Asset Insulators*

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Abstract

We construct a new dataset tracking the daily value of life insurers' assets at the security level. Outside of the 2008-09 crisis, a $1 drop in the market value of assets reduces an insurer's market equity by $0.10. During the financial crisis, this pass-through rises to 1. We explain this pattern by viewing insurance companies as asset insulators, institutions with stable, long-term liabilities that can ride out transitory dislocations in market prices. Illustrating the macroeconomic importance of insulation, insurers' market equity declined by $50 billion less than the duration-adjusted value of their securities during the crisis.

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1 Introduction

Financial intermediaries hold tens of trillions of dollars of securities. How does the value of these institutions respond to a decline in the prices of these securities? Under Modigliani-Miller, a dollar of assets translates directly into a dollar of firm value. In theories of financial distress, a decline in prices additionally reduces the financial health of the institution, yielding a more than one-to-one effect. This amplification can start an adverse feedback loop in the financial system and the economy more broadly. But an alternative possibility exists, propounded by many practitioners: certain types of financial institutions, such as banks, life insurers, and pension funds, are long-term investors that can "ride out" fluctuations in asset prices without seeing their own valuations significantly affected. We refer to this second view as *asset insulation*.

We investigate this question in the context of the life insurance sector. We make three contributions. First, we empirically estimate the pass-through from asset holdings to equity. Outside of the 2008-2009 crisis, a dollar lost on assets creates an approximately 10 cent loss to equity value. The pass-through rises to 1 during the crisis. Second, we interpret this pattern using the asset insulation framework; (i) the low pass-through in normal conditions exemplifies asset insulation, but (ii) in crisis periods such as 2008-09, the risk of liquidation reduces insurers' ability to insulate *at the margin*. Third, despite reducing the ability to insulate *at the margin* during the crisis, the continued ability to partially insulate the broad part of their balance sheet from the large dislocation in market prices of securities kept many insurers from insolvency. We conclude that asset insulation offers a coherent framework for understanding a number of important facts about life insurers.

We start our analysis by developing the pass-through measure: the marginal response of the equity of an institution to a change in the market value of its asset holdings. We measure the pass-through for life insurance companies, a sector which holds $4 trillion of financial assets. We obtain the pass-through by regressing for each day the equity return on the change in asset values in the cross-section of insurers. In order to track asset values, we merge daily, security-level asset positions of each publicly-traded insurer with the universe of corporate bond returns on each date, giving rise to 8.7 million bond-level portfolio shocks.

Measurement of the pass-through must overcome the identification challenge that the observed return on asset holdings may be correlated with the change in value of other assets, of insurers' liabilities, and of the value of future business. Our empirical strategy exploits large, idiosyncratic movements in bond prices held by some insurers and not others. Specifically, we instrument for the overall daily change in the market value of an insurer's corporate bond holdings using only the part coming from large idiosyncratic bond returns.

The empirical pass-through differs markedly in and out of the 2008-2009 financial crisis. Outside of the crisis, a dollar lost on assets creates an approximately 10 cent loss to equity value, economically and statistically significantly much less than one. The pass-through rises during the crisis. Both the OLS and IV estimates reject equality of the pass-through in and out of the crisis, but do not reject equality of the crisis pass-through and 1. We show extensive robustness to the definition of the portfolio shocks, control variables, and sample restrictions, and also implement an alternative granular IV identification strategy proposed by Gabaix and Koijen (2019) to confirm the validity of our results.

The behavior of the pass-through across these two market conditions constitutes a useful test of asset insulation in the presence of limits to arbitrage. An insulator creates value for its stakeholders by holding for the long run securities otherwise subject to valuation shocks in the open market. This activity results in shareholders pricing the market value of an insulator's equity differently than the gap between the market value of its assets and liabilities. The value of holding an asset inside an insulator increases with the size of the wedge between these two valuations. The ability to extract this value relies on maintaining good financial health: if market conditions deteriorate sufficiently, the institution may have to liquidate its holdings at market prices. The interaction of these two forces shapes the relation between the value of an insulator and that of its assets. In normal times, the ability to insulate from transitory fluctuations in asset prices in the open market yields a pass-through from asset holdings to equity below 1. As the risk of forced liquidation increases, however, the ability to insulate diminishes and even transitory fluctuations affect equity. Moreover, each lost dollar of assets pushes the firm closer to liquidation, reducing the value of insulation on the entire balance sheet. Thus, the pass-through rises during a crisis. This pattern is not only consistent with our empirical findings, but also unique to the insulator theory; theories of financial institutions rooted in costs of financial distress or risk-shifting due to government guarantees do not predict this behavior. We provide additional evidence that poor financial health during this period contributed to lower insulation from market movements, as the pass-through rises most for those insurers most affected by the crisis.

The possibility of asset insulation presumes the existence of frictions in security markets that cause the long-run and market valuations of securities to differ. In the presence of such pricing frictions, could actions by insurers themselves or common investors in insurers and the bonds they hold have affected the prices of the securities, giving rise to an alternative, reverse causality or omitted variable interpretation of our results? We report a number of exercises suggesting not, including that insurers rarely sell bonds following a large abnormal return and that we obtain similar pass-through estimates when restricting to securities in which the insurer holds a small share of the total issuance. More difficult to dismiss is that the behavior of the pass-through is driven by changes in investor attention in and out of the crisis, although we present evidence of similar pass-through when restricting to large or small shocks or excluding volatile trading days that appears inconsistent with a simple salience explanation. However, the evidence for insulation extends beyond the pass-through. If security prices indeed experience temporary dislocations, the long-term, stable liabilities of insurers rationalize their investments in risky securities to exploit these profitable trading opportunities (Chodorow-Reich, Ghent, and Haddad (2020)). Consistent with insurers actively targeting these dislocations, we show that corporate bonds purchased by insurers in the secondary market have on average recently fallen in value but subsequently experience positive abnormal returns.

Finally we show that a loss of the ability to insulate at the margin does not imply that insulators provide *no* insulation during crisis periods. To the contrary, we demonstrate that insulation is critical to understanding the survival of the life insurance sector during the 2008-09 crisis. Specifically, without the value created by insulation, the market equity of life insurers during the 2008-09 period would have declined by additional tens of billions of dollars, likely rendering much of the sector insolvent. The reason this did not happen is that the difference between the sector's equity and the market value of its financial assets net of liabilities – what we term the franchise value – increased during the crisis. This calculation involves two steps. First, the sharp drop in safe interest rates during 2008 increased the value of publicly-traded insurers' policy liabilities by an estimated \$97 billion. Second, the market value of the risky assets held by these insurers declined by \$30 billion. A constant franchise value would therefore have implied a more than \$127 billion loss in the value of insurers' equity. Instead, equity dropped by "only" \$80 billion. The \$47 billion increase in franchise value reflects an increase in the value of insulation during the crisis, due to forces such as fire sale discounts and increases in illiquidity that depressed market prices of bonds. As such, insulation helped insurance companies withstand the brunt of the crisis. Nevertheless, the behavior of the pass-through during this period highlights a core tension in the provision of asset insulation, as the crisis coincided with a deterioration in the financial health of insurers, threatening their ability to insulate assets from market movements exactly when such insulation is most valuable.

The remainder of the paper proceeds as follows. We next situate our findings in the existing literature. Section 2 provides background on life insurers and describes our data. Section 3 contains the pass-through exercise. We formalize the concept of an asset insulator in Section 4 and discuss the implications of this theory and various alternatives for the pass-through. In Section 5 we measure the change in franchise value during the financial crisis. Section 6 concludes.

Related literature. Our paper relates to a large body of work on financial institutions in episodes of economic trouble. Going back to Bernanke (1983), a large literature emphasizes how deteriorating health of financial institutions can amplify adverse conditions. He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) articulate formal theories of this view motivated by the 2008-09 period. We focus instead on the ability of certain intermediaries to avoid frictions in the market for securities. In this insulator role, shocks originating on financial markets can actually be mitigated by the intermediary.

The life insurance industry during the 2008-09 crisis exemplifies both of these views. Consistent with an amplification role and our own evidence on some insurers' losing their ability to insulate at the margin, Ellul, Jotikasthira, and Lundblad (2011) document that regulatory constraints prompted life insurers to liquidate some bond positions during this period, pushing the prices of these bonds further down, while Koijen and Yogo (2015) show how binding regulatory constraints distorted the pricing of insurance policies. Our work highlights that life insurers also may have mitigated the link from security prices to the market equity of the financial sector. While insurers certainly suffered during the crisis, their ability to insulate prevented the destruction of nearly $50 billion of market equity in the financial sector at a crucial moment.

An important ingredient for insulators to create value is the stability of their liabilities. Diamond and Dybvig (1983), Gorton and Pennacchi (1990), and Calomiris and Kahn (1991) discuss how financial institutions can manufacture stable liabilities. In the case of insurers, the long contractual horizon of policies naturally gives rise to stable liabilities. Our main focus is how such funding stability facilitates insulation in securities markets. Two papers related to ours illustrate such a comparative advantage in the context of commercial banks and closed-end funds. In Hanson, Shleifer, Stein, and Vishny (2015), commercial banks have "sleepy" liabilities because government deposit insurance makes depositors insensitive to the value of the bank's assets, allowing them to ride out periods of fire sales. In Cherkes, Sagi, and Stanton (2009), fully equity-financed closed-end funds face no redemption risk. Our framework emphasizes that any institution with stable liabilities may adopt the role of an asset insulator. In contrast, Diamond and Rajan (2011) study how institutions with *unstable* funding interact with fire sales.

Finally, an insulator is a specific type of arbitrageur. Hence, our work also relates to the literature on the limits to arbitrage and fire sales.[1] This literature has traditionally focused on sophisticated institutions created with the explicit goal of making profits by taking advantage of financial market inefficiencies. We highlight how a broader set of large financial institutions derive value from differences in valuation and how this activity shapes the evolution of the market equity of these institutions. Our approach echoes a literature which tries to resolve the closed-end fund puzzle by valuing the comparative advantage of the institution (Lee, Shleifer, and Thaler, 1991; Berk and Stanton, 2007; Cherkes et al., 2009). In addition, our results add to

[1] Shleifer and Vishny (1997) originate the term "limits to arbitrage" and provide the first formal model of it. Barberis and Thaler (2003), Gromb and Vayanos (2010), and Shleifer and Vishny (2011) provide surveys of the literature.

the evidence of multiple valuations of seemingly the same asset (e.g., Malkiel, 1977; Lamont and Thaler, 2003), in our case corporate bonds.

2 Background on Life Insurers and Data

In the remainder of the paper we use the life insurance sector as our empirical laboratory. This sector is large, managing assets in excess of 20% of GDP, and we make use of detailed regulatory data on their asset holdings. We provide here a brief background on the life insurance sector and our data.

Like all financial institutions, insurers issue liabilities and invest in assets. The type of liabilities issued, primarily life insurance contracts and annuities, defines what it means to be a life insurer for regulatory purposes. Insurers segregate their balance sheets into general account assets which back fixed rate liabilities and death benefits, and separate account assets linked to variable rate products. As their name suggests, gains and losses on separate account assets flow directly to the policyholder and hence do not directly affect the equity in the insurance company. We exclude separate accounts in all of our analysis hereafter. Insurers issue two broad types of liabilities against their general account assets: fixed rate (either annuities or life insurance contracts), and variable rate with minimum income guarantees.[2]

State guaranty funds protect policyholders against the risk of insurer default up to a coverage cap. In exchange, insurers are subjected to regulation at the state level. Since the 1990s, such regulation has taken the form of a risk-based capital regime.

Our data on asset holdings come from mandatory statutory annual filings by insurance companies in operation in the United States to the National Association of Insurance Commissioners (NAIC). We supplement these annual filings with manda-

[2]See Paulson, Rosen, McMenamin, and Mohey-Deen (2012) and McMillan (2013) for an overview of the different products life insurers offer consumers. Koijen, Van Nieuwerburgh, and Yogo (2016) discuss the demand for the various products. Koijen and Yogo (2016) describe additional complications relating to how liabilities appear on the balance sheet or are ceded to reinsurance subsidiaries.

tory quarterly filings on insurers' trades to update insurers' portfolio positions within years. We use the version of these data provided by SNL Financial. Our main sample includes all life insurers in the United States and covers the period 2004-2014. In sections 3 and 5, we consider a subsample of publicly-traded U.S. life insurers that are substantively life insurers.[3] Appendix Table A.1 reports the total quantity of general account assets under management in the life insurance industry as a fraction of GDP. The first column uses data from the Financial Accounts of the United States (FAUS, formerly known as the Flow of Funds). General account assets exceed 20% of GDP. For comparison, in 2014 assets of commercial banks equaled 77% of GDP, assets of property and casualty insurers 9% of GDP, and assets of closed-end funds 2% of GDP. The second column reports general account assets for the universe of insurers in the SNL database. The FAUS and SNL track each other extremely closely; in fact, SNL provides the source data for the FAUS. The third column reports assets at the life insurers in our publicly-traded subsample. This subset of insurers manages roughly one quarter of total insurer assets despite containing only 15 of the approximately 400 insurance companies in the SNL data.

[3] The set of publicly-traded insurers (tickers) in our sample is: Aflac Inc. (AFL), Allstate Corp. (ALL), American Equity Investment (AEL), American National Insurance (ANAT), Citizens Inc. (CIA), CNO Financial Group Inc. (CNO), Farm Bureau Financial Services (FFG), Independence Holding (IHC), Kansas City Life Insurance Co. (KCLI), Lincoln Financial Group (LNC), MetLife Inc. (MET), Phoenix Companies Inc. (PNX), Prudential Financial Inc. (PRU), Protective Life (PL), and Torchmark Corp. (TMK). Our publicly-traded sample excludes financial conglomerates or foreign insurers that have a small fraction of their assets in U.S. life insurance companies, and reinsurers. Many insurance companies have multiple subsidiaries. To maximize the comprehensiveness of our data, we include holdings of Property and Causalty (P&C) subsidiaries as well. SNL aggregates the data up to the parent company level and applies inter-company adjustments to present historical balance sheet data on an "As-is" data. We convert to an "As-was" basis by subtracting balance sheet holdings for companies acquired after the filing date. Similarly, for major mergers and acquisitions, we add in holdings of insurance companies that were divested by the parent company after the reporting date but before 2014.

3 Pass-through

In this section, we estimate the pass-through from asset holdings to equity for the life insurance sector. The pass-through answers the question: what is the effect on the equity of an institution of a one dollar change in the value of the securities it holds? Formally, we seek to consistently estimate the coefficient ρ_t^A in the law of motion for firm value:

$$R_{i,t}^E = \rho_t^A R_{i,t}^A - \rho_t^L R_{i,t}^L + R_{i,t}^{OB}, \tag{1}$$

where $R_{i,t}^E$ denotes the return on market equity, $R_{i,t}^m$ the change in value of assets ($m = A$) or liabilities ($m = L$) scaled by market equity, and $R_{i,t}^{OB}$ the scaled return to franchise value with respect to other variables. Scaling by market equity throughout ensures that ρ_t^A is in dollar-to-dollar units. Under Modigliani-Miller, the market value of equity equates the difference between the market value of assets and liabilities: $\rho_t^A = 1$ and $\rho_t^L = 1$. In Section 4, we show that deviations from this value for the pass-through help distinguish a richer set of theories of financial intermediaries.

We exploit two unique features of life insurance companies – detailed regulatory data and publicly-traded equity – to estimate the pass-through ρ_t^A. In our main approach we measure the pass-through using the cross-section of insurer portfolio corporate bond returns and equity returns on 2,600 trading days before, during, and after the financial crisis. In Appendix C we use insurer-reported fair values of assets at the end of each year to confirm the basic patterns also hold at an annual frequency for a broader part of the balance sheet.

3.1 Empirical Framework

An OLS regression of equity returns on scaled asset returns may yield a biased estimate of ρ_t^A because the observed return on corporate bonds may be correlated with the changes in the value of other assets on insurers' balance sheets, of their liabilities, and of future business. For example, a decrease in the risk free rate would raise the value of both assets and liabilities. Likewise, because some policy contracts include payoffs linked to index returns, changes in aggregate asset prices would also affect the value of liabilities.[4] Our econometric procedure addresses this challenge by exploiting variation across insurers in their holdings of corporate bond returns that deviate substantially from their benchmark index on each date. We focus on abnormal, rather than raw, bond returns to control for aggregate and industry-specific movements in bond prices and on large abnormal returns because it is especially unlikely that an omitted factor could generate such returns.

Specifically, we first partition $R^A_{i,t}$, the levered return on assets, into the part coming from corporate bonds for which we can construct a return, $R^A_{i,t}(T)$ (T for "traded"), and the remaining assets for which we do not know the return, $R^A_{i,t}(NT)$. Let $R^{A,x}_{i,t}$ denote the levered excess return over the bond's benchmark. We further partition $R^{A,x}_{i,t}(T)$ into the part coming from bonds with large abnormal (unscaled) returns $R^{A,x}_{i,t}(b)$, $b \subseteq T$ (b for "big"), and the part coming from bonds without large abnormal returns $R^{A,x}_{i,t}(b^c)$, $b^c \subseteq T \backslash b$. We then implement an instrumental variables specification to estimate the pass-through ρ^A separately for the crisis and non-crisis periods. The structural equation takes the form:

$$R^E_{i,t} = \rho^A_{\text{crisis}} \mathbf{I}\{t \subseteq \text{crisis}\} R^{A,x}_{i,t}(T) + \rho^A_{\text{noncrisis}} \mathbf{I}\{t \nsubseteq \text{crisis}\} R^{A,x}_{i,t}(T) + \alpha_t + \gamma_i' X_t + \epsilon_{i,t}, \qquad (2)$$

where crisis denotes the period from January 2008 to December 2009. The first stage uses $\mathbf{I}\{t \subseteq \text{crisis}\} \times R^{A,x}_{i,t}(b)$ and $\mathbf{I}\{t \subseteq \text{noncrisis}\} \times R^{A,x}_{i,t}(b)$ as excluded instruments for $\mathbf{I}\{t \subseteq \text{crisis}\} \times R^{A,x}_{i,t}(T)$ and $\mathbf{I}\{t \subseteq \text{noncrisis}\} \times R^{A,x}_{i,t}(T)$.

We construct $R^{A,x}_{i,t}(T)$ and $R^{A,x}_{i,t}(b)$ as follows. Data on bond prices come from the

[4] Berends, McMenamin, Plestis, and Rosen (2013) discuss the contracts issued by insurance companies.

FINRA TRACE data set. TRACE reports the date, time, and transaction price of all over-the-counter trades of corporate bonds in the U.S. We form a daily price series for each bond using the last trade on each date and match the bonds by CUSIP to our data set of insurers' daily portfolio holdings. Let $P_{j,t}$ denote the (open market TRACE) price of bond j, $Q_{i,j,t-1}$ the quantity of bond j held by insurer i, and $\tilde{R}^A_{j,t} = \frac{P_{j,t}-P_{j,t-1}}{P_{j,t-1}}$ the raw unscaled return based on the actual TRACE transaction prices.[5] We match each bond by CUSIP to the Mergent database to obtain the current rating of the bond and the NAICS industry code of the issuer. We obtain the return on the BAML index of the same rating and the return on the ICE BAML index of the same industry (using a hand-constructed crosswalk) and compute the abnormal return $\tilde{R}^{A,x}_{j,t}$ as the residual in a pooled regression of the bond returns $\tilde{R}^A_{j,t}$ on the index returns, allowing the loadings to vary by rating-industry cell. A bond belongs to the large abnormal return set b if $\tilde{R}^{A,x}_{j,t}$ exceeds 6 percentage points in absolute value. We then aggregate the abnormal returns for each insurer to generate an insurer-level abnormal return on its corporate bond portfolio and the return coming only from large abnormal returns: $R^{A,x}_{i,t}(T) = \sum_j s_{i,j,t-1}\tilde{R}^{A,x}_{j,t}$ and $R^{A,x}_{i,t}(b) = \sum_{j\in b} s_{i,j,t-1}\tilde{R}^{A,x}_{j,t}$, where $s_{i,j,t} \equiv P_{j,t}Q_{i,j,t}/E_{i,t}$ denotes holdings of bond j by insurer i as a share of insurer i's market equity.[6]

We now discuss how this research design overcomes the identification challenge. First, the excluded instrument $R^{A,x}_{i,t}(b)$ includes only those bond returns which deviate substantially from the return on bonds of similar industry and rating. If large returns reflect idiosyncratic movements in the particular bond rather than systematic char-

[5]We exclude corrected or canceled trades, trades reported with delay, and trades which include a dealer commission. In order to have a current market value of each bond position, we require that the bond transact at least once on a date when an insurer reports the fair value price in a regulatory filing. Since we rely on actual transaction prices, we observe $\tilde{R}^A_{j,t}$ only on dates where the bond has transacted on consecutive trading days.

[6]Importantly, market participants could have constructed these portfolio returns in real time. The NAIC end-of-year filings of security holdings become public about two months after the end of the calendar year, and quarterly filings of transactions a few months after the end of the quarter. If insurers engaged in frequent turnover of their portfolios, then equity analysts and traders might not know which insurers experienced large abnormal portfolio returns on a particular date. However, in our data, the fraction of large abnormal bond returns occurring in positions which insurers had established before the previous regulatory filing exceeds 98% both in and out of the crisis.

acteristics targeted by the insurer for its portfolio, then they will be uncorrelated with other parts of the balance sheet or aspects of its business. Second, both the instrument and the endogenous variable include only the part of the return on these bonds not explained by rating or industry. Therefore, factors common to all bond returns on a particular date do not contaminate estimation of the pass-through. Third, the date fixed effect α_t controls non-parametrically for macroeconomic shocks which affect all insurers equally. In particular, a rise in cross-asset correlations during the financial crisis cannot explain the finding of a higher pass-through. Finally, the term $\gamma_i' X_t$ allows insurers to load differently on aggregate factors contained in X_t which might also correlate with their portfolio choices. In our baseline specification, X_t contains the return on the 10 year Treasury bond and we allow the insurer-specific loadings to vary by year. This factor absorbs differences in duration mismatch across insurers which might also correlate with the duration of their assets.

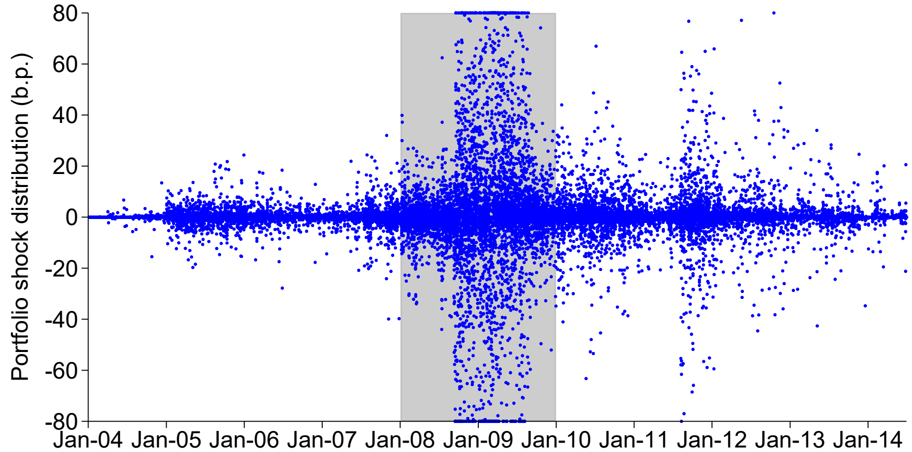
In summary, cross-sectional differences in portfolio holdings and equity returns make possible identification of the pass-through. The identifying assumption is that $R_{i,t}^{A,x}(b)$ is uncorrelated with the returns on other parts of the insurer's balance sheet and with changes in the value of other business not captured by time fixed effects or the insurer-specific loadings.

Figure 1 plots the distribution of the excluded instrument $R_{i,t}^{A,x}(b)$ over time, with the gray shaded area demarcating the crisis period 2008-09. The figure shows the concentration of large shocks during the crisis period but also that large portfolio shocks occur before and especially after the crisis.

3.2 Attributes of Portfolio Shocks

Before presenting our main results, we describe important aspects of corporate bond returns and insurer holdings which give the pass-through exercise power. First, insurers hold large positions in corporate bonds with volatile idiosyncratic returns.

Figure 1: Portfolio Shocks by Date



Each point in the figure shows the instrument $R_{i,t}^{A,x}(b)$ for one insurer-date. Shocks larger than 80 basis points in absolute value are top and bottom-coded for readability.

Therefore, large shocks to the market value of the portfolio happen with sufficient frequency. Next, the portfolio shocks due to large abnormal returns appear uncorrelated with other parts of insurers' balance sheets. Finally, the bond-level shocks decay substantially over time, implying a low pass-through for an investor with a long holding horizon.

Panel A of table 1 demonstrates the volatility of bond returns. Our sample contains more than 8 million observations of a bond held by an insurer for which we can calculate a daily abnormal return $\tilde{R}_{j,t}^{A,x}$. The standard deviation of abnormal returns in the whole sample is 2.4%, with higher volatility during the crisis. Just over 1% of all bond returns satisfy our criterion for a large abnormal return.[7] The rarity of such large returns gives *a priori* plausibility to the assumption that they do not reflect systematic variation in insurers' holdings. Nonetheless, the large number of total observations means we have 100,000 observations that qualify as large abnormal returns.

Panel B reports statistics on insurer positions and the total portfolio levered abnormal return. The first three rows describe the size of insurers' positions in those

[7]We chose the 6 p.p. threshold to ensure a ratio of large abornmal returns to total holdings of roughly 1%. We have experimented with other thresholds and obtain similar results.

Table 1: Daily Return Summary Statistics

Variable	Symbol	Period	Mean	SD	Abs. value P95	Abs. value P99	Obs.
			Panel A: All returns				
Abnorm. ret. (%)	$\tilde{R}_{j,t}^{A,x}$	All	–0.0	2.4	3.2	6.4	8 729 411
Abnorm. ret. (%)	$\tilde{R}_{j,t}^{A,x}$	Not crisis	–0.0	1.5	2.6	4.4	7 096 165
Abnorm. ret. (%)	$\tilde{R}_{j,t}^{A,x}$	Crisis	0.1	4.7	5.9	12.6	1 633 246
			Panel B: All returns				
Position size (%)	$s_{i,j,t-1}$	All	0.3	0.8	1.3	3.3	8 729 411
Position size (%)	$s_{i,j,t-1}$	Not crisis	0.3	0.6	1.3	3.0	7 096 165
Position size (%)	$s_{i,j,t-1}$	Crisis	0.4	1.2	1.8	4.6	1 633 246
Contribution (b.p.)	$s_{i,j,t-1}\tilde{R}_{j,t}^{A,x}$	All	–0.0	1.9	1.4	4.9	8 729 411
Contribution (b.p.)	$s_{i,j,t-1}\tilde{R}_{j,t}^{A,x}$	Not crisis	–0.0	0.9	1.0	3.4	7 096 165
Contribution (b.p.)	$s_{i,j,t-1}\tilde{R}_{j,t}^{A,x}$	Crisis	0.0	4.1	3.2	11.9	1 633 246
Insurer level (b.p.)	$R_{i,t}^{A,x}(T)$	All	–1.4	38.3	52.8	137.8	36 822
Insurer level (b.p.)	$R_{i,t}^{A,x}(T)$	Not crisis	–1.9	22.2	38.4	99.1	29 697
Insurer level (b.p.)	$R_{i,t}^{A,x}(T)$	Crisis	0.8	74.3	107.9	264.4	7125
			Panel C: $\lvert\tilde{R}_{j,t}^{A,x}\rvert > 6$				
Position size (%)	$s_{i,j,t-1}$	All	0.4	1.2	1.8	4.9	101 348
Position size (%)	$s_{i,j,t-1}$	Not crisis	0.2	0.5	1.1	2.7	22 967
Position size (%)	$s_{i,j,t-1}$	Crisis	0.5	1.3	2.0	5.5	78 381
Contribution (b.p.)	$s_{i,j,t-1}\tilde{R}_{j,t}^{A,x}$	All	0.2	12.9	17.1	47.5	101 348
Contribution (b.p.)	$s_{i,j,t-1}\tilde{R}_{j,t}^{A,x}$	Not crisis	0.1	4.8	8.7	21.8	22 967
Contribution (b.p.)	$s_{i,j,t-1}\tilde{R}_{j,t}^{A,x}$	Crisis	0.2	14.5	19.7	54.3	78 381
Insurer level (b.p.)	$R_{i,t}^{A,x}(b) \neq 0$	All	0.9	34.3	36.5	120.4	17 324
Insurer level (b.p.)	$R_{i,t}^{A,x}(b) \neq 0$	Not crisis	0.2	7.0	13.3	31.4	11 125
Insurer level (b.p.)	$R_{i,t}^{A,x}(b) \neq 0$	Crisis	2.2	56.5	79.8	213.7	6199
Insurer level (b.p.)	$R_{i,t}^{A,x}(b)$	All	0.4	23.5	17.4	69.4	36 822
Insurer level (b.p.)	$R_{i,t}^{A,x}(b)$	Not crisis	0.1	4.3	5.9	19.8	29 697
Insurer level (b.p.)	$R_{i,t}^{A,x}(b)$	Crisis	1.9	52.7	71.2	195.6	7125

Notes: Panel A reports statistics for all abnormal bond returns in TRACE that are held by insurers. Panel B reports statistics on insurer positions, the product of position and return, and the insurer portfolio levered return from summing all individual bond contributions. Panel C includes only bonds with an abnormal return greater than 6% in absolute value.

bonds relative to their market equity, $s_{i,j,t-1}$. The mean position in a bond is 0.3% of an insurer's market equity with a standard deviation of 0.8%. The insurer's initial position exceeds 1.3% of equity in 5% of the bonds and the largest percentile of initial positions equal 3.3% of the insurer's equity. These large positions reflect both concentrated asset portfolios and high leverage. The decline in insurer equity and concomitant rise in leverage in 2008 and 2009 explains why position sizes rise in the crisis. The next three rows report statistics for the total contribution of each bond return to the open market value of the portfolio relative to equity, $s_{i,j,t-1}\tilde{R}^{A,x}_{j,t}$, equal to the product of the initial position and the abnormal return.

The last three rows of Panel B show that the individual bonds aggregate to large insurer-level portfolio changes. The standard deviation of the daily portfolio levered return, $R^{A,x}_{i,t}(T) = \sum_j s_{i,j,t-1}\tilde{R}^{A,x}_{j,t}$, is 38 basis points. The standard deviation is larger during the crisis period, but even out of the crisis the standard deviation is 22 basis points of insurer equity. Thus, concentrated positions and leverage mean that abnormal bond returns meaningfully impact insurer equity.

Panel C repeats the statistics for the set of abnormal bond returns larger than 6% in absolute value. These are the returns which aggregate into the excluded instrument. Insurer positions in these bonds exhibit a similar level of concentration as in all bonds. Therefore, the contribution of a large abnormal return to insurer equity is larger, with a standard deviation of 12.9 b.p. and the largest (in absolute value) 1% of contributions exceeding 45 b.p. Not surprisingly, more large contributions occur during the crisis, but many also occur outside the crisis period.

The exclusion restriction requires that the portfolio shocks generated by large abnormal returns occur independently of shocks to other parts of the insurer's balance sheet or other aspects of its business. The relative magnitude of the variances of the insurer-level shocks and the individual contributions is informative on whether the data satisfy this criterion. We use only the abnormal part of the bond return and focus on the largest abnormal returns precisely to isolate plausibly independent bond-level shocks. If indeed the bond-level shocks are independent of each other, then the ratio of variances should equal the average number of bonds held by an insurer which experience a large abnormal return, whereas if the bond-level shocks to an insurer were perfectly correlated the ratio of variances would equal the square of the number of bonds experiencing a large abnormal return. In the data, the average number of holdings with a large abnormal return equals 5.9 (101,348 insurer-bond-date observations divided by 17,324 insurer-date observations with at least one bond with an abnormal return above 6%) and the ratio of variances equals 7.1, consistent with the independence assumption. Furthermore, only about one-half of all insurer-dates contain a bond with an abnormal return above 6%.

Table 2 provides further evidence of the idiosyncrasy of insurers' bond returns. The top panel reports the pooled (over all insurers and dates) correlation of the abnormal returns corresponding to the five largest portfolio positions held by each insurer on each date. The abnormal returns corresponding to the two largest positions held by an insurer have a correlation coefficient of 0.018, and no pairwise correlation exceeds 0.035 in absolute value. Therefore, after controlling for industry and rating, insurers do not appear to concentrate their corporate bond positions in securities with similar return characteristics. The bottom panel repeats the exercise but for (up to) the five largest contributions to the insurer-level portfolio shock among bonds with an abnormal return of at least 6% in absolute value. These returns correspond to the bonds that drive the excluded instrument; once again, the largest and next largest returns for each insurer appear virtually uncorrelated with each other. Moreover, in the majority of insurer-dates with at least one large abnormal bond return, the insurer holds only one or two such bonds, whereas a systematic loading of the portfolio would predict a large number of bonds with large abnormal returns on these dates.

Our specification goes further by also removing date fixed effects and insurer-year

Table 2: Pair-wise Return Correlations Among Largest Bond Positions

	Largest	Second largest	Third largest	Fourth largest	Fifth largest	Observations
Panel A: All returns, largest 5 positions						
Largest	1					36,656
Second largest	0.018	1				36,451
Third largest	0.035	0.025	1			36,242
Fourth largest	0.023	0.012	0.013	1		35,950
Fifth largest	0.003	0.005	0.019	0.024	1	35,685
Panel B: $\lvert\tilde{R}^{A,x}_{j,t}\rvert > 6$, largest 5 portfolio contributions						
	Largest	Second largest	Third largest	Fourth largest	Fifth largest	Observations
Largest	1					17,324
Second largest	0.051	1				10,643
Third largest	0.043	0.020	1			7,541
Fourth largest	0.010	0.027	0.049	1		5,836
Fifth largest	0.056	0.029	0.030	0.062	1	4,697

Notes: the table reports pairwise correlations pooling all insurers and dates. In the top panel, the variables are the abnormal bond returns corresponding to the five largest portfolio positions for each insurer and date. In the bottom panel, the variables are the abnormal bond returns corresponding to up to the five largest portfolio shock contributions among bonds with an abnormal return greater than 6% in absolute value.

specific duration loadings. Table 3 incorporates these controls and provides further evidence that large idiosyncratic bond returns are uncorrelated with the rest of an insurer's balance sheet by comparing the large abnormal returns to the rest of the transacted portfolio, conditional on these controls. Column 1 reports the partial correlation coefficients of the unscaled large returns $\tilde{R}^{A,x}_{i,t}(b) = \sum_{j\in b} \frac{P_{j,t-1}Q_{j,t-1}}{\sum_{k\in b} P_{k,t-1}Q_{k,t-1}} \tilde{R}^{A,x}_{j,t}$ and small returns $\tilde{R}^{A,x}_{i,t}(b^c) = \sum_{j\notin b} \frac{P_{j,t-1}Q_{j,t-1}}{\sum_{k\notin b} P_{k,t-1}Q_{k,t-1}} \tilde{R}^{A,x}_{j,t}$ in and out of the crisis period. These correlations are less than 0.02 in absolute value. Column 2 reports the first stage regression of the total scaled abnormal return $R^{A,x}_{i,t}(T)$ on the part coming from the large abnormal returns $R^{A,x}_{i,t}(b)$. We find coefficients close to albeit slightly above one, again consistent with idiosyncracy of the large abnormal returns. The regression also shows that the abnormal return component is a strong instrument for the overall change in the portfolio.

Table 3: Large Abnormal Returns Versus Other Parts of the Portfolio

	Dependent variable:	
	$\tilde{R}^{A,x}_{i,t}(b^c)$	$R^{A,x}_{i,t}(T)$
	(1)	(2)
Right hand side variable:		
$\tilde{R}^{A,x}_{i,t}(b) \times$ Not crisis	0.0021	
	(0.0035)	
$\tilde{R}^{A,x}_{i,t}(b) \times$ Crisis	0.019	
	(0.024)	
$R^{A,x}_{i,t}(b) \times$ Not crisis		1.29^{**}
		(0.11)
$R^{A,x}_{i,t}(b) \times$ Crisis		1.03^{**}
		(0.10)
Date FE	Yes	Yes
Treasury factor control	Yes	Yes
R^2	0.23	0.63
Observations	36,822	36,822

Notes: In column 1, $\tilde{R}^{A,x}_{i,t}(b^c)$ is the insurer-level unscaled abnormal return on corporate bonds with small abnormal returns and $\tilde{R}^{A,x}_{i,t}(b)$ is the unscaled abnormal return on corporate bonds with large (6 p.p. or more) abnormal returns. Both variables are demeaned on each date and normalized to have unit variance in and out of the crisis such that the reported coefficients are correlations. In column 2, $R^{A,x}_{i,t}(T)$ is the insurer-level abnormal return on all traded bonds and $R^{A,x}_{i,t}(b)$ is the abnormal return on bonds with large abnormal returns, with both variables scaled by the ratio of the holdings to market equity. The crisis is defined as January 2008-December 2009. Standard errors clustered by date in parentheses. ** denotes statistical significance at the 1% level. The data cover 2004-2014.

3.3 Results

Table 4 presents our main finding. Column 1 reports the OLS specification of the equity return regressed on the scaled abnormal bond return $R^{A,x}_{i,t}(T)$, controlling only for the date fixed effects and the general movement in interest rates by including in X_t the return on the 10-year Treasury and allowing the coefficient to vary across insurers and by year. Column (2) reports the reduced form specification of the equity return regressed on the part of the insurer portfolio return coming from large abnormal bond returns, $R^{A,x}_{i,t}(b)$. Column (3) reports the IV specification. In the IV specification, the pass-through is 0.06 out of the crisis and 1.01 during the crisis. In words, an additional dollar of assets translates into an additional \$0.06 of equity out of the crisis and \$1.01 of equity during the crisis. Because the first stage coefficients are close to one, the reduced form specification yields similar estimates. The coefficients in the OLS specification are also similar albeit slightly smaller. The similarity of the OLS and IV coefficients suggests that the extraction of the abnormal part of the return and the control variables already address many of the identification concerns. Column (4) shows that pass-through into the value of public debt exhibits a similar pattern.[8]

The data strongly reject equality of the pass-through coefficients and that the pass-through out of the crisis equals one. We cannot reject that the equity pass-through during the crisis equals one at any conventional confidence level. These p-values use standard errors clustered by date to allow for arbitrary correlation across insurers on each date.

Heterogeneity. We investigate further the pass-through behavior during the crisis by splitting the sample according to the level of financial distress. Specifically, we form two subgroups of insurers based on each insurer's stock return during the period September 12, 2008 to October 10, 2008. This four-week period begins with the day of the Lehman bankruptcy and contains the most acute drop in insurer stock prices in our sample. To avoid a mechanical correlation between stock price decline and crisis pass-through from sorting based on decline, we then drop this four-week period from the sample. Table 5 reports the results from estimating the IV specification separately for each subsample. The pass-through coefficient rises during the crisis in both

[8]The sample in column (4) is restricted to insurers with liquid CDS on their outstanding public debt throughout our sample period. The tickers of these insurers are: AFL, ALL, LNC, MET, PRU, TMK. To compute the return on public debt, we first use Compustat and Mergent FISD to construct the maturity structure of public debt for each company. We then use the CDS yield curve from Markit to price the debt using a no-arbitrage condition. The equity pass-through is lower for this subgroup so that pass-through on the total value of the firm is not higher.

Table 4: Pass-through Estimates

	Dependent variable:			
	Equity			Debt
	(1)	(2)	(3)	(4)
Insurer portfolio levered return interacted with:				
Not crisis	0.04	0.08	0.06	–0.12
	(0.07)	(0.32)	(0.25)	(0.11)
Crisis	0.81**	1.04**	1.01**	0.37*
	(0.25)	(0.32)	(0.31)	(0.17)
Estimator	OLS	RF	IV	IV
Date FE	Yes	Yes	Yes	Yes
Dep. var. winsorized	Yes	Yes	Yes	Yes
Treasury factor control	Yes	Yes	Yes	Yes
R^2	0.56	0.56	0.02	0.00
p(Homog. effect)	0.002	0.017	0.007	0.014
Observations	36,822	36,822	36,822	13,149

Notes: The estimating equation in column (1) is: $R^E_{i,t} = \rho^A_{\text{crisis}}\mathbf{I}\{t \subseteq \text{crisis}\}R^{A,x}_{i,t}(T) + \rho^A_{\text{noncrisis}}\mathbf{I}\{t \nsubseteq \text{crisis}\}R^{A,x}_{i,t}(T) + \alpha_t + \gamma_i' X_t + \epsilon_{i,t}$, where $R^E_{i,t}$ denotes the equity return and $R^{A,x}_{i,t}(T)$ the market-capitalization scaled abnormal return on the insurer's holdings of corporate bonds, X_t includes the return on the 10 year Treasury bond, and we allow γ_i to vary by calendar year. The specification in column (2) replaces $R^{A,x}_{i,t}(T)$ with $R^{A,x}_{i,t}(b)$, the market-capitalization scaled abnormal return on the insurer's holdings of corporate bonds with abnormal returns larger than 6% in absolute value. The specification in column (3) is two stage least squares with $\mathbf{I}\{t \subseteq \text{crisis}\} \times R^{A,x}_{i,t}(b)$ and $\mathbf{I}\{t \subseteq \text{noncrisis}\} \times R^{A,x}_{i,t}(b)$ the excluded instruments and $\mathbf{I}\{t \subseteq \text{crisis}\} \times R^{A,x}_{i,t}(T)$ and $\mathbf{I}\{t \subseteq \text{noncrisis}\} \times R^{A,x}_{i,t}(T)$ the endogenous variables. The specification in column (4) is the same as in column (3) but with the dependent variable the return on debt. The dependent variables are winsorized each month at the median $\pm$ 2.5 standard deviations. Standard errors clustered by date are reported in parentheses. ** and * denote statistical at the 1 and 5% levels. The data cover 2004-2014.

groups. However, the pass-through coefficient for the healthier subgroup rises by only half as much as for the more distressed subgroup. The limited sample size generates too little power to formally reject equality of the crisis pass-through coefficients at conventional levels, but the difference of 0.6 is consistent with an insurer's distress raising the pass-through.

Table 5: Pass-through by Insurer Distress

	Dependent variable: equity return	
Sample:	Equity return 09/12/08-10/10/08 < Median	Equity return 09/12/08-10/10/08 > Median
	(1)	(2)
Insurer portfolio levered return interacted with:		
Not crisis × Large bond returns / market cap	0.08	0.17
	(0.46)	(0.31)
Crisis × Large bond returns / market cap	0.99**	0.50
	(0.36)	(0.42)
Date FE	Yes	Yes
Drop 09/15/08-10/10/08	Yes	Yes
Dep. var. winsorized	Yes	Yes
Treasury factor	Yes	Yes
P(Crisis pass-through equal)	0.536	0.536
R^2	0.62	0.59
Observations	17,174	19,345

Notes: The table shows the extent to which pass-through differs by how much the insurer's stock fell in the period September 12, 2008 - October 10, 2008. The crisis period is January 2008-December 2009, excluding the interval between September 12, 2008 and October 10, 2008. Standard errors clustered by date in parentheses. ** denotes statistical significance at the 1% level. The data cover 2004-2014 excluding the period September 12, 2008 - October 10, 2008.

3.4 Robustness

Table 6 establishes the robustness of the basic pattern of a low pass-through out of the crisis and a higher pass-through during the crisis, focusing on the equity response. The first row repeats the results from column (3) of table 4. Rows 2-4 show the basic pattern remains robust to expanding the amount of variation used in the regression. Row 2 removes the Treasury factor control and row 3 additionally removes the date fixed effects. The regression coefficients change little without the Treasury factor control or the date fixed effects, indicating that many macroeconomic confounding factors such as interest rate or overall market changes are already accounted for in the construction of the abnormal returns. In row 4 we use the raw rather than the winsorized equity return as the dependent variable, with the result that the standard errors roughly double.

The next rows more tightly restrict the variation. Row 5 allows the loadings used to construct abnormal bond returns to vary by year, for example if the cross-sectional variance of betas increased during the crisis. Row 6 allows the loadings to also vary by bond maturity bin. Row 7 constructs bond returns at the issuer (rather than issue) level. Row 8 includes insurer-specific loadings on the three Fama-French factors in X_t. Rows 9 and 10 explore sensitivity to the large declines in equity during the crisis for some insurers, in row 9 by including the interaction of the inverse of market capitalization and a date fixed effect and in row 20 by scaling the changes in equity and bond holdings by the sample mean of market capitalization for each insurer rather than the $t-1$ market capitalization.

Rows 11-19 trim the sample along various dimensions. Row 11 restricts the sample to dates on which the excluded instrument takes a value of at least 0.1% of equity for at least one insurer. Restricting the variation to coming from large shocks sheds light on whether inattention to small shocks drives the low pass-through coefficients out of the crisis. While the number of observations falls by roughly half, there is almost no change in the pass-through coefficients. To interpret the stability of coefficients in row 11, it helps to recall the OLS identity that the coefficient estimated on a full sample is equal to a weighted average of the coefficients estimated on separate sub-samples where the weights are the contributions from each sample to the total variance of the regressors. Thus, even in the full sample the pass-through coefficients overwhelmingly reflect the pass-through from large shocks. Similarly, the row 12 sample only includes dates on which the absolute value of the return on the aggregate stock market exceeds 1%, as investors might pay particular attention to portfolio performance on days in which the overall market exhibits large movements.

However, while the standard errors rise in this smaller sample, the point estimates of pass-through in and out of the crisis remain almost unchanged.

Rows 13 to 15 instead restrict the variation to coming from smaller shocks. In row 13 we exclude dates on which the overall market moved more than 1%, in row 14 we drop observations where the aggregate large abnormal returns exceed 20 b.p. of insurer equity, and in row 15 we drop any date identified on the St. Louis Fed crisis timeline.[9] While the standard error of the crisis pass-through rises in rows 14 and 15, the coefficients remain significantly larger than the non-crisis pass-through. Row 16 removes dates with a Federal Reserve Open Market Committee meeting or announcement as bond price changes on these data are especially likely to reflect changes in interest rates. Row 17 drops observations from before 2008, showing that pass-through falls back to a low level after 2009. In row 18, we show that the pass-through results are not driven by transitory bond returns, by excluding bond returns with an absolute value of 10% or more that revert to within 2% of their previous value by the end of the following day.

Rows 19 and 20 explore the extent to which our results are driven by issuer-specific news.[10] In row 19, we exclude all shocks that coincide with a rating change for that issuer and obtain results very similar to our benchmark specification. Thus, our passthrough estimates are largely not picking up news about ratings that would affect insurers' ability to hold an issue due to ratings-based capital regulation. In row 20, we include only shocks that coincide with issuer-specific news. The coefficients and standard errors both rise when we confine our analysis to issue-dates with news

[9]These are available at `https://www.stlouisfed.org/financial-crisis/full-timeline`. We thank Ralph Koijen for suggesting this last sample filter when he first discussed the paper and for providing us with a data set of the timeline dates.

[10]We define a news event as one in the universe of Capital IQ's Key Developments database or a rating upgrade or downgrade. Approximately 14% of large abnormal returns coincide with issuer-specific news on the same day, and 46% with news within a week. Of the same-day news, 13% corresponds to rating changes (mostly downgrades) and 22% is earnings-related news (broadly defined). In total, 67% of the news events are non-ratings business-related news such as earnings, client announcements, product-related announcements, M&A-related news, legal issues, executive changes, or corporate governance issues.

Table 6: Pass-through Robustness

Specification	$\rho^A_{\text{noncrisis}}$	s.e.	ρ^A_{crisis}	s.e.	$p(\rho^A_{\text{crisis}} = \rho^A_{\text{noncrisis}})$	Obs.
1. Baseline	0.06	0.25	1.01	0.31	0.016	36,822
2. No Treasury factor control	0.01	0.22	0.90	0.28	0.013	37,385
3. No controls	−0.11	0.47	1.59	0.34	0.003	37,386
4. Dep. var. not winsorized	−0.13	0.50	1.81	0.77	0.035	36,822
5. Time-varying loadings	0.03	0.26	1.00	0.33	0.020	36,822
6. Maturity-specific loadings	0.15	0.30	1.10	0.41	0.064	36,822
7. Issuer return	0.49	0.40	0.89	0.28	0.409	36,822
8. Fama-French factors control	0.09	0.21	0.88	0.32	0.041	36,822
9. Size control	−0.03	0.25	0.99	0.33	0.012	36,807
10. Alternative denominator	0.10	0.20	0.62	0.43	0.271	36,807
11. Dates with $\lvert R^{A,x}_{i,t}(b)\rvert > 10$ b.p.	0.07	0.27	1.02	0.31	0.020	13,723
12. $\lvert R^{\text{mkt}}_t\rvert > 1$ p.p.	0.01	0.40	1.02	0.54	0.133	10,168
13. $\lvert R^{\text{mkt}}_t\rvert < 1$ p.p.	0.13	0.31	1.04	0.15	0.008	26,639
14. $\lvert R^{A,x}_{i,t}(b)\rvert < 20$ b.p.	0.28	0.40	1.93	0.88	0.086	35,196
15. Drop crisis timeline dates	0.02	0.25	0.77	0.77	0.358	33,657
16. Drop FOMC dates	0.18	0.23	0.89	0.36	0.093	35,568
17. Drop pre-crisis	0.06	0.26	1.01	0.31	0.018	23,220
18. Drop 1 day reversals	0.10	0.28	0.90	0.43	0.117	36,822
19. No ratings news	0.09	0.25	1.02	0.35	0.029	36,822
20. News only (excl. ratings)	0.18	0.56	1.84	0.97	0.136	36,822
21. Below median ownership share	0.23	0.57	1.17	0.51	0.217	36,822
22. Granular IV	−0.17	0.12	1.21	0.60	0.025	36,750
23. 3 day return	−0.03	0.46	1.11	0.37	0.055	36,784
24. 7 day return	−0.36	0.48	1.20	0.79	0.093	36,889

Notes: The structural equation is: $R^E_{i,t} = \rho^A_{\text{crisis}}\mathbf{I}\{t \subseteq \text{crisis}\}R^{A,x}_{i,t}(T) + \rho^A_{\text{noncrisis}}\mathbf{I}\{t \nsubseteq \text{crisis}\}R^{A,x}_{i,t}(T) + \alpha_t + \gamma_i' X_t + \epsilon_{i,t}$, where $R^E_{i,t}$ denotes the equity return, $R^{A,x}_{i,t}(T)$ the market-capitalization scaled return on the insurer's holdings of corporate bonds, and the excluded instruments are $\mathbf{I}\{t \subseteq \text{crisis}\} \times R^{A,x}_{i,t}(b)$ and $\mathbf{I}\{t \subseteq \text{noncrisis}\} \times R^{A,x}_{i,t}(b)$. Each row reports the results from a separate regression. Row 1 reproduces the baseline result. In row 2 X_t is empty. In row 3 X_t is empty and α_t is omitted from the regression. In row 4 the dependent variable is not winsorized. In row 5 the abnormal bond returns are constructed using rating and industry loadings that vary by year and in row 6 that vary by bond maturity bin. Row 7 uses bond returns aggregated by issuer. In row 8 X_t additionally includes the three Fama-French factors. In row 9 X_t includes an interaction of a date fixed effect with the inverse of insurer market capitalization. In row 10 $R^E_{i,t}$, $R^{A,x}_{i,t}(T)$, and $R^{A,x}_{i,t}(b)$ are rescaled by the ratio of one-day lagged market capitalization to the insurer's sample mean market capitalization. Row 11 only includes dates with at least one insurer with a value of $R^{A,x}_{i,t}(b)$ of at least 10 b.p. in absolute value. Row 12 only includes dates where the absolute value of the return on the Russell 3000 exceeds 1 p.p. while row 13 excludes these dates. Row 14 drops observations where the instrument $R^{A,x}_{i,t}(b)$ exceeds 20 b.p. in absolute value. Row 15 drops dates included on the St. Louis Fed crisis timeline. Row 16 drops any date with an FOMC meeting. Row 17 drops observations before 2008. Row 18 excludes from the instrument returns exceeding 10% that reverse within one day. Row 19 excludes returns from issue-dates that coincide with credit rating changes. Row 20 includes only returns occurring on issue-dates with issuer-specific news. Row 21 excludes bonds for which the insurer owns a large fraction of the total issue. Row 22 uses the Granular IV methodology of Gabaix and Koijen (2019). Rows 23 and 24 report the baseline specification for a 3- and 7-day horizon, with excess return threshold increased to 8 p.p. and 10 p.p., respectively. Standard errors clustered by date in rows 1-22 and are Driscoll-Kraay with bandwidth equal to the return horizon in rows 23 and 24.

but the coefficient during the crisis remains much larger than the coefficient outside of the crisis.

Row 21 tests for reverse causality arising from insurers' distress directly affecting the prices of securities for which an insurer is a dominant holder. We therefore include only bonds for which an insurer's holdings relative to the bond's total issue size falls below the sample median. The standard errors rise substantially but the point estimates remain in line with the baseline values.

Row 22 implements granular IV as in Gabaix and Koijen (2019). To understand the logic of granular IV in our setting, it helps to contrast it with our baseline specification, which attempts to purge portfolio returns of a systematic component by constructing an excluded instrument using only abnormally large bond returns. Instead, the granular IV excluded instrument is the actual portfolio abnormal return less the levered unweighted mean abnormal portfolio return, or in our notation for an insurer holding J bonds that trade on date t, $R_{i,t}^{A,x}(T) - \left(\sum_{j=1}^{J} s_{i,j,t-1}\right)\left(\frac{1}{J}\sum_{j=1}^{J}\tilde{R}_{j,t}^{A,x}\right)$. Thus, both approaches seek to isolate the idiosyncratic part of portfolio returns, either by focusing on large abnormal returns (our baseline) or on the behavior of a few returns that have exceptionally large weight in insurers' portfolios (granular IV). Using this alternative source of variation confirms the basic pattern.

Finally, rows 23 and 24 explore the sensitivity of our results to the window over which we estimate the pass-through. In row 23 we estimate the pass-through over a 3-day horizon and in row 24 we estimate the pass-through over a 7-day horizon. Since the variance of returns may increase with horizon, we raise the threshold for inclusion in the idiosyncratic component b to 8 p.p. for the 3-day horizon and to 10 p.p. for the 7-day horizon. The pass-through out of the crisis remains low as the horizon increases, while the pass-through in the crisis remains roughly 1.

The evidence of differential pass-through in and out of the crisis also does not depend on the asset price behavior of only a few insurers. To make this point, we selectively drop three insurers at a time, or 20% of our sample, and re-estimate the baseline IV regression in column (3) of table 4. Figure A.1 of the online appendix reports the histogram of coefficients from these $\frac{15!}{12!3!} = 455$ regressions. Most coefficients cluster around the level estimated in the baseline specification in the full sample and the two distributions of coefficients in and out of the crisis do not overlap. The gap between the crisis and out of crisis coefficients estimated for each sample ranges between 0.55 and 1.25.

To summarize, the pass-through from asset values to equity value is economically and statistically significantly below one in normal times and increases during periods of insurer financial distress and overall market illiquidity.

4 Asset Insulation and Other Explanations of Pass-Through Behavior

We now turn to potential explanations for the estimated behavior of the pass-through. We first explain why theories without mispricing cannot generate the empirical pattern of the pass-through, even allowing for other frictions facing life insurers. We then present our favored interpretation: insurance companies act as asset insulators, institutions that protect assets from price fluctuations using a stable balance sheet. Finally, we review alternative theories of mispricing.

4.1 Frictionless Pricing

Irrelevance. The simplest view of financial institutions is that they are irrelevant. Under the Modigliani-Miller theorem, a financial institution acts as a shell, raising capital at market prices and buying securities at market prices. In this view, the value of an insurer's equity is

$$E_t = \mathbb{E}_t^* \left[\int_t^T e^{-r(\tau - t)} C_\tau d\tau \quad + e^{-r(T-t)} A_T - \int_t^\infty e^{-r(\tau - t)} \ell d\tau \right], \tag{3}$$

where $\mathbb{E}_t^*$ is the risk-neutral expectation, C_t are the coupons received from asset positions, A_t is the market value of the assets, and for simplicity we assume fixed liability payments of ℓ per period which will be paid in full. Finally T is the time (unknown at date t) at which the insurer fails and has to liquidate its asset holdings.[11] With frictionless asset pricing, the prices of assets coincide exactly with the present value of cash flow at each point in time. The sum of the first two terms is therefore always equal to the market value of the assets and $E_t = A_t - \ell/r$. As such, the pass-through to equity of a shock to asset values (unrelated to the value of liabilities) is always equal to 1. Our estimate of the pass-through out of the crisis rejects this view.

Costs of financial distress. Frictionless pricing of securities does not mean that frictions do not affect firms. A plausibly important source of frictions is bankruptcy costs, or more generally costs of financial distress. If an insurer gets in trouble, it could have to inefficiently liquidate non-financial assets, lose expertise or market power in pricing life insurance policies, or see a destruction of its reputation capital. In our simple framework, these costs materialize as a positive fixed payment D made at liquidation:

$$E_t = \mathbb{E}_t^* \left[\int_t^T e^{-r(\tau - t)} C_\tau d\tau \quad + e^{-r(T-t)} (A_T - D) - \int_t^\infty e^{-r(\tau - t)} \ell d\tau \right]. \tag{4}$$

[11] In practice, intermediaries face a combination of capital requirements, accounting rules, and direct regulatory pressure which make liquidation of the portfolio a progressive rather than a discrete event. In the case of insurers, Ellul et al. (2011) provide evidence of capital-constrained insurers selling downgraded corporate bonds, Ellul, Jotikasthira, Lundblad, and Wang (2015) show how the interaction of accounting rules and asset downgrades led to early selling of assets, and Merrill, Nadauld, Stulz, and Sherlund (2014) document liquidations of mortgage-backed securities by capital-constrained insurers in distressed markets.

In terms of pass-through, a dollar lost on the assets still directly reduces market equity by a dollar. However, this dollar lost on assets has an additional impact: it makes liquidation more likely, increasing the present value of the costs of financial distress. Therefore, the pass-through is always greater than 1. Moreover, this second force is stronger closer to liquidation, making the pass-through increase during a crisis. While the latter holds in our data, the out-of-crisis pass-through of much less than 1 rejects this theory.

Government guarantees. Financial institutions may also derive some private value from government guarantees of their liabilities. These guarantees may include explicit backing of liabilities, for example deposit insurance in the case of commercial banks and state guaranty funds in the case of life insurers, as well as an implicit expectation of bailouts following large shocks. The presence of guarantees allows intermediaries to extract private value by investing in risky assets. A negative value of the fixed payment D in equation (4) captures such guarantees or bailouts.[12] Thus, the implications of costs of financial distress are reversed. A dollar lost on assets yields less than a dollar lost in equity because it makes the receipts of government guarantees more likely. However, because government guarantees are a larger part of the valuation close to liquidation, the pass-through declines during episodes of distress. The increase in pass-through during the crisis rejects this explanation.

In summary, the empirical behavior of the pass-through is inconsistent with frictionless pricing of securities, even allowing for other types of frictions affecting insurers.

[12]Even if the guarantees accrue to debtholders, their presence will affect the value of equity. For instance, the insurance company might let liabilities go under water before liquidating to get bailed out.

4.2 Asset Insulation

Framework. We now describe a theory of mispricing that can explain our pass-through results: asset insulation. The starting point is that two valuations for the same asset can coexist. One valuation is the price observed on the market where the asset is traded. This price reflects any transitory conditions in this market. The other valuation is a more stable long-term value, reflecting the value of the asset to a long-term investor. An asset insulator is an institution capable, to some extent, of exploiting such a valuation differential. Concretely, we think of insurers as buying securities traded in specialized markets (for example, corporate bonds or mortgage-backed securities), but with their equity valued in the broader stock market. Formally, let $A_t^* = \mathbb{E}_t^* \left[\int_t^\infty e^{-r(\tau-t)} C_\tau d\tau\right]$ denote the value of the assets using the stochastic discount factor of equity investors and $A_t = \omega_t A_t^*$ the market price of the assets. Then we can represent the asset insulation view by replacing A_T in equation (3) with $\omega_T A_T^*$:

$$E_t = \mathbb{E}_t^* \left[\int_t^T e^{-r(\tau-t)} C_\tau d\tau \quad + e^{-r(T-t)} \omega_T A_T^* - \int_t^\infty e^{-r(\tau-t)} \ell d\tau \right]. \tag{5}$$

Clearly, for ω_t to differ from one, some limits to arbitrage must prevent insulators from expanding their balance sheet until the difference between the market price and its value to an insulator disappeared.[13]

Implications for the pass-through. To derive implications for the pass-through, it helps to consider two polar cases: normal times and a crisis. In appendix B, we show how the insights below extend beyond these two cases. We specify dynamics for A_t and ω_t and determine the value of the equity of an insulator as well as the pass-through, and show how they depend on the level of ω and the distance to liquidation.

[13]For example, the presence of noise trader risk and short-term arbitrageurs would give rise to such a wedge (De Long, Shleifer, Summers, and Waldmann (1990)). Other motivations include temporary fire sale discounts (Shleifer and Vishny, 2011), the price impact from large trades, transaction costs that distort prices (Amihud and Mendelson, 1986; Duffie, Gârleanu, and Pedersen, 2005), or differences in information (Berk and Stanton, 2007).

In *normal times*, the insurance company is far from liquidation. In this case, the equity value is entirely driven by the present value of cash flows. Shocks to this present value pass through into the equity value, $\partial E_t / \partial A_t^* = 1$. However, shocks specific to the market value that do not affect the long-term value of the assets do not affect the equity value, $\partial E_t / \partial \omega_t = 0$. The average of these two effects (weighted by the variances of the respective shocks) yields a pass-through less than 1 in *normal times*.

In a *crisis*, the insurance company is close to liquidation and the assets trade at a large discount relative to their long-term values, that is, ω_t is substantially below 1. This setting captures salient aspects of the 2008-2009 period, namely the distress of insurers and the large discounts observed in bond markets. Two effects now push the pass-through towards and potentially above 1. First, because liquidation is likely, the valuation of the insurers depends on the liquidation value of the assets. In the limit as liquidation becomes imminent, the insurer loses its ability to insulate and its equity is the liquidation value of the assets minus the value of its liabilities, $\omega_t A_t^* - \ell / r$. Thus, $\partial E_t / \partial \omega_t > 0$. Second, poor asset performance moves the insurer closer to liquidation. This movement further decreases the equity value because investors now put more weight on the current market prices of all assets on the balance sheet, and these assets trade at discounts relative to their long run values. This endogenous cost of financial distress further increases the pass-through, potentially to above one. Thus, asset insulation also predicts a larger pass-through during a *crisis*. Both the low pass-through in *normal times* and the larger pass-through during a *crisis* accord with our empirical results.

Further predictions. The insulator framework can also account for several other key facts about life insurers' portfolios. First, insurers concentrate their portfolio holdings in risky, illiquid assets, with their largest portfolio holdings in corporate bonds, commercial mortgages, and non-Agency asset-backed securities; see Chodorow-

Reich et al. (2020). The insulator framework *prescribes* such asset holdings since they maximize the comparative advantage of investors that hold assets for the long-run. In contrast, theories that emphasize insurers' expertise in pricing policy liabilities as their only source of value creation (Briys and De Varenne, 1997) counterfactually predict large holdings in safe and liquid securities such as Treasuries. Second, consistent with a long-run objective, the typical security remains on an insurer's balance sheet for about 8 years.

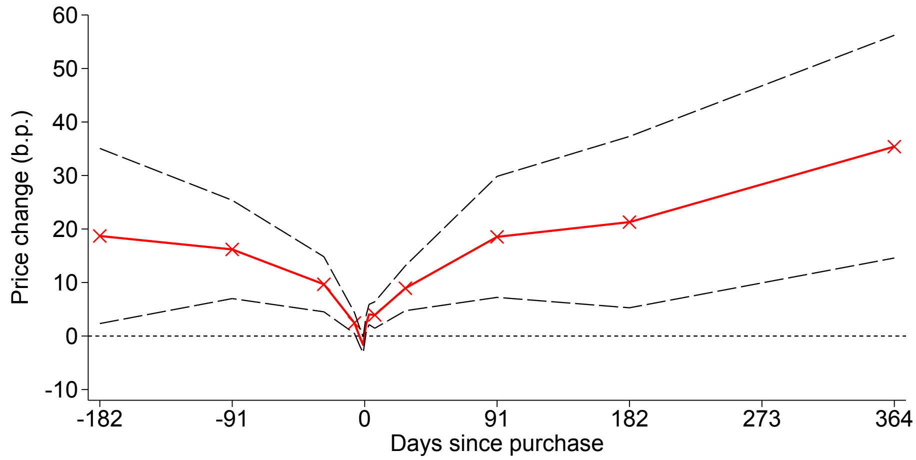
Third, the performance of insurers trades is consistent with a comparative advantage in identifying underpriced securities. Insurers buy bonds in the secondary market that have on average recently fallen in value but subsequently experience positive abnormal returns. Figure 2 provides a visual representation of this result using the FINRA TRACE data. For each horizon h, we estimate

$$\frac{P_{j,t+h}}{P_{j,t}} = \delta[insbuy_{j,t}] + \Gamma X_{j,t} + \epsilon_{j,t}, \tag{6}$$

where j indexes a corporate bond, t is a day, $insbuy_{j,t}$ takes a value of 1 if any insurer bought bond j on date t, $X_{j,t}$ is a vector of characteristics of bond j on date t, and $P_{j,t}$ is the ex-coupon clean price. To help ensure that we isolate an effect specific to insurers rather than simple observable differences across bonds, we include in the control set date fixed effects, the coupon rate and squared coupon rate of the bond, the return on a duration-matched treasury and a maturity-bin fixed effects.

The part of the figure to the left of 0 shows that bonds purchased by insurers have experienced abnormal price declines over the previous 3 months. Indeed, insurers appear to purchase bonds exactly at their price trough. The more distant coefficients show that these bonds appear to earn positive abnormal returns past the 91 day horizon, although we cannot reject equality of the 91 day and subsequent cumulative excess returns. The positive post-purchase abnormal return survives controls for

Figure 2: Price Patterns of Insurers' Secondary Market Corporate Bond Purchases



Notes: The figures plot the coefficients δ_h from the regression $\frac{P_{j,t+h}}{P_{j,t}} = \delta_h insbuy_{j,t} + \Gamma_h X_{j,t} + \epsilon_{j,h,t}$, where $insbuy_{j,t}$ takes a value of 1 if an insurer bought bond j on date t and $X_{j,t}$ is a vector of bond characteristics including the coupon, the return on the duration-matched Treasury, categories of remaining maturity, the rating, and date fixed effects. The dashed lines indicate 90% confidence intervals on the point estimates for each horizon based on standard errors clustered by calendar quarter.

purchase date, rating, coupon, and maturity, suggesting that insurers actively seek bonds with market value below long-run value.

Finally, the liability side of insurer's balance sheet naturally anchors their ability to act as insulators. Insurers issue stable, predictable, long-term liabilities in the form of life insurance contracts and annuities. These liabilities make insurers natural holders of illiquid assets. This aspect also points to the frictions in financing markets that may limit the capital flowing to insulators. Obtaining long-term financing such as equity and large amounts of long-term debt can be challenging, in particular for financial institutions. Such frictions explain the preponderance of open-end contracts for mutual funds and the frequent use of short-term debt in the shadow banking sector. Meanwhile, insurance companies naturally have access to a captive source of funding – policy liabilities – explaining why they can host insulation activities. Even so, the optimal size of insurers should equate the marginal cost of funds to the benefit from providing additional insulation. If insurers face an upward-sloping cost of stable funding, for example because of a downward-sloping demand curve for insurance policies, then they naturally will not grow large enough to compete away all insulation profits.

4.3 Other Sources of Mispricing

Endogenous liquidity and fire sales. A premise of the insulator theory is the presence of non-fundamental fluctuations in the prices of securities held by insurers. A common motivation for this type of fluctuations is the presence of so-called fire sales: some investors exert buying or selling pressure in the market and a limited amount of capital is willing to absorb them (e.g., Shleifer and Vishny (1997) or Diamond and Rajan (2011)). A related view is that who owns the securities affects liquidity in the market, which in turn feeds back into the price all investors are willing to pay (e.g. Dow (2004)). In the presence of either type of friction, insurers themselves could affect corporate bond prices, as a number of articles have found.[14]

These forces suggest an alternative interpretation of the pass-through measure, with the causality flowing from insurer's equity to bond returns. In this view, as insurers get more distressed – i.e. experience poor equity returns – the prices of the assets they own respond, generating co-movement between portfolio returns and equity. Yet, a number of other features militate against this interpretation, including the absence of correlation among large bond returns shown in table 2, of large bond returns with the rest of the portfolio shown in table 3, and the granular IV robustness exercise. Furthermore, row 20 of Table 6 shows that splitting positions based on ownership share by the insurer does not meaningfully affect our estimates, as would be the case if reverse causality were a larger concern for bonds where the insurer

[14]Ellul et al. (2011) show that regulatory constraints lead insurers to sell bonds following downgrades, and that the price of these bonds subsequently declines. Irani, Iyer, Meisenzahl, and Peydro (2018) present related evidence in the context of banks, finding that undercapitalized banks sell loans to shadow banks, and that these loans experience greater price volatility. Musto, Nini, and Schwarz (2018) document that insurers seeking liquidity moved into more liquid Treasury securities even as these securities were getting more expensive during the crisis, suggesting that insurers contributed to the increase in the illiquidity discount for less liquid Treasuries.

owns a larger share of the issuance. Finally, in Appendix E we consider the role of bond-insurer specific news, again finding no support for reverse causality.

Diamond and Rajan (2011) discuss another endogenous effect of fire sales, driven by limited liability of financial institutions. If insurers do not always repay their liabilities in full, they might be insolvent before being pushed into liquidating their portfolios by regulators. This force would give rise to what Diamond and Rajan (2011) call a "tipping point" where the insurer actually wants to hold *more* of distressed assets to risk shift. Our evidence is not consistent with increased risk shifting. If limited liability becomes binding, the marginal asset losses would start to accrue mostly to policy holders rather than equity-holders of the insurer. This situation would lead to a decreased pass-through during the crisis, at odds with our findings. On the other hand, the pattern of delaying sales outside of the crisis is consistent with increased future insulation profits from holding the bond following a temporary price decrease.

Common ownership. Common shocks to the demand for a particular insurer's stock and the bonds held by that insurer pose another potential concern. Such an effect could arise if the same investors hold both assets, and these investors experienced shocks during the financial crisis. For example, Anton and Polk (2014) document that stocks with shared ownership by active mutual funds experience stronger co-movement. In broader terms, this challenge to our interpretation of the pass-through posits the presence of an omitted common factor.

Our results do not favor such an interpretation either. Specifically, most versions of common ownership should create co-movement between the insurer's equity and the market value of *all* the bonds held by the insurer. The absence of correlation *within* an insurer's bond portfolio is inconsistent with this requirement. Nonetheless, direct tests of this type of mechanism would involve tracking ownership of specific corporate bonds and insurer stocks by market participants outside of insurance companies, a task we do not undertake here.

Inattention. A different type of explanation for our results relies on information frictions. Investors in insurers' stocks might be more or less aware of fluctuations in corporate bond prices, which will affect how these changes are reflected in the valuation of the insurers. In equation (5), this corresponds to an expectation for the valuation of the insurer, $\mathbb{E}^*$, formed with imperfect information. For example, if it is costly to process information about bond returns, investors might choose to ignore them when they are small but pay more attention when they are large. Such changes would rationalize the low pass-through outside of the crisis and a pass-through that increases during the volatile period of the crisis.[15]

Interestingly, information decisions are not necessarily an alternative to insulation, but rather can amplify its effect. If equity market participants must pay a cost to monitor developments on insurers' portfolios, they will do so only if the mis-valuation from not paying the cost exceeds the cost itself. With a target pass-through absent information costs already low due to insulation, the gains from monitoring are small and participants will choose not to pay the cost, pushing the realized pass-through even lower. Similarly, with low target pass-through, valuing assets strictly at book value may be preferred to valuing strictly at market value. The valuation conventions of equity analysts of insurance companies comport with such an "active" inattention mechanism. According to Nissim (2013), most equity analysts value insurance companies using a price-to-book ratio which excludes accumulated other comprehensive

[15] One version of this mechanism we can test for is a form of attention decisions based on the salience of returns. If large corporate bond returns are more salient, we should see them reflected more strongly in the stock price of insurers. Rows 10 and 13 of Table 6 concentrate on dates with some large shocks, or on small shocks only, and find similar coefficients as our baseline. These results suggest that salience does not explain our results. A more challenging alternative is if attention is decided *ex ante*, and for long periods of time. For example, investors might know that, in general, bond returns are not that volatile so they choose to ignore them. But, during the crisis, they decide to pay more attention due to the heightened volatility. Our empirical setting alone cannot rule out such an alternative.

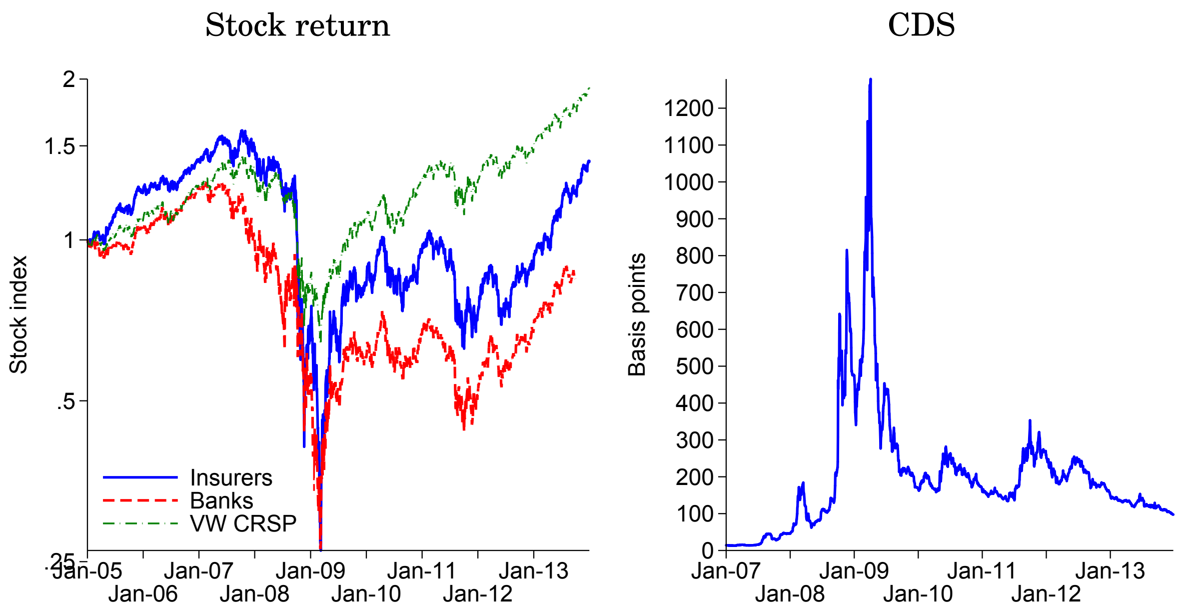
income (AOCI) from the book valuation. Our own conversations with market participants confirm the popularity of this approach. The category AOCI includes all of the unrealized gains and losses from the asset portfolio. Nissim (2013, p. 326) describes the rationale for excluding AOCI as stemming from a desire to smooth the high volatility of investment gains and losses, consistent with the asset insulator view. In our language, the industry practice of ignoring AOCI when doing valuation amounts to a target pass-through of close to zero in normal conditions. We are not aware of whether this practice changed during the crisis.

5 Macroeconomic Implications

In this section we document the macroeconomic importance of the asset insulator role of life insurers for their survival during the 2008-09 crisis. As a starting point, figure 3 illustrates the financial distress of the life insurance sector during the period. The left panel shows the stock return index for publicly traded life insurers plotted against commercial banks and the value-weighted CRSP index for comparison. The insurance sector has the largest peak-to-trough decline of the three sectors. The right panel shows the equity value-weighted average CDS spread for the six insurers with liquid CDS throughout the period. From a low of essentially zero before the crisis, the spread rises beginning in 2008 and peaks above 1200 basis points in March 2009 before declining to a "new normal" range in the latter part of that year. The distress evident in figure 3 explains why we treat the 2008-09 period as one of heightened liquidation risk.

Does the decline in the market equity of life insurers simply reflect a decline in the market value of all assets, with no role for insulation? Figure 4 compares the aggregate dollar change in insurers' assets net of liabilities during the crisis to the drop in equity, using our detailed balance sheet data. To construct the figure, we first calcu-

Figure 3: Insurer Distress During Crisis

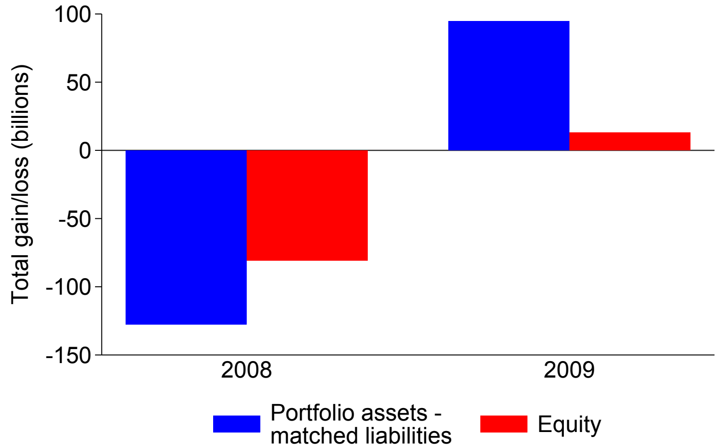


Notes: The left panel plots the value-weighted total return index for publicly traded insurers, banks, and the entire CRSP value-weighted index. The right panel plots the equity value-weighted annual premium to insure $10,000 of debt for a period of 5 years for AFL, ALL, LNC, MET, PRU, and TMK.

late the capital gain/loss on the market (i.e., outside) value of publicly-traded insurers' securities holdings using the fair value reporting requirements imposed by NAIC and the procedure described in Appendix C to compute security-level gains and losses. For 2008, the fair market value of securities declined by $30 billion. Next, using the effective duration of each security together with the Treasury yield curve we calculate the change in the value of the assets due to interest rate changes alone by summing over securities the buy-and-hold return for a Treasury security of the same effective duration.[16] For 2008, the decline in interest rates alone would have raised the market value of insurers' securities holdings by $97 billion instead of the $30 billion decline actually observed. Thus, the non-interest rate component of the market value of securities declined by $127 billion. If insurers' liabilities have duration equal to their security holdings (a conservative assumption), then the net change in the market

[16]When the holding changes due to purchases, sales, dividends, or pre-payments, we adjust the matched Treasury holding accordingly.

Figure 4: Aggregate Changes in Assets, Liabilities, and Market Equity



Notes: The blue bars show the fair value capital gain/loss on assets reported in NAIC schedule BA and D minus the gain/loss on a portfolio of Treasuries constructed by matching each cusip to a U.S. Treasury of the same duration. The red bars show the total change in market equity.

value of assets less liabilities arising from the decline in market prices of securities equals this $127 billion decline, shown in the left blue bar in figure 4. This calculation *understates* the decline in the market value of all assets less liabilities to the extent that insurers experienced losses on other parts of their balance sheet including from guaranteed income annuities (Koijen and Yogo, 2018; Ellul, Jotikasthira, Kartasheva, Lundblad, and Wagner, 2018), direct holdings of mortgages or real estate, and assets held outside of the insurance subsidiary (Koijen and Yogo, 2018).[17]

The $127 billion decline in the market value of assets net of liabilities compares to an $80 billion decline in the market value of equity in 2008, shown in the left red bar.

[17]Industry analysts generally agree that insurance company liabilities are longer duration than their assets, providing an additional reason this calculation understates the increase in the value of liabilities due to the sharp drop in interest rates in 2008. Unfortunately, direct data on the duration of liabilities are difficult to obtain. In the other direction, the figure does not include the changes in the value of public debt since we do not have CDS prices for most of our sample. However, this omission should not affect the result much. For example, in 2008 total equity at the 6 insurers for which we do have CDS prices declined by $75 billion. Applying the CDS curve and Treasury yield curve to the maturity structure of public debt outstanding for these insurers, we estimate a decline in the value of debt of $2 billion, the result of an increase in value of $6 billion from the decrease in interest rates and a fall in value of $8 billion from the higher default risk.

The difference between these two values is the increase in franchise value. This result is inconsistent with Modigliani-Miller and is even more at odds with the financial distress view that a deteriorating financial situation destroys firm value. The dynamic reverses in 2009 as the market prices of assets recover by more than insurer equity. The insulator theory can explain why insurers were partly shielded from the large fluctuations in market prices of assets during the crisis and why their stock price did not rebound as strongly as the assets afterwards. Indeed, if the large aggregate drop in asset value in the crisis reflected temporary underpricing (for example due to fire sales), the overall equity value of insurers should not have reacted much on impact. This is because despite the low market value of the assets, the *overall* value from insulating them as increased. However, as we have argued before, the *marginal* ability to insulate could then be threatened, generating an increased pass-through.[18]

These results highlight a core tension. Periods of financial turmoil and market dislocation represent prime opportunities for asset insulators. Yet, such periods may also coincide with insulators becoming financially distressed, jeopardizing their ability to insulate. Thus, asset insulation may be most fragile exactly when it is most valuable. The combination of high pass-through of the marginal dollar of assets and high franchise value during the financial crisis demonstrates this tension for life insurers.[19]

[18]Formally, we suppose 2008 consisted of an increased prevalence of fire sale prices of securities, meaning a decline in ω, and a drop in expected cash flows A_t^*. The decline in ω translates into an increase in insulation value, but by pushing insurers closer to insolvency, the combined effect hampers insurers' ability to insulate at the margin.

[19]These results may also bear on issues of systemic risk. Acharya, Philippon, and Richardson (2016) define a firm's systemic risk as its contribution to an aggregate capital shortfall in the financial sector. While the comovement of stock prices in figure 3 indicates a strong correlation of life insurer distress and the overall market, figure 4 suggests the capital shortfall would be even worse if the assets were not insulated inside the life insurance sector. Further, the failure of some life insurers could contribute to even deeper fire sales.

6 Conclusion

Using detailed security-level holdings of publicly-traded life insurance companies matched to the universe of corporate bond trades, we estimate that outside of the 2008-09 financial crisis a life insurer's equity decreases by as little as 10 cents in response to a one dollar drop in the market value of its assets. During the crisis, the pass-through rises to approximately 1. We have proposed a theory of financial intermediaries as asset insulators to account for this pattern. Through the lens of our theory, the pass-through of substantially less than one outside of the crisis is evidence of limits to arbitrage in the corporate bond market that generate variation in the market prices of bonds unrelated to their long-term values. The higher pass-through during the crisis instead results from the deterioration in the financial health of insurers, which threatened their ability to act as long-lived investors. And yet, while the high pass-through during the crisis indicates that insurers lost the ability to insulate at the margin, the nearly \$50 billion difference between the decline in the duration-adjusted value of the securities they held and their actual market equity decline during the crisis signifies a substantial amount of insulation across their overall balance sheet.

The ability to hold risky, illiquid assets for long intervals and through market turmoil creates value for the equity holders of life insurers. Ascertaining whether these institutions create social value requires answering additional questions. On the one hand, the insulation view suggests a stabilizing role in financial markets. For example, fire sale spirals typically involve a self-reinforcing loop: declining prices of securities $\rightarrow$ lower market equity of institutions holding those securities $\rightarrow$ additional securities sales $\rightarrow$ further price declines. Asset insulation breaks this spiral by preventing the market equity declines. Proposals to tightly regulate asset holdings might impair this function. On the other hand, the correlation between market illiquidity and the health of the financial sector makes the asset insulation function most fragile exactly when it is most valuable, as during the 2008-09 period. We also have not considered the the social benefits of having a large share of assets actively trade on financial markets, such as price discovery and liquidity.

We have studied life insurers because of the large size of the sector and because the availability of security-level holdings data permits estimation of the pass-through. Other financial institutions with stable liabilities also may act as asset insulators. Hanson et al. (2015) emphasize the stable liabilities of commercial banks and P&C insurance companies. Other candidate institutions include pension and endowment funds. In contrast, open-end mutual funds or money market funds that face short-term redemption risk cannot perform this role. In this respect, life insurers' ability to insulate depends crucially on their liabilities remaining stable and predictable. Shifts in insurers' liability structures away from life insurance policies and annuities could reduce their insulation role. Likewise, our analysis suggests that periods of financial turmoil that coincide with sudden, unexpected increases in payouts on life insurance policies, such as during war or pandemic, could involve particularly severe price dislocations as insurers go from insulators to instigators of fire sale dynamics.

References

ACHARYA, V., T. PHILIPPON, AND M. RICHARDSON (2016): *The Economics, Regulation and Systemic Risk of Insurance Markets*, Oxford University Press, chap. Measuring Systemic Risk For Insurance Companies.

AMIHUD, Y. AND H. MENDELSON (1986): "Asset pricing and the bid-ask spread," *Journal of Financial Economics*, 17, 223–249.

ANTON, M. AND C. POLK (2014): "Connected stocks," *The Journal of Finance*, 69, 1099–1127.

BAI, J. (2009): "Panel data models with interactive fixed effects," *Econometrica*, 77, 1229–1279.

BARBERIS, N. AND R. THALER (2003): "A survey of behavioral finance," *Handbook of the Economics of Finance*, 18, 1051–1121.

BERENDS, K., R. MCMENAMIN, T. PLESTIS, AND R. J. ROSEN (2013): "The sensitivity of life insurance firms to interest rate changes," *Economic Perspectives*, 37.

BERK, J. B. AND R. STANTON (2007): "Managerial ability, compensation, and the closed-end fund discount," *The Journal of Finance*, 62, 529–556.

BERNANKE, B. (1983): "Nonmonetary effects of the financial crisis in the propagation of the Great Depression," *American Economic Review*, 73, 257–276.

BESSEMBINDER, H., W. F. MAXWELL, AND K. VENKATARAMAN (2013): "Trading activity and transaction costs in structured credit products," *Financial Analysts Journal*, 69, 55–67.

BRIYS, E. AND F. DE VARENNE (1997): "On the risk of insurance liabilities: debunking some common pitfalls," *Journal of Risk and Insurance*, 673–694.

BRUNNERMEIER, M. K. AND Y. SANNIKOV (2014): "A macroeconomic model with a financial sector," *American Economic Review*, 104, 379–421.

CALOMIRIS, C. W. AND C. M. KAHN (1991): "The role of demandable debt in structuring optimal banking arrangements," *The American Economic Review*, 497–513.

CHERKES, M., J. SAGI, AND R. STANTON (2009): "A liquidity-based theory of closed-end funds," *Review of Financial Studies*, 22, 257–297.

CHODOROW-REICH, G., A. C. GHENT, AND V. HADDAD (2020): "The Portfolios of Asset Insulators," Tech. rep., Harvard University.

DE LONG, J. B., A. SHLEIFER, L. H. SUMMERS, AND R. J. WALDMANN (1990): "Noise trader risk in financial markets," *Journal of Political Economy*, 98, 703–738.

DIAMOND, D. W. AND P. H. DYBVIG (1983): "Bank runs, deposit insurance, and liquidity," *Journal of Political Economy*, 91, 401–419.

DIAMOND, D. W. AND R. G. RAJAN (2011): "Fear of fire sales, illiquidity seeking, and credit freezes," *The Quarterly Journal of Economics*, 126, 557–591.

DOW, J. (2004): "Is liquidity self-fulfilling?" *The Journal of Business*, 77, 895–908.

DUFFIE, D., N. GÂRLEANU, AND L. H. PEDERSEN (2005): "Over-the-counter markets," *Econometrica*, 73, 1815–1847.

EDWARDS, A. K., L. E. HARRIS, AND M. S. PIWOWAR (2007): "Corporate bond market transaction costs and transparency," *The Journal of Finance*, 62, 1421–1451.

ELLUL, A., C. JOTIKASTHIRA, A. KARTASHEVA, C. T. LUNDBLAD, AND W. WAGNER (2018): "Insurers as asset managers and systemic risk," Tech. rep., University of North Carolina-Chapel Hill.

ELLUL, A., C. JOTIKASTHIRA, AND C. T. LUNDBLAD (2011): "Regulatory pressure and fire sales in the corporate bond market," *Journal of Financial Economics*, 101, 596 – 620.

ELLUL, A., C. JOTIKASTHIRA, C. T. LUNDBLAD, AND Y. WANG (2015): "Is historical cost accounting a panacea? Market stress, incentive distortions, and gains trading," *The Journal of Finance*, 70, 2489–2538.

GABAIX, X. AND R. KOIJEN (2019): "Granular Instrumental Variables," Tech. rep., University of Chicago.

GORTON, G. AND G. PENNACCHI (1990): "Financial intermediaries and liquidity creation," *The Journal of Finance*, 45, 49–71.

GROMB, D. AND D. VAYANOS (2010): "Limits of arbitrage," *Annual Review of Financial Economics*, 2, 251–276.

HANSON, S. G., A. SHLEIFER, J. C. STEIN, AND R. W. VISHNY (2015): "Banks as patient fixed-income investors," *Journal of Financial Economics*, 117, 449–469.

HE, Z. AND A. KRISHNAMURTHY (2013): "Intermediary asset pricing," *American Economic Review*, 103, 732–70.

IRANI, R. M., R. IYER, R. R. MEISENZAHL, AND J.-L. PEYDRO (2018): "The rise of shadow banking: evidence from capital regulation," Tech. rep., University of Illinois at Urbana-Champaign.

KOIJEN, R. AND M. YOGO (2018): "The fragility of market risk insurance," NBER Working Paper No. 24182.

KOIJEN, R. S., S. VAN NIEUWERBURGH, AND M. YOGO (2016): "Health and mortality delta: assessing the welfare cost of household insurance choice," *The Journal of Finance*, 71, 957–1010.

KOIJEN, R. S. AND M. YOGO (2015): "The cost of financial frictions for life insurers," *American Economic Review*, 105, 445–75.

——— (2016): "Shadow insurance," *Econometrica*, 84, 1265–1287.

LAMONT, O. AND R. THALER (2003): "Can the market add and subtract? Mispricing in tech stock carve-outs," *Journal of Political Economy*, 111, 227–268.

LEE, C., A. SHLEIFER, AND R. H. THALER (1991): "Investor sentiment and the closed-end fund puzzle," *The Journal of Finance*, 46, 75–109.

MALKIEL, B. G. (1977): "The valuation of closed-end investment-company shares," *The Journal of Finance*, 32, 847–859.

MCMILLAN, R. (2013): "Industry surveys: Insurance: Life & health," .

MERRILL, C., T. D. NADAULD, R. M. STULZ, AND S. M. SHERLUND (2014): "Were there fire sales in the RMBS market?" Tech. rep., Federal Reserve Board of Governors.

MUSTO, D., G. NINI, AND K. SCHWARZ (2018): "Notes on bonds: illiquidity feedback during the financial crisis," *The Review of Financial Studies*, 31, 2983–3018.

NISSIM, D. (2013): "Relative valuation of US insurance companies," *Review of Accounting Studies*, 18, 324–359.

PAULSON, A., R. J. ROSEN, R. MCMENAMIN, AND Z. MOHEY-DEEN (2012): "How liquid are US life insurance liabilities?" *Chicago Fed Letter*, 302.

SHLEIFER, A. AND R. VISHNY (1997): "The limits of arbitrage," *Journal of Finance*, 52, 35–55.

——— (2011): "Fire sales in finance and macroeconomics," *Journal of Economic Perspectives*, 25, 29–48.

Asset Insulators

Online Appendix

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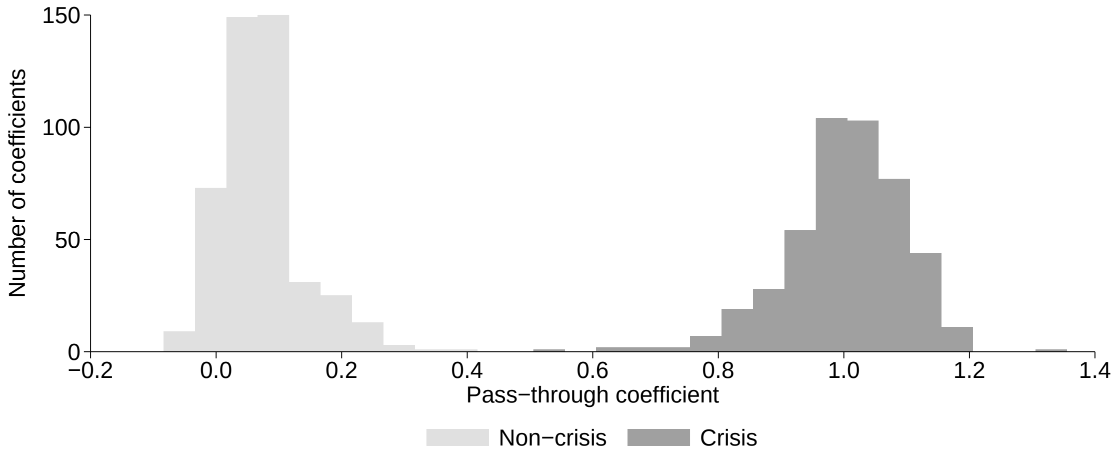
A Additional Empirical Results

Table A.1: Assets Under Management at Life Insurers

	FAUS	SNL	Traded
		(Percent of GDP)	
2006	21.2	21.3	5.6
2010	21.9	22.0	5.8
2014	21.6	21.8	5.2

Notes: The table shows total general account assets under management at life insurance companies as reported in the Financial Accounts of the United States table L.116.g (FAUS), for all life insurance companies in the SNL database (SNL), and for the 15 life insurers in our publicly-traded sample (Traded).

Figure A.1: Pass-through Sample Robustness



Notes: The figure reports the histogram of coefficients of pass-through in and out of the crisis from the regression specification in column (3) of table 4 when we exclude three insurers at a time from the sample. The crisis period is January 2008-December 2009. The data cover 2004-2014.

B Solving the Model

In this appendix, we specify dynamics for A_t and ω_t and show how they determine the equity value of an insulator. We provide expressions for the pass-through and graphically illustrate how A_t and ω_t affect the pass-through and franchise value during normal and crisis periods.

B.1 Value of equity

The exogenous risk-neutral laws of motions are

$$\frac{dA_t^*}{A_t^*} = (r-c)dt + \sigma_A dZ_t^A, \tag{B.1}$$

$$d\omega_t = -\kappa_\omega(\omega_t - \bar{\omega})dt + \sigma_\omega \sqrt{\omega_t} dZ_t^\omega. \tag{B.2}$$

The asset pays off coupons at a rate c, that is $C_t = cA_t^*$, and r is the risk-free rate. Furthermore, we assume that liquidation occurs when A_t^* first hits the threshold $\underline{A}$, and denote the corresponding stopping time by T.

The value of the equity is

$$E_t = \mathbb{E}_t \left[\int_t^T e^{-r(\tau - t)} c A_\tau^* d\tau + e^{-r(T-t)} \omega_T \underline{A} - \int_t^\infty e^{-r(\tau - t)} \ell d\tau \right]. \tag{B.3}$$

We reorganize the equation:

$$\begin{aligned} E_t &= \mathbb{E}_t \left[\int_t^T e^{-r(\tau - t)} c A_\tau^* d\tau + e^{-r(T-t)} \omega_T \underline{A} - \int_t^\infty e^{-r(\tau - t)} \ell d\tau \right] && \text{(B.4)} \\ &= \underbrace{\mathbb{E}_t \left[\int_t^\infty e^{-r(\tau - t)} c A_\tau^* d\tau \right]}_{\text{no-liquidation asset value}} + \underbrace{\mathbb{E}_t \left[e^{-r(T-t)} \omega_T \underline{A} - \int_T^\infty e^{-r(\tau - t)} c A_\tau^* d\tau \right]}_{\text{liquidation adjustment}} \\ &\quad - \underbrace{\mathbb{E}_t \left[\int_t^\infty e^{-r(\tau - t)} \ell d\tau \right]}_{\text{liabilities}}. && \text{(B.5)} \end{aligned}$$

The present value of liabilities is

$$\int_t^\infty e^{-r(\tau - t)} \ell d\tau = \frac{\ell}{r}. \tag{B.6}$$

Note that $\mathbb{E}_t \left[A_\tau^* | A_t^* \right] = A_t^* \exp\left(r - c \right) \left(\tau - t \right)$. Therefore,

$$\begin{aligned} \mathbb{E}_t \left[\int_t^\infty e^{-r(\tau - t)} c A_\tau^* d\tau \right] &= A_t^* \int_t^\infty c \exp\left(-c \left(\tau - t \right) \right) d\tau && \text{(B.7)} \\ &= A_t^*, && \text{(B.8)} \end{aligned}$$

and

$$\begin{aligned} \mathbb{E}_T \left[\int_T^\infty e^{-r(\tau - t)} c A_\tau^* d\tau \right] &= \mathbb{E}_T \left[\int_T^\infty e^{-r(\tau - t)} c e^{(r-c)(\tau - T)} A_T^* d\tau \right] && \text{(B.9)} \\ &= e^{-r(T-t)} A_{T.}^* && \text{(B.10)} \end{aligned}$$

We can also compute expectations of ω_τ for various values of τ. For this remember the conditional mean of a CIR process is

$$\mathbb{E}_t\left[\omega_\tau|\omega_t\right] = \omega_t e^{-\kappa_\omega(\tau-t)} + \bar{\omega}\left(1 - e^{-\kappa_\omega(\tau-t)}\right). \tag{B.11}$$

Plugging these results in the liquidation adjustment, and using the fact that, by definition, $A_T^* = A_0$, we have

$$\mathbb{E}_t\left[e^{-r(T-t)}\omega_T \underline{A} - \int_T^\infty e^{-r(\tau-t)} A_\tau^* d\tau\right] = \underline{A}\mathbb{E}_t\left[e^{-r(T-t)}\left[\left(\omega_t - \bar{\omega}\right)e^{-\kappa_\omega(T-t)} + \bar{\omega} - 1\right]\right] \tag{B.12}$$

We are left with computing $\mathbb{E}_t\left[e^{-r(T-t)}\right]$ and $\mathbb{E}_t\left[e^{-(r+\kappa_\omega)(T-t)}\right]$. The following lemma gives a general expression for this type of expectations.

Lemma 1. *For any* $\alpha \geq 0$ *, we have*

$$\mathbb{E}_t\left[e^{-\alpha(T-t)}\right] = \left(\frac{A_t^*}{\underline{A}}\right)^{-f(\alpha)}, \tag{B.13}$$

with

$$f(\alpha) = \frac{r - c - \frac{1}{2}\sigma_A^2 + \sqrt{\left(r - c - \frac{1}{2}\sigma_A^2\right)^2 + 2\sigma_A^2\alpha}}{\sigma_A^2}. \tag{B.14}$$

The function f *is positive and increasing.*

Proof. Define $M_t = e^{-\alpha t}\left[\frac{A_t^*}{\underline{A}}\right]^{-\tilde{\gamma}_1}$. Applying Ito's lemma gives

$$dM_t = M_t\left[-\alpha - \tilde{\gamma}_1(r-c) + \frac{1}{2}\sigma_A^2\tilde{\gamma}_1\left(1+\tilde{\gamma}_1\right)\right]dt - \tilde{\gamma}_1\sigma_A M_t dZ_t^A. \tag{B.15}$$

Hence M_t is a martingale if $\tilde{\gamma}_1$ solves

$$0 = \left[\frac{1}{2}\sigma_A^2\right]\tilde{\gamma}_1^2 + \left[-(r-c) + \frac{1}{2}\sigma_A^2\right]\tilde{\gamma}_1 + [-\alpha] \tag{B.16}$$

$$\tilde{\gamma}_1 = \frac{(r-c) - \frac{1}{2}\sigma_A^2 \pm \sqrt{\left((r-c) - \frac{1}{2}\sigma_A^2\right)^2 + 2\sigma_A^2\alpha}}{\sigma_A^2}. \tag{B.17}$$

Let us consider the positive root, calling it γ_1. In this case M_t is uniformly bounded before the stopping time T. Doob's optional stopping theorem applies: $M_t = E_t[M_T]$. Hence, substituting the definition of M_t,

$$e^{-\alpha t}\left[\frac{A_t^*}{\underline{A}}\right]^{-\gamma_1} = E_t\left[e^{-\alpha T}\right], \tag{B.18}$$

$$E_t\left[e^{-\alpha(T-t)}\right] = \left[\frac{A_t^*}{\underline{A}}\right]^{-\gamma_1}. \tag{B.19}$$

This last expression coincides with our lemma. ■

Using this lemma, we obtain the value of equity:

$$E_t = A_t^* + \underline{A}\left(\frac{A_t^*}{\underline{A}}\right)^{-f(r+\kappa_\omega)}(\omega_t - \bar{\omega}) + \underline{A}\left(\frac{A_t^*}{\underline{A}}\right)^{-f(r)}(\bar{\omega} - 1) - \frac{\ell}{r}. \tag{B.20}$$

B.2 Pass-through

We can compute the laws of motion for E_t and A_t^{out} using Ito's lemma. We drop the dt terms as they do not enter the pass-through calculation, and ignore the "in" superscript. For the equity value, we obtain:

$$\begin{aligned} dE_t = &\left(1 - \frac{f(r+\kappa_\omega)}{A_t^*}\left(\frac{A_t^*}{\underline{A}}\right)^{-f(r+\kappa_\omega)}\underline{A}(\omega_t - \bar{\omega}) - \frac{f(r)}{A_t^*}\left(\frac{A_t^*}{\underline{A}}\right)^{-f(r)}\underline{A}(\bar{\omega} - 1)\right) dA_t^* \\ &+ \underline{A}\left(\frac{A_t^*}{\underline{A}}\right)^{-f(r+\kappa_\omega)} d\omega_t \end{aligned} \tag{B.21}$$

For the outside value of the assets, we obtain:

$$dA_t = \omega_t dA_t^* + A_t^* d\omega_t \tag{B.22}$$

We can then compute the pass-through, remembering that cov $(dA_t^*, d\omega_t) = 0$:

$$PT = \frac{< dE_t, dA_t >}{(dA_t)^2} \tag{B.23}$$

$$= V_{A^*}\left[\frac{1}{\omega_t} - \frac{f(r+\kappa_\omega)}{\omega_t A_t^*}\left(\frac{A_t^*}{\underline{A}}\right)^{-f(r+\kappa_\omega)} \underline{A}\left(\omega_t - \bar{\omega}\right) - \frac{f(r)}{\omega_t A_t^*}\left(\frac{A_t^*}{\underline{A}}\right)^{-f(r)} \underline{A}\left(\bar{\omega} - 1\right)\right]$$

$$+ V_\omega\left[\left(\frac{A_t^*}{\underline{A}}\right)^{-f(r+\kappa_\omega)-1}\right], \tag{B.24}$$

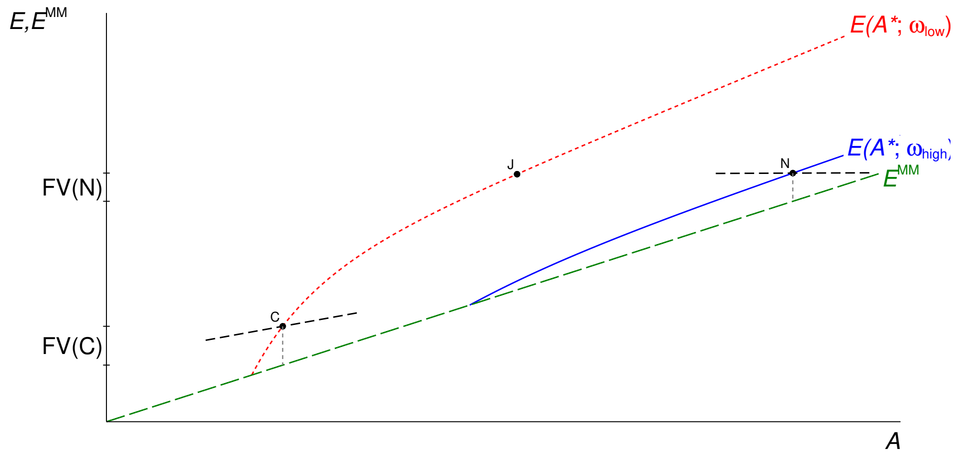
where we define the fractions of variance of dA_t^{out} coming from the two shocks

$$V_{A^*} = \frac{\omega_t^2 dA_t^{*2}}{\omega_t^2 dA_t^{*2} + A_t^{*2} d\omega_t^2}, \tag{B.25}$$

$$V_\omega = \frac{A_t^{*2} d\omega_t^2}{\omega_t^2 dA_t^{*2} + A_t^{*2} d\omega_t^2}. \tag{B.26}$$

Figure B.1 illustrates these predictions graphically. The figure plots equity valuations as a function of the market value of the asset A. The figure contains three lines: the Modigliani-Miller benchmark (the dashed green line), the equity for a fixed, high ω (the solid blue line), and the equity for a fixed, low ω (the dotted red line). The Modigliani-Miller benchmark has a slope of 1. The point N (for normal) corresponds to out of the crisis, with a high ω and high A^*. The point C (for crisis) corresponds to insurers during the crisis, with a low ω and low A^*. The slopes of the blue and red lines give the conditional pass-through with respect to a change in the market value of the asset coming from a change in A^*, while the dashed black lines give the conditional pass-through with respect to a change in the market value of the asset coming from a change in ω at the two points N and C. Both conditional pass-throughs rise at point C relative to point N, generating a higher unconditional pass-through at point

Figure B.1: Pass-through in the Asset Insulator Framework



Notes: The figure illustrates the relation between equity and asset value in the asset insulator framework. The dashed green line is the Modigliani-Miller benchmark and has a slope of 1. The solid blue line plots equity as a function of the market value of the asset for a fixed value ω_{high}, while the dotted red line plots equity as a function of the market value of the asset for a fixed value ω_{low}. The slopes of the blue and red lines give the conditional pass-through with respect to a change in the market value of the asset coming from a change in A^*. The slopes of the dashed black lines give the conditional pass-through with respect to a change in the market value of the asset coming from a change in ω at the two points N (for normal) and C (for crisis). Point J shows the equity value holding A^* fixed at its value at point N but for ω_{low}. The distance between the equity value and the Modigliani-Miller benchmark gives the franchise value (FV) and is shown on the vertical axis for the two points N and C.

C as well.

Figure B.1 also illustrates that a prediction that the pass-through increases during the crisis does not imply that insurers provide no insulation during crises. We show that franchise value can increase — a higher total value of insulation — can increase even though the pass-through also increases — a lower marginal ability to insulate. An increase in market illiquidity corresponds to a decline in the wedge ω. This change lowers directly the value of the assets in the market and hence the Modigliani-Miller value of the firm. However, far from default, a change in ω has a small effect on firm equity. As a result, franchise value rises. In the figure, the two points N and J derive from the same value of A^* but different values of ω. The increase in vertical distance from the Modigliani-Miller line when moving from point N to point J reveals the increase in franchise value. Of course, life insurers also became financially distressed during the 2008-09 crisis. We represent this distress as a decline in A^*, or a movement from point J to point C. As they approach default, insurers lose the ability to insulate assets from the market. Indeed, a large enough decrease in A^* could reverse the increase in value creation coming from the lower ω; in the extreme case of $A^* \to \underline{A}$, value creation from insulation ceases. Which of the two effects dominate is an empirical question. In the figure, as in the data, the overall change in franchise value when moving from N to C is positive.

C Annual Pass-through

An exercise based on regulatory data reported at the end of each calendar year complements the previous results. These data have the advantage of much fuller coverage of assets, but at the cost of limited power as we have one observation per insurer-year. The annual data do allow us to exploit variation by insurer in broad asset class allocation as well as within asset class returns. Indeed, as documented in Chodorow-Reich et al. (2020), insurers differ substantially in their broad asset class allocation with some heavily exposed to ABS and PLRMBS before the crisis and others with virtually no exposure.

We construct annual portfolio returns from the NAIC regulatory data. NAIC Schedules BA and D require insurers to report a fair value per unit for all securities held on their balance sheet on December 31st of each year, regardless of whether valuation of the assets occurs at fair value or historical cost for accounting and regulatory purposes. These schedules also list the value of dividends received during the year, pre-payments, and purchases and sales. We use this information to construct for each asset a total dollar gain equal to the sum of mark-to-market capital gains and net dividends. Summing over assets then gives the total dollar value of investment gains and losses in a year. We obtain information on derivatives holdings from Schedule DB. Like bonds, insurers must include a fair value of each derivative position in their filing, but depending on the hedging classification may not include unrealized gains and losses in their accounting totals. We use a string matching algorithm to match open derivatives positions across consecutive filing years and the fair value reported in each year to construct mark-to-market gains and losses on the derivatives portfolio.[20] Our measure differs, sometimes substantially, from the investment gains and losses reported by insurers in their statutory filings because it attributes gains and losses to the period in which the underlying investments change value rather than the year in which they are recognized for accounting purposes.

Table C.1 reports regressions of the same form as equation (2) but using the NAIC data at the annual frequency. The specification in column 1 includes no controls other than the year fixed effects and reports pass-through with respect to the scaled return on the portfolio assets. We obtain a coefficient of 0.72 for the year 2008 and of essentially zero for all other years. In columns 2 and 3 we construct abnormal portfolio returns by first demeaning each asset class return with respect to its yearly mean across all insurers (column 2) or as the residual after extracting one asset-class specific factor as chosen by the Bai (2009) interactive effects factor model (column 3). The 2008 pass-through changes little, while the non-crisis pass-through falls to be a bit negative.[21] The 2009 pass-through increases in these specifications. In column 4 we augment the Schedule D and BA holdings with the mark-to-market capital gain/loss on each insurer's derivatives portfolio. The pass-through coefficients change little, in part because the gains and losses on the non-derivatives holdings dwarf those from the derivatives portfolio. In sum, while less powerful and well-identified than the

[20]The annual filings also contain detailed data on wholly owned mortgages (Schedule B) and directly held real estate (Schedule A), but value these assets only at historical cost. We exclude these assets in our calculations.

[21]In interpreting the negative coefficients, recall that while more comprehensive than the set of corporate bonds which transact on consecutive days, the annual filings nonetheless lack mark-to-market prices of directly held mortgages, real estate, assets held outside the insurance company, and, especially, liabilities.

Table C.1: Annual Portfolio Return Pass-through

	Dependent variable: stock return			
	Portfolio capital gains measured as:			
		Excess return w.r.t.:		
	Actual	Asset-class year mean	1 factor	Actual incl. derivatives
	(1)	(2)	(3)	(4)
Right hand side variables: scaled portfolio return in:				
Not crisis	−0.047	−0.33**	−0.48**	−0.029
	(0.036)	(0.11)	(0.15)	(0.042)
2008	0.72*	0.77*	0.71	0.87+
	(0.29)	(0.33)	(0.50)	(0.51)
2009	0.022	0.31	0.86	0.022
	(0.052)	(0.42)	(0.93)	(0.050)
Year FE	Yes	Yes	Yes	Yes
R^2	0.55	0.55	0.56	0.54
Observations	150	150	150	150

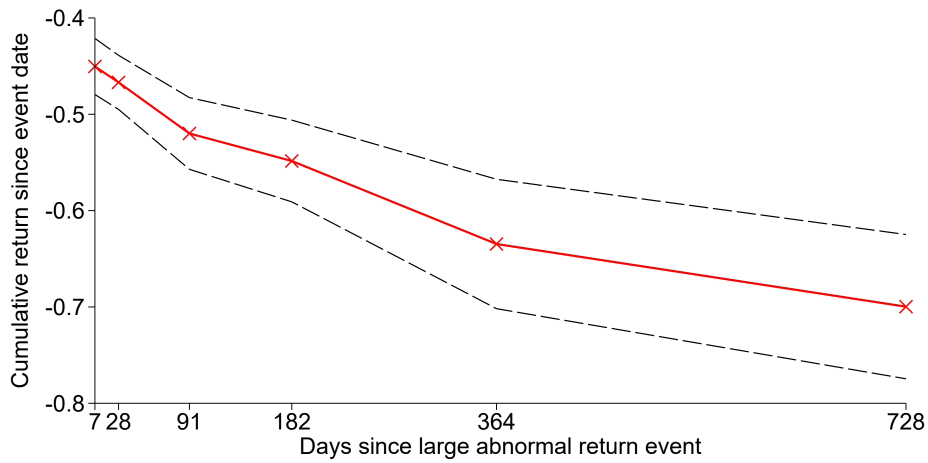
Notes: The table presents the coefficients from regressions of the insurance company's total stock return on the change in the value of its asset holdings. The right hand side variable is the total return on the insurer's asset portfolio. In column (2), we adjust the portfolio capital gains by removing the asset-class mean in each year before aggregating to the individual insurer level. We provide details on our asset class definitions in the online appendix. In column (3), we control for differences across insurers in initial holdings by extracting the first principal component for each asset class before aggregating to the individual insurer level. In column (4), we include derivative positions in addition to the securities held. Heteroskedasticity-robust standard errors in parentheses. **, *, and + denote statistically significant at the 1, 5, and 10% levels. The data cover 2004-2014.

results based on daily returns, annual data confirm the basic result of a low pass-through out of the crisis and a higher pass-through during the crisis.

D Reversion of Portfolio Shocks

Figure D.1 shows that portfolio shocks substantially mean revert. The figure plots the coefficients from a regression of the bond-level, subsequent cumulative abnormal return over the horizon shown on the lower axis, $\tilde{R}^{A,x}_{j,t,t+h}$, on the abnormal return on

Figure D.1: Reversion of Large Abnormal Bond Returns



Notes: The figures plot the coefficients δ_h from the regression $\tilde{R}^{A,x}_{j,t,t+h} = \delta_{h,0} + \delta_h \times \tilde{R}^{A,x}_{j,t-1,t} + \epsilon_{j,t,t+h}$, where $\tilde{R}^{A,x}_{j,t,t+h}$ denotes the excess return of bond j between dates t and $t+h$. The dashed lines indicate 90% confidence intervals on the point estimates for each horizon based on standard errors two-way clustered by CUSIP and calendar quarter.

the bond on date t, $\tilde{R}^{A,x}_{j,t-1,t}$, for a balanced sample of the large abnormal returns which contribute to the portfolio shocks. We weight the regressions by portfolio holdings of each bond. Some of the mean reversion occurs fairly quickly, within a week of the shock. A substantial part occurs at lower frequency. By the two year horizon, two-thirds of the typical shock has dissipated. Thus, an investor able to hold a bond for two years past a large abnormal return can expect two-thirds of that return to eventually reverse itself. [22]

E Insurer Bond Sales

A variant of the reverse causality hypothesis is more challenging to address within our regression framework: maybe there is bond-insurer specific news about a position being sold in the future following a drop in insurer stock price, which explains the

[22]The long-run mean reversion is slightly higher for large abnormal returns during the crisis, possibly reflecting a higher share of ω-type fluctuations due to the disruption in markets during that period. However, even out of the crisis the long-run reversion exceeds one-half. Moreover, a rising share of fluctuations due to ω during the crisis would bias our results *away* from finding a rising pass-through.

presence of a large return for this specific bond. We can assess the plausibility of this explanation by measuring whether insurers sell bonds following large negative returns. We implement this analysis by comparing the propensity to sell for bonds that experiences a large negative abnormal return (at least -6%) to that for other bonds on an insurer's balance sheet on the same date. Table E.1 reports the results. We find that a large negative return predicts very small changes in the propensity to sell the bond in the following year: about a 1 p.p. increase in the propensity during the crisis, and a 1 p.p. decrease outside of the crisis. Even assuming an extremely large price impact conditional on an actual sale, these effects cannot explain the pass-through results. To summarize, while insurers can contribute to fire sales, this type of reverse causality does not seem capable of explaining our empirical results.

Table E.1: Insurer Bond Sales

	(1)	(2)	(3)	(4)	(5)	(6)
bigneg	-0.0083***	-0.00091	-0.0017**	-0.0028***	-0.0091***	-0.0097***
	(0.00071)	(0.0015)	(0.00070)	(0.00070)	(0.0015)	(0.0015)
crisis		-0.015***				
		(0.00011)				
bignegcrisis		0.0015			0.0082***	0.0080***
		(0.0017)			(0.0017)	(0.0017)
Constant	0.021***	0.024***	0.021***	0.0046***	0.0046***	0.0051***
	(0.000042)	(0.000046)	(0.000041)	(0.00027)	(0.00027)	(0.00030)
Observations	11,876,209	11,876,209	11,876,209	9,104,401	9,104,401	7,805,673
R^2	0.000	0.002	0.035	0.078	0.078	0.080
Date FEs	No	No	Yes	Yes	Yes	Yes
Insurer FEs	No	No	No	Yes	Yes	Yes
Risk FEs	No	No	No	Yes	Yes	Yes
Only Traded	No	No	No	No	No	Yes

Notes: Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Dependent variable = 1 if insurer sells bond within one year. Independent variable of interest is bigneg and = 1 if bond price falls by 6% or more. Sample in columns (1)-(5) is all corporate bonds held by insurer on dates with large negative returns; in column (6), we restrict the sample of comparison bonds to those with a return available on the same date as the large abnormal negative return occurs. The specifications in columns (4)-(6) include fixed effects for the NAICs risk-weighting category of the corporate bond.

F Performance of Portfolio of Bonds Insurers Purchase on Secondary Market

We assess whether a strategy of buying all bonds insurers purchase on the secondary market and shorting all other bonds might be profitable. Because the composition of insurers' portfolio differs from the composition of the bond market as a whole, we perform this within a credit rating category.[23]

For each quarter, we construct a portfolio that goes long any bond an insurer buys in the secondary market and goes short all other bonds in the same rating category. We construct two portfolios each quarter, one that weights the bonds equally (EW) and one that weights them by the offering amount of the bond (VW). We then look at the performance of the portfolio in the next quarter such that there is no overlap between the portfolio formation period and the performance period measured.

Table F.1 shows that this strategy earns positive returns on average. The annualized Sharpe ratios from this strategy vary between 0.05 and 0.56. In the rating categories where insurers make the majority of their secondary market purchases, A and BBB, the VW Sharpe ratios are 0.27 and 0.14.

[23]The analysis in Section 4 considers the relative performance of individual bonds insurers purchase and we are thus able to control for a broader set of observable bond characteristics in that analysis.

Table F.1: Long-Short Portfolio Performance

Rating Category	Mean	SD	Sharpe Ratio	Avg. No. of Bonds in Long Portfolio	N
Equally-Weighted:					
AAA	34.0	289.3	0.24	9.7	35
AA	1.7	140.1	0.02	70.3	36
A	11.4	82.1	0.28	286.0	36
BBB	2.7	83.2	0.06	325.5	36
Value-Weighted:					
AAA	31.2	303.2	0.21	9.7	35
AA	8.0	140.0	0.11	70.3	36
A	13.4	97.6	0.27	286.0	36
BBB	6.8	95.3	0.14	325.5	36

Notes: The table shows the quarterly performance of a portfolio that goes long bonds the 15 publicly-traded insurers held in the previous quarter and short all other bonds in the same rating category that trade. The mean and standard deviation (SD) of portfolio returns shown are in basis points per quarter. The Sharpe Ratios shown are annualized, i.e., $2\times$ Mean/SD.

G Additional Data Information

We assess the accuracy of insurers' self-reported valuations of their assets in two ways. First, we collect prices for as many assets as possible from external sources such as TRACE, CRSP, and Bloomberg terminals. We are able to obtain external prices for approximately 38% of insurers' securities by value in any given year. The primary difficulty in obtaining external prices is that many of the assets they hold are highly illiquid.[24] Table G.1 summarizes the difference in prices from what the insurers themselves report and third-party prices. In general, there is very little variation in asset prices reported in NAICs and external quotes. When we include outliers, insurers appear to slightly underreport the values of some securities as the mean raw price difference is -1.2%. However, after excluding outliers, the mean raw price difference is 0.2%. The absolute price differences with and without outliers are 3.6% and 1.8%. We thus feel confident using that insurers are reporting their asset values without significant bias to NAICs.

The second way we assess the accuracy of insurers' self-reported valuations is by comparing the prices reported by multiple insurers in our sample that hold the same asset. Approximately 55% of insurers' securities by value are held in securities that multiple insurers hold. Table G.2 details the deviations in prices reported across insurers. The mean and median standard deviations are 4.3% and 0.0%. After excluding outliers, these statistics fall to just 0.9% and 0.0%.

[24]Edwards, Harris, and Piwowar (2007) report that about half of corporate bonds trade very infrequently. Bessembinder, Maxwell, and Venkataraman (2013) find that only 20% of structured finance securities trade at all in a 20-month period.

Table G.1: Differences Between Insurer-Reported and Third-Party Log Prices

	All Cusips	Excluding Outliers
N	328,230	326,684
Mean Absolute	0.036	0.018
Median Absolute	0.006	0.006
Mean Raw	-0.012	0.002
Median Raw	0.000	0.000
Mean Squared	0.082	0.002
Standard Deviation	0.286	0.050
P75 Absolute	0.018	0.017
P90 Absolute	0.043	0.042
P95 Absolute	0.073	0.070
P99 Absolute	0.283	0.187
Maximum Absolute	13.816	0.999

Notes: All values as of Q4. Count (N) refers to number of CUSIPS for which external prices are available. Fair value per unit used for insurer-reported price. Raw difference calculated as log of insurer-reported less third-party value. Outliers are CUSIPS for which the insurer-reported value deviates by more than 100% from that reported by third-parties.

Table G.2: Cross-Insurer Standard Deviations for Insurer-Reported Log Prices by CUSIP

	All CUSIPS	Excluding Outliers
N	287,903	285,774
Mean	0.043	0.009
Median	0.000	0.000
Standard Deviation	0.277	0.036
P75	0.004	0.004
P90	0.017	0.016
P95	0.043	0.035
P99	1.687	0.190
Maximum	11.209	1.354

Notes: Q4 fair values used to calculate standard deviations. Count (N) refers to number of CUSIPS held by multiple insurers. Outliers are CUSIPS for which the differences in prices across insurers exceed 100%.