

# In Safe Hands: The Financial and Real Impact of Investor Composition Over the Credit Cycle

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## Abstract

This paper demonstrates that investor base composition is an important determinant of bond price dynamics and capital allocation outcomes in response to aggregate credit cycle fluctuations. I use large-scale security-level holdings data and exploit variation in ownership bases across nearly identical bonds issued by the same firms to causally identify the elasticities of bond returns to investor base composition. In the U.S. corporate bond market, bonds held predominantly by domestic insurance companies rather than mutual funds suffer milder losses in crises: increasing insurer holdings in a bond by 50 percentage points leads to value losses in a market downturn that are 20% shallower. I implement a shift-share instrument to further sharpen the focus on identifying variation coming from idiosyncrasies in large insurers' portfolio allocations at the time of bond issuance. These empirical patterns hold pervasively across countries. The results emerge from differences in the contractual structure of liabilities across intermediation sectors, in that insurers are less exposed to sudden, household-driven capital withdrawals. During crises, firms whose bonds are owned by investors less prone to fire sales face relatively better credit conditions: they maintain higher levels of borrowing, pay a lower cost of capital, and have higher real investment rates. I discuss implications for macro-prudential regulation.

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Large institutional investors dominate the bond markets and vary widely in their propensities to participate in fire sales of their assets. Accordingly, market practitioners and policymakers often refer to certain patient, long-term investors as *safe hands*, in contrast to *weak hand* investors who are prone to quickly liquidate their investments in times of market-wide distress. This market environment points to the consequential interplay of two distinct ideas in macro-finance. On the one hand, models that are now canonical stress the key role of credit market disruptions and asset fire sales (Williamson 1988) in firm dynamics during macroeconomic crises (Kiyotaki and Moore 1997, Bernanke et al. 1999). On the other hand, a class of asset pricing models emphasizing portfolio balance (Modigliani and Sutch 1966, Brainard and Tobin 1968, Kouri 1976) highlights the importance of diverse institutional demand in determining equilibrium in financial markets. Bridging these concepts, in this paper I provide quantitative causal evidence that the distribution of ownership of financial assets across heterogeneous institutional investors is an important determinant of the magnitude of fire sales over the credit cycle, ultimately impacting capital allocation and real investment outcomes.

These findings contrast with the traditional frictionless view of bond markets, in which prices and allocative outcomes are entirely determined by a common discount factor and fundamentals such as borrower financials, by instead highlighting a role for the institutional structure of ownership in the market. They also have a parallel in the policy discourse. Institutional behavior in the bond market, for instance, shapes the domestic response to quantitative easing policies. In international macroeconomics, similarly, sovereign and corporate reliance on bond-market credit from flighty foreign investors has traditionally given rise to concerns about investor fickleness and sudden capital flow reversals (Calvo 1998). Hence one might hear reassurances that Argentina’s sovereign bonds are in *safe hands* and unlikely to soar in yield if they are instead held by investors who fully understand Argentina’s risks and will stay steady during volatile market conditions.<sup>1</sup>

To measure the quantitative impact of this form of investor heterogeneity on fire sale dynamics in a causally identified manner, I turn to the corporate bond market as a laboratory. I focus on two investor sectors, insurance companies and mutual funds, which are the most important participants in the market: together, they own two thirds of all U.S. investment-

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<sup>1</sup>For an example of the *safe hands* and *weak hands* terminology, see [The Economist \(2006\)](#). Differences in propensities to engage in fire sales across institutional sectors are of course not primitive demand parameters, but rather—as I emphasize throughout the paper—emerge in equilibrium as the result of differences in the liability structures and contractual provisions involved in financial intermediation.

grade corporate bonds and therefore constitute a major source of debt financing for firms. Financial intermediation in these two sectors is starkly different. Mutual fund liabilities predominantly adopt an open-end contractual structure, which allows clients to redeem their capital easily at any time, but at the same time exposes funds to sudden, household-driven capital withdrawals. In contrast, insurers enter into long-term contracts with policyholders that typically stipulate constraints and penalties on early capital withdrawals. As a result of these differences in the contractual structure of liabilities across sectors, in equilibrium mutual funds have a higher propensity to engage in fire sales than insurers.

I show that during crises bonds held predominantly by insurance companies fall in value less than bonds held largely by mutual funds. All else equal, increasing insurance holdings in a bond by 50 percentage points leads to price declines during downturns that are 20 percent shallower. Firms whose bonds are held mainly by insurers therefore experience less severe slumps in the value of their existing debt, with significant real consequences. These firms are more likely to raise new bond financing in crises and face a lower cost of capital when doing so, which enables them to invest relatively more. Partly because of regulatory reform following the Great Recession, the share of corporate bonds held by funds has been steadily rising over the past two decades, which makes it all the more relevant to examine this source of financial fragility and understand its spillovers on the real economy.<sup>2</sup>

I carry out my analysis using comprehensive security-level portfolio holdings data for these institutional sectors. As outlined in Section 1, I combine regulatory data on the security holdings of U.S. insurance firms with an extensive dataset covering the holdings of mutual funds and exchange-traded funds (ETFs) around the world.<sup>3</sup> By 2020, the security-level positions in this combined dataset represent nearly \$60 trillion in wealth held globally. I begin in Section 2 by investigating *investor base effects* in the context of the U.S. domestic corporate bond market. In this setting, I show that bonds held *ex ante* by domestic insurers experience lower losses in value in market downturns including the financial crisis of 2008-09, the COVID crisis of March 2020, and other periods featuring spikes in credit spreads.

The key empirical challenge is that the assignment of bonds to insurers or mutual funds

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<sup>2</sup>The Dodd-Frank Act of 2010, for example, sharply curtailed the corporate bond holdings of banks, shifting intermediation away from this sector and towards less leveraged institutions such as mutual funds.

<sup>3</sup>Corporate bond holdings by ETFs are small relative to those of mutual funds, although they have been growing in importance: they are less than 1 percent of the fund sector’s total holdings in 2005 and grow to 12 percent by 2020. For ease of exposition, I often omit the mention of the word “ETFs” and simply refer to the entire sector as “mutual funds” or “funds”. Appendix Section G discusses the role of ETFs more extensively.

might not be random, but rather endogenous to the bonds' inherent safety. Insurers might, for instance, disproportionately hold bonds that are issued by firms whose revenues are more resilient and that will therefore do better in a crisis. I address this challenge with a two-pronged econometric approach. I start by introducing issuer-level fixed effects interacted with fixed effects for bond characteristics (such as credit rating, duration, issue size, debt seniority, and so forth). This approach fully absorbs any confounding variation that is fixed at the issuer level or explained by observable bond characteristics. Intuitively, the resulting estimates only compare bonds issued by the same firms, with the same credit rating, of very similar duration and size, and so on, one of which is held relatively more by insurers and the other by funds.

In Section 3, I show that insurers hold certain bonds more than others, even conditionally on being issued by the same firms and having the same characteristics, because of three institutional features of the market. First, large insurers mostly buy bonds when they are initially issued (on what is known as the *primary bond market*) and hold them for a long time—unlike mutual funds, which generally trade more actively.<sup>4</sup> Second, even the very largest insurers are each only allocated a small subset of bonds at issuance through the primary-market distribution process: each insurer therefore ends up holding relatively few of the bonds available at any given time. These allocations at issuance in one particular bond versus a nearly identical one are driven by each insurer's idiosyncratic liquidity needs, relationships with underwriters, and purchase timing, so that they are plausibly exogenous. Third, these idiosyncratic allocations do not cancel out in the aggregate—but rather they affect the overall holdings of the insurance sector—because of the heavily fat-tailed nature of the size distribution of insurers.

These institutional features motivate a shift-share instrument that zeroes in on this exogenous component of the identifying variation—the second prong of my empirical strategy. I remove all potentially endogenous variation due to trading that happens after a bond is first issued, as well as variation stemming from fluctuations over time in the total amount of capital available for new bond purchases by the insurance sector. Instead, I focus purely on the *extensive margin* of primary market allocations: that is, on whether each insurer is allocated a particular bond at issuance. Formally, the first stage regresses the insurance sector's aggregate holdings of a bond on binary indicators for whether each insurer purchased that

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<sup>4</sup>Primary market distributions are often the only occasions when these large insurers can accumulate their desired substantial positions. In the primary market the entire bond is available for sale, while on the secondary market only small shares of the bond turn over. Smaller insurers and funds are more active participants in the secondary market.

bond at issuance, combined linearly according to insurer sizes. The instrument thus captures the overall size of the set of insurers that buy a bond at issuance: intuitively, it takes a high value if a bond is allocated to large rather than small insurers. The identifying assumption (via an approach akin to Goldsmith-Pinkham et al. 2020) is that this matching between *individual insurers* and *particular bonds* on the primary market is uncorrelated with unobserved determinants of price dynamics in crises that are not explained by issuer effects and observed bond characteristics. In Section 3, I provide further supportive evidence for this assumption.

The effects that I highlight imply relative mispricing of related securities that persists for several quarters. In times of distress, the prices of very similar corporate bonds can in fact diverge significantly: for instance, at the height of the Great Recession the market yields of corporate bonds issued by the same firms and sharing the same characteristics differed by as much as 90 basis points or more. While the most extreme price dislocations only occur at the worst of the crisis and rapidly abate afterwards, more muted yield differentials of the order of 40 to 50 basis points tend to persist for several quarters following severe downturns. It is not unusual to observe persistent mispricing of similar securities during crises (Duffie 2010), even for extremely liquid assets such as U.S. Treasury bonds.<sup>5</sup>

In Section 4, I show that these effects are not specific to the U.S. context, but rather occur pervasively across countries. I study the price dynamics of bonds issued by firms in three other advanced economies: the European Monetary Union (EMU), the United Kingdom, and Canada. Since outside of the United States I do not observe the holdings of domestic investors other than funds, I focus on the positions of funds. The complement of the funds' positions proxies for the holdings of domestic insurers as well as other investor sectors that one might expect to have a low propensity to engage in fire sales, such as defined-benefit pension funds.<sup>6</sup> This analysis shows that the same pattern of investor base effects is pervasive across markets, with magnitudes similar to the ones that I estimate in the baseline.

In Section 5, I document how these fire sales ultimately associate with real firm outcomes. I focus on an event study of the dynamics of firms' real investment, new bond issuance, and cost of capital in the Great Recession for U.S. firms. Since this analysis is at the firm level, I cannot use the identification strategy employed so far, which relies on variation across securities issued

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<sup>5</sup>See for example Hu et al. (2013), who show that yield differentials for nearly identical U.S. Treasuries reach the order of about 20 to 30 basis points at the peak of the financial crisis.

<sup>6</sup>In Section 4, I verify that this indirect proxy would have also worked well in the U.S. context.

by the same firm. Instead, I couple a difference-in-differences design with an aggregated version of the instrument, which continues to be relevant at the firm level since the cross-section of bonds outstanding per firm is on average sufficiently small. Naturally, as common in most macro-finance settings (Khwaja and Mian 2008), this firm-level aggregation requires stronger assumptions than the within-firm analysis. Ranking firms by the share of their bonds held by insurers prior to the crisis, firms at the 90<sup>th</sup> percentile of the distribution—as compared to firms at the 10<sup>th</sup> percentile—have capital expenditure rates higher by 1.5 percentage points, are 25 percentage points more likely to issue new bonds in each of the crisis years, and pay offering yields lower by 120 basis points when doing so. The association between fire sales and investment dynamics is especially pronounced for firms that have a high share of their existing bond debt due during the crisis and hence experience rollover issues. These magnitudes are broadly consistent with those found in the bank lending literature: for example, Amiti and Weinstein (2018) find that a 20 percent contraction in bank lending supply leads to a decline of about 2 percentage points in firm investment rates. Additionally, I discuss the role that lending relationships (Diamond 1984) in the bond market play in these financing outcomes.

Together, these facts indicate that—all else equal—from a firm’s perspective it is valuable to place bonds in the *safe hands* of patient investors such as insurers, who will mitigate fire sales and will be more prone to continue supplying new credit in bad times. There is, however, a tradeoff, in that insurers do not engage in liquidity provision to the same extent as funds. The open-end structure of mutual fund intermediation provides liquidity on demand to clients, but it also leaves the door open to fire sales if these demands for liquidity occur simultaneously, for instance because of aggregate shocks, with deleterious impacts on firms’ real activities. In Section 6, I discuss the resulting tradeoff between liquidity provision and financial stability from the perspective of macro-prudential regulation. This tradeoff parallels the one explored in banking theory by Calomiris and Kahn (1991) and Diamond and Rajan (2001). Further, I show that this differential degree of liquidity provision is reflected in the securities markets. Since insurers are also less likely to trade bonds in normal times, when credit spreads are low, bonds held predominantly by insurers become endogenously less liquid. I conclude by elaborating on how equilibrium models may generate the empirical patterns that I document.

**Related Literature.** By documenting the causal role of investor heterogeneity in the dynamics of fire sales, I contribute to the research agenda studying the determinants and out-

comes of fire sales in financial markets (Williamson 1988, Shleifer and Vishny 1992), including theoretical work that links credit market disruptions to aggregate macroeconomic fluctuations (Bernanke and Gertler 1986, Kiyotaki and Moore 1997, Bernanke et al. 1999) and a class of more recent macro-finance models (He and Krishnamurthy 2013, Brunnermeier and Sannikov 2014, Di Tella 2017). I connect this literature to asset pricing models emphasizing portfolio balance and institutional investor heterogeneity (Modigliani and Sutch 1966, Brainard and Tobin 1968, Tobin 1969, Gromb and Vayanos 2002, Kojien and Yogo 2019, Gabaix and Kojien 2020, Vayanos and Vila 2021), as well as to empirical work studying market segmentation in fixed income (Mitchell et al. 2007, Hu et al. 2013, Greenwood and Vayanos 2014, Siriwardane 2019) and equity markets (Greenwood and Thesmar 2011, Anton and Polk 2014).<sup>7</sup>

In the context of the bond market, papers have highlighted that investor characteristics contribute to equilibrium prices in particular settings. Ellul et al. (2011) highlight the role of regulatory constraints in shaping insurers’ bond sales when bonds are downgraded to speculative grade.<sup>8</sup> Barbosa and Ozdagli (2021) stress the importance of relationship lending by insurers in insulating firm financing during the COVID episode. Bretscher et al. (2020) apply the methodology of Kojien and Yogo (2019) to study U.S. corporate bond holdings and find heterogeneity in estimated demand elasticities across sectors. Jiang et al. (2021) examine the financial stability implications of liquidity transformation by fixed income mutual funds, while Falato et al. (2021a) document a fire-sale spillover channel within the bond fund sector.

Understanding the consequences of the heterogeneous behavior of different classes of investors is similarly important in international finance, where it matters in modeling the dynamics of sudden stops (Calvo 1998, Caballero and Krishnamurthy 2001, Mendoza 2010, Forbes and Warnock 2012, Caballero and Simsek 2020) and is key in the exchange rate portfolio balance literature (Kouri 1976, Gabaix and Maggiori 2015, Itskhoki and Mukhin 2021).

In studying the real effects of bond market dynamics on firm financing and investment, I

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<sup>7</sup>A key advantage of studying investor base effects in the bond market is that I can compare similar bonds issued by the same firms, since—unlike equity securities—many bonds are normally issued by the same firm. This allows me to isolate the causal effect of the investor base on pricing. For earlier work related to the equity literature, see also Barberis and Shleifer (2003) and Barberis et al. (2005). Work on asset pricing with heterogeneous investors in complete markets includes Dumas (1989), Alvarez and Jermann (2000), and Alvarez et al. (2002). In addition, for models that integrate segmented fixed income markets with the portfolio balance view of exchange rates, see Greenwood et al. (2020) and Gourinchas et al. (2020).

<sup>8</sup>In Ellul et al. (2011), regulation-driven insurer behavior *exacerbates* fire sales in this localized sense. Within the universe of investment-grade bonds, which comprises the majority of bond financing, I show that insurer behavior *mitigates* fire sales. Relatedly, see also Becker et al. (2021), who show that regulatory incentives shape insurers’ holdings of mortgage-backed securities.

relate to work including Gilchrist and Zakrajšek (2007), Philippon (2009), Almeida et al. (2011, 2017), Harford and Uysal (2014), Benmelech et al. (2019), Darmouni et al. (2020). Kundu (2021) studies the real impact of the related market for collateralized loan obligations. Further, I contribute to the literature on financial intermediation in the mutual fund and insurance sectors, which has examined the importance of the liability structure of these institutions (Coval and Stafford 2007, Frazzini and Lamont 2008, Lou 2012, Goldstein et al. 2017, Wardlaw 2020, Chodorow-Reich et al. 2021) and of their behavior (Becker and Ivashina 2015, Ellul et al. 2015, Kojien and Yogo 2015, Kojien and Yogo 2016, Sen 2020, Sen and Sharma 2020).

My shift-share approach employs recent advances in the applied econometrics literature on Bartik instruments (Bartik 1991, Blanchard and Katz 1992, Goldsmith-Pinkham et al. 2020, Borusyak et al. 2021a), while the difference-in-differences strategy that I use to quantify firm outcomes relates to the literature on event study designs (Autor 2003, Borusyak et al. 2021b, Callaway and Sant’Anna 2021, Wooldridge 2021).

This paper contributes to the above strands of the literature by offering causal evidence that quantifies how the liability structure of two major institutional investor sectors impacts bond price dynamics over the credit cycle. I do so across a number of countries, stressing the commonality of these patterns rather than the idiosyncrasy of each market, and trace out the linkage between these mechanisms and real economic outcomes.

## 1 Institutional Setting and Security-Level Holdings

The insurance sector and the mutual fund sector (including ETFs) are some of the largest holders of corporate debt securities. I use two sets of micro-data on security-level holdings covering the positions of these two institutional sectors. The data on U.S. insurers’ holdings come from the Schedule D regulatory filings that insurance firms file quarterly with the National Association of Insurance Commissioners (NAIC).<sup>9</sup> The data cover the complete universe of security holdings of U.S. insurers and have been previously used in several papers (Ellul et al. 2011, Chodorow-Reich et al. 2021, Coppola et al. 2021). As shown in Table 1, in 2015 the sample contains 1,225 insurers with an average of \$3.5 billion invested in bonds and equities each, although with considerable dispersion. The insurance sector is very concentrated: the

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<sup>9</sup>I use the version of the data provided by S&P Global via its division formerly known as SNL Financial.



largest 10 insurers hold 34 percent of the sector’s assets, while the largest 50 own 71 percent.

Data on the holdings of mutual funds and ETFs come from Morningstar, as used in [Maggiore et al. \(2020\)](#) and [Coppola et al. \(2021\)](#).<sup>10</sup> As reported in [Table 1](#), in 2015 the sample includes 8,193 funds domiciled in the United States and 22,069 funds domiciled abroad, with an average of \$1.9 billion and \$0.9 billion in assets each. The fund industry holds a wider range of securities than the insurance sector, which is instead predominantly invested in bonds. Hence, in comparing the two sectors it is helpful to focus on funds that are specialists in fixed income. These specialist funds hold more than 80 percent of all corporate bond positions in the Morningstar data.<sup>11</sup> In 2015, there are 1,957 U.S. specialist funds and 5,090 non-U.S. ones, with an average of \$1.7 billion and \$0.7 billion in assets each. The fund sector is less concentrated than the insurance sector. In the United States, the largest 10 specialist funds only hold 21 percent of all securities, while the largest 50 own 44 percent. Outside of the United States, these numbers are 12 and 26 percent.<sup>12</sup>

Data on transacted bond prices in my baseline analysis are from the TRACE database, which includes nearly all corporate bond transactions in the United States.<sup>13</sup> [Table 2](#) shows the characteristics of the corporate bond holdings of insurance firms and fixed income specialist funds. The two sectors are fairly well-aligned, for instance in terms of the size of the average bond held and the shares of bonds held that are senior or have callable features. However, there are also some differences: for example, insurers tend to hold bonds of slightly longer duration, with an average duration of 7 years as opposed to 5.5 years for U.S. funds. These differences highlight the necessity of imposing fixed effects for bond characteristics, as they could otherwise introduce confounding variation. Importantly, insurers are very averse to holding high-yield bonds (that is, bonds with a speculative-grade rating). While 37 percent of U.S. funds’ corporate bond holdings are in high-yield debt, only 5 percent of insurers’ positions

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<sup>10</sup>[Chen et al. \(2021\)](#) confirm the accuracy of the Morningstar holdings data, while pointing out that the summary descriptions of fund portfolios reported to Morningstar can be inaccurate. I do not use these latter summary descriptions. See also [Lilley et al. \(2020\)](#) for work using the Morningstar holdings data.

<sup>11</sup>I classify funds as fixed income specialists using Morningstar’s industry categorization. I select funds where Morningstar’s *broad category group* is fixed income.

<sup>12</sup>My analysis also makes use of additional data on bond characteristics, sourced from Mergent’s Fixed Income Securities Database (FISD), Factset, S&P Global, and Moody’s Default and Debt Recovery (DRD) Database. [Appendix Section A](#) provides more details on data construction and further descriptive statistics.

<sup>13</sup>TRACE is distributed by FINRA. I apply to it the data cleaning steps in [Dick-Nielsen \(2014\)](#), which are common in the literature. Throughout the paper, I define U.S. corporate bonds as bonds that are reportable in TRACE. These include virtually all U.S. dollar-denominated bonds issued by U.S. firms and by U.S. affiliates of foreign corporate groups. Bonds denominated in non-USD currencies are not included in TRACE.

are. This pattern results from the significantly higher risk-based regulatory capital charges on high-yield bonds faced by U.S. insurers (Ellul et al. 2011, Becker and Ivashina 2015). Since high-yield bonds are rarely held by insurers, my analysis throughout the paper excludes them.

Figure 1 plots the aggregate value of the positions in U.S. investment-grade corporate bonds observed in the insurance and fund holdings micro-data over time, alongside the total size of the market. An advantage of this empirical setting is the high degree of coverage of the entire market that I can achieve with security-level holdings. By 2020, insurers’ positions cover 35 percent of the market, with a further 22 and 9 percent accounted for by U.S. and foreign mutual funds and ETFs. Altogether, the positions in the micro-data account for two thirds of the entire size of the market. The share of these bonds held by insurers has been declining, starting at 52 percent in 2007, while the share held by funds has been increasing, from a baseline level of 14 percent for U.S. funds and 4 percent for foreign funds in 2007.

## 2 Investor Base Effects for U.S. Corporate Bonds

This section of the paper introduces the baseline empirical results in the setting of the U.S. domestic corporate bond market. I discuss their robustness to varying empirical specifications, and finally document the sharply different propensities of insurers and funds to fire-sell corporate bonds in a crisis, which constitutes the portfolio mechanism underlying my estimates.

### 2.1 Empirical Definitions

My baseline empirical analysis focuses on the universe of U.S. investment-grade corporate bonds that are actively traded, as reported in TRACE. The number of outstanding bonds in the sample grows from 7,951 in 2007 to 11,293 in 2020, while the average issue size increases from \$407 million to \$698 million.<sup>14</sup> For each bond in TRACE, I construct a time series of returns in excess of Treasury bonds of matched duration. I let  $P_{i,t}$  be the traded price of bond  $i$  in week  $t$ : this is constructed as the median price in the last day of week  $t$  in which bond  $i$  trades, plus accrued coupon interest. The *raw* weekly net return on bond  $i$  is then  $R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$ . I also let  $D_{i,t}$  be the duration of bond  $i$  at time  $t$ , and  $R_t^f(D)$  be the weekly

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<sup>14</sup>Appendix Table A.2 provides summary statistics on the sample of U.S. investment-grade corporate bonds.

return on a basket of Treasury bonds of duration  $D$ .<sup>15</sup> The *hedged* return on bond  $i$  is then:<sup>16</sup>

$$R_{i,t}^H = R_{i,t} - R_t^f(D_{i,t}). \quad (1)$$

Subtracting the returns on a matched basket of Treasuries lets me remove the component of returns that is purely due to risk-free interest rate variation, and instead focus on that which is due to credit spread variation. I refer to the cumulative hedged return since the first trading date  $t_i^0$  of bond  $i$  as  $CR_{i,t}^H = \prod_{\tau=t_i^0}^t (1 + R_{i,\tau}^H)$ .

The *insurer share* in bond  $i$  at time  $t$  is

$$\phi_{i,t} = \frac{X_{i,t}^I}{V_{i,t}}, \quad (2)$$

where  $V_{i,t}$  is the outstanding market value of bond  $i$  and  $X_{i,t}^I$  is the market value of all insurers' holdings in bond  $i$ . Given the frequency of the holdings data, these positions are measured on a quarterly basis, so in practice  $X_{i,t}^I$  corresponds to the latest recorded position.

The baseline analysis hones in on the return properties of corporate bonds during aggregate market downturns. In order to do this, I compute *drawdowns* for each bond in each of the major market downturns in the U.S. corporate bond market: these are summary measures that capture a bond's total loss in value during a given downturn event. With  $t_e^S$  denoting the start date of event  $e$  and  $t_e^E$  its end date, the drawdown of corporate bond  $i$  in the event window  $\mathcal{T}_e = (t_e^S, \dots, t_e^E)$  is defined as

$$\zeta_{i,e} = \max_{\tau \in \mathcal{T}_e} \left( 1 - \frac{CR_{i,\tau}^H}{CR_{i,t_e^S}^H} \right). \quad (3)$$

The drawdown is therefore a number between 0 and 1, with a higher value corresponding to a more severe loss in value of a particular bond in a given market downturn episode. Consider, for example, the bond with CUSIP code 494550AT3 issued by Kinder-Morgan, a leading oil infrastructure company. At its trough during the Great Recession of 2008-09, the cumulative return index  $CR_{i,t}^H$  reached a value equal to 38 percent of its starting one in June 2007. The

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<sup>15</sup>The sovereign returns at varying durations are obtained from CRSP whenever available, including only regular non-callable Treasury issues, and from Factset's zero-coupon sovereign benchmarks otherwise.

<sup>16</sup>If a bond does not trade in a given week, the returns  $R_{i,t}$  and  $R_t^f(D_{i,t})$  are computed relative to the latest trading week. I show in Section 2.3 that excluding these cases does not meaningfully affect my estimates.

drawdown on this bond in the Great Recession is therefore  $\zeta_{i,e} = .62$ .<sup>17</sup>

## 2.2 Insurer Ownership and Bond Return Properties in Crises

I investigate how bond drawdowns vary with investor base composition in the four largest bond market downturns in the sample period. The shaded areas of Figure 2 highlight the event periods, whose start and end dates correspond to the prior trough and subsequent peak values in the Gilchrist and Zakrajšek (2012, henceforth GZ) index, which provides an aggregate measure of credit spreads on U.S. corporate bonds. The first downturn event is the Great Recession of 2008-09, during which the GZ index rose more than four-fold from a prior trough of 1.7 percent in June 2007 to a peak of 7.9 percent in December 2008. The second event window, during which the U.S. sovereign debt was downgraded and global markets tumbled, starts in April 2011 and ends in October 2011. The third window runs from August 2014 to February 2016, a period which featured large collapses in commodity prices. Finally, the fourth event window, starting in January 2020 and ending in March 2020, corresponds to the global COVID crisis and the resulting market crash, which involved large price dislocations for corporate bonds (Haddad et al. 2021, Ma et al. 2021).<sup>18</sup>

The baseline specification pools these events and regresses the log drawdown on bond  $i$  in event  $e$  on *ex ante* insurer shares  $\phi_{i,t_e^S-12}$  and a series of interacted fixed effects that are progressively saturated:

$$\log \zeta_{i,e} = \alpha + \beta \cdot \phi_{i,t_e^S-12} + \text{Interacted Fixed Effects} + \varepsilon_{i,e}. \quad (4)$$

The coefficient of interest in these regressions is  $\beta$ , which (in the absence of confounders) approximates the semi-elasticity of drawdowns to *ex ante* insurer shares. Importantly, the insurer shares  $\phi_{i,t_e^S-12}$  are measured in the quarter prior to the start of each event window, in order to avoid concerns of reverse causation.

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<sup>17</sup>As detailed in Section 2.2, the start and end dates for each episode are chosen mechanically by identifying peaks and the corresponding prior troughs in the Gilchrist and Zakrajšek (2012) corporate credit spread index. The event window corresponding to the Great Recession starts in June 2007 and ends in December 2008. My results are not dependent on the use of the maximum operator in equation (3): in fact, computing drawdowns on a fixed window corresponding to the full event range yields analogous results, as I show in Section 2.3.

<sup>18</sup>The unusually rapid recovery of the corporate bond market in 2020 might be linked to the Federal Reserve’s announcement of its willingness to intervene in the market. See also Becker and Benmelech (2021) and Falato et al. (2021b) for discussions of the resilience of the U.S. corporate bond market in the COVID crisis. Relatedly, Kargar et al. (2021) and O’Hara and Zhou (2021) study corporate bond liquidity in the COVID episode.

The inclusion of fixed effects in equation (4) is necessary in order to tackle the concern that the estimated relationship between insurer shares and subsequent drawdowns may be driven by omitted factors that influence both the inherent riskiness of a given security and the likelihood of insurers to hold it. At their most saturated level, these fixed effects interact event dummies, issuer dummies, and security characteristics dummies.<sup>19</sup> The security characteristics in the fixed effects set include all of the following: (i) bond credit rating, measured using S&P and Moody’s ratings and ranging from AAA to BBB,<sup>20</sup> which is the threshold between high-yield and investment-grade debt; (ii) bond duration, which is non-parametrically clustered into categories;<sup>21</sup> (iii) bond size, as captured by dummies for deciles of value outstanding; (iv) bond seniority, as captured by a binary dummy variable; (v) bond coupon type, either floating-rate or variable-rate; and (vi) bond callability, also captured via a binary dummy variable. I do not include currency fixed effects since TRACE only includes U.S. dollar-denominated bonds.

When including the most saturated set of interacted fixed effects, therefore, the estimates only rely on variation in insurer ownership and drawdowns across nearly identical bonds. Intuitively, the regression only compares bonds issued by the same legal entity, of similar duration and size, with the same credit rating, and so forth. Figure 3 provides an example of the identifying variation in this empirical exercise. The dashed blue line plots the cumulative returns on Kinder-Morgan’s bond with CUSIP code 494550AT3, normalized to one at the beginning of the Great Recession event window, while the solid red line plots the cumulative returns on a second bond issued by Kinder-Morgan, with CUSIP code 494550AL0, also normalized to one on the same date. These two bonds had analogous characteristics: besides being issued by the same firm, they were both rated BBB, had comparable durations of 13 and 12 years respectively, and matched on all other characteristics included in the fixed effect set. In the quarter prior to the Great Recession, however, these two bonds had very different investor bases: while bond “T3” had a 17 percent *ex ante* insurer share, bond “L0” had a much higher

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<sup>19</sup>Issuers are defined via Mergent FISD’s issuer IDs, which capture legal entities. In the few cases in which Mergent FISD issuer IDs are not available, issuers are defined by pooling six-digit CUSIP issuer codes at the legal entity level via the CUSIP Global Services (CGS) associated issuers file. These issuer definitions are tighter than at the ultimate parent level since they correspond to individual firm subsidiaries. This provides a more rigorous degree of control for issuer fixed effects.

<sup>20</sup>I use the S&P conventions in listing credit ratings, although the analysis uses ratings from both S&P and Moody’s. The Moody’s ratings are converted to the equivalent on the S&P scale.

<sup>21</sup>The duration categories used in the baseline exercise are the following, which correspond to commonly used industry classifications: 0-1 years, 1-3 years, 3-5 years, 5-10 years, 10-15 years, 15-20 years, and greater than 20 years. Section 2.3 shows that these results are robust to using stricter categories in which duration is rounded to the nearest year. It also demonstrates robustness to other varying specification choices.

one at 58 percent. Despite their similarities, these two bonds experienced markedly different drawdowns during the Great Recession, with the former one losing 62 percent of its value at its trough, and the latter one only losing 33 percent of its value. This exemplifies the type of sample variation that the estimates are based on.

Table 3 reports the estimates from equation (4) as I progressively saturate the set of included fixed effects. These estimates are obtained via weighted least squares (WLS) using bond sizes as weights. Column 1 reports results with event fixed effects only, with an estimate of  $\hat{\beta} = -.41$ . Moving to the right, as more interactions are added to the fixed effects set, the estimated coefficient remains stable. Column 2 interacts event dummies with size and duration dummies, while columns 3 and 4 further introduce rating and issuer dummies. Finally, the estimates in column 5 include the fully-saturated set of fixed effects described above, which encompasses all of event, size, duration, rating, issuer, bond callability, seniority, and coupon type. The estimated regression coefficient from the fully-saturated specification in column 5 is  $\hat{\beta} = -.42$ . This semi-elasticity estimate has the interpretation that increasing *ex ante* insurer holdings in each bond by 50 percentage points (half of the issue size) reduces the drawdown in a subsequent crisis by about 20 percent.

These effects have some heterogeneity across the various events. Appendix Figure A.1 demonstrates this by estimating equation (4) on different subsamples of the data, split by event.<sup>22</sup> The estimates are higher in magnitude for the Great Recession and the COVID crisis than for the other two events in the sample. The market downturns in the Great Recession and in the COVID crisis were faster and more severe than those in 2011 and 2014-16, suggesting a certain degree of non-linearity, with investor base effects mattering more in harsher crises. I explore this non-linearity further in Section 2.4, while Appendix Section E investigates heterogeneity within the insurance sector, including across more and less financially constrained insurers (Kojien and Yogo 2015, Becker et al. 2021, Ge and Weisbach 2021).

Figure 4 quantifies the degree of relative bond mispricing that accompanies these effects. The blue line plots the monthly average standard deviation of yield spreads to Treasury within groups of matching bonds—that is, bonds issued by the same firms and having the same characteristics. This metric provides a simple measure of the level of mispricing in the

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<sup>22</sup>Appendix Figure A.1 also repeats the estimation on two mutually exclusive and collectively exhaustive subsamples, one for bonds rated AAA through A- and one for bonds rated BBB+ through BBB-. The estimates are quite homogeneous across these two credit rating groups.

corporate bond market over time. Prior to the Great Recession, the standard deviation of yield spreads for matching bonds averaged less than 20 basis points. However, the metric increases gradually over the course of the Great Recession event window, reaching a peak of nearly 100 basis points between September and December of 2008, and it remains elevated for several quarters after the crisis. This metric similarly spikes during other crisis periods, particularly in the COVID episode, peaking at nearly 60 basis points in March 2020, consistent with the evidence of price dislocations in this period by [Haddad et al. \(2021\)](#). These magnitudes align with other instances of relative mispricing of related securities in crises: for example, [Hu et al. \(2013\)](#) document yield differences with a standard deviation of about 20 basis point for nearly identical U.S. Treasuries during the 2008-09 financial crisis. Given the vastly lower liquidity and higher degree of segmentation of the corporate bond market relative to the Treasury market, it is natural to expect yield discrepancies to be more pronounced in the former.<sup>23</sup>

An elevated degree of relative mispricing for nearly identical bonds indicates the presence of some persistent limits to arbitrage in the corporate bond market. While a full investigation of the reasons for these limits to arbitrage is beyond the scope of this paper, several institutional features make these limits likely. Limits to arbitrage may be supported, for example, by search and matching frictions, given the over-the-counter (OTC), decentralized nature of the corporate bond market ([Duffie et al. 2005, 2007](#)). Perhaps most saliently, in large crises arbitrage capital is unavailable because all investor sectors with a large presence in the corporate bond market are, on net, attempting to sell. Appendix Figure [A.2](#), for example, uses transactions data from the U.S. Flow of Funds to demonstrate that between 2008Q1 and 2009Q1 banks, broker-dealers, government-sponsored enterprises, insurers, mutual funds and ETFs, pensions funds, and foreign investors were all net sellers of corporate bonds.<sup>24</sup>

## 2.3 Ruling Out Other Potential Explanations

I now consider the robustness of these baseline estimates to further variations in the empirical specification. The bars labeled 2 through 4 in Figure [5](#) demonstrate the robustness of the

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<sup>23</sup>Indeed, the magnitude of the price discrepancies I document more closely aligns with spreads such as the CDS-bond basis, which persistently amounted to hundreds of basis points for investment-grade debt after the financial crisis ([Bai and Collin-Dufresne 2019](#)). See [Musto et al. \(2018\)](#) for further evidence from Treasuries.

<sup>24</sup>The only non-corporate sector that was a net buyer of corporate bonds in the financial crisis was the household sector. In the Flow of Funds, the household sector is a residual category, including various institutions such as hedge funds and nonprofits. A further limitation of these statistics is that the Flow of Funds does not report asset holdings separately for U.S. corporate bonds and foreign bonds held by U.S. investors.

estimates to the introduction of further interactions to the full set of fixed effects. Bar 2 introduces an additional interaction with stricter duration categories, with duration rounded to the nearest year, in order to provide an even more stringent matching of similar bonds. Bar 3 adds an interaction with bond age, rounded to the nearest year, to rule out alternative explanations based on the differential properties of on-the-run and off-the-run bonds. Lastly, bar 4 includes an additional interaction with a dummy for whether a bond is issued under SEC rule 144A, which establishes special trading rules for certain restricted or controlled securities.

Additionally, bars 5 through 10 in Figure 5 consider alternative sample treatments. Bar 5 excludes bonds with a zero insurer share. Bar 6 excludes the holdings of AIG from the computation of the insurer positions  $X_{i,t}^I$ , to rule out that the results may be influenced by AIG’s special financial situation following its bailout under the Troubled Asset Relief Program (TARP) in 2008-09. Bar 7 repeats the estimation using drawdowns that are computed by cumulating the raw returns  $R_{i,t}$  rather than the hedged returns  $R_{i,t}^H$ . Bar 8 uses an alternative measure of drawdowns,  $\tilde{\zeta}_{i,e} = 1 - CR_{i,t_e}^H / CR_{i,t_e^S}^H$ , which applies the same window to all bonds for a given event. Bar 9 drops any bonds that trade less frequently than once a week in a given event period. Finally, bar 10 excludes callable bonds. In all cases, these alternative empirical specifications result in what are substantively the same estimates as the baseline one.

## 2.4 Investor Composition and Bond Betas Over the Credit Cycle

The baseline empirical analysis in Section 2.2 focuses on bond price dynamics in times of crisis. This particular focus is due to the asymmetry in the magnitude of investor base effects over the credit cycle. In order to understand this asymmetry more clearly, it is helpful to also consider a complementary full-panel approach that studies investor base effects over the entire credit cycle. In order to do this, I begin by computing the betas of each bond  $i$  with respect to the returns on a value-weighted index of all actively traded investment-grade bonds in the United States. These betas are estimated on a two-year rolling window, and I refer to them as  $b_{i,t}$ .<sup>25</sup> I then consider the following regression specification:

$$b_{i,t} = \alpha + \bar{\Gamma} \phi_{i,t-12} + \tilde{\Gamma} \phi_{i,t-12} \text{GZ}_t + \text{Interacted Fixed Effects} + \varepsilon_{i,t}, \quad (5)$$

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<sup>25</sup> Appendix Figure A.3 repeats the estimates with betas computed on a shorter one-quarter rolling window. The results are analogous, albeit with larger standard errors.



where  $GZ_t$  is the value of the [Gilchrist and Zakrajšek \(2012\)](#) index at time  $t$ . The interaction between *ex ante* insurer shares and the GZ index serves to capture variation in investor base effects over the credit cycle in a simple parametric way. Consistent with the analysis carried out so far, the sample includes all actively traded U.S. investment-grade corporate bonds, and the fixed effects interact issuer dummies with all the security characteristics included in the baseline, plus time fixed effects. These regressions include one observation per security-month pair, with all variables measured at the end of the month.

The estimated total effect of insurer ownership on bond betas is  $\Gamma_t = \bar{\Gamma} + \tilde{\Gamma} GZ_t$ . The red line in [Figure 6](#) plots the estimated value of  $\Gamma_t$  over time. This figure clearly demonstrates the non-linear nature of the relationship between insurer ownership and bond return properties. When aggregate credit spreads are low, as in 2018-19 or before 2007, investor base effects are negligible—as evidenced by the small estimated values of  $\Gamma_t$ , often statistically indistinguishable from zero. When credit spreads spike, however, higher insurer ownership leads to significantly lower betas with respect to market returns. For instance, at the height of the Great Recession the estimates reach a value of  $\Gamma_t = -.54$ , which is broadly consistent with the baseline results of [Section 2.2](#): as the *ex ante* insurer share rises from 0 to 1, the passthrough from aggregate market returns to individual bond returns roughly halves. In this sense, bonds with a higher insurer share are more insulated from market-wide fluctuations in crises.

## 2.5 Inspecting the Mechanism

The portfolio mechanism resulting in the presence of investor base effects is best understood by comparing the trading behavior of insurers and funds in market downturns. [Figure 7](#) does this in the context of the Great Recession. The solid green line plots the cumulative change in corporate bond holdings for the asset-weighted average insurer in the sample over the course of the Great Recession, relative to their level in 2008Q1. The changes in corporate bond holdings are measured using par values, so that they reflect pure quantity changes rather than any valuation effects owing to variation in market prices. By 2009Q1, the (asset-weighted) average insurer had reduced its holdings of corporate bonds by less than 5 percent. The solid blue line shows the equivalent portfolio dynamics for the asset-weighted average mutual fund or ETF in the sample: over the same time period, funds had reduced their corporate bond holdings by 15 percent, more than three times as much as insurers. The much more aggressive

portfolio response of funds relative to insurers is consistent with the safe hands hypothesis laid out in the introduction and exemplifies the heterogeneity in quantity dynamics that accompanies the price dynamics documented in Section 2.2.

The reason for such a dramatic portfolio response of investment funds in the Great Recession does not primarily trace back to discretionary trading decisions made by fund portfolio managers, but rather to redemptions coming from their clients. The dashed red line in Figure 7 plots the component of the cumulative net corporate bond sales by funds that is *household-driven*. The household-driven sales measure is defined by constructing counterfactual portfolio holdings for each fund assuming the fund were to maintain the same portfolio allocation weights as in 2008Q1, and varying the overall size of its portfolio according to its net redemptions. The household-driven net sales shown in the dashed red line therefore purely reflect household decisions to redeem assets from the fund sector, and abstract from active portfolio management choices of allocation across asset classes.<sup>26</sup> Comparing the dashed red and solid blue lines, more than two thirds of the net sales of corporate bonds by the fund sector in the Great Recession were household-driven.

In contrast, insurers do not face such aggressive capital redemptions from their clients. Figure 8 compares the time series properties of the net inflows and outflows of assets for funds and insurance firms. The dashed red line plots the quarterly value of the aggregate net client inflows for fixed income specialist funds in the sample, scaled by the lagged value of their total assets under management. The solid blue line plots the analogous concept for U.S. insurance firms, which is the quarterly net change in the sector’s aggregate policy reserves, scaled by lagged total policy reserves.<sup>27</sup> Funds face volatile and oftentimes negative net client inflows, which are strongly procyclical (Feroli et al. 2014, Goldstein et al. 2017). Clients withdraw their capital from funds precisely at the time when the market is doing worst, as evidenced by a quarterly time-series correlation of -44 percent between net fund inflows and the GZ index. In contrast, the net growth in insurers’ policy reserves is almost never negative: while funds can experience severe household-driven capital liquidations, insurers are by and large

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<sup>26</sup>For work on mutual funds’ liquidity management following capital withdrawals, see Chernenko and Sunderam (2016), Choi et al. (2020), and Ma et al. (2021). For ease of exposition, here I abstract from differences in the redemption process for ETFs, which are instead detailed in Appendix Section G.

<sup>27</sup>Policy reserves are the primary liability item on insurers’ balance sheets and correspond to the actuarial value of future expected payments to policyholders: they therefore increase when clients subscribe to insurance products. As I discuss in Appendix Section D, the same-quarter net change in insurers’ policy reserves is the chief determinant of the net amount of new bond purchases by the insurer sector.

insulated. Moreover, net inflows into the insurance sector have diametrically opposite dynamic properties: they are countercyclical, being largest when the market is doing poorly, with a quarterly correlation with the GZ index of 32 percent.<sup>28</sup>

This sharp contrast between the properties of net capital inflows into the two sectors is explained by differences in the contractual structure of their liabilities. Mutual funds predominantly adopt an open-end contractual structure, which allows clients to redeem capital continuously and with no limitations or charges. Capital intermediated by insurance companies, on the other hand, is not as easily redeemable. Most insurance products, for example annuity policies (a popular product offered by life insurers consisting of fixed income asset management with embedded longevity insurance), impose contractual restrictions and surrender charges for early capital withdrawals (Securities and Exchange Commission 2020). Contractual provisions of this kind shield insurers from sudden, household-driven capital withdrawals.

### 3 Shift-Share Approach and Discussion of Identification

In this section I investigate why nearly identical bonds have different investor bases. I show that this results from the combination of three institutional features of the market. First, large insurers mostly buy bonds on the primary market and hold them for a long time. Second, each insurer only purchases a small subset of all the bonds available on the primary market at any given time. Third, these random idiosyncratic purchase decisions matter in the aggregate because of a deviation from the law of large numbers, as the size distribution of insurers is unusually kurtotic (that is, fat-tailed). I exploit these institutional features to construct a shift-share instrument and outline how the instrument relates to the identifying variation exploited by the baseline ordinary least squares (OLS) regression. I discuss causal identification, both via the shift-share IV approach and via a complementary partial identification approach.

#### 3.1 Understanding Variation in Insurer Ownership

The results in Section 2 demonstrate that similar bonds with different investor base composition experience different drawdowns during crises. Figure 9 shows that these results rely on the presence of sizable residual variation in insurer ownership for bonds issued by the same

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<sup>28</sup>The counter-cyclicity of flows into the insurance sector may reflect rising household risk aversion and increased demand for defined-benefit investment products such as annuities following severe market downturns.

firms and with the same characteristics. The blue histograms plot the sample distribution of drawdowns and insurer shares, both pooled across events. The red histograms show the distribution of the same quantities after residualizing them against the fixed effects included in the baseline.<sup>29</sup> It is evident that, even after accounting for all these observables, there is still considerable dispersion in both drawdowns and ownership.

This residual variation in insurer ownership across similar securities results from the idiosyncratic portfolio allocations of a few large insurers, made predominantly at the time of bond issuance. Corporate bond markets have a much lower degree of liquidity and higher transaction costs than equity markets, so that it is difficult for market participants to hold all outstanding, actively traded securities. This low degree of liquidity and ease of trading leads to idiosyncrasy in holdings at the security level. To show this, I compare insurers' holdings in the largest 500 actively traded investment-grade bonds to their holdings of equities in the S&P 500, an equally-sized benchmark in a different market.<sup>30</sup> Figure 10 ranks insurers by the overall size of their portfolios, and shows the share of the 500 largest investment-grade bonds that they hold an open position in (*blue dots*) alongside the share of S&P 500 equities that they hold an open position in (*red dots*), all measured cross-sectionally as of 2017Q4. While there is some dispersion in the share of S&P 500 equities that each insurer holds, a large number of insurers cluster at 100 percent, which reflects the feasibility of holding all securities in the market portfolio in equity markets. In contrast, none of the 300 largest insurers hold an open position in more than 61 percent of the 500 largest bonds, and most have positions in a much lower share of these bonds, often less than 20 percent.<sup>31</sup> Appendix Figure A.5

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<sup>29</sup>Formally, the red histograms show the residuals  $\nu_{i,e}^{\zeta}$  and  $\nu_{i,e}^{\phi}$  from the following regressions of drawdowns  $\zeta_{i,e}$  and insurer shares  $\phi_{i,t_e^s-12}$  on the fully-saturated set of interacted fixed effects:

$$\zeta_{i,e} = \alpha + \text{Interacted Fixed Effects} + \nu_{i,e}^{\zeta}, \quad (6)$$

$$\phi_{i,t_e^s-12} = \alpha + \text{Interacted Fixed Effects} + \nu_{i,e}^{\phi}. \quad (7)$$

<sup>30</sup>Since some insurers hold equities through mutual funds and ETFs rather than directly, these estimates are based on a version of the holdings data that unwinds positions in funds and attributes ownership of the underlying positions to the insurers. Indirect ownership of corporate bonds by insurers through investment funds, in contrast, is very rare. While insurers specialize in fixed income investing in order to support their policy liabilities, equity holdings are small relative to their bond positions.

<sup>31</sup>A *t*-test for differences in means across the bond and equity data in Figure 10 rejects the hypothesis of equal means with  $p < .01$ . Further, these results are not driven by the particular choice of bonds. To show this, Appendix Figure A.4 repeats the analysis in Figure 10 with smaller reference sets of bonds—either the 100 largest or the 250 largest actively traded U.S. investment corporate bonds. The results within these smaller sets of securities are analogous.

repeats this exercise for mutual funds and ETFs and shows similar patterns, while Appendix Section D gives an overview of the primary-market bond distribution process—which is led by *underwriters* who collect institutional investors’ bids—and discusses further the incentives that insurers have to acquire large positions in a small number of bonds.

Importantly, most of the corporate bond trading of large insurers is on the primary market. The absence of sizable follow-up portfolio rebalancing means that the ownership initially determined at issuance persists strongly over time. To quantify this persistence, I let  $\tau(i)$  be the date of issuance of bond  $i$  and consider the following regressions of insurer shares over time against insurer shares at issuance,  $\phi_{i,\tau(i)}$ , at varying quarterly horizons  $s$ :

$$\phi_{i,\tau(i)+12s} = \alpha_s + \lambda_s \phi_{i,\tau(i)} + \varepsilon_{i,s}. \quad (8)$$

The solid blue line in Figure 11a plots the estimated passthrough coefficients  $\lambda_s$  for progressively longer horizons  $s$ , which remain stably close to 1 up to a 36-quarter horizon. The solid red line in Figure 11b plots the R-squared values from these regressions, which plateau at a remarkably high level: nearly 10 years after the initial issuance of an investment-grade corporate bond, the insurer shares first determined at bond issuance still explain 40 percent of the variation in contemporaneous ownership. For comparison, Figure 11 also plots the same regression coefficients (*dashed blue line*) and R-squared values (*dashed red line*) using mutual fund and ETF ownership shares in place of insurer shares in equation (8), both of which decay much faster than the equivalent metrics for insurers. The faster decay for funds reflects the more active trading of this investor sector over time. In contrast, the absence of meaningful portfolio rebalancing by insurers adds to the idiosyncratic nature of their bond investments.

Large insurers do so much of their trading on the primary market because of the drastically higher degree of liquidity on it vis-à-vis the secondary market. To characterize the decay in liquidity as bond trading moves to the secondary market, I consider the following specification for varying quarterly horizons  $s$  after bond issuance, which takes the same form as (8):

$$\mathcal{T}_{i,\tau(i)+12s} = \alpha_s + \lambda_s \mathcal{T}_{i,\tau(i)} + \varepsilon_{i,s}, \quad (9)$$

where  $\mathcal{T}_{i,t}$  is a measure of quarterly trading activity in bond  $i$ , either the quarterly number of trades or quarterly dollar trading volume (both from TRACE). Figure 12 plots the estimated

coefficients  $\lambda_s$  for U.S. investment-grade corporate bonds. Quarterly trading volume drops off sharply after issuance, on average being just 10 percent of the issuance-quarter level a single quarter after issuance. The number of trades decays as well starting in the first quarter after issuance, although less markedly, as the average size of a trade also diminishes. Appendix Figure A.6 compares the size distribution of trades on the primary versus the secondary market: it shows that indeed the average trade on the primary market is more than five times as large as on the secondary market. Consistent with the view that large insurers buy on the primary market because of its enhanced liquidity, the preference for buying at issuance increases with insurer portfolio size. Appendix Figure A.7 plots the share of corporate bond holdings purchased on the primary market by insurer size decile and shows that this metric increases monotonically with insurer size: larger insurers value the primary market more.

Lastly, one might expect the idiosyncratic portfolio allocations that I have highlighted to cancel out in the aggregate if the law of large numbers applies in this particular empirical context. As already seen in Table 1, however, asset holdings in the insurance sector are very concentrated, with the largest 50 insurers owning more than 70 percent of the sector's total invested assets. The idiosyncratic portfolio decisions of individual insurers matter in determining the sector's aggregate ownership because of a large deviation from the law of large numbers, resulting from the heavily fat-tailed size distribution of insurer portfolios. Appendix Section B provides a formal statistical test and quantifies these deviations from the law of large numbers, thanks to which idiosyncratic portfolio decisions—made mostly at the time of bond issuance—generate the sizable residual variation in aggregate insurer ownership shown in Figure 9. As a concrete example of this data-generating process, suppose that MetLife—one of the very largest insurance firms—bids for an allocation in IBM's 10-year bond issued in a given year but, having obtained this allocation, does not then go to the trouble of participating in the following year's 10-year IBM offering, which it might view as largely substitutable. Since MetLife accounts for a large share of the insurance sector's total assets, its lack of participation in the latter bond's offering will tend to lower the resulting aggregate insurer share—even if underwriters might have otherwise allocated the two bonds so as to have a similar institutional ownership profile.

### 3.2 An Instrument Based on Random Purchases at Issuance

I now further narrow down the identifying variation in order to purely exploit the idiosyncratic allocations to large insurers on the primary market. I begin with an accounting decomposition that highlights the various sources of identifying variation in the OLS regressions of Section 2. The insurer share  $\phi_{i,t}$  is the sum of its value at issuance  $\phi_{i,\tau(i)}$  and deviations from it due to trading on the secondary market,  $\hat{\phi}_{i,t} = \phi_{i,t} - \phi_{i,\tau(i)}$ . One can further decompose the insurer share at issuance  $\phi_{i,\tau(i)}$  by summing over potential outcomes for individual insurers:

$$\phi_{i,t} = \sum_{j \in \mathcal{J}} \xi_{i,j} \cdot \tilde{\phi}_{i,j,\tau(i)} + \hat{\phi}_{i,t}, \quad (10)$$

where  $\mathcal{J}$  is the set of insurers in the sample,  $\xi_{i,j}$  is a dummy variable indicating whether insurer  $j$  acquired bond  $i$  at issuance, and  $\tilde{\phi}_{i,j,\tau(i)}$  is a potential outcome—the share in bond  $i$  acquired by insurer  $j$  on the primary market conditionally on purchasing the bond.<sup>32</sup>

This expression has three sets of terms, which correspond to three distinct sources of variation. The variation due to secondary-market trading, which one might worry could be endogenous,<sup>33</sup> is captured by  $\hat{\phi}_{i,t}$ . A second source of variation comes from the *intensive margin* of primary-market trading and is captured by the potential outcomes  $\tilde{\phi}_{i,j,\tau(i)}$ : when insurers have more capital available to invest in new bonds, they will acquire bigger positions. As shown in Section 2.5, however, the capital available to insurers for new investments is not orthogonal to credit market conditions: rather, insurers have more capital on hand when aggregate credit spreads are high. Since the credit quality of new corporate bond issues is known to vary systematically over the credit cycle (Greenwood and Hanson 2013), it might be desirable to strip away this variation as well. This leaves us with the third and last source of variation in ownership: the *extensive margin* of primary market trading—meaning the binary allocations of new bonds to each insurer, captured by the purchase indicators  $\xi_{i,j}$ .

I construct a shift-share instrument that isolates the variation coming from this last channel. The instrument removes the secondary-market component  $\hat{\phi}_{i,t}$  and replaces the intensive

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<sup>32</sup>Naturally, the potential outcome  $\tilde{\phi}_{i,j,\tau(i)}$  is only observable for insurers who actually acquire bond  $i$  at issuance, so that  $\xi_{i,j} = 1$ . This potential outcomes interpretation corresponds to an assumed data generating process in which purchases are strictly positive conditionally on entering the market, so that  $\tilde{\phi}_{i,j,\tau(i)} > 0$ . This assumption is innocuous and only matters for exposition.

<sup>33</sup>The analysis in Section 2.2 mitigates this concern by using insurer shares measured one quarter before each event, which are close to those at issuance, as shown in Section 3.1.

margin terms  $\tilde{\phi}_{i,j,\tau(i)}$  with measures of insurer size that are time- and bond-invariant. Insurer size,  $\bar{\phi}_j$ , is measured as the average size of insurer  $j$ 's primary market bond purchases relative to the aggregate insurance sector (so that  $\sum_{j \in \mathcal{J}} \bar{\phi}_j = 1$ ). The instrument therefore captures the collective size of the set of insurers that acquire bond  $i$  at issuance:

$$Z_i = \sum_{j \in \mathcal{J}} \xi_{i,j} \bar{\phi}_j. \quad (11)$$

This instrument follows the shift-share structure studied in the applied econometrics literature (Goldsmith-Pinkham et al. 2020, Borusyak et al. 2021a), with the purchase indicators  $\xi_{i,j}$  functioning as the *shares* and the size coefficients  $\bar{\phi}_j$  functioning as the *shifters*. Intuitively, the instrument takes a high value if the insurers who acquire a bond at issuance are particularly large ones rather than small ones.

The exclusion restriction requires that  $\mathbb{E}[Z_i \varepsilon_{i,e} \mid \mathcal{F}_{i,e}] = 0$ , where  $\mathcal{F}_{i,e}$  contains all the observables included in the regressions and  $\varepsilon_{i,e}$  is the error term from the linear model specified in equation (4). A sufficient condition for this restriction is that:<sup>34</sup>

$$\mathbb{E}[\xi_{i,j} \varepsilon_{i,e} \mid \mathcal{F}_{i,e}] = 0 \text{ for all } i, j. \quad (13)$$

Intuitively, the identifying assumption corresponding to condition (13) is that the matching between *individual insurers* and *particular bonds* on the primary market in a given quarter is uncorrelated with unobserved determinants of future drawdowns that are not explained by issuer effects and observed bond characteristics. This identification approach, which relies on the exogeneity of the shares in the shift-share instrument, is similar to the one outlined and studied by Goldsmith-Pinkham et al. (2020).<sup>35</sup>

This identifying assumption relies on the idea that insurers are not able to (or do not

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<sup>34</sup>The proof is simple. Using the linearity of expectations:

$$0 = \mathbb{E}[Z_i \varepsilon_{i,e} \mid \mathcal{F}_{i,e}] = \mathbb{E}\left[\sum_j \xi_{i,j} \bar{\phi}_j \varepsilon_{i,e} \mid \mathcal{F}_{i,e}\right] = \sum_j \bar{\phi}_j \mathbb{E}[\xi_{i,j} \varepsilon_{i,e} \mid \mathcal{F}_{i,e}]. \quad (12)$$

<sup>35</sup>In Appendix Section F, I discuss the interpretation of the shift-share IV estimates if insurers are heterogeneous in their impact on bond drawdowns. Following Goldsmith-Pinkham et al. (2020), I decompose the IV estimator in terms of Rotemberg (1983) weights. In the presence of heterogeneity, the IV approach continues to provide a valid causal estimator—although it should then be interpreted as estimating the weighted average of heterogeneous treatment effects.



attempt to) select bonds that will draw down less in a market downturn for reasons not explained by issuer effects or any of the included observable bond characteristics. If larger insurers were to systematically acquire bonds that do better in crises for unobservable reasons, for example, that would generate problematic sorting, as it would introduce confounding correlation between the purchase indicators  $\xi_{i,j}$  and the error terms  $\varepsilon_{i,e}$ . This kind of sorting constitutes the primary threat to identification within the IV framework, but there is *a priori* reason to believe that it should be absent in practice. Insurers are benchmark investors who do not generally try to outperform the broad investment-grade bond market—and therefore do not engage in strategic allocations across similar bonds. Moreover, while the identifying assumption is not directly testable, one can test a related condition: whether some insurers systematically acquire bonds with a high *residual alpha*—that is, a component of returns that is not explained by the performance of the overall bond market and by observable bond characteristics or issuer effects. The finance literature has developed approaches to tackle this kind of question and differentiate investment ability from noise in the cross-section of investors. Appendix Section C introduces a bootstrap approach following Fama and French (2010). The bootstrap-based test rejects the presence of residual alpha in the cross-section of insurers, providing further support for the identifying assumption.<sup>36</sup>

Table 4 reports the results from estimating the baseline specification (4) via two-stage least squares (2SLS), using the shift-share variable  $Z_i$  to instrument for the aggregate insurer shares  $\phi_{i,t_e^s-12}$ . The 2SLS estimates are shown in columns 3 and 4, with the corresponding OLS estimates shown in columns 1 and 2. The instrument is highly relevant, with first-stage  $F$  statistics ranging from 71.6 to 72.9, and the point estimates are similar to the ones from the OLS regressions, although with larger standard errors. Once I impose the fully saturated set of interacted fixed effects in column 8, the point estimate is  $\hat{\beta} = -.45$ , which aligns with the corresponding OLS estimate  $\hat{\beta} = -.42$ .<sup>37</sup>

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<sup>36</sup>The reverse concern—that issuers might be able to forecast insurer demand and time their issuance accordingly—does not pose an issue. This is because the instrument only needs to be exogenous *conditionally* on issuer fixed effects, which would absorb this confounding firm-level behavior.

<sup>37</sup>Since the insurance holdings data start in 2005, in constructing the instrument for bonds issued prior to this year I use insurers’ holdings in 2005 as a proxy for their holdings at issuance. As shown in Appendix Table A.3, the results are quantitatively consistent when restricting the sample to bonds issued in 2005 or later. Further, Appendix Figure A.8 visualizes the first-stage relationship using a binned scatterplot, while Appendix Figure A.9 demonstrates the robustness of the 2SLS estimates under a range of different specification variations similar to those introduced in the OLS case. The shift-share IV estimates remain significant at the 95 percent confidence level when adopting the *AKM* and *AKM0* inference procedures of Adão et al. (2019).

The relevance of the instrument results precisely from the same institutional features discussed in Section 3.1. The fact that insurers mostly trade on the primary market makes the primary-market purchase indicators  $\xi_{i,j}$  a relevant predictor of the subsequent positions of each insurer  $j$ . Moreover, the high degree of idiosyncrasy in each insurer’s purchases generates dispersion in the distribution of the indicators  $\xi_{i,j}$ , and the deviations from the law of large numbers (reflected in the size terms  $\bar{\phi}_j$ ) imply that this dispersion does not cancel out once I aggregate over insurers. On the whole, the shift-share IV approach discussed in this section provides a sharp characterization of the identifying variation underlying my estimates and confirms causal point-identification.

### 3.3 Partial Identification Approach

Beyond the shift-share IV framework laid out above, I also consider a complementary partial identification approach in the context of the baseline OLS regressions of Section 2. Suppose that the true data-generating model follows the specification in equation (4), but that it however also includes some relevant unobservable omitted variables. In Appendix Section I, I follow Oster (2019) and define a ratio  $\delta$  that relays the strength of selection on the unobservables relative to selection on the observables included in the regression, which correspond the fully-saturated set of interacted fixed effects for issuer and bond characteristics.

I use the partial identification econometric approach of Oster (2019) in order to ask how large the ratio  $\delta$  would have to be in order for the baseline estimates of equation (4) to be consistent with a zero treatment effect of insurer ownership on bond drawdowns. This methodology uses variation in the estimated regression coefficients and R-squared values as I include the observed regressors in order to estimate this threshold value of  $\delta$ . In this sense, it formalizes common informal arguments that appeal to coefficient stability in the face of selection on observables to argue for robustness to selection on unobservables.

The estimated threshold value of  $\delta$  for a zero treatment effect is  $\bar{\delta} = 3.3$ . That is, one would require selection on unobservables to be more than three times as strong as selection on the included observables in order to generate a zero treatment effect. Both Altonji et al. (2005) and Oster (2019) argue that results with a threshold value  $\bar{\delta}$  greater than or equal to 1 should be viewed as robust to the potential presence of selection on unobservables. This partial identification approach provides strong evidence that the baseline OLS results obtained

by estimating equation (4) are robust to the potential presence of residual omitted variable bias resulting from selection on unobservables. While point-identification of  $\beta$  in equation (4) through OLS requires the absence of residual omitted variable bias once we include the fully-saturated fixed effects (that is,  $\delta = 0$ ), the partial identification of a negative treatment effect  $\beta < 0$  only requires the much weaker assumption that selection on unobservables is less than roughly three times as strong as selection on the included observables ( $\delta < 3.3$ ).

## 4 Investor Base Effects in Non-U.S. Markets

Having documented the presence of sizable investor base effects in the U.S. corporate bond market, I now turn to investigating this phenomenon across countries, and show that the same empirical patterns hold pervasively. I focus on corporate bonds issued by firms in three large advanced economies with well-developed securities markets: the European Monetary Union (EMU), the United Kingdom, and Canada. More specifically, I include in the analysis all firms resident in these countries as well as their foreign subsidiaries.<sup>38</sup> The sample includes the universe of investment-grade bonds issued by these firms except for those that are TRACE-reportable, which are instead included in the analysis of Section 2 and are predominantly U.S. dollar-denominated bonds issued by U.S. subsidiaries.

### 4.1 Empirical Setup

In the non-U.S. setting, I focus on the holdings of mutual funds and ETFs, since I do not directly observe the portfolios of other domestic institutional sectors. I define the proxy *safe hands share* in bond  $i$  at time  $t$  by looking at the complement of fund holdings:

$$\tilde{\phi}_{i,t} = 1 - \frac{X_{i,t}^F}{V_{i,t}}, \quad (14)$$

where  $X_{i,t}^F$  is the market value of total mutual fund and ETF holdings in bond  $i$ . The measure  $\tilde{\phi}_{i,t}$  is intended to proxy for the holdings of investors such as domestic insurers and pension funds that have a lower propensity to fire-sell their assets in market downturns. The positions  $X_{i,t}^F$  include the holdings both of funds domiciled in the same country as the issuer of bond

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<sup>38</sup>To establish links between affiliates and their corporate parents, I use the ultimate parent aggregation algorithm of Coppola et al. (2021).

$i$  and of foreign funds, although the former are usually dominant given the presence of home bias in portfolio investment. To confirm the validity of this proxy approach, I repeat my baseline estimates for U.S. corporate bonds, as in equation (4), using the proxy safe hands shares  $\tilde{\phi}_{i,t}$  instead of the insurer shares  $\phi_{i,t}$ . Column 1 of Table 5 reports the resulting estimate ( $\hat{\beta} = -.39$ ), which is very similar to the baseline ( $\hat{\beta} = -.42$ ). The proxy shares and the insurer shares accordingly have a high correlation of 51 percent in the U.S. sample.

A second difference between the U.S. and non-U.S. settings is that traded prices (as in TRACE) are generally not available for the universe of corporate bonds outside the United States. I therefore use prices provided by S&P Global, which are traded when possible and otherwise estimated. Estimated bond prices are widely used in fixed income portfolio management and index construction (Bloomberg L.P. 2017) and have also been commonly used in academic research (He et al. 2017, Nozawa 2017, Kelly et al. 2021). In computing hedged returns per equation (1), I use the risk-free returns applicable to each economy: these are returns on duration-matched baskets of German bunds for EMU corporate bonds, British gilts for U.K. corporate bonds, and Canadian sovereign bonds for Canadian corporate bonds.

## 4.2 Investor Composition and Bond Returns Across Countries

I consider the following specification for non-U.S. corporate bonds, which is analogous to the baseline one in equation (4). Letting  $c(i)$  be the currency of denomination of bond  $i$ , the regression specification is:

$$\log \zeta_{i,e} = \alpha + \beta \cdot \tilde{\phi}_{i,t_e^s-12} + \rho_{c(i)} + \text{Interacted Fixed Effects} + \varepsilon_{i,e}. \quad (15)$$

This specification additionally includes dummies for the currency of denomination of each bond  $i$ . In the U.S. exercise, this is unnecessary since all bonds in the sample are denominated in U.S. dollars. In the non-U.S. sample, however, there is currency variation, with significant shares of the bonds in the sample denominated in Euros, British pounds, or Canadian dollars. While all bond prices are measured in the currency of denomination of the bond, so that nominal exchange rate movements do not directly contribute to variation in the drawdown measures  $\zeta_{i,e}$ , the currency dummies absorb any systematic variation in drawdowns that might indirectly be determined by a bond’s currency of denomination. For parsimony and consistency with the

U.S. exercise, I use the same set of events, with the same start and end dates, as in Section 2.

Column 2 in Table 5 shows the estimate from equation (15) in a pooled sample that includes all of the EMU, the United Kingdom, and Canada. Columns 3 through 5 show the estimates individually for each of the three countries. In all cases, the estimates show a negative and significant relationship between *ex ante* safe-hand shares  $\tilde{\phi}_{i,t_e^s-12}$  and subsequent drawdowns. Moreover, the estimates are quantitatively consistent with the ones obtained from the U.S. exercise. For instance, the pooled non-U.S. semi-elasticity estimate  $\hat{\beta} = -.51$  in column 2 aligns with the  $\hat{\beta} = -.42$  estimate obtained in the U.S. setting. Altogether, the non-U.S. estimates shown in Table 5 demonstrate that the presence of investor base effects in corporate bond markets is pervasive across countries, in a way that is consistent with the mechanism laid out in this paper. These further results rule out potential alternative explanations that rely on the idiosyncratic characteristics of the U.S. corporate bond market and insurance or mutual fund sector, and underscore the generality of the effects that I document.

## 5 How Fire Sales Transmit to Real Firm Outcomes

An important question is whether the differential price impact for bonds in the secondary market that I documented in the preceding sections transmits to real firm outcomes. In this section, I focus on an event study of U.S. firms in the Great Recession and show that secondary market fire sales significantly influence funding conditions in the primary bond market for the affected firms, ultimately with consequences for their real investment dynamics. In documenting that variation in a firm’s cost of capital in the bond market impacts real investment, I provide evidence for a channel that, although theoretically central in macro-finance (Gilchrist and Zakrajšek 2007, Philippon 2009, Almeida et al. 2017), has been difficult to establish empirically. Since this analysis is at the firm level, I cannot use the identification strategy employed so far, which focuses on variation across similar bonds issued by the same firms. My approach instead couples a difference-in-differences empirical strategy with a version of the shift-share instrument of Section 3 that is aggregated to the firm level. This firm-level empirical strategy allows me to remove potential confounders, although under stronger identifying assumptions than required in the security-level exercise.

## 5.1 Aggregating the Instrument to the Firm Level

I begin by defining the relevant quantities at the firm level. Letting  $\mathcal{I}_k$  be the set of bonds issued by firm  $k$  and outstanding in 2007Q1, I construct the firm-level insurer share  $\Phi_k$  by aggregating insurer ownership across securities, with all positions also measured in 2007Q1, before the start of the financial crisis:

$$\Phi_k = \frac{\sum_{i \in \mathcal{I}_k} X_{i,2007Q1}^I}{\sum_{i \in \mathcal{I}_k} V_{i,2007Q1}}. \quad (16)$$

The firm-level insurer share  $\Phi_k$  is plausibly endogenous to firm outcomes during the Great Recession, since for example insurers might sort into holding bonds issued by firms that are inherently more resilient in crises. To remove this type of confounding variation, I construct a firm-level instrument by aggregating the security-level instrument  $Z_i$  defined in equation (11):

$$\mathcal{Z}_k = \sum_{i \in \mathcal{I}_k} \rho_{i,k} \cdot Z_i, \quad (17)$$

where the terms  $\rho_{i,k} = \frac{V_{i,2007Q1}}{\sum_{i' \in \mathcal{I}_k} V_{i',2007Q1}}$  are weights proportional to bond size. The firm-level instrument  $\mathcal{Z}_k$  captures whether the bonds issued by a given firm are *on average* allocated to large rather than smaller insurers at issuance.

Aggregating to the firm level still retains the majority of the variation present at the security level: the sample standard deviation for the firm-level instrument  $\mathcal{Z}_k$ , for instance, only shrinks to 76 percent of that for the unaggregated firm-level instrument  $Z_i$ . This variation persists at the firm level because the cross-section of bonds outstanding per firm is generally small, although it has long right tails: within the sample, the median and mean number of bonds outstanding per firm in 2007 are 3 and 17, respectively.<sup>39</sup> The idiosyncratic portfolio allocations of the few largest insurers therefore matter even once I aggregate to the borrower level, so that the instrument continues to be relevant.

The identifying assumption required for the firm-level instrument to be valid is stronger than the one required for the security-level regressions of Section 3. Namely, the firm-level identifying assumption is that the matching between individual insurers and particular bonds

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<sup>39</sup>Naturally, these numbers are higher within the set of firms that contribute identifying variation in the highly-saturated, baseline security-level analysis. For example, among the 437 firms that contribute variation in the most saturated specification (column 5) reported in Table 3, the median and mean number of bonds outstanding per firm at a given time are 8 and 30.

on the primary market is uncorrelated with determinants of firm outcomes during the crisis that are not explained by *observable firm characteristics*, including average firm-level bond attributes. In contrast, identification at the security level only requires the much weaker condition that the primary-market matching between insurers and bonds is exogenous conditionally on *issuer fixed effects* interacted with *observed bond characteristics*. In requiring stronger assumptions for identification at progressively higher levels of aggregation, this setting parallels themes that are common in the macro-finance literature (Khwaja and Mian 2008, Wolf 2021).

## 5.2 Firm Financing and Investment Outcomes

To assess the association between bond ownership and firm investment outcomes, I merge the data on bond ownership with yearly firm financials from Compustat.<sup>40</sup> I estimate the following dynamic difference-in-differences specification with continuous treatment intensity:

$$\text{Investment}_{k,t} = \alpha_k + \gamma_t + \sum_{\tau} \beta_{\tau} \Phi_k \mathbb{1}_{\tau=t} + \text{Controls} + \varepsilon_{k,t}, \quad (18)$$

where  $\text{Investment}_{k,t}$  is the investment rate of firm  $k$  in year  $t$ , measured either as yearly capital expenditures (CAPX) over lagged total assets or as yearly CAPX plus acquisitions over lagged total assets. The firm fixed effects  $\alpha_k$  remove confounding variation that is fixed at the firm level and is state- and time-invariant, while the time fixed effects  $\gamma_t$  absorb time trends in investment that are common to all firms. In turn, the coefficients  $\beta_{\tau}$  trace out the dynamic equilibrium association between firm investment and the pre-crisis share of the firm’s bonds that is owned by insurers.

The controls consist of firm-level covariates, all measured prior to the crisis, interacted with time dummies: these include fixed effects for issuer rating, average duration of the firm’s outstanding bonds (using the same categories as in the baseline regressions), two-digit industry, and deciles of firm size and firm leverage. I estimate this specification via just-identified two-stage least squares, by also interacting the firm-level instrument  $\mathcal{Z}_k$  with time dummies (Wooldridge 2010). The sample excludes speculative-grade issuers. While a series of recent papers has shown that two-way fixed effects specifications such as the one in equation (18) can suffer from bias in settings with staggered treatment adoption (Callaway and Sant’Anna

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<sup>40</sup>In order to match the level at which the Compustat data is reported, I aggregate the security-level data to the ultimate parent level.

2021, Goodman-Bacon 2021), this type of design does not face the same issues when treatment timing is common across observations (Wooldridge 2021), as is the case here.<sup>41</sup>

Figure 13 displays the estimates from this instrumented dynamic difference-in-differences specification. The red line plots the estimated coefficients using the CAPX measure, while the blue line plots the estimates for the CAPX plus acquisitions measure. The pre-crisis coefficients serve as an effective placebo test and are all close to zero. Following the crisis, there is a large and significant impact of *ex ante* insurer shares on firm investment, which gradually fades toward zero in 2010 and 2011. Increasing firm-level insurer ownership by 50 percentage points—which is equivalent to a movement from the 10<sup>th</sup> to the 90<sup>th</sup> percentile in the distribution of the insurer shares  $\Phi_k$ —is associated with an increase in CAPX equal to roughly 1.5 percent of assets, and with an increase in CAPX and acquisitions ranging from 2 to 3 percent of assets. These estimated magnitudes are broadly similar to those found in the literature studying bank lending. Amiti and Weinstein (2018), for example, show that a 20 percent contraction in bank lending supply leads to a decline of about 2 percentage points in annualized fixed physical investment rates in a sample of Japanese firms.<sup>42</sup>

These effects are particularly strong for firms that have a high share of their existing debt coming due during the crisis. To see this, I estimate the following static version of the difference-in-differences design in equation (18):

$$\text{Investment}_{k,t} = \alpha_k + \gamma_t + \beta \cdot \Phi_k \cdot \text{Post}_t + \eta \cdot \Phi_k \cdot \text{Post}_t \cdot \mathcal{M}_k + \text{Controls} + \varepsilon_{k,t}, \quad (19)$$

where  $\text{Post}_t$  is a dummy that takes the value of one for post-crisis observations (i.e. observations for the years starting in 2008) and zero otherwise, and  $\mathcal{M}_k$  is the share (by value) of a firm’s bonds outstanding as of 2007Q1 that are maturing in 2008 or 2009. The coefficient  $\eta$  captures the incremental impact of insurer ownership on firm investment that is due to maturing debt. Table 6 shows the estimates from this regression. Since the instrumented regressions are under-identified when including the additional parameter  $\eta$ , I show these results using ordinary least squares. Increasing the share of maturing bonds by 50 percentage points has a further impact

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<sup>41</sup>The regressions include observations up to the year 2011. I end the sample in 2011 since later observations overlap with the U.S. sovereign downgrade event. The excluded year dummy is for 2007, so that all coefficients estimate effects relative to 2007. All financial ratios are winsorized at the 1<sup>st</sup> and 99<sup>th</sup> percentiles.

<sup>42</sup>See column 5 of Table 2 in Amiti and Weinstein (2018). In non-crisis years, the average investment rates for firms in the sample are 6 percent (CAPX over assets) and 9.3 percent (CAPX and acquisitions over assets).



of about 1 percent of assets on CAPX and of 1.5 percent of assets on CAPX plus acquisitions: fire sales matter more for firms with more debt coming due, which face challenges in rolling over existing bond financing.<sup>43</sup>

The reason fire sales ultimately matter for these real investment outcomes is that they impact the allocation of capital to firms via new bond issues: while secondary market prices are not directly allocative, they set the reference point for what investors are willing to pay for new issues on the primary market. To investigate this channel, I examine the impact of investor composition on the dynamics of new bond issuance. I estimate the following instrumented dynamic specification, which is equivalent to the one in equation (18):

$$Y_{k,t} = \alpha_k + \gamma_t + \sum_{\tau} \beta_{\tau} \Phi_k \mathbb{1}_{\tau=t} + \text{Controls} + \varepsilon_{k,t}, \quad (20)$$

where  $Y_{k,t}$  is one of two outcomes—either an indicator for whether firm  $k$  issued a *new* bond in year  $t$ , or the average offering yield on new bonds offered by firm  $k$  in year  $t$ , conditionally on issuing a new bond. I continue to use the same set of controls as in specification (18), and I estimate these regressions via two-stage least squares. Figure 14a shows the estimated dynamic coefficients when using the new issuance indicators as the outcome. These coefficients capture the dynamic response of the probability that a firm will issue a new bond in each of the crisis years. Figure 14b plots the coefficients when using offering yields as the outcome: these coefficients capture the impact of insurer ownership on firms’ cost of new borrowing in the corporate bond market.

Firms with a higher *ex ante* insurer share have a substantially higher likelihood of issuing new debt following the crisis and face a lower user cost of capital when doing so: increasing the firm-level insurer share by 50 percentage points is associated with an increase in the likelihood of new bond issuances of between 25 and 30 percentage points in 2008 and 2009, and with a reduction in offering yields on new debt of the order of 120 basis points. In accordance with the idea that secondary market dynamics directly impact the pricing of new issues on the primary market, estimating specification (20) with secondary-market rather than primary-

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<sup>43</sup>For related discussions of the role of corporate debt maturity on real firm outcomes in crises, see also Almeida et al. (2011) and Benmelech et al. (2019, 2021). Additionally, He and Xiong (2012) introduce a model where rollover problems impact priced credit risk. Massa et al. (2013) study the relationship between bondholders’ investment horizon and firm capital structure.

market yields results in quantitatively analogous dynamics.<sup>44</sup>

Summing up, these results are consistent with the notion that fire sales impact real outcomes because firms become less able to raise new bond financing at a low cost when their existing debt trades at a large discount. In this view, firms whose debt is owned predominantly by insurers suffer milder declines in the demand for their bonds during sharp market downturns, or equivalently do not face as high an increase in their cost of capital. Firms that are unable to access new financing through the corporate bond market ultimately reduce their investment in response to the reduced availability of capital, particularly if they need to use cash on hand to pay for existing debt that is coming due. These outcomes highlight the value of a safe-handed investor base from an issuer’s perspective.<sup>45</sup>

### 5.3 Relationship Finance in the Corporate Bond Market

As mentioned above, secondary-market bond prices set the reference point for investors’ willingness to pay for new issues on the primary market. I now show that the role of lending relationships further reinforces this link between the secondary and the primary market. Extending the notation of Section 3, I let  $\xi_{i,j,k,t}$  be an indicator for whether investor  $j$  purchased bond  $i$ , issued by firm  $k$ , at the time of its issuance  $t$ . Further, I let  $\mathcal{R}_{i,j,k,t}$  be an indicator for whether investor  $j$  already held in its portfolio other bonds issued by firm  $k$  at the time of issuance of the new bond  $i$ . I estimate the following specification:

$$\xi_{i,j,k,t} = \eta_t + \alpha_k + \gamma \mathcal{R}_{i,j,k,t} + \sum_s \beta_s \mathcal{R}_{i,j,k,t} D_{s,k,t} + \sum_s \rho_s D_{s,k,t} + \varepsilon_{i,j,k,t}, \quad (21)$$

where  $D_{s,k,t}$  is a dummy indicating whether the average secondary-market yield spread to Treasury of firm  $k$  at time  $t$  falls within the decile  $s$  of firm-level yield spreads. This specification quantifies how existing bond market lending relationships (captured by  $\mathcal{R}_{i,j,k,t}$ ) impact the probability that an investor will purchase a firm’s new bond issues (captured by  $\xi_{i,j,k,t}$ ): this effect is expressed by the coefficient  $\gamma$ . Further, the specification investigates how the impact of relationships on purchase likelihoods varies as a firm’s existing bonds trade at a discount: this *incremental* fire sale effect is captured by the sequence of coefficients  $\beta_s$ . The

<sup>44</sup>The secondary-market yield estimates are shown in Appendix Figure A.10.

<sup>45</sup>For related themes in equity markets, see Derrien et al. (2013) and Aghion et al. (2013), who study the impact of the institutional composition of firm equity-holders on real outcomes. Appendix Section H provides a structural interpretation of my real-side results using a  $q$ -theoretic model with costly external financing.

firm fixed effects  $\alpha_k$  absorb firm-specific but time-invariant differences in purchase likelihoods, while the time fixed effects  $\eta_t$  absorb common time trends.

Figure 15 plots the estimated coefficients  $\beta_s$  from specification (21), as well as the baseline relationship effect  $\gamma$ , for the sample including all new investment-grade U.S. bond issuances between 2005 and 2020, and all U.S. insurance firms. The estimated value of  $\gamma$  shows the presence of a strong relationship effect to begin with: insurers are 5.5 percentage points more likely to buy a firm’s new bonds if they have an existing lending relationship in place, which is a large effect when compared to the average value of the purchase indicator  $\xi_{i,j,k,t}$  in the sample, equal to 4.8 percent. Strikingly, this relationship effect strongly increases as the secondary-market yields on a firm’s existing bonds go up: going from the bottom decile to the top decile of yield spreads, the relationship effect increases by nearly 8 percentage points.

These estimates illustrate that investors not only strongly favor buying bonds from the firms they already hold in their portfolios, but also become more and more reluctant to lend via the bond market to new firms as their debt falls in value on the secondary market. This behavior would be compatible, for example, with a model in which institutional investors carry out in-depth research on a new firm before adding its bonds to their portfolio, and in which secondary-market yields are a particularly salient signal of risk in these initial issuer assessments. These facts are also consistent with the results of [Barbosa and Ozdagli \(2021\)](#), who find that, on the intensive margin, life insurance companies purchase larger amounts of new bond issues if they have existing relationships with corporate borrowers, and that during the COVID crisis these relationships insulated bonds from market-wide shocks. While “relationship finance” is commonly seen as a key feature of bank lending ([Diamond 1984](#), [Rajan 1992](#)), parallel mechanisms are hence also at play in the bond market. From a firm’s perspective, these relationship effects compound the value of placing bonds in the safe hands of patient investors such as insurers, who will not contribute to fire sales, and beyond that will continue to provide new credit in bad times.

## 6 Regulatory Implications and Interpreting the Facts

While bond ownership by safe-handed investors such as insurers mitigates the risk of fire sales, there are tradeoffs in terms of reduced liquidity. Insurers engage in less *liquidity provision*

than mutual funds do, in two respects. First, the predominant open-end contractual structure of fund liabilities provides clients with ease of capital redeemability, which may be socially valuable insofar as it accommodates households' liquidity demand shocks. If these liquidity demand shocks are purely idiosyncratic, no financial stability issues arise. Aggregate shocks, however, can lead to the kind of forced selling explored in Section 2.5, which ultimately impacts firms' credit availability and real investment activities. Second, as funds are more willing than insurers to trade in normal times, they enhance the market liquidity of the securities that they hold. In contrast, the bonds held by insurers become endogenously more illiquid. This tradeoff between financial stability and liquidity provision, which I highlight in the context of non-bank financial intermediation, bears a conceptual similarity with the theories of banking of Calomiris and Kahn (1991) and Diamond and Rajan (2001).

Equilibrium price outcomes reveal the endogenous illiquidity of insurer-held bonds. To see this, I consider the following specification, which is analogous to the one in equation (5) but has each bond's yield spread to Treasury  $s_{i,t}$ , measured in basis points, on the left hand side:

$$s_{i,t} = \alpha + \bar{\Lambda} \phi_{i,t-12} + \tilde{\Lambda} \phi_{i,t-12} \text{GZ}_t + \text{Interacted Fixed Effects} + \varepsilon_{i,t}. \quad (22)$$

As in equation (5), the interaction with the Gilchrist and Zakrajšek (2012) index serves to capture variation in the relationship between insurer ownership and yield spreads over the credit cycle in a simple parametric manner, and as before the fixed effects interaction also includes time fixed effects. The red line in Figure 16 plots the estimated total effect  $\Lambda_t = \bar{\Lambda} + \tilde{\Lambda} \text{GZ}_t$  over time in the sample of U.S. investment-grade bonds, while the blue shaded area shows the 95 percent confidence band. These estimates show that outside of crises higher insurance ownership is associated with higher yield spreads, with a total effect of the order of 20 basis points as the insurer share varies from 0 to 1. During crises, the sign of the estimated effect inverts as bonds with higher insurer ownership experience lower value losses.

A literature in finance has documented the presence of a corporate bond liquidity premium, leading less liquid corporate bonds to have higher equilibrium yield spreads (Chen et al. 2007, Bao et al. 2011). Higher yield spreads on insurer-held bonds reflect these bonds' endogenous liquidity properties. This liquidity channel may interact with a potential additional channel owing to the endogenous differences in intertemporal risk generated by investor base heterogeneity. The return properties I have documented give bonds with a higher insurer

share desirable state-contingent properties, in that they do better in bad states of the world: if these properties are priced, this channel would tend to counteract the liquidity mechanism, increasing the prices of bonds with a high insurer share (and therefore lowering their yield spreads). The price outcomes documented in Figure 16 plausibly reflect the equilibrium interaction of these two pricing channels, although I do not quantitatively disentangle them as that would require imposing a specific asset pricing model.

From a macro-prudential regulator’s perspective, it may be ideal for financial intermediaries to engage in liquidity provision in a state-dependent manner, by providing liquidity (like funds do) in normal times, while at the same not contributing to large-scale fire sales during crises.<sup>46</sup> Since the financial intermediation structures that are prevalent in the market land at opposite poles of this dichotomy, simply incentivizing one type of intermediation contract over another may not necessarily be an optimal solution. Optimal policy in this setting may include instruments such as incentives towards *gating* provisions—that is, contractual provisions that limit the redeemability of capital in a state-dependent way. Of course, a rigorous analysis of optimal policy would require a fully-fledged structural approach able to capture general equilibrium effects in a model featuring intermediaries with heterogeneous fire-sale propensities. It would be interesting for future literature to theoretically and quantitatively explore this dimension of macro-prudential regulation, also in its interaction with policies aimed at addressing externalities in leverage choice. This paper provides causal evidence identifying some of the key deep parameters and elasticities of interest in that analysis.

The endogenous illiquidity of bonds held by insurers similarly points to how a positive equilibrium asset pricing model might generate the empirical patterns that I have documented in this paper. Such a model might feature, for example, an OTC market structure (Duffie et al. 2005) in which dealers have *limited market-making capacity*, in that they require compensation for intermediating sales volumes in excess of those encountered during normal trading days. If funds are disproportionately likely to increase their bond sale volumes on stress days, bonds held predominantly by this sector will suffer particularly severe losses in crises—with the price declines serving as compensation for dealers to enter into these trades.<sup>47</sup> In order for relative

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<sup>46</sup>Private outcomes in this setting may diverge from the socially optimal ones, giving a role to policy, because of an externality leading to excessive liquidity provision. Dávila and Korinek (2018) discuss the welfare relevance of pecuniary externalities arising from fire sales, which reflects the generic inefficiency of competitive equilibrium in incomplete markets (Geanakoplos and Polemarchakis 1986, Greenwald and Stiglitz 1986). See also Lorenzoni (2008), Stein (2012), and Farhi and Werning (2016) for related normative approaches.

<sup>47</sup>The specific details of the market’s structure are not central here. Rather, the key point is the presence

mispricings to persist over time, of course, the model would also have to feature some degree of market segmentation and slow-moving arbitrage capital (Duffie 2010). On the real side, the model would have to include financial frictions à la Kiyotaki and Moore (1997) to link these credit market disruptions to macroeconomic dynamics. The key empirical prediction of the overall framework is that higher fund ownership should forecast a larger increase in secondary-market bond turnover during downturns. As I show in Appendix Section J, this prediction is strongly supported by the data. I conjecture that this kind of environment would generate many of the facts presented here, although I leave it to future work to formalize and quantitatively calibrate this logic.

## 7 Conclusion

In this paper I provide quantitative causal evidence demonstrating that investor base composition is an important determinant of bond price dynamics and firm financing outcomes in response to aggregate credit cycle fluctuations. I establish causal identification by comparing nearly identical bonds issued by the same firms and via a complementary shift-share instrumental variable approach. In both the United States and in international markets, ownership by *safe-handed* institutional investors such as insurers shields securities from large value losses in crises, to a large extent thanks to the lower exposures of these financial intermediaries' liabilities to sizable household-driven capital withdrawals. Firms whose debt is owned by investors less prone to fire sales experience milder disruptions in their primary-market bond financing and real investment during crises: they issue more new bonds and pay a lower cost of capital when doing so, which ultimately allows them to invest relatively more. My estimates are of interest to the broader debate on which forms of financial intermediation should be incentivized: they point towards a tradeoff between liquidity provision in normal times and financial stability in crises, which arises from the contractual structures of financial intermediaries' liabilities. These facts clearly demonstrate how the distribution of ownership of financial assets across heterogeneous institutional investors affects the magnitudes of fire sales and real firm outcomes over the credit cycle.

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of limited capital willing to take the other side of these large trades without sizable price concessions.

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	<i>N</i>	Total Invested Assets (\$M)				Concentration Ratios			
		Mean	Median	95 <sup>th</sup> Percentile	SD	CR <sub>10</sub>	CR <sub>50</sub>	CR <sub>100</sub>	
<b>A. US Insurers</b>									
2005	1,208	2,804	110	10,914	12,616	0.34	0.73	0.85	
2010	1,242	3,048	118	12,397	13,994	0.34	0.72	0.86	
2015	1,225	3,510	138	14,770	15,399	0.34	0.71	0.85	
2020	1,216	4,396	163	19,813	19,821	0.35	0.70	0.85	
<b>B. US Funds (All)</b>									
2005	5,597	1,080	219	3,816	4,948	0.14	0.32	0.42	
2010	6,675	1,570	267	6,000	6,587	0.11	0.29	0.39	
2015	8,193	1,948	291	7,167	8,546	0.11	0.27	0.37	
2020	8,418	3,715	404	12,768	23,616	0.16	0.34	0.44	
<b>C. Non-US Funds (All)</b>									
2005	11,135	681	97	1,989	5,303	0.18	0.38	0.46	
2010	20,135	580	81	1,676	9,360	0.22	0.33	0.39	
2015	22,069	878	118	2,449	8,563	0.18	0.33	0.40	
2020	25,152	1,136	151	3,441	10,209	0.13	0.25	0.33	
<b>D. US Funds (Specialists)</b>									
2005	1,565	794	196	2,839	4,968	0.28	0.46	0.58	
2010	1,529	1,503	307	6,160	7,243	0.26	0.48	0.61	
2015	1,957	1,667	324	6,236	6,206	0.21	0.44	0.56	
2020	2,097	2,881	464	11,197	11,666	0.21	0.45	0.58	
<b>E. Non-US Funds (Specialists)</b>									
2005	2,506	574	150	2,454	1,527	0.12	0.29	0.42	
2010	4,150	522	119	2,135	1,624	0.11	0.27	0.38	
2015	5,090	687	149	2,744	2,481	0.12	0.26	0.36	
2020	6,087	980	208	3,716	3,884	0.12	0.27	0.36	

Table 1: **Holdings data: sample summary statistics.** This table shows the total number of insurers as well as mutual funds and exchange traded funds (ETFs) in the sample. I report statistics separately for all funds and for fixed income specialist funds (as determined via Morningstar’s categorization). I also show statistics on total invested assets (equities and bonds), as well as concentration ratios detailing the share of total invested assets held by largest 10, 50, and 100 institutions in each group. Insurers and funds with less than \$25 million in total invested assets are excluded. Data shown for the years 2005, 2010, 2015, and 2020.

	Average Duration (Years)	Average Issue Size (\$M)	Share of Holdings in Category (%)			
			High Yield	Junior	Floating	Callable
<b>A. US Insurers</b>						
2005	6.2	563	8	8	3	57
2010	6.4	678	6	5	2	70
2015	7.0	726	5	4	1	78
2020	8.1	785	4	4	4	77
<b>B. US Funds*</b>						
2005	4.9	556	55	4	9	66
2010	5.1	733	40	5	7	61
2015	5.5	761	37	6	7	71
2020	5.9	814	27	6	13	77
<b>C. Non-US Funds*</b>						
2005	5.7	615	18	9	19	24
2010	4.7	688	28	7	17	28
2015	5.3	772	36	10	15	32
2020	5.4	808	30	11	21	45

\*Fixed income specialists only

Table 2: **Overview of corporate bond holdings of insurers and fixed income specialist funds.** This table reports summary statistics on the characteristics of the corporate bond holdings of insurance companies and fixed income specialist funds. These include average bond duration, the share of holdings that is in high-yield bonds, the share of holdings that is in junior bonds, the share of holdings that is in floating-rate bonds, the share of holdings that is in bonds with callable features, and the average issue size for bonds held.



	Log Bond Drawdown				
	(1)	(2)	(3)	(4)	(5)
Insurer Share	-.41 (.06)	-.60 (.05)	-.47 (.05)	-.41 (.10)	-.42 (.10)
<i>Fixed Effects Interaction:</i>					
Event Dummy	Yes	Yes	Yes	Yes	Yes
Bond Size	—	Yes	Yes	Yes	Yes
Bond Duration	—	Yes	Yes	Yes	Yes
Bond Rating	—	—	Yes	Yes	Yes
Issuer Dummy	—	—	—	Yes	Yes
Callable Dummy	—	—	—	—	Yes
Senior Dummy	—	—	—	—	Yes
Coupon Type	—	—	—	—	Yes
Identifying Observations	15,012	14,996	14,649	5,328	4,945
Identifying Issuers	1,430	1,430	1,412	452	437
$R^2$	.27	.60	.68	.84	.85

Table 3: **Investor base effects for U.S. corporate bonds: baseline OLS estimates.** This table reports the estimates of the regression specification in equation (4) in the sample of actively traded investment-grade U.S. corporate bonds. The specification in column 1 includes event fixed effects. Column 2 includes interacted event by bond size decile by duration category fixed effects. Columns 3 and 4 add additional interactions with rating and issuer dummies. Column 5 includes the fully-saturated set of interacted fixed effects, which include all of the above variables plus dummies for bond seniority, bond callability, and coupon type. The estimates are from weighted least squares (WLS) regressions, with bond sizes as weights. Standard errors are clustered at the issuer by event level and are reported in parentheses.

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Insurer Share	-.41 (.10)	-.42 (.10)	-.54 (.15)	-.45 (.15)
<i>Fixed Effects Interaction:</i>				
Bond Size	Yes	Yes	Yes	Yes
Event Dummy	Yes	Yes	Yes	Yes
Bond Duration	Yes	Yes	Yes	Yes
Bond Rating	Yes	Yes	Yes	Yes
Issuer Dummy	Yes	Yes	Yes	Yes
Callable Dummy	—	Yes	—	Yes
Senior Dummy	—	Yes	—	Yes
Coupon Type	—	Yes	—	Yes
Identifying Observations	5,328	4,945	5,328	4,945
Identifying Issuers	452	437	452	437
$R^2$	.84	.85	.84	.85
First Stage $F$	—	—	71.6	72.9

Table 4: **Shift-share IV estimates.** This table reports the estimates of the shift-share instrumental variable (IV) regression specification in equation (4) in the sample of actively traded investment-grade U.S. corporate bonds, alongside the baseline OLS estimates (for comparison). The OLS estimates are shown in columns 1 and 2, while the two-stage least squares (2SLS) IV estimates are shown in columns 3 and 4. The various columns correspond to differing sets of bond characteristics included in the interacted fixed effects. The estimates are from weighted least squares (WLS) regressions, with bond sizes as weights. Standard errors are clustered at the issuer by event level and are reported in parentheses.

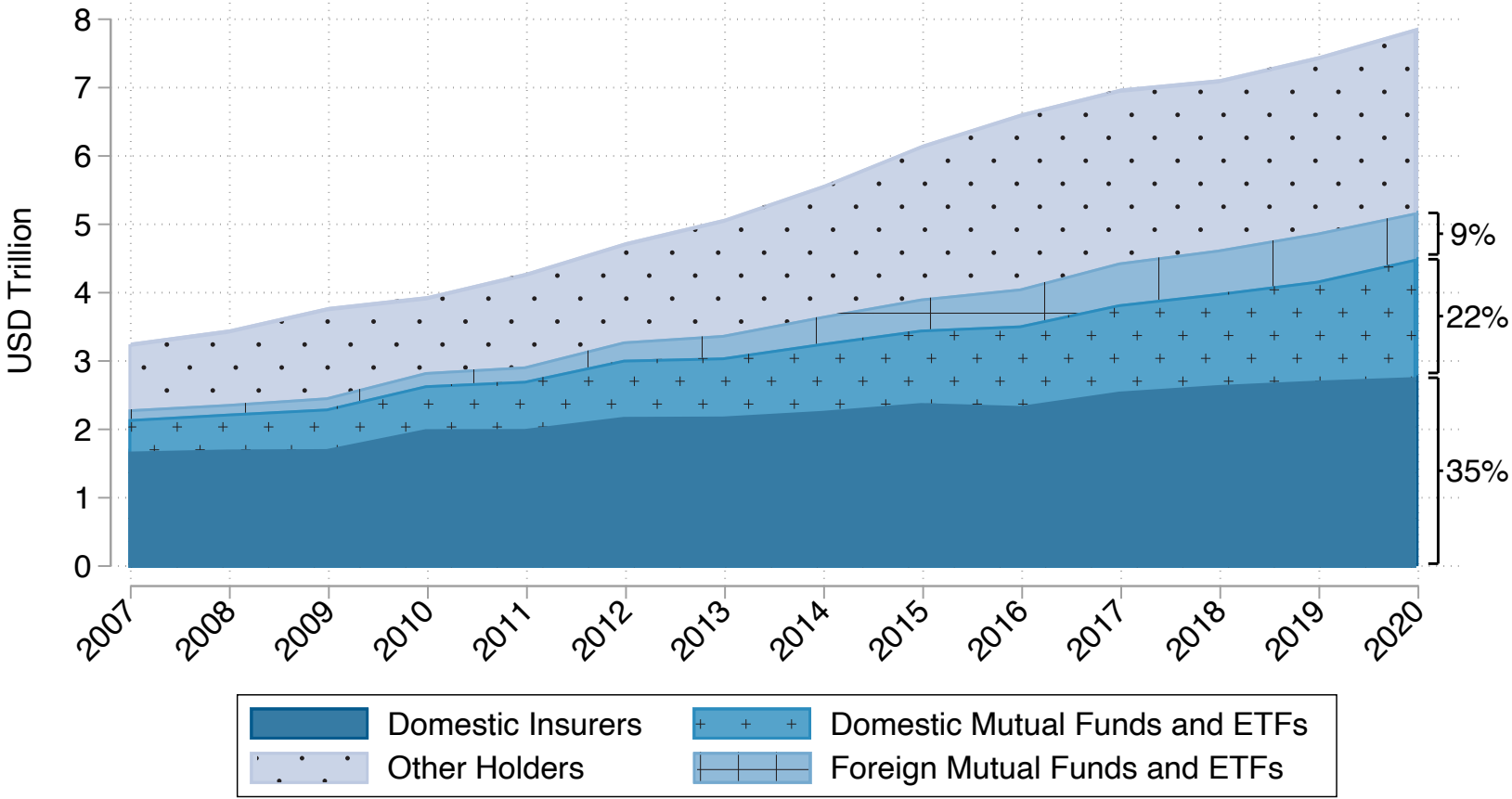
	Log Bond Drawdown				
	(1)	(2)	(3)	(4)	(5)
Proxy Safe Share	-.39 (.14)	-.51 (.12)	-.40 (.15)	-.64 (.21)	-.35 (.20)
Sample	USA	Pooled Non-US	EMU	GBR	CAN
<i>Fixed Effects Interaction:</i>					
Event Dummy	Yes	Yes	Yes	Yes	Yes
Bond Size	Yes	Yes	Yes	Yes	Yes
Bond Duration	Yes	Yes	Yes	Yes	Yes
Bond Rating	Yes	Yes	Yes	Yes	Yes
Issuer Dummy	Yes	Yes	Yes	Yes	Yes
Callable Dummy	Yes	Yes	Yes	Yes	Yes
Senior Dummy	Yes	Yes	Yes	Yes	Yes
Coupon Type	Yes	Yes	Yes	Yes	Yes
Currency FE	—	Yes	Yes	Yes	Yes
Identifying Observations	4,945	6,890	4,090	1,484	1,316
Identifying Issuers	437	582	393	102	87
$R^2$	.85	.87	.84	.89	.88

Table 5: **Investor base effects for non-U.S. corporate bonds and proxy approach for U.S. corporate bonds.** Column 1 reports the estimates of the regression specification in equation (4), estimated by proxying safe-hand holdings via the complement of fund positions, in the sample of actively traded investment-grade U.S. corporate bonds. Columns 2 through 5 report the estimates of the regression specification in equation (15). The sample in column 2 pools all investment-grade corporate bonds issued by firms in the European Monetary Union (EMU), United Kingdom, and Canada that are not TRACE-reportable. Columns 3 through 5 show the results separately for each of these three economies. All specifications include fully-saturated interacted fixed effects. The estimates are from weighted least squares (WLS) regressions, with bond sizes as weights. Standard errors are clustered at the issuer by event level and are reported in parentheses.

	Investment Rate (%)					
	CAPX			CAPX and Acquisitions		
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}$	2.80** (1.11)	2.14** (.68)	1.80** (.69)	5.42** (1.73)	3.94** (1.04)	2.93** (1.08)
$\hat{\eta}$	— —	— —	1.95** (.88)	— —	— —	3.27** (1.31)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,994	7,994	7,994	7,994	7,994	7,994
Firms	1,028	1,028	1,028	1,028	1,028	1,028
$R^2$	.80	.80	.80	.57	.57	.57
Estimator	IV	OLS	OLS	IV	OLS	OLS
First Stage $F$	65.3	—	—	74.2	—	—

Table 6: **Insurer ownership and investment dynamics in the Great Recession.** This table reports estimates from the static difference-in-differences specification of equation (19). The dependent variables in these regressions are firm-level annual investment rates for U.S. firms. The coefficient  $\hat{\beta}$  captures the effect of the interaction between the insurer share and the post-period dummy. The coefficient  $\hat{\eta}$  captures the effect of the interaction of the insurer share, the post-period dummy, and the share of the firm’s outstanding bonds that is due in 2008 or 2009. All regressions include two-way fixed effects for firm and year, as well as controls for firm-level covariates, measured in the pre-period and interacted with the post-period dummy: these are fixed effects for issuer rating, average duration of the firm’s outstanding bonds, two-digit industry, and deciles of firm size and firm leverage. Columns 1 and 4 show estimates from two-stage least-squares, using the firm-level instrument in equation (17), interacted with the post-period dummy. The remaining columns use ordinary least squares. Standard errors are clustered at the firm level and reported in parentheses.

### US Investment-Grade Corporate Bonds



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Figure 1: **Aggregate value of U.S. investment-grade corporate bonds and market coverage via security-level holdings micro-data.** The total shaded region shows the aggregate outstanding value of U.S. investment-grade corporate bonds in the sample, defined as bonds that are reportable in TRACE. The *dark blue area* shows the aggregate value of the positions in these bonds held by U.S. insurers, as reported in the NAIC data. The remaining shaded areas show the value of the positions in these bonds held by investment funds (mutual funds and ETFs) in the Morningstar data, split according to whether the funds are U.S. domiciled or not.

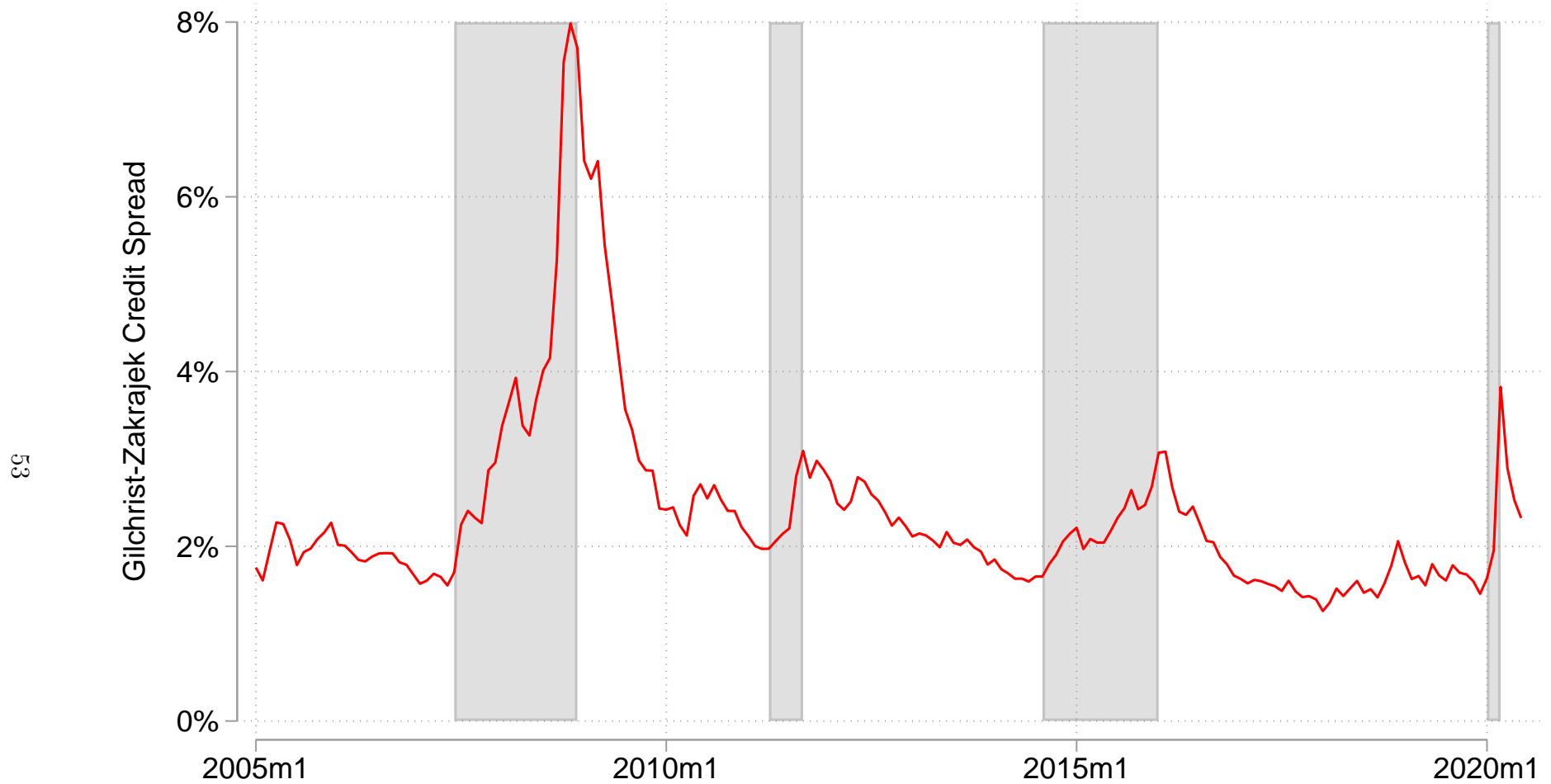


Figure 2: **Events of focus.** The *solid red line* plots the [Gilchrist and Zakrajšek \(2012\)](#) index, which provides an aggregate measure of credit spreads on U.S. corporate bonds. The *shaded gray areas* show the event windows used to estimate bond drawdowns in my analysis. The start and end dates for each event are defined mechanically so that they correspond to the prior trough and subsequent peak values in the GZ index. Section [2.2](#) discusses the drivers of aggregate credit spread variation in these episodes.

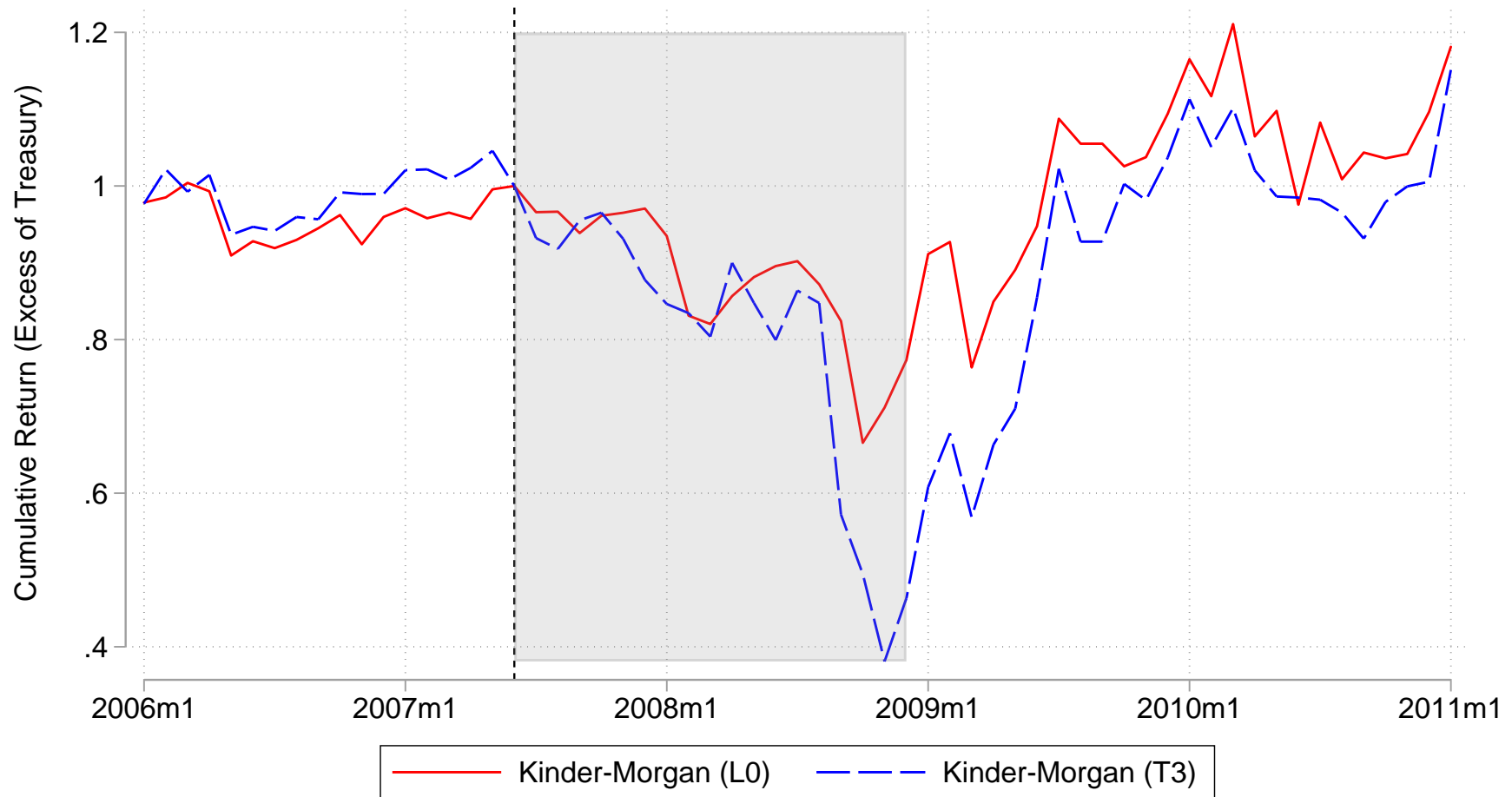


Figure 3: **An example of the identifying variation.** This figure provides an example of the identifying variation. The *dashed blue line* plots the cumulative returns in excess of Treasury,  $CR_{i,t}^H$ , on Kinder-Morgan’s bond with CUSIP code 494550AT3, normalized to one at the beginning of the Great Recession event window (*gray shaded area*). The *solid red line* plots the cumulative returns in excess of Treasury on a second bond issued by Kinder-Morgan, with CUSIP code 494550AL0, with matching characteristics and also normalized to one on the same date. In the quarter prior to the event, the insurer shares in these two bonds were respectively 17 percent (bond “T3”) and 58 percent (bond “L0”).

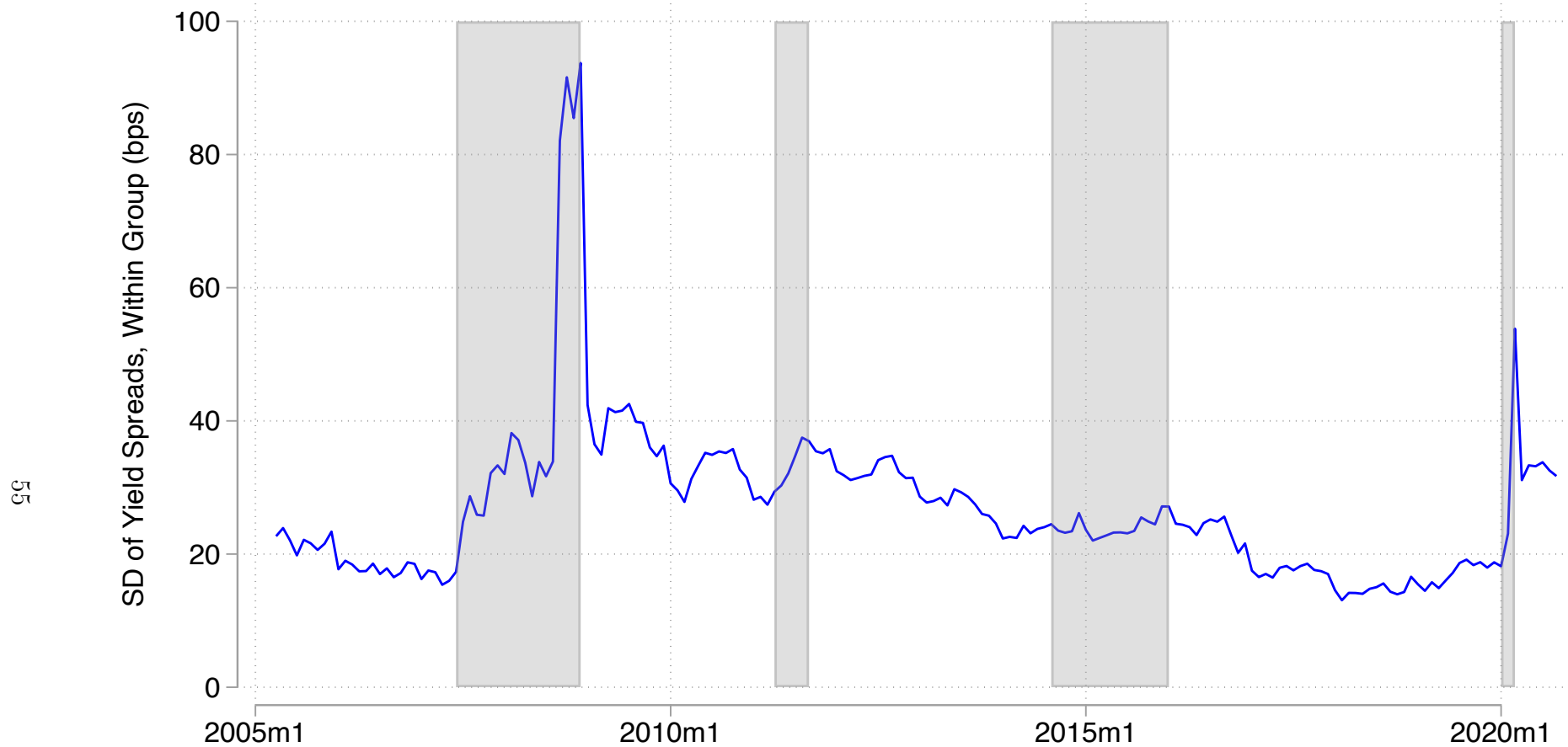


Figure 4: **Variation of yield spreads to Treasury within fixed effect categories, U.S. investment-grade corporate bonds.** This figure shows the standard deviation of yield spreads to Treasury among corporate bonds that match along all dimensions included in the fully-saturated baseline interacted fixed effects specifications: that is, standard deviations are computed within groups of bonds from the same issuers and with the same characteristics. The series is computed at a monthly frequency. The *shaded gray areas* show the event windows used to estimate drawdowns in the baseline analysis.



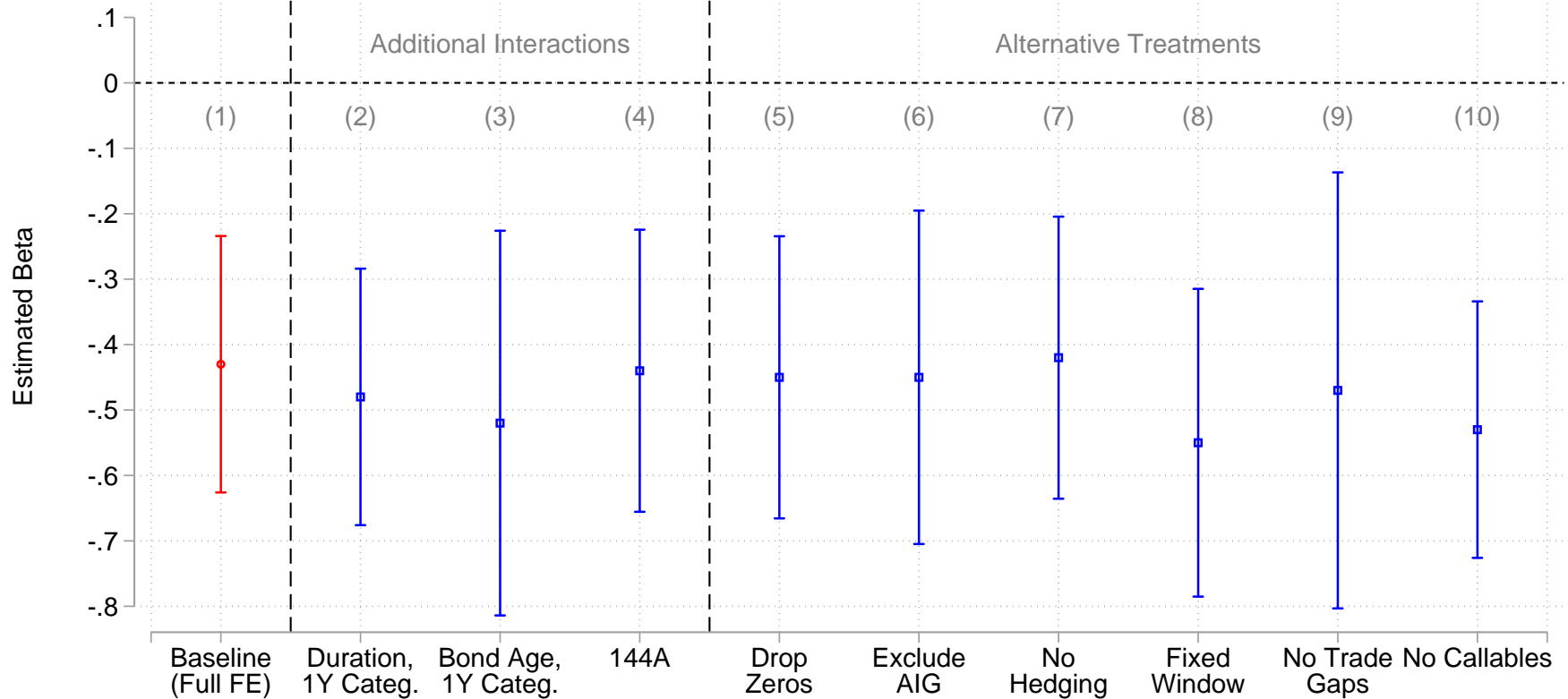


Figure 5: **Investor base effects for U.S. corporate bonds: robustness.** This figure demonstrates the robustness of the baseline estimate (*red bar*) from column 5 of Table 3 to further variations in the empirical specification. Bars 2 through 4 introduce further interactions to the fully-saturated set of fixed effects. Bar 2 introduces an additional interaction with stricter duration categories, with duration rounded to the nearest year. Bar 3 adds an interaction with bond age, rounded to the nearest year. Bar 4 includes an additional interaction with a dummy indicating whether a bond is issued under SEC rule 144A. Additionally, bars 5 through 10 consider alternative sample treatments. Bar 5 excludes bonds with a zero insurer share from the sample. Bar 6 excludes the positions of AIG from the computation of the insurer positions  $X_{i,t}^I$ . Bar 7 uses raw returns  $R_{i,t}$  in place of the hedged returns  $R_{i,t}^H$ . Bar 8 uses an alternative measure of drawdowns which applies the same window to all bonds for a given event. Bar 9 drops any bonds that trade less frequently than once a week in a given event period. Bar 10 excludes callable bonds. The displayed confidence intervals are at the 95 percent confidence level and are clustered at the issuer by event level.

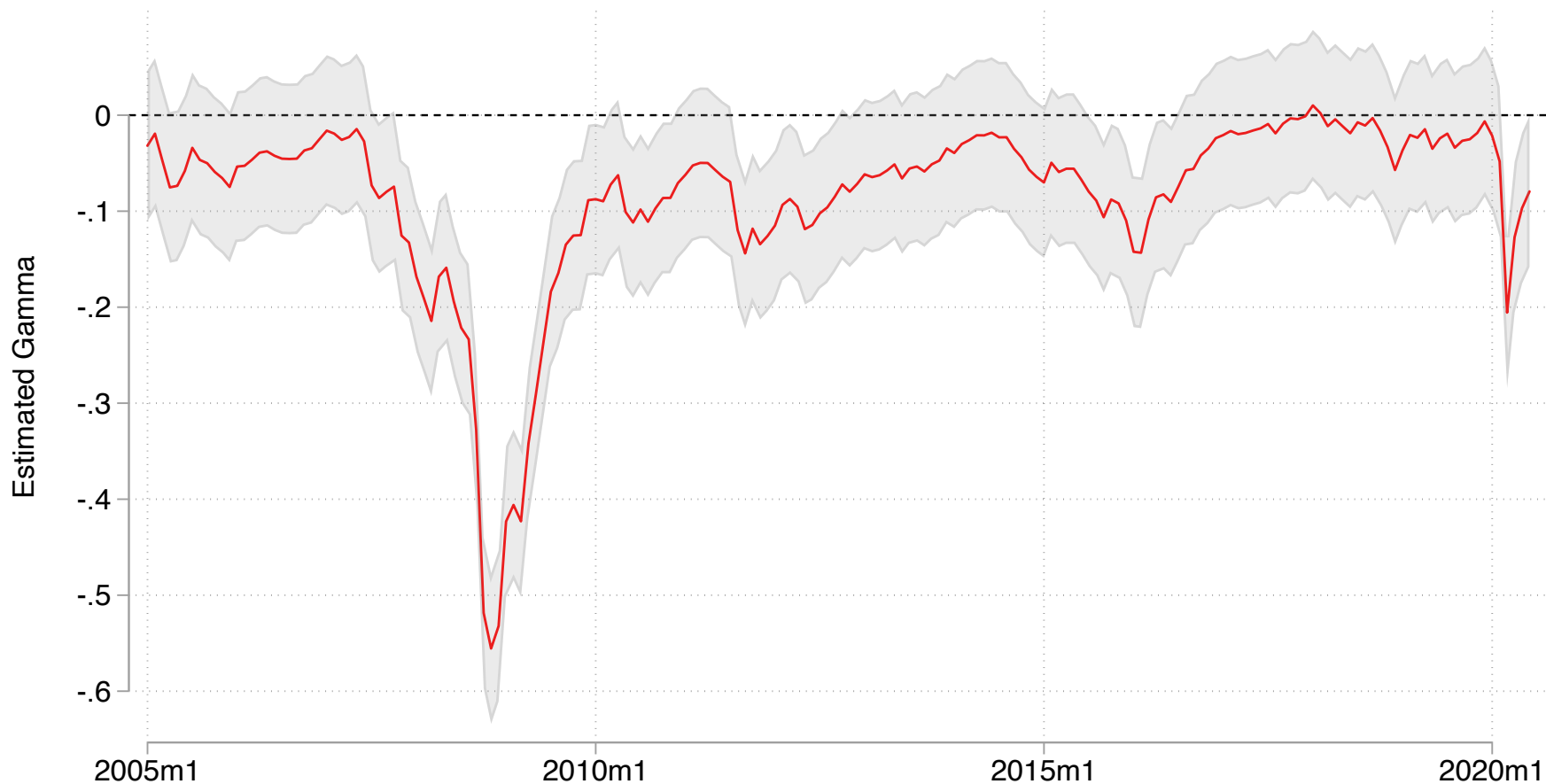


Figure 6: **Insurer ownership and bond betas over the credit cycle.** This figure shows the estimates from the regression specification in equation (5). The *red line* plots the total estimated effect  $\Gamma_t = \bar{\Gamma} + \tilde{\Gamma} GZ_t$  of security-level insurer shares on bond betas against time. The *blue shaded area* corresponds to a 95 percent confidence band estimated using [Newey and West \(1987\)](#) HAC standard errors, with lag selection as in [Newey and West \(1994\)](#).

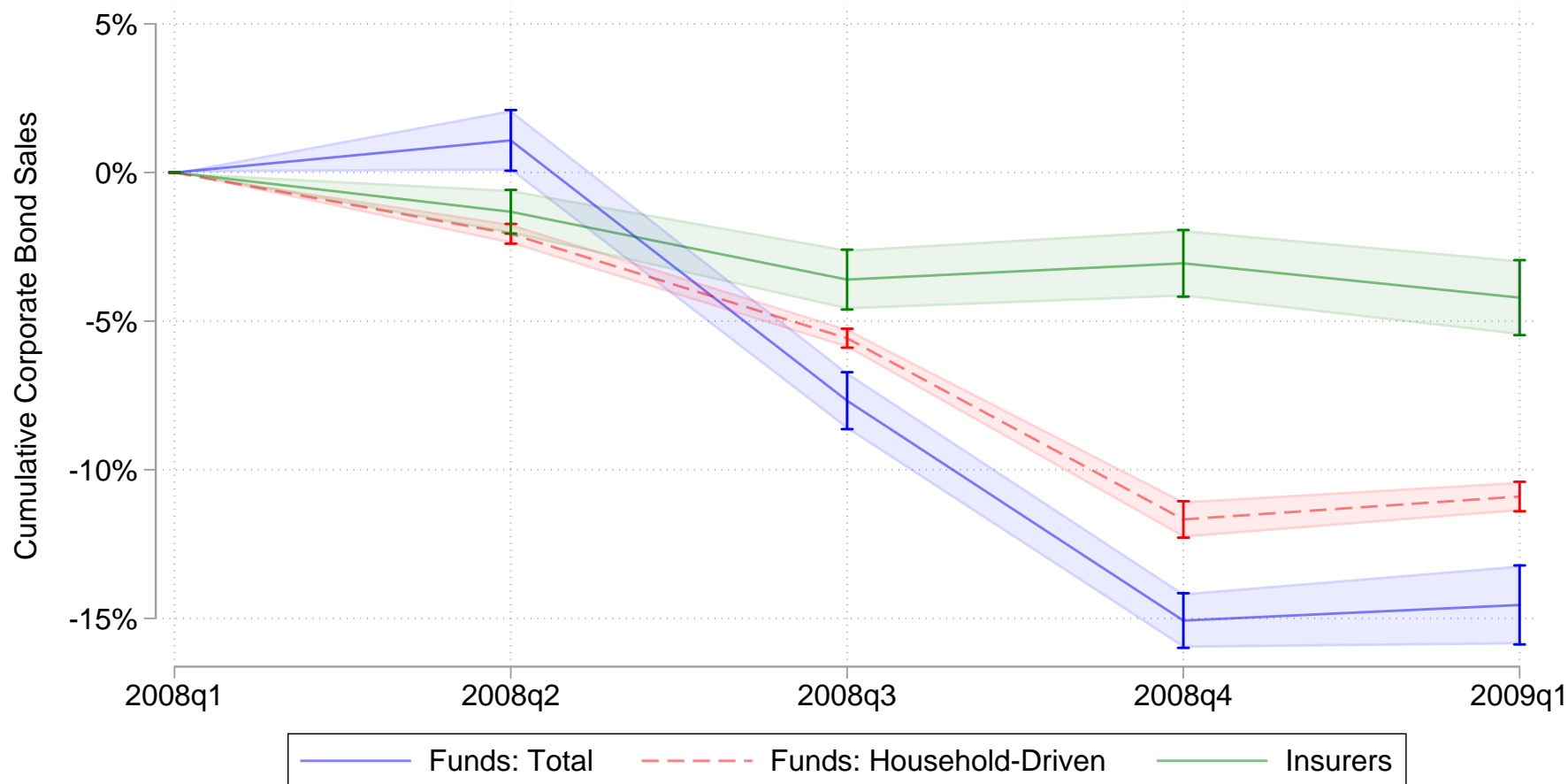


Figure 7: **Corporate bond sales dynamics in the Great Recession.** The *solid green line* plots the cumulative change in corporate bond holdings for the asset-weighted average insurer in the sample over the course of the Great Recession, relative to their level in 2008Q1. The changes in corporate bond holdings are measured using par values, so that they reflect pure quantity changes rather than any valuation effects owing to variation in market prices. The *solid blue line* shows the equivalent portfolio dynamics for the asset-weighted average mutual fund or ETF in the sample. The *dashed red line* plots the component of the cumulative net corporate bond sales by funds that is household-driven, as defined in Section 2.5. The vertical bars show 95 percent confidence intervals around these estimates.

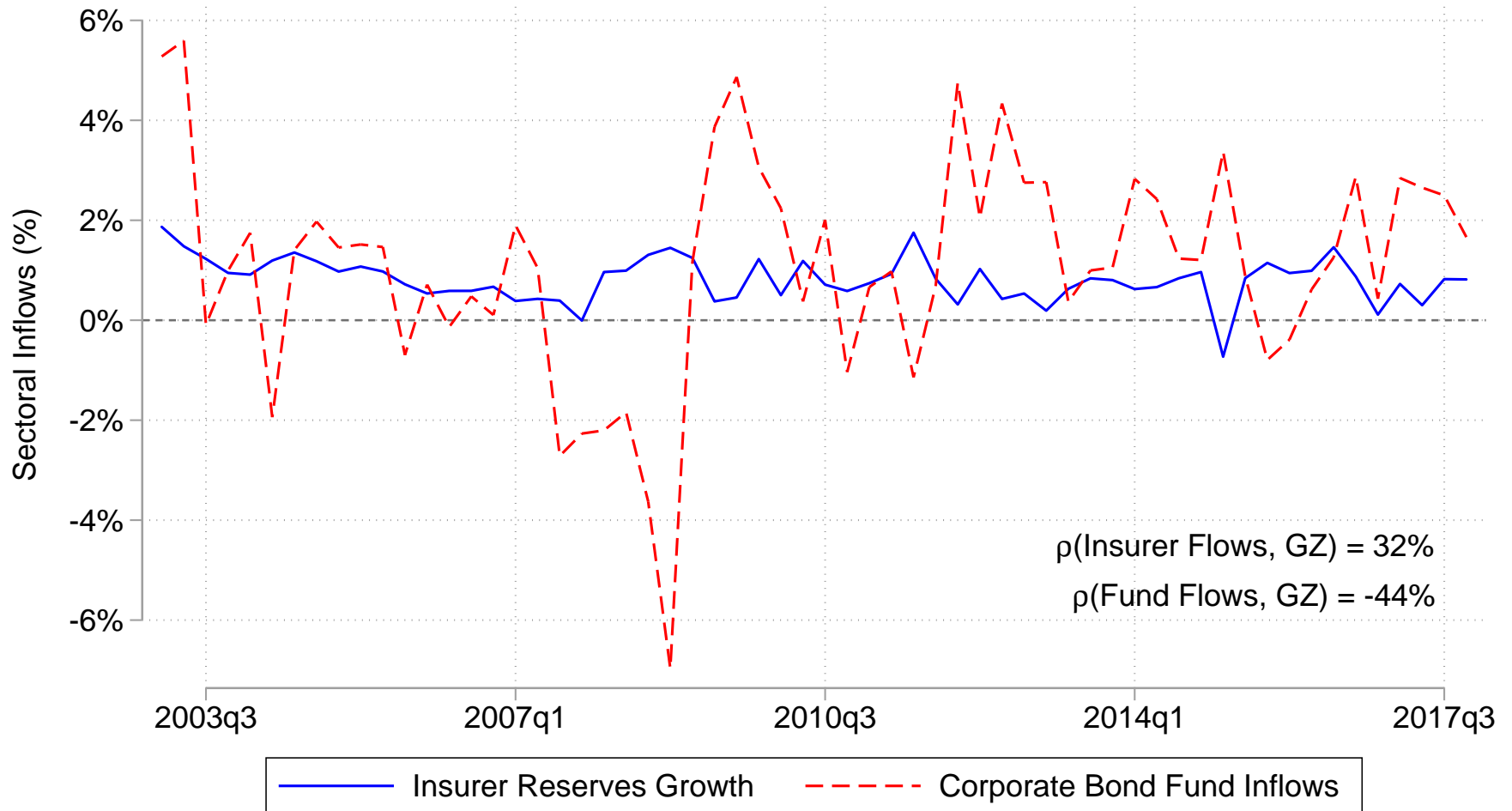
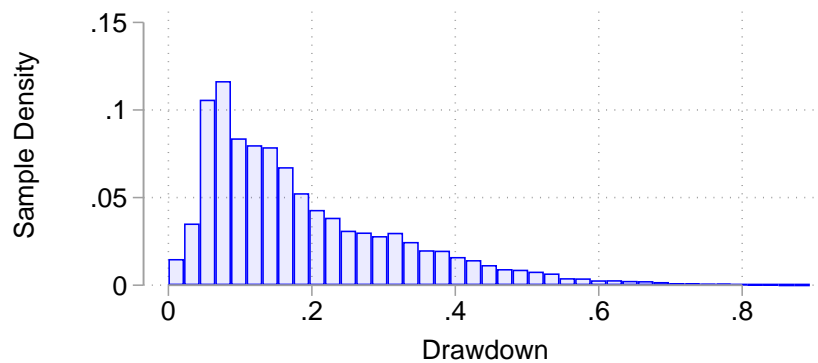
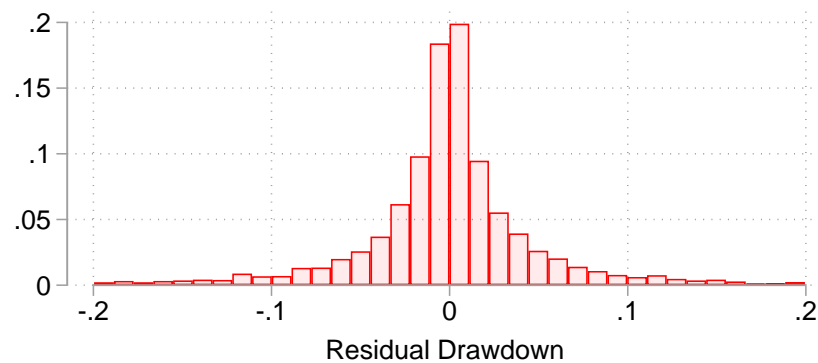


Figure 8: **Flows in and out of insurers and fixed income funds.** The *solid blue line* shows the quarterly net change in policy reserves for the aggregate insurance sector, scaled by lagged total policy reserves. The *dashed red line* shows the quarterly value of aggregate net client inflows and outflows for fixed income mutual funds and ETFs in the sample, scaled by lagged total assets under management. The *black annotations* report the correlation of these series with the quarterly GZ spread index.

(A) Unconditional Distribution



(B) Residualized vs. Fixed Effects



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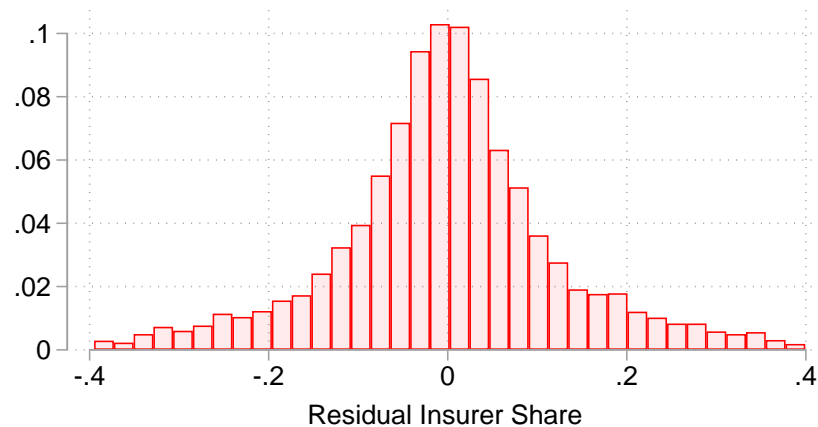
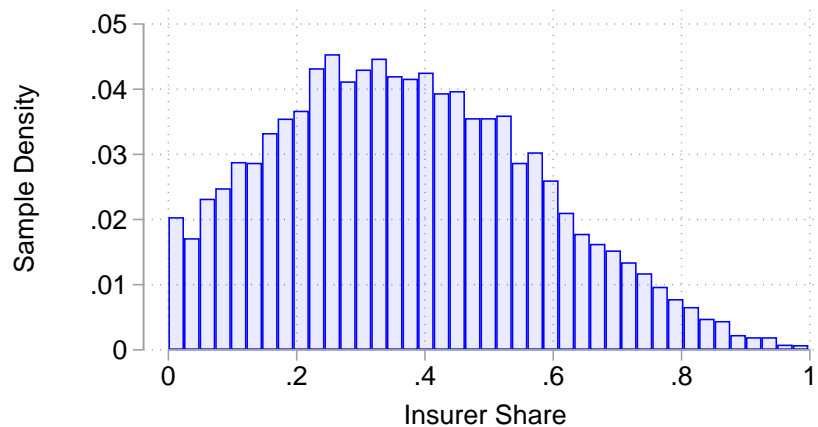


Figure 9: **Residual variation within the fixed effects.** The *blue histograms* in Panel A plot the sample distribution of drawdowns and insurer shares in the sample of actively traded U.S. investment-grade corporate bonds that underlies the regression estimates in Table 3. The *red histograms* in Panel B plot the sample distribution of the same quantities after residualizing them against the fully-saturated set of interacted fixed effects.

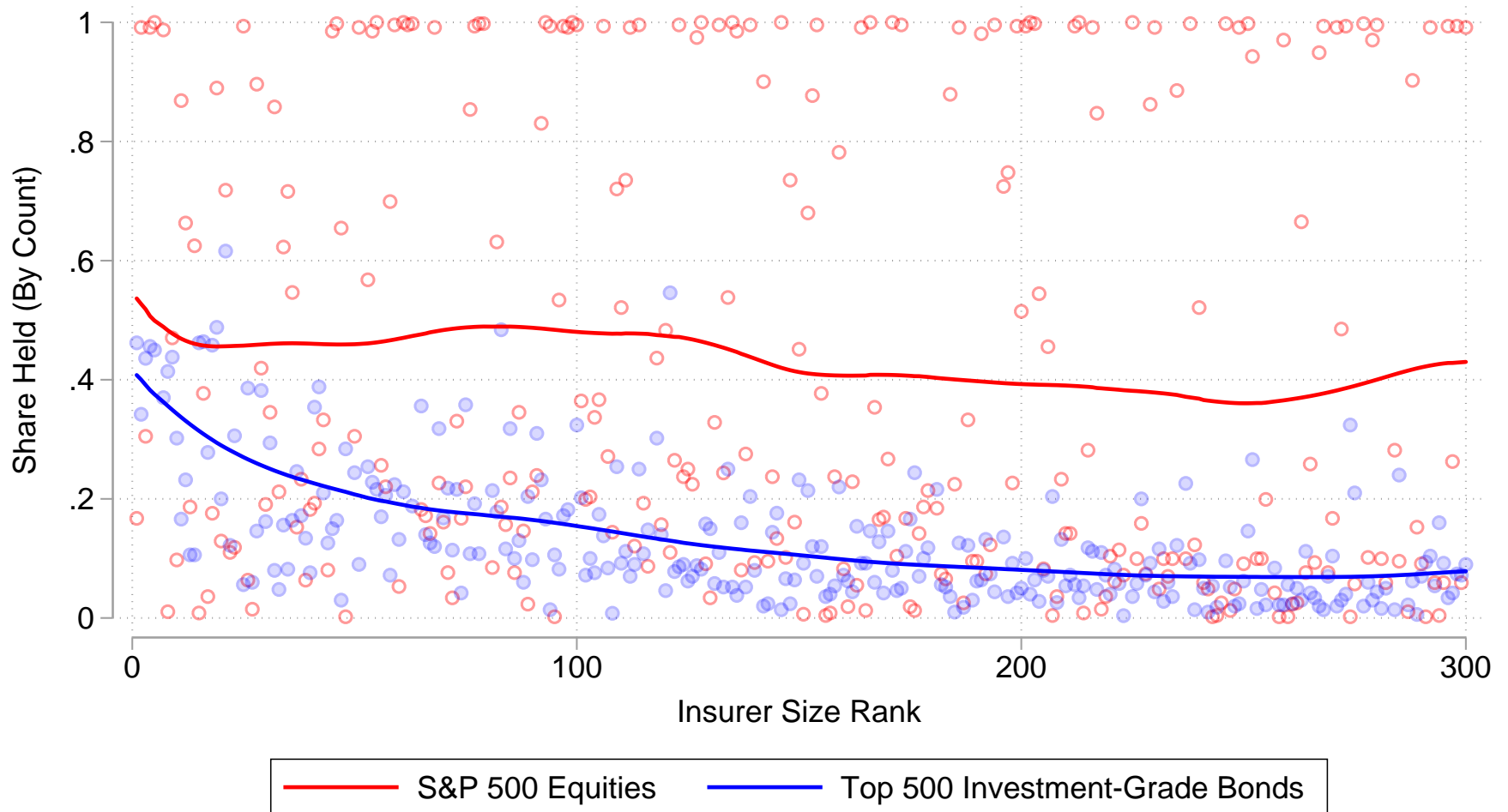


Figure 10: **Idiosyncrasy in insurers' corporate bond holdings at the security level.** This figure ranks insurers by the overall size of their portfolio investment, and shows the share of the 500 largest actively traded investment-grade U.S. corporate bonds that they hold an open position in (*blue dots*) as well as the share of S&P 500 equities that they hold an open position in (*red dots*), all measured cross-sectionally as of 2017Q4. Indirect equity positions held through mutual funds and ETFs are included. The thick lines display the fit from lowest regressions of the investment shares (shown by the dots) on the insurer rank.

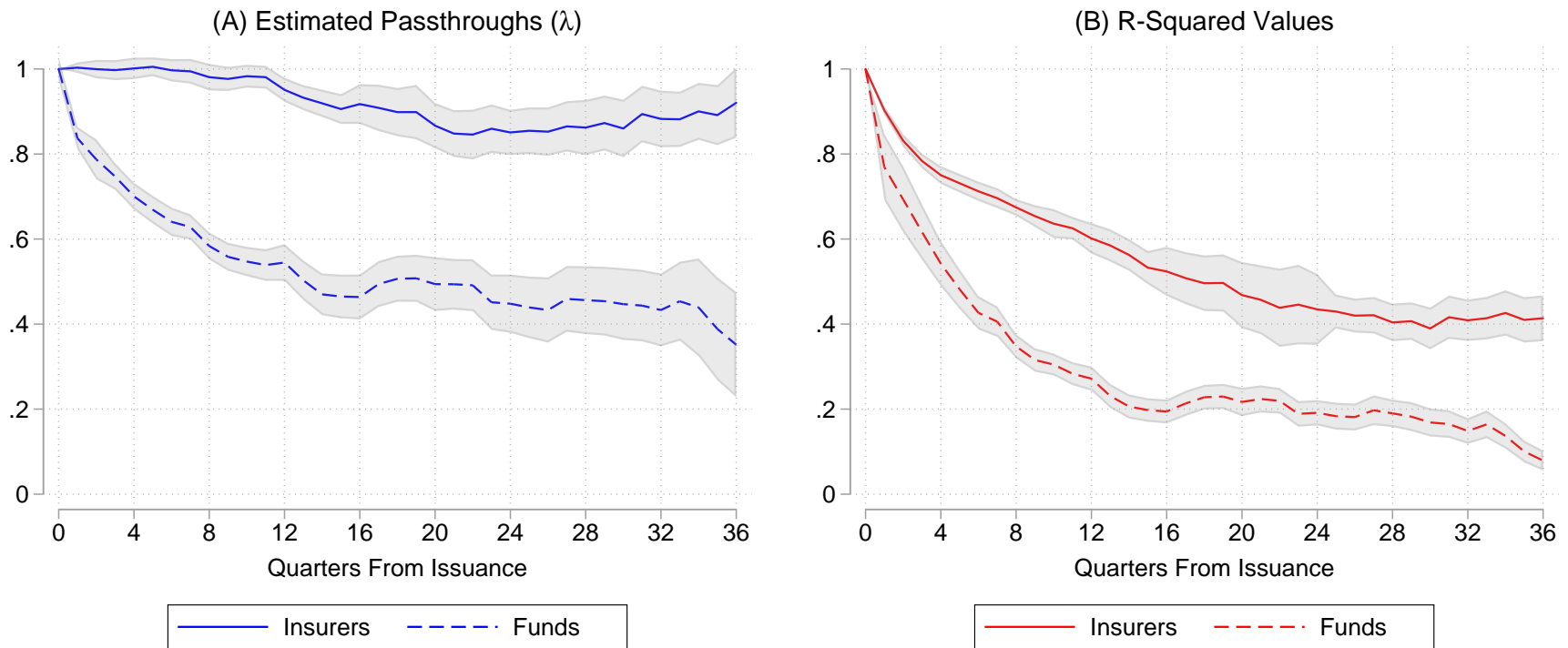


Figure 11: **Persistence of holdings decisions made at bond issuance.** This figure shows estimates from the regression specification in equation (8). The *solid blue line* in Panel A plots the estimated passthrough coefficients  $\lambda_s$  for insurer holdings against the quarterly horizon  $s$ . For comparison, the *dashed blue line* plots the same regression coefficients using mutual fund and ETF ownership shares in place of the insurer shares in equation (8). The *solid red line* and *dashed red line* in Panel B plot the corresponding R-squared values from these regressions. The *gray shaded areas* show 95 percent confidence bands, which use heteroskedasticity-robust standard errors in Panel A and are bootstrapped in Panel B.

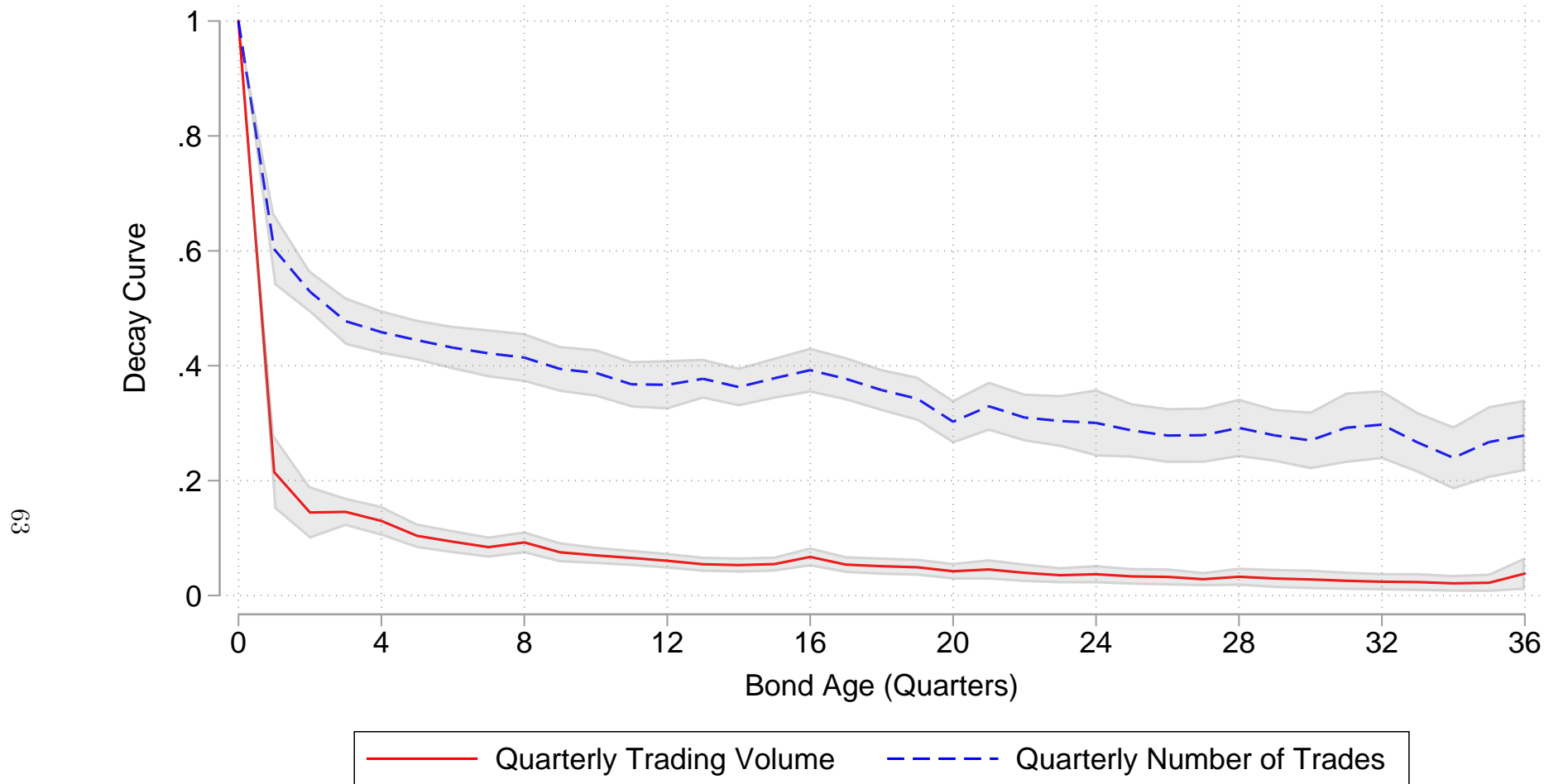


Figure 12: **Corporate bond liquidity in the primary market vs. the secondary market.** This figure shows the estimated coefficients from equation (9), at varying quarterly horizon. For each horizon, the specification regresses quarterly trading volume (*red solid line*) and quarterly number of trades (*dashed blue line*) for each U.S. investment-grade corporate bond against the same measures in the quarter of bond issuance. The estimated coefficients display a rapid decay toward zero as a consequence of the sharply reduced liquidity of the secondary corporate bond market as compared to the primary market. Standard errors are heteroskedasticity-robust. The *gray shared areas* correspond to 95 percent confidence bands.



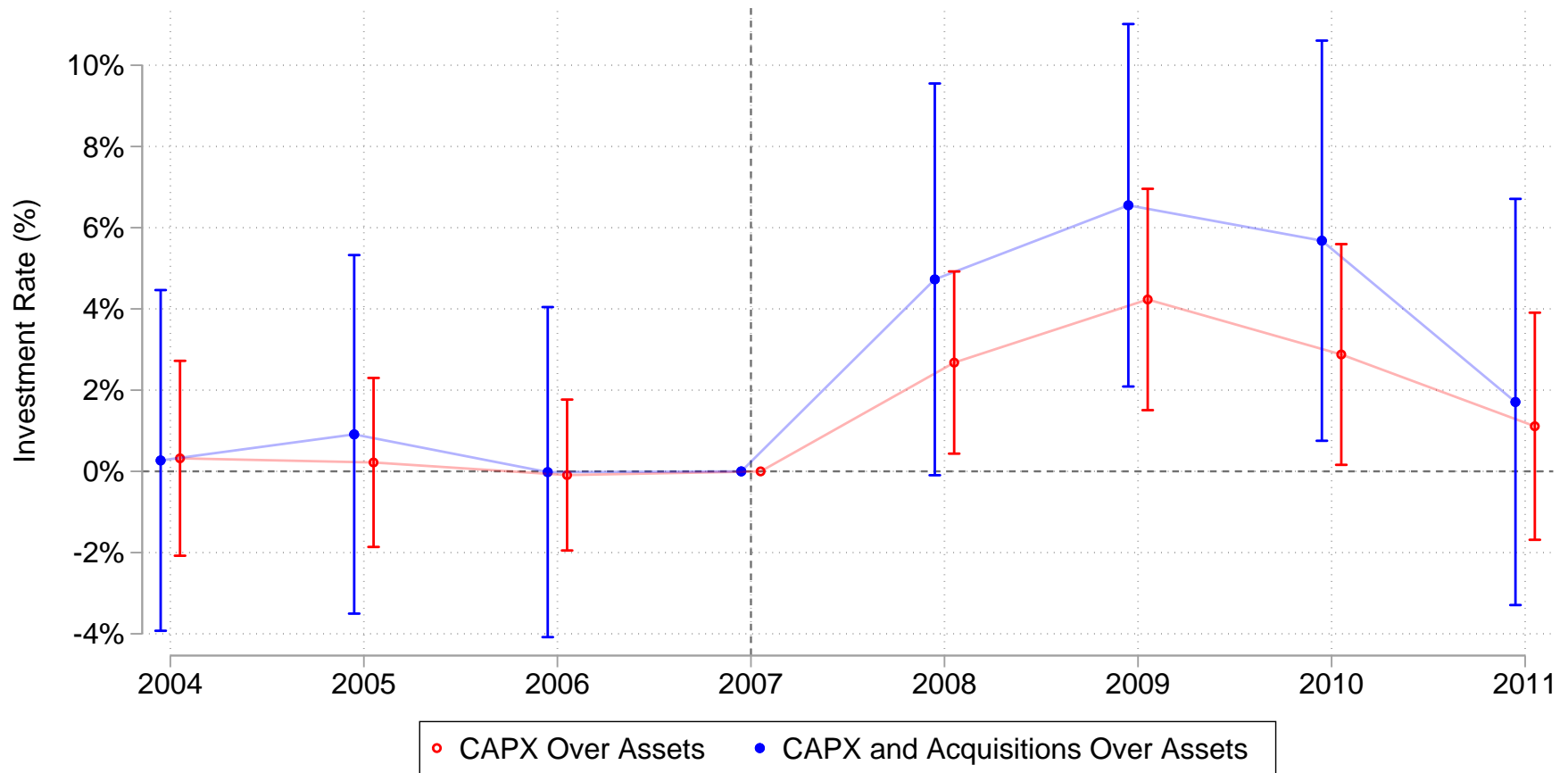


Figure 13: **Insurer ownership and firm investment dynamics in the Great Recession.** This figure shows the estimated coefficients from the difference-in-differences specification in equation (18), estimated on the sample of U.S. firms with outstanding bonds in 2007Q1, excluding speculative-grade issuers. The estimates are from just-identified two-stage least-squares, using the firm-level instrument in equation (17), interacted with year dummies. The coefficients quantify the dynamic association between firm investment rates and the share of a firm's bonds held by domestic insurers in 2007Q1. The controls consist of firm-level covariates, measured in the pre-period and interacted with time dummies: these include fixed effects for issuer rating, average duration of the firm's outstanding bonds, two-digit industry, and deciles of firm size and firm leverage. The *red line* shows the estimates for capital expenditures (CAPX) over lagged total assets, while the *blue line* shows the estimates for CAPX plus acquisitions over lagged total assets. Standard errors are clustered at the firm level. Bars correspond to 95 percent confidence intervals.

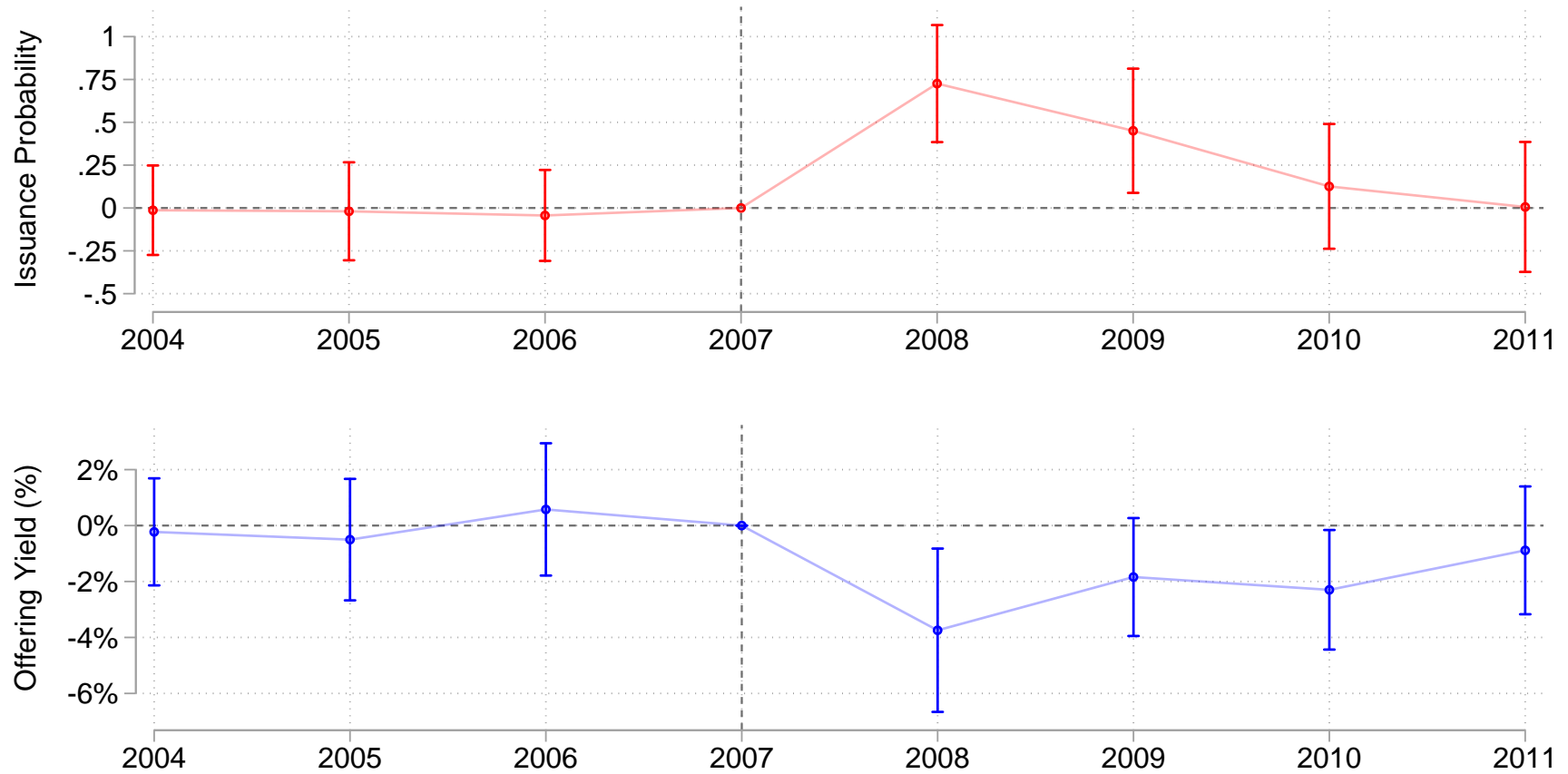


Figure 14: **Insurer ownership and firm credit outcomes in the Great Recession.** This figure shows the estimated coefficients from the difference-in-differences specification in equation (20), estimated on the sample of U.S. firms with outstanding bonds in 2007Q1, excluding speculative-grade issuers. The estimates are from just-identified two-stage least-squares, using the firm-level instrument in equation (17), interacted with year dummies. The coefficients quantify the association of yearly firm bond issuance probability (*red line*) and offering yields on new bonds (*blue line*) with the share of a firm's bonds held by domestic insurers in 2007Q1. The controls consist of firm-level covariates, measured in the pre-period and interacted with time dummies: these include fixed effects for issuer rating, average duration of the firm's outstanding bonds, two-digit industry, and deciles of firm size and firm leverage. Standard errors are clustered at the firm level. Bars correspond to 95 percent confidence intervals.

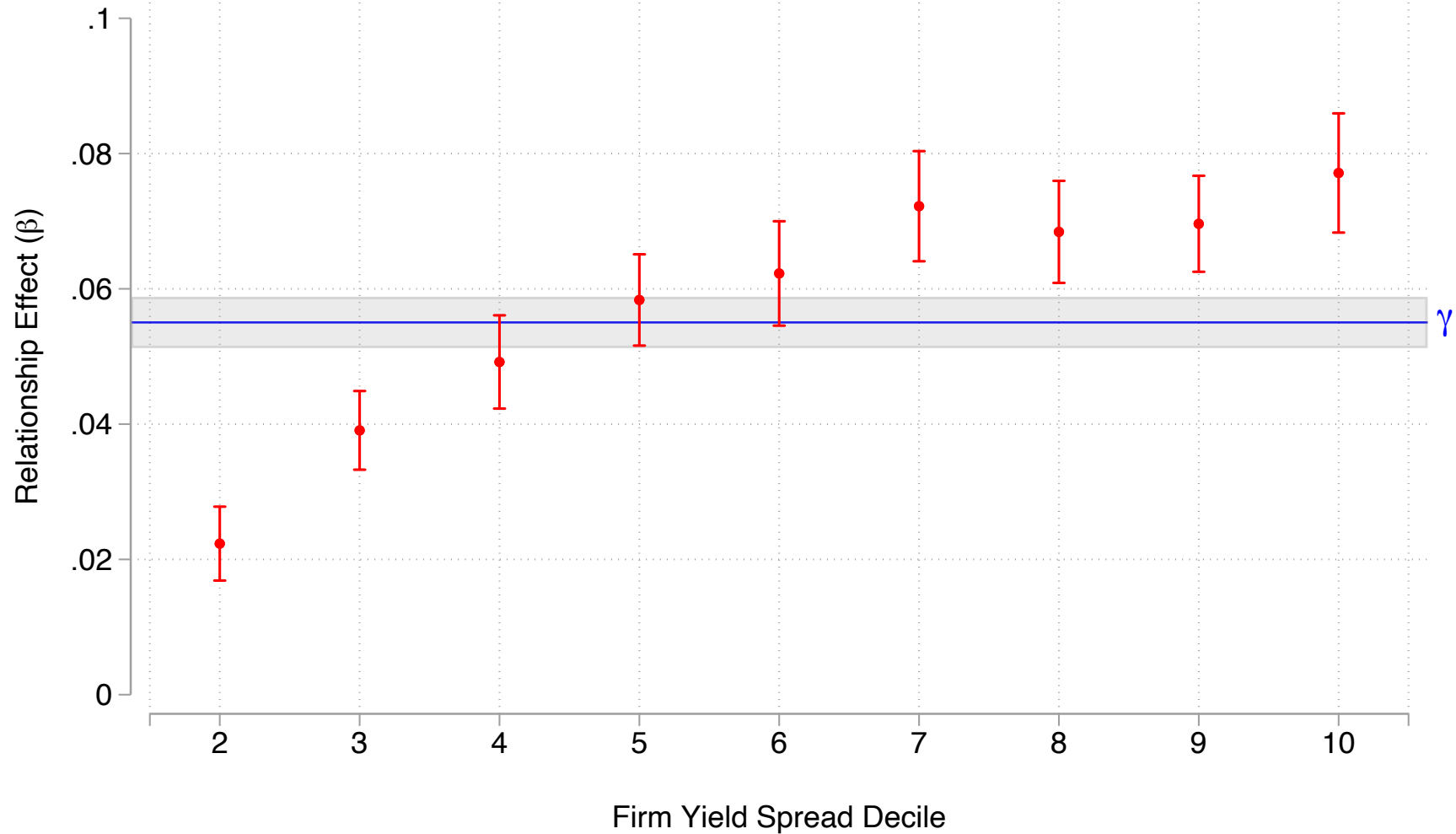


Figure 15: **The role of relationships in corporate bond market financing.** This figure displays the estimated coefficients from the regression specification in equation (21). The *solid blue line* displays the coefficient on the relationship indicators  $\mathcal{R}_{i,j,k,t}$ , which quantifies how much an existing lending relationship increases the probability that a given insurer will buy a firm's new bond offerings for firms in the lowest decile of secondary-market yield spreads. The *red dots* show the estimated coefficients on the interaction between the relationship indicators and firm spread decile dummies, quantifying how this relationship effect varies as firm yield spreads rise. The *red bars* and the *gray shaded area* plot 95 percent confidence intervals for these estimates. Standard errors are clustered at the issuer level.

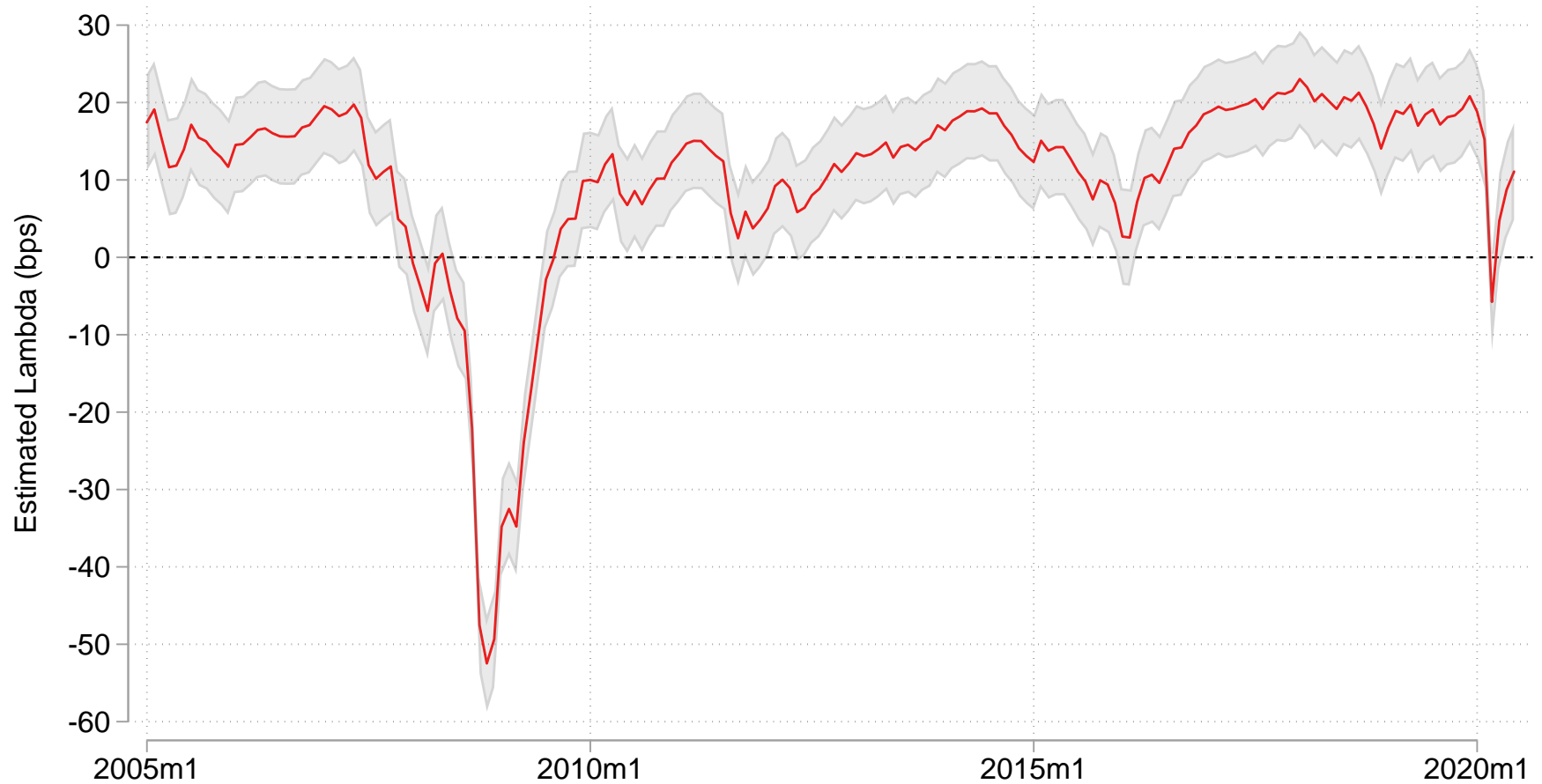


Figure 16: **Insurer ownership and yield spread levels.** This figure shows the estimates from the regression specification in equation (22). The *red line* plots the total estimated effect  $\Lambda_t = \bar{\Lambda} + \tilde{\Lambda} GZ_t$  of security-level insurer shares on yield spreads to Treasury. The *blue shaded area* corresponds to a 95 percent confidence band estimated using [Newey and West \(1987\)](#) HAC standard errors, with lag selection as in [Newey and West \(1994\)](#).

ONLINE APPENDIX FOR  
“IN SAFE HANDS: THE FINANCIAL AND REAL IMPACT OF INVESTOR  
COMPOSITION OVER THE CREDIT CYCLE”

Antonio Coppola

December 2021

Not for Publication

This appendix contains the following sections:

1. Section **A** provides further details on the security-level holdings data used in the paper.
2. Section **B** outlines further results concerning deviations from the law of large numbers (LLN) in the holdings of insurance companies.
3. Section **C** details the Fama-French bootstrap approach used to test for the presence of residual alpha in the cross-section of insurers.
4. Section **D** discusses the institutional features of the primary corporate bond market.
5. Section **E** provides further analysis on heterogeneity within the insurance sector.
6. Section **F** discusses the interpretation of the IV estimates in the presence of within-sector heterogeneity.
7. Section **G** explores the role of exchange traded funds (ETFs) in greater depth.
8. Section **H** outlines a structural interpretation of the real-side results under  $q$ -theory with costly external financing.
9. Section **I** provides further details on the Oster test of Section **3**.
10. Section **J** shows that investor base composition forecasts the volatility of bond turnover over time.

## **A Further Details on Holdings Data**

In this section I provide further details on the two sets of security-level holdings data that I use throughout the paper: the Morningstar data on the holdings of worldwide mutual funds and ETFs, and the NAIC holdings data on the holdings of U.S. insurance firms.

**Morningstar holdings data.** The Morningstar data on the holdings of worldwide mutual funds and ETFs are self-reported by each fund on a monthly or sometimes quarterly basis. These data are collected by funds in all sub-sectors of the asset management industry, including funds that specialize in investing in equity, fixed income, real estate, commodities, and other asset classes. The funds report all their positions, including those in bonds, stocks, cash, and financial derivatives. Morningstar collects data for funds resident both in the United States and abroad. Throughout the paper, I use the same sample of nine developed economies as [Maggiori et al. \(2020\)](#) and [Coppola et al. \(2021\)](#), which these authors selected because of their high degree of data coverage and quality.<sup>1</sup> Altogether, the dataset includes observations on over 1.3 billion individual positions across asset classes. Positions in the Morningstar data are reported together with their nine-digit CUSIP codes. When CUSIP codes are missing, funds often report instead twelve-digit ISIN codes, which I convert to CUSIP codes using mapping data from CUSIP Global Services (CGS). In a few cases, funds will not report either a CUSIP or ISIN code, but rather a different type of security identifier, such as a SEDOL code, a FIGI identifier, or a Bloomberg ID. In these cases, I map the positions to CUSIP codes by performing a search for the codes via Bloomberg’s OpenFIGI API.<sup>2</sup>

The Morningstar data offer a high degree of coverage of the universe of mutual funds and ETFs. To show this, here I focus on fixed income specialist funds, which are the most relevant for my analysis. The dashed blue line in [Figure A.12a](#) shows the aggregate market value of the positions held by U.S. domiciled fixed income specialist investment funds in the Morningstar data over time, which has grown from about \$1 trillion in 2005 to nearly \$6 trillion by 2020. The red line in the same graph shows the aggregate value of the positions of U.S. fixed income mutual funds and ETFs estimated by the Investment Company Institute (ICI), a major industry association. The red line serves as a benchmark, and a comparison with the dashed blue line demonstrates a high degree of coverage of the Morningstar data in the United States. [Figure A.12b](#) repeats the same exercise for funds domiciled outside of the United States, plotting the total value of the positions of fixed income funds in the micro-data in the dashed blue line and the relevant ICI benchmark figures in the red line. Coverage outside of the United States is also high, although somewhat lower than in the U.S. setting.

**NAIC holdings data.** The NAIC data cover the full universe of security holdings of U.S. insurance firms. The primary security identifiers in the NAIC data are nine-digit CUSIP codes, which I use to perform merges with the rest of the data sources. Insurers report both the par value and the estimated market value of their bond holdings. However, since insurers have some discretion in determining the market value of their bond positions in these regulatory

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<sup>1</sup>The sample includes funds domiciled in the United States, the European Monetary Union (EMU), the United Kingdom, Canada, Switzerland, Australia, Sweden, Denmark, and Norway.

<sup>2</sup>These steps are analogous to the ones used in [Maggiori et al. \(2020\)](#) and [Coppola et al. \(2021\)](#).

filings (Sen and Sharma 2020), I recompute market values by multiplying the par value of reported holdings by the latest available transacted prices from TRACE: this ensures that positions in the same bonds are marked to market consistently across insurers. For bonds that do not have recent traded prices in TRACE, I use price data from S&P Global where available, and otherwise default to the market value originally reported to NAIC. Since the empirical analysis focuses strictly on bonds that are in TRACE and are actively traded, this is immaterial to any of the results shown in the paper.

**Further descriptive statistics.** Table A.1 details the composition of the overall portfolios of insurers and fixed income specialist funds. Slightly more than half of insurers’ assets (57 percent in 2015) are invested in corporate bonds—nearly all U.S. corporate bonds. A further 23 percent of insurer portfolios is in sovereign bonds, with smaller shares in asset-backed securities (ABS) and equities. Specialist funds in the United States have a significant share of their assets (39 percent) in ABS, while ABS holdings are small for non-U.S. funds. Funds’ corporate bond holdings reflect a strong home bias: while U.S. funds hold 31 percent of their assets in U.S. corporate bonds and only 2 percent in non-U.S. corporate bonds, funds domiciled outside the United States hold 23 percent of their assets in U.S. corporate bonds and 37 percent in non-U.S. corporate bonds.

## B Further Results on LLN Deviations

In this section I elaborate on the deviations of the law of large numbers (LLN) in insurer holdings introduced in Section 3. In order to study these LLN deviations, I examine the rate at which information is lost as we exclude the positions of the largest holders underlying each insurer share  $\phi_{i,t}$ . Letting  $N$  denote the number of insurers in the sample, I define  $X_{i,t}^{I,k}$  to be the  $k$ -th largest position of an individual insurer in bond  $i$  at time  $t$ , so that  $X_{i,t}^{I,1} \geq X_{i,t}^{I,2} \geq \dots \geq X_{i,t}^{I,N}$  and  $X_{i,t}^I = \sum_{k=1}^N X_{i,t}^{I,k}$ . I then construct the *truncated* insurer shares

$$\phi_{i,t}^{(K)} = \frac{\sum_{k=1+K}^N X_{i,t}^{I,k}}{V_{i,t}}, \quad (\text{A.1})$$

which exclude the largest  $K$  positions underlying each individual aggregate insurer share.

Consider now a regression of the actual insurer shares on the truncated insurer shares as we vary the number of excluded insurers  $K$ :

$$\phi_{i,t} = \alpha_K + \pi_K \phi_{i,t}^{(K)} + \alpha_{i,t,K}. \quad (\text{A.2})$$

A theoretical benchmark in which the LLN applies delivers sharp predictions for how the

R-squared values from this regression should decay with  $K$ . Namely, consider a benchmark model with equal-sized insurers whose holdings are subject to *i.i.d.* shocks, which I refer to as the *LLN benchmark*. In the theoretical LLN benchmark, the R-squared value from regression (A.2) declines with the number of excluded holders  $K$  as:<sup>3</sup>

$$R_{\text{LLN}}^2(K) \approx \sqrt{1 - \frac{K}{N}}. \quad (\text{A.3})$$

The solid red line in Figure A.14 plots this theoretical benchmark, while the solid blue line plots the empirical R-squared values for insurer shares obtained from estimating equation (A.2). The large discrepancy between the solid red line and the solid blue line demonstrates the presence of a large deviation from the law of large numbers: while in the LLN benchmark excluding the ten largest holders underlying each position leads to negligible information loss, in reality this removes most of the power of the truncated insurer shares in explaining the actual insurer shares. In this sense, the decisions of the few largest insurers matter disproportionately. For comparison, the dashed blue line in Figure A.14 also plots the same estimates for mutual funds and ETFs, which serve as a further empirical benchmark. While the fund sector also exhibits some degree of deviation from the LLN benchmark, this is less pronounced than for the insurance sector.

The empirical patterns documented here and in Section 3 also suggest a series of placebo exercises. A first placebo replaces the true insurer shares  $\phi_{i,t_e^S-12}$  with the truncated shares  $\phi_{i,t_e^S-12}^{(10)}$ , which exclude the largest underlying 10 holders for each bond. A second placebo exercise regresses the true insurer shares  $\phi_{i,t_e^S-12}$  against the insurer shares at issuance  $\phi_{i,\tau(i)}$ , and then uses the residuals from this regression as the right-hand side argument in equation (4). In both cases, we are removing some of the most informative components of the regressors, and we would expect to see the estimates attenuate. Figure A.15 shows the estimates from these placebo exercises, and in both cases the estimated coefficients are indeed driven to zero.

## C Residual Alpha in the Cross-Section of Insurers

As discussed in Section 3, the identifying assumption in my shift-share IV approach requires that insurers are not able to (or do not attempt to) select bonds that will draw down less in a market downturn for reasons not explained by issuer effects or any of the included observable bond characteristics. While this condition is not directly testable, I test the related condition that certain insurers systematically acquire bonds with a high *residual alpha*—that is, alpha with respect to the overall bond market that is not explained by observable bond characteristics or issuer effects.

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<sup>3</sup>The accuracy of this approximation was confirmed via Monte Carlo simulation.



Distinguishing between investment ability and noise in a cross-section of investors is a well-trodden question in finance. Here I use the methodology of Fama and French (2010), which is a non-parametric approach relying on the bootstrap. This method generates bootstrap distributions of measured alphas in the cross-section using simulations under which the null hypothesis of no true alphas is true by construction, and compares these bootstrap distributions to the actual empirical distribution of measured alphas.

I start by constructing, for each insurer and at a quarterly frequency, returns on their overall holdings of U.S. investment-grade corporate bonds. The portfolio return for insurer  $j$  in quarter  $t$  is  $R_{j,t}$ . I also estimate a quarterly benchmark market return  $R_t^m$  using a value-weighted basket of all outstanding U.S. investment-grade corporate bonds. I then consider, separately for each insurer  $j$ , the following time-series regressions:

$$R_{j,t} = \alpha_j + \beta_j R_t^m + \varepsilon_{j,t}. \tag{A.4}$$

The coefficient  $\alpha_j$  estimates the alpha of insurer  $j$ 's portfolio with respect to the market portfolio. The blue curves in Figure A.13 plot kernel density estimates of the measured empirical alphas  $\alpha_j$  and their corresponding  $t$ -statistics  $t_j^\alpha$  in the cross-section of insurers.

Next, I construct bootstrap distributions in which the null of no residual alpha holds by construction. For each bootstrap simulation, I independently replace each insurer's bond positions with an equal-sized position in a randomly chosen matching bond: that is, a bond by the same issuer and with the same characteristics (using all characteristics included in the fully-saturated set of interacted fixed effects specified in Section 2, and sampling with replacement).<sup>4</sup> The red curves in Figure A.13 plot kernel density estimates of the simulated measured alphas  $\alpha_j$  and their corresponding  $t$ -statistics  $t_j^\alpha$ , with each red curve averaging over 1000 independent bootstrap simulations.

If certain insurers were able to systematically select bonds with a high residual alpha, we would expect the empirical distributions of  $\alpha_j$  and  $t_j^\alpha$  (the blue curves) to have heavier right tails than the corresponding simulated bootstrap distributions (the red curves). Instead, the blue curves fall squarely within the range traced out by the red curves, so that this bootstrap-based test rejects the presence of residual alpha in the cross-section of insurers.

## D Additional Institutional Details

In this section I provide an overview of the functioning of the primary corporate bond market, as surveyed for example in ? and ?. Firms that wish to raise debt financing by issuing new corporate bonds normally hire a financial intermediary—such as an investment bank's capital markets desk—to act as the lead underwriter for the offering. The lead underwriter typically

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<sup>4</sup>Naturally, if there is no bond that matches a given one, that position is simply left as-is in the simulation.

invites other institutions to be part of the underwriting syndicate and drafts the initial terms of the offering (such as issue size, target pricing, and so forth) after review with the issuer.

The terms of the offering are only finalized after the completion of a process known as *book-building*. The book-building process commences with the underwriting syndicates reaching out to prospective institutional investors (such as insurers and funds) with the preliminary terms of the issue. Institutional investors submit information about their demand to the underwriters in the form of indications of interest (IOIs), which specify how much of the issue the investor is willing buy at a given offering yield. The lead underwriter then adjusts the terms of the issue to clear the market. Finally, the lead underwriter and the underwriting syndicate establish and distribute allocations in the new bond to the investors who submitted IOIs.

New issues are typically oversubscribed, so that the process of receiving a primary-market allocation is competitive from the perspective of the investors. Allocations are valuable given the high liquidity of the primary market and because new issues are typically slightly underpriced relative to current secondary-market yields. ? show that investors who have prior trading relationships with underwriters tend to receive larger allocations. Since data on IOIs in the corporate bond market are private, it is difficult to study further determinants of primary-market bond allocations directly.<sup>5</sup>

The corporate bond underwriting process described here, however, is very similar to the one used for equity initial public offerings (IPOs), for which ? are able to study the bids submitted by institutional investors during book-building. ? find that larger IOI bid sizes are strongly associated with higher relative allocations (that is, allocations relative to the bid), even after controlling for investor size. These results indicate that investors have an incentive to place large orders on the primary market. While the evidence does not come directly from the bond market (but rather from the equity market), this highlights one reason why insurers might prefer to place bids for a few large positions rather than many smaller positions on the primary market—besides the simple fact that few large positions might be institutionally easier to manage, and that insurers might view similar bonds as largely substitutable.

As mentioned in Section 2.5, the most important determinant of the volume of insurers' purchases of new bonds on the primary market in a given time period is the same-quarter net change in their policy reserves. Policy reserves correspond to the actuarial value of future expected payments to policyholders and constitute the main liabilities of insurers. A univariate regression of quarterly changes in the insurance sectors' total holdings of bonds on the sectors' growth in policy reserves, for example, yields a high R-squared value of 64 percent and shows that for each dollar of new reserves insurers invest 82 cents in new bonds.

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<sup>5</sup>The role of relationships with underwriters in the primary bond market may play a part in generating the patterns of bond-market relationship finance documented in Section 5.3. For a related discussion of the role of bilateral relationships in the interbank repo market, see also ?, who study data from Chinese banks.

## E Heterogeneity Within the Insurance Sector

In this section I investigate heterogeneity in the impact of bond ownership by different institutions *within* the insurance sector. A first salient dimension of heterogeneity is the degree to which insurers face financial constraints. At a regulatory level, insurance firms in the United States are subject to risk-based capital (RBC) requirements and report their RBC ratios (corresponding to total capital over required risk-based capital) in their statutory filings. Besides the statutory RBC ratios, another widely followed measure of insurer capital constraints is the Best’s Capital Adequacy Ratio (BCAR) distributed by A.M. Best, a leading provider of financial strength ratings for insurance firms.

BCAR scores are an important factor in A.M. Best’s rating methodology, with each rating category having a guideline for the minimum score required to support that rating. [Kojien and Yogo \(2015\)](#) show that risk-based capital (as measured via BCAR scores) relative to the guideline for the current rating is an important determinant of insurer behavior: for instance, insurers with low risk-based capital relative to guideline were particularly likely to reduce the price of long-term policies during the financial crisis, in order to improve their capital positions and ultimately avoid a downgrade as well as possible regulatory repercussions.

One might expect this kind of heterogeneity in financial constraints to also affect the impact of insurer ownership on bond price dynamics. In crises, more financially constrained insurers might be particularly eager to shift out of corporate bond positions and into assets with lower risk-based capital requirements (such as U.S. Treasury bonds) in order to improve their capital adequacy metrics: as a result, these more financially constrained insurers may be especially prone to engaging in fire sales of their corporate bond holdings. To investigate this hypothesis, I consider the following counterpart to the baseline specification of [Section 2.2](#):

$$\log \zeta_{i,e} = \alpha + \beta_{\text{HC}} \cdot \phi_{i,t_e^s-12}^{\text{High Capital}} + \beta_{\text{LC}} \cdot \phi_{i,t_e^s-12}^{\text{Low Capital}} + \text{Interacted Fixed Effects} + \varepsilon_{i,e}, \quad (\text{A.5})$$

where  $\phi_{i,t}^{\text{High Capital}}$  is the share of bond  $i$  that is owned by insurers with above-median risk-based capital relative to guideline (measured as the difference between the insurer’s BCAR score and the guideline for its current A.M. Best rating), while  $\phi_{i,t}^{\text{Low Capital}}$  is the share owned by insurers with below-median values of the same. I estimate this specification for the Great Recession, with risk-based capital relative to guideline measured as of 2007.<sup>6</sup> The regression includes the fully saturated set of interacted fixed effects introduced in [Section 2.2](#), which encompasses firm dummies as well as dummies for bond characteristics (such as credit rating, duration, issue size, and so forth).

The point estimates from this specification, displayed in [Figure A.16](#), are  $\hat{\beta}_{\text{HC}} = -.58$

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<sup>6</sup>I exclude later events because of data availability and because A.M. Best modified the BCAR methodology and the corresponding rating guidelines in more recent years. I compute the median value of risk-based capital relative to guideline cross-sectionally, across all the insurance firms in the sample.

and  $\hat{\beta}_{LC} = -.29$ , and a Wald test rejects the null hypothesis of coefficient equality at the 1 percent significance level. These estimates imply that bonds do particularly well in a crisis when they are owned by insurers that are less financially constrained, in the sense of having a robust risk-based capital position relative to rating guidelines. This finding parallels the results of [Ellul et al. \(2011\)](#), who show that more constrained insurers are particularly likely to sell corporate bonds that are downgraded to speculative grade. It also relates to [Becker et al. \(2021\)](#), who show that more financially constrained insurers are particularly likely to retain downgraded non-agency mortgage-backed securities (MBS) as compared to other downgraded assets, following a 2009 regulatory reform that nearly eliminated capital requirements associated with non-agency MBS positions.

A second notable dimension of heterogeneity within the insurance sector is in the structure of corporate ownership. While the majority of the assets of U.S. insurance firms are now held by regular stock companies, which are owned by their shareholders, a second type of ownership structure also remains prevalent in the form of *mutual* companies. In a mutual company, policyholders are also equity holders, so that the incentives of the firm’s owners and those of its clients are perfectly aligned. As compared to stock companies, mutual companies on average tend to engage in less risk-taking, have better risk-based capital ratios, and have stronger balance sheet strength ratings (?). For these reasons, it is plausible to expect mutuals to be particularly unlikely to engage in corporate bond fire sales in market downturns. I test this hypothesis with the following specification:

$$\log \zeta_{i,e} = \alpha + \beta_M \cdot \phi_{i,t}^{\text{Mutuals}} + \beta_{SC} \cdot \phi_{i,t}^{\text{Stock Companies}} + \text{Interacted Fixed Effects} + \varepsilon_{i,e}, \quad (\text{A.6})$$

where  $\phi_{i,t}^{\text{Mutuals}}$  is the share of bond  $i$  owned by insurance mutuals, while  $\phi_{i,t}^{\text{Stock Companies}}$  is the share owned by stock insurance firms.

I estimate this specification across events, as in the baseline of Section 2.2. As before, Figure A.16 displays the point estimates from this specification, which are  $\hat{\beta}_M = -.79$  and  $\hat{\beta}_{LC} = -.33$ . In this case, too, a Wald test rejects the null hypothesis of coefficient equality at the 1 percent significance level. These results confirm that bonds held by mutuals have particularly mild drawdowns in crises, which is consistent with the hypothesis that mutuals have an especially low propensity to engage in fire sales.

## F Shift-Share Interpretation Under Heterogeneity

For simplicity of exposition, in Section 3 I discussed the shift-share IV estimates under the null hypothesis of homogeneous treatment effects, whereby all insurers impact bond price dynamics with the same quantitative elasticities. Here I discuss the interpretation of the shift-share IV estimates if there is heterogeneity in the causal impact of ownership *across insurers*. This

heterogeneity would arise, for example, if certain groups of insurers are especially unlikely to engage in fire sales, even relative to their peers within the insurance sector: as I show in Appendix Section E, these patterns can result from factors such as each insurer’s degree of financial constraints. The shift-share IV approach continues to provide a valid causal estimator in the presence of heterogeneity—although it should then be interpreted as estimating a weighted average of heterogeneous treatment effects.

Without loss of generality, suppose the heterogeneity is across groups of insurers  $g \in \mathcal{G}$ . The share of bond  $i$  held by the group of insurers  $g$  at time  $t$  is  $\phi_i^g$ , where for simplicity I suppress time indices. Naturally, these shares sum to the aggregate insurer share, so that  $\sum_{g \in \mathcal{G}} \phi_i^g = \phi_i$ . All insurers within group  $g$  are assumed to have the same causal impact  $\beta_g$  on bond drawdowns  $\zeta_i$ :

$$\beta_g = \frac{\partial \log \zeta_i}{\partial \phi_i^g}. \quad (\text{A.7})$$

In the most extreme case, this framework can accommodate treatment effects  $\beta_g$  that are different for each individual insurer: in that case, one can simply take  $\mathcal{G} = \{\{j\} : j \in \mathcal{J}\}$ , where as in the main text  $\mathcal{J}$  is the set of all insurers.

Following the notation in Goldsmith-Pinkham et al. (2020), let  $Z$  be the vector stacking the shift-share instruments  $Z_i$  defined in equation (11),  $X$  be the vector stacking the insurer shares  $\phi_i$ , and  $Y$  be the vector stacking the outcomes  $\zeta_i$ . Further, let  $D$  be the matrix containing the dummies corresponding to controls included in the regressions (that is, a constant term plus dummies for the interacted fixed effects). The shift-share estimator  $\hat{\beta}_{\text{Bartik}}$  obtained from the 2SLS regressions of Section 3 is

$$\hat{\beta}_{\text{Bartik}} = (Z'X^\perp)^{-1}Z'Y^\perp, \quad (\text{A.8})$$

where  $X^\perp = M_D X$  and  $Y^\perp = M_D Y$ , with  $M_D = I - D(D'D)^{-1}D'$  the annihilator matrix for  $D$ . Next, define the following group-specific instruments, which only aggregate the extensive margin indicators  $\xi_{i,j}$  for insurers in each group  $g$ :

$$Z_i^g = \sum_{j \in g} \xi_{i,j} \bar{\phi}_j. \quad (\text{A.9})$$

Each of these group-specific shift-share instruments estimates an individual heterogeneous treatment effect  $\beta_g$ :

$$\hat{\beta}_g = (Z_g'X^\perp)^{-1}Z_g'Y^\perp, \quad (\text{A.10})$$

where  $Z_g$  is the vector stacking the instruments  $Z_i^g$ , and I correspondingly define  $\bar{\phi}_g = \sum_{j \in g} \bar{\phi}_j$ .

Using the results in Proposition 3 of Goldsmith-Pinkham et al. (2020), the shift-share estimator  $\hat{\beta}_{\text{Bartik}}$  can be decomposed in terms of the individual estimators  $\hat{\beta}_g$ :

$$\hat{\beta}_{\text{Bartik}} = \sum_g \hat{\alpha}_g \hat{\beta}_g, \quad (\text{A.11})$$

where terms  $\hat{\alpha}_g$  are estimated Rotemberg (1983) weights that sum to one (so that  $\sum_g \hat{\alpha}_g = 1$ ),

$$\hat{\alpha}_g = \frac{\bar{\phi}_g Z'_g X^\perp}{\sum_{g'} \bar{\phi}_{g'} Z'_{g'} X^\perp}. \quad (\text{A.12})$$

Goldsmith-Pinkham et al. (2020) point out that the Rotemberg weights  $\hat{\alpha}_g$  can take negative values, although this does not necessarily pose a conceptual problem as long as the component of  $\hat{\beta}_{\text{Bartik}}$  with negative weights  $\hat{\alpha}_g$  does not have a relatively large magnitude. As a practical way to assess this, they recommend splitting the estimate into the component with positive  $\hat{\alpha}_g$  (that is,  $\sum_{g|\alpha_g > 0} \hat{\alpha}_g \hat{\beta}_g$ ) and that with negative  $\hat{\alpha}_g$  (that is,  $\sum_{g|\alpha_g < 0} \hat{\alpha}_g \hat{\beta}_g$ ), and compare their magnitudes.

To start with, I implement this check by defining the partitioning set  $\mathcal{G}$  using the dimensions of heterogeneity that are motivated by prior and I explored in Appendix Section E. First I separate insurers according to their degree of financial constraints, so that  $\mathcal{G}$  splits insurers into two equal-sized groups, sorting them according to their risk-based capital relative to guideline as in equation (A.5). Second, I split insurers according to their corporate ownership structure, so that  $\mathcal{G}$  contains two groups—mutuals and stock companies, as in equation (A.6). In both of these cases, none of the estimated Rotemberg weights  $\hat{\alpha}_g$  are negative, so that the magnitude of the negative-weighted component of  $\hat{\beta}_{\text{Bartik}}$  is exactly zero. Even in the most extreme and conservative case, in which I assume that the treatment effects  $\beta_g$  are different for each individual insurer, so that  $\mathcal{G} = \{\{j\} : j \in \mathcal{J}\}$ , the negative-weighted component is more than 20 times smaller in magnitude than the positive-weighted component.

## G The Role of ETFs: Additional Details

For simplicity of exposition, my analysis in the main text considers open-end mutual funds and exchange traded funds (ETFs) jointly. In this section, I disentangle these two types of funds and discuss the role of ETFs in greater depth, focusing particularly on differences in redemption mechanisms and their relationship to corporate bond fire sales. I investigate whether ownership by ETFs impacts corporate bond price dynamics in crises differently from ownership by open-end mutual funds, but cannot reject the null hypothesis of no differences with a sufficiently high level of statistical confidence.

In the corporate bond market, ETFs have historically been very small, although they have

been growing in size in recent year. Corporate bond holdings by ETFs account for just 1 percent of the fund sector’s total holdings in my sample in 2005, but this figure grows to 12 percent by 2020.<sup>7</sup> ? and ? provide an overview of the structure of ETFs and their differences with regular open-end mutual funds, and also review the growing academic literature studying them. Most saliently, shares in ETFs are traded continuously on public exchanges, and the task of keeping an ETF’s price in line with that of the securities it holds is delegated to financial institutions known as authorized participants (APs). To perform arbitrage, APs trade in-kind with the ETF sponsor in what’s known as the *primary* ETF market. APs can carry out redemptions by returning an ETF share to the ETF provider in exchange for a basket of the underlying securities. Alternatively, they can create ETF shares via the reverse primary market process.

Importantly, trades of ETF shares among the general public—which constitute the *secondary* ETF market—do not directly involve trades in the underlying securities. This process contrasts with flows in and out of open-end mutual funds. Abstracting from cash buffers, open-end mutual funds have to physically liquidate their security holdings when faced with investor redemptions, since contractually these redemptions must be met in-kind (and conversely, they must purchase securities to accommodate inflows).

The question of whether ETFs threaten or improve financial stability, particularly in the bond market, has been contentious among researchers and policymakers. On the one hand, ETFs may cater to an investor base that is particularly prone to liquidate its investments in times of distress, thus exposing the bond markets to a source of destabilizing demand: ?, for example, show that the flow-performance sensitivity of ETFs is more than double that of open-end mutual funds.

On the other hand, there are at least two reasons to believe that bond ETFs may actually be beneficial in times of crisis. First, the open-end mutual fund structure is subject to run incentives à la ?, as highlighted and formally modeled by ? and ?. The ETF structure removes these run incentives (Goldstein et al. 2017). Second, the ETF structure also removes the mechanical link between fund-investor sales and sales of the underlying securities. Large investor sales of ETF shares on the secondary ETF market do not necessarily have to lead to ETF outflows, since the latter require APs to conduct in-kind redemptions. Further, APs may decide to keep the redeemed bonds on their balance sheets (for instance, to avoid liquidation costs) and thus not go on to sell them in the secondary bond market.

To empirically assess the impact of ETF ownership on bond price dynamics during crises, I consider the following counterpart to the baseline specification of Section 2.2:

$$\log \zeta_{i,e} = \alpha + \beta_{\text{OE}} \cdot \phi_{i,t_e^S-12}^{\text{Open-End}} + \beta_{\text{ETF}} \cdot \phi_{i,t_e^S-12}^{\text{ETF}} + \text{Interacted Fixed Effects} + \varepsilon_{i,e}, \quad (\text{A.13})$$

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<sup>7</sup>Precisely because of their small relative size, simply excluding ETFs from the sample does not meaningfully impact any of the analyses that I present throughout the paper.

where  $\phi_{i,t}^{\text{Open-End}}$  is the share of bond  $i$  that is owned by open-end mutual funds, while  $\phi_{i,t}^{\text{ETF}}$  is the share owned by ETFs. I estimate this specification across events, with fully saturated interacted fixed effects (encompassing event dummies, issuer dummies, and bond characteristics dummies) as in Section 2.2. The point estimates from this specification, displayed in Figure A.17, are  $\hat{\beta}_{\text{OE}} = .40$  and  $\hat{\beta}_{\text{ETF}} = .98$ , but the coefficient on the ETF share is estimated imprecisely, as evidenced by the wide confidence interval. Importantly, a Wald test fails to reject the null hypothesis of coefficient equality at the 10 percent confidence level.

The low statistical power of this analysis is plausibly due to the small relative size of ETFs in the corporate bond market.<sup>8</sup> A larger point estimate for  $\hat{\beta}_{\text{ETF}}$ , as compared to  $\hat{\beta}_{\text{OE}}$ , would imply that ETF ownership is particularly destabilizing for bond prices in crises—which may result from the clientele effects discussed above. However, the high degree of statistical uncertainty around these estimates prevents me from drawing strong conclusions.

## H Real Effects: A Structural Interpretation

In this section I present a simple organizing framework that yields a structural interpretation of the real-side results in the paper. More specifically, I outline how the estimated impact of firm-level insurer ownership on firm investment dynamics can be interpreted in terms of its effects on firms’ marginal cost of financing and effective Tobin’s  $q$ . I begin by characterizing the first-order condition for optimal firm investment as a function of marginal  $q$  and marginal costs of financing in the presence of costly external financing. I derive this same first-order condition in the context of a continuous-time model of investment with endogenous cash management. To focus on the economic intuition that is relevant for my analysis, I show how the same condition can be obtained in a simpler, discrete-time model with exogenous external financing episodes. I then show how to use the first-order condition for firm investment to derive estimating equations that relate my empirical estimates to structural elasticities. I follow conventions that are common in the  $q$ -theory literature (see, e.g., ?), and my notation follows ?.

### H.1 A Model of Firm Investment With Costly External Financing

A firm produces output  $Y_t$  using its capital stock  $K_t$  and labor  $L_t$  with a technology  $f(K_t, L_t)$ . Labor is frictionlessly adjustable, so I focus on the choice of capital investment, implicitly assuming optimal labor choice. The dynamics of the capital stock are given by

$$K_{t+1} = (1 - \delta)K_t + I_t, \tag{A.14}$$

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<sup>8</sup>These results are qualitatively analogous if I restrict the sample to only include observations corresponding to the COVID crash of 2020, when the relative importance of ETF corporate bond holdings was highest.



where  $I_t$  is investment. Note that  $K_{t+1}$  is known at time  $t$ . The firm's profits are  $\Pi_t$ . Capital investment  $I_t$  incurs physical adjustment costs that depend only on the ratio of investment to total capital. With  $i_t = \frac{I_t}{K_t}$  the investment rate at time  $t$ , adjustment costs are given by

$$\Omega(i_t) = \omega(i_t) K_t, \quad (\text{A.15})$$

with  $\omega(\cdot) > 0$  and convex in  $i_t$ . The firm has a cash stock  $W_t$  that evolves as

$$W_{t+1} = W_t + \Pi_t - \Omega_t - D_t, \quad (\text{A.16})$$

and pays out a share  $\lambda_t$  of its cash stock as dividend each period:<sup>9</sup>

$$D_t = \lambda_t W_t. \quad (\text{A.17})$$

For simplicity, I take the external financing policy to be exogenous. I assume that the firm raises external financing (which may be interpreted as either debt or equity) whenever its cash stocks hits a lower barrier  $\underline{W}$ , which brings it back to a cash level  $\overline{W} > \underline{W}$ . In doing this, the firm incurs a cost

$$\tau \Delta_W, \quad (\text{A.18})$$

where  $\Delta_W \equiv \overline{W} - \underline{W}$ , and  $\tau \geq 1$  represents a wedge between the costs of internal and external financing.

The firm seeks to maximize the present discounted value  $V_t$  of present and future dividends with its investment policy. I let  $M_{t,t+\tau}$  be the (possibly stochastic) time- $t$  discount factor for cash flows happening at time  $t + \tau$ . The firm's value therefore satisfies

$$V_t = \max_{\{I_t\}} \mathbb{E}_t \sum_{\tau=0}^{\infty} M_{t,t+\tau} D_{t+\tau}. \quad (\text{A.19})$$

Because of the presence of costly external financing, firm value is (weakly) increasing in its cash holdings. We can define the marginal value of cash as

$$\text{MVC}_t = \frac{\partial V_t}{\partial W_t}, \quad (\text{A.20})$$

which can be equivalently interpreted as the marginal cost of financing (MCF) that the firm faces at a given point in time:

$$\text{MCF}_t = \text{MVC}_t. \quad (\text{A.21})$$

In the frictionless benchmark,  $\tau = \text{MCF}_t = \text{MVC}_t = 1$ . When we have a positive financing

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<sup>9</sup>As with other elements of the firm's cash management policy, I leave  $\lambda_t$  unmodeled. Here it is effectively taken as exogenous.

wedge  $\tau > 1$ ,  $\text{MCF}_t$  will be greater than one, reflecting the marginal cost of depletion of the firm's cash stock.

The solution to the firm's optimization problem specified in (A.19) is characterized recursively by the following Bellman equation:

$$V_t = \max_{I_t} \{D_t + \mathbb{E}_t[M_{t,t+1}V_{t+1}]\}. \quad (\text{A.22})$$

The first-order condition for this optimization problem equates the marginal cost of today's investment with its marginal impact on total firm value:

$$\text{MCF}_t \omega'(i_t) = q_t, \quad (\text{A.23})$$

where marginal Tobin's  $q$  is

$$q_t = \mathbb{E}_t \left[ M_{t,t+1} \frac{\partial V_{t+1}}{\partial K_{t+1}} \right]. \quad (\text{A.24})$$

Importantly, the optimality condition (A.23) shows that in the presence of financial frictions the key sufficient statistic for investment is not marginal  $q$ , as in the frictionless benchmark, but rather the ratio between marginal  $q$  and marginal cost of financing, which I refer to as effective  $q$ :

$$q_t^{\text{eff}} = \frac{q_t}{\text{MCF}_t} \quad (\text{A.25})$$

For simplicity, I assume the following commonly-used quadratic form for  $\phi$ :

$$\phi(i_t) = i_t + \frac{\theta}{2} i_t^2, \quad (\text{A.26})$$

where the scalar parameter  $\theta > 0$  governs the magnitude of physical adjustment costs. With this functional specification, the firm's optimality condition takes the simple form

$$i_t = \frac{1}{\theta} \left( \frac{q_t}{\text{MCF}_t} - 1 \right). \quad (\text{A.27})$$

## H.2 Relating the Empirical Estimates to the Model

The real-side estimates of the impact of *ex ante* firm-level insurer shares  $\phi$  measure (in the absence of confounders) the cross-sectional effect  $\frac{\partial i}{\partial \phi}$ . Using the first-order condition for firm investment in equation (A.27), these estimated investment effects allow me to assess the cross-sectional impact of investor base composition on the marginal cost of financing and effective  $q$  for the representative firm in a crisis. The estimating equations are

$$\frac{\partial q^{\text{eff}}}{\partial \phi} = \theta \frac{\partial i}{\partial \phi}, \quad (\text{A.28})$$

and

$$\frac{\partial \text{MCF}}{\partial \phi} = -\theta \frac{q}{(1 + \theta i)^2} \frac{\partial i}{\partial \phi}. \quad (\text{A.29})$$

All terms in these estimating equations are measurable from the data, with the exception of the adjustment cost parameter  $\theta$ , which needs to be calibrated. Figure A.19 plots the estimated values of  $\frac{\partial q^{\text{eff}}}{\partial \phi}$  and  $\frac{\partial \text{MCF}}{\partial \phi}$  as a function of the adjustment cost parameter  $\theta$ . Depending on the calibrated value of  $\theta$ , a 50 percentage point increase in the firm-level insurer share leads to an increase in effective Tobin's  $q$  of the order of 2 to 6 percentage points, and a decrease in the marginal cost of financing of the order of 1 to 4 percentage points.<sup>10</sup>

## I Details on Oster Test

In this section I provide further details on the partial identification methodology of Section 3.3. I follow the notation and results in Oster (2019). I let  $F_{i,e}$  be a vector including dummies for the fully-saturated set of interacted fixed effects in the baseline estimates, entering the regression model with population parameters  $\gamma$ . I refer to the product  $\gamma F_{i,e}$  as  $O_{i,e}$ , which stands for *observables*. Suppose that the true model also includes some relevant omitted variables  $Q_{i,e}$ , which enter into the linear specification with some non-zero population parameters  $\eta$ :

$$\log \zeta_{i,e} = \alpha + \beta \cdot \phi_{i,t_e^s-12} + \underbrace{\gamma F_{i,e}}_{\equiv O_{i,e}} + \underbrace{\eta Q_{i,e}}_{\equiv U_{i,e}} + \varepsilon_{i,e}, \quad (\text{A.30})$$

where I refer to the product  $\eta Q_{i,e}$  as  $U_{i,e}$ , which stands for *unobservables*. I define the following ratio, whose numerator captures the extent to which the excluded unobservables co-vary with the insurer shares  $\phi_{i,t_e^s-12}$ , and whose denominator captures the extent to which the included observables co-vary with them:

$$\delta = \frac{\text{Cov}(U, \phi)}{\text{Var}(U)} \left[ \frac{\text{Cov}(O, \phi)}{\text{Var}(O)} \right]^{-1}. \quad (\text{A.31})$$

The ratio  $\delta$  therefore relays the strength of selection of unobservables relative to selection on observables in the extended model of equation (A.30). It is the object of primary interest in the analysis of Section 3.3.

The sample variances of log drawdowns and insurer shares in the regression specification of equation (A.30) are  $\hat{\sigma}_y^2$  and  $\hat{\sigma}_x^2$ . The *short regression* estimates the model (A.30) via OLS while only including event fixed effects: this corresponds to the estimates in column 1 of Table 3. The estimated beta and R-squared values from the short regression are  $\beta^\circ$  and  $R^\circ$ . The *long regression* estimates the same model but including the fully saturated set of interacted

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<sup>10</sup>Complementary work on the real effects of equity markets (as opposed to bond markets) includes ?, ?, ?, and ?.

fixed effects: this corresponds to the estimates in column 5 of Table 3. The estimated beta and R-squared values from the long regression are  $\tilde{\beta}$  and  $\tilde{R}$ . Let  $R_{\max}$  be the R-squared from a hypothetical regression that also includes all relevant unobservables. As in Oster (2019), I let  $R_{\max} = \min(1.3\tilde{R}, 1)$ .

We are interested in estimating the value of  $\delta$  consistent with a true treatment effect  $\hat{\beta} = 0$ . Also define  $\hat{\tau}_x$  as the variance of the residuals from a regression of the insurer shares  $\phi_{i,t}^S_{-12}$  in equation (A.30) on the interacted fixed effects. Then the threshold value  $\bar{\delta}$  is computed as

$$\bar{\delta} = \frac{\nu_1}{\nu_2}, \quad (\text{A.32})$$

where

$$\begin{aligned} \nu_1 = & (\tilde{\beta} - \hat{\beta})(\tilde{R} - R^\circ)\hat{\sigma}_y^2\hat{\tau}_x + (\tilde{\beta} - \hat{\beta})\hat{\sigma}_x^2\hat{\tau}_x(\beta^\circ - \tilde{\beta})^2 \\ & + 2((\tilde{\beta} - \hat{\beta}))^2 \left( \hat{\tau}_x(\beta^\circ - \tilde{\beta})\hat{\sigma}_x^2 \right) + (\tilde{\beta} - \hat{\beta})^3 \left( \hat{\tau}_x\hat{\sigma}_x^2 - \hat{\tau}_x^2 \right) \end{aligned} \quad (\text{A.33})$$

and

$$\begin{aligned} \nu_2 = & \left( R_{\max} - \tilde{R} \right) \hat{\sigma}_y^2(\beta^\circ - \tilde{\beta})\hat{\sigma}_x^2 + (\tilde{\beta} - \hat{\beta}) \left( R_{\max} - \tilde{R} \right) \hat{\sigma}_y^2 \left( \hat{\sigma}_x^2 - \hat{\tau}_x \right) \\ & + (\tilde{\beta} - \hat{\beta})^2 \left( \hat{\tau}_x \left( (\beta^\circ - \tilde{\beta})\hat{\sigma}_x^2 \right) + (\tilde{\beta} - \hat{\beta})^3 \left( \hat{\tau}_x\hat{\sigma}_x^2 - \hat{\tau}_x^2 \right) \right). \end{aligned} \quad (\text{A.34})$$

As mentioned in the main text, both Altonji et al. (2005) and Oster (2019) argue that results with a threshold value  $\bar{\delta}$  greater than or equal to 1 should be viewed as robust to the potential presence of selection on unobservables. A first argument for the  $\bar{\delta} \geq 1$  bound is empirical. Oster (2019), for example, studies a sample of all articles published in the *American Economic Review*, the *Quarterly Journal of Economics*, the *Journal of Political Economy*, and *Econometrica* between 2008 and 2010, and finds that only 30 percent of published empirical results are robust to a  $\bar{\delta} \geq 1$  bound. A second argument is theoretical: since the observables included in a researcher's baseline specification are normally the ones that she *a priori* reputes to be the most important, the  $\bar{\delta} \geq 1$  bound follows from a straightforward ordering argument.

## J Investor Composition and Bond Turnover Volatility

In Section 6, I discussed how a structural equilibrium asset pricing model might generate the empirical patterns that I have documented in this paper. The key empirical prediction resulting from this discussion is that higher fund ownership should forecast a larger increase in secondary-market bond turnover during downturns. Here I show that this prediction is strongly supported by the data. I define monthly *turnover* for each bond as the ratio of total trading volume to the value outstanding of the bond. I then consider the following counterpart of equations (5) and (22), which regresses turnover on quarter-lagged insurer shares:

$$\text{Turnover}_{i,t} = \alpha + \bar{\Lambda} \phi_{i,t-12} + \tilde{\Lambda} \phi_{i,t-12} \text{GZ}_t + \text{Interacted Fixed Effects} + \varepsilon_{i,t}. \quad (\text{A.35})$$

As in the previous specifications, I include an interaction with the [Gilchrist and Zakrajšek \(2012\)](#) index ( $GZ_t$ ) to capture variation in the estimated effects over the credit cycle. I also continue to include issuer dummies, bond characteristics dummies, and time dummies in the fixed effects interaction.

Figure [A.20](#) plots the estimated total effect  $\Lambda_t = \bar{\Lambda} + \tilde{\Lambda} GZ_t$  over time. Two features are apparent from these estimates. First, insurer ownership substantially reduces bond turnover in normal times, when credit spreads are low. For example, in quiet periods such as 2005-07 and 2017-19, the estimated total effect is  $\Lambda_t = -.06$ , which is economically large given that the unconditional average of monthly turnover in the sample is about 10 percent. Second, investor base composition is a strong predictor of spikes in bond turnover in crisis times, as evident from the dynamics of the estimated  $\Lambda_t$ . Lower insurer ownership (and therefore higher fund ownership) forecasts a larger increase in secondary-market bond turnover during downturns, which is precisely the empirical prediction of interest outlined in [Section 6](#).

	US Insurers				US Funds*				Non-US Funds*			
	2005	2010	2015	2020	2005	2010	2015	2020	2005	2010	2015	2020
<b>Asset Allocation (%)</b>												
Bonds: Corporate, US	49	51	54	57	18	25	31	29	6	14	23	23
Bonds: Corporate, Non-US	5	4	3	3	2	3	2	2	33	40	37	33
Bonds: Sovereign, US	23	23	21	17	16	21	21	21	3	3	5	6
Bonds: Sovereign, Non-US	2	2	2	1	4	6	7	6	51	39	32	31
Bonds: Other, Incl. ABS	6	6	5	5	59	44	39	41	7	3	3	7
Equities	14	14	15	17	1	1	1	1	0	0	0	0

*\*Fixed income specialists only*

Table A.1: **Overview of overall portfolio holdings of insurers and fixed income specialist funds.** This table shows the composition of the portfolio of invested assets of insurance companies and fixed income specialist funds. I show the share of the aggregate portfolio of these institutions that is invested in US corporate bonds (defined as TRACE-reportable bonds), non-US corporate bonds, US sovereign bonds, non-US sovereign bonds, other bonds including asset-backed securities, and equities.

	<b>US Investment Grade Corporate Bonds</b>			
	<b>2007</b>	<b>2010</b>	<b>2015</b>	<b>2020</b>
<b>Number of Securities</b>	7,951	7,835	9,561	11,293
<b>Value Outstanding (\$M)</b>				
Mean	407	501	645	698
Median	250	300	474	500
95 <sup>th</sup> Percentile	1,500	1,750	2,000	2,000
<b>Total Value (\$B)</b>	3,236	3,925	6,165	7,880
<b>Number of Issuers</b>	1,255	1,411	1,492	1,868
<b>Other Characteristics</b>				
Average Duration (Yrs)	5.4	5.6	6.0	7.4
Share Junior (%)	7	6	5	7
Share Floating (%)	13	12	7	7
Share Callable (%)	48	57	66	76

Table A.2: **U.S. investment-grade corporate bonds: additional summary statistics.** This table reports summary statistics for the U.S. investment grade corporate bonds in the sample, including number of securities, statistics on their face value outstanding, the total size of the market, the number of issuers, average bond duration, and the share of bonds that is junior, floating-rate, or has callable features. Data is shown for the years 2007, 2010, 2015, and 2020. Bonds with a reported face value of less than \$25 million are excluded.

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Insurer Share	-.41 (.10)	-.42 (.10)	-.56 (.20)	-.49 (.20)
<i>Fixed Effects Interaction:</i>				
Bond Size	Yes	Yes	Yes	Yes
Event Dummy	Yes	Yes	Yes	Yes
Bond Duration	Yes	Yes	Yes	Yes
Bond Rating	Yes	Yes	Yes	Yes
Issuer Dummy	Yes	Yes	Yes	Yes
Callable Dummy	—	Yes	—	Yes
Senior Dummy	—	Yes	—	Yes
Coupon Type	—	Yes	—	Yes
Identifying Observations	5,328	4,945	2,381	2,304
Identifying Issuers	452	437	373	363
$R^2$	.84	.85	.88	.89
First Stage $F$	—	—	56.3	54.0

Table A.3: **Shift-share IV estimates, excluding bonds issued prior to 2005.** This table repeats the estimates in Table 4, excluding bonds issued prior to 2005 from the shift-share instrumental variable (IV) regressions. Since the insurance holdings data start in 2005, in constructing the shift-share instrument for bonds issued prior to 2005 the baseline analysis uses insurers' holdings in 2005 to proxy for holdings at issuance. The estimates in this table confirm that excluding these bonds does not materially impact the results. The estimates are from weighted least squares (WLS) regressions, with bond sizes as weights. Standard errors are clustered at the issuer by event level and are reported in parentheses.



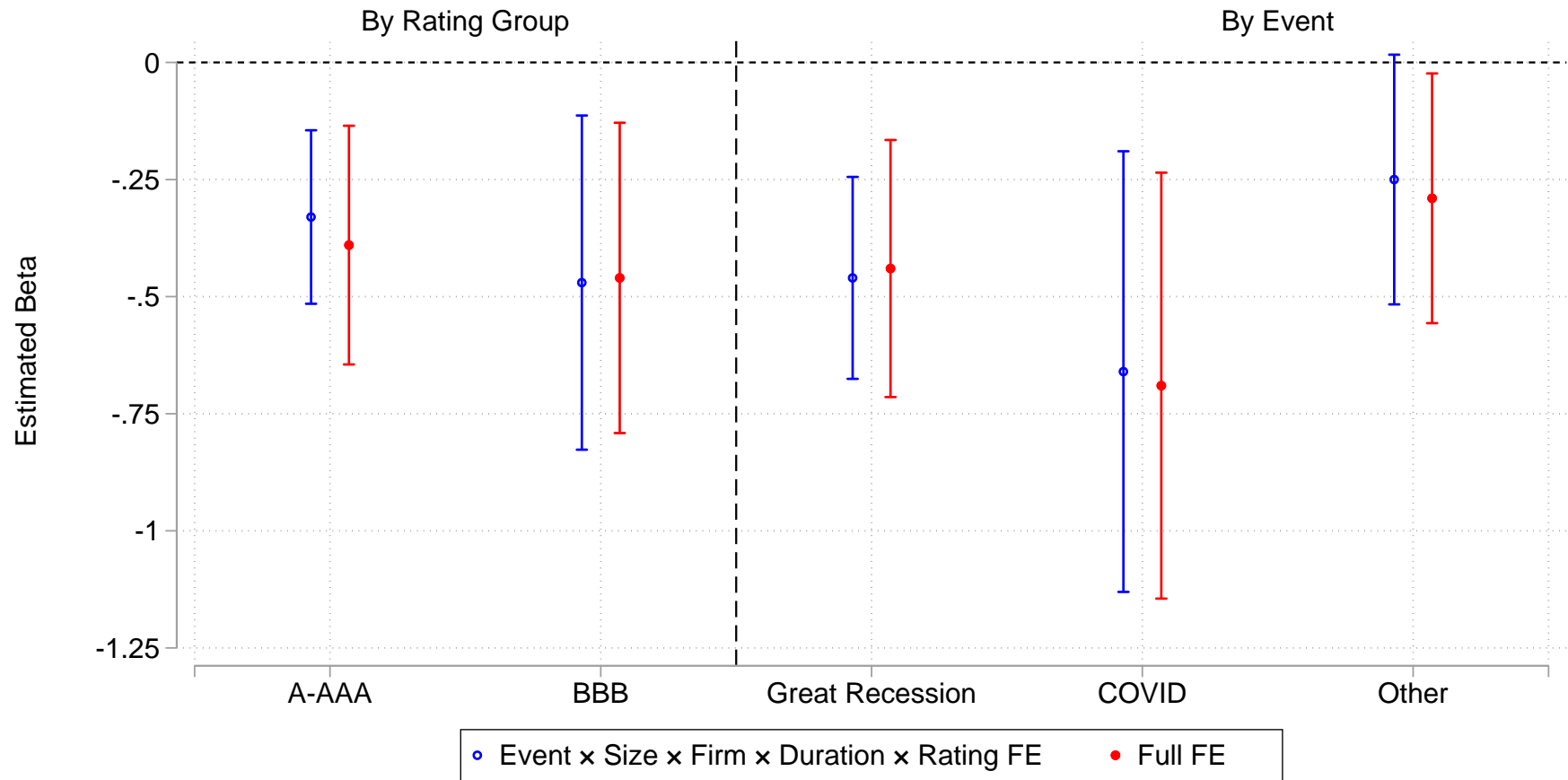
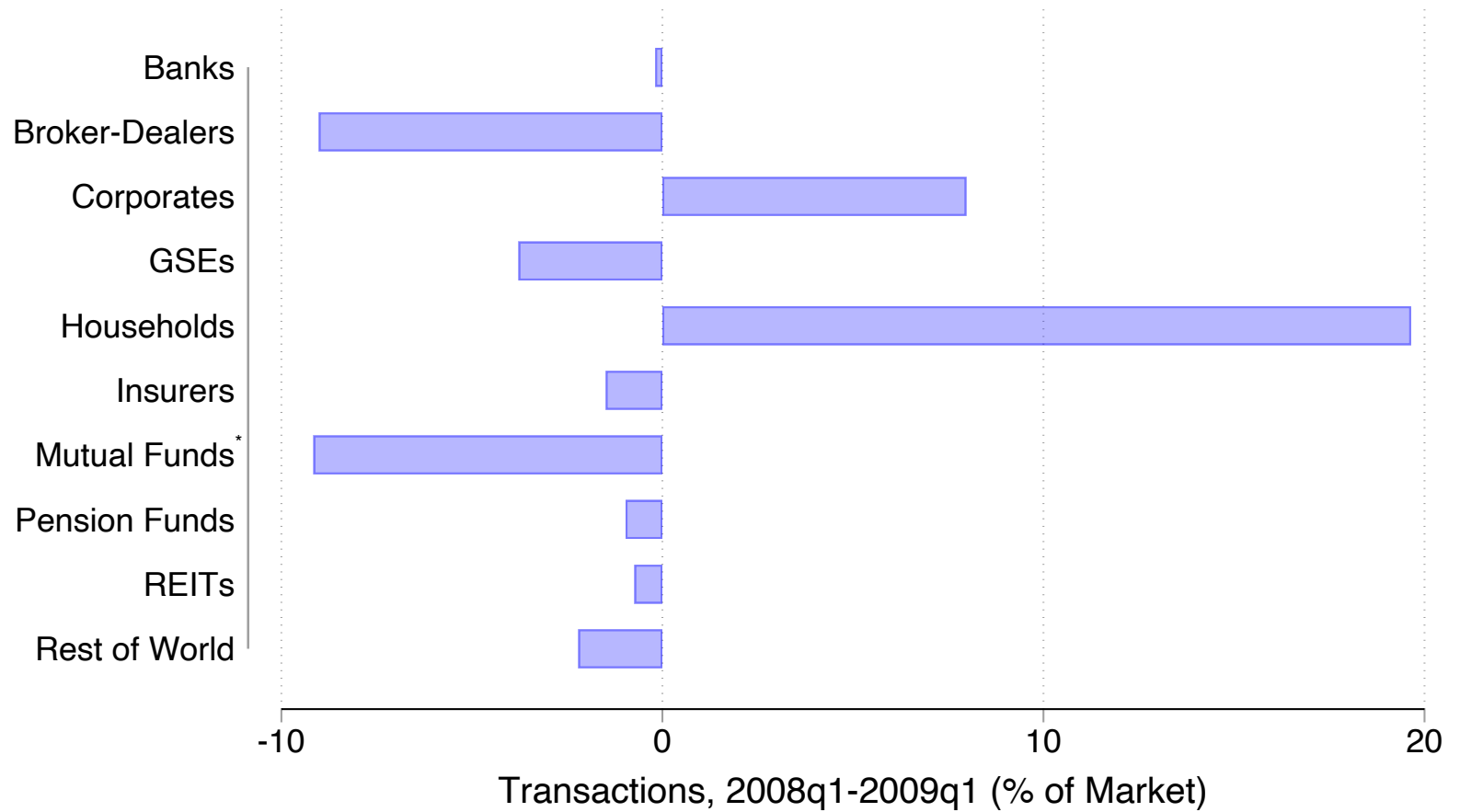


Figure A.1: **Heterogeneity in the estimated effects across rating groups and events.** This figure shows estimates from the regression specification in equation (4) on various subsamples for U.S. investment grade bonds. The first two groups of bars show estimates in the subsample of bonds rated AAA through A- and in the subsample of bonds rated BBB+ through BBB-, respectively. The remaining bars display separate estimates for different events. The estimates are from weighted least squares (WLS) regressions, with bond sizes as weights. The displayed confidence intervals are at the 95 percent confidence level and are clustered at the issuer by event level.



\*Includes ETFs and money market funds

Figure A.2: **Net transactions in corporate and foreign bonds by institutional sector, from the U.S. Flow of Funds.** This figure plots the net transactions in corporate and foreign bonds by institutional sector between 2008Q1 and 2009Q1 from the Flow of Funds (FoF). The net transactions are scaled by the lagged total amount of corporate and foreign bonds reported in the FoF. By construction, the bars sum to zero, so that the figure shows the reallocation of ownership across sectors over the course of the financial crisis. The household sector in the FoF is a residual category that includes entities such as nonprofits and hedge funds. Transactions by the corporate sector include net bond issuance.

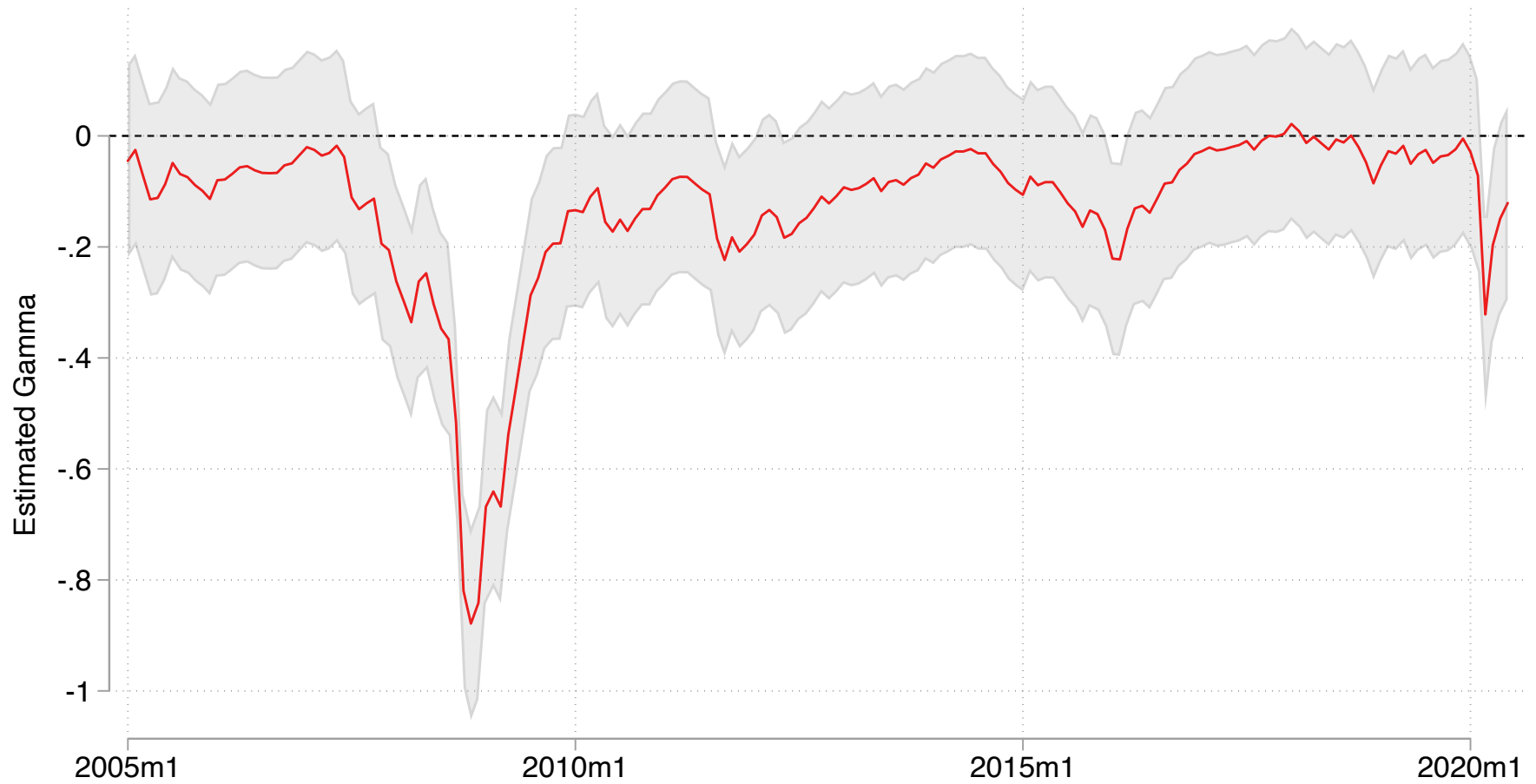


Figure A.3: **Insurer shares and bond betas: specification with one-quarter betas.** This figure replicates the results in Figure 6 using betas that are estimated on a one-quarter rolling window.

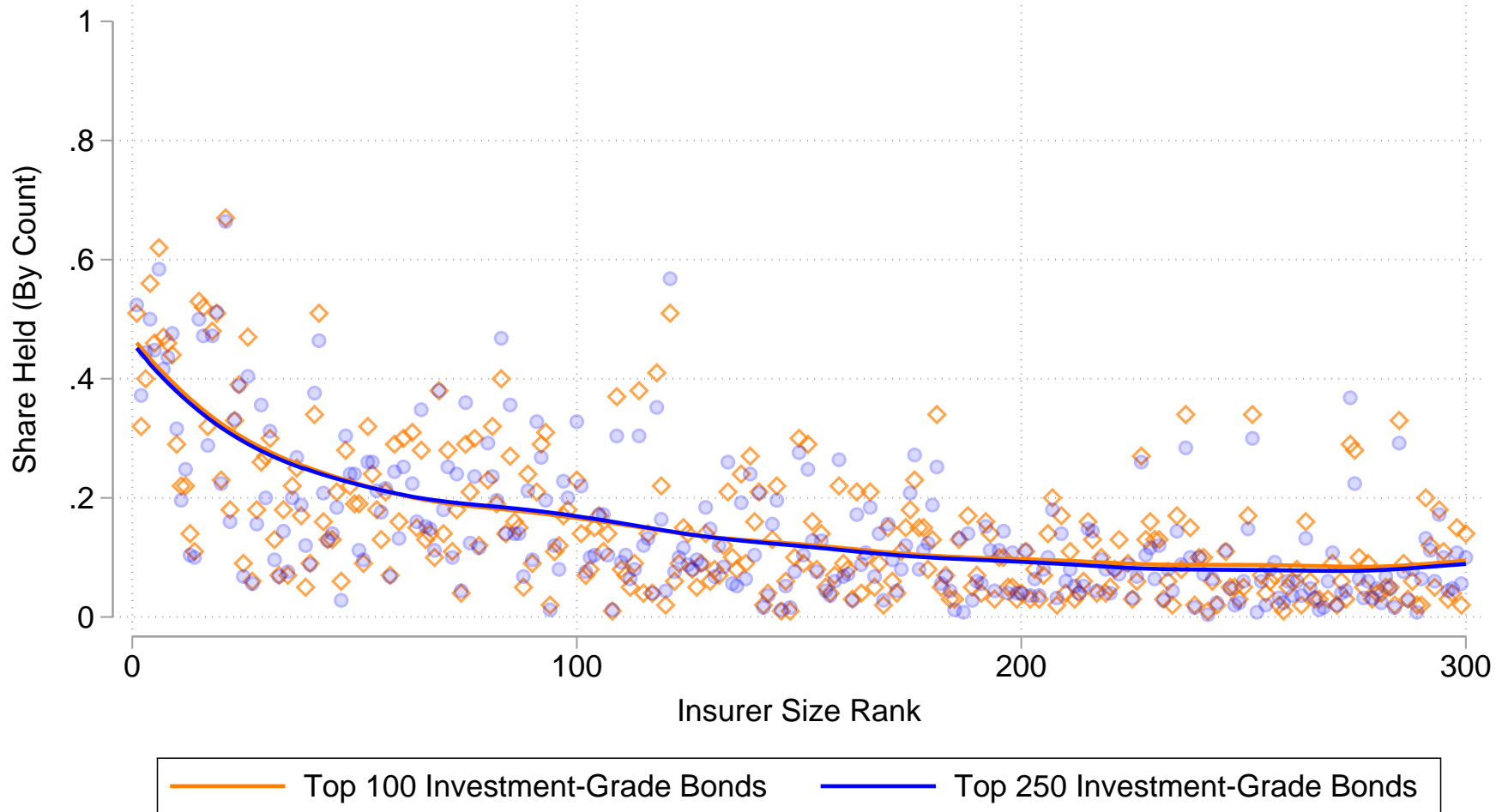


Figure A.4: **Holdings idiosyncrasy: robustness.** This figure replicates the analysis in Figure 10 with smaller sets of bonds. The figure ranks insurers by the overall size of their portfolio investment, and shows the share of the 100 largest (*orange diamonds*) and 250 largest (*blue dots*) actively traded investment-grade U.S. corporate bonds that they hold an open position in, all measured cross-sectionally as of 2017Q4. The thick lines show the fit from lowess regressions of the investment shares on the fund rank.

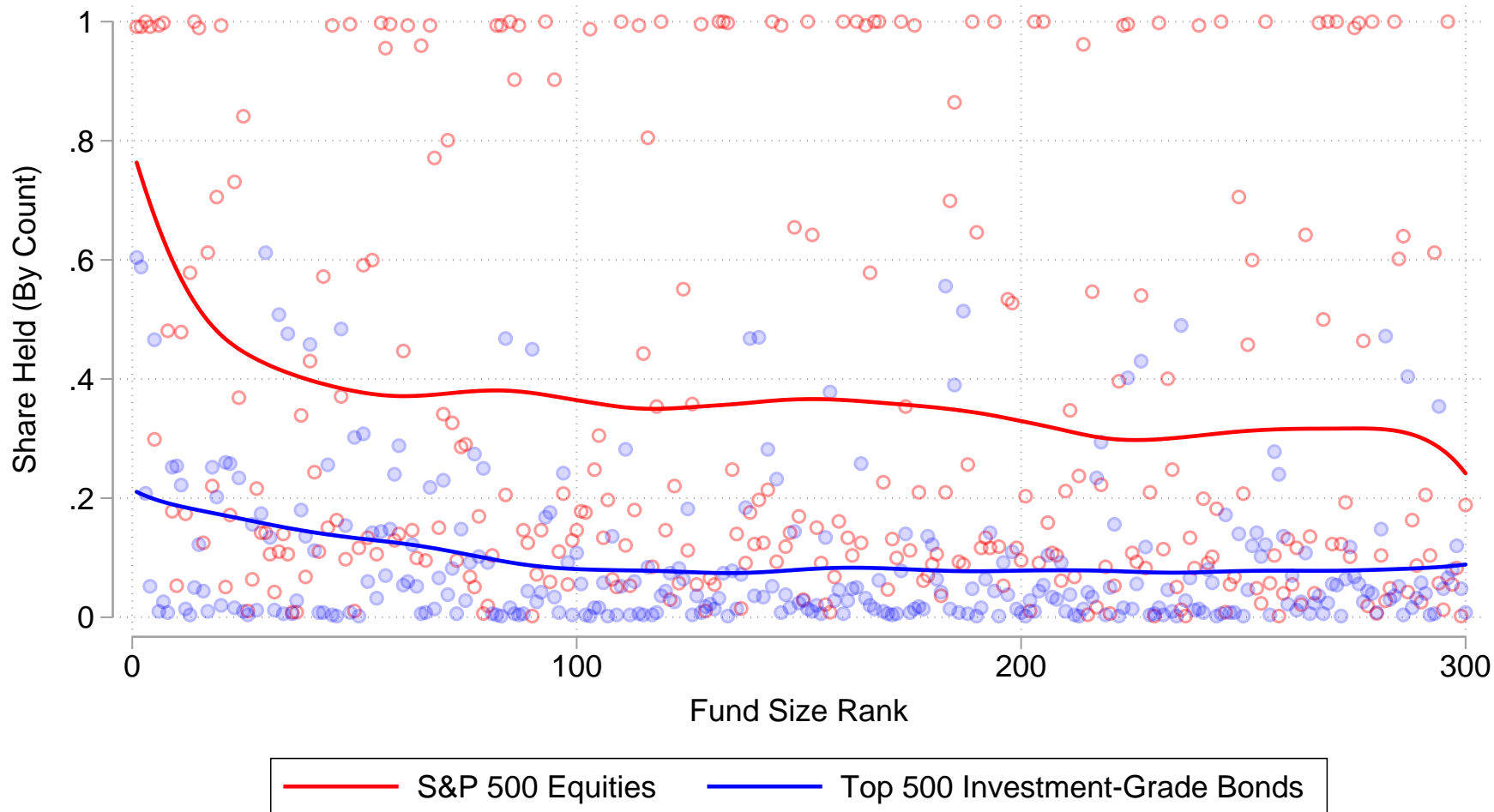


Figure A.5: **Holdings idiosyncrasy: mutual funds and ETFs.** This figure replicates the analysis in Figure 10 for mutual funds and ETFs. The figure ranks funds by the overall size of their portfolio investment, separately for equity specialists (*red dots*) and fixed income specialists (*blue dots*). The *blue dots* show the share of the 500 largest actively traded investment-grade U.S. corporate bonds that each fund holds an open position in, while the *red dots* show the share of S&P 500 equities that it holds an open position in, all measured cross-sectionally as of 2017Q4. The thick lines display the fit from lowess regressions of the investment shares (shown by the dots) on the fund rank.

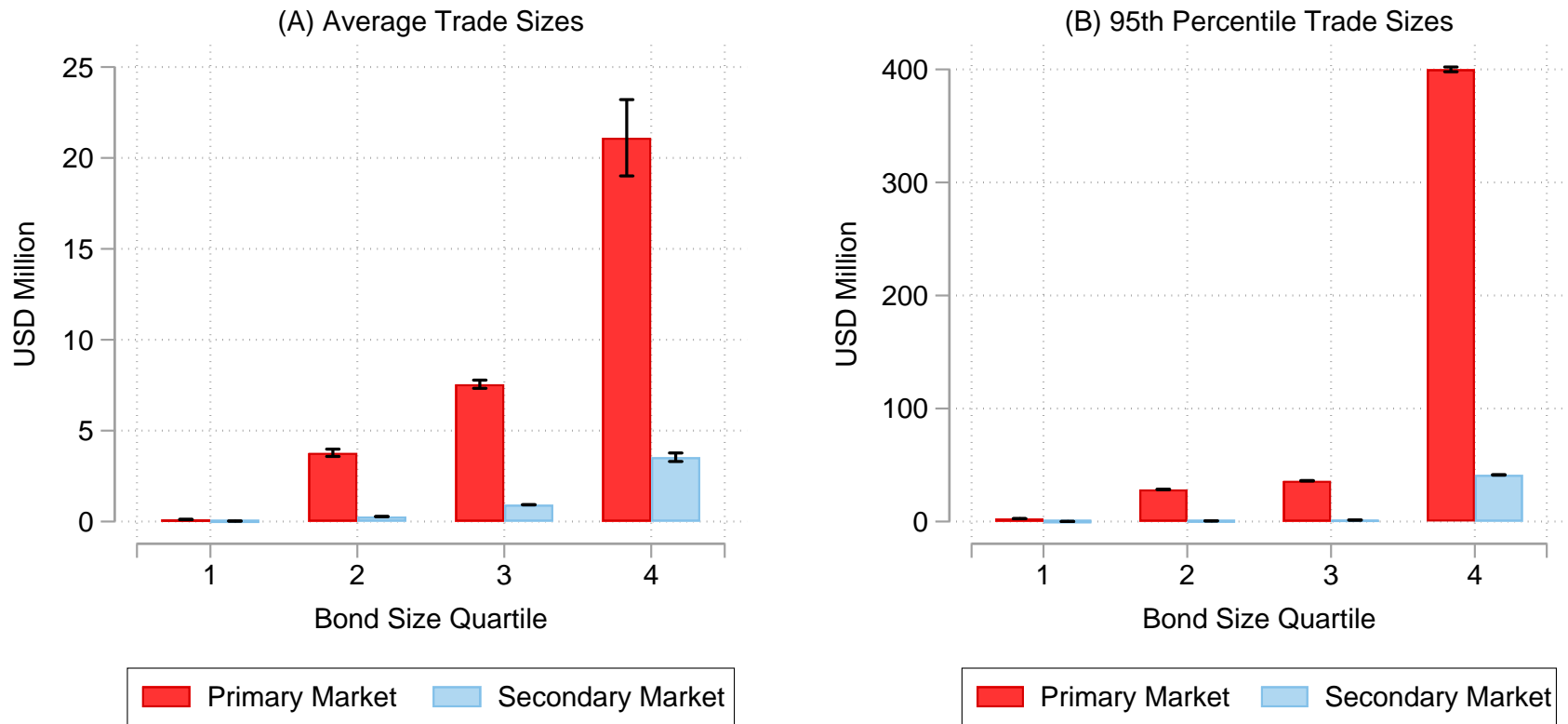


Figure A.6: **Trade sizes in the primary and secondary U.S. investment-grade corporate bond market.** Panel A plots the average trade size on the primary market (*red bars*) and on the secondary market (*blue bars*), by quartile of bond trade size, in the full sample of transactions in U.S. investment-grade corporate bonds from TRACE Academic. Panel B plots the size of trades at the 95th percentile of the trade size distribution.

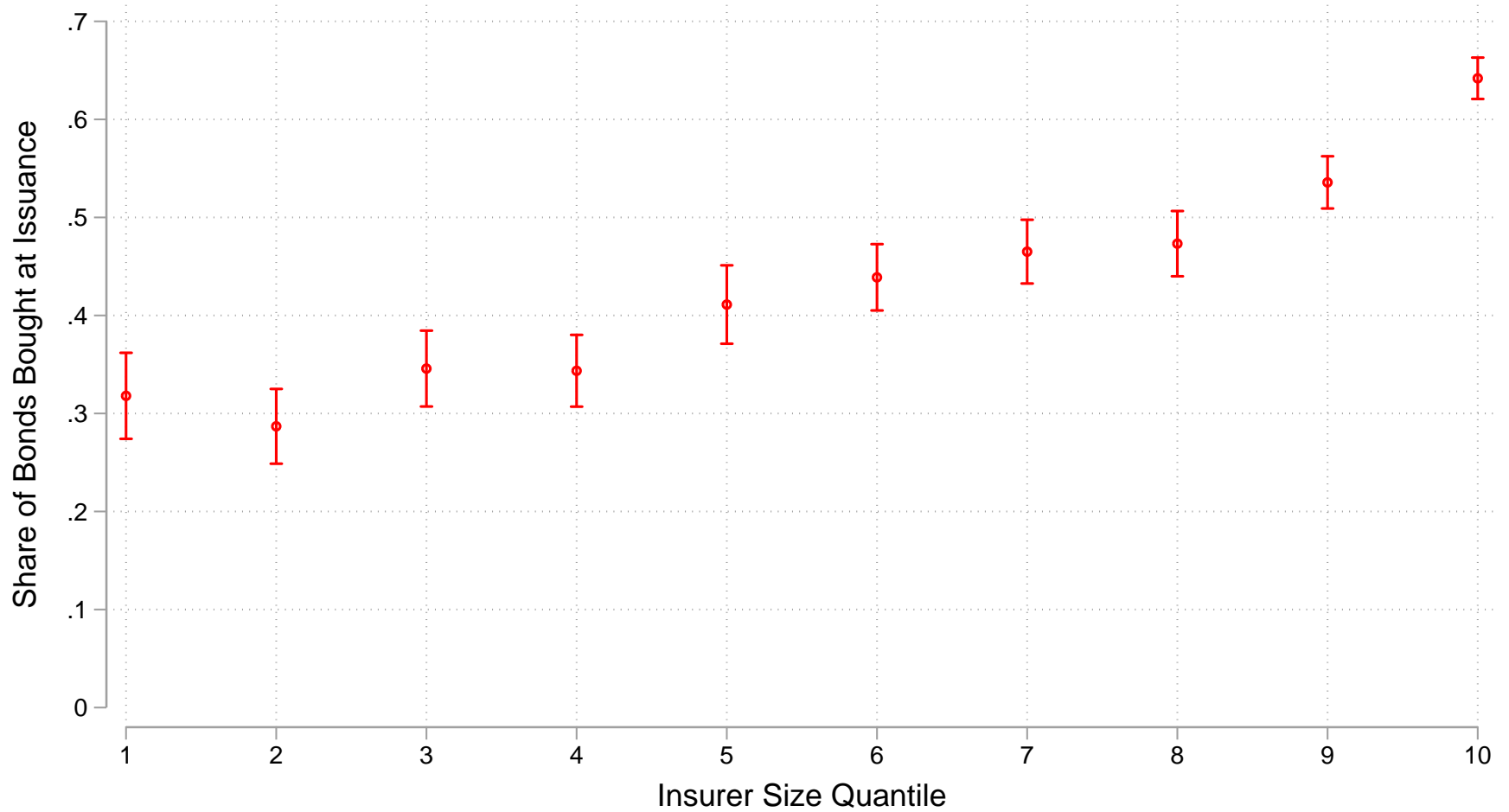


Figure A.7: **Share of bonds purchased on the primary market across the insurer size distribution.** This figure plots the share of all insurer bond purchases that are made on the primary market by insurer size decile. The bars correspond to 95 percent confidence intervals.

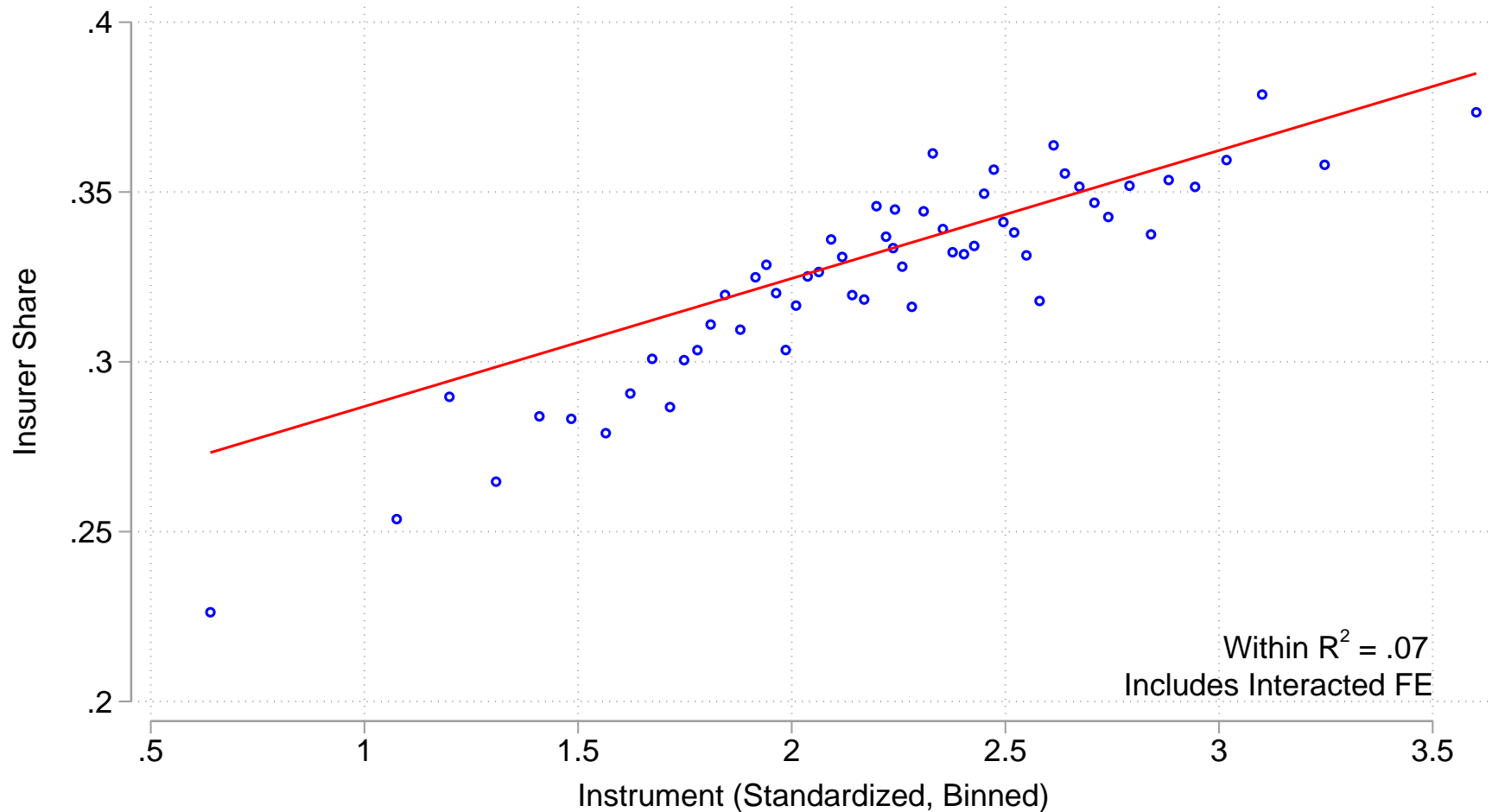


Figure A.8: **Shift-share IV: first stage relationship.** This plot shows a binned scatter plot of insurer shares against the instrument  $Z_i$  from the first stage of the 2SLS regression with fully saturated interacted fixed effects in Section 3 and Table 4. For expositional purpose, the instrument is standardized so that its standard deviation is equal to one.



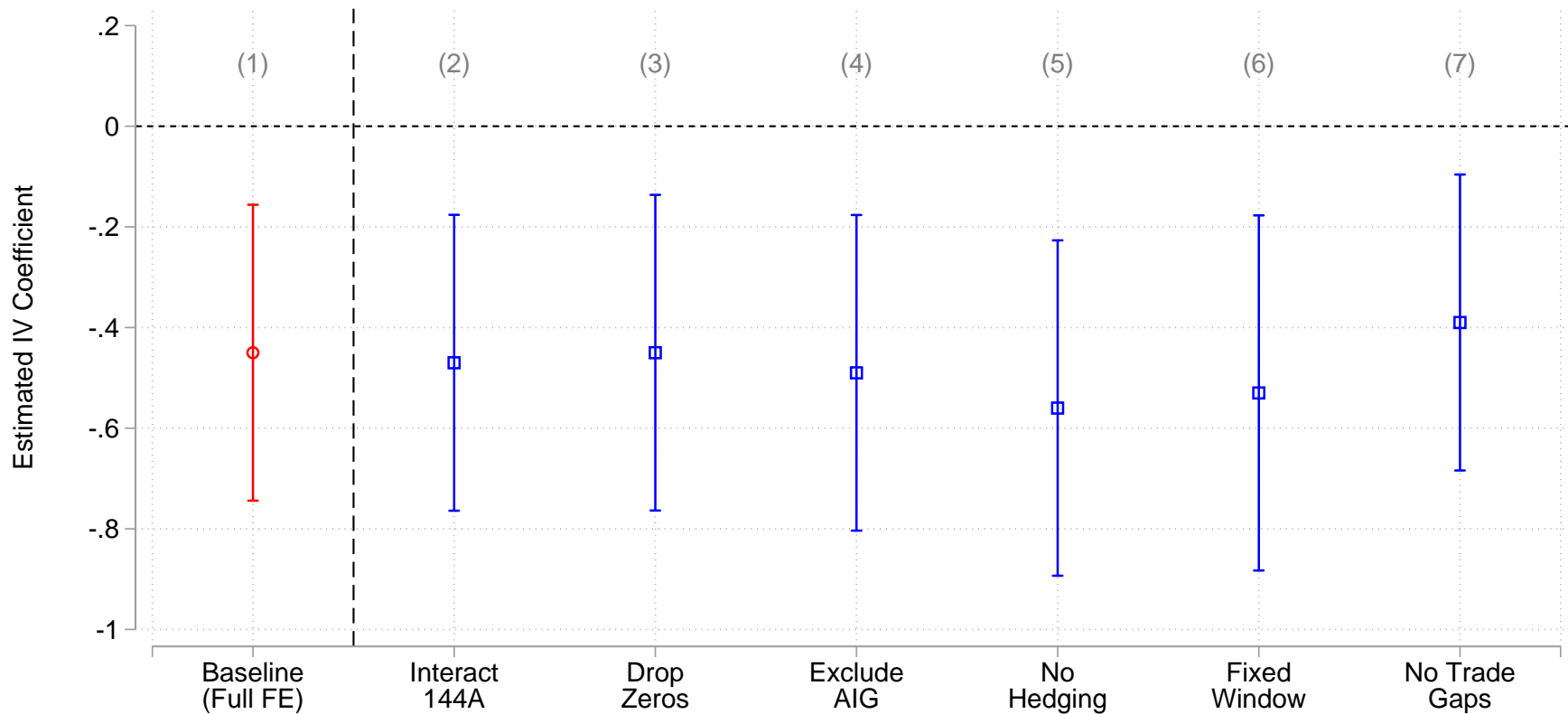


Figure A.9: **Shift-share IV: robustness to alternative specifications.** This figure demonstrates the robustness of the baseline 2SLS estimate (*red bar*) from column 8 of Table 4 to further variations in the empirical specification. Bar 2 introduces an additional interaction with a dummy indicating whether a bond is issued under SEC rule 144A. Bar 3 excludes bonds with a zero insurer share from the sample. Bar 4 excludes the positions of AIG from the computation of the insurer positions  $X_{i,t}^I$ . Bar 5 uses raw returns  $R_{i,t}$  in place of the hedged returns  $R_{i,t}^H$ . Bar 6 uses an alternative measure of drawdowns which applies the same window to all bonds for a given event. Bar 7 drops any bonds that trade less frequently than once a week in a given event period. The displayed confidence intervals are at the 95 percent confidence level and are clustered at the issuer by event level.

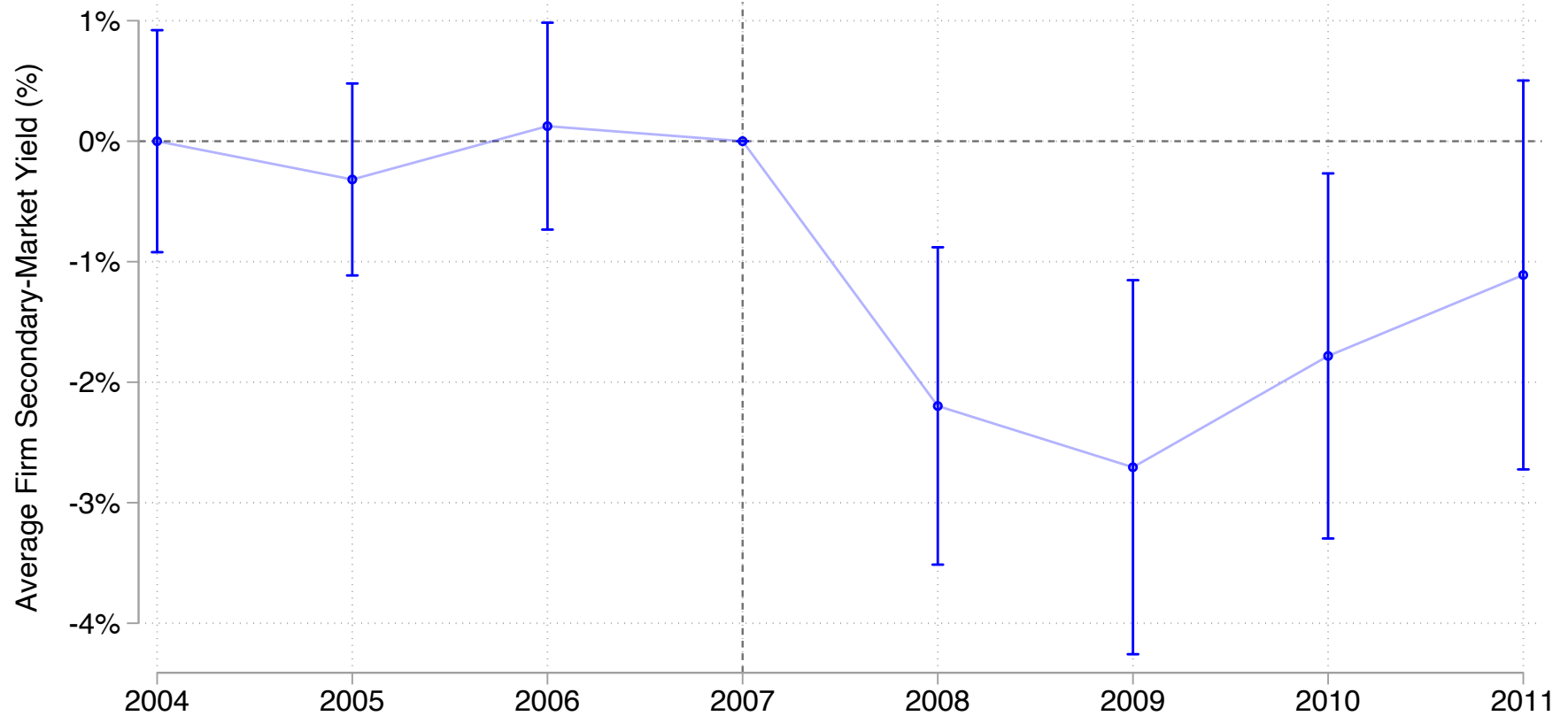


Figure A.10: **The association between insurer bond ownership and firm-level secondary-market yield dynamics in the Great Recession.** This figure shows the estimated coefficients from the dynamic difference-in-differences specification in equation (20), when using average firm secondary-market bond yields rather than primary-market offering yields. The specification is estimated on the sample of U.S. firms with outstanding bonds in 2007Q1, excluding speculative-grade issuers. The estimates are from just-identified two-stage least-squares, using the firm-level instrument in equation (17), interacted with year dummies. The coefficients quantify the association of average firm secondary-market yields (*blue line*) with the share of a firm's bonds held by domestic insurers in 2007Q1. The controls consist of firm-level covariates, measured in 2007 and interacted with time dummies: these include fixed effects for issuer rating, average duration of the firm's outstanding bonds, two-digit industry, and deciles of firm size and firm leverage. Standard errors are clustered at the firm level. Bars correspond to 95 percent confidence intervals.

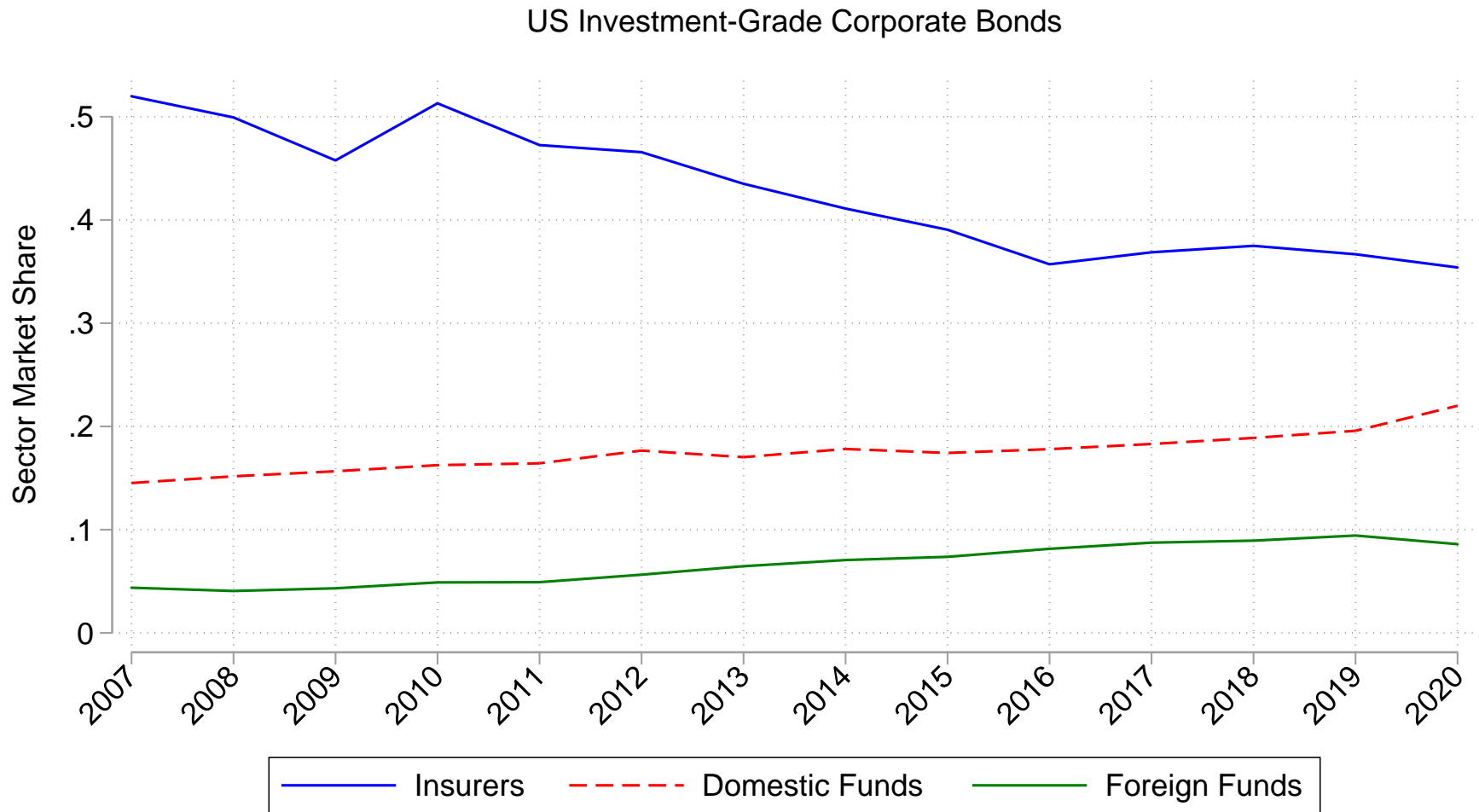


Figure A.11: **Sectoral ownership shares: U.S. investment-grade corporate bonds.** This figure plots time series for the shares of all U.S. investment-grade corporate bonds owned by domestic insurance companies, domestic mutual funds and ETFs, and foreign mutual funds and ETFs, as observed in the holdings micro-data. The underlying dollar amounts correspond to the ones shown in Figure 1.

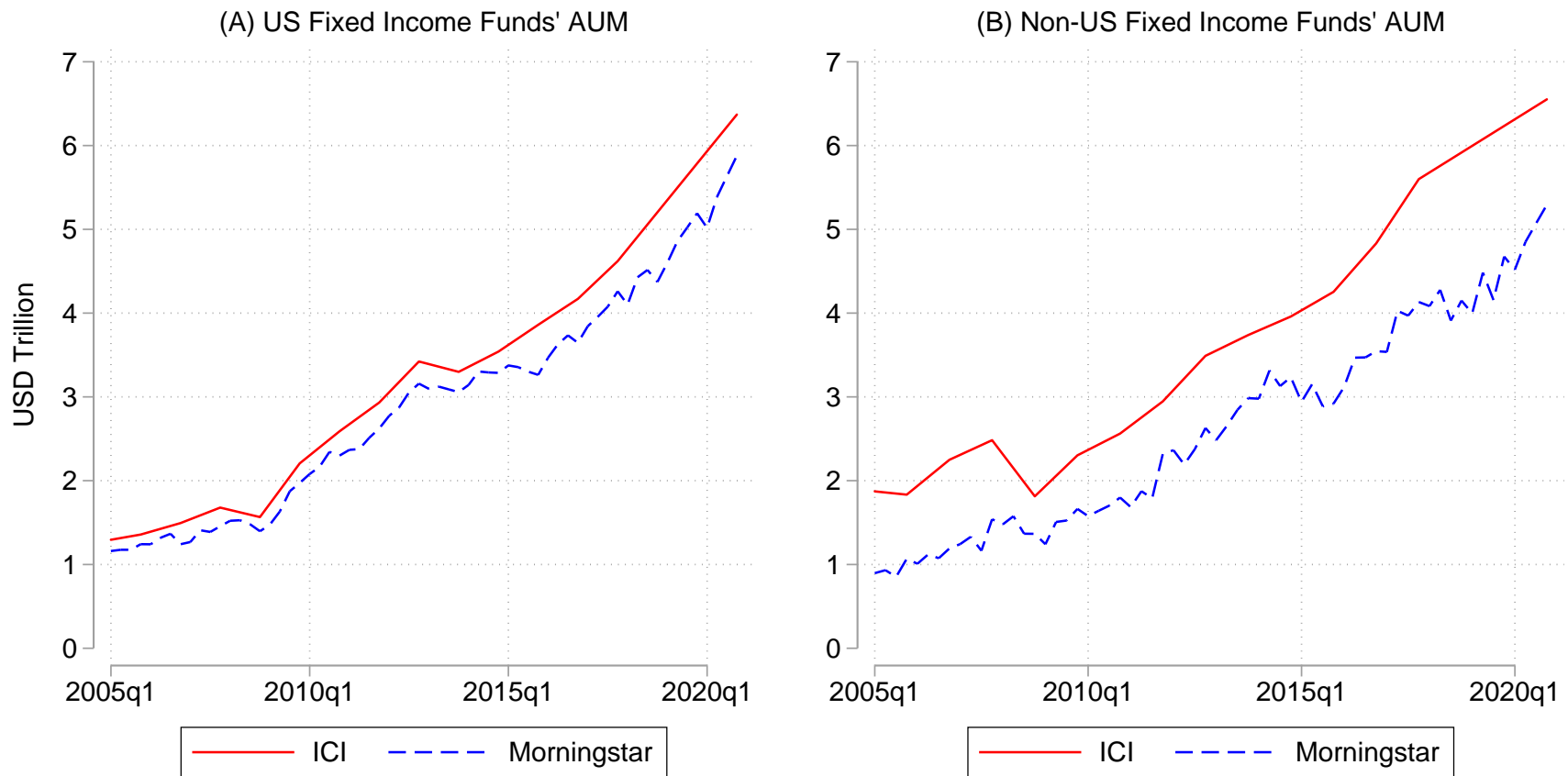


Figure A.12: **Aggregate value of fixed income funds' positions in the Morningstar data, compared to ICI benchmarks.** Panel A shows the aggregate market value of all positions held by U.S. domiciled fixed income investment funds in the Morningstar data (*dashed blue line*), alongside the aggregate value of the positions of U.S. fixed income mutual funds and ETFs reported by the Investment Company Institute (ICI, *solid red line*). Panel B shows the aggregate market value of all positions held by fixed income investment funds domiciled outside of the United States in the Morningstar data (*dashed blue line*), alongside the corresponding ICI benchmark (*solid red line*).

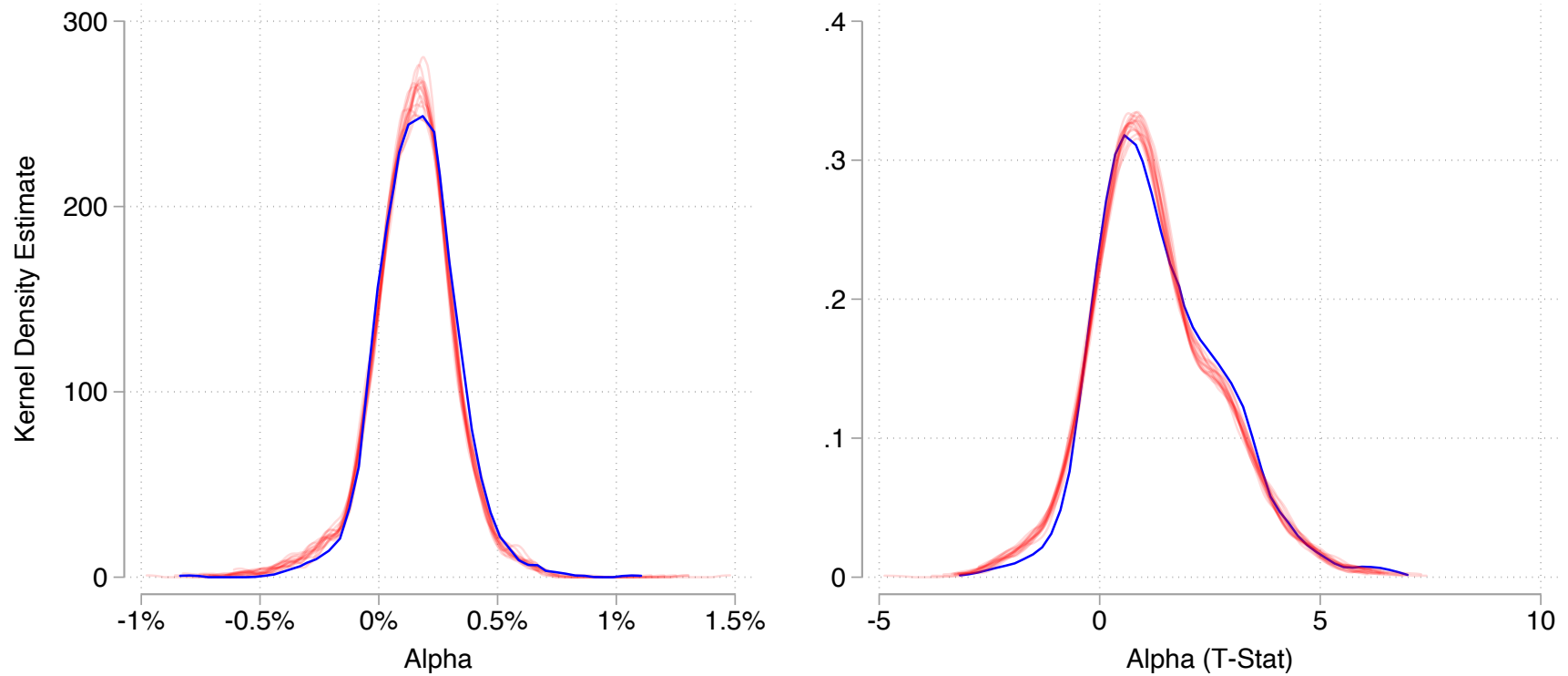


Figure A.13: **Testing for the presence of skill in the cross-section of insurers: Fama-French bootstrap approach.** This figure plots kernel density estimates of the empirical distribution of residual alphas and their  $t$  statistics in the cross-section of insurance firms (*blue curves*), estimated as described in Appendix Section C, alongside bootstrap realizations of the same (*red curves*). The bootstrap simulations impose zero residual alphas by construction. Each red curve averages over 1000 independent bootstrap simulations.

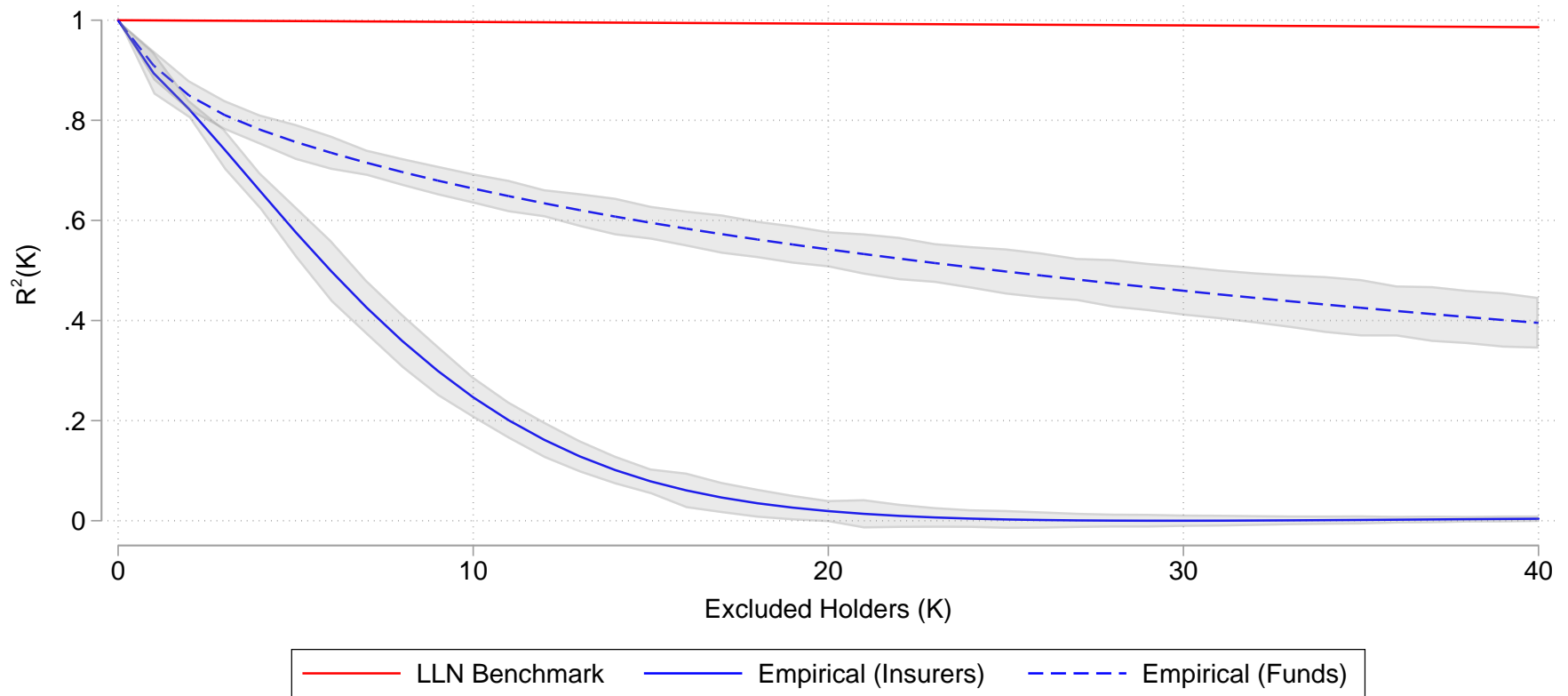


Figure A.14: **Deviations from the law of large numbers in insurer holdings.** The *solid blue line* plots the empirical R-squared values obtained from estimating equation (A.2). These estimates regress insurer shares  $\phi_{i,t}$  against truncated insurer shares  $\phi_{i,t}^{(K)}$ , which exclude the holdings of the largest  $K$  holders underlying each position. The *solid red line* plots the theoretical R-squared values as we vary  $K$  from the benchmark model in equation (A.2), in which the law of large numbers applies. For comparison, the *dashed blue line* also plots the same estimates for mutual funds and ETFs.

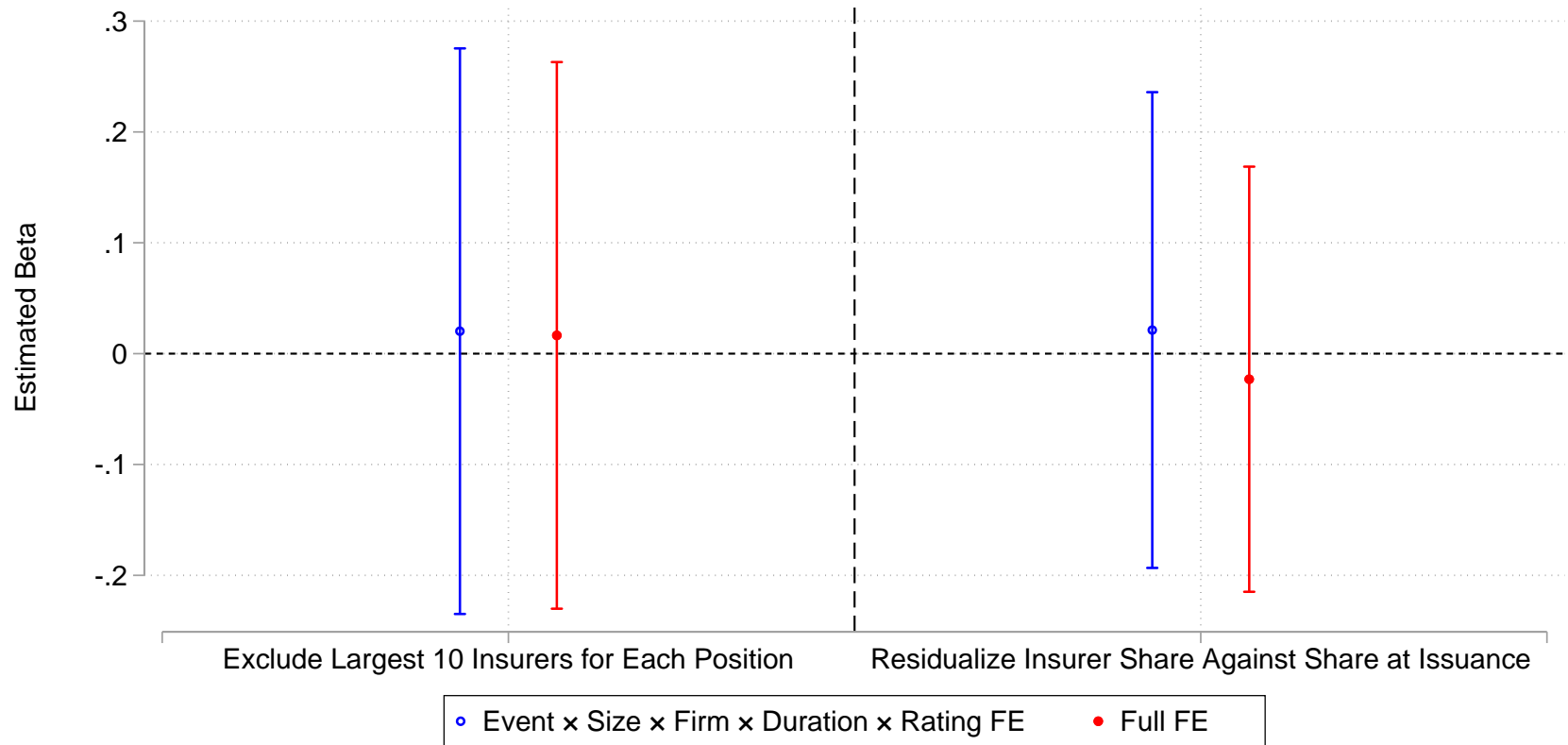


Figure A.15: **Further placebo exercises for baseline OLS regressions.** This figure shows placebo estimates obtained from estimating two variants of equation (4) for U.S. investment-grade corporate bonds. The first placebo exercise replaces the true insurer shares  $\phi_{i,t_e^s-12}$  with the truncated shares  $\phi_{i,t_e^s-12}^{(10)}$ , which exclude the largest underlying 10 holders for each bond. The second placebo exercise regresses the true insurer shares  $\phi_{i,t_e^s-12}$  against the insurer shares at issuance  $\phi_{i,\tau(i)}$ , and then uses the residuals from this regression as the right-hand side argument in equation (4). The displayed confidence intervals are at the 95 percent confidence level and are clustered at the issuer by event level.

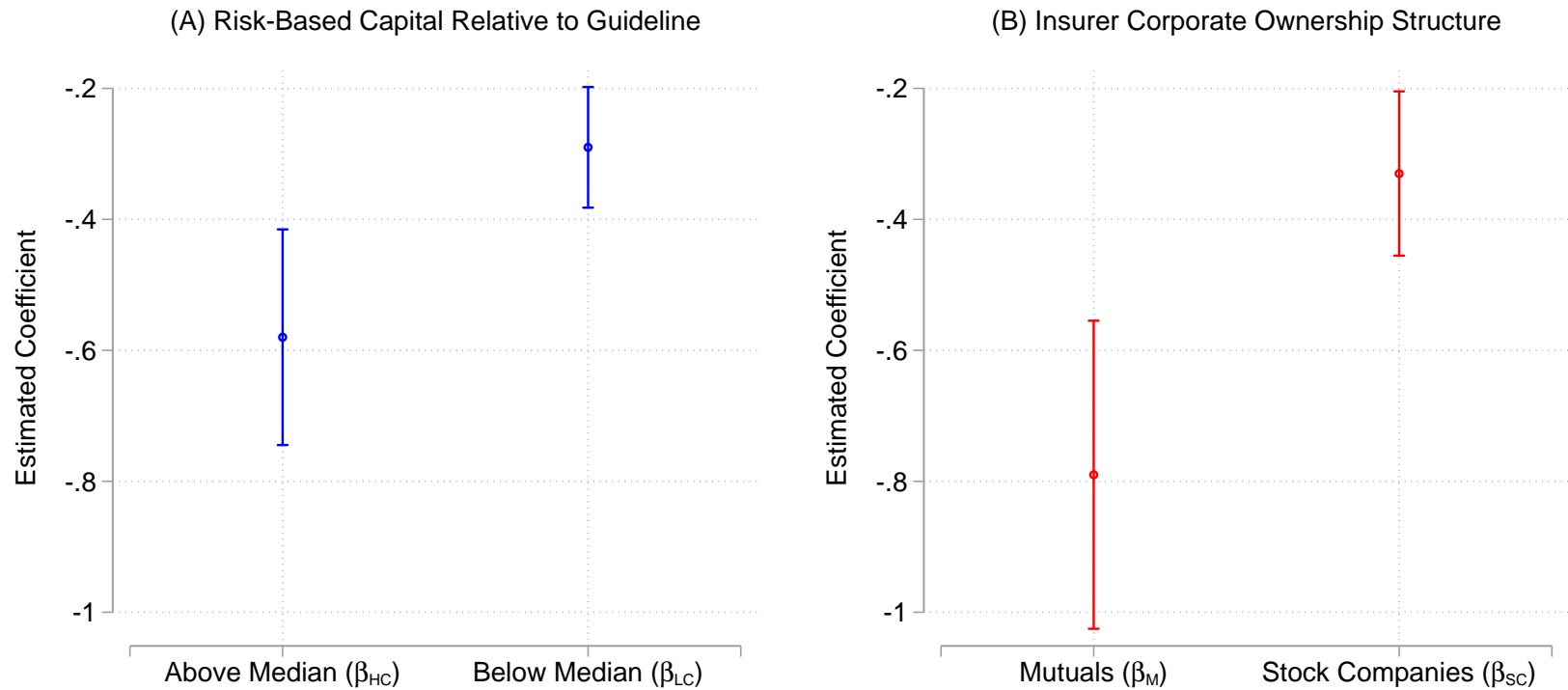


Figure A.16: **Heterogeneity within the insurance sector.** This figure displays the results concerning heterogeneity within the insurance sector introduced in Appendix Section E. Panel A shows the estimated coefficients  $\hat{\beta}_{HC}$  and  $\hat{\beta}_{LC}$  for the specification in equation (A.5). These coefficients respectively quantify the impact on bond drawdowns of ownership by insurers with above-median and below-median risk-based capital relative to guideline (as measured by the difference between each insurer's A.M. Best Capital Adequacy Ratio and the guideline for the insurer's current rating). Panel B shows the estimated coefficients  $\hat{\beta}_M$  and  $\hat{\beta}_{SC}$  for the specification in equation (A.6), which measure the impact on bond drawdowns of ownership by mutuals and stocks companies. Standard errors are clustered at the issuer by event level, and bars correspond to 95 percent confidence intervals. For both pairs of estimates, a Wald test rejects the null hypothesis of coefficient equality with  $p < .01$ .



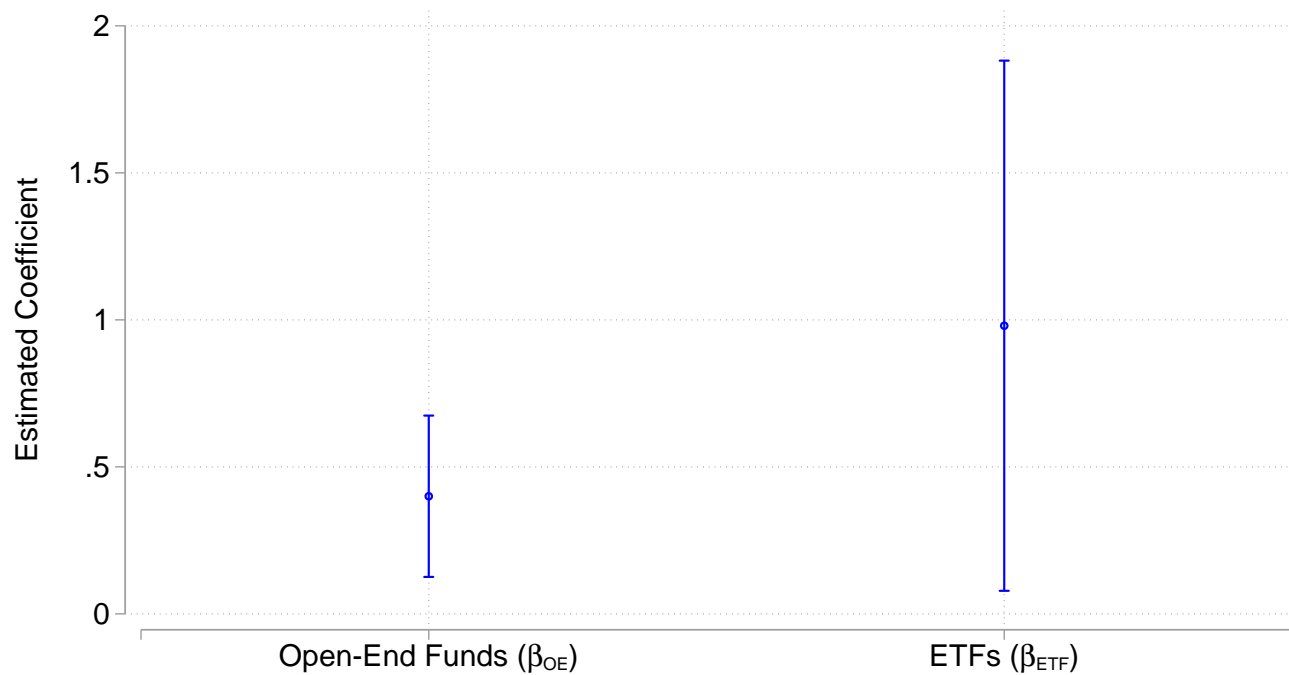


Figure A.17: **Heterogeneity between open-end mutual funds and ETFs.** This figure displays the results concerning heterogeneity between open-end mutual funds and exchange traded funds (ETFs) introduced in Appendix Section G. The dots show the estimated coefficients  $\hat{\beta}_{OE}$  and  $\hat{\beta}_{ETF}$  for the specification in equation (A.13). These coefficients respectively quantify the impact on bond drawdowns of ownership by open-end mutual funds and ETFs. Standard errors are clustered at the issuer by event level, and bars correspond to 95 percent confidence intervals. A Wald test fails to reject the null hypothesis of coefficient equality at the 10 percent confidence level.

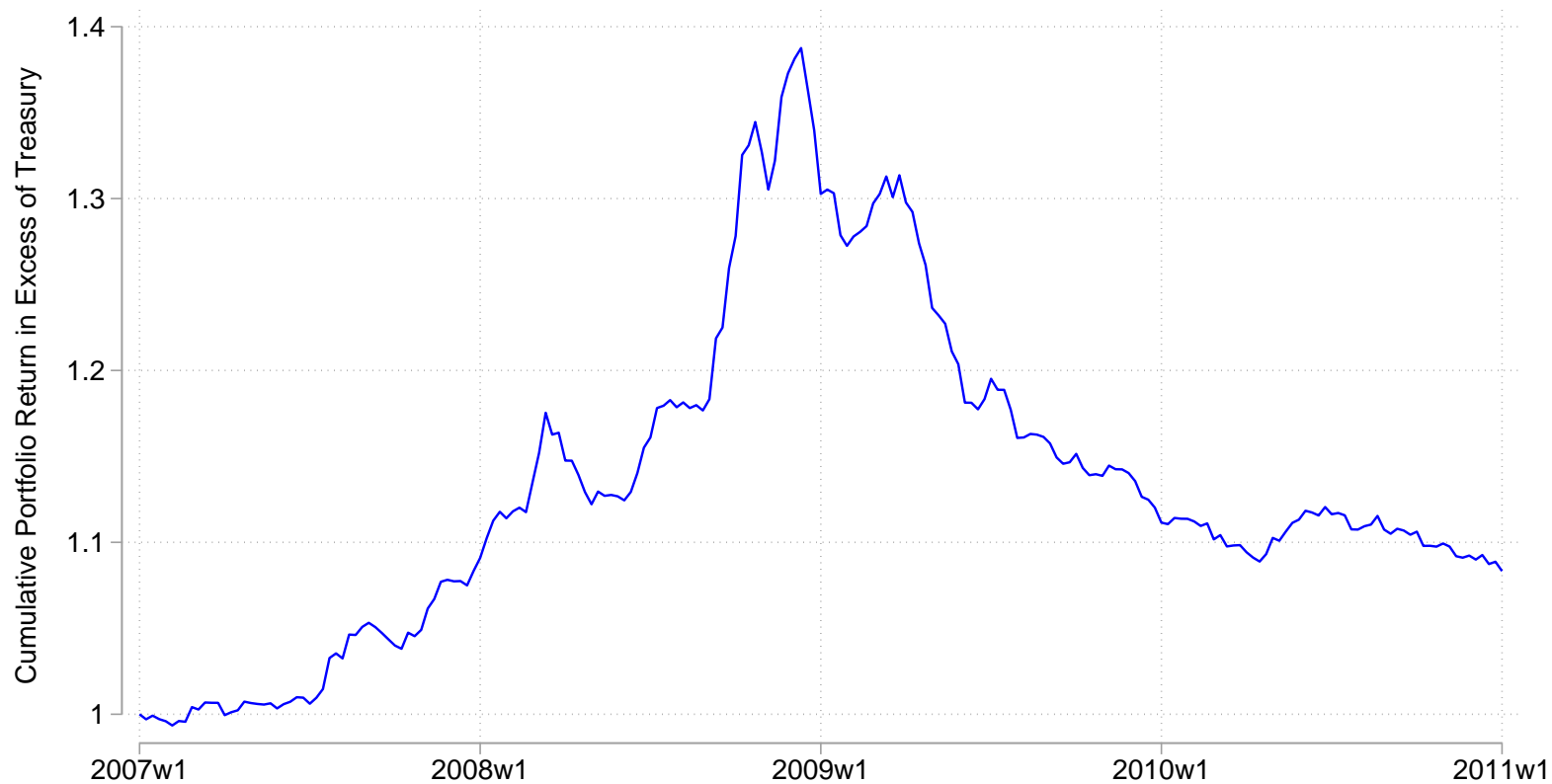


Figure A.18: **Reversion of fire sale returns.** This figure shows reversion in the abnormal returns due to fire sales in the Great Recession. I construct a portfolio with positions in investment-grade bonds that are outstanding as of 2007Q1 and have at least one counterpart bond that is issued by the same firm and has the same characteristics (duration, rating, issue size, seniority, and so forth). Within each group of matching bonds, I sort bonds according to their pre-crisis insurer share. The portfolio takes long positions in bonds that have an insurer share above the group median, and short positions in bonds below the group median. The positions in each bond are equal-sized, in dollar terms. The graph shows the cumulative returns on this portfolio in excess of a basket of Treasuries of matched duration, abstracting from transaction costs.

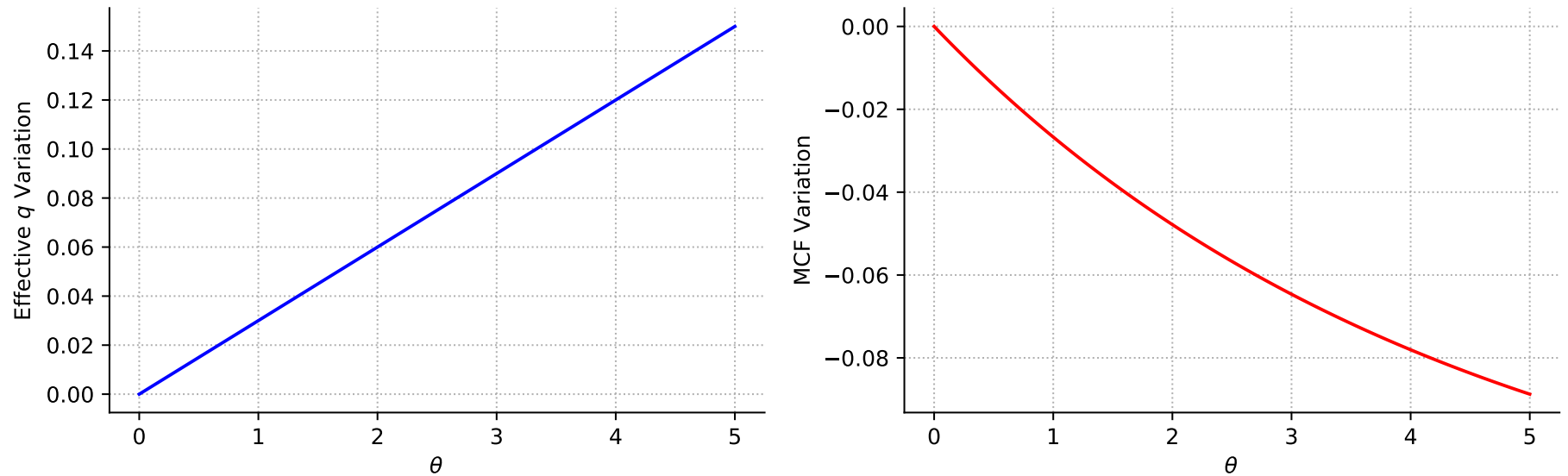


Figure A.19: **Structural interpretation under  $q$ -theory with costly external financing: calibrated results.** This figure plots the calibrated values of the impact of ex-ante firm-level insurer ownership on effective marginal Tobin's  $q$ ,  $\frac{\partial q^{\text{eff}}}{\partial \phi}$ , and on a firm's marginal cost of financing,  $\frac{\partial \text{MCF}}{\partial \phi}$ , as derived in Appendix Section H. These are plotted against the adjustment cost parameter  $\theta$  in the *blue curve* and *red curve*, respectively.

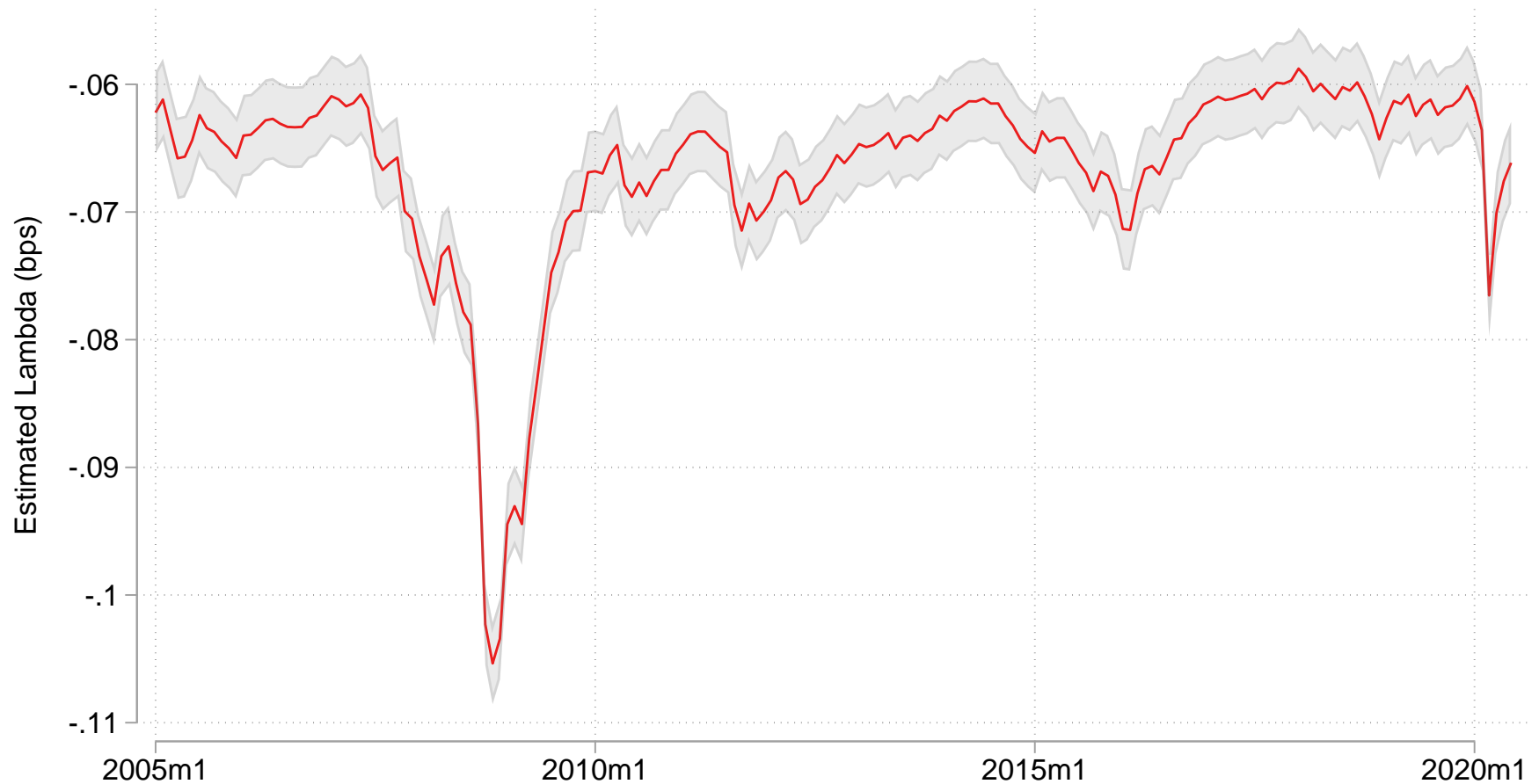


Figure A.20: **Insurer ownership and secondary-market bond turnover.** This figure shows the estimates from the regression specification in equation (A.35). The *red line* plots the total estimated effect  $\Lambda_t = \bar{\Lambda} + \tilde{\Lambda}GZ_t$  of security-level insurer shares on monthly bond turnover. The *blue shaded area* corresponds to a 95 percent confidence band estimated using Newey and West (1987) HAC standard errors, with lag selection as in Newey and West (1994).