lambda} & \text{if } x = x', s = S, s' = B, \\ 0 & \text{otherwise.} \end{cases}$$

When the dealer takes the action $(1, 0)$, he may increase his inventory by trading with the incoming sell orders. Similarly, for dealer action $(0,1)$, we have

$$\mathbb{P}\left((x',s')|(x,s),(0,1)\right)=\begin{cases}\frac{(1-y)\lambda+p\mu}{\mu+\lambda} & \text{if } x-1=x', s=s'=B,\\ \frac{y\lambda}{\mu+\lambda} & \text{if } x=x', s=s'=B,\\ \frac{(1-p)\mu}{\mu+\lambda} & \text{if } x=x', s=B, s'=S,\\ \frac{y\lambda+q\mu}{\mu+\lambda} & \text{if } x=x', s=s'=S,\\ \frac{(1-y)\lambda}{\mu+\lambda} & \text{if } x-1=x', s=s'=S,\\ \frac{(1-q)\mu}{\mu+\lambda} & \text{if } x-1=x', s=S, s'=B,\\ 0 & \text{otherwise.}\end{cases}$$

Finally, when the dealer quotes on both sides of the market, we obtain

$$\mathbb{P}\left((x',s')|(x,s),(1,1)\right)=\begin{cases}\frac{(1-y)\lambda+p\mu}{\mu+\lambda} & \text{if } x-1=x', s=s'=B,\\ \frac{y\lambda}{\mu+\lambda} & \text{if } x+1=x', s=s'=B,\\ \frac{(1-p)\mu}{\mu+\lambda} & \text{if } x+1=x', s=B, s'=S,\\ \frac{y\lambda+q\mu}{\mu+\lambda} & \text{if } x+1=x', s=s'=S,\\ \frac{(1-y)\lambda}{\mu+\lambda} & \text{if } x-1=x', s=s'=S,\\ \frac{(1-q)\mu}{\mu+\lambda} & \text{if } x-1=x', s=S, s'=B,\\ 0 & \text{otherwise.}\end{cases}$$

A.2 Reward Function

Let $R((x',s')|(x,s),(\ell^b,\ell^a))$ be the total reward achieved by the dealer when the system is in state (x,s), the dealer chooses quoting actions ℓ^b and ℓ^a and the system reaches the state (x',s'). We would like to write the dealer's objective in (1) in the form of an MDP objective function as in (A1). We first introduce the following notation. Let t_k be the time of the kth state transition due to an order from an NIT or IC (by convention $t_0=0$) and let τ_k be the length of this cycle, i.e., $\tau_k=t_k-t_{k-1}$. We start with the first two terms in (1) that measure the spreads earned by the dealer when there is a trade. First observe that

$$\delta \sum_{i=1}^{\infty} e^{-\beta T_i^{\mathsf{sell}}} \mathbb{1}\left(\ell^b_{T_i^{\mathsf{buy}}} = 1\right) + \delta \sum_{j=1}^{\infty} e^{-\beta T_j^b} \mathbb{1}\left(\ell^a_{T_j^b} = 1\right) = \delta \sum_{k=1}^{\infty} e^{-\beta t_k} R^+(x_{t_k}|x_{t_{k-1}}, \ell^b_{t_{k-1}}, \ell^a_{t_{k-1}}),$$

where we define $R^+(x'|x,\ell^b,\ell^a) = \mathbb{1}\,(x \neq x')\, \mathbb{1}\left(\ell^a = 1 \text{ or } \ell^b = 1\right)$. We can take the expectation of the dealer's discounted earnings using the independence of each cycle length, τ_i, which is an exponentially distributed random variable with mean $1/(\lambda+\mu)$:

$$\begin{aligned}
\mathbb{E}\left[\delta \textstyle\sum_{k=1}^{\infty} e^{-\beta t_k} R^+(x_{t_k}|x_{t_{k-1}}, \ell^b_{t_{k-1}}, \ell^a_{t_{k-1}})\right] &= \delta \textstyle\sum_{k=1}^{\infty} \mathbb{E}\left[e^{-\beta \sum_{i=1}^{k} \tau_i}\right] \mathbb{E}\left[R^+(x_{t_k}|x_{t_{k-1}}, \ell^b_{t_{k-1}}, \ell^a_{t_{k-1}})\right] \\
&= \delta \textstyle\sum_{k=1}^{\infty} \mathbb{E}\left[e^{-\beta\tau_1}\right]^k \mathbb{E}\left[R^+(x_{t_k}|x_{t_{k-1}}, \ell^b_{t_{k-1}}, \ell^a_{t_{k-1}})\right] \\
&= \delta \textstyle\sum_{k=1}^{\infty} \left(\int_0^{\infty} (\lambda+\mu) e^{-(\lambda+\mu+\beta)t} dt\right)^k \mathbb{E}\left[R^+(x_{t_k}|x_{t_{k-1}}, \ell^b_{t_{k-1}}, \ell^a_{t_{k-1}})\right] \\
&= \delta \textstyle\sum_{k=1}^{\infty} \left(\frac{\lambda+\mu}{\lambda+\mu+\beta}\right)^k \mathbb{E}\left[R^+(x_{t_k}|x_{t_{k-1}}, \ell^b_{t_{k-1}}, \ell^a_{t_{k-1}})\right] \\
&= \alpha\delta \textstyle\sum_{k=0}^{\infty} \alpha^k \mathbb{E}\left[R^+(x_{t_{k+1}}|x_{t_k}, \ell^b_{t_k}, \ell^a_{t_k})\right].
\end{aligned}$$

where α is the "adjusted discount factor," defined in (2).

Inventory costs in the third term of (1) can be simplified as

$$\begin{aligned}
\mathbb{E}\left[\Gamma \textstyle\int_0^{\infty} e^{-\beta t}|x_t|dt\right] &= \Gamma \textstyle\sum_{k=0}^{\infty} \mathbb{E}\left[\int_{t_k}^{t_{k+1}} e^{-\beta t}|x_t|dt\right] \\
&= \Gamma \textstyle\sum_{k=0}^{\infty} \mathbb{E}\left[\int_{t_k}^{t_{k+1}} e^{-\beta t}dt\right] \mathbb{E}\left[|x_{t_k}|\right] \\
&= \frac{\Gamma}{\beta} \textstyle\sum_{k=0}^{\infty} \mathbb{E}\left[e^{-\beta t_k}\right] \left(1 - \mathbb{E}\left[e^{-\beta\tau_{k+1}}\right]\right) \mathbb{E}\left[|x_{t_k}|\right] \\
&= \frac{\Gamma}{\beta} \textstyle\sum_{k=0}^{\infty} \alpha^k \left(\frac{\beta}{\lambda+\mu+\beta}\right) \mathbb{E}\left[|x_{t_k}|\right] \\
&= \frac{\Gamma}{\lambda+\mu+\beta} \textstyle\sum_{k=0}^{\infty} \alpha^k \mathbb{E}\left[|x_{t_k}|\right].
\end{aligned}$$

Let $\mathbb{R}((x',s')|(x,s),(\ell^b,\ell^a))$ be the reward of switching to (x',s') from state (x,s) when the trader takes the actions of ℓ^b and ℓ^a. We are now ready to define the total reward matrix. Let

$$\mathbb{R}\left((x',s')|(x,s),(\ell^b,\ell^a)\right) = \alpha\delta \mathbb{1}\,(x \neq x')\, \mathbb{1}\left(\ell^a = 1 \text{ or } \ell^b = 1\right) - \gamma|x| \qquad \forall(s,s'), \tag{A3}$$

where $\alpha\delta$ and γ, defined in (2) are the "adjusted spread" and "adjusted inventory aversion" parameters for the discrete-time formulation. Then, the dealer maximizes

$$v(x,s) = \max_{\ell} \mathbb{E}^{\ell}\left[\sum_{k=0}^{\infty} \alpha^k \mathbb{R}\left((x_{t_{k+1}}, s_{t_{k+1}})|(x_{t_k}, s_{t_k}), (\ell^b_{t_k}, \ell^a_{t_k})\right) \Big| (x_0,s_0) = (x,s)\right], \tag{A4}$$

starting from his initial state, (x,s), following the policy implied by ℓ. Note that this representation is in the requisite MDP form described in Section A.

B Determination and Computation of the Optimal Policy

B.1 Value Function

We have now transformed our continuous-time problem into an equivalent discrete-time MDP. Using the Hamilton-Jacobi-Bellman optimality equation given in (A2), $v(x,s)$ in (A4) can be computed by solving the following set of equations:

$$v(x,s) = \max_{\ell^b,\ \ell^a} \left\{ \sum_{(x',s')} \mathbb{P}\left((x',s')|(x,s),(\ell^b,\ell^a)\right) \left\{\mathbb{R}\left((x',s')|(x,s),(\ell^b,\ell^a)\right) + \delta v(x',s')\right\} \right\}. \tag{A5}$$

By substituting the corresponding expressions for $\mathbb{P}\left(.|(x,s),(\ell^b,\ell^a)\right)$ and $\mathbb{R}\left(.|(x,s),(\ell^b,\ell^a)\right)$, Proposition 1 simplifies the implicit equations for the value functions in (A5) and shows that the optimal decisions on ℓ^b and ℓ^a are separable. The result of the lemma shows that the maximum taken over all possible actions in (A5) can actually be separated into two maxima in each of which the dealer decides to quote or not to quote at the best bid or at the best ask.

B.2 Optimal Market Making Solution

Proof of Theorem 1. Using the value iteration algorithm, we first establish by induction that $v(x,B)$ and $v(x,S)$ are concave functions. Let $v^{(0)}(x,B) = 0$ and $v^{(0)}(x,S) = 0$ for all x. Then, the base case states that

$$v^{(1)}(x,B) = -\gamma|x| + \alpha\delta, \qquad v^{(1)}(x,S) = -\gamma|x| + \alpha\delta$$

which are both concave functions of x. Assume that $v^{(n)}(x,B)$ and $v^{(n)}(x,S)$ are concave. Then,

$$v^{(n+1)}(x,B) = -\gamma|x| + \frac{\alpha}{\lambda+\mu}\Big(\max\Big\{\delta(y\lambda+(1-p)\mu)+v^{(n)}(x+1,B)y\lambda+v^{(n)}(x+1,S)(1-p)\mu,$$
$$v^{(n)}(x,B)y\lambda+v^{(n)}(x,S)(1-p)\mu\Big\} + \max\Big\{\delta((1-y)\lambda+p\mu)+v^{(n)}(x-1,B)\left((1-y)\lambda+p\mu\right),$$
$$v^{(n)}(x,B)((1-y)\lambda+p\mu)\Big\}\Big)$$

In order to establish the concavity of $v^{(n+1)}(x,B)$, we need the following lemma.

Lemma 1. *Fix $z \in \mathbb{R}$ and define $g(i) \triangleq \max\{z+f(i+1), f(i)\}$. $g(i)$ is concave if $f(i)$ is concave.*

Proof. Define $i^* \triangleq \min\{i : f(i) > z+f(i+1)\}$. For $i^* \leq i-2$, $g(i)-g(i+1) = f(i+1)-f(i+2) \leq z$ and is nondecreasing in i as $f(i)$ is assumed to be concave. If $i \geq i^*$, $g(i)-g(i+1) = f(i)-f(i+1) > z$ and is also nondecreasing in i due to concavity of $f(i)$. If $i = i^*-1$, $g(i)-g(i+1) = r+f(i+1)-f(i+1) = z$. Thus, for all i, $g(i)-g(i+1)$ is nondecreasing which makes $g(i)$ concave. ☐

A direct application of Lemma 1 also asserts that $g(i) \triangleq \max\{z+f(i-1), f(i)\}$ is also concave as it can be rewritten as $g(i) = z + \max\{f(i-1), f(i)-z\}$. Using Lemma 1, $v^{(n+1)}(x,B)$ becomes concave as the expressions can be written in the form of $\max\{z+f(x+1), f(x)\}$. Since $v^{(n)}(x,B)$ converges to $v(x,B)$, $v(x,B)$ is concave in x. Due to the same structure in $v^{(n+1)}(x,S)$, $v(x,S)$ is also concave. Since the expressions can be written in the form of $\max\{z+f(x+1), f(x)\}$ where f is concave, $f(x+1)-f(x)$ must be non-decreasing in x. Therefore, there exists L^*_{bB} and L^*_{aB} such that

$$\ell^*_b(x,B) = \begin{cases} 1 & x < L^*_{bB}, \\ 0 & x \geq L^*_{bB}. \end{cases} \quad \ell^*_a(x,B) = \begin{cases} 1 & x > L^*_{aB}, \\ 0 & x \leq L^*_{aB}. \end{cases}$$

The proof is identical for the case of $s = S$.

☐

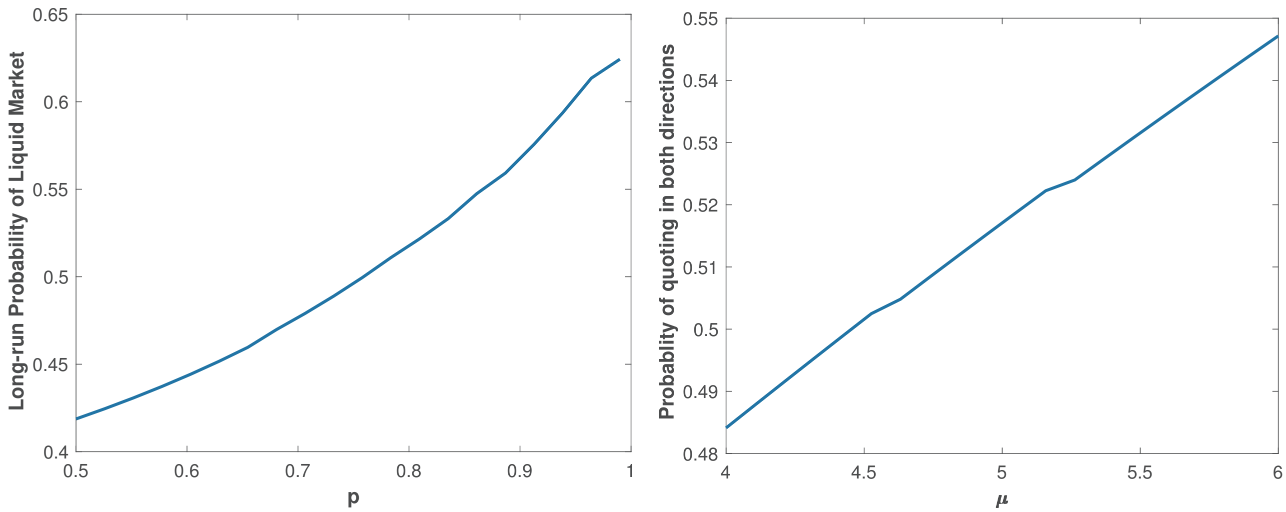

Figure A1: The fraction of the time the dealer quotes in both directions as a function of p (left) and the arrival rate of insurance orders, μ (right). The model's parameters are as follows: $\delta = \$5000$, $\Gamma = \$10000$, $q = 0.55$, $y = 0.75$, $\mu = 5$, $\lambda = 20$, $\beta = 0.04\%$.

B.3 Alternative Calibrations

In this section, we rerun the empirical predictions of the model with regards to p and μ in different calibrations. In Figure A1, we use smaller assumptions for δ and Γ compared to the base calibration reported in the paper. In this case, the dealer makes $\delta = \$5{,}000$ which amounts to 0.5% of the par value and his inventory costs are given by $\Gamma = \$10{,}000$ which amounts to 1% of the par value. In Figure A2, we increase the arrival rate of the orders for both types but the ratio of IC orders are smaller. In this case, $\mu = 10$ and $\lambda = 100$, and the remaining parameters remain the same.

C Liquidity Measures

In this section, we briefly describe our monthly illiquidity measures. Following Roll (1984), we get *Roll* measure which captures the negative auto-covariance of trade price changes.

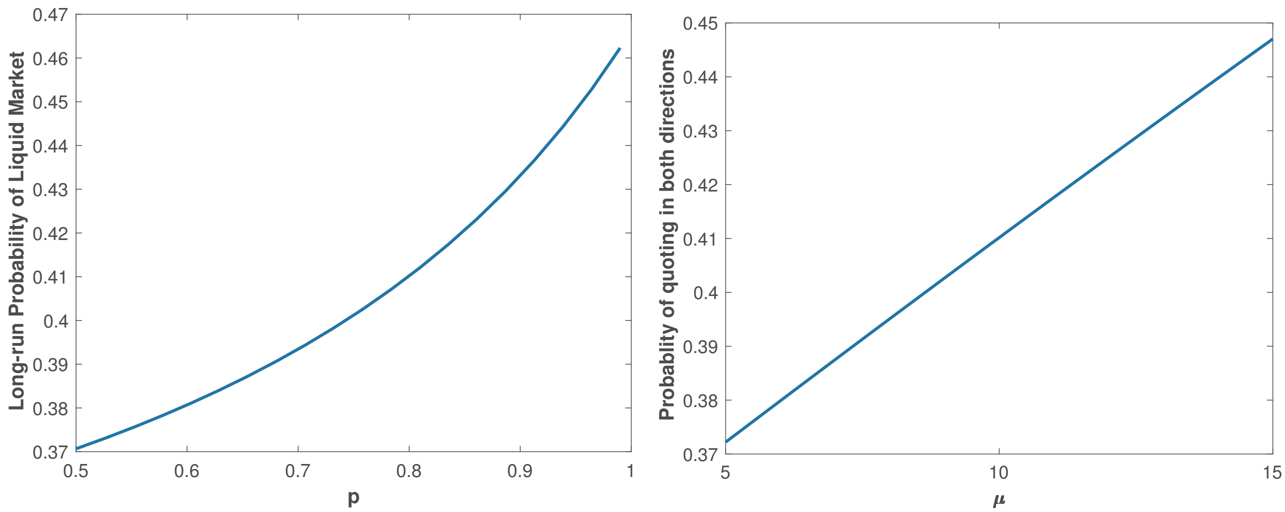

Figure A2: The fraction of the time the dealer quotes in both directions as a function of p (left) and the arrival rate of insurance orders, μ (right). The model's parameters are as follows: $\delta = \$20000$, $\Gamma = \$50000$, $q = 0.55$, $y = 0.75$, $\mu = 10$, $\lambda = 100$, $\beta = 0.04\%$.

Specially, we compute the monthly *Roll* measure as:

$$\text{Roll}_{j,m} = 2\sqrt{-cov(R_{j,t,m}, R_{j,t-1,m})} \tag{A6}$$

where $R_{j,t,m}$ and $R_{j,t-1,m}$ are returns of two consecutive available trading days, and the covariance is computed for bond j in the same month m. *Roll* is set to be zero when the monthly covariance is positive.

Following Amihud (2002), we utilize bond returns and trading dollar volume to construct *Amihud* illiquidity ratio. Specially, the monthly Amihud measure is:

$$\text{Amihud}_{j,m} = \frac{1}{N}\sum_{t=1}^{N}\frac{R_{j,t}}{Q_{j,t}} \tag{A7}$$

where N is the number of positive-volume trading days for bond j in a given month m. $R_{j,t}$ and $Q_{j,t}$ are the return and dollar trading volume, per million dollars, for bond j when there is at least a trade in day t of month m. The return $R_{j,t}$ is calculated from daily closing prices on day t and its most recent trading day.

The third measure is the spread between the high and low daily transaction prices. Corwin and Schultz (2012) propose that daily high prices correspond to buy orders and low prices are likely from sell orders. They utilize the *Highlow* ratio on consecutive days to separate security's variance and the bid-ask spread. Because the variance component is proportional to time while the bid-ask spread should be constant, we follow them to construct *Highlow* illiquidity measure as:

$$\text{Highlow} = \frac{2 \cdot (e^{\alpha} - 1)}{1 + e^{\alpha}} \tag{A8}$$

where

$$\alpha = \frac{\sqrt{2 \cdot \beta} - \sqrt{\beta}}{3 - 2 \cdot \sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2 \cdot \sqrt{2}}}, \tag{A9}$$

$$\beta = \sum_{j=0}^{1} \left(log \left(\frac{H_{t+j}}{L_{t+j}} \right) \right)^2, \tag{A10}$$

$$\gamma = \left(log \left(\frac{H_{t,t+1}}{L_{t,t+1}} \right) \right)^2 \tag{A11}$$

H_t and L_t are the highest and lowest price on day t. We use the mean value of daily *Highlow* values in a month to get a monthly *Highlow* illiquidity measure for each bond.

Table A1: 15 Largest Insurer Corporate Bond Buyers and Sellers

This list provides the top 15 insurers most frequently purchasing and selling corporate bonds based on aggregate par values of bond transactions. The sample data are from Schedule D of insurers' annual statements filed to state insurance departments. The sample period is from 2000 to 2014.

Top 15 Buyers	**Top 15 Sellers**
Northwestern Mutual Life Insurance Company	Northwestern Mutual Life Insurance Company
Teachers Insurance & Annuity Association Of America	Prudential Insurance Company of America
Prudential Insurance Company Of America	Metropolitan Life Insurance Company
Metropolitan Life Insurance Company	PFL Life Insurance Company
American General Annuity Insurance Company	Teachers Insurance & Annuity Association of America
PFL Life Insurance Company	American General Annuity Insurance Company
Allianz Life Insurance Company of North America	American General Life Insurance Company
New York Life Insurance Company	Allstate Life Insurance Company
American General Life Insurance Company	Continental Casualty Company
Lincoln National Life Insurance Company	New York Life Insurance Company
Jackson National Life Insurance Company	Jackson National Life Insurance Company
Continental Casualty Company	American Life Insurance Company
New York Life Insurance & Annuity Company	Guardian Life Insurance Company of America
Allstate Life Insurance Company	Travelers Insurance Company life
Guardian Life Insurance Company Of America	Variable Annuity Life Insurance Company

Table A2: Determinants of Insurer Transactions

This table reports the results of panel regressions for insurers' bond transactions. The dependent variable is the aggregate par value purchased (sold) by all insurance companies in the sample scaled by the par value of a bond. The independent variables include bond rating dummy, bond illiquidity, bond coupon rate, bond age, bond size, bond maturity, and indicator variables for callable bonds, puttable bonds, exchangeable bonds, convertible bonds, credit enhancements bonds, senior bonds, and secured bonds. All bonds in the sample are divided into three groups, threshold bonds dummy (*Thr*) equals 1 if bonds are rated between BB and BBB+, inferior bonds dummy (*Inf*) equals 1 for bonds rated BB- and below. Illiquidity measures are *Roll*, *Amihud*, and *Highlow* respectively. Other variables are defined in Table 2. The full sample period is from July 2002 to December 2014. The crisis period is from July 2007 to April 2009. The regressions include the month fixed effects. The t-statistics reported in the parentheses are based on two-way clustered (by time and by bond issuer) standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	ILQ measure: *Roll*				ILQ measure: *Amihud*				ILQ measure: *Highlow*			
	Full		Crisis		Full		Crisis		Full		Crisis	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Thr	0.08***	0.07***	0.05***	0.04***	0.08***	0.07***	0.05***	0.03***	0.08***	0.07***	0.05***	0.04***
	(3.79)	(4.31)	(2.96)	(2.82)	(3.70)	(3.99)	(2.97)	(2.63)	(4.39)	(4.32)	(2.74)	(2.86)
Inf	-0.10***	0.03***	-0.05***	0.01	-0.10***	0.04***	-0.06***	0.00	-0.10***	0.03***	-0.05***	0.01
	(-6.07)	(3.11)	(-4.19)	(0.46)	(-6.91)	(3.67)	(-4.32)	(0.07)	(-6.08)	(3.19)	(-4.27)	(0.34)
ILQ	0.02***	-0.01**	0.02**	-0.02	0.02**	-0.04***	0.06***	-0.05***	0.03***	-0.00	0.04***	-0.01
	(3.03)	(-2.19)	(2.02)	(-1.00)	(2.29)	(-5.75)	(4.41)	(-2.68)	(4.19)	(-0.50)	(3.20)	(-0.69)
Coupon	0.50**	-3.05***	1.25***	-0.61	0.53**	-3.21***	1.17***	-0.94	0.53**	-3.06***	1.22***	-0.67
	(2.22)	(-7.69)	(3.72)	(-1.03)	(2.33)	(-7.81)	(3.48)	(-1.61)	(2.35)	(-7.67)	(3.61)	(-1.14)
BondAge	-0.21***	0.04***	-0.15***	0.03***	-0.20***	0.05***	-0.14***	0.04***	-0.20***	0.04***	-0.15***	0.03***
	(-6.45)	(3.02)	(-4.83)	(3.08)	(-5.93)	(3.81)	(-4.72)	(3.29)	(-5.75)	(2.82)	(-4.82)	(3.04)
BondSize	-0.07***	-0.06***	-0.06***	-0.07***	-0.08***	-0.08***	-0.08***	-0.09***	-0.07***	-0.06***	-0.06***	-0.07***
	(-5.91)	(-5.41)	(-5.18)	(-5.81)	(-6.24)	(-6.55)	(-6.21)	(-6.75)	(-5.41)	(-5.21)	(-6.33)	(-6.44)
Maturity	0.12***	0.01	0.05***	-0.08**	0.13***	0.02	0.05***	-0.06*	0.13***	0.01	0.06***	-0.07**
	(8.16)	(0.78)	(5.15)	(-2.28)	(8.33)	(1.25)	(4.92)	(-1.91)	(8.61)	(0.65)	(5.43)	(-2.12)
Callable	0.06***	0.08***	0.09***	0.06***	0.06***	0.08***	0.09***	0.05***	0.06***	0.08***	0.09***	0.06***
	(3.75)	(5.14)	(5.32)	(3.12)	(3.47)	(5.27)	(5.34)	(2.59)	(3.23)	(5.35)	(5.44)	(3.24)
Puttable	-0.06**	0.02	0.01	0.16***	-0.06**	0.01	0.01	0.15***	-0.06**	0.02	0.00	0.16***
	(-2.14)	(0.71)	(0.31)	(2.98)	(-2.22)	(0.28)	(0.30)	(2.75)	(-2.40)	(0.91)	(0.10)	(2.93)
Exch	-0.22***	-0.32***	-0.12**	-0.30***	-0.22***	-0.31***	-0.12**	-0.31***	-0.23***	-0.32***	-0.13**	-0.30***
	(-2.68)	(-3.10)	(-2.16)	(-2.88)	(-2.84)	(-2.91)	(-2.17)	(-3.11)	(-2.94)	(-3.01)	(-2.33)	(-2.92)
Conv	-0.22***	-0.34***	-0.11***	-0.33***	-0.22***	-0.34***	-0.11***	-0.36***	-0.23***	-0.34***	-0.12***	-0.34***
	(-3.26)	(-4.24)	(-3.31)	(-5.44)	(-3.29)	(-4.49)	(-3.55)	(-6.05)	(-3.58)	(-4.28)	(-3.73)	(-5.56)
Enhanced	-0.04***	-0.04***	-0.06***	-0.02	-0.04***	-0.05***	-0.06***	-0.03	-0.04***	-0.04***	-0.06***	-0.02
	(-5.11)	(-5.80)	(-4.84)	(-1.21)	(-5.15)	(-6.56)	(-4.92)	(-1.57)	(-5.78)	(-5.58)	(-5.17)	(-1.06)
Senior	-0.01	0.01	0.02**	-0.03	-0.01	0.02*	0.03**	-0.02	-0.01	0.01	0.02**	-0.03
	(-1.32)	(1.13)	(2.03)	(-1.34)	(-1.15)	(1.69)	(2.41)	(-1.10)	(-1.22)	(1.10)	(2.01)	(-1.38)
Secured	-0.01	-0.03**	0.09***	-0.01	-0.01	-0.03**	0.09***	-0.02	-0.01	-0.03**	0.09***	-0.01
	(-1.04)	(-2.51)	(2.86)	(-0.36)	(-0.79)	(-2.46)	(2.87)	(-0.53)	(-0.91)	(-2.36)	(2.79)	(-0.39)
Adj R^2	0.07	0.02	0.05	0.01	0.07	0.02	0.05	0.01	0.07	0.02	0.05	0.01
N	475,975	475,975	55,865	55,865	476,969	476,969	56,092	56,092	476,969	476,969	56,101	56,101

Table A3: Cross Persistence of Matching Bonds

This table reports the results of the analysis on cross persistence of bonds with matching characteristics with insurers trading bonds. A matching bond is defined as a bond with the same bond rating, maturity difference within a year, and the same liquidity quintile group as the sample bond in a month. Panel A reports the analysis of the persistence in insurers' buy and sell transactions in the sample period across bonds. The dependent variable is the aggregate par value purchased (sold) by all insurance companies in the subsequent month/quarter/year scaled by the par value of the matching bond. The independent variable is the aggregate par value purchased (sold) by all insurance companies in a month scaled by the par value of the sample bond in that month. Panel B is on the effect of insurers' cash flow on their trading persistence. In each year, we break down insurers into two groups based on cash flow, measured as insurers' cash flow from insurance operations cash flow scaled by total assets. Robust cash flow insurers are those whose cash flow above the annual sample median; weak cash flow insurers are those below the annual sample median. R and W represent, respectively, the robust and weak cash flow insurer groups. The dependent variable is the aggregate par value purchased (sold) by all insurance companies in the subsequent month/quarter/year scaled by the par value of the matching bond. The independent variable is the aggregate par value purchased (sold) by robust or weak insurance companies in a month scaled by the par value of the sample bond in that month. Panel C reports the analysis of the persistence in insurers' buy and sell transactions across bonds during the financial crisis. Panel D reports the analysis of the persistence in robust and weak cash flow insurers' buy and sell transactions across bonds during the financial crisis. The full sample period is from July 2002 to December 2014. The crisis period is from July 2007 to April 2009. The regressions include the month fixed effects. The t-statistics reported in the parentheses are based on bond issuer clustered standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Trading Persistence across Bonds: Full Sample

	Following Month		Following Quarter		Following Year	
	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}
Buy	0.06***		0.15***		0.42***	
	(5.33)		(6.02)		(6.19)	
Sell		0.01**		0.04**		0.13**
		(2.40)		(2.21)		(2.38)
Adj R^2	0.03	0.01	0.04	0.01	0.06	0.02
N	2,841,548	2,841,548	2,841,548	2,841,548	2,841,548	2,841,548

Panel B: Insurer Cash Flow and Trading Persistence across Bonds: Full Sample

	Following Month		Following Quarter		Following Year	
	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}
$\sum_{j\in R}\text{Buy}_j$	0.08***		0.18***		0.46***	
	(2.87)		(2.76)		(2.81)	
$\sum_{j\in W}\text{Buy}_j$	0.04**		0.13**		0.39**	
	(2.03)		(2.31)		(2.19)	
$\sum_{j\in R}\text{Sell}_j$		0.01		0.03		0.09*
		(0.98)		(0.85)		(1.91)
$\sum_{j\in W}\text{Sell}_j$		0.02		0.04**		0.12**
		(1.31)		(1.98)		(2.13)
Adj R^2	0.03	0.02	0.06	0.04	0.11	0.04
N	2,841,548	2,841,548	2,841,548	2,841,548	2,841,548	2,841,548

Panel C: Trading Persistence across Bonds: Financial Crisis

	Following Month		Following Quarter		Following Year	
	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}
Buy	0.04***		0.16***		0.39***	
	(4.35)		(5.02)		(5.75)	
Sell		0.01***		0.03***		0.10***
		(2.65)		(3.05)		(2.74)
Adj R^2	0.01	0.01	0.02	0.01	0.03	0.02
N	297,298	297,298	297,298	297,298	297,298	297,298

Panel D: Insurer Cash Flow and Trading Persistence across Bonds: Financial Crisis

	Following Month		Following Quarter		Following Year	
	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}	Buy_{t+1}	Sell_{t+1}
$\sum_{j \in R} \text{Buy}_j$	0.08***		0.21***		0.54***	
	(2.95)		(2.99)		(3.02)	
$\sum_{j \in W} \text{Buy}_j$	0.03*		0.12**		0.32***	
	(1.85)		(2.14)		(2.63)	
$\sum_{j \in R} \text{Sell}_j$		0.01		0.04		0.08*
		(0.77)		(1.28)		(1.87)
$\sum_{j \in W} \text{Sell}_j$		0.02		0.03**		0.11**
		(1.23)		(2.00)		(2.07)
Adj R^2	0.02	0.02	0.05	0.03	0.09	0.04
N	297,298	297,298	297,298	297,298	297,298	297,298

Table A4: Rainy Day Liquidity Provision for Life and PC Insurers

This table reports the different rainy day liquidity provision effects of life and PC insurance companies. Panel A reports the results of life and PC insurer purchases of threshold bonds and inferiorly rated corporate bonds. Two insurer purchase measures are used as the dependent variable: buy (results reported in the first three columns) and net buy (results reported in the subsequent three columns). Independent variables include the threshold bond dummy (*Thr*), the inferior bond dummy (*Inf*), and the same set of bond control variables used in Table 4. *Diff* is the coefficients difference between life insurers and PC insurers. Panel B reports the results for the panel regressions of corporate bond illiquidity on insurers' transactions when we separate corporate bond transactions based on life or PC insurers. In both panels, the regressions include time fixed effects, and the coefficients on some bond control variables as well as the regression intercepts are suppressed to preserve space. *p-value* is for the null hypothesis on the equality between the coefficients on $\sum_{j \in Life} \text{Buy}_j$ and on $\sum_{j \in PC} \text{Buy}_j$ using the Wald test. The t-statistics reported in the parentheses are based on two-way clustered (by time and by bond issuer) standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Threshold Bond Purchase: Life vs. PC Insurers

	Buy			Net		
	Life	PC	Diff	Life	PC	Diff
Threshold	0.11***	0.06***	0.05***	0.02**	0.00	0.02**
	(4.77)	(2.74)	(2.92)	(2.12)	(0.04)	(2.01)
Inferior	-0.09***	-0.11***	0.02	-0.10***	-0.13***	0.03**
	(-3.97)	(-4.12)	(1.34)	(-4.09)	(-5.68)	(2.46)
Adj R^2	0.07	0.07		0.06	0.06	

Panel B: Life and PC Insurers' Purchases and Liquidity Provision

	ILQ measure: *Roll*			ILQ measure: *Amihud*			ILQ measure: *Highlow*		
	Sup	Thr	Inf	Sup	Thr	Inf	Sup	Thr	Inf
$\sum_{j \in Life} \text{Buy}_j$	0.41	-3.04***	-2.66*	0.13	-0.48***	-0.79***	-0.14	-0.85***	-0.78**
	(0.91)	(-7.76)	(-1.85)	(1.00)	(-4.54)	(-3.22)	(-0.86)	(-5.76)	(-2.54)
$\sum_{j \in PC} \text{Buy}_j$	-0.65	-2.30***	-2.49	-0.03	-0.30*	-1.14*	0.19	-0.78**	-0.24
	(-0.84)	(-2.94)	(-1.13)	(-0.22)	(-1.82)	(-1.78)	(0.51)	(-2.24)	(-0.22)
$\sum_{j \in Life} \text{Sell}_j$	-0.33	0.49	2.01***	-0.16	0.01	-0.13	0.25	0.57***	0.63***
	(-0.74)	(1.18)	(2.82)	(-1.14)	(0.10)	(-0.43)	(1.06)	(3.13)	(3.21)
$\sum_{j \in PC} \text{Sell}_j$	1.03	1.66*	1.03	-0.43	0.51	1.14	0.57	0.87**	0.54
	(0.78)	(1.73)	(1.47)	(-1.46)	(1.23)	(1.60)	(1.41)	(2.34)	(1.60)
p-value	0.18	0.07	0.35	0.16	0.09	0.15	0.21	0.13	0.04
Adj R^2	0.38	0.39	0.38	0.34	0.34	0.29	0.36	0.35	0.39