The Dark Side of Liquid Bonds in Fire Sales*

Maria Chaderina Alexander Mürmann Christoph Scheuch

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Abstract

We show that in fire sales institutional investors chose to sell bonds that were trading in liquid markets before. Surprisingly, the price drops of these bonds are larger than of bonds that were trading in less liquid markets. We argue that this is because institutions fail to internalize the negative effect selling common bonds has on other market participants. After controlling for commonality of bonds, liquid bonds exhibit smaller price impacts in fire sales. Regulatory measures of systemic risk should thus take into account the portfolio overlap in liquid bonds as it exacerbates fire-sale losses.

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*Chaderina, Mürmann, and Scheuch are at WU (Vienna University of Economics and Business) and Vienna Graduate School of Finance (VGSF), Welthandelsplatz 1, Building D4, 1020 Vienna, Austria. Corresponding author: maria.chaderina@wu.ac.at. We are grateful for insightful comments and suggestions by Tobias Berg, Nathan Foley-Fisher, Thomas Gehrig, Christian Kubitza, Christian Laux, Alberto Manconi, and Olivia Mitchell. This paper replaces an earlier draft titled "Which Bonds to Sell in Fire Sales? Liquidity versus Commonality of Holdings".

1 Introduction

Asset fire sales can pose substantial losses to the liquidating parties and are therefore a concern of investors as well as policymakers (Economist, 2016). How can a portfolio manager in a bank, mutual fund, insurance company or other financial institution, who faces the task to raise funds on short notice, liquidate assets to minimize fire-sale losses? Much of the recent literature on fire sales rests on the assumption that financial institutions liquidate a fixed proportion of all assets within their portfolios. This assumption leads authors to conclude that overlaps in illiquid assets are dangerous, as they intensify fire-sale losses (Greenwood et al., 2015; Cont and Schaanning, 2017). However, there is no empirical support for this assumption within asset classes and in most circumstances such a strategy is not optimal. In our study, we find that insurance companies sell on average only 3 out of 100 corporate bonds in fire sales triggered by large natural catastrophes.

If financial institutions do not sell a fixed proportion of their holdings, which strategy do they follow in fire sales? We argue that they act strategically and sell assets according to the anticipated market liquidity to minimize losses. That is, financial institutions sell more of assets that are liquid and less of assets that are illiquid. This strategy is in striking contrast to selling a fixed proportion of assets regardless of their liquidity. Confirming our hypothesis, we document that property and casualty (P&C) insurance companies sell mostly the liquid assets in their portfolios during fire sales.

One might, however, question whether our observations constitute an equilibrium strategy in response to selling behavior of others. In particular, prior literature documents that bonds that traded in liquid bonds before fire sales experience larger price impacts in fire sales (Gorton, 2010; Ellul et al., 2011; Boudoukh et al., 2016; Shin, 2016). This seemingly puzzling observation might suggest that institutions act irrationally, all rushing to sell the same assets and not anticipating that other agents are selling the same bonds. We argue though that institutions' actions are rational even if they knew what others sold. While this is an equilibrium outcome, it is not efficient due to the externality that institutions impose on each other. Institutions do not take into account the negative effect that their sales have on revenues of other companies, much like Cournot competitors oversell relative to a monopoly. So they sell marginally too much of bonds they have in common with other institutions. Because there are very few liquid corporate bonds in the market and they end up being commonly held, we argue that institutions oversell liquid bonds.[1]

The overselling we consider is relative to the case of an integrated financial institution that would have taken into account negative externalities of price impacts in maximizing joint liquidation revenues. Independent companies fail to do so because they cannot credibly commit to a joint liquidation policy which favors less common bonds. Integration into a single financial institution solves the commitment problem. The integrated institution would sell assets to equalize price impacts. This means selling twice as much of a twice more liquid bond, so that its price impact is the same as that of a twice less liquid bond. Independent companies sell more of common bonds than the integrated company, so price impacts on common bonds are larger than on less-common bonds. And since liquid bonds are commonly-held, during fire sales this leads to larger price impacts for bonds that typically trade in liquid markets. We demonstrate that this is due to the commonality of liquid bonds rather than their liquidity in itself.[2]

Further, we argue that a reduction in the overlap in liquid holdings can decrease aggregate fire-sale losses. If the holdings overlap is in less liquid bonds, as liquid bonds

[1] We refer to bonds as being 'liquid' when they trade in liquid markets during normal times, as measured in the 6-month window before fire sales. These bonds have larger trading volumes and smaller price impacts per unit of the trading volume.

[2] It is important to point out that overselling arises not because of asymmetric information, but because of lack of commitment. It is in the interest of all insurance companies as a group to coordinate and commit to sell less of commonly held bonds, but absent commitment in a Nash equilibrium they sell too much. Hence, the problem arises from the lack of credible commitment, rather than the failure to communicate or share information on asset holdings or plans to sell particular assets. Therefore, policies aimed at mitigating fire sales risk should address the misalignment of incentives rather than merely facilitate information sharing or transparency.

are different, then fire sales occur in neighboring but not the same markets. The price impacts are then smaller because markets are not crowded. So we argue that *commonality of liquid bonds* is dangerous. This is in contrast to the fire-sales cascades literature (e.g., Greenwood et al., 2015), which based on the assumption of proportional sales argues that the commonality of *illiquid* assets is the threat. We highlight that encouraging financial institutions to hold more liquid assets might result in an increase in the commonality of these bonds and destabilize the financial system.

To study which bonds are sold in fire sales, we analyze the way US P&C insurance companies liquidate bonds in the weeks prior to and following large catastrophes. While the primary business model of insurance companies is not liquidity transformation, unlike that of mutual funds investing in corporate bonds or more traditionally banks, P&C insurance companies are exposed to fire sale risks in a similar manner. When a catastrophe occurs and insurance companies anticipate a dramatic increase in claims to be paid, they liquidate part of the bond portfolio to meet their obligations. These bond sales are large in magnitude and have a significant price impact on bonds that are being liquidated (Massa and Zhang, 2011; Manconi et al., 2016). We chose to investigate liquidation strategies of P&C insurance companies because of data availability. While mutual funds report their holdings of assets to the regulatory authorities quarterly, they do not report individual trades. Insurance companies, on the other hand, report their holdings and all transactions to the National Association of Insurance Commissioners (NAIC), the regulatory body overseeing insurance companies. Using this information, we identify their trading activity within a narrow fire-sale window of a few weeks. Moreover, we identify company-specific transaction costs.

We combine the data on holdings and transactions of P&C insurance companies from NAIC with trading data on corporate bonds from the Trade Reporting and Compliance Engine (TRACE) and data on bond characteristics from the Mergent Fixed-Income Securities Database (FISD) for 2005-2014. First, we measure the liquidity of bonds in the portfolios of insurance companies using the trade-volume data from TRACE prior to catastrophes. We observe that insurance companies hold few liquid bonds and many highly illiquid bonds. Moreover, the gap in liquidity between most and least liquid is substantial — the top 1% of the most liquid bonds account for more trading volume than the bottom 70% of the most illiquid bonds. We then measure commonality of bonds by counting the number of insurance companies in our sample that hold a specific bond, normalized by the total number of companies. We find that liquidity and commonality of bonds are strongly positively related.

We then identify the insurance companies affected by large catastrophes during our sample period through losses paid on direct business of insurance companies by state. We consider them to be the financial institutions that suffered a withdrawal shock and were required to raise funds. Indeed, we find that these affected companies were more likely to sell bonds than other insurance companies in our sample. When we investigate which bonds were sold around catastrophes, we see that the sell volume is concentrated in commonly held and liquid bonds.

Next, we investigate the relation between the price impacts and the liquidity of bonds, measured prior to the fire-sale windows. We see that bonds that were trading in more liquid markets before fire sales exhibit larger price impacts than less liquid bonds during fire sales. This seemingly puzzling observation though is consistent with the predictions of our model and is rationalized by observing that liquidity serves as a proxy for commonality of the bond. Indeed, once we control for the commonality of bonds, the relation between liquidity and price impacts reverses — liquid bonds, holding the commonality fixed, exhibit smaller price impacts than illiquid bonds. Importantly, we observe this phenomenon only in fire sales. We conduct a placebo test and select a random date as a start of a hypothetical fire-sale window. Liquidity of a bond in the placebo test is negatively related to price impacts, even without controlling for commonality. Therefore, in normal times liquid bonds indeed exhibit smaller price impacts, while in fire sales they exhibit smaller price impacts only after controlling for their commonality.

We observe that the average commonality of liquid bonds in the P&C insurance sector was highest in 2010, and decreased towards the end of our sample, while the commonality of illiquid bonds increased. The commonality of liquid bonds contributes the most to the fire-sale risk and, while being higher than that of the illiquid bonds, it does not seem to increase over time. Therefore, we find evidence that the largest fire-sale risk in the P&C insurance sector was present in 2010.

Affected companies in 2005 alone lost $20M selling corporate bonds in fire sales, while raising $850M. While fire sales are costly for insurance companies, we do not take the position that fire-sale losses are identical to social losses. A fire sale is first of all a re-distribution of surplus. The losses of financial institutions engaged in fire sales are profits to liquidity providers (Meier and Servaes, 2016). The price distortions that fire sales generate, however, are likely to distort real decisions (Dávila and Korinek, 2016; van Binsbergen and Opp, 2017).

Commonality does not mechanically determine liquidity. We define commonality of a bond on a small subset of market participants. P&C insurance companies hold on average only about 5.5% of a given corporate bond and they contribute on average not more than 6% to the overall trading volume. When measuring liquidity we take the overall market liquidity of the bond. Other market participants, such as life insurance companies, fixed-income mutual funds, or hedge funds, provide liquidity through dealers. Therefore, a bond can be liquid but not commonly held by P&C insurance companies.[3]

[3]Changes in commonality also do not unambiguously determine changes in liquidity. A bond sale by a P&C company to other market participants decreases commonality, but can increase or decrease liquidity of the bond, depending on the counterparty. If an active trader, such as a hedge fund, purchases the bond, then liquidity is likely to increase. However, if a buy and hold investor, such as a life insurance company, buys it, then liquidity can decrease or stay the same. Insurance companies account for these dependencies when forming their portfolios, and our analysis is robust to such potential feedback loops

Fire sales happen when there are not enough buyers to purchase liquidated assets. The limited liquidity provision on the buy-side of the market might come from capital constraints. Ellul et al. (2011) document that higher capital in high-yield mutual and hedge funds is associated with smaller price impacts in corporate bonds after rating downgrades. Therefore, the prevailing level of capital is not sufficient to eliminate price impacts in fire sales. Moreover, even if uninformed market participants are not constrained, fire sales amplify adverse-selection problems and discourage uninformed investors' liquidity provision (Dow and Han, 2017). Either way, we observe substantial price impacts during the two weeks prior to and two weeks after large natural catastrophes and take these as evidence of fire sales.

Related Literature. We contribute to several strands of literature. First, we contribute to the recent evidence of liquidity transformation in non-bank financial institutions, in particular insurance companies. Foley-Fisher et al. (2015) show that life insurance companies borrow from liquid short-term liabilities and invest in long-term illiquid assets, exposing themselves to run risks. Chodorow-Reich et al. (2016) argue that insurance companies generate value by insulating illiquid assets from temporary market fluctuations. We demonstrate that the commonality of liquid bonds exacerbates the costs of liquidity transformation and that these costs are most pronounced during market-wide shocks.

Our paper is also related to the literature that studies correlated trading among financial institutions (Chiang and Niehaus, 2016; Cai et al., 2016). We provide a new rational explanation of correlated selling, namely the failure to fully account for the negative externality of selling on other institutions.

We further contribute to the literature that analyzes the larger price impact of liquid bonds in fire sales. Shin (2016) argues that agents sell more of liquid bonds during market-wide shocks due to the lower search friction of liquid bonds. We complement his

between commonality and liquidity.

findings by explicitly allowing asset holders to choose which assets to sell and how much to sell of each asset in response to a liquidity shock. We find that commonality of bonds, not liquidity, aggravates price impacts.

The bond liquidation problem we consider is very different from the optimal execution of portfolio transactions in equity markets (e.g., Almgren and Chriss, 2001). Unlike in equity markets, in bond markets order splits are discouraged (Schultz, 2001; Edwards et al., 2007), while the fundamental volatility is rather low. Instead, institutions face the trade-off between selling more of liquid assets and the costs that these assets are commonly-held and sold. Under empirically plausible price impact functions à la Chacko et al. (2008), we find that the optimal liquidation strategy of a single institution yields equal price impacts across all markets.

Finally, we contribute to the literature on the interconnectedness of financial institutions and fire sale cascades.[4] The main difference between this literature and our study is the role of liquid assets. For instance, Cont and Schaanning (2017) measure the exposure of institutions to price-mediated deleveraging risk by looking at liquidity-weighted portfolio overlaps. In their measure, more liquid assets have lower weights and the perceived problem of joint ownership of liquid assets is small. We, in contrast, argue that the overlap in liquid assets should receive a higher weight. We find that the more liquid the commonly-held asset is, the higher is its price impact in fire sales. These contrasting results arise from the different approaches to the portfolio liquidation problem. The commonly-used assumption of proportional liquidation strategies implies that institutions sell a certain fraction of holdings irrespective of liquidity (e.g. Greenwood et al., 2015). Therefore, the resulting price impacts of liquid assets are smaller. In our setting, financial institutions act strategically and optimally sell more of liquid assets, resulting in larger price impacts. We thus highlight that the commonality of liquid assets poses a larger

[4]See Braverman and Minca (2014), Duarte and Eisenbach (2015), Greenwood et al. (2015), Falato et al. (2016), Guo et al. (2016), Adam and Klipper (2017), Cont and Schaanning (2017), and Nanda et al. (2017) among others.

problem than the commonality of illiquid assets.

2 Hypothesis Development

2.1 Microstructure of the Corporate Bond Market

Our theoretical analysis proceeds under two key assumptions regarding the microstructure of the corporate bond market — downward-sloping demand curves and limits to arbitrage capital flows between markets.

Corporate bonds are traded over the counter, in a network intermediated by broker-dealers (Maggio et al., 2016). Holding inventories is costly for dealers (Ho and Hans, 1983; Grossman and Miller, 1988),[5] even more so under the Volcker rule, which prohibits proprietary trading to manage risk exposure (Duffie, 2012; Wyman, 2012). Dealers also have local market power over the immediacy of order executions (Chacko et al., 2008). Moreover, arbitrage capital is slow-moving (Duffie, 2010) and limited (Ellul et al., 2011), while asymmetric information disturbs its flow (Dow and Han, 2017). All these arguments support the idea that the larger the order size, the larger its execution costs, or equivalently, the demand curve is downward slopping. Furthermore, it also follows that some bonds might trade at prices below fundamentals while other could trade at the fair value.

2.2 Overselling of Commonly-Held Bonds

In this section, we explain why insurance companies might sell too much of the commonly-held assets in the event of an aggregate liquidity shock. We assume that insurance companies cannot credibly commit to a liquidation strategy, which is why we characterize the decentralized equilibrium as a Nash equilibrium. In this setting, insurance companies

[5] See Friewald and Nagler (2015) for recent supportive evidence.

do not incorporate the impact that one company's selling has on the revenue of other companies through higher price impacts. We compare it to the reference case — the trading strategy of an integrated insurance company which takes this externality into account. The integrated insurance company acts in a way that is identical to the case when insurance companies commit to the optimal liquidation strategies.

Consider a setting in which two insurance companies 1 and 2 both hold an asset A, while insurance company 1 also holds an asset B, and company 2 holds an asset C. Denote by $\bar{P}_i$ the fundamental price of each asset i. As we focus on bonds, we think of the fundamental value as the present value of coupon payments and the principal value if the bond is held until maturity. Denote by Q_i the units of asset i and let $q_i \equiv \bar{P}_i Q_i$ represent the dollar value of Q_i units of asset i. Both insurance companies are simultaneously hit with a liquidity shock and each needs to raise an amount I by liquidating part of its portfolio. Each asset is traded in a market with a downward sloping demand curve $P_i(q_i)$, which means there is a price impact of the trades insurance companies execute. Moreover, we assume that the selling in market i has no impact on the cost of trading in market j,[6] because arbitrage capital is limited and slow-moving.

Some assets are traded in more liquid markets than others. We define a relative price impact on asset i as

$$\rho_i = 1 - \frac{P_i}{\bar{P}_i}.$$

We consider price impact functions $\rho_i = \rho(q_i, \lambda_i)$ that explicitly depend on an asset's liquidity λ_i. We say that the market of asset i is more liquid than the market of the asset j, if the price impact of asset i is smaller than the price impact of asset j given the same value q of each asset is sold, i.e. if $\rho_i(q) < \rho_j(q)$. That is, we assume that the

[6] Our results remain qualitatively unchanged as long as we assume anything less than perfect liquidity flows between markets i and j.

higher λ_i, the smaller the price impact that selling q_i dollars of the asset generates, i.e. $\frac{\partial}{\partial \lambda_i}\rho(q_i, \lambda_i) < 0$.[7]

The objective of each company is then to decide how much of each asset to sell such that they each collect I in proceeds, taking the price impacts they generate in each asset market into account. Denote by $\rho_i(q_i)$ the price impact in market i, which is equal to $\rho(\lambda_i, q_i^1 + q_i^2)$. Formally, the objective function of insurance company 1 is

$$\min_{\{q_A^1, q_B^1\}} \quad \rho_A(q_A^1 + q_A^2)q_A^1 + \rho_B(q_B^1)q_B^1$$
$$\text{s.t. } \left(1 - \rho_A(q_A^1 + q_A^2)\right) q_A^1 + \left(1 - \rho_B(q_B^1)\right) q_B^1 = I,$$

and for company 2

$$\min_{\{q_A^2, q_C^2\}} \quad \rho_A(q_A^1 + q_A^2)q_A^2 + \rho_C(q_C^2)q_C^2$$
$$\text{s.t. } \left(1 - \rho_A(q_A^1 + q_A^2)\right) q_A^2 + \left(1 - \rho_C(q_C^2)\right) q_C^2 = I.$$

We look for a Nash equilibrium in pure strategies in a simultaneous-move game. The

[7] Chacko et al. (2008) provide a bid-ask spread parametrization that is suitable for our analysis. In their setting, the price impact of trades arises due to monopoly power of a market maker who is the sole provider of immediate trade execution. Then

$$\begin{aligned} \rho_i(q_i) &= \frac{1}{\phi_i(q_i)} \qquad (1) \\ \phi_i(q_i) &= \left(\frac{1}{2} - \frac{r_i}{\sigma_i^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{r_i}{\sigma_i^2}\right)^2 + \frac{2(r_i + \lambda_i(q_i))}{\sigma_i^2}} \\ \lambda_i(q_i) &= \frac{\lambda_i}{q_i}, \end{aligned}$$

where r_i and σ_i are drift and volatility of the fundamental value of the asset i, and λ_i measures the arrival rate of buy orders to the dealer market of the asset i per unit of time. The higher λ_i is, the more liquid is the asset. To make measures of asset liquidity λ_i comparable across assets, we measure arrival rates not in number of contracts, but in dollars of the fundamental value q_i.

first-order condition of the optimization problem by company 1 implies that

$$\rho'_A(q_A^{1NE}+q_A^{2NE})q_A^{1NE}+\rho_A(q_A^{1NE}+q_A^{2NE})=\rho'_B(q_B^{1NE})q_B^{1NE}+\rho_B(q_B^{1NE}), \tag{2}$$

where $\rho'_i(q_i)=\frac{\partial\rho(q_i,\lambda_i)}{\partial q_i}$ is the partial derivative of the price-impact function with respect to quantity sold.

Now let us re-formulate the same setting in terms of an integrated insurance company with the objective to minimize total transaction costs while raising at least $2I$ and taking the joint price impact into account. Formally,

$$\begin{aligned}\min_{\{q_A^1,q_A^2,q_B^1,q_C^2\}} \quad & \rho_A(q_A^1+q_A^2)(q_A^1+q_A^2)+\rho_B(q_B^1)q_B^1+\rho_C(q_C^2)q_C^2 \\ \text{s.t.} \quad & \left(1-\rho_A(q_A^1+q_A^2)\right)(q_A^1+q_A^2)+\left(1-\rho_B(q_B^1)\right)q_B^1+\left(1-\rho_C(q_C^2)\right)q_C^2=2I.\end{aligned}$$

The optimal liquidation strategy of the integrated insurer for assets A and B is given by its first-order condition

$$\rho'_A(q_A^{1*}+q_A^{2*})(q_A^{1*}+q_A^{2*})+\rho_A(q_A^{1*}+q_A^{2*}) \quad = \quad \rho'_B(q_B^{1*})q_B^{1*}+\rho_B(q_B^{1*}) \tag{3}$$

The following lemma formally compares the two equilibrium outcomes – the case when the two companies are competitors (no commitment), and the case when they act as one integrated company (commitment).

Lemma 1. *If $\rho'_i(q_i)>0$ for all assets, then $q_A^{1*}+q_A^{2*}<q_A^{1NE}+q_A^{2NE}$.*

The Lemma states that the commonly-held asset is over-sold in a competitive equilibrium relative to the case of an integrated insurance company. In that sense, we say that insurance companies sell too much of commonly-held assets to mean that if they could credibly commit to a liquidations strategy, this strategy would imply selling less of commonly-held assets and more of individually-held assets.

The intuition behind this result is immediate if we evaluate the first-order condition (3) at the Nash solution (q_A^{1NE}, q_B^{1NE}). In this case, the marginal cost of selling the last unit of the commonly held asset A is larger than the marginal cost of selling the last unit of the individually-held asset B. This follows from the fact that insurance company 1 only considers its negative impact of selling asset A, i.e. $\rho'_A(q_A^1) \cdot q_A^1$, while the integrated insurance company considers $\rho'_A(q_A^1 + q_A^2) \cdot (q_A^1 + q_A^2)$. Since the joint price impact is larger and the marginal revenue from selling asset A is small, the integrated insurance company prefers to sell less of asset A and more of asset B relative to the competitive solution.

This result is another way of saying that insurance companies do not internalize the price impact they have on other market participants. Therefore, they sell too much of the commonly held assets. The goal of our empirical analysis is to quantify to what extent insurance companies over-sell commonly-held assets and how that affects price impacts in fire sales .

2.3 Price Impacts

We further investigate the consequences of over-selling the commonly-held asset due to the failure to internalize the negative price impact of trading on the proceeds of other companies.

We show in the previous section that over-selling the commonly-held asset A means that in the equilibrium insurance companies liquidate more of asset A than is optimal from the perspective of an integrated company. This means that the price impact in asset A would be larger than in the integrated optimum – but is it larger than in the not commonly-held assets?

To investigate this question, recall the first-order condition from the competitive equilibrium (3), which states that a company sells assets until the marginal price impacts equalize. This is in contrast to the intuition of a price-taking portfolio manager, who sells only the asset with the smallest prevailing price impact.[8] That is, even if asset A is more liquid than asset B, the manager sells both A and B. What does the first-order condition for the competitive equilibrium (3) imply about ρ_A vs. ρ_B, where we use abbreviated notation $\rho_i = \rho(q_i, \lambda_i)$? The following Lemma is helpful to address this question.

Lemma 2. *If $\frac{\partial}{\partial q_i}\rho(\lambda_i, q_i) = k\rho(\lambda_i, q_i)/q_i$ for both assets A and B and some constant $k > 0$, then the manager liquidates the portfolio in such a way that $\rho^*_A = \rho^*_B$.*

The proof follows immediately from plugging the condition into the first-order conditions. The k in the condition of the Lemma is a coefficient of proportionality, which is the same for two assets. The condition $\frac{\partial}{\partial q_i}\rho(q_i, \lambda_i) = k\rho(q_i, \lambda_i)/q_i$ states that the marginal price impact is proportional to the average price impact. Functions of the form $F(q/\lambda)^\alpha$ satisfy this property, where the degree of proportionality is $k = \alpha$. Therefore, the conditions of the lemma are satisfied for linear or square-root price-impact functions, which fall into a more general form of $F(q/\lambda)^\alpha$. It is particularly useful to note that $\rho(q) = F\sqrt{q/\lambda}$ closely approximates the price-impact functions of Chacko et al. (2008). Hence, this condition holds, at least approximately, for many empirically plausible price-impact functions.

Lemma 2 immediately gives us the following corollary.

Corollary 1. *In the Nash equilibrium, the price impact of the commonly-held asset is larger than the price impacts of less-commonly held assets, i.e. $\rho^{NE}_{B,C} < \rho^{NE}_A$.*

According to Lemma 2, the integrated insurance company sells each asset such that the price impacts on all assets equalize, that is, $\rho^*_A = \rho^*_B = \rho^*_C$. Lemma 1 shows that

[8] All models of portfolio liquidation with proportional trading costs effectively assume that portfolio managers are price takers. For example, Vayanos (2004) considers a related problem – liquidating assets in case of an outflow from a fund – and assumes that the different liquidity of assets translates into different proportional trading costs. This leads to the result that only the asset with the smallest trading costs is liquidated first, and only if there is still financing need left, the less liquid asset is liquidated.

the optimal solution of individual insurance companies features more liquidation of the commonly-held asset A. Therefore, asset market A features a larger price impact in the decentralized equilibrium than in the integrated case, i.e. $\rho_A^* < \rho_A^{NE}$. Therefore, $\rho_A^{NE} > \rho_B^* = \rho_C^*$ and also larger than the price impacts of assets B and C in the Nash equilibrium, since these separately-held assets are under-sold relative to the integrated insurance company case. In the end, we have $\rho_{B,C}^{NE} < \rho_A^* = \rho_B^* = \rho_C^* < \rho_A^{NE}$.

Note that this result is due to the commonality of asset A. The role of liquidity in this result is neutral — from a theoretical point of view, asset A could be more or less liquid than assets B and C, yet we would expect a larger price impact in asset A than in assets B and C.[9]

Figure 1 graphically represents the larger price impact of liquid asset A than less liquid assets B or C. The downward sloping curves are the price-impact functions as in (1). The higher the line, the more liquid is the asset. The top line corresponds to the asset A, which is also the only commonly-held asset. Vertical solid lines represent the solution to the integrated insurance company's liquidation problem. Notice that the price impacts caused by this liquidation policy equalize. This is consistent with the prediction of Lemma 2. The dot-dashed lines represent the liquidation policy of the individual insurance companies. It corresponds to selling more of asset A and less of both B and C than what the integrated insurance company would have chosen, as predicted by Lemma 1. Note that the price impact in the market for asset A is larger than price impacts in B or C, even though the asset A is the most liquid.

[9]Liquidity of a bond, everything else constant, is a desirable feature for insurance companies due to lower trading costs. However, commonality of a bond, everything else constant, is not. In the data, we see that there are just a few very liquid bonds in the portfolios of insurers, as demonstrated by Figure 5. Not surprisingly, these few liquid bonds are also more likely to be held by many insurance companies. The extent to which liquidity of the bond and its commonality tend to be related, is shown in Figure 7. It is indeed the case that the most liquid bonds tend to be the ones held by many insurance companies. Therefore, this empirical observation supports the assumption in our example that asset A is more liquid than assets B or C.

2.4 Effects of Liquidity and Commonality on Losses

In this subsection we establish the effect of liquidity and commonality of assets on the liquidation losses for a company in a competitive equilibrium. In each analysis, we compare the outcomes of different Nash equilibria, which are the result of a change in either liquidity of an asset or commonality of an asset.

First, we generalize the setting used above and consider a market that consists of n identical insurance companies hit with the same liquidity shock. There are a total of N assets and liquidity is given by a vector λ. Consider an equilibrium in which holdings of each asset for each company are sufficient to implement the optimal liquidation strategy, in other words, an interior equilibrium. Then first-order conditions of the loss minimization problem for each company in each asset would imply that

$$K = \frac{\partial}{\partial q_i}\rho(nq_i, \lambda_i)q_i + \rho(nq_i, \lambda_i), \tag{4}$$

where K represents the marginal losses due to price impacts incurred by selling the last unit of each asset i. Since all companies are the same, the total quantity sold on the market is then given by nq_i, where q_i is the quantity sold by each company.

The total losses to each company in equilibrium, taking into account symmetric strategies of other companies, are then $J(\lambda, q_i,)$. The total differential of the losses is given by:

$$dJ = \sum_i^N \frac{\partial}{\partial q_i}(\rho_i q_i)dq_i = K\sum_i^N \, dq_i. \tag{5}$$

The larger K is, the larger the liquidation losses J. Hence, we can think of the problem of minimizing liquidation losses as the problem of minimizing the marginal price impacts of assets sold.

Lemma 3. *For any company j, the liquidation losses decrease in a liquidity of any asset* *traded in the market:*

$$\frac{dJ^{NE}(\lambda, q^j, q^{-j})}{d\lambda_i} < 0. \tag{6}$$

Larger liquidity has two effects on the total liquidation losses. First, for a given allocation of sold quantities, the resulting price impacts in the market of asset i are smaller. Next, companies re-allocate more liquidation volume to the asset market i and reduce the overall losses in other markets as well ($\frac{\partial}{\partial \lambda_i} K < 0$).

We now proceed to establish the effect of asset commonality on the liquidation losses. To do so, we look at how the liquidation losses change if an asset becomes more commonly-held. Consider a market that is populated by two types of companies - n_1 companies hold all assets, just like in the setting above, while n_2 companies hold only assets of $\{1, ..., i^* - 1\}$. We analyze a situation when asset i^* is now also held by all companies and, therefore, can be liquidated by all companies. Denote by J_1^{NE} the losses of a company from group 1 when i^* is held only by n_1 companies and by $\tilde{J}_1^{NE}$ the losses of the same company when the asset i^* is held by all companies.

Lemma 4. *For any company that experiences an increase in the commonality of the assets it sells, the liquidation losses increase:*

$$J_1^{NE} < \tilde{J}_1^{NE}. \tag{7}$$

The proof of this Lemma proceeds as follows. Before the change, the two groups of companies were both in an interior equilibrium such that K_1 and K_2 were the marginal liquidation losses. Because group 1 has access to more markets than group 2, they can better allocate their assets across markets, so $K_1 < K_2$. After the change, consider what happens to the market of asset i^*. At the old equilibrium quantities, we see that companies in group 2 now have access to the market where the marginal losses are smaller than K_2, the marginal losses in other markets. Hence, they decide to sell more of asset i^* and less of other assets $\{1, ..., i^* - 1\}$.

$$K_1 = \frac{\partial}{\partial q_i} \rho(n_1 q^1_{i^*}, \lambda_{i^*}) q^1_{i^*} + \rho(n_1 q^1_{i^*}, \lambda_{i^*}) < K_2, \tag{8}$$

$$K_2 > \frac{\partial}{\partial q_i} \rho(n_1 q^1_{i^*}, \lambda_{i^*}) \cdot 0 + \rho(n_1 q^1_{i^*}, \lambda_{i^*}). \tag{9}$$

This leads to a new equilibrium:

$$\tilde{K}_1 = \frac{\partial}{\partial q_i} \rho(n_1 \tilde{q}^1_{i^*} + n_2 \tilde{q}^2_{i^*}, \lambda_{i^*}) \tilde{q}^1_{i^*} + \rho(n_1 \tilde{q}^1_{i^*} + n_2 \tilde{q}^2_{i^*}, \lambda_{i^*}), \tag{10}$$

$$\tilde{K}_2 = \frac{\partial}{\partial q_i} \rho(n_1 \tilde{q}^1_{i^*} + n_2 \tilde{q}^2_{i^*}, \lambda_{i^*}) \tilde{q}^2_{i^*} + \rho(n_1 \tilde{q}^1_{i^*} + n_2 \tilde{q}^2_{i^*}, \lambda_{i^*}). \tag{11}$$

Moreover, comparing the two equilibria, we notice that $K_1 < \tilde{K}_1$ while $K_2 > \tilde{K}_2$. That is, the group of companies that did not have access to the market i^* before, is now better off, while the group of companies that had access to market i^* before, but now has to share it with more companies, is worse off. Therefore, liquidation losses are higher if any asset in the company's portfolio has higher commonality, everything else equal.

2.5 Pre-Selection of Assets to Liquidate

In this section we consider an additional market imperfection – a minimum quantity $\hat{q}$ that the companies can sell of any asset. The microfoundation of this assumption lies in the nature of the OTC market where corporate bonds are traded. It is a market of dealers, and the minimum transaction sizes are substantially larger than those in equity markets which are operated through centralized exchanges. The consequence of this assumption is that companies will not sell all of the assets in their portfolios, but only some.

We augment our notion of equilibrium by analyzing the selection stage of the liquidation process where companies make decisions on what subset of assets to liquidate. We look for a Nash equilibrium in pure strategies, where we consider a strategy to be a set of assets that the companies choose to sell. Subsequently, once assets are chosen, companies play the game that we analyzed above. Denote by N^1 the set of assets that company 1 chooses to sell.

We measure two dimensions of commonality in this setting — the holding commonality and the selling commonality. The holding commonality refers to the number of companies holding this asset. Going back to the previous subsection, it is $n_1 + n_2$ for assets with an index in $\{1, ..., i^* - 1\}$ and n_1 only for assets with an index $\{i^*, ..., N\}$. We consider $\hat{q}$ high enough so that all companies choosing to sell all assets is not an equilibrium, yet not too high so that all n_2 companies choose to sell all assets they hold, while n_1 companies choose to sell only some assets. In particular, they choose to sell all assets in the set $\{i^*, ..., N\}$, but only some of those that companies from group 2 also hold. The selling commonality of assets in the set $\{i^*, ..., N\}$ is equal to their holding commonality and is n_1. The selling commonality of assets in the set $\{1, ..., i^* - 1\}$ is smaller than the holding commonality $(n_1 + n_2)$, and we denote it $n^*_{1,i} + n_{2,i}$ for each asset i. Then holding commonality in our setting is one-to-one related to selling commonality, while more generally one can expect them to be simply positively related.

In the next theorem, we characterize which assets the company prefers to sell:

Theorem 1. *Consider an asset j not in N^1 but $\bar{q}^1_j > 0$, then it must be case that:*

- *for all i in N^1 s.t. $\lambda_i = \lambda_j$, the commonality of asset j is higher than the commonality of asset i;*
- *for all i in N^1 s.t. their commonality is the same as that of asset j, $\lambda_i > \lambda_j$.*

Comparison between assets i and j is made taking the choice of assets to sell (but not the quantities) of all other companies as given (pure strategy Nash equilibrium). An insurance company has revealed its preference by choosing to sell an asset i over selling an asset j so, therefore, it must be the case that if it would have chosen to sell asset j *instead* of asset i, then its trading losses would have been higher.

The theorem above states that if we look at the asset that has not been chosen to be liquidated by an insurance company, then it must be the case that among the chosen ones with the same liquidity, there is no asset with smaller commonality, which would also then mean smaller liquidation losses by Lemma 4. And among the chosen assets with the same commonality, there is no asset with a lower liquidity. Otherwise, the company should have chosen a different asset to liquidate, as it would have allowed to reduce losses. This result rests on the Lemma 3, from which we know that liquidation costs decrease in liquidity.

Commonality of the assets, everything else equal, leads to a higher equilibrium quantity sold and therefore higher liquidation losses for two reasons. One is that there would be more agents in the market who could sell the asset, which is a standard crowding-out argument. The second is the amplification of the crowding effect through over-selling of the commonly-held assets that we discussed above. Therefore, the theorem 1 states that for a given liquidity, insurance companies will choose to sell less commonly-held assets, anticipating smaller selling pressure in these markets. Moreover, for a given commonality, insurance companies prefer to sell assets with higher liquidity.

In the data, we expect to find the following patterns:

1. Everything else constant, insurance companies are more likely to sell liquid assets.

2. Everything else constant, insurance companies are less likely to sell commonly-held assets.

3. Everything else constant, among the assets that are liquidated, those that are sold by more insurance companies exhibit larger price impacts.

2.6 Overlap in Liquid and Illiquid Assets

Consider two scenarios — one where the commonly-held assets are liquid, and the other when the commonly-held assets are illiquid. When would the fire-sale losses be higher? We argue that in the market of corporate bonds the overlap of liquid assets leads to larger fire-sale losses.

The reason is the following. Given that only some assets are chosen to be sold in a fire sale, insurance companies sell common liquid assets, but do not liquidate common illiquid assets. Effectively, the illiquidity of common assets deters the over-selling of such assets, and reduces overall liquidation losses.

A numerical example in Table 1 illustrates this argument. Two identical insurance companies have two common assets and each hold one asset individually. We compare two scenarios, in which companies always have two liquid and one illiquid asset. In the first scenario it is the separately-held assets that are illiquid, and we refer to this scenario as 'overlap in liquid assets'. In the second scenario the illiquid asset is commonly-held.

If companies were to sell each bond in their portfolio, then the trading losses are larger when the overlap is in illiquid assets. That is because commonality of the assets generates inefficient over-selling in that asset, and if this asset has low liquidity, the trading losses are amplified. However, if companies face restrictions on the minimum selling quantity, we obtain the opposite result. The reason is because they chose not to sell the commonly-held illiquid asset 'D'. This reduces the externality from common ownership and lowers the trading losses.

Note also that with overlap in illiquid assets the trading losses are lower in the constrained case than in the unconstrained case. This is because the requirement to sell a minimum quantity acts as a commitment not to participate in the joint market and eliminates the negative externality of common ownership in asset 'D'. The opposite is true if the overlap is in liquid assets. The minimum-quantity constraint forces all selling into the joint markets, increasing liquidation losses.

Overall we conclude that in the market of corporate bonds, where the OTC nature of transactions imposes a minimum trading quantity, the commonality of liquid assets exaggerates fire-sale losses.

2.7 Portfolio Formation

In the analysis above we treated asset portfolios as given. It is natural to ask how much of fire-sale risk can be avoided by foreseeing the dangers of commonality in liquid bonds and avoiding investing in them to begin with. Unfortunately, there are only a few liquid corporate bonds, as we document in our empirical analysis. So insurance companies cannot choose to hold liquid bonds that are not held by other insurance companies, because there are no such bonds. However, everything else equal, we can expect insurance companies to take into account the dangers of commonality in liquid bonds. With an increase in the corporate bond holdings that leads to commonality, insurance companies prefer commonality in less liquid bonds to commonality in liquid bonds. That is, with an increase in bond holdings, insurance companies invest in illiquid bonds, allowing the commonality of such bonds to increase. This is another empirical prediction that we test in data.

3 Data

3.1 Bond Level Data

The Financial Industry Regulatory Agency (FINRA) launched the Trade Reporting and Compliance Engine (TRACE) on July 1, 2002 to provide detailed information on secondary market corporate bond transactions. Since the implementation of the final phase on October 1, 2004, essentially all US corporate bond transactions are reported. We use the enhanced TRACE data base, which contains uncapped volumes and therefore more information for our liquidity measure. The raw disseminated TRACE data contains errors such as duplicates, reversals and same-day corrections, which lead to liquidity biases. Therefore, Dick-Nielsen (2014) proposes a filter to eliminate these erroneous data points. We apply this filter and other standard procedures to the enhanced TRACE data. We also complement transaction level data with bond characteristics from FISD. We keep only bonds where we have information about issue size, issuance date and maturity date. All bonds that survive the filtering procedure constitute our baseline corporate bond universe. We refer to Appendix A.2 for details on the cleaning procedure.

3.2 Individual Bond Trades

The National Association of Insurance Commissioners (NAIC) provides comprehensive data of US insurance companies. As part of their annual statements, insurers have to file individual bond and equity transactions (Schedule D). We use information on insurers' individual year-end bond holdings (Part 1), all bonds acquired during a year (Part 3), all bonds sold, redeemed or otherwise disposed of during a year (Part 4), and all bonds acquired and fully disposed of in a year (Part 5). The data contains Committee on Uniform Security Identification Procedures (CUSIP) identification, a date of disposal or acquisition (which is typically the trade date plus one day, not the settlement date), the actual costs (including broker commission and other related fees, excluding accrued interest and dividends), and the par value of the trade.

Schedule D – Parts 3-5 contains different types of erroneous records (e.g. negative bond prices, negative or zero transaction amounts, transaction amounts larger than the initial offering amount) which we excluded for obvious reasons. We also drop all transactions with missing or useless CUSIPs (e.g. containing punctuation characters or being of a length unequal to 9) and missing dates or dates before or after the year where the filing was submitted. Furthermore, the data contains every disposal or acquisition of a bond. In particular, this includes non-market transactions such as option exercises (called, converted, put), redemptions, direct transfers, pay downs, adjustments, write-offs, tax-free exchanges or maturity. We label these transactions as *non-trades*, while the remaining transactions are denoted by *trades*. We need both non-trades and trades to back out portfolios during a year from reported year-end portfolios.

After the initial cleaning, we only keep observations that have a matching CUSIP in our corporate bond universe. We are left with a total of 638,169 trades in 21,998 bonds and 122,676 non-trades in 14,599 bonds from 2005 to 2015. Furthermore, we define primary trades as trades smaller or equal to issue size that happen on trading days after the minimum of issuance date and dated date and before maturity date plus 30 days. Secondary market trades are defined as primary market trades that happen within 14 days after issuance, but before 14 days before maturity. Table 3 shows the differences in sample composition. We focus our attention on secondary market transactions, excluding the purchases at the origination and disposals right before the maturity of bonds. The purpose is to exclude transactions that happen for mechanical reasons related to the life cycle of a bond.

3.3 Individual Portfolios

Schedule D – Part 1 data contains company-level year-end bond portfolios. Similar to the transaction data, we only keep observations with positive par and fair values and with par values smaller than issue size. Again, we only keep observations with a matching CUSIP in the clean TRACE data. We use both trades and non-trades to construct pre-catastrophe portfolios from year-end data. We aggregate the par value of incoming and outgoing trades and non-trades between the date before a catastrophe hit and the year-end on a company-bond level. Then we add the preceding outflows and subtract the inflows to the par values in year-end portfolios.[10]

3.4 Institutional Characteristics

An important source of information about how strongly individual companies are affected by catastrophes is given by Schedule T - Exhibit of Premiums Written. This section of the quarterly statement filings contains information on direct premiums written, losses unpaid and losses paid. The latter is defined as the amount actually paid out to policyholders. We use losses paid in the states hit by a catastrophe to identify which insurers might face the risk of fire sales.[11]

We complement the data with quarterly insurer characteristics from SNL Financial, which collects and processes annual and quarterly statement pages filed by individual companies to NAIC. In particular, we get the total value of assets as a measure for company size and the risk-based capital (RBC) as a measure for financial constraints. We also get the total value of liquid assets, which includes cash, cash-equivalents and short-term investments of less than 3 months.

3.5 Identification of Affected Companies

We interpret unusually devastating catastrophes as liquidity shocks for P&C insurance companies. Once a catastrophe hits, insurers have to evaluate their liquidity needs in order to service policyholders' claims. While it is possible to anticipate disasters to some extent (e.g. hurricane season), it is very hard to predict the exact date and location on short notice (e.g. less than a week), let alone the actual intensity. Swiss Re sigma

[10] To support the validity of our procedure, we apply the same procedure to construct previous year-end portfolios from year-end data. On average, we are able to exactly match the par value of about 97% of all insurer-bond observations.

[11] Manconi et al. (2016) identify affected insurers by looking at the market share of insurers in 2004. Then they select the top then largest insurers in the disaster states and add 8 re-insurers that faced rating changes during or after Katrina. Liu (2016) measures insurance companies' liquidity needs by calculating an expected claim variable.

reports from 2005 to 2015 contain information on aggregated insured losses of major catastrophes (i.e. property and business interruption losses, excluding life and liability insurance losses).[12] Table 2 shows the catastrophe events with insured losses above $10B between 2005 and 2015.

Based on the Spatial Hazard Events and Losses Database for the United States (SHELDUS), the Hazards & Vulnerability Research Institute provides information about the affected states for each of these catastrophes.[13] Together with insurer activity in each state we can identify (potentially) affected insurers.

Losses paid on direct business are net of reinsurance, i.e. they represent only the losses that insurance companies have to bear themselves. They do, however, have to pay out the whole insured amount to the policyholders, which includes the re-insured part. We observe the total amount paid to the policyholders including reinsurance at the annual level and see that in the years relevant for our analysis insurance companies paid out more than what their direct losses were. Therefore, they recovered reinsured amounts in subsequent years. So losses paid on direct business underestimate (for the periods in question) the amount that insurance companies actually paid out.

We sum over the direct losses paid in the states affected by catastrophes in the quarter where the disaster hit and the subsequent quarter. We then normalize the resulting amount by the total amount of liquid assets insurance companies held at the end of the last quarter before a catastrophe. We identify insurance companies as affected if their loss to cash ratio is above a certain threshold. We report the results using a 75% threshold, but our findings are robust to using 100% and 50% as thresholds.

As can be seen from Figure 2, the aggregate losses paid on direct business peak following the catastrophes that we classify as aggregate shocks. This supports the validity of using losses on direct business as the measure of upcoming payments that insurance

[12] All reports can be found at `www.swissre.com/sigma/`.

[13] All reports can be downloaded from `http://hvri.geog.sc.edu/SHELDUS/index.cfm?page=reports`.

companies had to prepare for.

While this measure works well for P&C insurers, it does not work well for reinsurance companies due to the different nature of their business model and corresponding reporting standards.[14] Figure 3 illustrates the difference in the dynamics of direct losses paid for by insurers and re-insurers. The losses paid on direct business for insurance companies (Panel A) increase following the catastrophes, which are marked by vertical dotted lines. For re-insurers we do not see the same pattern (Panel B). While losses paid on direct business increase after some catastrophes, like in 2008, they do not increase after others, such as in 2005. Moreover, the level of losses paid for by reinsurers is only marginal compared to P&C insurers. Therefore, we focus our analysis on insurance companies, as our identification strategy seems to be the most accurate for their business model.

3.6 Fire-Sale Windows

We define a fire-sale window as two weeks before until two weeks after a catastrophe occurred. During such a time window, insurance companies observe the damage and form expectations about claims they have to service in the near future. Because state-level information on ex-post losses paid is available on a quarterly basis, we have to group some catastrophes and extend the fire-sale window accordingly. For instance, there were three hurricanes in 2005 – Katrina, Rita and Wilma – where we see corresponding losses paid in the last quarter of 2005 and the first quarter of 2006. In this case, the fire-sale window ranges from August 11, 2005 (two weeks before Katrina) to November 2, 2005 (two weeks after Wilma).

The second fire-sale window is given by hurricane Ike, which hit on September 6, 2008. The third and fourth are both in the same year again and given by a drought in the Corn Belt, which started on July 15, 2012 and hurricane Sandy, which made landfall

[14] We identify reinsurance companies by looking at the business focus reported in SNL. We classify each company that reports a (large) reinsurance focus as a reinsurer.

on October 24, 2012.

The 2005 fire-sale window provides an ideal environment for testing our hypotheses. First, the cumulative insured damage of the three hurricanes was exceptional in recent history. This ensures that insurers cannot simply rely on reinsurance contracts to cover all their expenses. Second, the losses are concentrated in five states. This helps our identification strategy in picking up affected companies. We therefore use the 2005 fire-sale window as our main empirical laboratory. However, we run robustness checks on a pooled sample of all fire-sale windows. For each fire-sale window, we construct portfolios at the beginning of the window and compute liquidity and commonality measures for these pre-catastrophe portfolios.

3.7 Liquidity Measures

In case of a liquidity shock, affected companies do not only care about the execution quality of a bond transaction, but also the dollar volume which can easily be traded in a particular bond. Moreover, daily liquidity measures based on transaction prices can typically only be computed for a small subsample of liquid bonds, since price-related measures are not defined when there is no trading activity. Therefore, we measure liquidity of a bond by averaging over the daily buy-side trading volume of a bond within a specific time interval. This has the advantage that the measure is defined even if there is no trading activity at all. We also use total trading volume as an alternative liquidity measure. Both measures indicate whether trading activity and hence liquidity are high or low (Friewald et al., 2012).

We interpret transactions in TRACE as buy (sell) orders if the dealer was a seller (buyer) and the customer a buyer (seller). The enhanced TRACE data provides uncapped trading volumes which we use to compute daily buy volumes for each bond. Then we average over the last 180 calendar days to get our liquidity measures. The resulting liquidity measure is in dollar and represents the directed order flow within a given period of time in the spirit of Chacko et al. (2008).

While bonds that are rarely traded are typically seen as illiquid, it does not necessarily mean that selling those bonds yields large price impacts. In our theoretical framework, price impacts are determined by the unobservable arrival rate of buy orders to the dealer market. We can therefore back out implied arrival rates from observed price impacts. We compute these implied arrival rates by comparing TRACE execution prices to the average Thomson Reuters Valuation mid-quotes[15] in the week prior to a trade. A higher implied arrival rate is associated with lower price impacts and thus reflects higher liquidity. We refer to this liquidity measure as *Lambda Sell*.

3.8 Commonality Measures

Commonality of a bond captures the extent to which a bond is common to the companies within a given sector. The sector is defined by the type of liquidity shocks that are likely to hit many firms in the sector at the same time. In our current analysis, we consider natural catastrophes as liquidity shocks to P&C insurance companies. We distinguish between two types of commonality of a bond — holding commonality and selling commonality.

To measure the holding commonality of a bond i we calculate the following

$$h_{i,t}^{\text{com}} = \frac{\text{\# of Companies holding bond } i}{N},$$

where $h_{i,t}^{\text{com}}$ is bounded between $[1/N, 1]$ with N being the total number of P&C insurance companies present in our sample at date t. This measure does not take into account how dispersed the ownership of the bond is between these companies. However, incorporating the effect of ownership concentration does not alter the results in a substantial way,

[15]These quotes can be obtained through Datastream and are denoted as 'clean prices', i.e. they exclude accrued interest and broker fees.

so we opt for a simpler measure.[16] We refer to *Commonality* as the commonality of the holdings. However, in the analysis of price impacts we complement the measure of holding commonality by the measure of selling commonality. We measure the commonality of selling by counting the number of companies that sold the bond during a fire-sale window, *Number of Sellers*. While the two measures of commonality are clearly positively related, the former captures the trade-off which bonds to sell, while the latter captures the realized crowding in the market due to the decisions to sell the same bond.

4 Bond Portfolios and Price Impacts

4.1 Bond Holdings of Insurance Companies

P&C insurance companies invest on average more than 60% of their assets in long-term bonds.[17] Figure 4 demonstrates that the total value of assets invested in bonds increased steadily from 2005 to 2015 (Panel A), but the distribution across asset classes remained essentially unchanged (Panel B). The trend in the value of bond holdings reflects the fact that insurance companies are net buyers of bonds. Due to restrictions on data availability, we focus on corporate bond holdings and transactions as defined in Section 3.

[16] To take into account how dispersed the ownership of the bond is between these companies, we could define the following weight

$$\omega_{i,t}^{\text{dis}} = \left(N \sum_{j=1}^{N} \omega_{j,i,t}^2 \right)^{-1} \quad \text{where } \omega_{j,i,t} = \frac{Q_{j,i,t}}{\sum_{j=1}^{N} Q_{j,i,t}},$$

which lies between $[1/N, 1]$. The higher $\omega_{i,t}^{\text{dis}}$, the higher the dispersion of bond holdings given a number of companies holding the bond, and, therefore, the higher the commonality of that bond. Then the product of the two measures, $h_{i,t}^{\text{com}} \cdot \omega_{i,t}^{\text{dis}}$, measures the commonality of a bond for the P&C insurance sector. The higher this number, the higher the commonality of the bond i in a given period t. It is harder to interpret the magnitude of $h_{i,t}^{\text{com}} \cdot \omega_{i,t}^{\text{dis}}$ than the magnitude of $h_{i,t}^{\text{com}}$, while both measures deliver very similar results. Therefore, we use only $h_{i,t}^{\text{com}}$ to capture the commonality of holdings.

[17] According to NAIC reporting standards these comprise all bonds with maturity dates greater than one year when purchased, excluding loan-backed and structured securities. In particular, this includes corporate, municipal and treasury bonds. On average, P&C insurers hold about 30% of their bond portfolio in corporate bonds, 35% in municipal bonds and 10% in US government bonds (see `http://www.naic.org/capital_markets_archive/130924.htm`).

As has been documented before, insurance companies hold overlapping portfolios of assets.[18] We measure to what extent a given bond is held by multiple insurance companies by calculating its commonality. Figure 5 depicts the cross-sectional distribution of commonality before the 2005 fire-sale window. The distribution is heavily skewed to the right, confirming that there are a few bonds that are held by many insurance companies, and a lot of bonds that are uniquely held by some companies.

The corporate bonds insurances companies hold are very heterogeneous with respect to their liquidity. Moreover, the distribution of liquidity measures is extremely skewed to the right, as can be seen in Figure 6. There are a few very liquid bonds, as represented by a few observations at the far right on the x-axis. There are also a lot of very illiquid bonds, which had very few transactions in the last 180 days before the measurement date, as represented by a mass of observations near the y-axis. More specifically, for the pre-catastrophe portfolios in 2005, about 9% of bonds had no transactions in the last 180 days, and the top 1% of most liquid bonds account for more average buy volume (our main liquidity measure) than the bottom 70% of most illiquid bonds.

Given that there are only a few highly liquid bonds, we investigate to what extent these bonds are the ones commonly held by insurance companies, i.e. they contribute to the similarity of corporate bond portfolios of insurance companies. Figure 7 shows that liquidity of the bond and its commonality are strongly positively related in our sample. When we split the sample of bonds into quintiles based on the measure of their liquidity, the averages and quartiles of commonality monotonically increase across quintiles. Corporate bonds that are more liquid are indeed more likely to be held by a larger number of companies.

[18] See Chiang and Niehaus (2016) for evidence about life insurance companies and Girardi et al. (2018) for all insurance companies, including P&C. The latter document that there is more similarity at the asset-class level than at the issue level within asset classes.

4.2 Liquidation Policy of Affected Companies

To identify fire sales and associated price effects, we follow Ellul et al. (2011) and investigate the liquidation policy of insurance companies following a liquidity shock. We look at bonds that have been liquidated in the fire-sale window and see which bonds were more likely to be sold, as well as which companies liquidated more of the bonds in their portfolios. We model the probability that an insurance company holding a bond before a liquidity shock will sell the bond when the catastrophe hit as a probit function

$$\Pr(D_{i,j} = 1) = \Phi(\beta_0 + \beta_D D_i^{\text{Aff}} + \beta_X X_i + \beta_Y Y_j + u_{i,j}), \tag{12}$$

where $D_{i,j}$ is equal to 1 if the company i holding a bond j sold the bond in the fire-sale window, and equal to zero if it did not sell it. We restrict our analysis to only the bonds that were in the portfolio of insurance companies prior to the aggregate shocks. D_i^{Aff} is equal to one if a company has a loss-to-liquid ratio above 75% and zero otherwise.

X_i are the characteristics of insurance companies that are likely to influence its decision to liquidate bonds. These are the (log) total assets as a proxy for size and (log) RBC as a proxy for regulatory constraints, and bond-specific par values for each company. Y_j are typical bond characteristics, namely the issue size, bond age, remaining bond life, arrival rate of buy orders, investment grade dummy, downgrade dummy, and commonality measure. We define all variables in Appendix Table A1.

First, we investigate the liquidation policy by the type of P&C insurance company. Estimation results for the year 2005 are in Table 5. The model in column 1 represents all insurance companies, column 2 contains only stock companies, column 3 represents mutual companies, and column 4 represents other companies.[19] The dummy of affected company is positive and significant for stock insurance companies. This means that

[19] Other insurance companies mostly consist of non-standard insurance business models, like risk retention groups and syndicates related to insurance exchanges such as Lloyd's.

stock insurance companies, which we identify as affected based on their ratio of losses paid on direct business relative to the amount of cash they hold, are more likely to sell bonds than insurance companies that we identify as not affected. This is consistent with our hypothesis that affected insurance companies liquidate part of their illiquid portfolio (bonds) to satisfy the payments on their claims.

However, the lack of significance for the affected dummy on mutual companies is consistent with Laux and Muermann (2010), who argue that mutual insurers have an advantage in raising capital during times of distress. Therefore, mutuals might be more likely to turn to other sources of funds to get funding rather than selling their bond holdings. Moreover, our dummy for the affected company seems to be inappropriate for other insurance business models, as indicated by the negative sign on the affected dummy in column 3. In the subsequent analysis we focus on stock insurance companies, as the primary players in the P&C insurance sector.

Insurance companies are more likely to sell bonds that are more liquid as proxied by larger issue size, smaller par value, shorter bond age and higher remaining bond life, as well as higher realized buy volume. Importantly, insurance companies liquidate less of commonly-held bonds, as indicated by the negative and statistically significant coefficient on the commonality measure. This is consistent with our hypothesis that crowding by other insurance companies creates larger price impacts and that insurance companies try to avoid selling commonly-held bonds.

We extend the analysis to incorporate other fire-sale windows in our sample. The estimation results are presented in Table 6. The affected dummy is positive and significant for the whole sample, for other types of insurance companies, and importantly, for stock insurance companies (column 4). Therefore, we are confident that our affected dummy is selecting companies that indeed had to sell correctly among the stock insurance companies on the whole sample. The effect of controls is as expected: more liquid bonds were more likely to be sold, as well as those that were below investment grade and downgraded during the fire-sale window, consistent with Ellul et al. (2011). Insurance companies took the commonality of bonds in their portfolios into account and were more likely to sell uniquely-hold bonds than commonly-held ones, everything else equal.

Next, we investigate further the impact of liquidity on stock insurance companies' decision to sell a bond. We look at alternative measures of liquidity. In Table 5 columns 5-7, we look at three additional liquidity measures. The first one is total realized trading volume (column 5), so instead of including only the transactions from TRACE that we identified as client-dealer transaction in which client is buying, the first measure of liquidity, we also look at the sell-transactions and inter-dealer trades. The results for this measure are essentially the same as in column 1 with our main liquidity measure.

Columns 6 and 7 show the results for the liquidity measures that are motivated by the model of Chacko et al. (2008), as described in Section 3.7. In column 3 we identify the implied liquidity of the bond using price impacts that only the selling volume in TRACE generated, and in column 4 we use a liquidity measure which is constructed using price impacts from all the trade volume in TRACE. All measures of liquidity have positive and statistically significant coefficients, confirming that more liquid bonds are more likely to be sold during a fire-sale window, while at the same time more commonly-held bonds are less likely to be sold.

We repeat this analysis of different liquidity measures on the whole sample and report results in Table 6. Realized buy and total trading volume positively predict the probability that the bond will be sold, while measures of implied liquidity in columns 3 and 4 are insignificant.

Overall, we observe that affected stock insurance companies are more likely to sell bonds. This indicates that there is indeed excessive selling pressure in our fire-sale windows, mostly coming from stock insurance companies. All else equal, they chose to sell more liquid and less-commonly held bonds. As a next step, we quantify the price impacts of these fire sales.

4.3 Market-Specific Price Impacts

Fire sales of insurance companies can influence the market and move prices of bonds they liquidate. In order to capture the extent of this effect, we measure price impacts that affected P&C insurance companies generate in the markets of liquidated bonds. We calculate price impacts as deviations of observed trading prices $P_{i,t}$ of bond i at time t from the estimate of a bond-specific unobserved fundamental price $\bar{P}_{i,t}$. With this measure, we aim to capture a temporary deviation of the market price from the fundamental value of the bond, as opposed to a permanent price change due to a revision in the fundamental value.

Measuring price impacts is challenging in our setting for at least two reasons: the fundamental price of a bond is hard to estimate, given asymmetric information about the liquidation process and potential recovery in case of a default, while observed trading prices are rather noisy due to the bilateral nature of trading in the OTC market.

We resolve these challenges in two ways. First, in the current subsection, we look at the whole market of a liquidated bond, while in the next subsection we restrict our analysis to only the NAIC trades by insurance companies.

To approximate the fundamental price before a shock hits, we add information from two additional sources. First, we obtain data from the Bank of America Merrill Lynch (BAML) Corporate Bond Master Index. BAML is one of the largest corporate bond dealers and its quotes are commonly used as benchmark prices (e.g., Hendershott et al., 2016). We use this index to account for movements in the overall bond market in our sample, as the fundamental price of the bond is likely to be influenced by aggregate factors, such as changes in the risk-free interest rate, aggregate recovery rates or aggregate risk aversion. To capture these effects, we use the Corporate Bond Master Index as a deflator. In particular, we approximate bond-specific time series of fundamental prices as $\bar{P}_{i,t} = \bar{P}_{i,0} \cdot \text{Index}_t$, where Index_t is normalized to 1 at $t = 0$ on the pre-catastrophe date. Here the $\bar{P}_{i,0}$ refers to the estimate of the bond-specific fundamental price before the fire sales. In order to estimate this, we add a second source of information — Thomson Reuter Valuations (mid-point) provided by Datastream. These are non-binding quotes that are available on a daily basis for more than 40,000 bonds. We use clean prices which are estimated without taking any trading fees into account. We get data prices from Datastream two weeks prior to the start of each fire-sale window.

For every bond, we calculate the 30-day expanding-window moving average of deviations of observed prices from the fundamental value $P_{i,t}/\bar{P}_{i,t} - 1$. The price impact is then measured as the largest relative drop of the traded prices below fundamental value within a fire-sale window, namely $|\min\{P_{i,t}/\bar{P}_{i,t} - 1, 0\}|$. Figure 8 illustrates the methodology for a sample of bonds. For further suggestive evidence, we plot the daily average price impact across fire sold bonds with a large trading volume relative to issue size. For these bonds, we expect the largest and most long-lasting price impacts. Indeed, Figure 9 shows that prices for these bonds, where the sales of affected companies exert a lot of price pressure, tend to reverse in about 7 months on average. This is consistent with a related finding by Massa and Zhang (2011). Bonds that are not subject to these fire sales do not show this pattern on average.

This approach allows us to compute bond-specific measures of price impacts to analyze their cross-sectional determinants. From our hypotheses, we expect a positive unconditional relationship between liquidity and price impact, which should disappear once we control for commonality. We account for commonality of each bond in two ways — we measure the commonality of the holdings in this particular bond in the portfolio two weeks prior to the fire-sale window, as well as count how many companies sold a specific bond. The latter quantity captures the commonality in the selling behavior of insurance companies during the fire sale. Our model predicts that insurance companies take into account the holding commonality of the bond, selling less of commonly-held bonds in order to minimize exerted price impacts and associated liquidation losses. This is confirmed in the analysis of the previous subsection in Tables 5 and 6. However, our model also predicts that insurance companies do not fully take into account the detrimental effect of a bond's commonality and therefore, the commonality in the selling behavior should cause larger price impacts. This means that the number of sellers should be positively related to price impacts.

Table 7 reports OLS regressions of price impact on these controls for 2005. There is indeed evidence of a positive relationship between liquidity and price impact, as results in columns (1) indicate. The higher the liquidity of the bond, as measured by the realized buy trading volume, the larger the price drop in the market during the 2005 fire-sale window. This result is consistent with evidence reported in the prior literature. In particular, Massa and Zhang (2011) showed that bonds with larger amounts outstanding (a proxy for liquidity) exhibited more negative abnormal returns during hurricane Katrina. Ellul et al. (2011) also report that younger bonds and bonds of larger size exhibited larger price reversals, indicating they experienced larger price drops during the fire-sale window.

A positive association between the liquidity of the bond and the price impact that this bond experiences during a fire-sale window might appear counter-intuitive, but it is fully consistent with our model predictions. Because liquid bonds are commonly-held, they are over-sold relative to the case of an integrated insurance company. Therefore, they experience larger price impacts than the bonds that are sold by fewer companies.

Including bond controls, such as issue size, bond age and remaining life, does not change the relation between liquidity and price impacts — more liquid bonds were more likely to be sold and resulting price impacts were larger than for less liquid bonds, as reported in column 2. The same holds for the total trading volume as a liquidity measure (see column 3).

Market participants take the commonality of bonds in their portfolios into account. As we report in Table 6, they sell less of bonds that are commonly-held. This leads to smaller price impacts for commonly-held bonds, everything else equal; see column 4 in Table 7 . However, the insurance companies do not fully take into account the negative externality that selling a commonly-held bond generates on other market participants. Commonly-sold bonds exhibit larger price impacts, as is shown by a positive coefficient on the "Number of Sellers" variable in column 4. This is consistent with predictions of our model that multiple insurance companies over-sell commonly-held bonds relative to the case of an integrated-insurance company. The magnitude of the coefficient on the variable "Number of Sellers" measures the extent of the fire-sales risk in the market. Buy-trading volume in column 4 is statistically insignificant, consistent with our hypothesis that once commonality of the bond is taken into account, liquidity is not related to the observed price impacts. Once we control for commonality of the bond, liquid bonds do not experience larger price impacts. The result holds after we include bond controls (column 5), or use alternative liquidity measures (column 6 and 7), and after we control for the quantity of the bond sold (column 8).

A similar pattern can be observed over the whole sample period, as reported in Table 8. Liquidity is positively associated with price impacts, controlling for bond characteristics (columns 2 and 3). Once we control for commonality of that bond (columns 4-8), liquidity is either not related to the price impacts, or is negatively associated with price impacts. This is consistent with our intuitive understanding of liquidity as measuring the ease of trading or smaller price movements in response to trades.

The key message of this analysis is that commonality of a bond influences its trading pattern — more commonly held bonds are sold less than uniquely-held bonds, but not “sufficiently” less because of negative externality that insurance companies fail to account for. This leads to larger price impacts for common bonds. If we look at the relation between liquidity and price impacts that bonds experienced during fire sales, we might observe a positive one. This is, however, due to the fact that liquid bonds are common bonds, because there are very few liquid bonds. Once we account for the commonality of bonds, liquidity is negatively related to price impacts, as one would expect.

4.4 Company-Specific Price Impacts

In this subsection we revisit the challenge of measuring price impacts generated by fire sales of bonds by affected insurance companies. Now we restrict our attention to the trades reported in the NAIC database by P&C insurance companies. The reason we focus on these trades is that we have more information regarding each transaction, including the identities of counter-parties. We incorporate this information in our analysis by including insurer-fixed effects. This allows us to reduce the cross-sectional noise in prices and eliminate partly the effects of the bilateral nature of trades on prices (e.g. Hendershott et al., 2016). We analyze then a relation between the commonality, liquidity of the bond and the price impacts that selling this bond generated, taking out the effect of who exactly sold that bond.

As an estimate of the fundamental value we take clean mid-quote valuations by Thomson Reuters from Datastream, two weeks prior to the fire-sale window. This is $\bar{P}_{i,0}$ in the notation from the previous section. A unit of observation in this analysis is a sale transaction reported in the NAIC data set by any P&C insurance company that took place during the fire-sale window. We include in our analysis only sale transactions where the transaction price $P_{i,t}$ is below the estimate of the fundamental value $\bar{P}_{i,0}$. We look at all P&C insurance companies as opposed to only those that we prior identified as affected by the catastrophes, because we are interested in price impacts on all market participants we can identify.

The estimation results are reported in Table 9 for catastrophes in 2005 and in Table 10 for the entire sample. The main results are the same as in the analysis of the whole market. Namely, liquidity unconditionally is positively related to the price impacts, as reported in columns 1-3 in Tables 9 and 10. Controlling for commonality changes the relation between liquidity and price impacts and makes it insignificant, as reported in columns 4-6 in Table 10. If liquidity of a bond is measured using the implied arrival rate of the buy orders (Lambda Sell), then the relation between liquidity and price impacts, controlling for commonality, is negative, as can be seen from columns 7-8 in Tables 9 and 10.

This result indicates that insurance companies indeed sell bonds in their portfolio in such a way that, controlling for the commonality, the average price impact on the bonds is the same, irrespective of the liquidity when measured by the realized trading volume before the fire sales. However, the price impacts on more liquid bonds are smaller when liquidity is inferred from the price reactions that these trades generated.

Regression results in Table 9 in columns 4-6 speak for a positive relation between liquidity and price impacts, even after controlling for commonality of bonds. This result can also be explained with the help of our model in the following way. Suppose that companies that were hit more severely happened to hold more liquid bonds than those that were hit less severely. Then, even controlling for the commonality of bonds, the insurance companies that had to sell more were the companies that had more liquid assets, depressing prices on liquid assets and generating more price impacts than in the markets of less liquid assets that were sold by less affected companies. Therefore, a positive relation between liquidity and price impact, controlling for commonality of bonds, is consistent with the story of our paper. Yet it requires an assumption that hardly always holds in practice: firms with the largest liquidity shocks are holding more liquid assets than other firms. Indeed, we only observe this pattern in 2005, and mostly for the sub-sample of stock companies.[20] In the whole sample of four fire-sale windows, as indicated in Table 10, this assumption seems not to hold, as the relation between liquidity and price impacts controlling for commonality (columns 4-6) is insignificant.

Overall, from the analysis in this section we conclude that insurance companies experienced larger price impacts selling bonds commonly sold by others. They balanced out selling less of commonly hold bonds with the benefit of selling more liquid bonds, as these bonds are more common than less liquid bonds. In the end, the price impacts that insurance companies faced during the fire-sale window are positively related to the commonality of bonds, and negatively or not significantly related to the liquidity of these bonds, consistent with the model predictions.

4.5 Placebo Test

In order to verify that the positive relation between liquidity and price impacts is present only during the periods of fire sales, we conduct a placebo test. We repeat the analysis of price impact determinants at an arbitrarily chosen date.

In our setting, we refer to a fire-sale event as a situation when many insurance companies are forced to sell part of their portfolio urgently. Our model predicts a positive relation between liquidity of the bond and price impacts in such events, given that liquid bonds are more commonly-held. On the other hand, during normal market times, when only a few insurance companies are selling bonds, liquidity is expected to be negatively related to price impacts. This is exactly what we expect to find during a placebo test.

We choose September 6, 2010 as a hypothetical beginning of the placebo fire-sale window. We estimate the model of aggregate market price impacts, as in Section 4.3, on a placebo window. Results are reported in Table 11. As can be seen from columns 1-3, liquidity is either negatively related to price impacts, or not significantly related.

[20] Regressions as in Table 9 run on sub-samples of stock, mutual, and only affected P&C companies are available upon request.

In other words, in normal times, one would expect liquid bonds to have smaller price impacts, irrespective of their commonality. The relation remains negative and significant once we control for commonality, as reported in columns 4-8. We conclude that during normal times more liquid bonds are expected to generate smaller price impacts, regardless of whether we control for commonality.

5 Fire-Sale Risk

Figure 10 indicates that affected companies indeed rush to sell the most liquid, most commonly held assets in fire sales. In this section we characterize the aggregate commonality of liquid bonds in the P&C insurance sector. We measure the extent to which liquid bonds of insurance companies are commonly-held. This is in contrast to the similarity measure of Girardi et al. (2018), which weights liquid and illiquid bonds equally, or to the commonality measures in Greenwood et al. (2015), who assign higher weight to the illiquid assets. Commonality of liquid bonds increases price impacts in fire sales. To access the evolution of the fire-sales risk in the P&C insurance sector, we look at the time series of the commonality of liquid bonds.

5.1 Liquidity of Holdings over Time

First, we look into how much insurance companies hold in liquid versus illiquid bonds. We group bonds into three liquidity brackets, based on the average realized buy trading volume (from TRACE) 180 days before the portfolio measurement date t.[21] We group the

[21]For robustness, we did this analysis also with a 180-days forward liquidity measure. The reason to take the trading volume 180 days after the transaction and not before is that insurance companies tend to acquire many bonds in the first few months of the bond's trading life and then hold them. Average buy volume in the 180 days before the transaction and 180 days after for an average bond in TRACE is very similar up to 2010; after this date the buy trading volume in 180 days before increases dramatically while the buy trading volume in the 180 days after the trade stays on the level before 2010. We attribute this change to the documented increase in the trading volume during the first month after bond issuances, which is a response of corporate bond underwriters to the regulation intended to disentangle the roles

lowest 50% of all bonds into the “illiquid” group, 10% of the most liquid bonds into the “liquid” group, and the middle 40% are labeled “less liquid”. The time-trend we observe is robust to different cut-offs.

Panel A of Figure 11 illustrates that insurance companies invest mostly in the less-liquid bonds, with approximately the same dollar volume invested in the most liquid and the most illiquid bonds up until 2009. After 2009 insurance companies in our sample invest more in bonds, in particular in less liquid and illiquid bonds. Panel B of Figure 11 highlights that while the share of less liquid investment stays approximately constant, the share of illiquid investment grows.

Overall, we observe an increase in the total holdings of corporate bonds by P&C insurance companies. Importantly, they invest more in less liquid and illiquid bonds, and the proportion of illiquid bonds is increasing.

5.2 Commonality of Holdings over Time

In order to evaluate how the increase in the investment in corporate bonds after 2009 affected the fire-sales risk in the P&C sector, we look at the dynamics of average commonality within the liquidity buckets. Panel A of Figure 12 illustrates that over the whole sample average commonality is highest among liquid bonds. While the commonality of liquid bonds experiences an increase in 2009, it declines and stays relatively constant towards the end of the sample. In contrast, the commonality of less liquid bonds, as well as illiquid bonds, is increasing steadily after 2009. Using the insights from Figure 11, we argue that insurance companies expand their investment in less liquid and illiquid bonds, increasing commonality of these bonds. They do not seem to expand their investment in the most liquid bonds, potentially anticipating adverse consequences of the increase

of bond under-writers and secondary-market dealers. See Nagler and Ottonello (2017). Therefore, we use the forward-looking 180-days average buy trading volume as an alternative measure of the bond’s liquidity. The results are qualitatively identical and differ only marginally quantitatively.

in commonality of the most liquid bonds. Therefore, we see evidence consistent with insurance companies taking into account the adverse effects of commonality of bonds at the stage of portfolio formation and balancing the benefits of liquidity with the costs of high commonality of liquid bonds.

Panel B of Figure 12 demonstrates that when we account for the dollar volume invested in the corresponding bonds, we see that the commonality of liquid investment is declining, while the commonality of less liquid and illiquid bonds is increasing. Using the insights of our model, we argue that the dangerous commonality is that of the liquid bonds. We see in Panel B of Figure 12 that it is declining, indicating that the aggregating risk was highest in 2010, and it has reduced by the end of the sample.

It is important to emphasize that in our analysis the commonality of liquid bonds contributes more to the fire-sales risk than the commonality of illiquid bonds. This is due to the endogenous decision of financial institutions to sell liquid assets more than illiquid ones in fire sales. Therefore, from our point of view, the fire-sale risk present in the P&C insurance sector in the past decades did not increase. This is in contrast to the view of the literature that considers a proportional liquidation strategy in fire-sales (e.g. Greenwood et al., 2015; Duarte and Eisenbach, 2015). If financial institutions indeed choose to liquidate assets proportionally, then the fire-sale risk is exaggerated by the commonality of illiquid assets. From that point of view, the fire-sales risk in the P&C insurance sector could be seen as increasing over the last few decades. Which approach is more relevant is an empirical question. In our regressions of the probability that a bond is sold (Tables 5 and 6) we see evidence that insurance companies are indeed more likely to sell liquid bonds and less likely to sell commonly-held bonds, everything else equal. This evidence lends support to our approach of an endogenous liquidation policy. Therefore, we conclude that while commonality of illiquid holdings might increase fire-sales risk, it is to a lesser extent than the commonality of liquid bonds.

5.3 Aggregate Commonality Measure

Building on the insights of the previous section, we construct a liquidity-weighted-average of corporate bonds' commonality in the portfolios of P&C insurance companies

$$\text{AggCom}_t = \sum_{i=1}^{I} h_{i,t}^{\text{com}} \cdot h_{i,t}^{\text{liq}} \cdot \omega_{i,t}^{\$},$$

where i references bonds present in the portfolios of P&C insurance companies at date t, $h_{i,t}^{\text{com}}$ is the % of companies holding this bond, capturing the commonality of the bond i, and $\omega_{i,t}^{\$}$ is the dollar-weight of the bond in the market-wide portfolio of all P&C insurance companies. The liquidity weights $h_{i,t}^{\text{liq}}$ are calculated using deciles of liquidity distribution of bonds at each point in time. Namely, bonds are sorted into 10 buckets based on their liquidity at time t, measured as realized trading volume 180 days before. Bonds in the most liquid bucket get the highest weights, while the bonds in the lowest bucket get the lowest weights, such that $\sum_{i=1}^{I} h_{i,t}^{\text{liq}} = 1 \; \forall t$.

We look at the evolution of this measure over time on a monthly frequency. The top part of Figure 13 illustrates that liquidity-weighted aggregate commonality was highest in 2010, and steadily declined afterwards towards the end of our sample. The speed of increase in the fire-sales risk was largest in the crisis, but then insurance companies adjusted their portfolios towards less liquid bonds, which decreased the relative weight of the commonality of liquid bonds, and, therefore, decreased the fire-sales risk in the system. The bottom panel plots a non-liquidity weighted commonality for comparison. In particular, we drop the liquidity weights, which changes the scale of the aggregate measure. Importantly, it also changes the dynamics of the aggregate commonality at the end of our sample. Without liquidity weights, we see that aggregate commonality declined after its peak in 2010, but stabilized in 2011 and then showed only a moderate decline towards 2015. The liquidity-weighted top plot and the non-liquidity weighted bottom plot tell a similar story — that fire-sales risk was highest in 2010 after the crisis, but the top plot emphasizes a substantial decline in the fire-sales risk from 2010 to 2015 driven by an increase in the holdings of less illiquid bonds where commonality is lower, and not as dangerous as commonality in liquid bonds. Therefore, it is important to incorporate liquidity weights in the analysis of aggregate commonality of portfolios with the goal of assessing inherent fire-sale risk, as ignoring the liquidity dimension paints a different picture.

6 Conclusion

We study the implications of commonality of bonds for fire-sale losses and generated price impacts. We argue that since there are only a few liquid bonds, financial institutions tend to hold them more commonly than less liquid bonds. Since liquid bonds, everything else equal, have smaller transaction costs, these bonds are more attractive to sell in order to raise funds. Hit with a market-wide liquidity shock, financial institutions over-sell commonly-held bonds, which are the more liquid bonds. Hence, we observe that liquid bonds have higher price impacts during fire sales than less liquid bonds. Once we control for commonality, though, the relation between liquidity and price impacts is negative. This implies that observed price impacts are larger for liquid bonds because liquidity proxies for the commonality of the bond.

The policy implications of our findings are twofold. First, while the average similarity of financial institutions' portfolios might be low, it is the similarity of the liquid assets, or commonality of the liquid bonds that matters the most for fire-sale risk. If liquid bonds are commonly held, then financial institutions are exposed to fire-sale risk, which results in larger price impacts and substantial liquidation losses. Therefore, the proper measurement of the similarity that contributes to fire-sale risk should emphasize the importance of liquid assets. Second, encouraging financial institutions to hold more liquid assets might increase commonality of their liquid holdings, thereby increasing fire-sale risk. However, providing incentives for financial institutions to minimize the commonality of their liquid assets may enhance financial stability.

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Tables

Table 1: The Effect of Overlap on Prices and Trading Losses

The table represents liquidation outcomes for when the overlap is in liquid assets (left-hand column) and when the overlap is in illiquid assets (right-hand column). Price-impact function is assumed to be $\rho_i = 0.1\sqrt{(\frac{Q_i}{\lambda_i})}$. Each of two firms is hit with a liquidity shock $I = 10$. The minimum selling quantity is $\bar{Q} = 4$ is imposed in the bottom part of the table. The two firms have overlap in assets 'A' and 'D', while only the 1st firm holds assets 'B', and the 2nd firm holds asset 'C'. In all scenarios both firms have two liquid and one illiquid assets. In the first scenario the illiquid asset is separately-held, so we describe it as 'overlap in liquid assets'. In the second scenario the illiquid asset is jointly-held, so we refer to it as 'overlap in illiquid assets'.

		Overlap is liquid				Overlap is illiquid			
		B	A	D	C	B	A	D	C
	Liquidity	1	2	2	1	2	2	1	2
$\bar{Q} = 0$	Quantity	3.25	4.68	4.68	3.25	5.94	4.27	2.14	5.94
	Price Impact ρ	0.18	0.216	0.216	0.18	0.172	0.207	0.207	0.172
	Total Losses	52.2%				55.8%			
$\bar{Q} = 4$	Quantity	0	6.76	6.76	0	7.34	5.28	0	7.34
	Price Impact ρ	0	0.26	0.26	0	0.192	0.23	0	0.192
	Total Losses	70.2%				52.4%			

Table 2: Most Costly Catastrophes in the US between 2005 and 2015
Insured losses of catastrophe events in the US taken from Swiss Re sigma No 1/2016, Table 10 - The 40 most costly insurance losses (1970-2015) in $M indexed to 2015. Insured losses are defined as property and business interruption, excluding liability and life insurance losses. The figures are based on based on data from Property Claim Services and the National Flood Insurance Program. We focus on large catastrophes with insured losses above $10B.

Insured Loss	Event	Date	Affected States
79,663	Hurricane Katrina	August 25, 2005	LA, MS, AL
12,252	Hurricane Rita	September 20, 2005	TX, LA
15,248	Hurricane Wilma	October 19, 2005	FL
22,343	Hurricane Ike	September 6, 2008	TX, LA, AR, IL, IN, KY, MO, OH, PA
11,351	Drought in Corn Belt	July 15, 2012	CA, NV, ID, MT, WY, UT, CO, AZ, NM, TX, ND, SD, NE, KS, OK, AR, MO, IA, MN, IL, IN, GA
36,115	Hurricane Sandy	October 24, 2012	MD, DE, NJ, NY, CT, MA, RI, NC, VA, WV, OH, PA, NH

Table 3: Corporate Bond Trading Statistics

All data are from NAIC. The first column represents all transactions that can be identified as trades. Primary trades have a par value smaller or equal to issue size and happen on trading days after the minimum of issuance date and dated date and before maturity date plus 30 days. Secondary trades are primary trades that happen after 14 days after issuance and 14 days before maturity.

	All	Primary	Secondary
No of Trades	638,169	631,771	489,368
No of Buys	383,661	381,320	247,401
No of Sells	254,508	250,451	241,967
No of Issues	21,998	21,870	20,388
Avg No of Trades per Issue	29	28.9	24
Avg No of Buys per Issue	19	19	14.2
Avg No of Sells per Issuer	13.2	13.1	12.9
Avg Trade Size ($M)	1.45	1.45	1.36
Avg Buy Size ($M)	1.47	1.46	1.3
Avg Sell Size ($M)	1.43	1.42	1.41
Avg Issue Size ($M)	946	946	955
Avg Bond Age	2.45	2.43	3.13
Avg Bond Life	7.61	7.62	7.35

Table 4: Average Company Statistics

All data are from SNL Financial, except for buy/sell volume. Reinsurers are identified as having a self-reported 'Reinsurance Focus' or 'Large Reinsurance Focus'. Stock and mutual companies exclude reinsurers and can be identified by their ownership structure. The remaining companies (non-reinsurer, non-stock, non-mutual) are mostly risk retention groups and syndicates related to insurance exchanges such as Lloyd's. Buy/sell volume are based on corporate bond transactions.

	All	Reinsurers	Stock	Mutual	Others
No of Companies	3,253	61	2,288	472	432
Total Assets (in $M)	782	3,974	726	845	435
Premium Written (in $M)	53.7	5.72	56.9	63.2	32
Losses Paid (in $M)	30.7	3.55	32.1	37.8	18
Losses Incurred (in $M)	31.6	3.45	33.2	38.7	18.4
Total Invested (in $M)	663	3,523	603	742	372
Share in Bonds	0.681	0.66	0.719	0.635	0.517
Share in Stocks	0.109	0.168	0.0882	0.192	0.112
Share in Cash	0.187	0.141	0.171	0.14	0.354
Buy Volume (in $M)	13.5	37.1	14	9.18	10.9
Sell Volume (in $M)	9.05	27.2	9.4	6.24	6.36

Table 5: Liquidation Policy Following the 2005 Liquidity Shock

This table reports probit model estimates for probability of the bond being sold as a function of bond and company characteristics. The dependent variable is a dummy that equals one if the insurance company (holding the bond) sells the bond when catastrophes hit, and zero otherwise. We measure the portfolio composition of insurance companies two weeks prior to each catastrophe, and we record the disposal of the bond as related to the catastrophe, if it was sold up to two weeks after the catastrophe. We define all variables in Table A1. We report t-statistics based on White's robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Probability of Bond Being Sold						
	All	Stock	Mutual	Others	Stock	Stock	Stock
Affected Company	0.007	0.082***	-0.058	-0.495***	0.083***	0.082***	0.085***
	(0.41)	(4.04)	(-1.18)	(-4.23)	(4.09)	(3.67)	(3.78)
Log(Commonality)	-0.100***	-0.080***	-0.148***	-0.120***	-0.073***	-0.082***	-0.081***
	(-8.67)	(-5.74)	(-5.12)	(-3.73)	(-5.22)	(-5.34)	(-5.31)
Log(Buy Volume)	0.062***	0.057***	0.089***	0.057*			
	(6.41)	(5.17)	(3.28)	(1.80)			
Log(Total Volume)					0.092***		
					(8.65)		
Log(Lambda Sell)						0.009**	
						(2.26)	
Log(Lambda Avg)							0.006*
							(1.91)
Log(Issue Size)	0.107***	0.095***	0.113***	0.130***	0.061***	0.150***	0.157***
	(7.10)	(5.45)	(2.82)	(2.80)	(3.65)	(8.17)	(8.62)
Log(Bond Age)	-0.059***	-0.050***	-0.032	-0.126***	-0.039***	-0.060***	-0.056***
	(-7.47)	(-5.22)	(-1.55)	(-5.40)	(-4.17)	(-5.59)	(-5.43)
Log(Bond Life)	0.055***	0.053***	0.060***	0.084***	0.052***	0.064***	0.059***
	(6.19)	(5.10)	(2.85)	(2.86)	(4.96)	(5.01)	(4.83)
Investment Grade	-0.328***	-0.212***	-0.455***	-0.828***	-0.197***	-0.227***	-0.228***
	(-15.95)	(-8.54)	(-8.58)	(-14.15)	(-7.96)	(-8.39)	(-8.32)
Downgrade	-0.061**	-0.075**	-0.051	-0.012	-0.073**	-0.093**	-0.094**
	(-1.99)	(-2.08)	(-0.66)	(-0.13)	(-2.02)	(-2.37)	(-2.39)
Log(Par Value)	-0.051***	-0.043***	-0.039*	-0.105***	-0.044***	-0.050***	-0.051***
	(-7.44)	(-5.50)	(-1.94)	(-4.85)	(-5.56)	(-5.60)	(-5.78)
Log(Insurer Size)	0.080***	0.057***	0.230***	0.066	0.056***	0.056***	0.058***
	(6.40)	(4.07)	(4.23)	(1.27)	(3.99)	(3.56)	(3.66)
Log(RBC)	-0.034***	-0.012	-0.186***	-0.024	-0.011	-0.005	-0.005
	(-3.08)	(-0.99)	(-3.79)	(-0.45)	(-0.93)	(-0.36)	(-0.35)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68759	49626	12751	6382	49626	38848	38608
Pseudo R^2	0.051	0.035	0.080	0.159	0.036	0.035	0.035

Table 6: Liquidation Policy Following All Liquidity Shocks

This table reports probit model estimates for probability of the bond being sold as a function of bond and company characteristics. The dependent variable is a dummy that equals one if the insurance company (holding the bond) sells the bond when catastrophes hit, and zero otherwise. We measure the portfolio composition of insurance companies two weeks prior to each catastrophe, and we record the disposal of the bond as related to the catastrophe, if it was sold up to two weeks after the catastrophe. Each model contains fire sale window dummies. We define all variables in Table A1. We report t-statistics based on White's robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Probability of Bond Being Sold						
	All	Stock	Mutual	Others	Stock	Stock	Stock
Affected Company	0.031***	0.048***	-0.077***	0.189***	0.048***	0.044***	0.044***
	(3.05)	(4.02)	(-2.85)	(6.29)	(4.07)	(3.56)	(3.55)
Log(Commonality)	-0.079***	-0.076***	-0.070***	-0.090***	-0.073***	-0.087***	-0.089***
	(-11.61)	(-9.22)	(-4.12)	(-5.22)	(-8.84)	(-10.17)	(-10.31)
Log(Buy Volume)	0.065***	0.059***	0.109***	0.047***			
	(12.43)	(9.83)	(7.45)	(3.19)			
Log(Total Volume)					0.076***		
					(13.05)		
Log(Lambda Sell)						0.000	
						(0.06)	
Log(Lambda Avg)							0.003
							(1.56)
Log(Issue Size)	0.085***	0.084***	0.042**	0.117***	0.068***	0.137***	0.136***
	(10.03)	(8.31)	(1.97)	(5.06)	(6.94)	(13.71)	(13.74)
Log(Bond Age)	-0.043***	-0.046***	-0.012	-0.055***	-0.040***	-0.094***	-0.085***
	(-8.00)	(-7.27)	(-0.83)	(-3.71)	(-6.64)	(-16.15)	(-15.68)
Log(Bond Life)	0.003	0.013**	-0.004	-0.041***	0.014**	0.002	0.006
	(0.63)	(2.01)	(-0.33)	(-2.64)	(2.13)	(0.28)	(0.78)
Investment Grade	-0.277***	-0.240***	-0.337***	-0.418***	-0.235***	-0.257***	-0.262***
	(-21.85)	(-15.95)	(-10.25)	(-12.53)	(-15.59)	(-16.37)	(-16.60)
Downgrade	0.157***	0.148***	0.173***	0.187***	0.147***	0.149***	0.142***
	(6.91)	(5.47)	(3.09)	(2.96)	(5.44)	(5.18)	(4.93)
Log(Par Value)	-0.011**	0.006	-0.026**	-0.071***	0.006	0.008	0.006
	(-2.47)	(1.14)	(-2.18)	(-6.33)	(1.15)	(1.37)	(1.07)
Log(Insurer Size)	0.035***	0.000	0.113***	0.173***	-0.000	-0.005	-0.004
	(4.46)	(0.03)	(4.47)	(6.83)	(-0.04)	(-0.47)	(-0.37)
Log(RBC)	-0.020***	0.004	-0.094***	-0.119***	0.004	0.005	0.006
	(-3.01)	(0.44)	(-4.05)	(-5.00)	(0.49)	(0.58)	(0.65)
Fire Sale Window FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	335577	240678	58941	35958	240678	220536	220308
Pseudo R^2	0.068	0.063	0.078	0.106	0.064	0.060	0.060

Table 7: Market-Specific Price Impacts in 2005

This table reports determinants of price impacts in bonds that were sold in the fire-sale window of 2005: two weeks prior to the Hurricane Katrina and two weeks after the Hurricane Wilma. The left-hand side variable is the price impact which is calculated as follows: first, we use the BoAML Corporate Bond Master Index to capture the aggregate pattern in the market of corporate bonds. We normalize it using the quotes from June 31, 2005. Then for every bond we take Datastream clean prices two weeks prior to the fire sale window, $\bar{P}_{i,0}$, and adjust it in subsequent days for the movement of the market, $\bar{P}_{i,t} = \bar{P}_{i,0} \cdot \text{Index}_t$. Next we deflate observed transaction prices from TRACE (value-weighted daily averages of dealer-client trades) to capture deviations from the trend: $P_{i,t}/\bar{P}_{i,t} - 1$. Then we calculate the 30-day moving average of these deviations to smooth out daily fluctuations. Next, we find a minimum of the moving-average over the fire-sale window and define the price impact as the absolute value of this minimum. Formally, for a bond i the price impact is calculated as

$$\rho_i = |\min_{t \in [11.08.2005 - 2.11.2005]} (MA_{30}(P_{i,t}/\bar{P}_{i,t} - 1))|.$$

It captures the largest drop in price that was observed in the market of that bond within the fire-sale window, relative to the proxy of the fundamental value. We define all variables in Table A1. We report t-statistics based on White's robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	0.117***	0.125**		0.009	0.062			
	(25.52)	(2.07)		(0.19)	(1.17)			
Log(Total Volume)			0.197**			0.063		
			(2.52)			(0.80)		
Log(Lambda Sell)							-0.131***	-0.136***
							(-4.54)	(-4.60)
Log(Commonality)				-0.792***	-0.568***	-0.565***	-0.567***	-0.570***
				(-10.07)	(-7.05)	(-6.76)	(-7.22)	(-7.27)
Number of Sellers				0.110***	0.090***	0.090***	0.094***	0.070**
				(3.12)	(2.70)	(2.69)	(2.76)	(2.19)
Log(Issue Size)		-0.377***	-0.433***		-0.055	-0.058	0.170*	0.150
		(-3.45)	(-3.78)		(-0.48)	(-0.46)	(1.72)	(1.48)
Log(Bond Age)		0.345***	0.366***		0.351***	0.350***	0.323***	0.317***
		(5.84)	(6.05)		(6.08)	(5.89)	(5.76)	(5.72)
Log(Bond Life)		0.520***	0.511***		0.400***	0.399***	0.302***	0.288***
		(7.78)	(7.78)		(5.81)	(5.85)	(3.63)	(3.42)
Investment Grade		-0.964***	-0.930***		-0.576***	-0.580***	-0.371***	-0.412***
		(-7.98)	(-7.60)		(-5.49)	(-5.44)	(-3.69)	(-3.88)
Log(Quantity Sold)								0.095**
								(2.11)
Constant		6.690***	6.613***	-2.887***	-1.964	-1.941	-3.193	-3.914*
		(3.53)	(3.50)	(-3.87)	(-0.92)	(-0.90)	(-1.52)	(-1.92)
Observations	2155	2155	2155	2155	2155	2155	2123	2123
Adjusted R^2	0.233	0.082	0.083	0.075	0.106	0.106	0.118	0.119

Table 8: Market-Specific Price Impacts for All Fire Sale Windows

This table reports determinants of price impacts in bonds that were sold in the fire-sale windows. The left-hand side variable is the price impact which is calculated as follows: first, we use the BoAML Corporate Bond Master Index to capture the aggregate pattern in the market of corporate bonds. We normalize it by its value two weeks prior to each fire sale window. Then for every bond we take Datastream clean prices two weeks prior to a fire sale window, $\bar{P}_{i,0}$, and adjust it in subsequent days for the movement of the market, $\bar{P}_{i,t} = \bar{P}_{i,0} \cdot \text{Index}_t$. Next we deflate observed transaction prices from TRACE (value-weighted daily averages of dealer-client trades) to capture deviations from the trend: $P_{i,t}/\bar{P}_{i,t} - 1$. Then we calculate the 30-day moving average of these deviations to smooth out daily fluctuations. Next, we find a minimum of the moving-average over the fire-sale window and define the price impact as the absolute value of this minimum. Formally, for a bond i the price impact is calculated as

$$\rho_i = |\min(MA_{30}(P_{i,t}/\bar{P}_{i,t} - 1))|.$$

It captures the largest drop in price that was observed in the market of that bond within the fire-sale window, relative to the proxy of the fundamental value. All models include fire sale window dummies. We define all variables in Table A1. We report t-statistics based on White's robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	-0.071**	0.090**		-0.070**	0.040			
	(-2.29)	(2.52)		(-2.29)	(1.15)			
Log(Total Volume)			0.109**			0.033		
			(2.57)			(0.78)		
Log(Lambda Sell)							-0.147***	-0.147***
							(-7.62)	(-7.57)
Log(Commonality)				-0.536***	-0.414***	-0.414***	-0.406***	-0.406***
				(-11.59)	(-7.95)	(-7.85)	(-7.90)	(-7.90)
Number of Sellers				0.160***	0.153***	0.154***	0.152***	0.152***
				(4.12)	(3.89)	(3.89)	(3.87)	(3.57)
Log(Issue Size)		-0.394***	-0.408***		-0.173**	-0.167**	0.042	0.042
		(-4.99)	(-5.26)		(-2.08)	(-2.01)	(0.53)	(0.52)
Log(Bond Age)		0.256***	0.260***		0.231***	0.225***	0.148***	0.148***
		(6.37)	(6.43)		(5.78)	(5.53)	(4.74)	(4.74)
Log(Bond Life)		0.296***	0.295***		0.221***	0.221***	0.093**	0.093**
		(6.93)	(6.92)		(5.28)	(5.26)	(2.00)	(2.00)
Investment Grade		-0.423***	-0.415***		-0.110	-0.114	0.097	0.096
		(-5.12)	(-5.04)		(-1.24)	(-1.29)	(1.05)	(1.03)
Log(Quantity Sold)								0.003
								(0.10)
Fire Sale Window FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5031	5031	5031	5031	5031	5031	4966	4966
Adjusted R^2	0.071	0.101	0.101	0.111	0.119	0.119	0.132	0.132

Table 9: Company-Specific Reported Price Impacts for 2005

This table reports determinants of price impacts reported by companies for bonds that were sold in the fire-sale window of 2005: two weeks prior to the Hurricane Katrina and two weeks after the Hurricane Wilma. The price impact is defined as the absolute value of the percentage deviation of company-bond-specific transaction prices reported in NAIC from Datastream clean prices two weeks prior to the fire sale window. We define all variables in Table A1. We report *t*-statistics based on White's robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	0.257***	0.632***		0.222**	0.448***			
	(3.15)	(4.88)		(2.57)	(3.68)			
Log(Total Volume)			0.743***			0.533***		
			(5.16)			(3.98)		
Log(Lambda Sell)							-0.151***	-0.158***
							(-4.28)	(-4.38)
Log(Commonality)				-1.223***	-0.829***	-0.807***	-0.928***	-0.963***
				(-6.71)	(-4.91)	(-4.82)	(-5.37)	(-5.35)
Number of Sellers				0.199***	0.178***	0.177***	0.186***	0.162***
				(7.05)	(6.68)	(6.67)	(6.97)	(5.51)
Log(Issue Size)		-1.021***	-1.114***		-0.630***	-0.713***	-0.064	-0.121
		(-4.33)	(-4.55)		(-2.67)	(-2.92)	(-0.33)	(-0.61)
Log(Bond Age)		0.343***	0.367***		0.327***	0.345***	0.207**	0.197**
		(3.59)	(3.74)		(3.47)	(3.59)	(2.47)	(2.38)
Log(Bond Life)		0.798***	0.779***		0.657***	0.648***	0.584***	0.561***
		(4.66)	(4.60)		(4.03)	(4.00)	(3.46)	(3.44)
Investment Grade		-1.381***	-1.323***		-1.048***	-1.012***	-0.928***	-1.000***
		(-6.21)	(-5.98)		(-5.06)	(-4.89)	(-4.41)	(-4.42)
Log(Quantity Sold)								0.158*
								(1.81)
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1817	1817	1817	1817	1817	1817	1810	1810
Adjusted R^2	0.157	0.225	0.227	0.230	0.260	0.261	0.260	0.262

Table 10: Company-Specific Reported Price Impacts for All Fire Sale Windows

This table reports determinants of price impacts reported by companies for bonds that were sold in the fire-sale windows. The price impact is defined as the absolute value of the percentage deviation of company-bond-specific transaction prices reported in NAIC from Datastream clean prices two weeks prior to the fire sale window. We define all variables in Table A1. We report t-statistics based on White's robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	0.238	0.313*		0.158	-0.028			
	(1.56)	(1.95)		(1.03)	(-0.18)			
Log(Total Volume)			0.489***			0.067		
			(2.76)			(0.39)		
Log(Lambda Sell)							-0.348***	-0.362***
							(-4.75)	(-4.92)
Log(Commonality)				-1.718***	-1.762***	-1.744***	-1.747***	-1.825***
				(-7.98)	(-6.77)	(-6.69)	(-6.68)	(-6.73)
Number of Sellers				0.556***	0.550***	0.548***	0.545***	0.456***
				(8.25)	(8.08)	(8.04)	(8.04)	(6.05)
Log(Issue Size)		-0.378	-0.525*		0.370	0.281	0.739**	0.578**
		(-1.34)	(-1.83)		(1.16)	(0.86)	(2.42)	(1.97)
Log(Bond Age)		0.193	0.253		0.074	0.112	-0.041	-0.046
		(1.09)	(1.44)		(0.42)	(0.65)	(-0.26)	(-0.29)
Log(Bond Life)		1.115***	1.117***		0.856***	0.861***	0.638***	0.599***
		(4.95)	(4.98)		(4.02)	(4.04)	(3.01)	(2.89)
Investment Grade		-0.484	-0.409		0.350	0.377	0.809*	0.566
		(-1.15)	(-0.97)		(0.76)	(0.82)	(1.67)	(1.17)
Log(Quantity Sold)								0.538***
								(2.66)
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fire Sale Window FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3726	3726	3726	3726	3726	3726	3713	3713
Adjusted R^2	0.429	0.435	0.435	0.460	0.463	0.463	0.467	0.469

Table 11: Bond-Specific Price Impacts for Placebo Window

This table reports determinants of price impacts in bonds that were sold in an arbitrary placebo fire sale window around 2010-09-06. We define all variables in Table A1. We report t-statistics based on White's robust standard errors are in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	-0.178***	-0.035		-0.134***	-0.070			
	(-7.57)	(-0.69)		(-6.16)	(-1.49)			
Log(Total Volume)			-0.042			-0.081*		
			(-0.83)			(-1.71)		
Log(Lambda Sell)							-0.076***	-0.077***
							(-3.72)	(-3.75)
Log(Commonality)				-0.297***	-0.315***	-0.316***	-0.288***	-0.290***
				(-5.26)	(-4.87)	(-4.84)	(-4.32)	(-4.32)
Number of Sellers				0.022	0.016	0.017	0.012	0.007
				(0.88)	(0.58)	(0.61)	(0.43)	(0.23)
Log(Issue Size)		-0.229**	-0.225**		-0.017	-0.012	0.001	-0.001
		(-2.45)	(-2.52)		(-0.20)	(-0.14)	(0.02)	(-0.02)
Log(Bond Age)		0.177***	0.174***		0.121**	0.119**	0.167***	0.168***
		(2.88)	(2.99)		(2.27)	(2.34)	(4.38)	(4.37)
Log(Bond Life)		0.303***	0.302***		0.251***	0.251***	0.197***	0.197***
		(5.74)	(5.78)		(5.51)	(5.54)	(4.01)	(4.01)
Investment Grade		0.085	0.082		0.364***	0.362***	0.461***	0.455***
		(0.83)	(0.81)		(2.76)	(2.77)	(3.71)	(3.72)
Log(Quantity Sold)								0.020
								(0.73)
Constant	3.278***	5.259***	5.314***	1.267***	-0.121	-0.024	-0.051	-0.261
	(9.37)	(3.77)	(3.94)	(3.08)	(-0.08)	(-0.02)	(-0.03)	(-0.16)
Observations	1170	1170	1170	1170	1170	1170	1150	1150
Adjusted R^2	0.038	0.093	0.093	0.086	0.124	0.124	0.144	0.144

Figures

Figure 1: Portfolio Liquidation

This figure illustrates the optimal liquidation policies of two agents. Agent 1 holds assets A and B, while agent 2 holds assets A and C. Asset A is the commonly-held asset. The down-ward slopping lines on the plot represent price-impact functions for the three assets, going from the top to the bottom in the order of decreasing liquidity. Asset A is assumed to be the most liquid, then asset C and asset B. If the two agents act as one, the case of an integrated insurance company, they chose to sell quantities of each asset such that the marginal price impacts on all assets are the same. This is represented by the horizontal dotted line, and solid vertical lines that indicated quantities of each asset sold. In the case when agents act separately in their own interest, they sell more of asset A and less of assets B and C. This equilibrium is represented by the dash-dotted vertical lines. The price impact on asset A is larger than before, while price impacts on assets B and C are smaller. This result illustrates that commonly-held assets exhibit larger price impacts than less commonly-held assets when there are multiple agents selling assets at the same time, i.e. in a fire-sale.

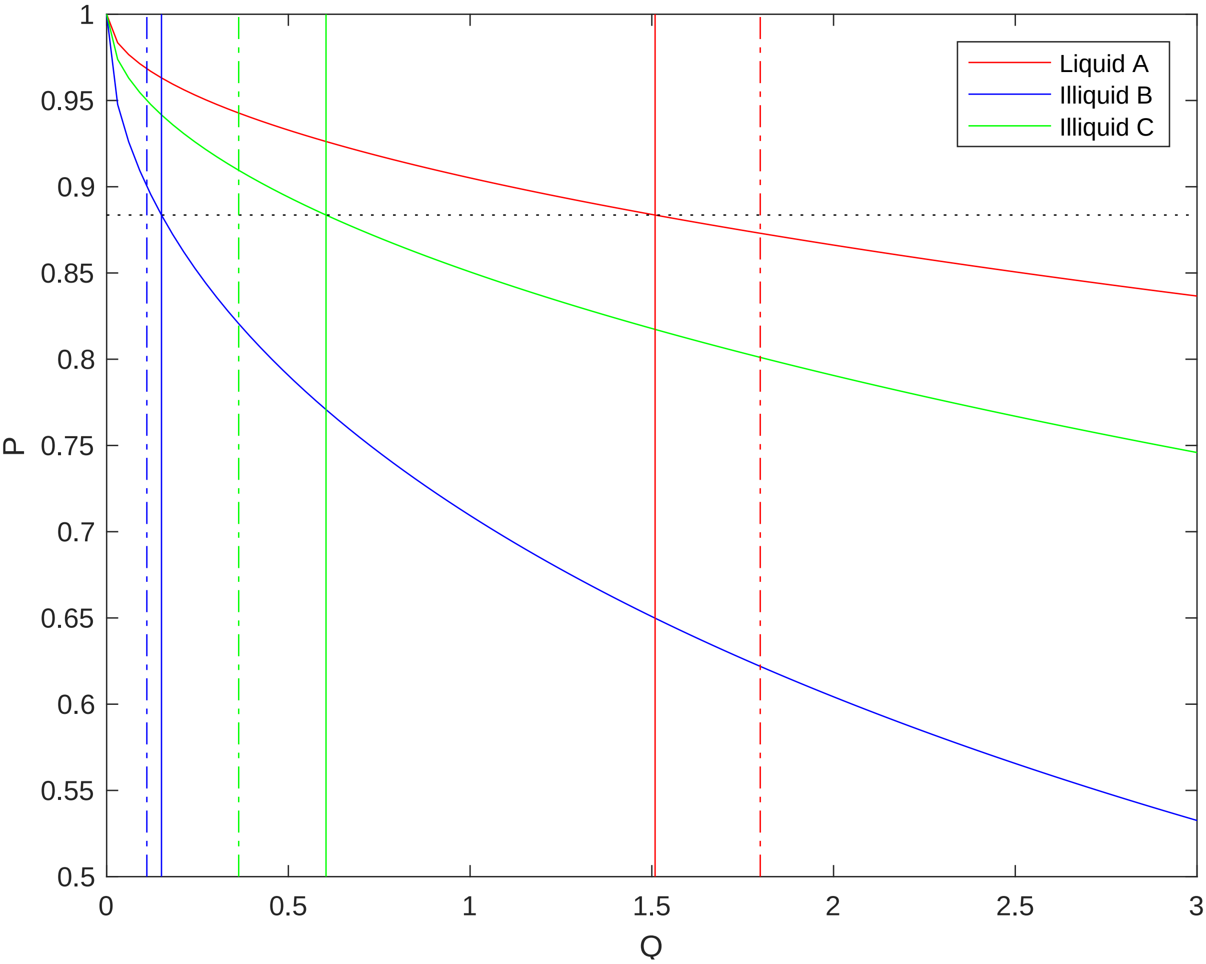


Figure 2: Aggregate Losses of P&C Insurance Companies
This figure demonstrates the dynamics of incurred (solid line) and paid (dashed line) losses on direct business in our sample. Both the incurred and paid losses increase following the catastrophes that we identified as aggregate shocks.

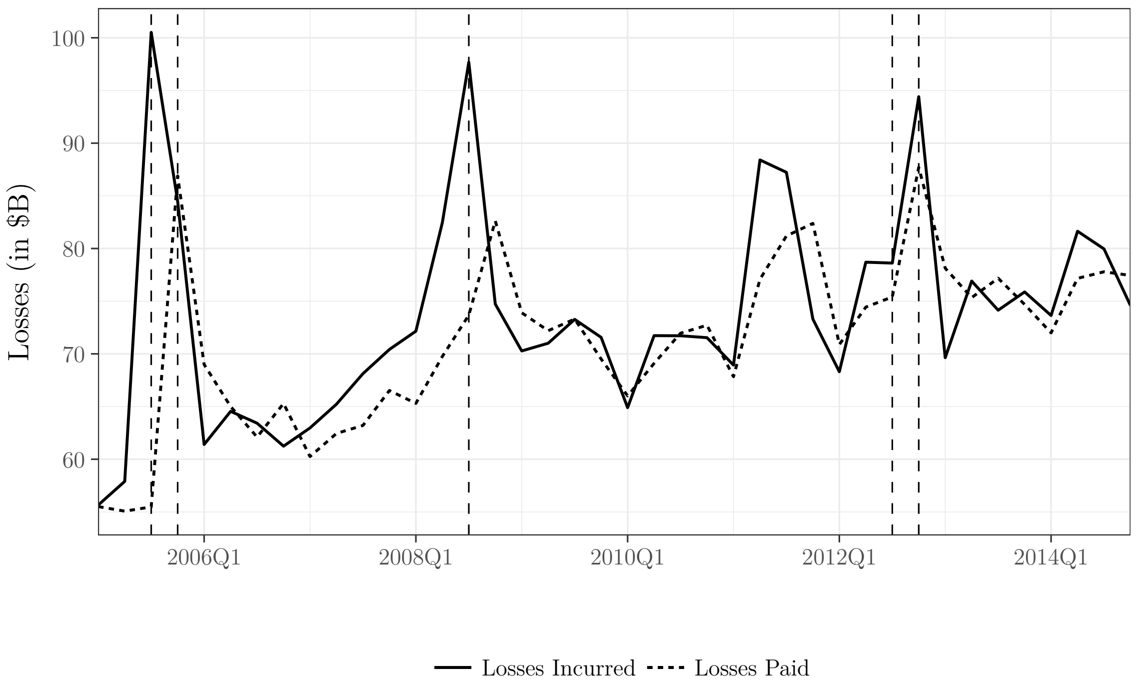
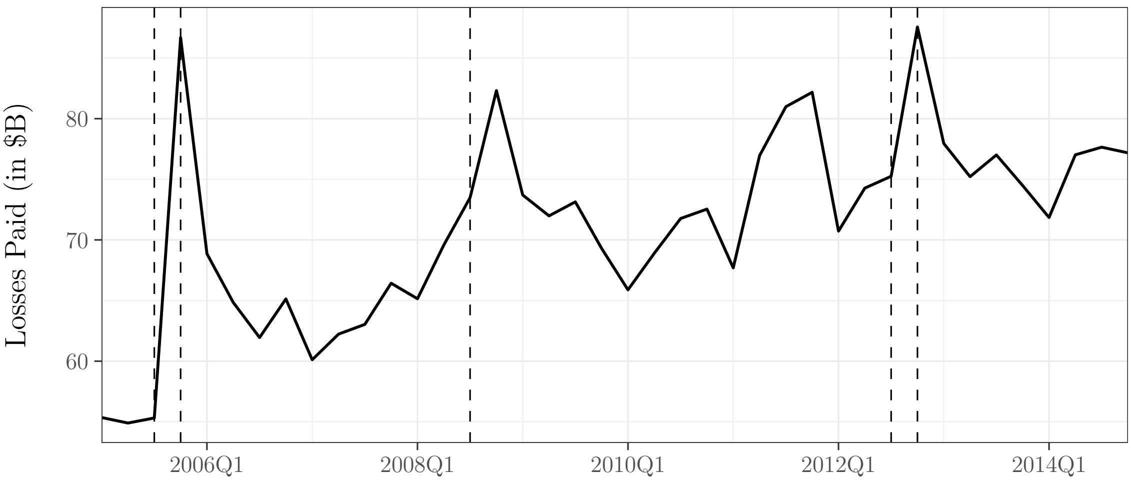


Figure 3: Losses Paid on Direct Business: P&C Insurers vs. Reinsurers
This figure demonstrates the difference between the dynamics of reported losses paid on direct business for insurers and re-insurers. It is clear that the difference in the business models of insurers and re-insurers commands a difference in the way losses are accounted for and reported. While losses paid on direct business increase for insurers following the catastrophes in our sample, we do not see the same patter for re-insurers

Panel A: P&C Insurers



Panel B: Reinsurers

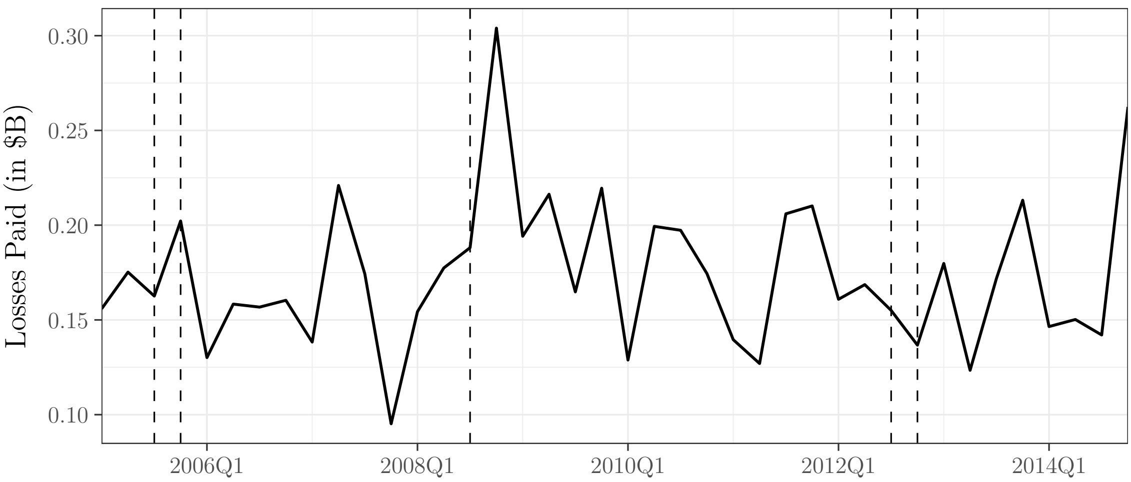


Figure 4: Asset Holdings in the P&C Insurance Sector
This figure demonstrates the composition of holdings by property and causality insurance companies and its evolution in time. The amount of assets invested in bonds has been increasing in time, making insurance companies net buyers on the bond market, even after accounting for replacement of maturing bonds. Panel A depicts the portfolio composition in absolute values, panel B in percentage terms.

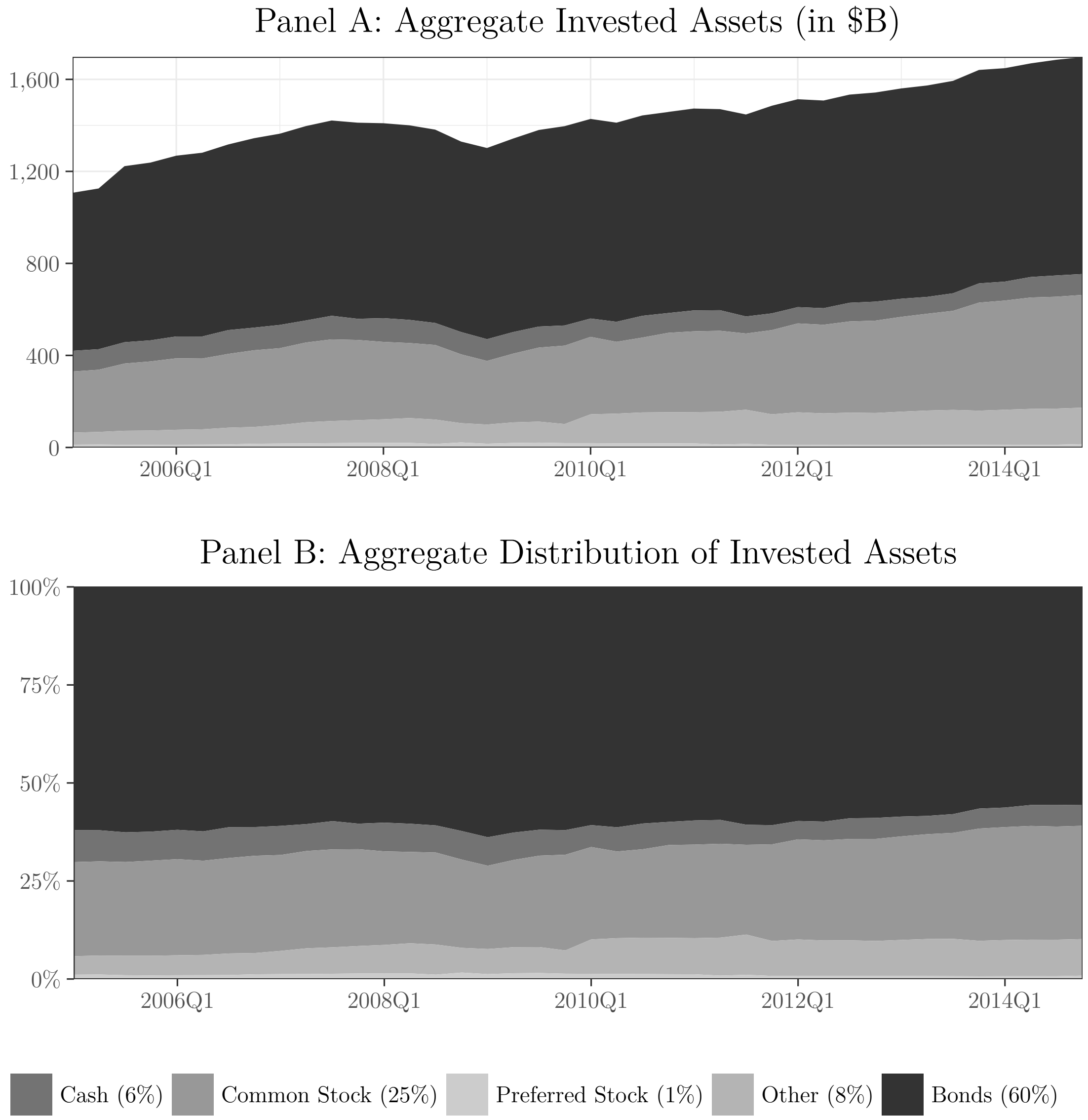


Figure 5: Commonality of Corporate Bonds

This graph shows commonality of corporate bonds, as measured on August 11, 2005 (two weeks before Hurricane Katrina). Commonality is defined as the number of companies that hold a specific bond divided by the total number of portfolios. To be present in the sample, the bond must appear in a portfolio of a P&C insurance company at least once in the sample.

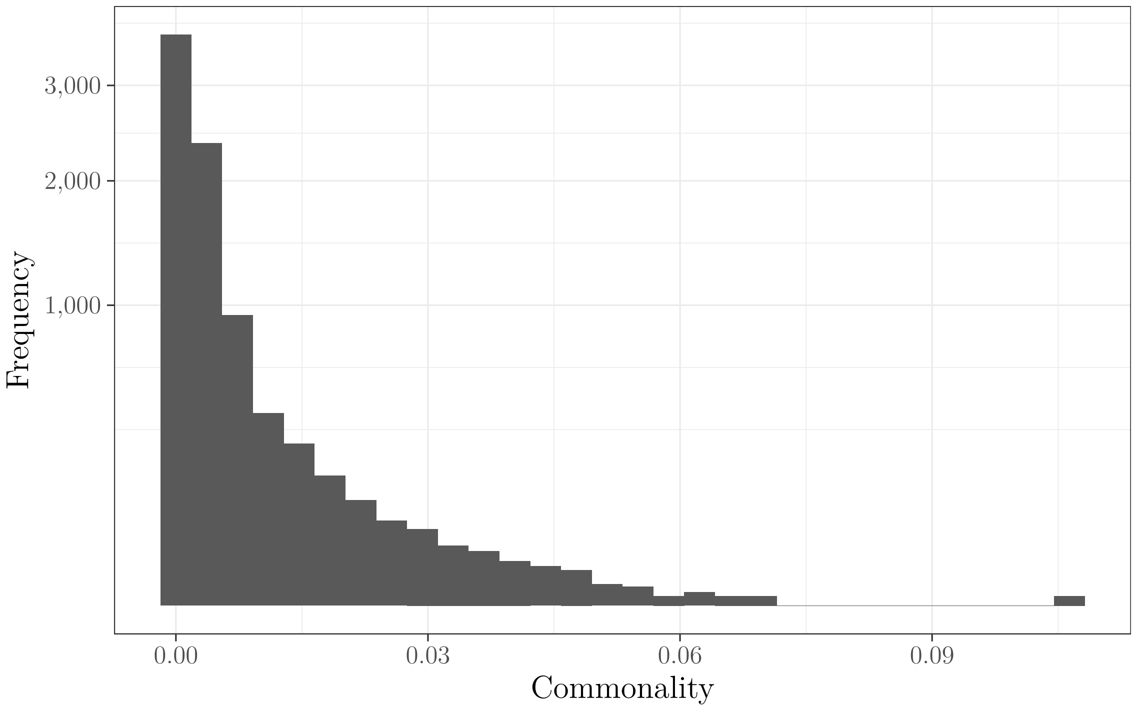


Figure 6: Liquidity of Corporate Bonds

This graph shows liquidity of corporate bonds, as measured on August 11, 2005 (two weeks before Hurricane Katrina) using a trading volume of the bond in the last 180 days. To be present in the sample, the bond must appear in a portfolio of a P&C insurance company at least once in the sample. The mass of observations on the y-axis represents bonds that did not have any transactions in the last 6 months of the measurement day. On the x-axis are the measures of trading volume in $M. On the y axis are a square root of the number of bonds (count). The most distinctive feature of this distribution is its extreme skew to the right. There are a few very liquid bonds, and a lot of very illiquid bonds in the portfolios.

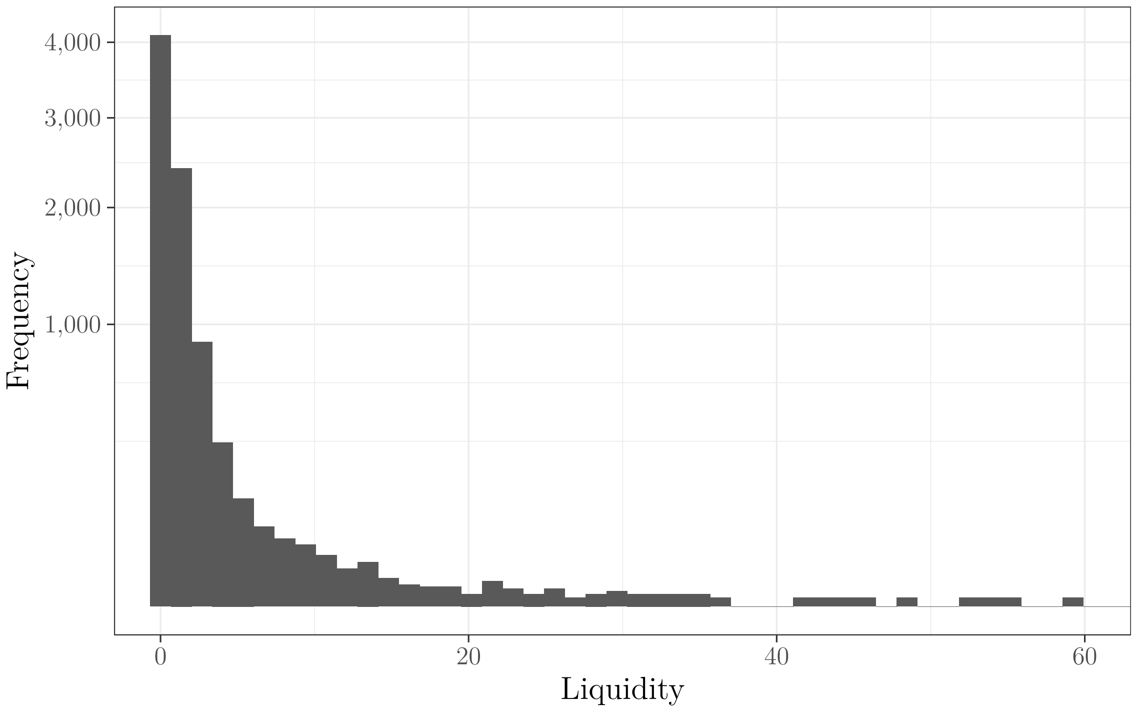


Figure 7: Liquidity-Commonality Boxplot

This boxplot shows the distribution of commonality of corporate bonds per liquidity quintile. Both measures are computed on August 11, 2005 (two weeks before Hurricane Katrina). More commonly held bonds tend to exhibit higher liquidity.

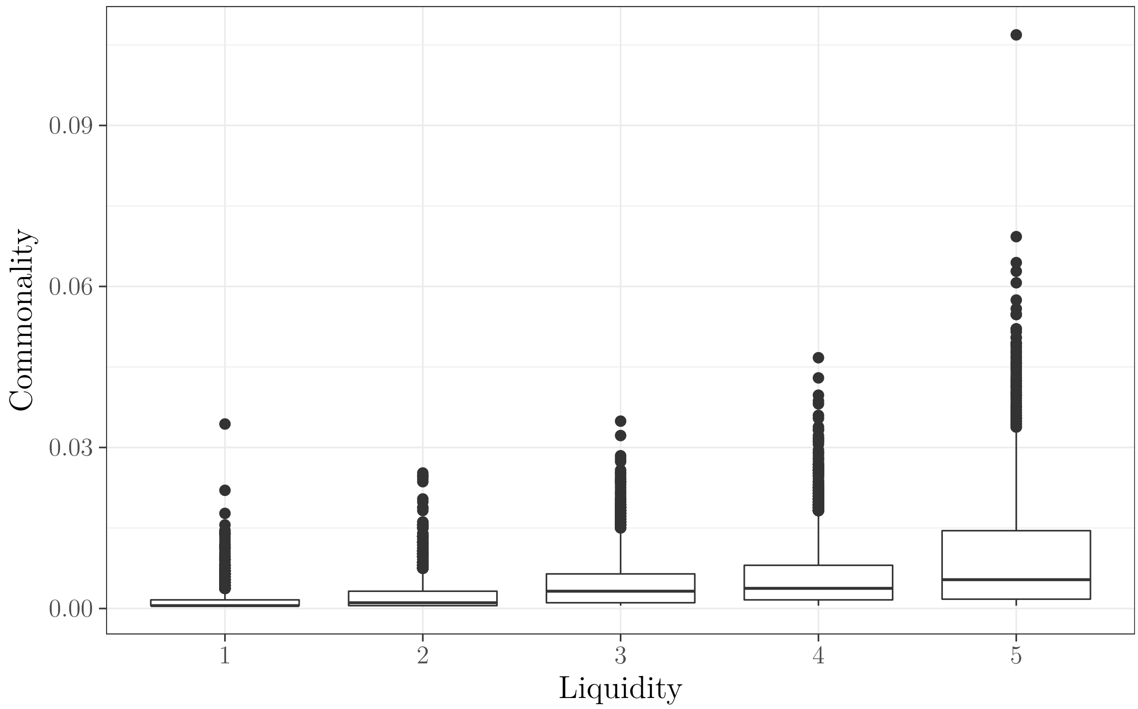


Figure 8: Examples for Bond-Specific Price Impacts

The dotted lines are daily price deviations of TRACE prices from the estimated fundamental price. The solid line is the 30-day moving average over these price deviations. The dashed vertical lines indicate the timing of catastrophes in 2005. CUSIPs and company names from left to right and top to bottom: 370442AY1 General Motors Corp, 013104AJ3 Albertsons Inc, 013104AG9 Albertsons Inc, 205363AF1 Computer Sciences Corp, 501044CE9 Kroger Co, 151313AS2 Cendant Corp, 652482BG4 News Amer Inc, 345370BQ2 Ford Motor Co.

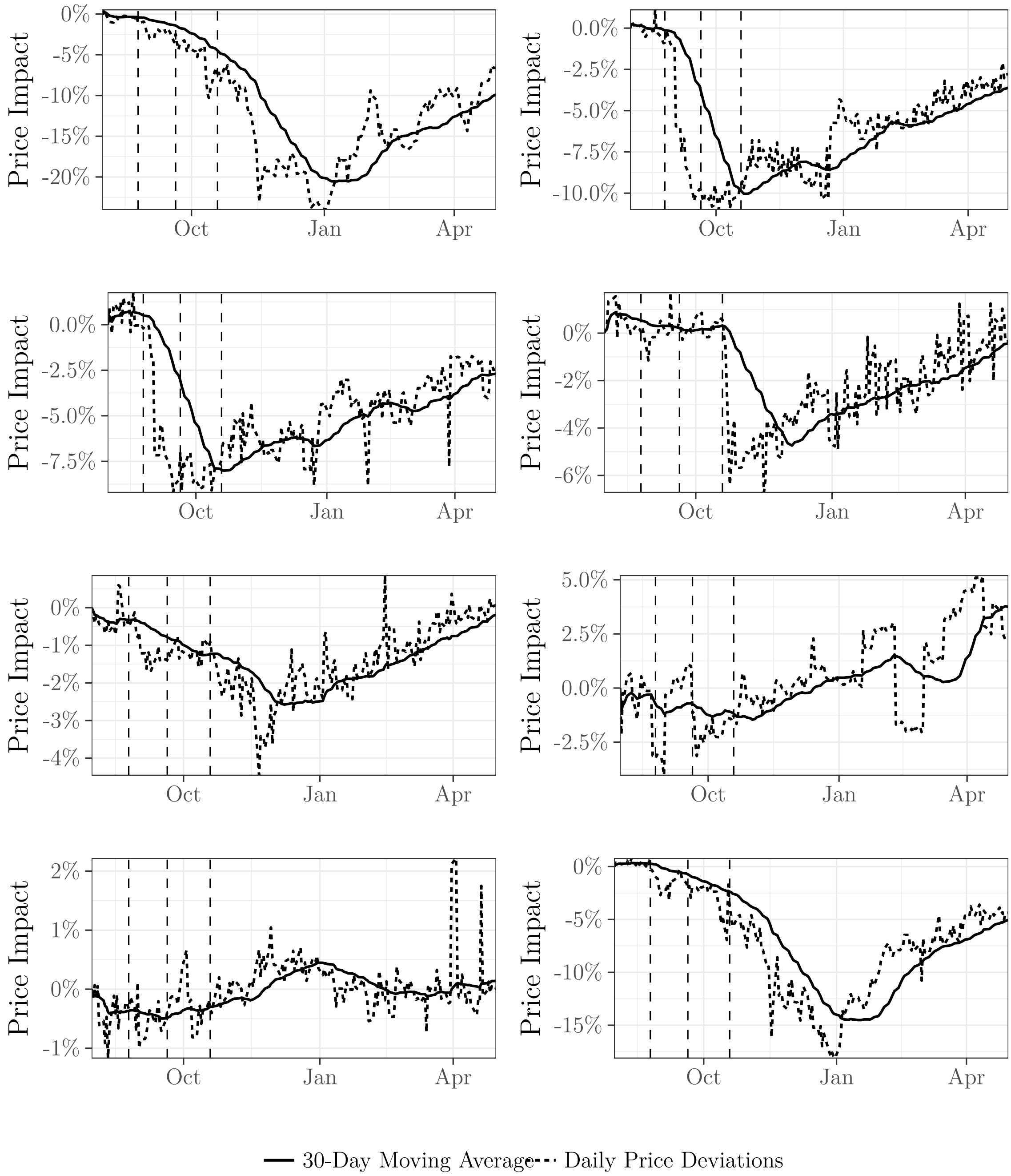


Figure 9: Average Price Impact of Fire Sold Bonds
The plot shows the daily average price impact of bonds sold by affected companies (solid line) with a total trade size of at least 2% of issue size. The dashed line shows the daily average over all other bonds. The dotted vertical lines indicate the timing of catastrophes in 2005.

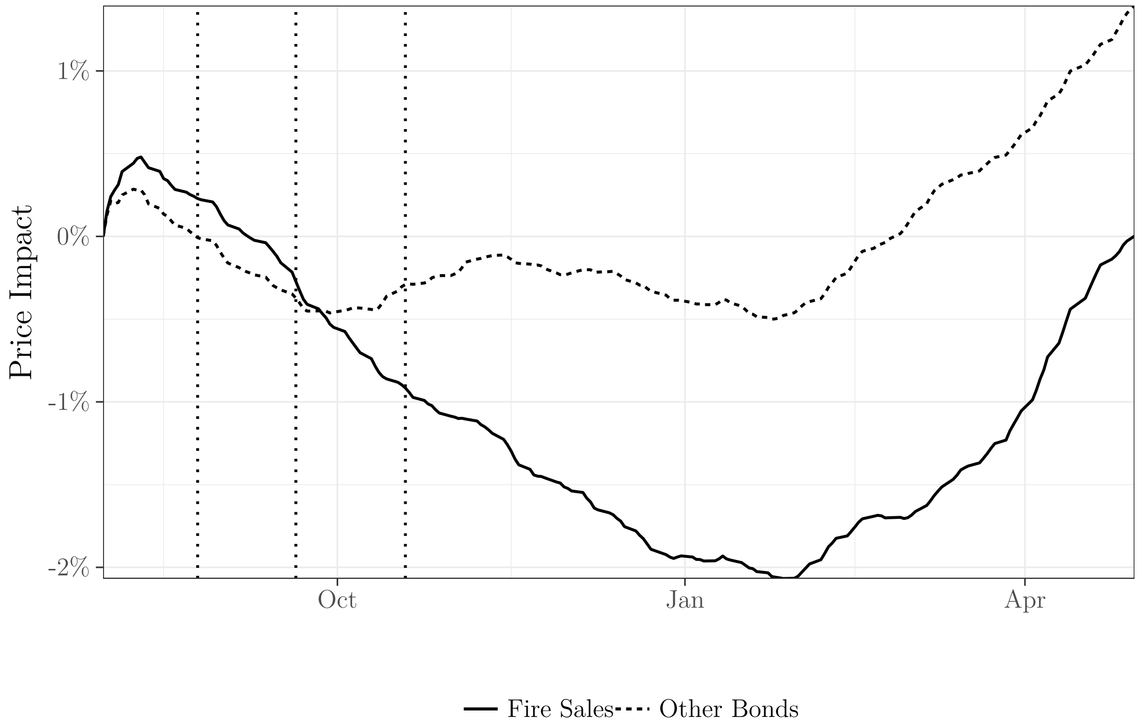


Figure 10: Heat Maps by Commonality and Liquidity Quintiles
These figures show the number of bonds and the total quantity held before the 2005 fire sale window, as well as the total quantity sold and the ratio of quantity sold and quantity held during the 2005 fire sale window.

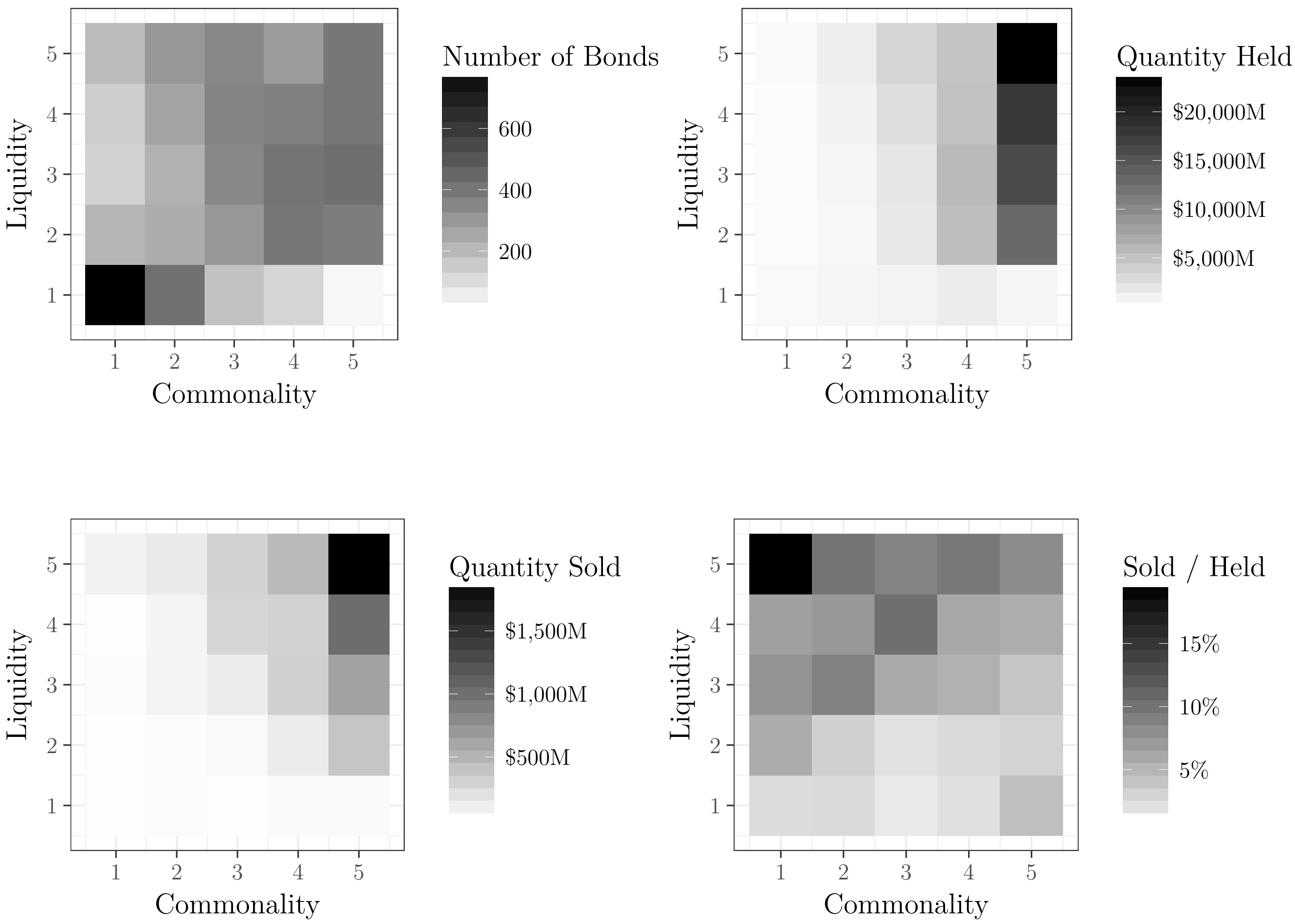


Figure 11: Invested Volume per Liquidity Category

This figure shows the evolution of the total invested corporate bond volume per liquidity category. We define liquid as the top decile of most liquid corporate bonds in the portfolios of insurers at the end of each month. Illiquid bonds are defined as the bottom 50% of least liquid bonds and the remaining bonds are denoted as less liquid.

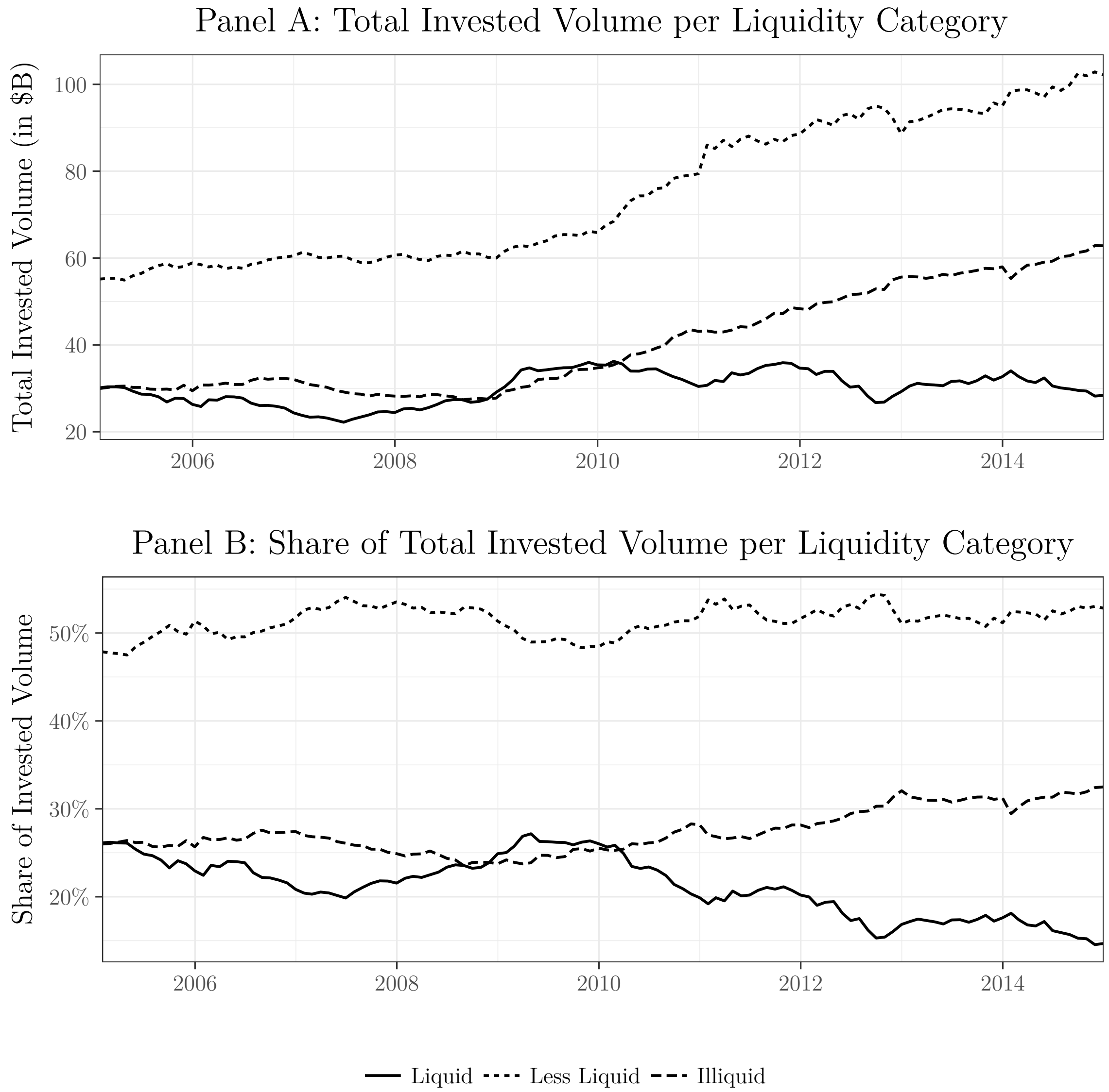


Figure 12: Average Commonality per Liquidity Category

This figure shows the average commonality of bonds in each liquidity category. We define liquid as the top decile of most liquid corporate bonds in the portfolios of insurers at the end of each month. Illiquid bonds are defined as the bottom 50% of least liquid bonds and the remaining bonds are denoted as less liquid. Commonality is defined as the number of companies holding a bond divided by the total number of companies. In Panel B, we weigh commonality by a portfolio weight given by the quantity all companies hold of a bond divided by the total amount invested across all bonds.

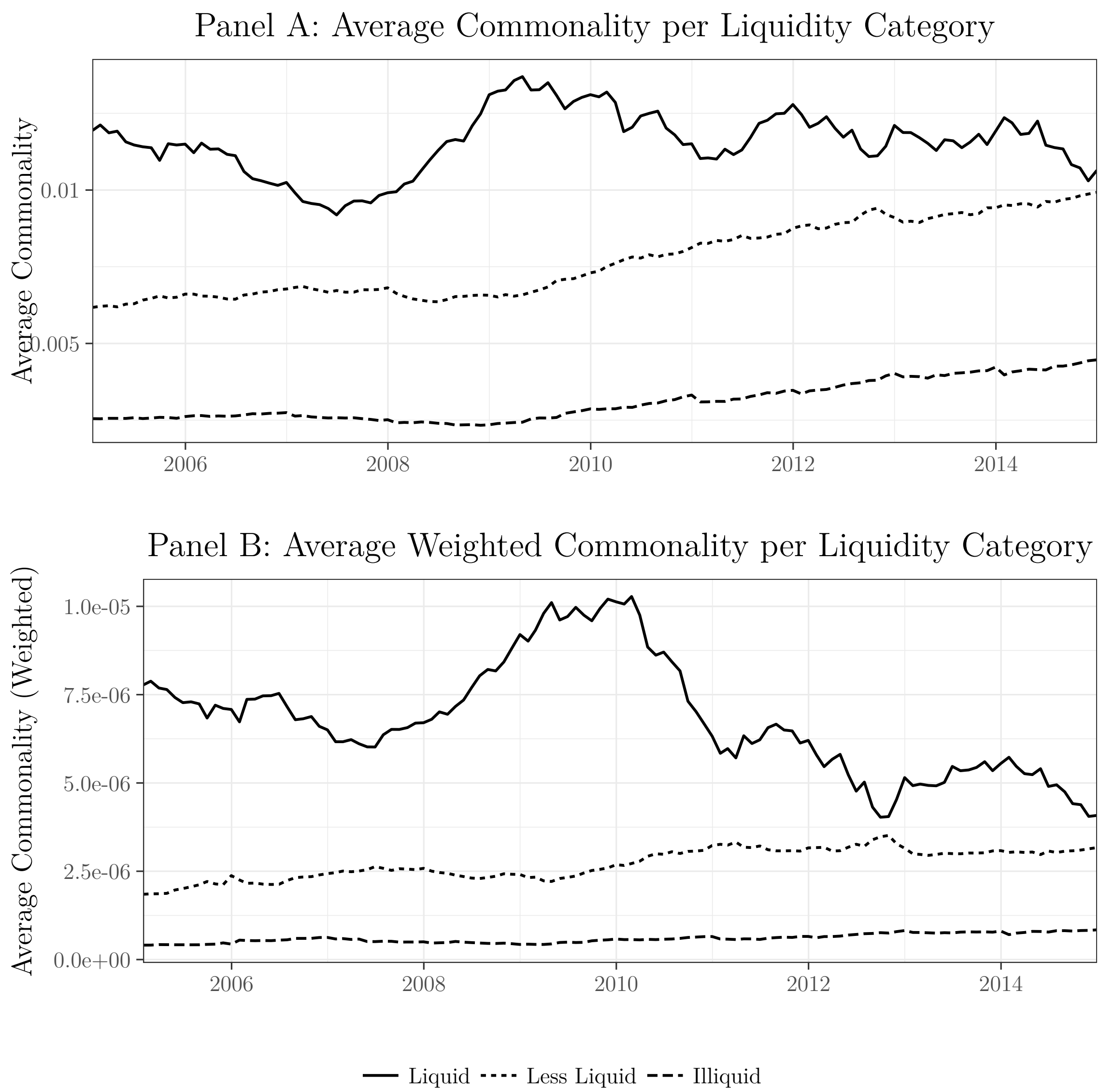
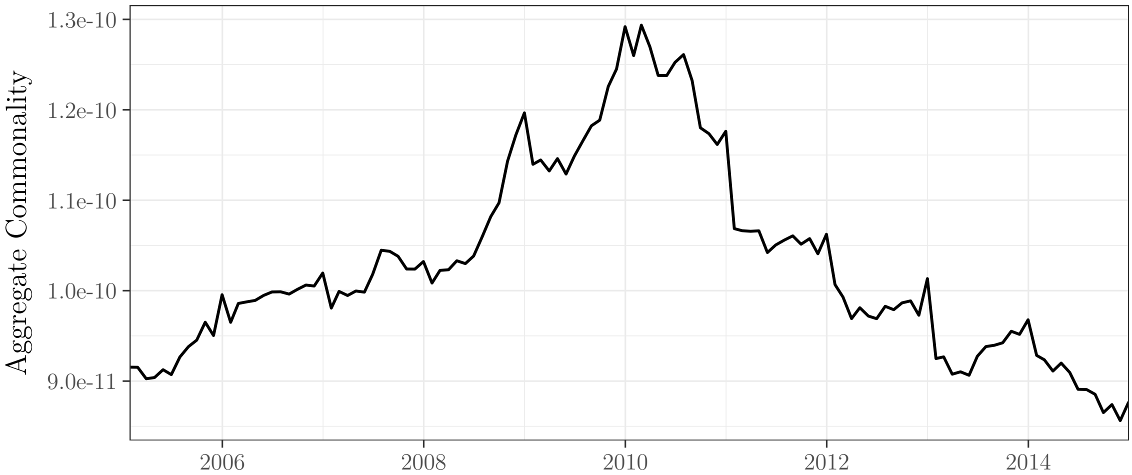
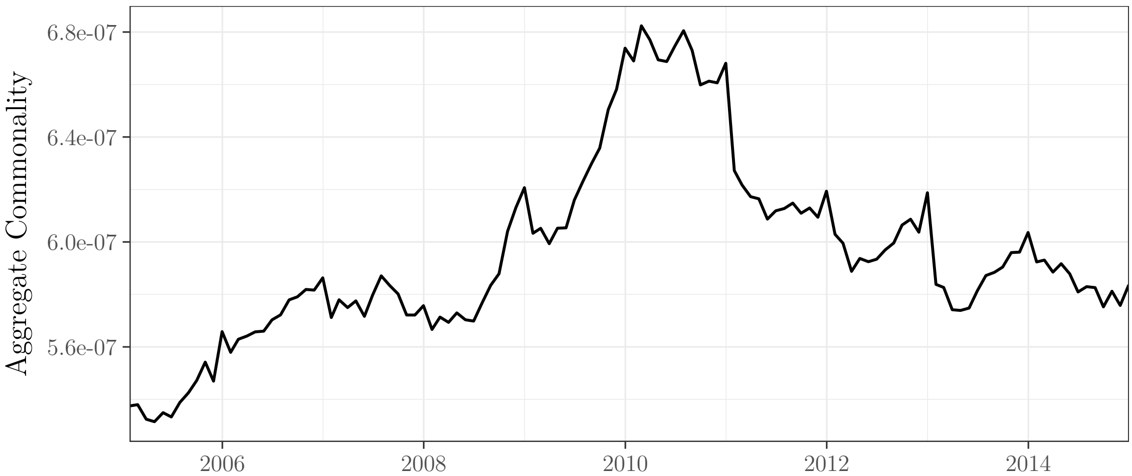


Figure 13: Aggregate Commonality Measures
Panel A depicts the extent to which liquid bonds are commonly-held by insurance companies. The more commonly-held the liquid bonds are, the larger is the fire-sales risk present in the industry. That is, given a liquidity shock which affects a group of insurance companies, the higher this measure is, the higher would be price impacts on the most liquid assets. Panel B shows the aggregate commonality measure without liquidity weights.

Panel A: Liquidity-Weighted Commonality



Panel B: Non-Liquidity-Weighted Commonality



A Appendix

A.1 Variable Definitions

Table A1: Variable Definitions and Data Sources

Bond Level Controls		
Issue Size	FISD	The par value of debt initially issued (FISD item OFFERING_AMT).
Bond Age	FISD	Current portfolio date minus issuance date (FISD item OFFERING_DATE) divided by 360.
Bond Life	FISD	Maturity (FISD item MATURITY) date minus current portfolio date divided by 360.
Buy Volume	TRACE	Average daily buy-side dollar trading volume as reported in TRACE over last 180 days before current date. In case of log-transformation we use 1+Buy Volume.
Trading Volume	TRACE	Average daily trading volume dollar trading volume as reported in TRACE over last 180 days before current date. In case of log-transformation we use 1+Trading Volume.
Lambda Sell	TRACE	Average over last 180 days before current portfolio date of implied sell-side arrival rates from TRACE dealer-client transactions based on Chacko et al. (2008): $\lambda^S = \left[\left(\left(\frac{r}{\sigma^2} - \frac{1}{\mathrm{PI}^S} - \frac{1}{2}\right)^2 - \left(\frac{1}{2} - \frac{r}{\sigma^2}\right)^2\right)\frac{\sigma^2}{2} - r\right] Q^S$ where PI^S is the price impact of a sell order of size Q^S. Price impacts are calculated as deviations of reported prices to Datastream clean prices one week prior to the trade.
Lambda Average	TRACE	Average over last 180 days before current portfolio date of mean of buy and sell-side implied arrival rates of TRACE dealer-client transactions based on Chacko et al. (2008).
Investment Grade	FISD	Dummy variable equal to one if bond has an investment grade rating, zero otherwise.
Downgrade	FISD	Dummy variable equal to one if bond was downgraded during a fire sale window, zero otherwise.
Commonality	NAIC	Number of portfolios where a specific bond appears in divided by the total number of portfolios in the sample. Simple measure of how commonly held a bond is.
Number of Sellers	NAIC	Number of companies that sold a specific bond during the catastrophe window.
Par Value	NAIC	Bond specific par amount of principal purchased/held by a company.

Total Assets	NAIC	Quarterly net admitted assets (excludes assets for which the sate does not allow the company to take credit). Measure for company size.
RBC	NAIC	Annual authorized control level risk-based capital. Quarterly data is linearly interpolated. Measure for financial constraints (NAIC).
Price Information		
$P_{i,t}$	TRACE	Bond-specific observed trading prices based on enhanced TRACE. Computed as the daily volume-weighted average of reported dealer-client prices.
$\bar{P}_{i,0}$	Datastream	Bond-specific mid-quotes from Thomson Reuters Valuations obtained through Datastream. Used as a proxy for fundamental prices.
Index_t	BoAML	Bank of America/Merrill Lynch (BoAML) Corporate Bond Master Index. Used to control for market movements.

A.2 Cleaning TRACE Data

We extract all unique CUSIPs from the complete enhanced TRACE data set from July 1, 2002 to December 31, 2014. This means we only look at 116,193 bonds that were reported at least once in the TRACE data. We drop 2 CUSIPs that can be identified as Treasuries since they appear in the TreasuryDirect database.[22] Next we merge the remaining CUSIPs with information from Mergent Fixed Income Securities Database (FISD) which leaves us with 93,466 bonds. Furthermore, we keep only bonds which have non-missing information for the following characteristics: issuance date, maturity date and offering size. This excludes perpetual bonds since they have no maturity date. Finally, dropping foreign-currency denominated and yankee bonds yields a sample of 71,119 bonds. Out of these bonds, 54,812 received at least one rating according to FISD (with a total of 675,155 ratings for the bonds in our sample).[23]

For each of these CUSIPs we run the following algorithm:

[22]See `https://www.treasurydirect.gov/instit/annceresult/annceresult_query.htm`

[23]For every bond we extract rating dates, rating types (MR, SPR, FR) and the actual rating. We assign each rating a number from 1 to 21 where 1 is the highest rating. In case of multiple disagreeing ratings on the same day, we take the worst available rating for that day.

1. Drop observations where CUSIP, reported price or trading volume is missing or prices are lower than 0.01.

2. Apply Dick-Nielsen (2014) filter.

3. Calculate daily trading statistics and liquidity measures.

4. Merge with ratings and fill up last available rating until the next rating change.

5. Keep only days which are actual business days and which are after issuance and before maturity

For each bond we record on how many trading days the bond was traded at least once. Excluding bonds that exhibit no trading activity after the above cleaning procedure, our final TRACE sample contains 70,731 bonds.

A.3 Extensions and Robustness Tests

Table A2: Liquidity Provision in Fire Sale Windows

This table reports probit model estimates for probability of the bond being bought as a function of bond and company characteristics. The dependent variable is a dummy that equals one if the insurance company (holding the bond) buys the bond when catastrophes hit, and zero otherwise. We measure the portfolio composition of insurance companies two weeks prior to each catastrophe, and we record the disposal of the bond as related to the catastrophe, if it was sold up to two weeks after the catastrophe. Each model contains fire sale window dummies. We define all variables in Table A1. We report t-statistics based on White's robust standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Probability of Bond Being Bought			
	(1) All	(2) Stock	(3) Mutual	(4) Others
Affected Company	-0.100***	-0.125***	0.116**	-0.218***
	(-4.93)	(-5.07)	(2.52)	(-3.31)
Log(Commonality)	0.074***	0.089***	0.108***	-0.004
	(5.09)	(4.92)	(2.95)	(-0.13)
Number of Sellers	0.020***	0.024***	0.013**	0.012
	(9.27)	(9.36)	(2.57)	(1.59)
Log(Buy Volume)	0.060***	0.038***	0.136***	0.054**
	(6.80)	(3.61)	(6.84)	(2.20)
Log(Bond Size)	0.005	-0.024	-0.026	0.149***
	(0.33)	(-1.30)	(-0.73)	(3.66)
Log(Bond Age)	0.036***	0.012	0.122***	0.038
	(3.58)	(1.06)	(5.19)	(1.34)
Log(Bond Life)	0.140***	0.171***	0.119***	0.058**
	(11.94)	(11.53)	(4.36)	(2.30)
Investment Grade	-0.318***	-0.284***	-0.413***	-0.403***
	(-14.15)	(-10.62)	(-7.23)	(-6.82)
Downgrade	0.059	0.097**	-0.227*	0.079
	(1.40)	(1.97)	(-1.67)	(0.73)
Log(Par Value)	-0.108***	-0.109***	-0.122***	-0.081***
	(-14.64)	(-11.90)	(-6.75)	(-4.53)
Log(Insurer Size)	0.030	0.022	0.076***	0.058
	(1.63)	(0.85)	(2.74)	(1.43)
Log(Insurer RBC)	0.031*	0.046**	-0.046*	-0.002
	(1.83)	(1.99)	(-1.80)	(-0.05)
Fire Sale Window FE	Yes	Yes	Yes	Yes
Observations	335109	240351	58846	35912
Pseudo R^2	0.078	0.085	0.083	0.086

Table A3: Liquidation Policy with Continuous Outcome Variable

This table reports results for linear regressions of the fraction of selling on bond and company characteristics. The dependent variable is a continuous variable that is computed as the fraction of the quantity a company sold of a bond in the fire sale window over the quantity a company held of a bond prior to a fire sale window. We measure the portfolio composition of insurance companies two weeks prior to each catastrophe, and we record the disposal of the bond as related to the catastrophe, if it was sold up to two weeks after the catastrophe. Each model contains fire sale window fixed effects. We define all variables in Table A1. We report t-statistics based on White's robust standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Quantity Sold / Quantity Held * 100			
	(1) All	(2) Stock	(3) Mutual	(4) Others
Affected Company	0.188***	0.340***	-0.392***	0.568**
	(3.30)	(5.09)	(-3.09)	(2.55)
Log(Commonality)	-0.428***	-0.452***	-0.266**	-0.482***
	(-9.88)	(-9.09)	(-2.22)	(-3.69)
Log(Buy Volume)	0.477***	0.417***	0.631***	0.587***
	(18.23)	(13.64)	(10.77)	(6.31)
Log(Bond Size)	0.281***	0.316***	0.024	0.360***
	(6.86)	(6.39)	(0.25)	(2.85)
Log(Bond Age)	-0.121***	-0.176***	0.113	-0.072
	(-3.52)	(-4.37)	(1.43)	(-0.64)
Log(Bond Life)	0.165***	0.162***	0.249***	0.055
	(5.40)	(4.93)	(3.08)	(0.47)
Investment Grade	-1.694***	-1.318***	-2.348***	-3.352***
	(-16.53)	(-11.99)	(-7.45)	(-9.14)
Downgrade	1.291***	1.277***	1.097**	1.727***
	(6.05)	(5.03)	(2.29)	(2.58)
Log(Par Value)	-0.174***	-0.094***	-0.308***	-0.430***
	(-5.65)	(-2.85)	(-3.14)	(-4.28)
Log(Insurer Size)	0.237***	0.091*	0.569***	0.794***
	(5.40)	(1.73)	(6.41)	(4.46)
Log(Insurer RBC)	-0.148***	-0.041	-0.418***	-0.612***
	(-3.96)	(-0.95)	(-5.64)	(-3.58)
Fire Sale Window FE	Yes	Yes	Yes	Yes
Observations	335109	240351	58846	35912
Adjusted R^2	0.017	0.016	0.017	0.028

Table A4: Liquidation Policy with Insurer-Specific Measures

This table reports probit model estimates for probability of the bond being sold as a function of bond and company characteristics. The dependent variable is a dummy that equals one if the insurance company (holding the bond) sells the bond when catastrophes hit, and zero otherwise. We calculate *Insurer-Specific Commonality (Liquidity)* for each company and each fire sale window as the fraction of a bonds commonality (liquidity) over the maximum commonality (liquidity) over all bonds a company holds prior to each fire sale window. The resulting measure is thus bounded between 0 and 1. We measure the portfolio composition of insurance companies two weeks prior to each catastrophe, and we record the disposal of the bond as related to the catastrophe, if it was sold up to two weeks after the catastrophe. Each model contains fire sale window dummies. We define all variables in Table A1. We report t-statistics based on White's robust standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Probability of Bond Being Sold			
	(1) All	(2) Stock	(3) Mutual	(4) Others
Affected Company	0.026**	0.045***	-0.096***	0.192***
	(2.55)	(3.76)	(-3.54)	(6.33)
Insurer-Specific Commonality	-0.060**	-0.066*	0.116*	-0.158*
	(-2.09)	(-1.92)	(1.71)	(-1.87)
Insurer-Specific Liquidity	0.071***	0.070**	0.153**	0.036
	(2.77)	(2.33)	(2.48)	(0.44)
Log(Bond Size)	0.096***	0.091***	0.074***	0.120***
	(14.03)	(10.91)	(4.78)	(6.09)
Log(Bond Age)	-0.072***	-0.073***	-0.062***	-0.073***
	(-16.34)	(-13.82)	(-5.62)	(-5.87)
Log(Bond Life)	0.032***	0.035***	0.039***	0.006
	(5.95)	(5.42)	(2.87)	(0.38)
Investment Grade	-0.350***	-0.307***	-0.446***	-0.481***
	(-29.13)	(-21.62)	(-14.14)	(-14.76)
Downgrade	0.162***	0.153***	0.170***	0.206***
	(7.10)	(5.61)	(3.01)	(3.22)
Log(Par Value)	-0.014***	0.003	-0.038***	-0.071***
	(-3.20)	(0.61)	(-3.20)	(-6.16)
Log(Insurer Size)	0.045***	0.008	0.155***	0.184***
	(5.71)	(0.80)	(5.81)	(7.07)
Log(Insurer RBC)	-0.023***	0.002	-0.116***	-0.129***
	(-3.45)	(0.29)	(-4.80)	(-5.24)
Fire Sale Window FE	Yes	Yes	Yes	Yes
Observations	335662	240737	58959	35966
Pseudo R^2	0.065	0.060	0.074	0.107

Table A5: Liquidation Policy with Interaction Terms

This table reports probit model estimates for probability of the bond being sold as a function of bond and company characteristics. The dependent variable is a dummy that equals one if the insurance company (holding the bond) sells the bond when catastrophes hit, and zero otherwise. We measure the portfolio composition of insurance companies two weeks prior to each catastrophe, and we record the disposal of the bond as related to the catastrophe, if it was sold up to two weeks after the catastrophe. Each model contains fire sale window dummies. We define all variables in Table A1. We report t-statistics based on White's robust standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Probability of Bond Being Sold			
	(1) All	(2) All	(3) All	(4) All
Affected Company	0.032***			0.195
	(3.17)			(1.63)
Log(Commonality)	-0.070***	-0.068***	-0.070***	-0.073***
	(-10.26)	(-9.92)	(-10.26)	(-9.68)
Log(Commonality) * Affected Company		-0.006***		0.010
		(-2.93)		(0.97)
Log(Buy Volume)	0.082***	0.081***	0.081***	0.084***
	(17.70)	(17.69)	(17.51)	(16.42)
Log(Buy Volume) * Affected Company			0.002***	-0.008
			(3.05)	(-1.19)
Log(Bond Size)	0.066***	0.066***	0.066***	0.066***
	(8.20)	(8.18)	(8.20)	(8.17)
Log(Bond Age)	-0.028***	-0.028***	-0.028***	-0.028***
	(-5.53)	(-5.54)	(-5.53)	(-5.51)
Log(Bond Life)	0.030***	0.030***	0.030***	0.030***
	(5.83)	(5.83)	(5.83)	(5.83)
Investment Grade	-0.272***	-0.271***	-0.272***	-0.272***
	(-21.42)	(-21.41)	(-21.42)	(-21.44)
Downgrade	0.154***	0.154***	0.154***	0.154***
	(6.75)	(6.76)	(6.75)	(6.74)
Log(Par Value)	-0.010**	-0.010**	-0.010**	-0.010**
	(-2.35)	(-2.32)	(-2.34)	(-2.39)
Log(Insurer Size)	0.038***	0.038***	0.038***	0.038***
	(4.91)	(4.92)	(4.92)	(4.89)
Log(Insurer RBC)	-0.022***	-0.023***	-0.022***	-0.022***
	(-3.40)	(-3.41)	(-3.40)	(-3.38)
Fire Sale Window FE	Yes	Yes	Yes	Yes
Observations	335109	335109	335109	335109
Pseudo R^2	0.070	0.070	0.070	0.070

Table A6: Liquidation Policy with Clustered Standard Errors

This table reports probit model estimates for probability of the bond being sold as a function of bond and company characteristics. The dependent variable is a dummy that equals one if the insurance company (holding the bond) sells the bond when catastrophes hit, and zero otherwise. We measure the portfolio composition of insurance companies two weeks prior to each catastrophe, and we record the disposal of the bond as related to the catastrophe, if it was sold up to two weeks after the catastrophe. Each model contains fire sale window dummies. We define all variables in Table A1. We report t-statistics based on standard errors clustered at the issuer level in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Probability of Bond Being Sold			
	(1) All	(2) Stock	(3) Mutual	(4) Others
Affected Company	0.032***	0.050***	-0.086***	0.200***
	(2.87)	(3.64)	(-3.11)	(6.50)
Log(Commonality)	-0.070***	-0.068***	-0.060**	-0.079***
	(-5.36)	(-5.23)	(-2.28)	(-3.75)
Log(Buy Volume)	0.082***	0.074***	0.128***	0.069***
	(9.20)	(7.95)	(8.04)	(4.45)
Log(Bond Size)	0.066***	0.066***	0.022	0.094***
	(3.94)	(4.08)	(0.75)	(3.31)
Log(Bond Age)	-0.028***	-0.033***	0.007	-0.033**
	(-3.05)	(-3.39)	(0.41)	(-2.14)
Log(Bond Life)	0.030***	0.034***	0.036*	-0.000
	(3.03)	(3.51)	(1.80)	(-0.02)
Investment Grade	-0.272***	-0.233***	-0.338***	-0.419***
	(-9.49)	(-8.19)	(-6.27)	(-10.35)
Downgrade	0.154	0.147	0.156	0.196*
	(1.43)	(1.28)	(1.46)	(1.79)
Log(Par Value)	-0.010*	0.006	-0.023*	-0.071***
	(-1.89)	(0.92)	(-1.75)	(-6.15)
Log(Insurer Size)	0.038***	0.002	0.136***	0.183***
	(4.27)	(0.15)	(4.69)	(7.03)
Log(Insurer RBC)	-0.022***	0.003	-0.115***	-0.129***
	(-2.99)	(0.33)	(-4.35)	(-5.23)
Fire Sale Window FE	Yes	Yes	Yes	Yes
Observations	335109	240351	58846	35912
Pseudo R^2	0.070	0.064	0.083	0.111