Which Bonds to Sell in Fire Sales? Liquidity versus Commonality of Holdings*

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Abstract

We analyze the problem of optimal bond liquidation when institutional investors are hit with a liquidity shock. Institutions fail to fully account for the effect of selling commonly-held bonds on other market participants. The over-selling of these bonds generates substantial price impacts. In data, there are few liquid bonds and they are more commonly-held. In fire-sales liquid bonds exhibit larger price impacts than illiquid ones. However, controlling for commonality of the bond, liquid bonds have smaller price impacts. We argue that even when portfolios have low similarity the commonality of liquid bonds matters for fire-sales losses and financial stability.

Keywords: Fire sales, aggregation risk, corporate bonds, insurance companies.

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1 Introduction

Fire sales of illiquid assets are rightly associated with losses to the liquidating party. The rise of mutual funds investing in corporate bonds makes the risk of fire sales a concern both to investors, retail and institutional, and to policymakers, concerned with the stability of the financial system.[1]

How can a portfolio manager, facing a task to raise funds on a short notice, minimize fire-sale losses? The naive solution is to sell the most liquid assets first. However, empirical evidence suggests that liquid assets during fire-sales exhibit larger price impacts than less liquid assets.[2] This counter-intuitive observation brings the naive liquidation strategy into question . In our study, we explicitly analyze which bonds are optimal to sell in a fire-sale, from both a theoretical and an empirical point of view.

We argue that illiquid assets like corporate bonds differ substantially in their liquidity. While it is also true that some shares are traded more often and with less price impact than others, the difference in liquidity within the equity class is smaller than the difference in liquidity among bonds. The implication of this observation is that there are a few actively-traded bonds relative to the large universe of rarely-traded bonds. Since there are just a few liquid bonds, and financial institutions value liquidity, these few liquid bonds tend to be commonly-held.[3] In times of aggregate shocks, commonality of these liquid bonds poses a problem, since other market participants will want to sell the same bonds to meet their funding needs. Financial institutions fail to account for the effect their sale of the commonly-held bonds will have on the trading costs of other financial institutions. This leads to over-selling of liquid commonly-held bonds, creating additional temporary price impacts and trading losses.[4] We refer to this as aggregation risk.[5] In

[1]See Economist (2016).

[2]See Boudoukh, Brooks, Richardson and Xu (2016) and Ellul, Jotikasthira and Lundblad (2011).

[3]In our analysis we refer to the commonality of a bond within a group of financial institutions. If more companies hold the same bond, then this bond has higher commonality. It is different from the commonality of liquidity discussed in Brunnermeier and Pedersen (2009) in a sense of co-movement in liquidity of multiple assets driven by common marginal investors.

[4]That is, each market participant imposes a negative externality on other market participants by selling a commonly-held bond. This is similar to the result that two firms in Cournot equilibrium produce more than a monopoly with identical cost structures due to failure to account for the effect their sale has on the revenue of the other firm.

[5]We use the term 'aggregation risk' in the spirit of Alexander (2005). We focus on the risk that arises

our paper, we study the contribution of commonality of liquid bonds to the price impacts in fire-sales.

The over-selling we consider is relative to the case of an integrated financial institution, which would have taken into account aggregation risk in maximizing joint liquidation revenues. Integration into a single financial institution solves the commitment problem. The integrated institution would have chosen to sell assets such that price impacts on all of them are equal, irrespective of their liquidity. It happens then that over-selling of the commonly-held bonds which are mainly the liquid bonds creates larger price impacts than in not-commonly-held less-liquid bonds. This leads to an observation that might look puzzling — bonds that are known to be liquid exhibit larger trading costs in terms of price impacts than less-liquid bonds during a market-wide selling. This phenomenon was documented before (Boudoukh, Brooks, Richardson and Xu (2016) and Shin (2016)). We argue that it is due to the commonality of liquid bonds rather than their liquidity in itself.

To study the magnitude of the aggregation risk that can arise due to the commonality of bonds, we analyze the way US property and casualty (P&C) insurance companies liquidate bonds in the weeks prior and following big catastrophes. While the primary business model of insurance companies is not liquidity transformation, unlike that of mutual funds investing in corporate bonds, P&C insurance companies are exposed to the aggregation risk 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 cause significant price impact on bonds that are being liquidated (Manconi et al. (2016), Massa and Zhang (2011)). The reason why P&C insurance companies are a good laboratory to study the magnitude of aggregation risk of financial institutions engaged in liquidity transformation is availability of data. While mutual funds report their holdings of assets, they do so at the dollar value. This makes it impossible to disentangle the effect of trading (selling) from the effect of falling asset prices on the value of their portfolio. Insurance companies, on the other hand, report their holdings and all transaction data to

because we aggregate actions of agents that are not independent. We focus on the market outcomes that are due to simultaneous trading by many agents, as opposed to the trading due to independent shocks.

the National Association of Insurance Commissioners (NAIC), the regulatory body overlooking insurance companies. Using this information, we aim to quantify the magnitude of fire-sale losses that could have been avoided if insurance companies could commit to a certain liquidation policy ex ante.[6]

It is worth to note that we do not take a stand that fire-sale losses of financial institutions 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 cause distortions to real decisions (Dávila and Korinek (2016), van Binsbergen and Opp (2017)). Therefore, we aim to quantify how commonality of bonds contributes to the temporary price impacts of fire sales.

We combine the data on holdings and transactions of P&C insurance companies from NAIC with trading data on corporate bonds from TRACE and data on bond characteristics from FISD for 2005-2014. First of all, we measure 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 most liquid bonds account for more trading volume than the bottom 70% of most illiquid bonds. We then measure commonality of bonds at the CUSIP level by counting the number of insurance companies in our sample that hold a specific bond. We find that liquidity and commonality of bonds are strongly positively related, confirming our hypothesis that the few existing liquid bonds are commonly held.

We then identify the insurance companies that were affected by major 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 received a withdrawal

[6] It is important to point out that aggregation risk arises not because of asymmetry of information, but because of lack of incentives to minimize overall trading costs as opposed to minimizing individual investor's trading costs. It is in the interest of all the insurance companies as a group to coordinate and commit to sell less of commonly-held bonds, but in a Nash rational-expectations equilibrium they will fail to do so. Hence, the aggregation risk 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 aggregation risk should address the mis-alignment of incentives rather than facilitate information sharing or transparency.

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 during the time 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 window. We see that liquid bonds exhibit larger price impacts than illiquid bonds during fire-sales. This seemingly puzzling observation is though consistent with the predictions of our model and is rationalized by observing that liquidity proxies 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.

The main implication of our finding is that commonality of bonds in portfolios of financial institutions makes them more susceptible to aggregation risk, increasing the losses during fire sales. While the portfolios of insurance companies at the bond level on average might appear not that similar (Getmansky, Girardi, Hanley, Nikolova and Pelizzon (2016)), what matters for stability is the commonality of the most liquid assets. The more liquid assets are more likely to be sold, also during a fire sale (Jiang et al. (2016)). If the sold assets are extremely common, the aggregation risk is large and price impacts are substantial. At the same time, the average similarity of portfolios might be low. Encouraging financial institutions to hold more liquid assets might result in an increase in the commonality of bonds in their portfolio, and destabilize the system. Stability, on the other hand, can be enhanced by providing incentives to financial institutions to minimize similarity of their liquid assets.

We observe that the average commonality of liquid bonds in the P&C insurance companies 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 aggregation 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 aggregation risk in the P&C insurance companies sector was present in 2010.

In our analysis, commonality does not mechanically determine liquidity. We examine the commonality of a bond as defined by holdings of that bond by a particular subset of market participants, namely P&C insurance companies. Those market participants are the relevant bondholders for our analysis as they are exposed to the same market-wide withdrawal shocks, in our case — natural catastrophes. However, they only constitute a small subset of market participants in the overall corporate bond market. In fact, 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. The reason is that liquidity is provided through dealers by other groups of market participants, such as life insurance companies, fixed-income mutual funds, or hedge funds.

While indeed P&C insurance companies contribute to the overall market liquidity of a bond at question, the effect of commonality of the bond within the P&C insurance industry on overall liquidity of the bond is undetermined. When the commonality of a bond within the P&C insurance industry increases, it could be due to a P&C insurance company buying a bond from another buy-and-hold investor. Overall market liquidity of that bond is then likely to be unaffected. Alternatively, an increase in commonality of a bond could be due to a P&C insurance company buying it from active trader, e.g. a hedge fund. In this case, overall market liquidity can be affected negatively.

Our analysis is robust to such dependencies between commonality of a bond within the P&C insurance industry and market-wide liquidity of that bond. Insurance companies anticipate potential feedback loops between commonality and liquidity and take them into account when forming their portfolio. In equilibrium, there are still very few very liquid bonds, so they end up being more commonly-held and commonly-sold in fire sales than other illiquid bonds. Moreover, we show that more commonly-held bonds are less likely to be sold, while more liquid bonds are more likely to be sold by P&C insurance companies. Therefore, commonality cannot just be a mere proxy for liquidity.

Our paper contributes to several strands of literature. The first one is the recent evidence on financial institutions, and insurance companies in particular, engaging in liquidity transformation as part of their business model. We are more familiar with banks fulfilling this role, but recent evidence suggests that insurance companies and potentially mutual funds investing in corporate bonds are following them. Chodorow-Reich, Ghent and Haddad (2016) argue that insurance companies generate value by insulating illiquid assets from temporary market fluctuations, and that this ability becomes limited in crisis times. Foley-Fisher, Narajabad and Verani (2015) present evidence that life insurance companies borrow from liquid short-term liabilities (targeted to money-market funds) and invest in long-term illiquid assets, exposing themselves to (partly self-fulfilling) runs. We add to this literature by demonstrating that the costs of liquidity transformation are exacerbated by the commonality of liquid bonds and are most pronounced during market-wide shocks.

The fact that financial institutions, including insurance companies, seem to trade in the same direction as their peers is documented by Chiang and Niehaus (2016) and Cai et al. (2016). The literature tends to attribute the observed behavior to herding. There is an important distinction to be made between herding and aggregation risk that we are analyzing in our paper. Herding occurs when the actions of agent A exhibit strategic complementaries to the actions of agent B — if company A sells the bond 'i', then it makes it more profitable for the company B to sell the same bond. The aggregation risk arises from the opposite — if company A sells the bond 'i', it makes it less profitable for company B to sell the same bond, but it does so due to bond 'i' being the optimal to be sold. In selling 'i' the company A does not take into account the effect its actions have on profits of B, yet actions of A and B are strategic substitutes — the more A wants to sell of bond 'i', the less B wants to sell.[7] Because of that, we interpret the commonality of bonds and large price impacts in fire sales as evidence of externalities and aggregation risk rather than herding.

We also contribute to the literature by providing evidence and a rational explanation as to why liquid bonds might exhibit larger price impacts during fire sales than less liquid

[7] In a similar way, two firms in a Cournot equilibrium will sell more at a lower price than a monopoly firm (with the same production technology), failing to take into account the effect of an extra unit sold on the revenue of the other firm.

bonds. Shin (2016) documents a similar pattern in the bonds of the same firm with the same time to maturity but with different issuance date and explains it with a search-based model of OTC trading. The crucial difference between Shin (2016)'s story and ours is that in his model asset holders are not allowed to chose which assets and how much to sell in response to a liquidity shock. This implies that the transmission of liquidity shock occurs through liquid market due to the fact that trade there is more likely to take place at all. We complement these findings by explicitly considering how liquidity plays a crucial role in the decision of which assets to sell. We find that it is the commonality of bonds that is responsible for exaggerated price impacts, not liquidity in itself.

In order to characterize the optimal liquidation policy of a portfolio manager, we need to take a stand on the specification of costs for trading corporate bonds. Since they are traded in an OTC market, this problem is far from trivial. First of all, we know that there can be a substantial heterogeneity of trading prices that exists for seemingly similar orders (Green, Hollifield and Schürhoff (2007)), potentially partly due to the nature of the agents involved in these transactions (Hendershott et al. (2016), O'Hara et al. (2016)). Moreover, unlike in equity markets, there is compelling evidence that trading costs decrease with the order size (Schultz (2001), Edwards et al. (2007)), implying that order-splits are discouraged.[8] The order size buckets, that are often used to measure order size, can be also seen as proxies for the whole-sale and retail market segments.[9] Then we see the trading costs decrease when comparing segments, but the costs could be increasing in the order size within a market segment. This is consistent with anecdotal evidence that we collected from interviews with portfolio managers of insurance companies, and is also supported by recent findings of Hendershott et al. (2016). They document that the order size positively affects trading costs of sell transactions, once the characteristics of a dealer and an investor are taken into account.[10] So, we opt for the interpretation of bid-ask spreads as monopoly rents that dealers collect for providing immediacy for

[8]This is potentially due to the long-term repeated-interaction nature of trading relationships in the OTC markets, see Zhang (2016).

[9]This is consistent with the observation in Schultz (2012) that as the municipal bond is traded from inter-dealer market towards the buy-and-hold investors, the order size decreases.

[10]These characteristics include the size of both counter-parties, and other proxies of the quality of networks that both agents have.

order executions, as in Chacko et al. (2008).[11] The resulting price-impact functions are upward-slopping in the oder size, implying that the price of immediacy increases with the size of the order. At the end, we consider a manager that faces trading costs that are increasing in the order size, but does not have the option to split orders.

The problem of optimal liquidation in equity markets is that of the trade-offs between the changes in the underlying fundamental value (encouraging earlier execution) and generated temporary price impacts (encouraging order splits and delays), see Almgren and Chriss (2001). The liquidation problem we formulate in the bond market balances the benefits of selling more of the liquid assets with the costs that these assets are commonly-held and sold, implying over-heated markets. To characterize this problem, we first look at the integrated financial institution that is the sole seller in the market and derive optimal liquidation policy by minimizing transaction costs, i.e. value-weighted price impacts. We find that it is optimal to liquidate assets such that price impacts equalize. This result is not immediately obvious, since the optimization problem suggest equalizing marginal price impacts, not average price impacts. But the functional form of the price impact functions in Chacko et al. (2008) is such that marginal price impacts are approximately equal to average price impacts.[12] If there are other agents selling assets, each portfolio manager still equalizes marginal price impacts on all sold assets, but the average price impacts on assets are different. The average price impacts would be larger for assets that are more commonly sold. Hence, selling a liquid asset has the advantage that, everything else equal, it generates a smaller price impact, but it has the disadvantage that liquid assets are commonly held and will also be sold by other agents, generating larger price impacts.

While the interconnectedness of financial institutions through overlaps in their portfolios has been brought into focus by multiple recent studies on fire-sales cascades (Greenwood et al. (2015), Duarte and Eisenbach (2015), Cont and Schaanning (2017), Nanda et al. (2017), Adam and Klipper (2017), Falato et al. (2016), Braverman and Minca (2014), Guo et al. (2016)), the main difference between our work and theirs is in the role

[11]The implications of this view are similar to that of bid-ask spreads arising from the costs of holding inventories for dealers, see Ho and Hans (1983), Grossman and Miller (1988) and recent empirical evidence in Friewald and Nagler (2015).

[12]This is also true for the linear price impact functions.

of liquidity of assets. For example, liquidity-weighted portfolio overlaps from Cont and Schaanning (2017) measure the exposure of institutions to price-mediated deleveraging risk, which corresponds to the need to sell assets because market prices of assets fall due to sell-offs of these assets by other institutions. In this measure, the more liquid the assets is, the smaller is its weight, and therefore, the smaller is the perceived problem that joint ownership of that asset creates. In our model, the result is quite the opposite — the more liquid is the commonly-held asset, the more price-impacts we expect this asset to have in fire-sales, and the larger is its aggregation risk. The difference in results is coming from different approaches to the portfolio-liquidation problem. The commonly-used assumption of proportional liquidation strategy (Greenwood et al. (2015), Cont and Wagalath (2016), Cont and Schaanning (2017)) implies that a said % of holdings is sold, irrespective of that asset's liquidity. Therefore, very liquid and very illiquid assets are liquidated to the same extent. Naturally then the price impacts associated with more liquid assets are smaller, and hence, the distortion from fire sales is smaller. In our setting, we look at the optimal portfolio-liquidation strategy. In other words, we let the financial institution be strategic about which assets to sell and adjust its liquidation policy with a goal of minimizing the fire-sale losses. It turns out that the optimal strategy dictates to sell proportionally more of liquid assets. Hence, during the fire-sales institutions sell relatively liquid assets. The more common these assets are, the larger are the price impacts due to over-selling of these assets. Hence, in our setting the commonality of liquid bonds poses a larger problem than the commonality of illiquid bonds.

Notably, Braouezec and Wagalath (2017) account for liquidity of the asset in the liquidation strategy in fire sales, but do not consider the effect of commonality of assets. In that sense, their approach is adequate for the case when only one financial institution is hit with a shock, or if financial institutions hold non-overlapping portfolios, as in our setting of an integrated insurance company.

In the next section we characterize the optimal liquidation policy of the portfolio manager and demonstrate that commonly-held bonds are over-sold relative to the case of the integrated financial institution, and exhibit larger price impacts than not-commonly-held bonds, even if the commonly-held bonds are more liquid. Then we proceed with the description of our data and sample construction, followed by the analysis of the choice which bonds insurance companies chose to sell, and the determinants of price impacts.

2 Hypothesis development

2.1 Over-selling of Commonly Held Bonds

In this section we explain why insurance companies in the event of the aggregate liquidity shock sell too much of the commonly-held assets. The reference case is the trading strategy of an integrated insurance company, that would have incorporated a price effect that each company has on the revenue of other insurance companies.

Consider a setting in which two insurance companies 1 and 2 both hold asset A, while insurance company 1 also holds asset B, and company 2 holds an asset C. Denote by $\bar{P}_i$ the fundamental price of each asset. In case of bonds, as is the focus of this paper, it is the present value of coupon payments and the principal value if the bond is held until maturity. Both insurance companies are simultaneously hit with a liquidity shock and need to raise each an amount I by selling part of their assets. Each asset is traded in a market with a downward sloping demand curve $P_i(Q_i)$, i.e. $P_i(\cdot) \leq \bar{P}_i$ and $P_i' < 0$. This means there is a price impact of trades that insurance companies execute. The objective function of insurance companies at deciding on how much of each asset to sell are then

$$\begin{aligned} \min \quad & [\bar{P}_A - P_A(Q_A^1 + Q_A^2)]Q_A^1 + [\bar{P}_B - P_B(Q_B^1)]Q_B^1 \\ \text{s.t. } & P_A(Q_A^1 + Q_A^2)Q_A^1 + P_B(Q_B^1)Q_B^1 = I, \end{aligned}$$

for company 1 and

$$\begin{aligned} \min \quad & [\bar{P}_A - P_A(Q_A^1 + Q_A^2)]Q_A^2 + [\bar{P}_C - P_C(Q_C^2)]Q_C^2, \\ \text{s.t. } & P_A(Q_A^1 + Q_A^2)Q_A^2 + P_C(Q_C^1)Q_C^2 = I, \end{aligned}$$

for company 2. From the first-order condition it is evident that company 1 will chose Q_A^1 and Q_B^1 such that

$$\frac{\bar{P}_A}{\bar{P}_B} = \frac{P_A' \cdot Q_A^1 + P_A}{P_B' \cdot Q_B^1 + P_B}$$

If insurance companies 1 and 2 were instead one integrated insurance company, then their objective function would be

$$\begin{aligned} \min \quad & [\bar{P}_A - P_A(Q_A^1 + Q_A^2)](Q_A^1 + Q_A^2) \\ & \qquad + [\bar{P}_B - P_B(Q_B^1)]Q_B^1 + [\bar{P}_C - P_C(Q_C^2)]Q_C^2 \\ \text{s.t. } & P_A(Q_A^1 + Q_A^2) \cdot (Q_A^1 + Q_A^2) + P_B(Q_B^1)Q_B^1 + [\bar{P}_C - P_C(Q_C^2)]Q_C^2 = 2I. \end{aligned} \tag{1}$$

with the corresponding first-order condition

$$\textbf{FOC: } \frac{\bar{P}_A}{\bar{P}_B} = \frac{P_A' \cdot (Q_A^1 + Q_A^2) + P_A}{P_B' \cdot Q_B^1 + P_B}. \tag{2}$$

Denote by Q_A^{1D}, Q_B^{1D} the optimal liquidation quantities for the decentralized case – when two insurance companies are independent, and by Q_A^{1I}, Q_B^{1I} the liquidation quantities for the centralized case - when two insurance companies are part of a single integrated insurance company.

Lemma 1. *$Q_A^{1D} > Q_A^{1I}$, that is, insurance companies sell too much of the commonly held asset when hit with an aggregate liquidity shock.*

The intuition behind this result is straight-forward to see if we evaluate the FOC in (2) at the decentralized solution Q_A^{1D}, Q_B^{1D}. In that case the marginal revenue from selling the last unit of the commonly held asset A is much smaller than the scaled marginal revenue from selling the last unit of the uniquely held asset B. That is because the negative impact from selling the asset A that the insurance company 1 considers is only $P_A' \cdot Q_A^1$, while for the integrated insurance company it is $P_A' \cdot (Q_A^1 + Q_A^2)$, which is larger in absolute terms, and being negative due to the price impact of trades, makes the marginal revenue from selling asset A smaller. Therefore, the integrated insurance company would have preferred to sell less of A and more of B relative to the optimum for the decentralized solution when two insurance companies are independent.

This result is another way of saying that insurance companies do not internalize the price impact they cause 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.

2.2 Price Impacts

We further investigate the consequences of over-selling the commonly-held asset due to the failure to internalize the negative price impact trading has on the proceeds of other companies. The framework is the same as in the previous subsection, but we are putting more structure on price impact functions. First, we define a relative price impact, or an ask trading margin as

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

Then we can represent the trading price as $P_i = \bar{P}_i(1 - \rho_i)$. We take the bid-ask spread functions from Chacko et al. (2008). In this setting, the price impact caused by a trade is due to monopoly power of a market maker who is the sole provider of immediate trade execution. In particular, we have

$$\begin{aligned} \rho_i &= \frac{1}{\phi_i(Q_i)} \\ \phi_i(Q_i) &= \left(\frac{1}{2} - \frac{r_i}{\sigma_i^2}\right) + \sqrt{\left(\frac{1}{2} - \frac{r_i}{\sigma_i^2}\right)^2 + \frac{2(r_i + \lambda_i(Q_i))}{\sigma_i^2}} \\ \lambda_i(Q_i) &= \frac{\lambda_i}{\bar{P}_i Q_i}, \end{aligned} \tag{3}$$

where r_i and σ_i are the parameters of the dynamics 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 is λ_i, 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 dollar of the fundamental value. That is why the order flow is represented by $\bar{P}_i Q_i$.

Since over-trading in the commonly held asset A means that in the equilibrium insurance companies will liquidate more of asset A than is optimal from the integrated company point of view, it means that the price impact in asset A would be larger than the optimal. But is it larger than in the not commonly held assets?

To investigate this question, we first characterize the solution of the problem of the portfolio manager who has holdings of assets A and B and is asked to raise I, while facing the price impact functions as in (3). Let $q_i = \bar{P}_i Q_i$. Formally:

$$\begin{aligned} \min_{Q_A, Q_B} \quad & \rho_A q_A + \rho_B q_B \\ & s.t. (1-\rho_A) q_A + (1-\rho_B) q_B = I. \end{aligned}$$

FOC for this optimization problem are:

$$\begin{aligned} \rho'_A(q_A) q_A + \rho_A &= \rho'_B(q_B) q_B + \rho_B \\ (1-\rho_A) q_A + (1-\rho_B) q_B &= I; \end{aligned} \tag{4}$$

In other words, a manager who is facing price impacts will sell assets until the marginal price impacts equalize. This is in contrast to the intuition of a price-taking portfolio manager, who will sell only the asset with the smallest prevailing price impact.[13] That is, even though asset A is more liquid than asset B, the manager will sell both A and B.

What does (A-1) imply about ρ_A vs. ρ_B? The answer is given by the following Lemma.

Lemma 2. *If $\rho'(q_i) = \rho(q_i)/q_i$ for both assets A and B, then the manager liquidates portfolio in such a way that $\rho_A = \rho_B$.*

See proof in the Appendix. The condition $\rho'(q_i) = \rho(q_i)/q_i$ states that the marginal price impact is equal to the average price impact. Functions of the form Kq^{α} satisfy this property. That is, if we consider linear or square-root price impact functions, then trading price impacts will be equalized in equilibrium. It is particularly useful to note that $\rho(q) = K\sqrt{q}$ closely approximates (3), the price-impact functions of Chacko et al.

[13] All models of portfolio liquidation featuring proportional trading costs effectively assume that the portfolio managers are price takers. For example, Vayanos (2004) considers a related problem – liquidating assets in case of an outflow from a fund, assumes that 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.

(2008). Hence, this condition holds, at least approximately, for many plausible price impact functions.

According to Lemma 2, the insurance company, when faced with the problem of liquidating some of its assets to raise funds, will sell such that the prices impacts on all assets equalize. This also applies to the case of integrated insurance company that we considered in (1). At the optimal Q_A, Q_B and Q_C, assuming that price impact functions satisfy the condition in the Lemma 2, we have $\rho_A = \rho_B = \rho_C$. Then the optimal solution to the problem of individual insurance companies, which features more liquidation in asset A, will feature a larger price impact on that asset. Note that this result is due to 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.[14]

Figure 1 represents graphically the larger price impact of liquid asset A than less liquid assets B or C. The downward slopping curves are the price-impact functions as in (3). The higher is the line, the more liquid is the assets. 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.

[14] Liquidity of the bond, everything else constant, is a desirable feature of the bond for insurance companies due to lower trading costs. However, commonality of the 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.

2.3 Effect of Commonality on Liquidation Policy

Finally, we investigate how commonality affects the amount of asset that the company liquidates. We compare two scenarios: (1) asset A is commonly held by insurance companies 1 and 2, while asset B is held only by company 1, and asset C only by company 2; (2) insurance company 1 holds A and B, while insurance company 2 holds assets C and D. Both cases correspond to the solution of individual insurance companies, unlike in the previous subsections where we were comparing individual insurance companies with an integrated insurance company.

Since in the second scenario asset A will be sold only by insurance company 1, it will have a smaller price impact for any Q_A^1 that the insurance company 1 decides to sell because $Q_A^2 = 0$. Hence, the first insurance company will sell more of asset A in the second scenario than in the first because the asset market A is less crowded. Empirically we should observe that everything else constant, commonly held assets are less likely to be liquidated than separately held assets.

3 Data

In this section we describe our data sources and identification strategy. We rely on market transactions to calculate observed trading prices and liquidity measures, and insurer transactions to identify fire sales. We also employ information on portfolios and insurer characteristics.

3.1 Bond Level Data

The Financial Industry Regulatory Agency (FINRA) launched the Trade Reporting and Compliance Engine (TRACE) in 2002-07-01 in order to provide detailed information on secondary market corporate bond transactions. Since the implementation of the final phase in 2004-10-01, essentially all US corporate bond transactions have been reported. We use the enhanced TRACE data base which contains uncapped volumes and therefore more information for our liquidity measure (see below). As of 2014-12-31 there are 116,193 unique CUSIPs that appear at least once in the full TRACE data base. 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 (see appendix B 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 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), par value of the trade and counter-party.

Schedule D Part 2-4 contain different types of erroneous records (e.g. negative bond prices, negative or zero transaction amounts, transaction amounts larger than the initial offering amount). These observations are excluded for obvious reasons. We also drop all transactions with missing or uselsess CUSIPs (e.g. containing punctuation characters or being of 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*. In the following, 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 transactions (trades and non-trades) that have a matching CUSIP in our corporate bond universe from above. This leaves us 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 after 14 days after issuance, but before 14 days before maturity. Table 4 shows the differences in sample composition. In most of our analysis 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 simply 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.[15]

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.

[15] As a check 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. This supports the validity of our procedure.

We use losses paid in the states hit by a catastrophe to identify which insurers might face the risk of fire sales.[16]

We complement the data from above 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, which we use to construct our identifying variable.

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 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).[17] Table 3 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.[18] Together with insurer activity in each state we can identify (potentially) affected insurers.

From NAIC data we take the information on losses paid on direct business, which companies have to file by state on a quarterly basis. Losses paid on direct business are

[16]Manconi et al. (2016) identify affected insurers by looking at the market share of insurers in 2004. Then they select the top then larges 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.

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

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

net of re-insurance, i.e. they represents only the losses that insurance companies have to bear themselves. They do, however, have to pay out the whole insured amount to the policy holders, which includes the re-insured part. We observe the total amount paid to the policy holders 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 re-insured amounts in subsequent years. So losses paid on direct business under-estimates (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. In the most of our analysis we consider 75%, but we do robustness checks with 100% and 50%.

As can be seen from the 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 companies had to prepare for.

While this measure works well for P&C insurers, it does not work well for the re-insurance companies due to a different nature of their business and corresponding reporting standards.[19] Figure 3 illustrates the difference in the dynamics of direct losses paid for 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, following others, as in 2005. Moreover, the level of losses paid 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.

[19]We identify reinsurance companies by looking at their self-reported business focus which can be found in SNL. We classify every company that reports a (large) reinsurance focus as a reinsurer.

3.6 Fire Sale Window

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 damages 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 are three hurricanes in 2005 – Katrina, Rita and Wilma – where we see corresponding losses paid in 2005-Q4 and 2006-Q1. In this case, the fire sale window is defined from 2005-08-11 (two weeks before Katrina) to 2005-11-02 (two weeks after Wilma).

The second fire sale window is given by hurricane Ike which hit on 2008-09-06. The third and fourth are both in the same year again and given by a drought in the corn belt which started on 2012-07-15 and hurricane Sandy which made landfall on 2012-10-24.

The 2005 fire sale window provides an ideal environment for testing our hypotheses. First, the cumulative insured damages of the three hurricanes are 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 5 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 fire sale 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 execution quality of a bond transaction, but also the dollar volume which can be easily 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. In addition, we also use total trading volume as an alternative 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 calender days to get our liquidity measures. The resulting liquidity measure is in $ 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 the framework developed in section 2.2, price impacts are determined by the unobservable arrival rate of buy orders to the dealer market. In principle, we can therefore back out *implied* arrival rates from observed price impacts. We compute such implied arrival rates by comparing TRACE execution prices to the average Thomson Reuters Valuation mid-quotes[20] 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 extend to which this bond is common to the insurance 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

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

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

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 did not alter the results in any substantial way, so we opted for a simpler measure.[21] In most of our analysis, 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 is capturing a trade-off which bonds to cell, while the latter is capturing a 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.[22] Figure 4 demonstrates that total value of invested assets in bonds increased

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

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

which lies between $[1/N, 1]$. The higher is $\omega_{i,t}^{\text{dis}}$, the higher is the dispersion of bond holdings given a number of companies holding the bond, and therefore, the higher is 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 companies sector. The higher is this number, the higher is 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 using both measures delivers very similar results. Therefore, in what follows we are using $h_{i,t}^{\text{com}}$ to capture the commonality of holdings.

[22]According to NAIC reporting standards these comprise of all bonds with maturity dates greater than one year when purchased, excluding loan-backed and structured securities. In particular, this

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.

As has been documented before, insurance companies hold overlapping portfolios of assets.[23] We measure to what extent a given bond is held by multiple insurance companies by calculating its *commonality.* This measure counts the number of companies in our sample that have positive holding of this bond in a given point in time, scaled by the total number of insurance companies in the sample. The cross-sectional distribution of this measure before the 2005 fire sale window is depicted in Figure 5. 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.

4.2 Liquidity Profile of Corporate Bonds

When we look at corporate bonds that insurance companies invest in, we see that they 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 in 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.

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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`).

[23]See Chiang and Niehaus (2016) for evidence about life insurance companies and Getmansky et al. (2016) 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.

4.3 Commonality and Liquidity

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 (the extent to which it is held by many rather than a few insurance companies) 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.

4.4 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 catastrophes hit as a probit function

$$\Pr(D_{i,j} = 1) = \Phi(\beta_0 + \beta_D D_i^{\text{Aff}} + \beta_Y Y_j + \beta_X X_i + u_{i,j}), \tag{5}$$

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% (see section 3 for details), and zero otherwise.

X_i are the characteristics of the 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. See Appendix C for details about variable definitions.

First we investigate the liquidation policy by the type of a P&C insurance company. Estimation results for the year 2005 are in Table 6. The model in column 1 represents all insurance companies, column 2 contains only mutual, column 4 represents stock companies, the focus of your analysis, and column 3 represents other companies.[24] The dummy of affected company is positive and significant for stock insurance companies (column 4). This means that 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 affected dummy is not significant for mutual insurance companies (column 2). This is consistent with Laux and Muermann (2010) who argue that mutual insurers have an advantage in raising capital during times of distress, and therefore they 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 companies sector (see Table 5).

As can be seen from the coefficient estimates, 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 is indicated by the negative and statistically significant coefficient on the commonality measure. This is consistent with the arguments in section 2.3 that crowding by other insurance companies creates larger price impacts and insurance companies sell more of separately-held bonds than commonly-held bonds, everything else equal.

We extend the analysis to incorporate other fire-sale windows in our sample. The

[24]For more details on different types of insurance companies in our sample see Table 5. Other insurance companies mostly consist of non-standard insurance business models, like risk retention groups and syndicates related to insurance exchanges such as Lloyds.

estimation results are presented in Table 8. 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 into account the commonality of bonds in their portfolios 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 several alternative measures of bond's liquidity. In Table 7 we look at three additional liquidity measures. The first one is total realized trading volume (column 2), 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.

The next two columns are looking at the liquidity measures that are motivated by the model of Chacko et al. (2008), as described in the 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, 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 9. 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.

4.5 Price Impacts: Market-Specific

Fire-sale trades of insurance companies can influence the market and move prices of bonds they liquidate. In order to capture the extent of this influence, we measure price impacts that trades by 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 regarding 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 the overall bond-market movements in our sample, as the fundamental price of the bond is likely to be influenced by the aggregate factors, such as changes in the risk-free interest rates, 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 it, 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 thousand of bonds. We use clean prices, that is, those that are estimated without taking into account any fees that actually trading a bond might incur. In particular, we take data prices from Datastream two weeks prior to the start of the fire-sale window. For example, for the year 2005 we took Datastream prices as of June 31, 2005.

For every bond, we calculate the 30-day 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 6 and 9. However, out model also predicts that insurance companies do not fully take into account the detrimental effect of 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 10 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 is the liquidity of the bond, as measured by the realized buy trading volume, the larger is 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 amount outstanding (a proxy for liquidity) exhibited more negative abnormal returns during the 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 liquidity of the bond and the price impact that this bond experiences during 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, do 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 reported in Table 9, 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 10 . 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 aggregation 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 11. 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.

4.6 Price Impacts: Company-Specific

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 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 bilateral nature of trades on prices (see 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 took 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 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 the Table 12 for catastrophes in 2005 and in the Table 13 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 12 and 13. Controlling for commonality changes the relation between liquidity and price impacts and makes it insignificant, as reported in columns 4-6 in Table 13. If liquidity of a bond is measured using 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 12 and 13.

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 12 in columns 4-6 speak towards 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 is hardly always holds in practice that firms with 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.[25] In the whole sample of 4 fire-sale windows, as indicated in Table 13, this assumption seems not to hold, as 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.

4.7 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. In our test we repeat the analysis of price-impact determinants at an arbitrary-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 the 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.

[25] Regressions as in Table 12 run on sub-samples of stock, mutual, and only affected P&C companies are available upon request.

We chose September 6, 2010 as a hypothetical beginning of the placebo fire-sale window. We estimated the model of aggregate market price impacts, as in Section 4.5 on a placebo window. Results are reported in Table 14. As can be seen from columns 1-3, liquidity is either negatively related to price impacts, or not significantly related. 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, controlling for commonality or not.

5 Aggregation 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 Getmansky et al. (2016), 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 constitutes aggregation risk that increases price impacts in fire sales. To access the evolution of the aggregation 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.[26] We group

[26]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 states on the level before 2010. We attribute

the 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.

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. Figure 12 highlights that while the share of less liquid investment stays approximately constant, the share of illiquid investment growths.

Overall, we observe an increase in the total holdings of corporate bonds by P&C insurance companies. Importantly, they invest more into 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 into corporate bonds after 2009 affected the aggregation risk in the P&C sector, we look at the dynamics of average commonality within the liquidity buckets. Figure 13 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. On the contrary, the commonality of less liquid bonds, as well as illiquid bonds are steadily increasing after 2009. Using the insights from Figure 11, we argue that insurance companies expand their investment into less liquid and illiquid bonds, increasing commonality of these bonds. They do not seem to expand their investment into the most liquid bonds, potentially anticipating adverse consequences of the increase 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

this change to the documented increase in the trading volume during the first month after issuance of bonds, which is a response of corporate bond under-writers to the regulation intended to dis-entangle the roles 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 only marginally differ quantitatively.

high commonality of liquid bonds.

Figure 14 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 Figure 14 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 aggregation risk than the commonality of illiquid bonds. And that 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 companies sector in the past decades did not increase. This is in contrast to the view of the literature that considers proportional liquidation strategy in fire-sales (Greenwood et al. (2015) and Duarte and Eisenbach (2015), among others). If financial institutions indeed chose to liquidate assets proportionally, then the fire-sale risk is exaggerated by the commonality of illiquid assets. From that point of view, the aggregation risk in the P&C insurance companies sector could be seen as increasing over the last decades. Which approach is more relevant is an empirical question. In our regressions of the probability that a bond is sold (see Tables 6, 7, 8 and 9) 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 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 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 in time on a monthly frequency. The top part of Figure 15 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 aggregation risk was largest in 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 aggregation 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 declines after its peak in 2010, but stabilizes in 2011 and then shows only a moderate decline towards 2015. The liquidity-weighted top plot and the non-liquidity weighted bottom plot tell a similar story — that aggregation risk was highest in 2010 after the crisis, but the top plot emphasizes a substantial decline in the aggregation 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 two-fold. 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 aggregation risk which results in larger price impacts and substantial fire-sale 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 holdings, thereby increasing aggregation risk. Stability, on the other hand, may be enhanced by providing incentives to financial institutions to minimize commonality of their liquid assets.

APPENDIX

A Proof of Lemma 2

Consider the FOC for the portfolio-liquidation problem:

$$\begin{aligned} \rho'_A(q_A)q_A + \rho_A &= \rho'_B(q_B)q_B + \rho_B \\ (1-\rho_A)q_A + (1-\rho_B)q_B &= I; \end{aligned} \tag{A-1}$$

The condition of the Lemma 2 implies that the marginal price impact is equal to the average price impact. Hence, the first equation in the FOC above can be re-written as:

$$\frac{\rho_A}{q_A}q_A + \rho_A = \frac{\rho_B}{q_B}q_B + \rho_B. \tag{A-2}$$

Re-arranging the terms, we arrive at:

$$\rho_A = \rho_B, \tag{A-3}$$

for positive quantities q_A and q_B, for which the average price impact is defined. Therefore, the price impacts of assets A and B are equal in equilibrium. □

B Cleaning TRACE Data

We extract all unique CUSIPs from the complete enhanced TRACE data set from 2002-07-01 to 2014-12-31. This means we only look at 116,193 bonds that have been 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[27]. 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

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

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).[28]

For each of these CUSIPs we run the following algorithm:

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 (also dropping double counted agency trades).
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 between 2002-07-01 and 2014-12-31 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.

C Definitions of Variables

[28] 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.

Table 1: Variable definitions.
This table summarizes all variables used in the empirical analysis.

Bond level controls	
Issue size	The par value of debt initially issued (FISD item OFFERING_AMT).
Bond age	Current portfolio date minus issuance date (FISD item OFFERING_DATE) divided by 360.
Bond life	Maturity (FISD item MATURITY) date minus current portfolio date divided by 360.
Buy Volume	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	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	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	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	Dummy variable equal to one if bond rating has a numerical value larger than 9, zero otherwise. See footnote 28 for details.
Downgrade	Dummy variable equal to one if bond was downgraded during the catastrophe windows, zero otherwise.
Commonality	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	Number of companies that sold a specific bond during the catastrophe window. Simple measure of how commonly sold a bond is.

Table 2: Variable definitions (continued).
This table summarizes all variables used in the empirical analysis.

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

Table 3: 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	Year	Date	Event	Affected States
79,663	2005	25.08.2005	Hurricane Katrina	LA, MS, AL
12,252	2005	20.09.2005	Hurricane Rita	TX, LA
15,248	2005	19.10.2005	Hurricane Wilma	FL
22,343	2008	06.09.2008	Hurricane Ike	TX, LA, AR, IL, IN, KY, MO, OH, PA
11,351	2012	15.07.2012	Drought in Corn Belt	CA, NV, ID, MT, WY, UT, CO, AZ, NM, TX, ND, SD, NE, KS, OK, AR, MO, IA, MN, IL, IN, GA
36,115	2012	24.10.2012	Hurricane Sandy	MD, DE, NJ, NY, CT, MA, RI, NC, VA, WV, OH, PA, NH

Table 4: 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 5: Average companies 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 6: Liquidation Policy Following the 2005 Liquidity Shock for Different Company Types. 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. White's robust standard errors are in parentheses.

	Probability of Bond Being Sold			
	All	Mutual	Others	Stock
	(1)	(2)	(3)	(4)
Affected dummy	0.007	−0.057	-0.494^{***}	0.081^{***}
	(0.018)	(0.049)	(0.118)	(0.020)
Log(Issue size)	0.110^{***}	0.113^{***}	0.135^{***}	0.098^{***}
	(0.016)	(0.044)	(0.048)	(0.018)
Log(Bond Age)	-0.062^{***}	−0.031	-0.128^{***}	-0.052^{***}
	(0.008)	(0.022)	(0.023)	(0.010)
Log(Bond life)	0.055^{***}	0.061^{***}	0.084^{***}	0.053^{***}
	(0.009)	(0.021)	(0.031)	(0.011)
Log(Buy Volume)	0.058^{***}	0.089^{***}	0.052	0.053^{***}
	(0.011)	(0.031)	(0.033)	(0.012)
Investment Grade	-0.332^{***}	-0.456^{***}	-0.831^{***}	-0.216^{***}
	(0.020)	(0.053)	(0.057)	(0.025)
Downgrade	-0.060^{**}	−0.042	−0.015	-0.075^{**}
	(0.031)	(0.078)	(0.097)	(0.036)
Log(Par value)	-0.052^{***}	-0.040^{**}	-0.107^{***}	-0.044^{***}
	(0.007)	(0.020)	(0.023)	(0.008)
Log(Commonality)	-0.100^{***}	-0.146^{***}	-0.120^{***}	-0.080^{***}
	(0.012)	(0.030)	(0.032)	(0.014)
Log(Total assets)	0.080^{***}	0.230^{***}	0.067	0.058^{***}
	(0.012)	(0.055)	(0.063)	(0.014)
Log(RBC)	-0.034^{***}	-0.184^{***}	−0.024	−0.012
	(0.011)	(0.050)	(0.066)	(0.012)
Constant	Yes	Yes	Yes	Yes
Observations	68,773	12,753	6,386	49,634
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7: Liquidation policy following the 2005 liquidity shock for different liquidity 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 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. White's robust standard errors are in parentheses.

	Probability of Bond Being Sold			
	Stock	Stock	Stock	Stock
	(1)	(2)	(3)	(4)
Affected dummy	0.081***	0.082***	0.082***	0.084***
	(0.020)	(0.020)	(0.022)	(0.022)
Log(Issue size)	0.098***	0.069***	0.150***	0.157***
	(0.018)	(0.018)	(0.019)	(0.018)
Log(Bond Age)	−0.052***	−0.043***	−0.060***	−0.056***
	(0.010)	(0.010)	(0.011)	(0.010)
Log(Bond life)	0.053***	0.052***	0.064***	0.059***
	(0.011)	(0.010)	(0.013)	(0.012)
Log(Buy Volume)	0.053***			
	(0.012)			
Log(Trading Volume)		0.083***		
		(0.012)		
Log(Lambda Sell)			0.009**	
			(0.004)	
Log(Lambda Average)				0.006*
				(0.003)
Investment Grade	−0.216***	−0.203***	−0.227***	−0.228***
	(0.025)	(0.025)	(0.027)	(0.027)
Downgrade	−0.075**	−0.073**	−0.093**	−0.094**
	(0.036)	(0.036)	(0.039)	(0.039)
Log(Par value)	−0.044***	−0.044***	−0.050***	−0.051***
	(0.008)	(0.008)	(0.009)	(0.009)
Log(Commonality)	−0.080***	−0.074***	−0.081***	−0.081***
	(0.014)	(0.014)	(0.016)	(0.016)
Log(Total assets)	0.058***	0.057***	0.057***	0.059***
	(0.014)	(0.014)	(0.016)	(0.016)
Log(RBC)	−0.012	−0.012	−0.005	−0.005
	(0.012)	(0.012)	(0.013)	(0.013)
Constant	Yes	Yes	Yes	Yes
Observations	49,634	49,634	38,848	38,608
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 8: Liquidation policy following liquidity shocks for different company types.
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. White's robust standard errors are in parentheses.

	Probability of Bond Being Sold			
	All	Mutual	Others	Stock
	(1)	(2)	(3)	(4)
Affected dummy	0.030^{***}	-0.078^{***}	0.188^{***}	0.047^{***}
	(0.010)	(0.027)	(0.030)	(0.012)
Log(Issue size)	0.086^{***}	0.043^{*}	0.120^{***}	0.084^{***}
	(0.009)	(0.022)	(0.023)	(0.010)
Log(Bond Age)	-0.044^{***}	-0.011	-0.057^{***}	-0.047^{***}
	(0.006)	(0.014)	(0.015)	(0.006)
Log(Bond life)	0.004	-0.004	-0.041^{**}	0.013^{**}
	(0.006)	(0.014)	(0.017)	(0.007)
Log(Buy Volume)	0.064^{***}	0.109^{***}	0.043^{***}	0.058^{***}
	(0.006)	(0.016)	(0.015)	(0.006)
Investment Grade	-0.278^{***}	-0.337^{***}	-0.418^{***}	-0.242^{***}
	(0.013)	(0.033)	(0.033)	(0.015)
Downgrade	0.157^{***}	0.176^{***}	0.187^{***}	0.148^{***}
	(0.023)	(0.057)	(0.064)	(0.027)
Log(Par value)	-0.011^{**}	-0.027^{**}	-0.072^{***}	0.006
	(0.004)	(0.012)	(0.011)	(0.005)
Log(Commonality)	-0.079^{***}	-0.071^{***}	-0.090^{***}	-0.076^{***}
	(0.007)	(0.017)	(0.017)	(0.008)
Log(Total assets)	0.035^{***}	0.114^{***}	0.173^{***}	0.001
	(0.008)	(0.025)	(0.027)	(0.010)
Log(RBC)	-0.020^{***}	-0.095^{***}	-0.119^{***}	0.003
	(0.007)	(0.023)	(0.025)	(0.008)
Fire Sale Window FE	Yes	Yes	Yes	Yes
Observations	335,593	58,945	35,962	240,686
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 9: Liquidation policy following liquidity shocks for different liquidity 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 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. White's robust standard errors are in parentheses.

	Probability of Bond Being Sold			
	Stock	Stock	Stock	Stock
	(1)	(2)	(3)	(4)
Affected dummy	0.047***	0.048***	0.043***	0.043***
	(0.012)	(0.012)	(0.012)	(0.012)
Log(Issue Size)	0.084***	0.070***	0.136***	0.136***
	(0.010)	(0.010)	(0.010)	(0.010)
Log(Bond Age)	−0.047***	−0.041***	−0.094***	−0.085***
	(0.006)	(0.006)	(0.006)	(0.005)
Log(Bond Life)	0.013**	0.014**	0.003	0.006
	(0.007)	(0.007)	(0.008)	(0.007)
Log(Buy Volume)	0.058***			
	(0.006)			
Log(Trading Volume)		0.074***		
		(0.006)		
Log(Lambda Sell)			0.0003	
			(0.002)	
Log(Lambda Average)				0.003
				(0.002)
Investment Grade	−0.242***	−0.237***	−0.258***	−0.263***
	(0.015)	(0.015)	(0.016)	(0.016)
Downgrade	0.148***	0.147***	0.149***	0.141***
	(0.027)	(0.027)	(0.029)	(0.029)
Log(Par value)	0.006	0.006	0.008	0.006
	(0.005)	(0.005)	(0.006)	(0.006)
Log(Commonality)	−0.076***	−0.073***	−0.087***	−0.088***
	(0.008)	(0.008)	(0.009)	(0.009)
Log(Total assets)	0.001	−0.00004	−0.005	−0.004
	(0.010)	(0.010)	(0.011)	(0.011)
Log(RBC)	0.003	0.004	0.005	0.005
	(0.008)	(0.008)	(0.009)	(0.009)
Fire Sale Window FE	Yes	Yes	Yes	Yes
Observations	240,686	240,686	220,536	220,308
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 10: 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. White's robust standard errors are in parentheses.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	0.12***	0.22***		0.01	0.10*			
	(0.005)	(0.07)		(0.05)	(0.06)			
Log(Trading Volume)			0.34***			0.12		
			(0.08)			(0.08)		
Log(Lambda Sell)							−0.15***	−0.15***
							(0.03)	(0.03)
Log(Issue Size)		−0.60***	−0.69***		−0.10	−0.12	0.19*	0.17*
		(0.12)	(0.13)		(0.12)	(0.13)	(0.10)	(0.10)
Log(Bond Age)		0.35***	0.39***		0.35***	0.36***	0.31***	0.30***
		(0.06)	(0.06)		(0.06)	(0.06)	(0.06)	(0.06)
Log(Bond Life)		0.61***	0.59***		0.42***	0.42***	0.30***	0.29***
		(0.06)	(0.06)		(0.07)	(0.07)	(0.08)	(0.08)
Log(Quantity Sold)								0.08*
								(0.04)
Log(Commonality)				−0.80***	−0.68***	−0.67***	−0.64***	−0.65***
				(0.08)	(0.08)	(0.09)	(0.08)	(0.08)
Number of Sellers				0.11***	0.10***	0.09***	0.10***	0.08**
				(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
Constant		9.08***	8.81***	−2.92***	−2.59	−2.49	−3.82*	−4.47**
		(2.03)	(2.02)	(0.75)	(2.14)	(2.16)	(2.08)	(2.02)
Observations	2,152	2,152	2,152	2,152	2,152	2,152	2,120	2,120
Adjusted R^2	0.23	0.06	0.06	0.07	0.10	0.10	0.12	0.12
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 11: 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. White's robust standard errors are in parentheses.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	−0.07**	0.13***		−0.07**	0.05			
	(0.03)	(0.04)		(0.03)	(0.04)			
Log(Trading Volume)			0.16***			0.04		
			(0.04)			(0.04)		
Log(Lambda Sell)							−0.14***	−0.14***
							(0.02)	(0.02)
Log(Issue Size)		−0.47***	−0.49***		−0.17**	−0.17**	0.03	0.03
		(0.08)	(0.08)		(0.08)	(0.08)	(0.08)	(0.08)
Log(Bond Age)		0.28***	0.28***		0.23***	0.23***	0.15***	0.15***
		(0.04)	(0.04)		(0.04)	(0.04)	(0.03)	(0.03)
Log(Bond Life)		0.33***	0.33***		0.22***	0.22***	0.09**	0.09**
		(0.04)	(0.04)		(0.04)	(0.04)	(0.05)	(0.05)
Log(Quantity Sold)								0.01
								(0.03)
Log(Commonality)				−0.54***	−0.44***	−0.44***	−0.39***	−0.39***
				(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Number of Sellers				0.16***	0.15***	0.15***	0.15***	0.15***
				(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Fire Sale Window FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,027	5,027	5,027	5,027	5,027	5,027	4,962	4,962
Adjusted R^2	0.23	0.25	0.25	0.27	0.27	0.27	0.28	0.28
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 12: 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. White's robust standard errors are in parentheses.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	0.26***	0.73***		0.22**	0.51***			
	(0.09)	(0.14)		(0.09)	(0.13)			
Log(Trading Volume)			0.87***			0.61***		
			(0.16)			(0.14)		
Log(Lambda Sell)							−0.19***	−0.19***
							(0.04)	(0.04)
Log(Issue Size)		−1.21***	−1.32***		−0.72***	−0.81***	−0.05	−0.09
		(0.26)	(0.27)		(0.25)	(0.26)	(0.20)	(0.21)
Log(Bond Age)		0.38***	0.41***		0.35***	0.37***	0.22**	0.21**
		(0.10)	(0.11)		(0.10)	(0.10)	(0.09)	(0.09)
Log(Bond Life)		0.84***	0.81***		0.67***	0.66***	0.57***	0.56***
		(0.18)	(0.18)		(0.17)	(0.17)	(0.18)	(0.17)
Log(Quantity Sold)								0.11
								(0.09)
Log(Commonality)				−1.22***	−0.92***	−0.89***	−1.02***	−1.05***
				(0.19)	(0.18)	(0.18)	(0.18)	(0.19)
Number of Sellers				0.20***	0.19***	0.19***	0.20***	0.18***
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,027	2,027	2,027	2,027	2,027	2,027	2,020	2,020
Adjusted R^2	0.40	0.44	0.44	0.45	0.47	0.47	0.47	0.47

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: 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. White's robust standard errors are in parentheses.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	0.25	0.35**		0.17	−0.04			
	(0.16)	(0.17)		(0.16)	(0.16)			
Log(Trading Volume)			0.53***			0.05		
			(0.19)			(0.18)		
Log(Lambda Sell)							−0.32***	−0.35***
							(0.07)	(0.07)
Log(Issue Size)		−0.43	−0.57*		0.40	0.32	0.73**	0.57*
		(0.30)	(0.31)		(0.34)	(0.35)	(0.32)	(0.30)
Log(Bond Age)		0.21	0.27		0.06	0.10	−0.05	−0.05
		(0.18)	(0.18)		(0.18)	(0.18)	(0.17)	(0.17)
Log(Bond Life)		1.14***	1.14***		0.85***	0.85***	0.63***	0.59***
		(0.23)	(0.23)		(0.22)	(0.22)	(0.22)	(0.22)
Log(Quantity Sold)								0.57***
								(0.21)
Log(Commonality)				−1.71***	−1.71***	−1.69***	−1.62***	−1.75***
				(0.23)	(0.25)	(0.26)	(0.26)	(0.27)
Number of Sellers				0.55***	0.55***	0.54***	0.54***	0.45***
				(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
Fire Sale Window FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,089	4,089	4,089	4,089	4,089	4,089	4,076	4,076
Adjusted R^2	0.53	0.53	0.53	0.55	0.56	0.56	0.56	0.56

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: 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. White's robust standard errors are in parentheses.

	|Price Impact|							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Buy Volume)	−0.17***	−0.04		−0.13***	−0.09**			
	(0.02)	(0.05)		(0.02)	(0.04)			
Log(Trading Volume)			−0.05			−0.10**		
			(0.05)			(0.04)		
Log(Lambda Sell)							−0.07***	−0.07***
							(0.02)	(0.02)
Log(Issue Size)		−0.22**	−0.21***		−0.02	−0.01	−0.03	−0.03
		(0.09)	(0.08)		(0.09)	(0.08)	(0.06)	(0.06)
Log(Bond Age)		0.17***	0.17***		0.12**	0.12**	0.18***	0.18***
		(0.06)	(0.06)		(0.05)	(0.05)	(0.04)	(0.04)
Log(Bond Life)		0.30***	0.30***		0.25***	0.25***	0.21***	0.20***
		(0.05)	(0.05)		(0.05)	(0.05)	(0.05)	(0.05)
Log(Quantity Sold)								0.03
								(0.03)
Log(Commonality)				−0.30***	−0.25***	−0.25***	−0.20***	−0.20***
				(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
Number of Sellers				0.02	0.01	0.02	0.01	−0.0004
				(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	3.23***	5.16***	5.23***	1.23***	0.78	0.91	1.23	0.85
	(0.34)	(1.35)	(1.31)	(0.41)	(1.51)	(1.49)	(1.46)	(1.52)
Observations	1,191	1,191	1,191	1,191	1,191	1,191	1,171	1,171
Adjusted R^2	0.04	0.09	0.09	0.09	0.12	0.12	0.13	0.13

Note: *p<0.1; **p<0.05; ***p<0.01

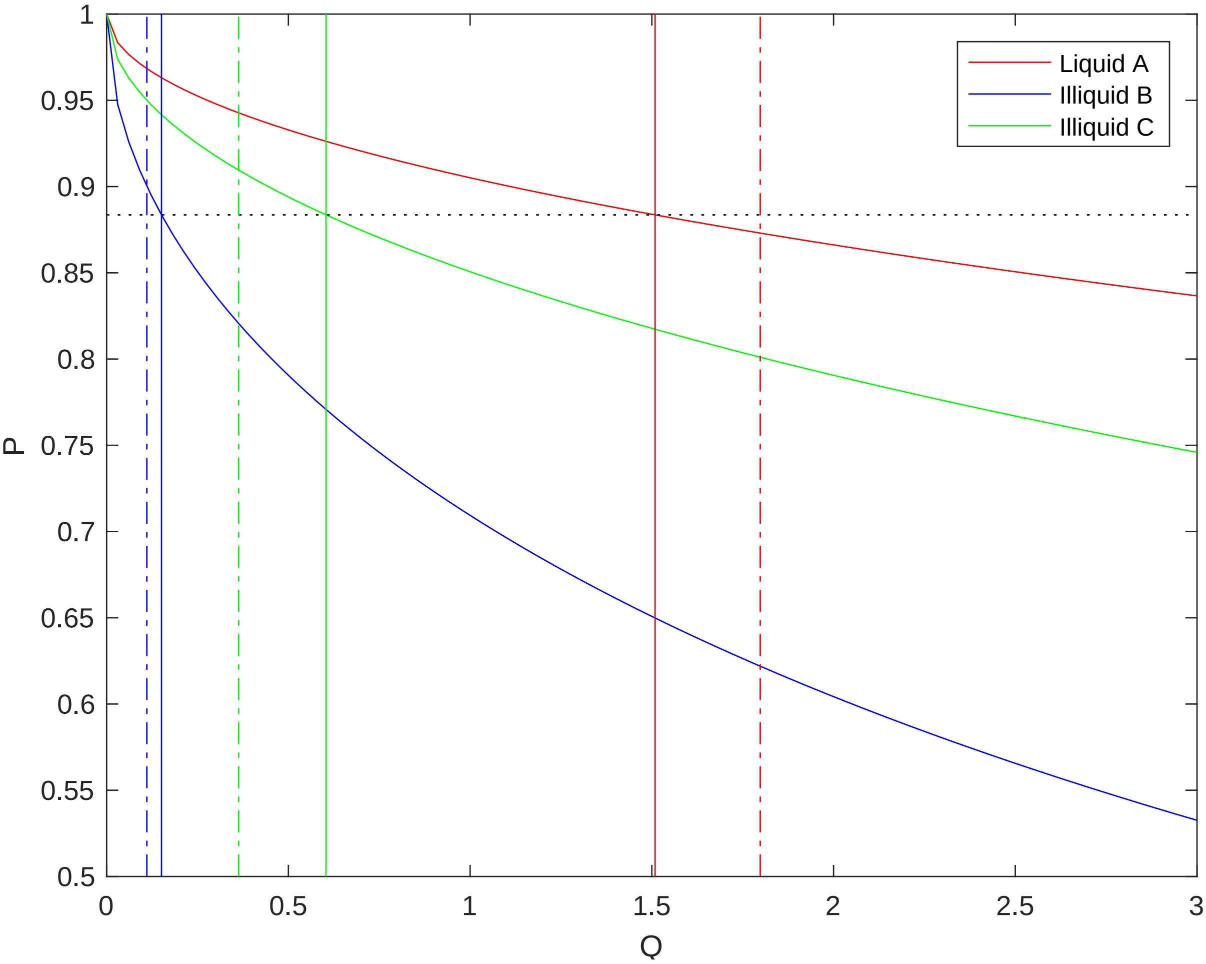


Figure 1: Portfolio Liquidation.
This figure illustrates the optimal liquidation policies of two agents. Agent 1 holds assets A and B, while agent 2 holds assets A and C. Asset A is the commonly-held asset. The down-ward slopping lines on the plot represent price-impact functions for the three assets, 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 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.

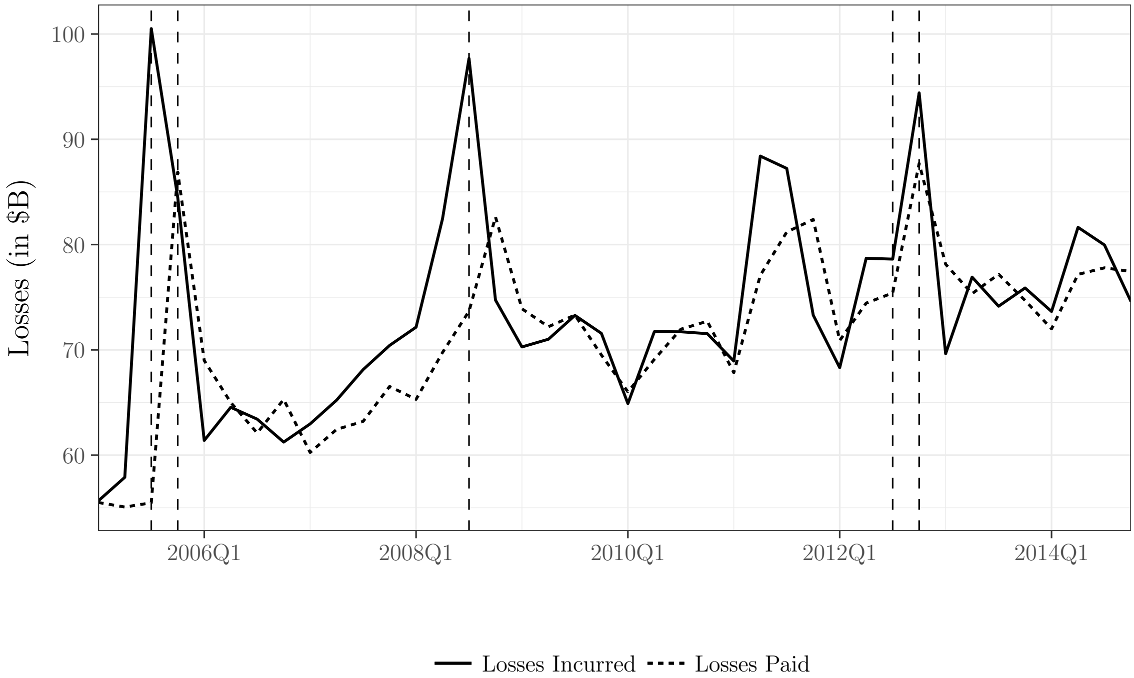


Figure 2: Aggregate losses of P&C insurance companies.
This figure demonstrates the dynamics of incurred (solid line) and paid (dashed line) losses on direct business in our sample. Both the incurred and paid losses increase following the catastrophes that we identified as aggregate shocks.

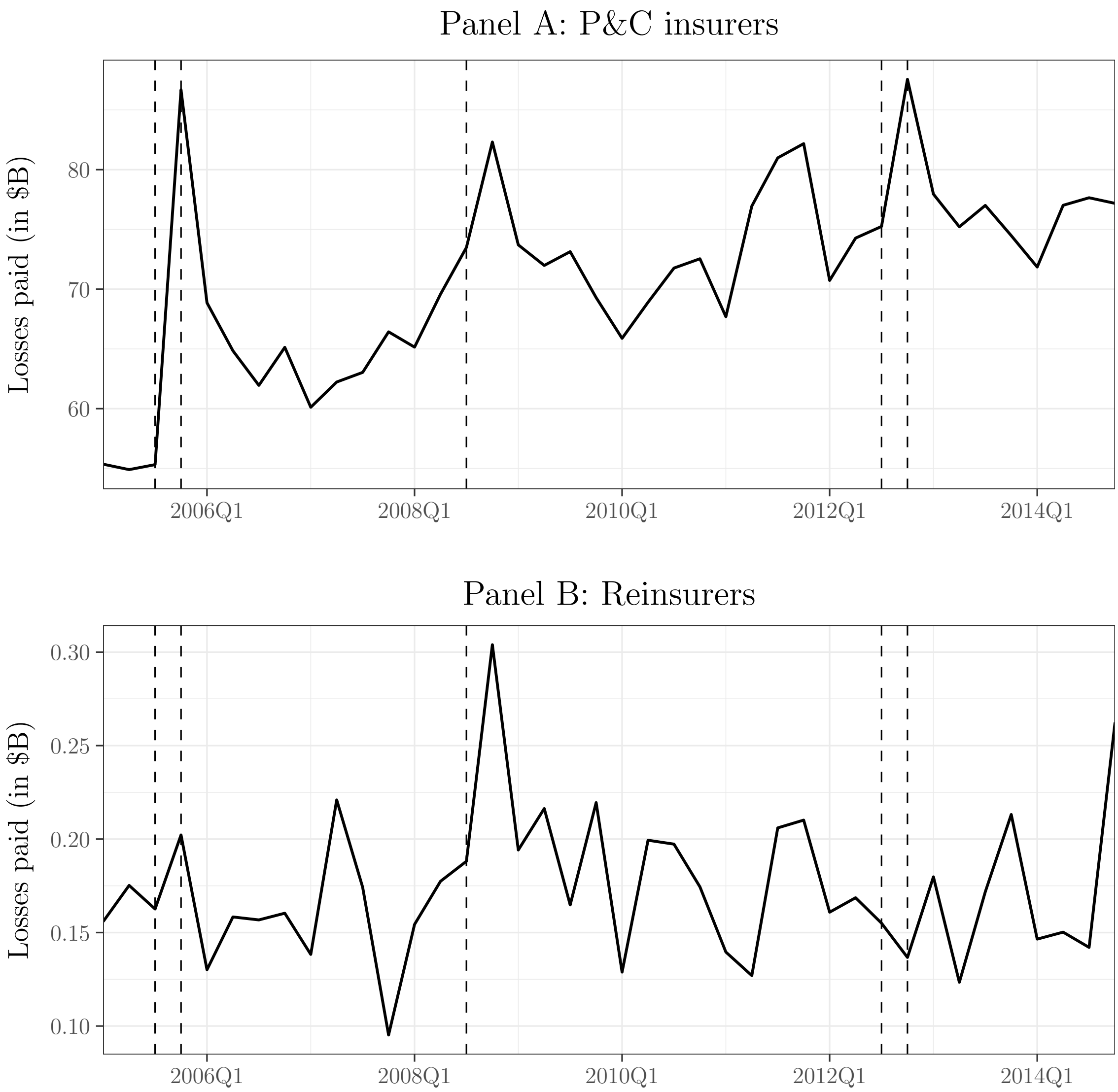


Figure 3: Losses paid on direct business: P&C insurers vs. reinsurers.
This figure demonstrates the difference between the dynamics of reported losses paid on direct business for insurers and re-insurers. It is clear that the difference in the business models of insurers and re-insurers commands a difference 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

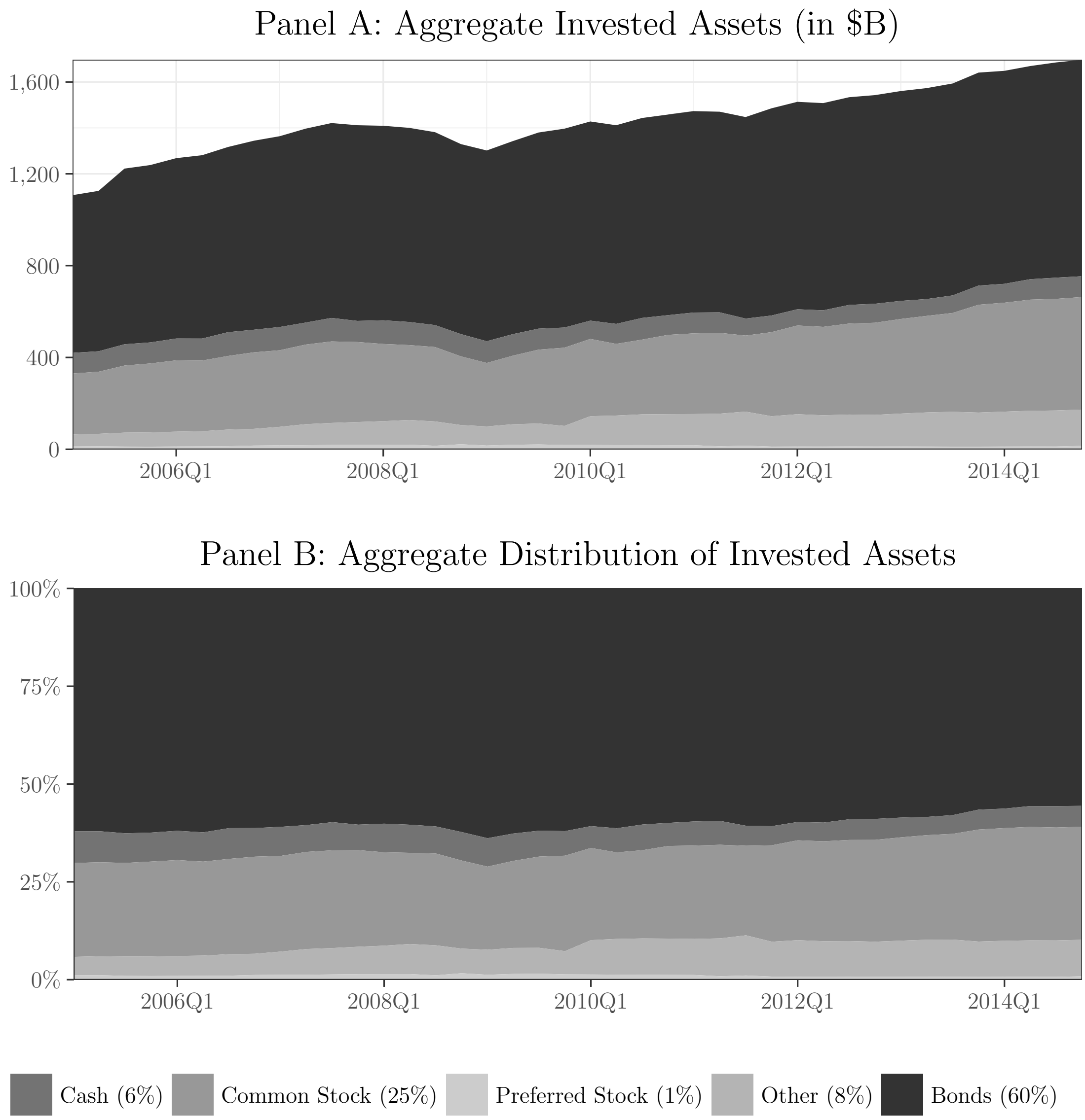


Figure 4: Asset holdings in the P&C insurance sector.
This figure demonstrates the composition of holdings by property and causality insurance companies and its evolution in time. The amount of assets invested in bonds has been increasing in time, making insurance companies net buyers on the bond market,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

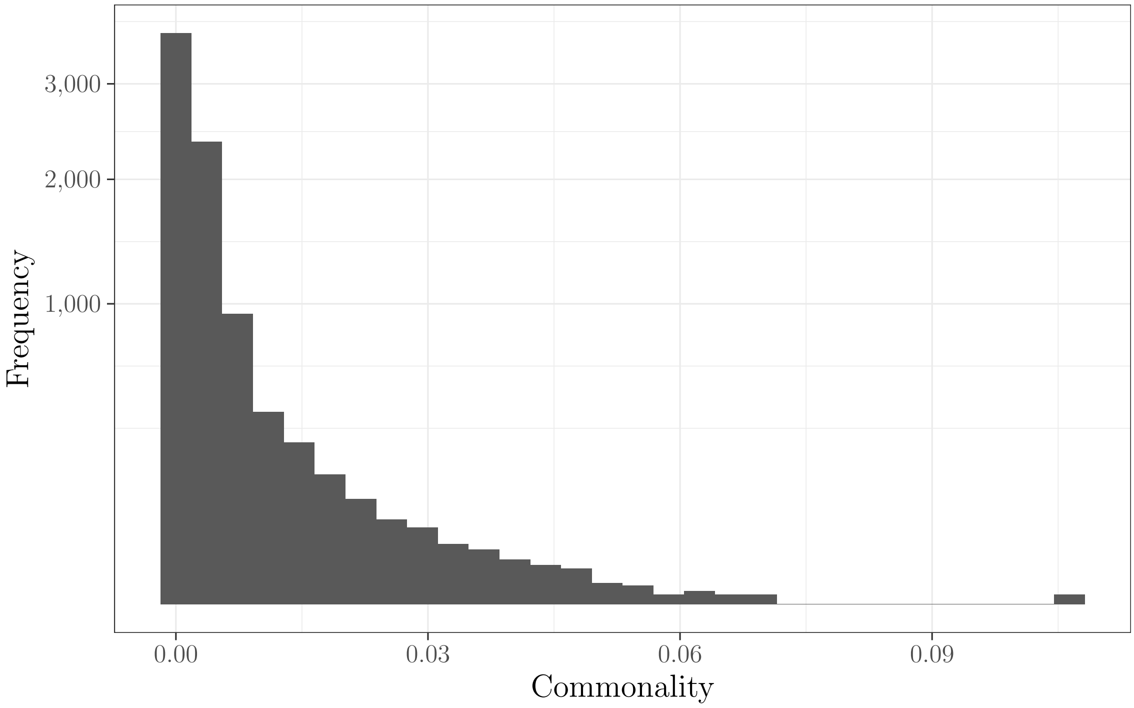


Figure 5: Commonality of corporate bonds.
This graph shows commonality of corporate bonds, as measured on 2005-08-11 (two weeks before Hurricane Katrina). Commonality is defined as the number of companies that hold a specific bond divided by the total number of portfolios. To be present in the sample, the bond must appear in a portfolio of a P&C insurance company at least once in the sample.

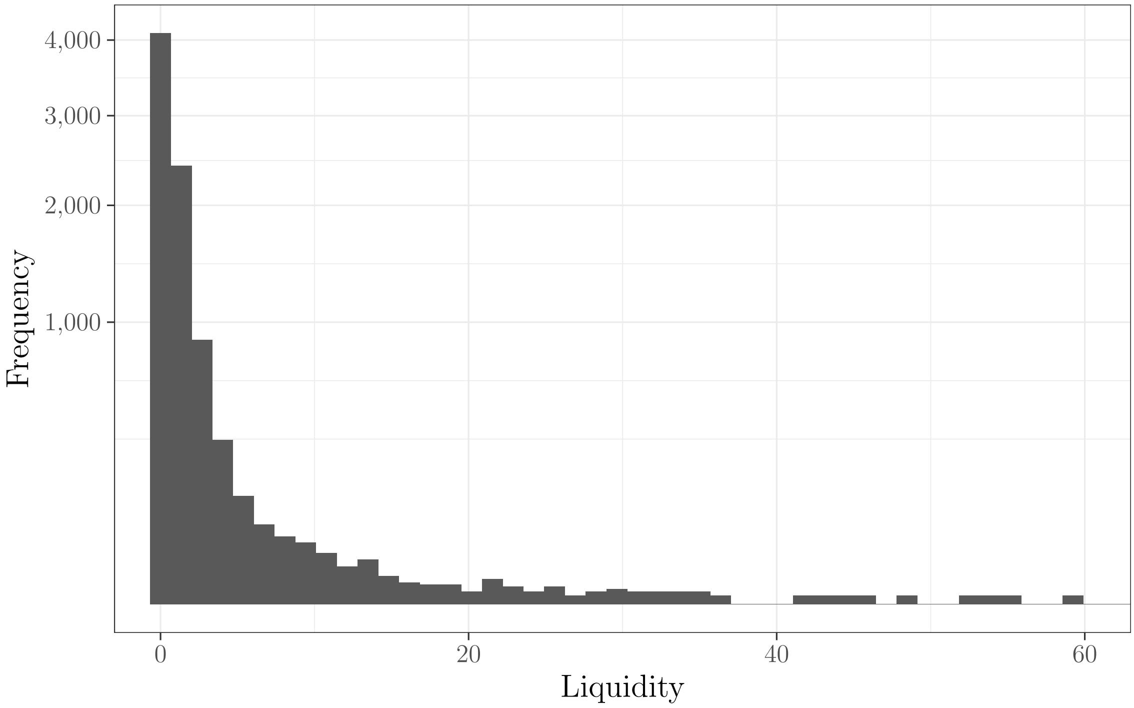


Figure 6: Liquidity of corporate bonds.
This graph shows liquidity of corporate bonds, as measured on 2005-08-11 (two weeks before Hurricane Katrina) using a trading volume of the bond in the last 180 days. To be present in the sample, the bond must appear in a portfolio of a P&C insurance company at 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.

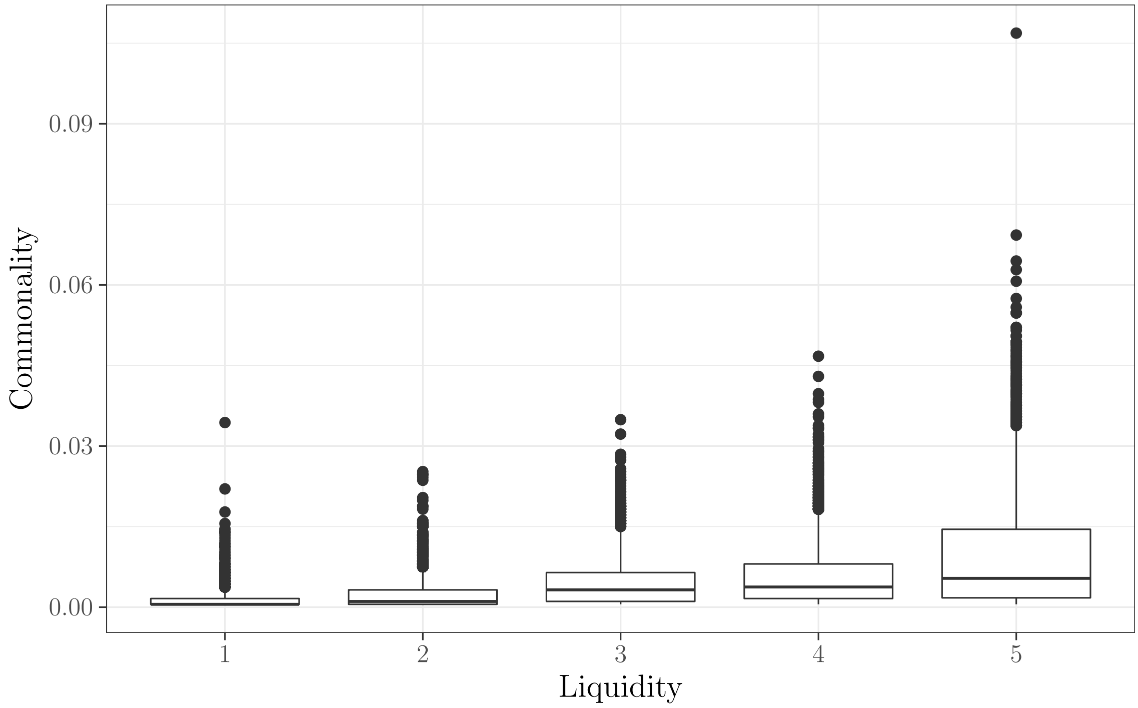


Figure 7: Liquidity-Commonality Boxplot.
This boxplot shows the distribution of commonality of corporate bonds per liquidity quintile. Both measures are computed on 2005-08-11 (two weeks before Hurricane Katrina). More commonly held bonds tend to exhibit higher liquidity.

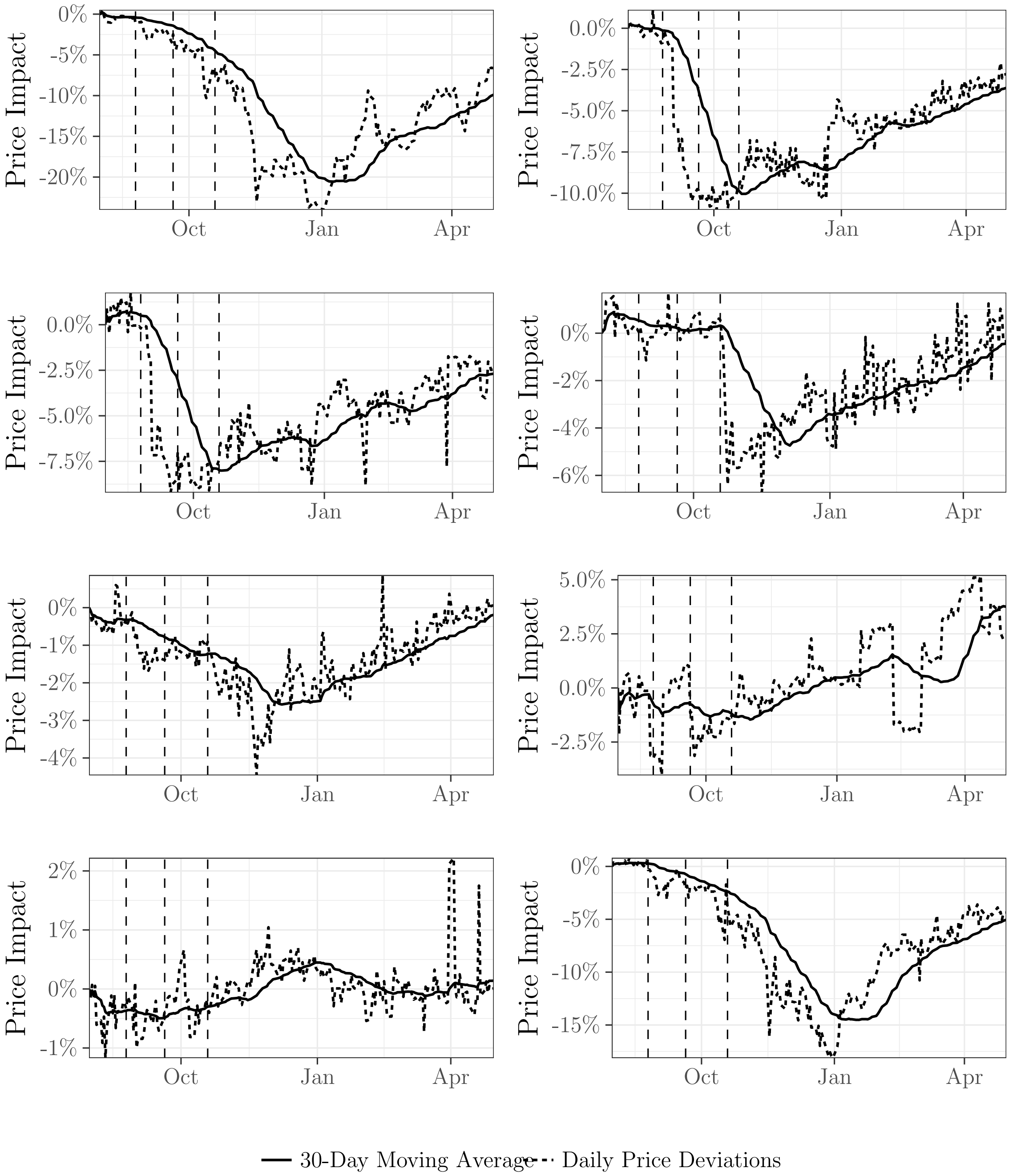


Figure 8: Individual price impacts - examples.
The dotted lines are daily price deviations of TRACE prices from the estimated fundamental price. The solid line is the 30-day moving average over these price deviations. The dashed vertical lines indicate the timing of catastrophes in 2005. CUSIPs and company 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.

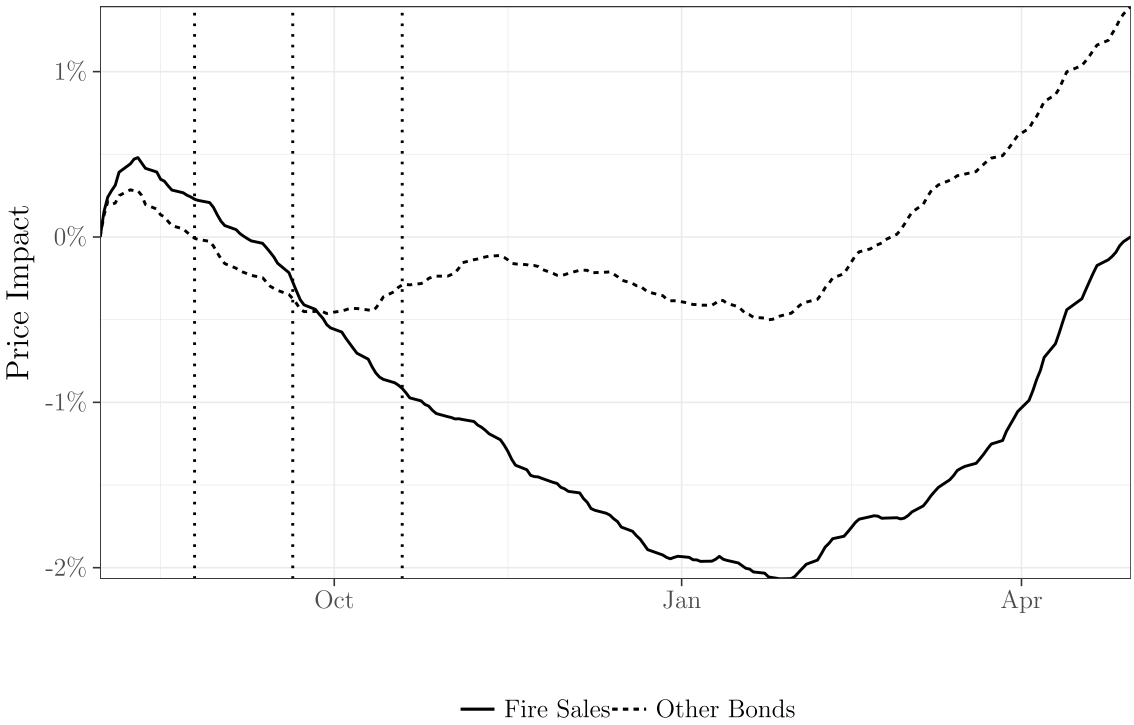


Figure 9: Average price impact of fire sold bonds.
The plot shows the daily average price impact of bonds sold by affected companies (solid line) with a total trade size of at least 2% of issue size. The dashed line shows the daily average over all other bonds. The dotted vertical lines indicate the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

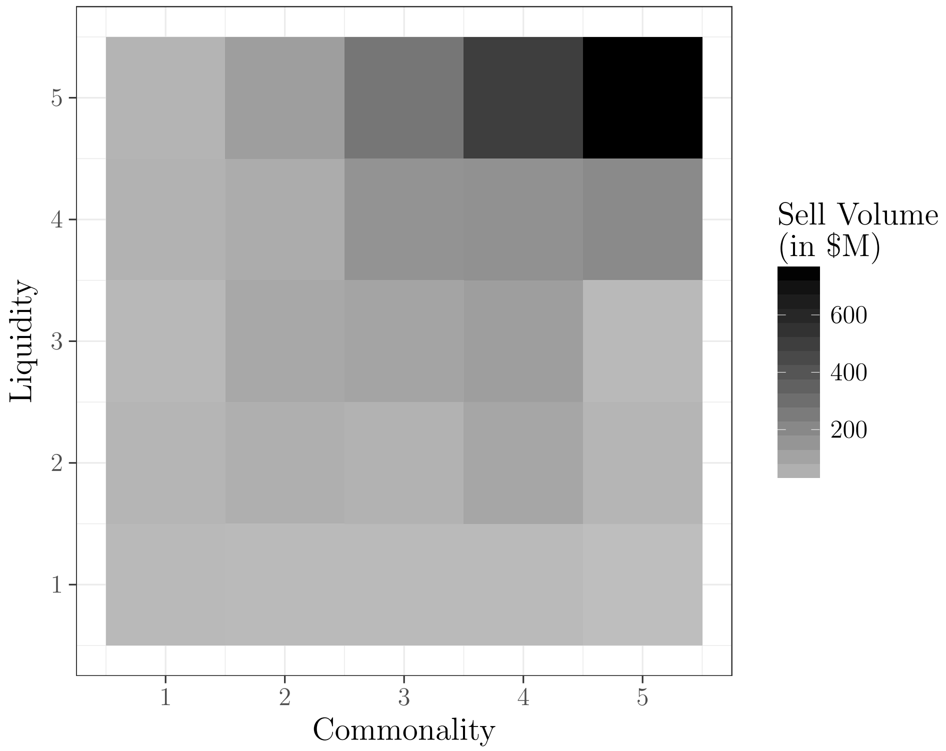


Figure 10: Heat map of sell volume by commonality and liquidity quintiles.
This figure shows the total sell volume of affected companies per liquidity and commonality quintiles. It shows that there is a concentration of total trading volume in the segment with the most liquid, most commonly held bonds.

Figure 11: Total Invested Volume per Liquidity Category.
This figure shows 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.

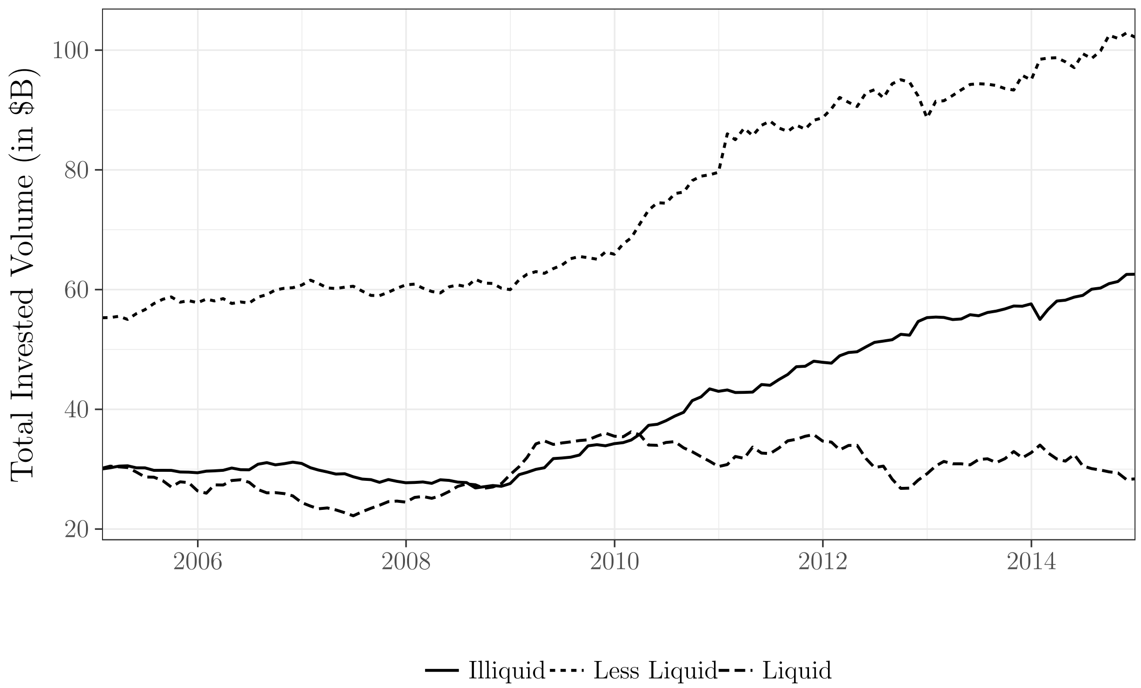


Figure 12: Share of Total Invested Volume per Liquidity Category.
This figure shows the share of total invested corporate bond volume per liquidity category. We define liquid as the top decile of most liquid corporate bonds in the portfolios of insurers at the end of each month. Illiquid bonds are defined as the bottom 50% of least liquid bonds and the remaining bonds are denoted as less liquid.

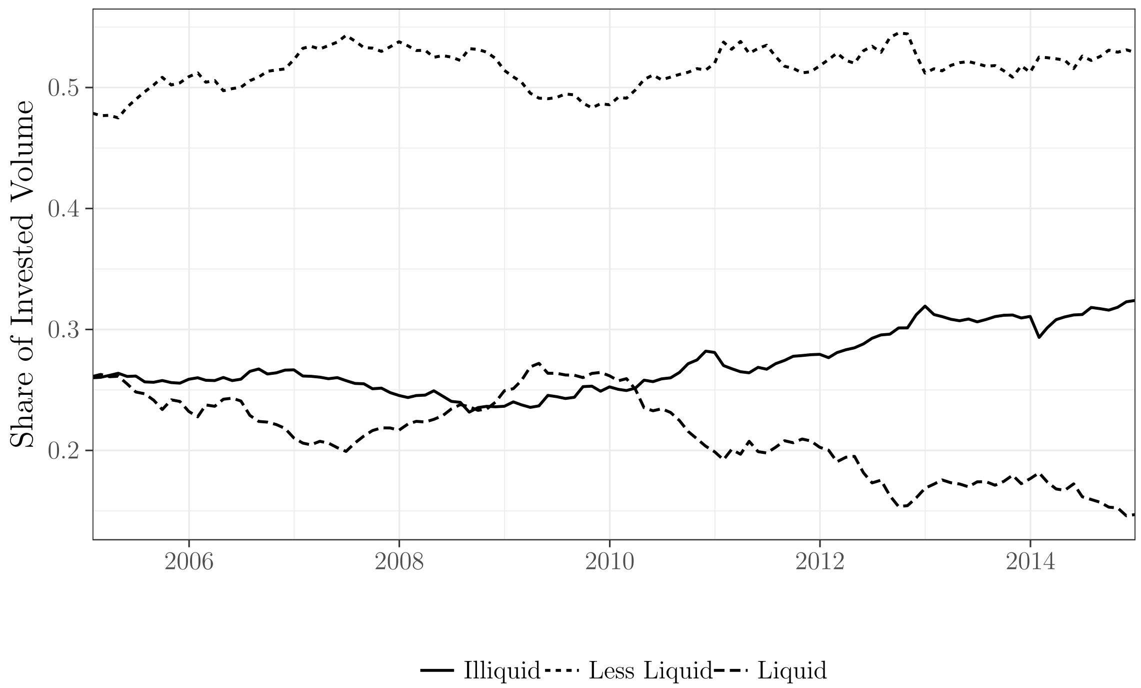


Figure 13: Average commonality per liquidity category.
This figure shows the average commonality of bonds in each liquidity category. We define liquid as the top decile of most liquid corporate bonds in the portfolios of insurers at the end of each month. Illiquid bonds are defined as the bottom 50% 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.

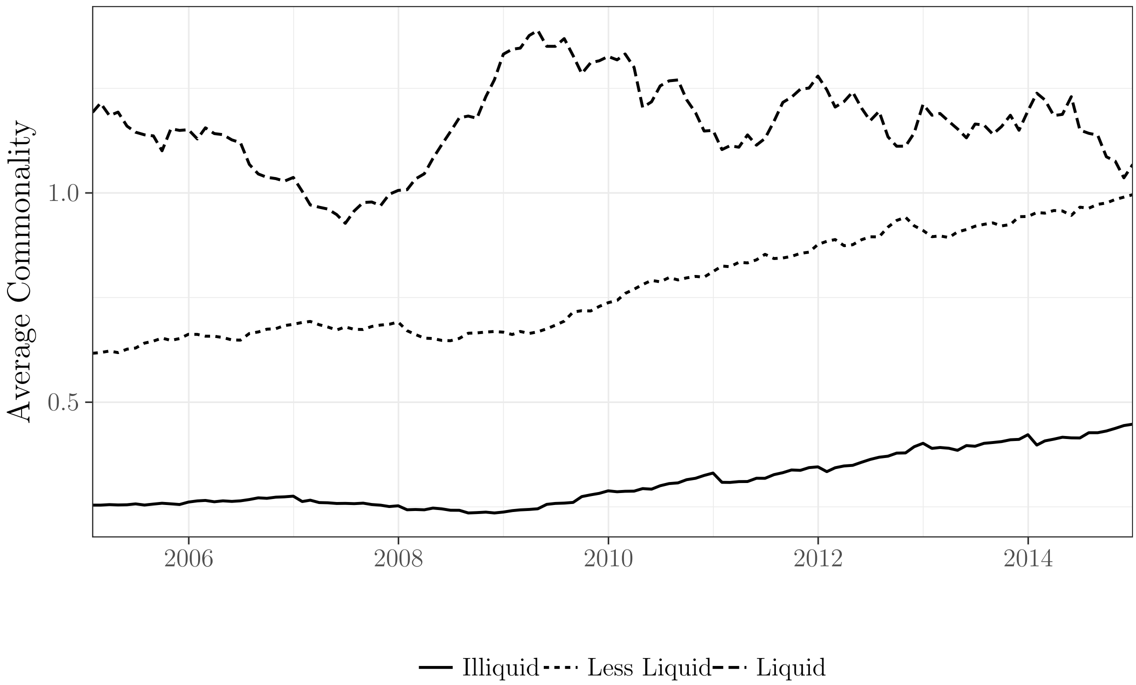


Figure 14: Average commonality per liquidity category weighted by sector-wide portfolio weights.
This figure shows the average commonality of bonds in each liquidity category. We define liquid as the top decile of most liquid corporate bonds in the portfolios of insurers at the end of each month. Illiquid 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. 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.

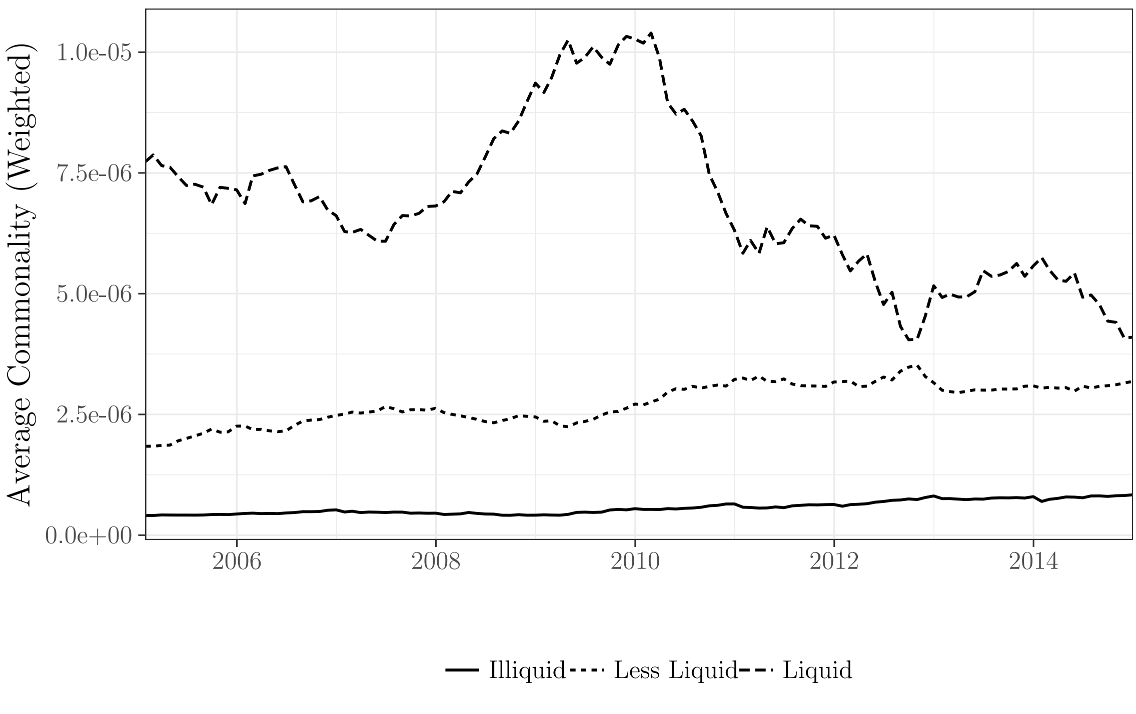
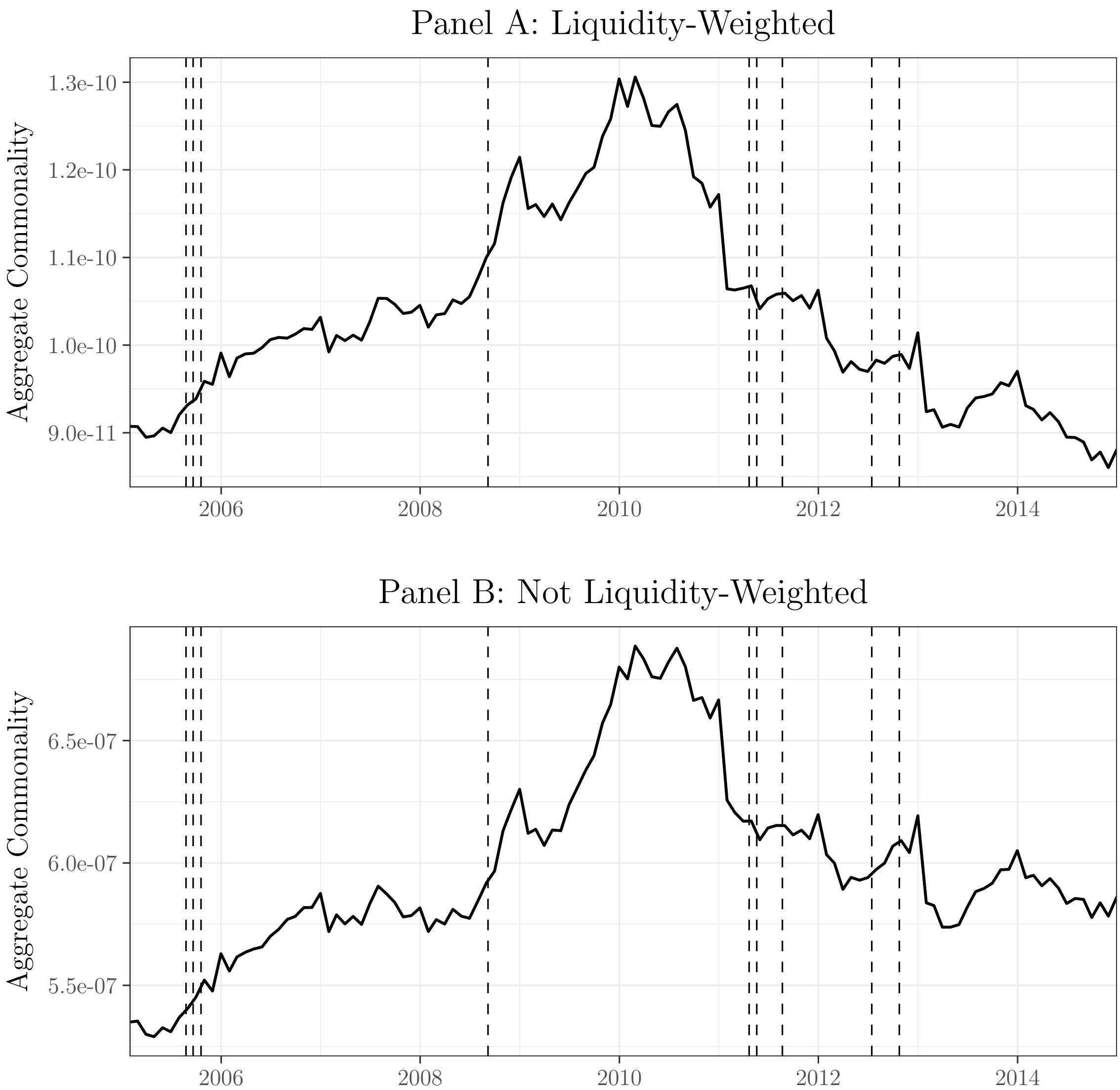


Figure 15: Aggregate Commonality Measures.
Panel A depicts the extent to which liquid bonds are commonly-held by insurance companies. The more commonly-held the liquid bonds are, the larger is the aggregation risk present in the industry. That is, given a liquidity shock which affects a group of insurance 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.



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