Complexity, Investor Composition, and Selective Pass-Through in Corporate Bonds

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Abstract

We show that issuer-level bond complexity reshapes how credit spreads respond to information versus non-information shocks through investor composition. Complex structures attract specialized investors who trade on contractual detail; with greater complexity, spreads react more to information and less to flow-driven shocks. Complexity raises ownership-based fragility (exposure to correlated redemptions) yet improves liquidity by filtering noise with informed trading. Using a shift–share instrument based on predetermined holdings and fund flows, we identify a causal role for ownership composition. These results link contractual design and investor base to monetary-policy transmission and corporate-bond market stability.

JEL code: G11; G14; G23

Keywords: corporate bonds; bond complexity; investor composition; information vs non-information shocks; monetary policy transmission; ownership-based fragility; liquidity

Introduction

We study an overlooked friction in corporate bond markets: valuing one bond often requires understanding the contractual terms of a firm's *other* outstanding bonds—a feature we call bond complexity. We analyze how complexity, by shaping investor composition, affects price sensitivity, fragility, and liquidity. Our questions are: (i) Does complexity amplify or dampen credit-spread reactions to information versus non-information shocks? (ii) Does ownership composition—measured by the share held by specialized investors—explain these patterns? (iii) What are the implications for monetary-policy transmission and market stability?

Firms typically issue multiple bonds with heterogeneous contractual features (e.g., maturity, collateral, putability, callability, covenants, convertibility). This heterogeneity makes single-bond valuation costly because payoffs depend on how each bond fits within the issuer's full debt structure (Kim and Massa, 2025). For example, protections embedded in one instrument can spill over to others; if a covenant-heavy, callable bond is redeemed, its protections vanish for the remaining bonds. Enforcement depends on who holds the protective bond: if those investors do not act on a breach, the protection is effectively void. Complexity is therefore not an idiosyncratic quirk of one issue but a structural attribute of the issuer's debt architecture.

Conventional wisdom links asset complexity to opacity and instability (e.g., Arora, Barak, and Brunnermeier, 2011; Coval, Jurek, and Stafford, 2009; Gennaioli, Shleifer, and Vishny, 2012). Yet the same features that complicate valuation attract specialists who read indentures and trade on contractual detail. We call them high-complexity investors (HCI); more generalist participants are REST. As contractual heterogeneity rises across an issuer's bonds, the valuation task becomes more informationally demanding, naturally selecting a specialized

owner base (e.g., bond-focused funds and fixed-income-specialist families). This selection is central to how prices react to shocks.

Complexity also shapes trading. In the spirit of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), when a common cash-flow anchor weakens, managers place more weight on private, manager-specific signals, and comovement across managers' trades falls. Applied here, HCI parse heterogeneous indentures and enforcement contingencies, so within-HCI trade comovement declines. REST lean more on shared priors and market cues, so within-REST comovement remains high (and can rise) as complexity increases. This yields our first hypothesis: *As bond complexity increases, HCI ownership rises and HCI trading becomes less synchronized than REST.*

This information gap implies selective shock responses. For information shocks (news about future cash flows), HCI's command of contractual structure reduces uncertainty and supports more decisive reactions; prices of complex bonds should respond more to fundamentals when HCI presence is high. For non-information shocks (mechanical rebalancing, benchmark flows, fire sales), many complex bonds embed protections (call features, puts, subordination limits) that mitigate forced-sale risk. HCI recognize and price these protections and are less likely to overreact to transitory supply shifts; REST are more prone to mirror market flows. Hence our second hypothesis: *with greater complexity/HCI, bonds react more to information shocks and less to non-information shocks.*

Complexity has a nuanced relationship with liquidity. By segmenting ownership toward specialized funds with similar mandates, it increases ownership-based fragility ex ante (Greenwood and Thesmar, 2011): correlated outflows can trigger synchronized sales. It also

changes who trades and how. Anticipating fragility, flow-sensitive open-end funds avoid the most complex bonds, shifting holdings toward long-horizon institutions (pensions/insurers) that trade less frequently, which can thin depth in normal times (Massa, Schumacher, and Wang, 2021). Where HCI do participate, trading is more selective and information-driven: adverse selection falls, fundamentals are incorporated faster, and overreaction to non-fundamental flows is dampened, improving effective liquidity. Our third hypothesis is that *complexity increases fragility through correlated specialized ownership yet improves liquidity ex post through informed, selective HCI trading*.

We test these predictions using all U.S. public corporate bonds issued by industrial firms (excluding financials and utilities) from 2005–2023, merging Mergent FISD with CRSP Mutual Funds. Following Kim and Massa (2025), we build an issuer-level complexity measure by coding 11 contractual features for each bond and quantifying heterogeneity across all outstanding bonds of the issuer. We measure ownership composition as the HCI share of mutual-fund holdings at the bond-quarter level, identifying HCI based on prior-year portfolios that tilt toward the market's more contractually complex bonds relative to style peers.

Three headline findings preview our results. First, selection and synchronization (H1): complexity is associated with a higher HCI share, lower within-HCI trade comovement, and higher within-REST comovement—consistent with specialization and heterogeneous private signals among HCI. Second, selective pass-through (H2): complexity and HCI sharpen spread reactions to fundamentals (macro yield changes and FOMC-window decompositions) while muting responses to flow-driven, non-information shocks; effects are economically meaningful (additional spread moves on the order of several basis points (bp) per one-standard-deviation

(SD) increase in complexity/HCI). Third, market functioning (H3): complexity/HCI raise ownership-based fragility yet improve liquidity (tighter bid-ask, lower Amihud and Roll), decoupling fragility from illiquidity.

A central identification concern is endogeneity in HCI ownership. We therefore implement a shift–share instrument (Bartik, 1991; Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 2022) that combines predetermined fund–bond holdings with time-varying fund flows. The instrument isolates variation in ownership driven by exogenous shifts in fund assets under management rather than bond-specific shocks or manager selection. Instrumental-variables estimates corroborate the baseline: higher (instrumented) HCI causally amplifies informational pass-through, dampens the price impact of non-fundamental flows, and improves liquidity.

This paper is closely related to Kim and Massa (2025) but offers a substantive extension by examining the *dynamic* pricing implications of bond complexity and its role in shaping market stability. Whereas the prior study introduced a novel measure of contractual complexity (issuer term variability) and documented its association with level differences in yield spreads and investor selection, the analysis remained largely static. The present paper advances by investigating how contractual complexity influences the transmission of shocks into bond prices *over time*. To ensure that our complexity measure reflects genuine contractual heterogeneity rather than confounding factors, we explicitly consider the broader debt architecture. In particular, we categorize issuers by their loan covenant environment—distinguishing between firms with no loans, covenant-light loans, and covenant-heavy loans—and demonstrate that the effects of bond complexity on credit spreads remain robust to these

loan-side controls. By integrating dynamic price reactions, investor composition effects, and the interplay between bond and loan covenants, this study delivers a meaningful advancement over Kim and Massa (2025) and contributes new insights into how contractual design shapes market behavior under varying information environments.

Our contributions are threefold. First, we reconceptualize complexity as an issuer-level debt architecture—valuation of one bond depends on the contractual menu of the issuer's other bonds—while our empirical tests are run at the bond level using issuer-level complexity mapped to each bond. Prior work typically links complexity to opacity and instability at the security level (e.g., Coval, Jurek, and Stafford, 2009; Gennaioli, Shleifer, and Vishny, 2012; Arora, Barak, and Brunnermeier, 2011), treating issues in isolation. Our cross-security perspective generates testable implications for prices, fragility, and liquidity at the bond level that are induced by the issuer's contract set.

Second, we identify an ownership channel through which complexity affects prices. The literature shows investor bases matter—for fragility from correlated flows and price pressure (e.g., Greenwood and Thesmar, 2011; Goldstein, Jiang, and Ng, 2017; Falato, Goldstein, and Hortaçsu, 2021)—but often treats ownership as an outcome or control. We show that investor composition is a mechanism: complexity selects high-complexity investors (HCI) who trade on contractual detail (cf. Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016; Kacperczyk and Schnabl, 2013). Empirically, we go beyond correlations by replacing complexity with ownership composition (HCI share) and instrumenting HCI via a shift–share design using predetermined holdings and fund flows (Bartik, 1991; Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 2022). The IV results support mediation—ownership

explains why complex issuers' bonds react more to information and less to non-information shocks—rather than mere moderation.

Third, we differentiate shock types and disentangle fragility from liquidity. Prior studies document average sensitivity to rates/news and flow-induced price pressure (e.g., Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Lou, 2012; Goldstein, Jiang, and Ng, 2017), often blending information and non-information forces. We show selective pass-through: complexity/HCI sharpen reactions to fundamentals while muting reactions to mechanical, flow-driven demand. At the same time, complexity/HCI raise ownership-based fragility ex ante (Greenwood and Thesmar, 2011) yet improve liquidity ex post, clarifying that fragility and illiquidity need not move together. This links contractual design and investor mix to monetary-policy transmission into credit and informs when policy or risk management should target flow vulnerabilities versus trading frictions.

2. Construction of Variables and Sample

Our data draw on several sources. Bond characteristics and indenture terms come from Mergent FISD (maturity, rating, coupon, offering date/amount; covenants, callability, putability, convertibility, credit enhancements). Prices are from TRACE (daily) and the WRDS Bond Returns database (monthly). Quarterly mutual-fund bond holdings are from CRSP Mutual Funds. The baseline universe is all public bond issuers in FISD from 2005Q2 to 2023Q1, excluding financials and utilities. We next define bond complexity and HCI ownership, then describe the sample.

2.1 Bond Complexity

Corporate bonds embed multiple contractual features—issue size, credit rating, maturity, security, seniority, coupon structure, protective covenants, call provisions, convertibility, and more. Because issuance is not standardized, a single issuer often has multiple bonds with dissimilar terms, making valuation depend on how any given bond fits within the issuer's broader debt structure.

Following Kim and Massa (2025), we construct a quarterly issuer-level complexity measure based on the cross-bond dispersion of binary features. Specifically, we represent each outstanding bond as a K-dimensional vector of feature indicators from FISD, compute pairwise distances across all bonds of the same issuer, and define bond complexity ($BComp$) as the average pairwise Euclidean distance:

$$BComp \equiv 2 \times \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\frac{\sum_{j=1}^{N}\left(\mathbb{I}_{jk}-\mu_k\right)^2}{N}\right)}, \qquad (1)$$

where N is the number of a firm's outstanding bonds, and K is the number of bond features considered. $\mathbb{I}_{jk}$ is a dummy variable indicating the presence of feature k on bond j, and μ_k is the issuer-level, value-weighted mean of feature k:

$$\mu_k = \sum_{j=1}^{N} \omega_j \mathbb{I}_{jk}, \qquad (2)$$

with ω_j equal to bond j's share of the issuer's total outstanding amount (See Kim and Massa 2025 for the full construction details).

We include eleven bond feature indicators: redeemability, callability, putability, convertibility, exchangeability, presence of covenants, credit enhancement, collateral, foreign currency denomination, coupon variability, and maturity variability.[1] These features are chosen to capture the key dimensions of contractual complexity in corporate bonds. Conceptually, our measure is related to Oehmke and Zawadowski's (2017) approach to assessing bond standardization in CDS trading, as both aim to capture heterogeneity in contractual design across securities issued by the same firm.

By construction, *BComp* equals twice the square root of the average cross-bond variance of feature indicators and bounded between 0 and 1. It equals 0 when each feature is identical across all outstanding bonds ($\mu_k \in \{0,1\}$ for all k), and 1 when every feature is split evenly across issues ($\mu_k = 0.5$ for all k). Intuitively, complexity is higher when issuers mix and match features on a bond-by-bond, ad hoc manner and lower when feature choices are systematic and consistent across issues.

2.2 HCI Ownership

To construct the measure of ownership by specialized investors—i.e., "High-Complexity Investors" (HCI)—we follow a three-step procedure based on bond complexity and mutual fund holdings data.

First, for each quarter q, we classify "complex bonds" by ranking bonds on their complexity scores and flagging those in the top tercile of the cross-sectional distribution. Second, we identify HCI funds based on each fund's style-adjusted exposure to complex bonds over the

[1] For covenants, we use detailed FISD data on specific bond covenants, categorizing them into fifteen types following Billett, King and Mauer (2007).

prior calendar year *t-1*. For fund *i*, let ${\omega_{i,q}}^{cx}$ be the portfolio share invested in complex bonds in quarter *q*. Define the fund's annual exposure and its style benchmark (fund style given by the Lipper Objective Code *s(i)*[2]) as:

$$E_{i,t-1} = \frac{1}{4} \sum_{\{q \in t-1\}} w_{i,q}^{cx}, \qquad \bar{E}_{s(i),t-1} = \frac{1}{4} \sum_{\{q \in t-1\}} \bar{w}_{s(i),q}^{cx} \quad (3)$$

The adjusted complexity exposure is then:

$$\tilde{E}_{i,t-1} = E_{i,t-1} - \bar{E}_{s(i),t-1} \quad (4)$$

A fund is designated as HCI for year *t* if its style-adjusted exposure $\tilde{E}_{i,t-1}$ ranks in the top tercile among all eligible funds in year *t–1*. HCI status is then held fixed for all four quarters of year *t*.

Finally, we compute HCI ownership (*HCIOwn*) at the bond-quarter level. For each bond *j* in quarter *q* of year *t*, *HCIOwn* is the share of that bond held by funds classified as HCI (based on the year *t–1* designation) relative to total mutual-fund holdings of that bond in that quarter[3]:

$$HCIOwn_{j,q} = \frac{\sum_{i \in HCI_{t-1}} H_{i,j,q}}{\sum_{i \in MF} H_{i,j,q}}. \quad (5)$$

where $H_{i,j,q}$ is fund *i*'s holdings of bond *j* in quarter *q*. Thus, both $\tilde{E}_{i,t-1}$ and $HCIOwn_{j,q}$ are defined using predetermined information from year *t–1*, ensuring that HCI ownership in year *t* is exogenous to bond outcomes in the same year. This timing convention underpins our identification strategy in subsequent empirical analysis. We later complement this approach

[2] Only corporate bond funds, identified by Lipper codes ('A', 'BBB', 'HY', 'SII', 'SID', 'IID'), are included in this classification.
[3] We define HCI ownership relative to total mutual-fund holdings of the bond—rather than the total amount outstanding—for both conceptual and empirical reasons. Conceptually, the measure captures relative ownership among mutual funds, reflecting the degree of specialized ownership within the active mutual-fund investor base. This aligns with our focus on fragility and trading behavior specific to the mutual-fund sector (e.g., flow-driven trades, fire-sale risk). Using total amount outstanding would dilute this channel by including inactive or opaque holders (e.g., buy-and-hold insurers, foreign entities). Empirically, our main results are robust when controlling for the overall mutual-fund share of bond ownership, so the estimated effects of HCI ownership reflect specialization within the active mutual-fund segment rather than variation in aggregate institutional presence.

with a shift–share instrument for HCI ownership—constructed by interacting funds' pre-determined base holdings with subsequent style-level capital flows—to provide plausibly exogenous variation.

2.3 Sample Construction

We begin by merging our bond-complexity measure with Mergent FISD and WRDS Bond Returns database. Following standard practice, we exclude bonds that are floating-rate, sinking fund, perpetual, convertible, preferred, asset-backed, denominated in foreign currency, Yankee bonds, or issued under Rule 144A. We restrict the sample to issuers in nonfinancial and non-utility industries and drop bonds issued with less than one year to maturity to avoid close-to-maturity bias. WRDS provides month-end corporate bond prices based on the last transaction of each month.

We compute yield to maturity from the month-end price and define the yield spread as the difference between a bond's yield to maturity and the maturity-matched Treasury rate. The Treasury yield curve is obtained from Liu and Wu (2021).[4] We then merge these data with mutual-fund holdings and firm stock returns from CRSP, and firm accounting data from COMPUSTAT. We also incorporate monthly interest-rate data for the 2-year U.S. Treasury.

High-frequency monetary policy shocks around FOMC announcements come from Nakamura and Steinsson (2018) and Gürkaynak, Sack, and Swanson (2005).[5] When daily transaction data are required, we apply the cleaning procedures of Dick-Nielsen (2014), including corrections for cancelled, amended, or reversed trades and adjustments to avoid

[4] We are grateful to Jing Cynthia Wu for publicly sharing the dataset used in Liu and Wu (2021).
[5] We are grateful to Miguel Acosta for publicly sharing the dataset used in Acosta, Brennan, and Jacobson (2024).

double-counting agency trades. After merging all sources, the final sample comprises 593,909 bond-month observations, covering 10,357 bonds across 1,726 issuers from July 2006 to June 2023. Aggregating to the quarterly level yields 195,360 bond-quarter observations.

Panel A of Table 1 presents summary statistics for the variables used in our analysis. We organize the data into three samples by empirical setting: quarterly (Tables 3, 4, 9, and 10), monthly (Tables 5, 6, and 8), and daily (Table 7).[6] In the monthly sample, the average change in bond yield spread *(*ΔYS) is –0.6 bp, with a SD of 30 bp. The change in the 2-year Treasury yield *(*$\Delta Trsy2$) averages 1.8 bp, with a SD of 17 bp. About 53% of bond-month observations occur during Treasury rate increases and 47% during decreases. The magnitudes are similar across regimes: average changes of 15 bp (SD of 17 bp) when rate rises and –13 bp (SD = 17 bp) when rate falls.

Bond complexity (*BComp*) has a mean of 0.44 (SD = 0.16), well below its theoretical maximum of 1, consistent with non-random contractual design choices (e.g., Kieschnick and Wardlaw 2019). As shown in Kim and Massa (2025), complexity varies meaningfully across firms and is positively associated with the issuer credit risk. For interpretability, we use the standardized version of *BComp* (mean 0, sd 1) in our analyses. HCI ownership (*HCIOwn*) averages 49% (sd = 35%). Mutual fund coverage (*MFOwn*)—the share of a bond held by mutual funds—averages 14% (sd = 10%), in line with prior estimates (e.g., Huang, Wang, and Wang, 2024). Among other bond characteristics, the typical bond in our sample is rated around BB+, has a duration of about 7 years, and an average age of 4.5 years. Our passive-ownership

[6] The choice of data frequency is guided by data availability and empirical relevance: daily data are used for event studies around FOMC dates, monthly observations capture security price dynamics, and quarterly frequency aligns with mutual fund holdings.

measure has a mean of 3.9% (SD = 2.9%), broadly comparable to Bretscher, Schmid, and Ye (2024), who report 5.3% (SD = 3.5%).

In the quarterly sample, ΔYS exhibits greater variability (mean –1.5 bp; SD 56 bp), while bond complexity and HCI ownership are similar in level and variability to the monthly sample. The average value of bond fragility ($\sqrt{BFragility}$) is 0.12, broadly comparable to 0.08 reported by Greenwood and Thesmar (2011). Additional variables include trade correlation measures—$CorrTrade_{HCI}$ and $CorrTrade_{REST}$ — with means of 0.73 and 15.84, respectively. The markedly lower trading correlation among HCI is consistent with their capacity to trade independently as specialized, informed investors.

The daily sample—used for high-frequency event studies around FOMC announcements—shows much smaller changes in yield spreads over the (–1,1) event window (mean –0.3 bp; SD 15 bp). Over the same window, changes in the 2-year Treasury yield average –1.2 bp (SD = 6.5 bp). While *BComp* and *HCIOwn* are defined analogously to the other samples, their distributions differ due to the concentration of trading around event windows.

3 Bond Complexity and Investor Composition

We begin with our first hypothesis: greater bond complexity is associated with a more specialized investor base and less synchronized trading by those specialists. Specifically, we test whether bonds of more complex issuers (i) have a higher fraction held by high-complexity investors (HCI) and (ii) exhibit lower cross-fund trading correlation among HCI (with the opposite pattern for generalist funds). To study investor composition at the bond level, we estimate the bond-quarter panel regression:

$$BondHolder_{j,q+1} = \beta_1 BComp_{f(j),q} + \boldsymbol{\beta}' \boldsymbol{X}_{i,q} + \alpha_{f(j)} + \lambda_q + \gamma_{r(j),m(j)} + \varepsilon_{j,q+1}, \quad (6)$$

where $BondHolder_{j,q+1}$ is either (i) $HCIOwn_{j,q+1}$, the fraction of a bond j's mutual-fund holdings held by HCI in quarter $q+1$, or (ii) a bond-level trading-correlation measures described below. $BComp_{f(j),q}$ is the standardized complexity of bond j's issuer $f(j)$ in quarter q. $\boldsymbol{X}_{j,q}$ includes bond characteristics (rating, duration, bid-ask spread, bond age, log amount outstanding), and issuer fundamentals (log assets, leverage, profitability, and cash). $\alpha_{f(j)}$, λ_q, and $\gamma_{r(j),m(j)}$ denote issuer, year-quarter, and rating-by-maturity fixed effects, respectively. Standard errors are double-clustered by issuer and year-quarter.[7]

Table 3 reports the results. Columns (1)–(4) use the full sample; Columns (5)–(6) split the sample by mutual-fund presence—(5) above-median and (6) below-median. Across specifications, the coefficient on complexity is positive and statistically significant. Point estimates range from 0.012 to 0.015, with *t*-statistics between 3.18 and 3.84. The magnitudes are economically meaningful: a one-SD increase in *BComp* is associated with a 1.2 percentage-point (pp) rise in HCI ownership—about 10% of its sample mean. The relationship is robust to the level of mutual-fund ownership, indicating that complexity itself—rather than institutional coverage—drives specialization. These findings support the first part of H1: as complexity rises, the investor base tilts toward specialists. Contract design thus shapes not only prices, but also who holds the bonds.

We next examine trading behavior within and across investor groups. Our hypothesis predicts that HCI—who possess a comparative advantage in processing contractual detail—

[7] For the rating-by-maturity fixed effects, bonds are classified into six NAIC credit rating categories (AAA to A, BBB, BB, B, CCC, and CC/C) and four maturity categories (1–3 years, 3–5 years, 5–10 years, and over 10 years).

will trade less in sync when bonds are complex, whereas REST may herd more, relying on peer behavior or market signals under valuation uncertainty. We also expect trading between HCI and REST to align less when complexity is high, reflecting segmentation in information and motives.

We construct two bond-quarter measures. Within-group trading correlation ($CorrTrade^{g}{}_{j,q+1}$, for $g \in \{\text{HCI}, \text{REST}\}$) is defined as the inverse of the cross-sectional SD of fund-level net buys within a group g for bond j in quarter $q+1$; higher values indicate more synchronized trading. Trading alignment ($TrdAlignment_{j,q+1}$) captures directional agreement across groups in quarter $q+1$: it equals +1 if HCI and REST are both net buyers or both net sellers of bond j, −1 if they trade in opposite directions, and 0 if either group's net activity is zero. We then estimate bond-quarter panel regressions analogous to Equation 6, using the same controls and fixed effects (issuer, year-quarter, and rating-by-maturity).

Table 4 presents the estimates: Columns (1) and (4) use $CorrTrade^{HCI}{}_{j,q+1}$, Columns (2) and (5) use $CorrTrade^{REST}{}_{j,q+1}$, and and Columns (3) and (6) use $TrdAlignment_{j,q+1}$. Bond complexity is associated with lower within-HCI trading correlation, consistent with more independent trading by specialists when evaluating complex instruments. The pattern remains when replacing complexity with HCI ownership, reinforcing the link between specialization and reduced herding. For REST, coefficients are positive but statistically weak, suggesting a tendency toward synchronized trading that is imprecisely estimated. Economically, a one–SD increase in complexity (HCI ownership) corresponds to about a 3% (10%) decline in within-HCI trading correlation relative to its sample mean. We find no tight relation between

complexity and cross-group trading alignment, indicating that how HCI and REST trade relative to each other is not mechanically tied to complexity at the bond-quarter level.

A natural interpretation follows Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). Managers combine a common information anchor with private, manager-specific signals; when the common anchor is weak, portfolios load more on heterogeneous private views and comovement across managers falls. In our setting, contractual complexity weakens the shared cash-flow–only anchor because payoff mapping depends on indenture details and other bondholders' actions. HCI are precisely the managers who invest in reading and interpreting those details, so their private signals are richer—and more heterogeneous—than the market's common cues. As complexity rises, HCI place greater weight on these idiosyncratic contract readings, producing lower synchronization within HCI. By contrast, REST rely more on the shared anchor and observable market signals; when the anchor is shakier under complexity, they lean on similar heuristics and peer moves, tending toward greater comovement. This KVN&V-style shift in information weights aligns with our estimates: complexity draws in specialists and reduces within-HCI synchronization, while effects for REST are weakly positive.

Finally, to validate that the specialization mechanism is persistent (rather than transitory), Table 2 examines fund characteristics. Consistent with complexity attracting bond specialists, HCI funds are more bond-focused—allocating a smaller share to common stocks (3.35% vs. 4.40% for REST) and more often belonging to bond-oriented families by aggregate corporate-bond holdings (Panel A). The classification is also stable: 65% of funds labeled HCI in year

t−*1* remain HCI in year *t* (Panel B). This persistence and bond focus reinforce our interpretation that the HCI indicator captures durable, complexity-specific expertise.

4 Bond Complexity and Shocks

We test our second hypothesis: bond complexity amplifies corporate bonds' sensitivity to information shocks while dampening their response to non-information demand shocks. This section examines these effects in turn.

4.1 Information Shocks

We proxy information shocks with monthly changes in the 2-year U.S. Treasury yield, a standard signal of the macro outlook and monetary-policy expectations. We estimate:

$$\Delta YS_{j,t} = \beta_1\left(BComp_{f(j),t-1} \times \Delta Trsy2_t\right) + \beta_2 \Delta Trsy2_t$$

$$+ \beta_3 BComp_{f(j),t-1} + \boldsymbol{\beta}' \boldsymbol{X}_{j,t-1} + \alpha_{f(j)} + \gamma_{r(j),m(j)} + \varepsilon_{j,t}. \quad (7)$$

where $\Delta YS_{j,t}$ is the month-*t* change in bond *j*'s credit spread; $BComp_{f(j),t-1}$ is issuer-level complexity (standardized); and $\Delta Trsy2_t$ is the change in the 2-year Treasury yield. $\boldsymbol{X}_{j,t-1}$ includes lagged bond and issuer controls (rating, duration, bid–ask, age, log amount; log assets, leverage, profitability, cash) and contemporaneous macro factors commonly used in credit-spread models—ΔVIX_t, S&P500 return, and yield-curve slope (Duffee, 1998; Collin-Dufresn, Goldstein, and Martin, 2001). We also include $\Delta PD_{f(j),t}$ and $StockRet_{f(j),t}$, which are the change in the issuer's probability of default (Merton, 1974) and issuer equity returns. We use issuer and rating-by-maturity fixed effects and double-cluster standard errors by issuer and year-month. We do not include year-month fixed effects because $\Delta Trsy2_t$ is aggregate and would be absorbed.

Table 5 confirms the well-known negative relation between spread changes and $\Delta Trsy2_t$: a 1 pp rise in the 2-year yield is associated with a 22–45 bp decline in credit spreads, consistent with Duffee (1998).[8] The interaction with complexity is negative and significant. Using *BComp* (Columns 1–3), β_1=−0.076 (t = −5.00): a one-sd increase in complexity adds roughly −8 bp to the spread decline for a +1 pp move in the 2-year. Replacing complexity with HCI share (Columns 4–6) yields a similar −8 bp incremental response for a one-sd higher HCI share. These magnitudes are comparable to the effect associated with a 10% increase in the issuer's default probability.

Because complexity correlates with credit quality (Kim and Massa, 2025), we add credit-risk controls—high-yield status, Altman's Z-score, and Merton PD—and interact them with $\Delta Trsy2_t$. As expected, lower-quality issuers display larger rate sensitivity (Duffee, 1998; Collin-Dufresn, Goldstein, and Martin, 2001). Crucially, the complexity/HCI interactions remain statistically and economically significant after these additions, indicating that complexity is not merely a proxy for credit risk.

We next test asymmetry by decomposing $\Delta Trsy2_t$ into positive and negative components, $\Delta Trsy2^+$ and $\Delta Trsy2^-$. Table 6 shows that complexity significantly magnifies spread responses in both directions. For a one-sd higher *BComp*, a −1 pp move in the 2-year is associated with

[8] The negative relationship between corporate bond spreads and Treasury yields is well documented (Duffee, 1998; Collin-Dufresn, Goldstein, and Martin, 2001). One common explanation is that rising Treasury yields often signal improving economic conditions or anticipated monetary tightening—both of which reduce perceived credit risk. As investors revise upward their expectations of corporate profitability and downward their expectations of default, they demand a smaller risk premium, causing credit spreads to narrow. Another mechanism is based on expectations of future interest rates. When Treasury yields rise in anticipation of policy tightening amid strong economic growth, investors may view this as a sign of economic resilience. This reduces concerns about corporate defaults and lessens the demand for yield compensation, narrowing credit spreads. Additionally, portfolio rebalancing may contribute. As Treasury yields rise, investors may reallocate capital toward higher-yielding corporate bonds, increasing demand and pushing spreads down. Finally, the yield curve itself matters. A flattening curve—or rising long-term yields—can signal reduced inflation risk or improved long-term growth, both of which alleviate concerns about future credit events. In all, stronger macroeconomic signals embedded in Treasury yields are typically associated with lower perceived corporate risk, driving a compression in spreads.

an additional +10.1 bp spread widening ($t = -3.54$), and a +1 pp move with an additional −6.7 bp tightening ($t = -2.52$). Using HCI share as the moderator yields similarly larger pass-throughs (+12 bp for declines, −8 bp for increases). These asymmetries are not a relabeling of credit risk: in Columns (2)–(3) and Columns (5)–(6), after adding Altman's Z and Merton PD, the complexity/HCI interactions remain significant, while credit-risk controls load primarily when yields fall (downturns) and matter little when yields rise (upturns), in line with prior work. By contrast, complexity and specialized ownership sharpen the pass-through in both regimes.

Taken together, the evidence supports our mechanism: complexity—operating through specialized ownership—increases the weight investors place on fundamental news, speeding the incorporation of both favorable and adverse information into complex-bond prices, above and beyond standard credit-risk channels.

4.2 Monetary Policy Shocks

We next study narrow windows around FOMC announcements, where rate changes are plausibly more exogenous to firm conditions, to test more cleanly whether complexity amplifies sensitivity to information. Treasury yields around announcements move for two reasons: (i) the policy action/forward guidance itself (a mechanical tightening/loosening channel that need not convey new fundamentals) and (ii) news about the economy revealed by the statement/press conference (growth, inflation, risk premia). A reduced-form regression on the total yield move mixes these channels and blurs interpretation. Accordingly, after a baseline specification, we decompose the announcement-window change in the 2-year yield into a policy component and a residual (information) component; if our mechanism is correct, the

amplification by complexity should load on the information piece rather than the mechanical policy piece.

For each meeting, we measure bond-level spread changes over the (−1,+1) trading-day window. In Columns (1) and (4) of Table 7, we estimate:

$$\Delta YS_{j,(-1,+1)} = \beta_1\left(BCOMP_{f(j),0} \times \Delta Trsy2_{(-1,+1)}\right) + \beta_2 BCOMP_{f(j),0} + \beta_3 \Delta Trsy2_{(-1,+1)}$$

$$+\boldsymbol{\beta}' \boldsymbol{X_{j,0}} + \alpha_{f(j)} + \gamma_{r(j),m(j)} + \delta_e + \varepsilon_{j,(-1,+1)}, \quad (8)$$

where $\Delta YS_{j,(-1,1)}$ is bond j's credit-spread change over days –1 to +1 around the FOMC announcement date (day 0); $BComp_{f(j),0}$ is issuer level complexity (standardized) measured at day 0; $\Delta Trsy2_{(-1,+1)}$ is 2-year yield change over the same window; and $\boldsymbol{X_{j,0}}$ includes day-0 bond and issuer covariates (rating, duration, bid–ask, age, log amount; log assets, leverage, profitability, cash). We include issuer fixed effects $\alpha_{f(j)}$, rating-by-maturity fixed effects $\gamma_{r(j),m(j)}$, and event-date fixed effects δ_e (one per FOMC meeting), and we double-cluster standard errors by issuer and event date. We do not include year-month fixed effects because the event-date fixed effects absorb all aggregate time variation. In Columns (4)–(6), we replace $BComp_{f(j),0}$ with $HCIOwn_{f(j),0}$, with all other specifications remaining identical.

We find a significant negative interaction between $BComp_{f(j),0}$ and $\Delta Trsy2_{(-1,+1)}$ (coefficient −0.069; t = −2.42). For a +1 pp increase in the 2-year yield, a one–SD higher *BComp* is associated with an additional 7 bp tightening in spreads; the event-window SD of ΔYS is roughly 15 bp. Replacing complexity with HCI share yields a similar amplification, mirroring the monthly results and indicating that bonds held more by specialists react more strongly to information embedded in announcement-window yield moves.

To separate policy mechanics from information, Columns (2)–(3) and (5)–(6) decompose the announcement-window 2-year move using two high-frequency monetary policy shock measures (Nakamura and Steinsson, 2018; Gürkaynak, Sack, and Swanson, 2005). For each measure $s \in \{NS, GSS\}$, we estimate:[9]

$$\Delta Trsy2_{(-1,+1)} = \{\Delta \widehat{Trsy2}\}^{(MP,s)}_{(-1,+1)} + r\left(\Delta Trsy2^{(RES,s)}_{(-1,+1)}\right), s \in \{NS, GSS\}, \quad (9)$$

Using this decomposition, we re-estimate the event-window specification by interacting issuer complexity (or, in Columns (5)–(6), HCI ownership) separately with the policy and residual components, and regressing three-day spread changes on those interactions, the two components themselves, and the same day-0 bond/issuer controls, with issuer, rating-by-maturity, and event-date fixed effects and double clustering by issuer and event date.

Complexity loads on the residual/information component but not on the policy component. With NS shocks, the interaction with the residual is −0.087 (t = −2.28), while the interaction with the policy component is small and statistically insignificant (0.070; t = 0.65). GSS shocks yield the same qualitative pattern. Replacing *BComp* with *HCIOwn* produces parallel results: specialized ownership strengthens the transmission of surprise information but not the mechanical policy move.

[9] $\Delta Trsy2_{(-1,+1)}$ is the change in the 2-year U.S. Treasury yield (in pp) from the close on day −1 to the close on day +1 around each FOMC announcement. The index $s \in \{NS, GSS\}$ denotes the high-frequency shock series used, where NS refers to Nakamura and Steinsson (2018) and GSS refers to Gürkaynak, Sack, and Swanson (2005). The term $\{\Delta \widehat{Trsy2}\}^{(MP,s)}_{(-1,+1)}$ is the policy (mechanical) component of the 2-year move implied by series *s*, obtained by projecting the announcement-window change onto the identified monetary policy surprise for that series. The term $r\left(\Delta Trsy2^{(RES,s)}_{(-1,+1)}\right)$ is the residual "information" component, defined as $\Delta Trsy2_{(-1,+1)}$ minus $\{\Delta \widehat{Trsy2}\}^{(MP,s)}_{(-1,+1)}$. All quantities are computed separately for each meeting using the same (−1, +1) window and the same units as $\Delta Trsy2_{(-1,+1)}$.

The high-frequency evidence indicates that complexity acts as an amplifier of unanticipated, information-rich news embedded in announcement-window rates—consistent with HCI parsing and acting on fundamentals quickly—rather than of the predictable policy move itself. The amplification persists with day-0 bond and issuer controls, issuer/rating-by-maturity/event-date fixed effects, and across both shock measures. Together with the monthly evidence, these results support the view that complexity—and the specialized ownership it attracts—sharpens price discovery in response to information shocks even in narrow, cleaner identification windows.

4.3 Demand Shocks

We now turn to non-information demand shocks—shifts in holdings driven mechanically by investor flows rather than firm fundamentals. Our hypothesis is that bond complexity attenuates the price impact of such shocks, in contrast to the amplification we documented for information shocks. To obtain plausibly exogenous variation in demand, we follow Bretscher, Schmid, and Ye (2024) and exploit rebalancing by maturity-mandated passive corporate-bond funds.[10] These funds migrate bonds across mandate buckets when remaining time-to-maturity crosses fixed thresholds (e.g., 10, 5, or 3 years). The resulting "switches" alter passive ownership for mechanical reasons unrelated to contemporaneous issuer news, providing an instrument for non-information demand.

[10] We identify passive fixed-income index funds and ETFs following the literature (see, e.g., Dannhauser and Dathan, 2023). A fund is classified as an index fund if the CRSP fund name contains any of the following strings: SP, DOW, Dow, DJ, or if the lowercase version of the fund name includes terms such as index, idx, indx, ind_ (_ indicating space), aggregate, composite, russell, s&p, s and p, s & p, msci, Bloomberg, kbw, nasdaq, nyse, stoxx, ftse, wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, or 5000. For maturity-mandated passive funds, we follow the list of funds identified in Bretscher, Schmid, and Ye (2024).

Implementation proceeds in two steps. First, for each bond *j* and month *t*, we define $Switch_{j,t}$ *=1* if its time-to-maturity crosses a mandate threshold in *t* (and 0 otherwise). Using CRSP flows for passive bond funds that previously held *j*, we estimate a first-stage equation over a six-month window centered on the switch:

$$\Delta PassiveOwn_{j,t-3\to t+3} = \pi_1 Switch_{j,t} + \boldsymbol{\pi}' \boldsymbol{X_{j,t}} + \alpha_{f(j)} + \lambda_t + \gamma_{r(j),m(j)} + \varepsilon_{j,t-3\to t+3}, \qquad (10)$$

where $\Delta PassiveOwn_{j,t-3\to t+3}$ is the change in passive ownership of bond *j* between months *t−3* and *t+3*; $\boldsymbol{X_{j,t}}$ contains bond and issuer covariates; $\alpha_{f(j)}$, λ_t, and $\gamma_{r(j),m(j)}$ are issuer, year-month, and rating-by-maturity fixed effects. The switch indicator serves as an instrument for mechanically induced changes in passive demand. In practice, first-stage coefficients on $Switch_{j,t}$ are positive and significant, and the F-statistics indicate strong instruments (reported with Table 8).

In the second stage, we relate bond-level spread changes around the switch to the fitted change in passive ownership and allow the effect to vary with complexity:

$$\Delta YS_{j,t-3\to t+3} = \beta_1 (BComp_{f(j),t} \times \Delta \widehat{PassiveOwn}_{j,t-3\to t+3}) + \beta_2 \Delta \widehat{PassiveOwn}_{j,t-3\to t+3} + \beta_3 BComp_{f(j),t} + \boldsymbol{\beta}' \boldsymbol{X}_{j,t} + \alpha_{f(j)} + \lambda_t + \gamma_{r(j),m(j)} + \varepsilon_{j,t-3\to t+3}. \qquad (11)$$

The dependent variable is the cumulative change in bond *j*'s credit spread from *t-3* to *t+3*. Controls and fixed effects mirror the first stage; standard errors are clustered by issuer. We also estimate a parallel specification replacing $BComp_{f(j),t}$ with $HCIOwn_{j,t}$.

Table 8 reports three main findings. First, instrumented increases in passive ownership compress credit spreads: the coefficient on $\Delta \widehat{PassiveOwn}$ is negative and statistically

significant across specifications (*t*-statistics between −1.76 and −2.46), consistent with mechanical inflows pushing prices up (Bretscher, Schmid, and Ye, 2024). Second, the interaction of passive demand with complexity is positive and significant in most columns (0.041 to 0.073). Because higher passive demand lowers spreads, a positive interaction implies smaller compression when complexity is higher. The economic magnitude is meaningful: a one-sd increase in *BComp* reduces the spread response to a one-pp rise in passive ownership by roughly 4–7 bp, offsetting a baseline elasticity of about 10–14 bp. Third, substituting *HCIOwn* for complexity yields even larger positive interactions (0.518 to 0.571), implying that a one-sd increase in specialized ownership dampens spread compression by about 10 bp. In other words, bonds held more by HCI react less to mechanical flows.

Overall, these results complement the information-shock evidence. Whereas complexity (and HCI presence) amplifies the pass-through of fundamental news, it mutes the price impact of non-informational, flow-driven demand. This pattern is consistent with selective, information-based trading by specialists who absorb rather than chase mechanical flows—stabilizing prices when shocks are not about fundamentals.

5 Bond Complexity, Financial Fragility and Bond Liquidity

The earlier sections show that bond complexity attracts specialized (HCI) owners who react more strongly to fundamental news while staying relatively unresponsive to non-fundamental demand shocks. What does this imply for bond market fragility and liquidity?

On the one hand, greater specialization—especially when ownership is concentrated in similarly positioned funds—can heighten financial fragility by fostering correlated trading and reducing heterogeneity in responses. This fragility translates into illiquidity because ownership

tilts away from flow-sensitive open-end funds toward long-horizon institutions that trade infrequently, thinning baseline depth so even modest flows move prices more (Massa, Schumacher, and Wang, 2021). On the other hand, specialized owners can enhance price informativeness and temper overreactions to uninformed trading, potentially improving liquidity.

To study fragility, we adapt Greenwood and Thesmar (2011) to corporate bonds using mutual-fund holdings and flows. For each bond *j* and month *t*, we identify all holding funds and compute their portfolio weights. Using a trailing 12-month rolling window, we estimate the variance-covariance matrix of monthly net flows Σ_t. Bond fragility is the bond's exposure to correlated trading across its investor base, scaled by its market depth (bond size) θ_j:

$$BFragility_{j,t} = \frac{1}{\theta_j^2} w_{j,t}^{'} \Sigma_t w_{j,t}, \quad (12)$$

where $\boldsymbol{w_{j,t}}$ is the vector of portfolio weights of bond *j* across holding funds. This measure captures both concentration and comovement in bondholders' liquidity needs, normalized by size, and reflects vulnerability to price pressure from coordinated flows. For interpretability, we multiply *BFragility* by 10,000.

We test whether complexity increases fragility by regressing the square root of fragility on bond complexity and controls, in lead form:

$$\sqrt{BFragility_{j,t+1}} = \beta_1 BComp_{f(j),t} + \boldsymbol{\beta}^{'} \boldsymbol{X}_{j,t} + \phi_i + \lambda_t + \gamma_{r(j),m(j)} + \varepsilon_{j,t}, \quad (13)$$

Columns (1)–(4) of Table 9 show a robust positive relation across control sets. A one-sd increase in bond complexity is associated with a 0.004 increase in $\sqrt{BFragility}$—about 3% of the sample mean. The same pattern holds when using HCI ownership.

We then ask whether fragility shapes responses to market shocks. First, we study information shocks, proxied by changes in 2-year Treasury yields:

$$\Delta YS_{j,t} = \beta_1 \cdot \sqrt{BFragility_{j,t-1}} \times \Delta Trsy2_t + \boldsymbol{\beta}' \boldsymbol{X}_{j,t} + \phi_{f(j)} + \lambda_t + \gamma_{r(j),m(j)} + \varepsilon_{j,t}. \quad (14)$$

Column (5) indicates that high-fragility bonds are more sensitive to Treasury moves: the interaction coefficient is –0.119, implying that a one-sd increase in fragility corresponds to an additional 2 bp decline in spreads when the 2-year yield rises by a 1 pp. Thus, fragile bonds react more to information shocks.

Next, we examine non-information shocks driven by passive demand. Using an IV framework from Section 4.3, we relate spread changes to instrumented changes in passive ownership::

$$\Delta YS_{j,t} = \beta_1 \cdot \sqrt{BFragility_{j,t-1}} \times \Delta \widehat{PassiveOwn}_{j,t} + \boldsymbol{\beta}' \boldsymbol{X_{j,t}}$$

$$+\phi_{f(j)} + \lambda_t + \gamma_{r(j),m(j)} + \varepsilon_{j,t}. \quad (15)$$

Column (6) shows that the interaction between fragility and instrumented passive flows is positive and marginally significant (coefficient = 0.529; t = 1.74), indicating that high-fragility bonds are less sensitive to demand shocks. Quantitatively, a one-SD increase in fragility implies about a 9 bp smaller spread compression for a given passive demand shift.

Together, these results suggest that while fragility is often viewed as destabilizing, here it also reflect the presence of informed, specialized ownership that limits the impact of non-fundamental shocks. Complexity contributes to fragility, but that fragility is associated with more selective trading and more stable price responses.

We then test implication for liquidity. Using three standard illiquidity proxies—the bid-ask spread, the Amihud (2002) measure, and Roll (1984)'s effective spread estimator—we estimate forward-looking specifications to mitigate reverse causality, measuring illiquidity at *t+1*

$$Illiquidity_{j,t+1} = \beta_1 \cdot BComp_{j,t} + \beta_2 \boldsymbol{X_{j,t}} + \phi_{f(j)} + \lambda_t + \gamma_{r(j),m(j)} + \varepsilon_{j,t.} \quad (16)$$

Table 10 shows that bond complexity is significantly negatively associated with subsequent illiquidity across all three measures. In Columns (1) to (3), the coefficient on *BComp* is –0.008 (*t* = –1.86) for bid-ask spreads, –0.004 (*t* = –1.80) for Amihud, and –0.008 (*t* = –1.76) for Roll. Economically, a one-sd increase in complexity is linked to a 0.8 bp reduction in bid-ask, a 0.004 decrease in Amihud, and a 0.008 decline in Roll—about 1.7%, 2.6%, and 1.0% of their respective sample means. Similar results hold when replacing bond complexity with HCI ownership (Columns 4–6). The effect of bond complexity, however, is quantitatively larger, suggesting that HCI amplify the informational benefits associated with complex bonds.

Overall, while complexity concentrates ownership and raises measured fragility, it simultaneously improves liquidity by channelling trading toward fundamental signals and filtering out non-fundamental noise. In this setting, complexity does not impair market functioning; rather, in the presence of specialized ownership, it fosters more informative prices and more resilient liquidity.

6. Robustness

6.1 Shift-Share IVs

A key identification challenge is that the observed HCI ownership share (*HCIOwn*) may reflect endogenous sorting—funds tilt toward bonds with favorable, time-varying characteristics—

and reverse causality, whereby changes in spreads or liquidity attract (or repel) HCI. These forces can bias the OLS estimates of the causal effect HCI ownership.

We address this with a shift-share instrument that leverages plausibly exogenous fund-level capital flows while holding bond-level portfolio weights fixed. Following the applied shift-share IV literature (Bartik 1991; Goldsmith-Pinkham, Sorkin, and Swift 2020; Borusyak, Hull, and Jaravel 2022) and implementation in Fang (2024) and Coppola (2025), the instrument scales each fund's baseline positions mechanically with changes in its asset under management (AUM), abstracting from time-varying, bond-specific rebalancing.

Let *j* index bonds, *f* index HCI funds, and t_0 be the baseline year. For each fund-bond pair (*f, j*), denote baseline dollar holding by $Holdings_{f,j}{}^{t_0}$ at t_0 and the cumulative percentage change in AUM between t_0 and *t* by $\%\Delta AUM_{f,t}$. The predicted dollar exposure of HCI to bond *j* at time *t* is:

$$Z_{j,t}{}^{level} = \sum_{f \in HCI} Holdings_{f,j}{}^{t_0} \times \left(1 + \%\Delta AUM_{f,t}\right). \qquad (17)$$

We convert this to a predicted ownership share by dividing by the bond's total mutual-fund dollar holdings at baseline (held fixed over time)[11]:

$$Z_{j,t}{}^{share} = \frac{Z_{j,t}{}^{level}}{Total\ Bond\ Fund\ Holdings_j{}^{t_0}}. \qquad (18)$$

[11] We use baseline total mutual-fund holdings in the denominator—rather than contemporaneous values—to preserve the instrument's exogeneity. The realized HCI ownership (*HCIOwn*) is defined with a current denominator, but doing the same in the instrument would reintroduce endogeneity, since total mutual-fund demand for bond *j* can respond to time-varying bond conditions. Holding the denominator fixed ensures that the only time-varying component of the instrument comes from fund-level AUM changes, which we treat as plausibly exogenous to bond-level shocks. Our identifying assumption is that, conditional on baseline holdings, the time path of HCI funds' AUM growth is orthogonal to bond-specific shocks that move aggregate mutual-fund demand for bond *j*. While total fund holdings can evolve between t_0 and *t*, those changes load into the endogenous regressor (actual *HCIOwn*) and controls, not the instrument's denominator, so the exclusion restriction is not violated provided HCI AUM growth is not itself driven by bond-specific demand conditions.

Intuitively, ${Z_{j,t}}^{share}$ varies with fund inflows/outflows and baseline HCI exposure while keeping portfolio weights predetermined. We compute $\%\Delta AUM_{f,t}$ using return-adjusted net flows and take baseline holdings from the prior calendar year. The instrument thus varies across bonds and time and is designed to purge contemporaneous selection and bond-specific information.

We estimate two-stage least squares (2SLS) specifications with ${Z_{j,t}}^{share}$ as the first-stage predictor. Table 11 reports the results. In Column (1), the instrument is strongly predictive of realized HCI ownership: the first-stage coefficient is large and significant, and a Kleibergen-Paap F-statistic exceeds 100, comfortably above conventional weak-IV thresholds. This supports instrument relevance and underidentification tests.

The subsequent columns replicate our core OLS results using instrumented HCI ownership. Across fragility, trading comovement, and liquidity outcomes, IV estimates match OLS in sign and significance; some magnitudes are larger. Higher HCI ownership is associated with greater bond fragility, lower intra-HCI trading correlation, and improved market liquidity, mitigating concerns that endogeneity in *HCIOwn* drives our findings.

Panel B examines how HCI ownership moderates bond responses to market-wide shocks. The shift-share IV estimates mirror earlier patterns: HCI ownership amplifies the pass-through of information shocks (Treasury yields) and attenuates the impact of non-fundamental demand shocks (instrumented changes in passive ownership). Effects are statistically robust and economically meaningful, consistent with HCI acting as informed liquidity providers and shock absorbers.

Overall, the shift-share design—grounded in predetermined holdings and external fund flows—supports a causal interpretation. The consistency between IV and OLS results indicates that bond complexity, through its effect on specialized ownership, meaningfully shapes fragility and liquidity, with implications for market stability and asset pricing.

6.2 Loan-Side Controls

Our measure of contractual complexity—derived from variation in bond terms—may be incomplete if it fails to account for protections embedded in loan agreements. This concern reflects a broader observation in the literature: while bonds indentures tend to be standardized and less restrictive, loan contracts—particularly syndicated credit facilities—commonly contain binding covenants. As a result, any measure of debt-side complexity that excludes the loan dimension risks omitting a key component of the firm's contractual environment (e.g., Bradley and Roberts, 2015; Ma, Stice, and Williams, 2019; Reisel, 2014).

To address this issue, we incorporate syndicated loan information from Dealscan to proxy for loan-side creditor protection. For each issuer-month, we classify firms into three groups based on the presence and coverage of financial covenants across their outstanding loans: (i) no outstanding syndicated loans ("No Loan"), (ii) outstanding loans without measurable covenant coverage ("Covenant-Light"), and (iii) loans with non-zero covenant exposure ("Covenant-Heavy"). These groupings account for both the extensive use of covenant-lite lending in recent years and the heterogeneity in enforcement power across lenders.

We incorporate these groupings into our core dynamic specifications—both reduced-form (Panel A) and IV (Panel B)—by interacting *Loan_Cov_Group* with interest-rate shock measures *(*$\Delta Trsy2$) and predicted changes in passive institutional demand ($\Delta \widehat{Passive Own}$).

Panel A of Table 12 reports regressions of monthly bond spread changes on interest-rate shocks. The coefficient on bond complexity interacted with $\Delta Trsy2$ remains negative and highly significant across all specifications, indicating that the amplifying effect of complexity on information sensitivity persists after conditioning on loan-side protections. While there is some weak evidence that covenant-heavy issuers are slightly less sensitive to Treasury shocks (i.e., positive and marginally significant estimates for *Loan_Cov_Group* × $\Delta Trsy2$), these effects are economically small and does not attenuate the core results.

Panel B presents the IV estimates linking passive ownership shifts to spread changes. The dampening role of high-conviction institutional ownership remains robust after controlling for loan covenant structures. Interaction terms involving *Loan_Cov_Group* are statistically insignificant and have limited economic magnitude, further suggesting that the selective pass-through of shocks operates primarily through bond-side complexity and investor specialization rather than loan-based contractual enforcement.

In sum, loan covenants clearly play an important role in creditor governance, our results show that bond complexity retains significant explanatory power even when accounting for heterogeneity in loan-side protections. This supports the interpretation that variation in bond contract structure—and the investor base it attracts—has distinct and persistent implications for the pricing of corporate debt in response to both information and non-information shocks.

Conclusion

We study how the complexity of a firm's bond structure shapes price responses to fundamental (information) and non-fundamental (demand) shocks, and the implications for financial fragility and bond liquidity. Bond complexity is defined from contractual features—maturity,

collateralization, putability, callability, covenants, and early redemption terms—and their interactions across the issuer's full debt structure. As these features accumulate, valuation requires specialized expertise, giving rise to High-Complexity Investors (HCI).

As complexity rises, the investor base tilts toward HCI. HCI act on differentiated private information and trade selectively, whereas non-specialists (REST) are more prone to herd in complex settings. This segmentation yields testable predictions: HCI react more to fundamental news and less to flow-driven, non-fundamental demand shifts, making complex bonds more sensitive to information and less reactive to noise.

Complexity also fosters investor specialization that increases financial fragility through strategic complementarities (Greenwood and Thesmar, 2011; Goldstein, Jiang, and Ng, 2017). Yet, because HCI filter out non-informational shocks, higher fragility need not imply worse liquidity. The net effect is a combination of greater measured fragility with improved liquidity.

These findings have policy and practical implications: the transmission of macroeconomic and monetary-policy shocks depends not only on shock type but also on bond design and the ownership composition. Assessment of market resilience should therefore account for contractual structure and investor specialization.

In sum, bond complexity is a double-edged sword—raising vulnerability through concentrated ownership yet, enhancing market functioning through more informed and selective trading.

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Appendix 1: Variables Description

Variable	Definition	Database
BComp	Bond complexity, measured as the average pairwise Euclidean distance across contractual features of a firm's outstanding bonds, as described in Kim and Massa (2025).	FISD
HCIOwn	Ownership share of High Complexity Investors (HCI) in a bond's total amount held by bond mutual funds.	CRSP MF, FISD, TRACE
BFragility	Bond fragility calculated following Greenwood and Thesmar (2011) as the portfolio-weighted variance-covariance of fund flows among mutual funds holding the bond, scaled by the square of bond market capitalization.	CRSP MF, FISD, TRACE
$\text{CorrTrade}_{\text{HCI}}$	The inverse of the cross-sectional standard deviation of fund-level net buys among HCI	CRSP MF
$\text{CorrTrade}_{\text{REST}}$	The inverse of the cross-sectional standard deviation of fund-level net buys among REST	CRSP MF
TrdAlignment	Directional trading correlation between investor groups. For each bond-quarter, we assign a value of +1 if both HCI and REST exhibit the same sign in their net buy activity (both net buyers or both net sellers), -1 if their trades are in opposite directions, and 0 if either group shows zero net activity.	CRSP MF
ΔYS	Change in bond yield spread (credit spread), in percentage points, over a specified window, computed by subtracting the maturity-matched U.S. Treasury rates from bond yields.	FISD, TRACE
Trsy2	2-year U.S. Treasury yield, in percentage points.	Liu and Wu (2021)
ΔTrsy2	Change in 2-year U.S. Treasury yield over a specified window.	Liu and Wu (2021)
PD	Probability of default, derived from Merton's (1974) model.	CRSP, Compustat
Δ PD	Change in Probability of default, derived from Merton's (1974) model over a specified window.	CRSP, Compustat
$\Delta\widehat{Trsy2^{(NS)}}$	Predicted component of ΔTrsy2 by monetary policy shocks from Nakamura and Steinsson (2018)	Acosta, Brennan, and Jacobson (2024), Liu and Wu (2021)
$\Delta Trsy2^{(GSS)}$	Predicted component of ΔTrsy2 by monetary policy shocks from Gürkaynak, Sack, and Swanson (2005)	
$r_{\Delta Trsy2^{(NS)}}$	Residual component of ΔTrsy2 by monetary policy shocks from Nakamura and Steinsson (2018)	
$r_{\Delta Trsy2^{(GSS)}}$	Residual component of ΔTrsy2 by monetary policy shocks from Gürkaynak, Sack, and Swanson (2005)	
StockRet	Return of the issuing firm's equity.	CRSP
Bid-Ask	Relative bid-ask spread of a bond.	TRACE
Amihud	Amihud (2002) illiquidity measure computed as absolute return divided by trading volume.	TRACE
Roll	Roll (1984)'s measure of bond illiquidity based on serial covariance of price changes.	TRACE

Treat	Treatment dummy for DiD analysis around Bill Gross's departure from PIMCO. 1 (or 0) if a firm has more than three percent of its outstanding bonds held by PIMCO (or, Prudential/Vanguard) at the end of 2014Q	CRSP MF
Post	Post-shock dummy equal to 1 for periods after 2014Q3.	
Switch	Instrument for IV regressions equal to 1 if bond moves across maturity thresholds triggering passive fund rebalancing.	FISD, TRACE
PassiveOwn	Ownership by maturity-mandated, passive bond funds from Bretscher, Schmidt and Ye (2024).	CRSP MF, TRACE,
$\Delta\widehat{PassiveOwn}$	Predicted components of PassiveOwn by Switch	FISD
ΔPassiveOwn	Change in passive bond fund ownership over a specified window.	TRACE, FISD
$\widehat{HCIOwn}$	Fitted values of HCI ownership obtained from the first stage of a two-stage least squares (2SLS) regression using a shift-share instrument. The instrument is constructed by interacting each HCI-designated fund's baseline holdings of a bond with the percentage change in that fund's assets under management (AUM) over time, then aggregating across all HCI funds and scaling by the bond's total mutual fund holdings at the baseline. See Section 6 for construction details.	CRSP MF, FISD, TRACE
Rating	A numerical transformation of S&P's bond credit ratings, where −8 = AAA, −7 = AA+, −6=AA,…,−1=BBB+, 0=BBB, 1= BBB−, 2=BB+, 3=BB,…,13=C.	FISD
Duration	The modified duration of the bond.	FISD, TRACE
Bond Age	The number of years since the bond's issue date.	FISD, TRACE
Log (Bond Amt)	The natural logarithm of the bond's par amount outstanding (in $000's).	FISD, TRACE
Log (Firm Size)	The natural logarithm of the firm's total assets	Compustat
Leverage	The ratio of the firm's total debt to its total assets	Compustat
Cash	The ratio of the firm's cash holding to its total assets	Compustat
Profitability	The ratio of the firm's profit to its total assets	Compustat
Loan_Cov_Group	Equals 0 for firms with no loans, 1 for firms with loans but zero covenant coverage, and 2 for firms with nonzero covenant coverage (based on covenant amount scaled by total loan exposure).	DealScan

Table 1 Summary Statistics

This table reports summary statistics for the main variables used in the analysis. ΔYS is the change in bond yield spread (pp). Δ*Trsy2* is the change in the 2-year U.S. Treasury yield (pp). $\Delta\widehat{Trsy2}^{(NS)}$ and $r_{\Delta Trsy2^{(NS)}}$ are the predicted and residual components of Δ*Trsy2* based on monetary policy shocks from Nakamura and Steinsson (2018); $\Delta\widehat{Trsy2}^{(GSS)}$ and $r_{\Delta Trsy2^{(GSS)}}$ are based on shocks from Gürkaynak, Sack, and Swanson (2005). *BComp* is bond complexity (issuer level). *HCIOwn* is the ownership share held by High-Complexity Investors (HCI). $CorrTrade_{HCI}$ and $CorrTrade_{REST}$ are within-group trading-correlation measures; *TrdAlignment* equals +1 (same direction), –1 (opposite), or 0 (zero activity by one group). *BFragility* follows Greenwood and Thesmar (2011). *Switch* equals 1 if a bond crosses maturity thresholds triggering passive rebalancing. $\Delta\widehat{PassiveOwn}$ is the predicted change in passive bond fund ownership. *PD* is the Merton (1974) default probability. *Bid-Ask*, *Amihud*, and *Roll* are bond illiquidity measures based on the bid-ask spread, Amihud (2002), and Roll (1984), respectively. See Appendix 1 for detailed definitions. The sample spans July 2006 to June 2023.

	N	Mean	SD	P1	P99
Monthly Sample					
ΔYS (%)	564,464	-.006	.297	-.649	.678
ΔTrsy2	593,909	.018	.167	-.33	.414
BComp	593,909	.441	.158	0	.661
HCIOwn	593,906	.491	.346	0	.971
MFOwn	593,682	.144	.103	.013	.38
Switch	485,574	.02	.139	0	1
$\Delta\widehat{PassiveOwn}$	430,157	.003	.009	-.015	.023
PD	545,853	.073	.197	0	.755
Zscore	482,473	1.856	1.157	.065	4.489
ΔSlope	593,909	-.016	.157	-.302	.317
ΔVIX	593,909	-.072	4.645	-8.55	10.34
ΔPD	545,853	.073	.197	0	.755
S&P500Ret	593,908	.008	.041	-.084	.079
StockRet	535,215	.009	.075	-.139	.157
Rating	593909	-.048	3.126	-5	7
Duration	589,350	6.91	4.43	1.56	15.91
Bid-Ask	583,878	.005	.004	.001	.014
Bond Age	593,909	4.478	3.538	.381	13.641
Log(Bond Amt)	593,692	13.202	.62	12.14	14.403
Log(Firm Size)	545,852	2.316	.128	2.059	2.525
Leverage	446,818	.683	.166	.432	1.056
Profitability	528,405	.036	.016	.009	.073
Cash	545,852	.08	.076	.004	.281
Quarterly Sample					
BComp	195,360	.441	.158	0	.661
ΔYS (%)	182,618	-.015	.564	-1.197	1.408
$\sqrt{BFragility}$	172,293	.121	.167	.001	.652
Bid-Ask (%)	191,512	.48	.342	.1	1.374
Amihud	191,514	.153	.171	.008	.65
Roll	191,113	.824	.507	.2	1.991
$CorrTrade_{HCI}$	123,673	.728	1.153	.037	4.583
$CorrTrade_{REST}$	139,453	15.844	43.444	.043	176.069
TrdAlignment	159,261	.049	.793	-1	1
Daily Sample					
ΔYS (bp)	258,785	-.308	14.873	-34	33
BComp	384,554	.445	.161	0	.665
HCIOwn	331045	.488	.344	0	.965
ΔTrsy2 (bp)	258785	-1.17	6.541	-16.282	11.726
$\Delta\widehat{Trsy2}^{(NS)}$ (bp)	384554	-.672	1.583	-4.021	2.901
$r_{\Delta Trsy2^{(NS)}}$ (bp)	383470	-.314	5.879	-13.226	11.185
$\Delta\widehat{Trsy2}^{(GSS)}$ (bp)	384554	-.722	1.798	-4.55	3.2
$r_{\Delta Trsy2^{(GSS)}}$ (bp)	383470	-.395	5.906	-14.046	10.951

Table 2 HCI vs. REST Fund Characteristics and Persistence

This table reports the portfolio composition (Panel A) and transition matrix (Panel B) of HCI and REST (non-HCI) funds. A fund is classified as HCI if its trailing average exposure to complex bonds falls within the top tercile of the fund distribution in a given year. To ensure stability in classification, HCI status is fixed at the fund-year level; that is, a fund's HCI designation in year *t* is based on its complexity exposure in year *t−1*. All other funds in year *t* are categorized as the REST. The observations are at the fund-year level.

Panel A Fund Portfolio Composition

		HCI	Rest	Diff.	*t*-statistics
Portfolio Composition (%)	Common Stock	3.35	4.40	-1.05	-2.78
	Preferred Stock	0.32	0.27	0.05	2.04
	Convertible Bond	0.16	0.11	0.05	3.81
	Corporate Bond	51.76	50.98	0.78	0.30
	Municipal Bond	0.99	1.06	-0.07	-0.79
	Government Bond	11.73	13.32	-1.65	-4.42
	Other securities	1.36	1.35	0.01	0.07
	Cash	3.03	1.59	1.44	6.30
Bond-focused Fund Family (=1)		0.05	0.03	0.02	3.30
N. Obs. (c.)		2,500	9,000		

Panel B Fund Classification Transition Matrix

	HCI (year *t*)		
HCI (year *t-1*)	0	1	Total
0	7,856	774	8,630
1	720	1,363	2,083
Total	8,576	2,137	10,713

Table 3 Bond Complexity and HCI Ownership

This table reports panel regressions of HCI ownership on bond complexity and other controls. The dependent variable is the percentage of HCI ownership. Columns 1–2 present results for the full sample, Columns 3–4 for firms with high mutual fund ownership, and Columns 5–6 for low mutual fund ownership. All specifications include issuer and year-quarter fixed effects, with and without rating-by-maturity fixed effects. Standard errors are clustered by issuer and year-quarter. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. See Appendix 1 for detailed variable definitions. The observations are at the bond-quarter level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*HCIOwn*					
	Full Sample				High MF	Low MF
BComp	0.015***	0.012***	0.012***	0.012***	0.010**	0.012**
	(3.84)	(3.18)	(3.20)	(3.55)	(2.58)	(2.65)
Rating		0.007**	0.007**	0.007**	0.016***	0.010***
		(2.36)	(2.59)	(2.13)	(5.28)	(2.79)
Duration		-0.002	0.000	0.000	0.001*	-0.001**
		(-1.47)	(0.20)	(0.13)	(1.67)	(-2.03)
Bid-Ask			-2.327***	-1.982***	-2.775***	-1.318**
			(-4.08)	(-3.18)	(-3.54)	(-2.11)
Bond Age			0.002***	0.001	0.003***	-0.000
			(2.84)	(1.64)	(3.73)	(-0.43)
Log (Bond Amt)			-0.002	-0.003	0.010*	-0.003
			(-0.48)	(-0.49)	(1.87)	(-0.48)
Log (Firm Size)				0.006	0.018	-0.062
				(0.10)	(0.22)	(-0.77)
Leverage				0.065**	-0.005	0.046
				(2.59)	(-0.20)	(1.38)
Profitability				-0.126	0.104	-0.193
				(-1.04)	(0.65)	(-1.24)
Cash				0.113***	0.074**	0.128***
				(3.43)	(2.14)	(3.06)
Constant	0.124***	0.074***	0.092	0.028	-0.205	0.189
	(54.90)	(2.74)	(1.24)	(0.17)	(-1.04)	(0.95)
Observations	189,234	187,817	187,120	139,418	70,901	68,438
R-squared	0.343	0.360	0.362	0.347	0.437	0.383
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4 Bond Complexity and Fund Trade Correlation

This table examines how bond complexity and HCI ownership influence correlated trading behavior. The dependent variable is a herding measure (HM) for HCI and REST investors. Columns 1 and 3 focus on HCI herding, while Columns 2 and 4 consider REST herding. The regressions include issuer, year-quarter, and rating-by-maturity fixed effects. Standard errors clustered by issuer and year-quarter. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. See Appendix 1 for detailed variable definitions. The observations are at the bond-quarter level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$CorrTrade_{HCI}$	$CorrTrade_{REST}$	*TrdAlignment*	$CorrTrade_{HCI}$	$CorrTrade_{REST}$	*TrdAlignment*
BComp	-0.033**	0.016	0.004			
	(-2.13)	(1.00)	(0.78)			
HCIOwn				-0.511***	0.096	-0.007
				(-7.85)	(1.40)	(-0.41)
Rating	-0.023	-0.051***	0.003	-0.019	-0.049***	0.003
	(-1.59)	(-3.35)	(0.90)	(-1.38)	(-3.20)	(0.89)
Duration	0.009**	0.005	-0.004**	0.009**	0.005	-0.004**
	(2.02)	(1.17)	(-2.60)	(2.12)	(1.25)	(-2.50)
Bid-Ask	3.770	3.472	0.047	3.022	3.707	0.012
	(1.38)	(1.26)	(0.04)	(1.15)	(1.32)	(0.01)
Bond Age	0.040***	0.044***	-0.003**	0.040***	0.044***	-0.003**
	(12.99)	(5.89)	(-2.42)	(13.10)	(5.82)	(-2.41)
Log (Bond Amt)	-0.536***	-0.305***	0.000	-0.532***	-0.304***	-0.001
	(-16.82)	(-9.19)	(0.02)	(-17.29)	(-9.10)	(-0.12)
Log (Firm Size)	-0.133	-0.774***	0.012	-0.154	-0.735**	0.013
	(-0.43)	(-2.67)	(0.14)	(-0.51)	(-2.52)	(0.16)
Leverage	-0.296***	0.139	-0.076**	-0.284***	0.128	-0.082**
	(-3.06)	(1.36)	(-2.08)	(-2.95)	(1.26)	(-2.25)
Profitability	1.244***	0.556	0.176	1.292***	0.612	0.172
	(2.91)	(1.22)	(0.61)	(3.02)	(1.34)	(0.59)
Cash	-0.252*	-0.093	-0.120**	-0.210*	-0.089	-0.116*
	(-1.99)	(-0.72)	(-2.01)	(-1.70)	(-0.68)	(-1.89)
Constant	7.621***	5.992***	0.091	7.643***	5.856***	0.105
	(9.26)	(7.15)	(0.46)	(9.40)	(6.95)	(0.51)
Observations	93,333	104,977	119,120	93,171	104,032	118,090
R-squared	0.230	0.213	0.015	0.235	0.207	0.015
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Double -Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5 Bond Complexity and Interest Rate Shocks

This table reports regressions of changes in credit spreads on interactions between bond complexity or HCI ownership and changes in 2-year Treasury rates. Columns 1–3 focus on bond complexity, while Columns 4–6 focus on HCI ownership. Additional interactions with default risk and illiquidity are included as robustness checks. All regressions include issuer and rating-by-maturity fixed effects with standard errors clustered by issuer and year-month. Other control variables, included but not reported for brevity, are *rating, duration, bid-ask, bond age, log(bond amt), log(firm size), leverage, profitability,* and *cash.* ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. See Appendix 1 for detailed variable definitions. The observations are at the bond-month level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			ΔYS			
BComp × Δ*Trsy2*	-0.087***	-0.066***	-0.076***			
	(-4.97)	(-4.52)	(-5.00)			
HCIOwn × Δ*Trsy2*				-0.521***	-0.442***	-0.427***
				(-5.42)	(-5.04)	(-4.60)
Δ*Trsy2*	-0.306***	-0.447***	-0.269***	-0.235***	-0.365***	-0.216***
	(-6.39)	(-6.11)	(-5.98)	(-4.96)	(-5.20)	(-4.69)
Zscore × Δ*Trsy2*		0.074***			0.062***	
		(3.56)			(3.23)	
PD × Δ*Trsy2*			-0.547***			-0.469***
			(-3.63)			(-3.12)
BComp	-0.000	0.000	-0.000			
	(-0.04)	(0.18)	(-0.09)			
HCIOwn				-0.010	-0.006	-0.008
				(-0.69)	(-0.46)	(-0.59)
Zscore		0.007			0.007	
		(1.41)			(1.41)	
PD			-0.075***			-0.075***
			(-2.66)			(-2.68)
Δ*Slope*	-0.229***	-0.222***	-0.223***	-0.230***	-0.222***	-0.225***
	(-4.01)	(-3.98)	(-4.08)	(-4.04)	(-4.00)	(-4.10)
Δ*VIX*	0.005*	0.005*	0.005*	0.005*	0.005*	0.005*
	(1.73)	(1.78)	(1.73)	(1.72)	(1.77)	(1.72)
S&P500Ret	-1.539***	-1.485***	-1.536***	-1.548***	-1.492***	-1.543***
	(-4.44)	(-4.39)	(-4.50)	(-4.48)	(-4.42)	(-4.52)
Δ*PD*	1.077***	1.128***	0.927***	1.096***	1.143***	0.940***
	(2.90)	(3.12)	(2.61)	(2.97)	(3.16)	(2.63)
StockRet	-0.681***	-0.670***	-0.678***	-0.677***	-0.667***	-0.675***
	(-12.26)	(-11.74)	(-12.16)	(-12.13)	(-11.67)	(-12.05)
Constant	-0.021	-0.029	0.033	-0.019	-0.028	0.026
	(-0.09)	(-0.12)	(0.14)	(-0.08)	(-0.11)	(0.11)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	392,251	367,297	392,251	392,251	367,297	392,251
R-squared	0.262	0.265	0.268	0.264	0.267	0.269
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	No	No	No	No	No	No
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6 Asymmetric Impact of Bond Complexity on Credit Spread Sensitivity

This table presents heterogeneity analyses of bond complexity effects on credit spread sensitivity. Panel A examines asymmetries for positive vs. negative Treasury rate changes. Panel B explores the persistence of effects over horizons from one to six months. Panel C shows results by bond maturity and credit rating groups. All regressions include issuer and rating-by-maturity fixed effects with standard errors clustered by issuer and year-month. Other control variables, included but not reported for brevity, are Δ*Slope*, Δ*VIX*, *S&P500Ret*, Δ*PD*, *S&P500Ret* as well as *rating*, *duration*, *bid-ask*, *bond age*, *log(bond amt)*, *log(firm size)*, *leverage*, *profitability*, and *cash*. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. See Appendix 1 for detailed variable definitions. The observations are at the bond-month level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			Δ*YS*			
BComp × $\Delta Trsy2^{-}$	-0.101***	-0.055**	-0.078***			
	(-3.54)	(-2.29)	(-3.07)			
BComp × $\Delta Trsy2^{+}$	-0.067**	-0.066***	-0.065***			
	(-2.52)	(-3.05)	(-2.78)			
HCIOwn × $\Delta Trsy2^{-}$				-0.604***	-0.385**	-0.435***
				(-3.63)	(-2.51)	(-2.84)
HCIOwn × $\Delta Trsy2^{+}$				-0.432**	-0.485***	-0.427**
				(-2.34)	(-2.94)	(-2.40)
Zscore × $\Delta Trsy2^{-}$		0.190***			0.182***	
		(5.79)			(5.68)	
Zscore × $\Delta Trsy2^{+}$		-0.014			-0.030	
		(-0.49)			(-1.29)	
PD × $\Delta Trsy2^{-}$			-1.036***			-0.987***
			(-4.28)			(-4.22)
PD × $\Delta Trsy2^{+}$			-0.066			0.048
			(-0.26)			(0.19)
$\Delta Trsy2^{-}$	-0.498***	-0.851***	-0.426***	-0.420***	-0.786***	-0.375***
	(-4.97)	(-7.29)	(-4.18)	(-3.91)	(-6.43)	(-3.45)
$\Delta Trsy2^{+}$	-0.162**	-0.137	-0.155**	-0.101	-0.038	-0.101*
	(-2.32)	(-1.22)	(-2.47)	(-1.62)	(-0.40)	(-1.72)
BComp	-0.001	0.002	-0.000			
	(-0.25)	(0.75)	(-0.06)			
HCIOwn				-0.024	-0.006	-0.014
				(-1.01)	(-0.27)	(-0.62)
Zscore		0.019***			0.019***	
		(3.46)			(3.59)	
PD			-0.138***			-0.142***
			(-3.81)			(-4.01)
Constant	0.080	-0.014	0.110	0.094	-0.006	0.113
	(0.33)	(-0.06)	(0.48)	(0.39)	(-0.03)	(0.48)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	392,251	367,297	392,251	392,251	367,297	392,251
R-squared	0.266	0.271	0.273	0.268	0.273	0.274
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	No	No	No	No	No	No
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7 Bond Complexity and Monetary Policy Shocks

This table presents event-study regressions using high-frequency monetary policy shocks (NS and GSS). Columns 1–3 use bond complexity as the moderating variable; Columns 4–6 use HCI ownership. The dependent variable is the change in credit spreads around FOMC dates. Treasury rate changes are decomposed into predicted and residual components. Issuer, rating-by-maturity, and FOMC-date fixed effects are included. Standard errors are clustered by issuer and FOMC-date. Other control variables, included but not reported for brevity, are Δ*Slope, ΔVIX, S&P500Ret, ΔPD, S&P500Ret* as well as *rating, duration, bid-ask, bond age, log(bond amt), log(firm size), leverage, profitability*, and *cash*. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. See Appendix 1 for detailed variable definitions. The observations are at the bond-FOMC date level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:				Δ*YS*		
BComp × Δ*Trsy2*	-0.069**					
	(-2.42)					
BComp × $\Delta\widehat{Trsy2}^{(NS)}$		0.075				
		(0.59)				
BComp × $r_{\Delta Trsy2^{(NS)}}$		-0.086**				
		(-2.20)				
BComp × $\Delta\widehat{Trsy2}^{(GSS)}$			0.070			
			(0.65)			
BComp × $r_{\Delta Trsy2^{(GSS)}}$			-0.087**			
			(-2.28)			
HCIOwn × Δ*Trsy2*				-0.575***		
				(-3.49)		
HCIOwn × $\Delta\widehat{Trsy2}^{(NS)}$					-0.332	
					(-0.45)	
HCIOwn × $r_{\Delta Trsy2^{(NS)}}$					-0.589***	
					(-2.81)	
HCIOwn × $\Delta\widehat{Trsy2}^{(GSS)}$						-0.324
						(-0.48)
HCIOwn × $r_{\Delta Trsy2^{(GSS)}}$						-0.570***
						(-2.84)
BComp	0.202	0.394**	0.357*	0.498**	0.349*	0.476**
	(1.30)	(2.38)	(1.83)	(2.56)	(1.84)	(2.61)
HCIOwn		-0.451		-0.127		-0.087
		(-1.48)		(-0.30)		(-0.22)
Constant	-3.054	-3.232	-3.230	-5.299	-5.411	-5.385
	(-0.62)	(-0.66)	(-0.66)	(-1.16)	(-1.19)	(-1.19)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,842	85,842	85,842	85,842	85,842	85,842
R-squared	0.142	0.142	0.142	0.144	0.144	0.143
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
FOMC-date FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8 Bond Complexity and Demand Shocks – IV Regressions

This table presents two-stage least squares regressions of credit spread changes on instrumented changes in passive bond ownership, moderated by bond complexity (Columns 1–3) or HCI ownership (Columns 4–6). Instruments are based on maturity-driven fund flows. All specifications include issuer, year-month, and rating-by-maturity fixed effects, with standard errors clustered by issuer. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. See Appendix 1 for detailed variable definitions. The observations are at the bond-month level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:				ΔYS		
BComp × $\Delta \widehat{Passive Own}$	0.056*	0.041	0.073**			
	(1.67)	(1.40)	(2.00)			
HCIOwn × $\Delta \widehat{Passive Own}$				0.571**	0.518**	0.543**
				(2.34)	(2.24)	(2.15)
$\Delta \widehat{Passive Own}$	-0.126**	-0.103*	-0.139*	-0.196**	-0.173**	-0.199**
	(-1.96)	(-1.76)	(-1.76)	(-2.46)	(-2.33)	(-2.25)
BComp	-0.015*	-0.010	-0.020**			
	(-1.66)	(-1.21)	(-2.01)			
HCIOwn				-0.130**	-0.113**	-0.111**
				(-2.57)	(-2.29)	(-2.04)
Rating		-0.028***	-0.028***		-0.028***	-0.029***
		(-5.48)	(-4.11)		(-5.30)	(-4.20)
Duration		0.003***	0.003***		0.003***	0.002**
		(3.74)	(3.20)		(2.83)	(2.31)
Bid-Ask		-2.688***	-2.904***		-2.693***	-2.820***
		(-4.78)	(-4.04)		(-4.50)	(-3.84)
Bond Age		-0.004***	-0.005***		-0.005***	-0.006***
		(-4.25)	(-3.32)		(-4.52)	(-3.73)
Log (Bond Amt)		-0.000	0.000		-0.002	-0.002
		(-0.00)	(0.07)		(-0.45)	(-0.45)
Log (Firm Size)			0.118			0.108
			(1.47)			(1.33)
Leverage			-0.080**			-0.088**
			(-2.20)			(-2.33)
Profitability			0.014			0.086
			(0.06)			(0.37)
Cash			-0.174***			-0.156***
			(-3.19)			(-2.81)
Observations	458,847	443,493	336,889	451,040	436,672	332,153
R-squared	-0.083	-0.050	-0.112	-0.123	-0.094	-0.130
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	33.006	44.674	24.756	38.762	42.639	29.117
Kleibergen-Paap Wald F statistic	17.923	25.033	13.515	20.487	23.365	15.534

Table 9 Bond Complexity and Bond Fragility

This table links *Bcomp*/HCI to $\sqrt{BFragility}$ and tests whether fragility amplifies responses to $\Delta Trsy2$. Columns (1)–(4) regress contemporaneous and lead $\sqrt{BFragility}$ on *BComp* and *HCIOwn*, respectively. Columns (5)–(6) interact fragility with shocks. Issuer, year–quarter, and rating-by-maturity fixed effects included; standard errors clustered by issuer and year–quarter (Columns 1–5) and by issuer (Column 6). ***, **, * denote 1%, 5%, 10% significance. Variable definitions in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$\sqrt{BFragility}$				ΔYS	ΔYS *(IV)*
BComp	0.004***	0.004**				
	(2.97)	(2.25)				
HCIOwn			0.026***	0.030***		
			(4.28)	(4.21)		
$\sqrt{BFragility} \times \Delta Trsy2$					-0.119*	
					(-1.67)	
$\sqrt{BFragility} \times \Delta\widehat{PassiveOwn}$						0.529*
						(1.74)
$\sqrt{BFragility}$					0.005	-0.218**
					(0.43)	(-1.97)
$\Delta\widehat{PassiveOwn}$						-0.292
						(-1.64)
Rating	0.004***	0.003*	0.004***	0.003*	-0.016***	-0.035***
	(2.97)	(1.89)	(2.95)	(1.89)	(-2.88)	(-3.27)
Duration	-0.004***	-0.004***	-0.004***	-0.004***	0.010***	0.002
	(-6.06)	(-5.25)	(-6.15)	(-5.33)	(4.05)	(1.14)
Bid-Ask	-1.591***	-1.575***	-1.565***	-1.546***	-8.250***	-3.613**
	(-5.60)	(-4.46)	(-5.40)	(-4.32)	(-4.64)	(-2.43)
Bond Age	-0.003***	-0.003***	-0.003***	-0.004***	0.001	-0.007**
	(-6.19)	(-5.76)	(-6.39)	(-6.02)	(1.07)	(-2.55)
Log (Bond Amt)	0.083***	0.085***	0.086***	0.087***	-0.011*	0.005
	(15.66)	(14.42)	(15.73)	(14.58)	(-1.75)	(0.43)
Log (Firm Size)		0.014		0.011	0.007	0.046
		(0.54)		(0.41)	(0.09)	(0.38)
Leverage		0.016		0.013	0.009	-0.158***
		(1.15)		(0.88)	(0.20)	(-2.84)
Profitability		0.094		0.106	-0.352	0.049
		(1.28)		(1.43)	(-0.81)	(0.13)
Cash		0.039**		0.041**	-0.133**	-0.169*
		(2.10)		(2.21)	(-2.00)	(-1.82)
ΔPD					1.338***	
					(9.49)	
Stock Return					-0.544***	
					(-5.43)	
Constant	-0.966***	-1.024***	-0.999***	-1.050***	0.233	
	(-13.17)	(-10.14)	(-13.25)	(-10.23)	(1.16)	
Observations	175,906	130,668	171,258	127,563	122,444	98,146
R-squared	0.252	0.249	0.250	0.247	0.573	-0.270
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10 Bond Complexity and Bond Illiquidity

This table assesses how bond complexity and HCI ownership affect bond illiquidity. The dependent variables are lead values of bid-ask spreads, Amihud (2002), and Roll (1984) illiquidity measures for Columns 1–2, 3–4, and 5–6, respectively. A higher value of the dependent variable indicates lower liquidity. Standard errors are clustered by issuer and year-quarter. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively. See Appendix 1 for detailed variable definitions. The observations are at the bond-quarter level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$Bid\text{-}Ask_{t+1}$	$Amihud_{t+1}$	$Roll_{t+1}$	$Bid\text{-}Ask_{t+1}$	$Amihud_{t+1}$	$Roll_{t+1}$
BComp	-0.008*	-0.004*	-0.008*			
	(-1.86)	(-1.80)	(-1.76)			
HCIOwn				-0.035***	-0.018***	-0.078***
				(-2.80)	(-3.45)	(-5.51)
Rating	0.019***	0.004**	0.012**	0.019***	0.005**	0.013**
	(4.14)	(2.28)	(2.36)	(4.12)	(2.51)	(2.55)
Duration	0.018***	-0.000	0.018***	0.018***	0.000	0.018***
	(11.92)	(-0.03)	(5.76)	(11.91)	(0.00)	(5.80)
Bond Age	0.010***	0.010***	0.024***	0.010***	0.010***	0.025***
	(8.64)	(14.87)	(18.27)	(8.58)	(14.65)	(18.25)
Log (Bond Amt)	-0.071***	-0.076***	-0.150***	-0.072***	-0.075***	-0.150***
	(-11.58)	(-22.17)	(-16.89)	(-12.16)	(-22.26)	(-17.38)
Log (Firm Size)	-0.035	-0.024	0.195**	-0.044	-0.026	0.206**
	(-0.42)	(-0.67)	(2.00)	(-0.53)	(-0.71)	(2.08)
Leverage	0.019	0.031**	0.083**	0.025	0.030**	0.091**
	(0.60)	(2.32)	(2.24)	(0.81)	(2.26)	(2.52)
Profitability	-1.681***	-0.550***	-1.660***	-1.673***	-0.534***	-1.632***
	(-6.85)	(-6.19)	(-6.89)	(-6.78)	(-6.05)	(-6.75)
Cash	-0.055	-0.001	0.016	-0.048	0.002	0.035
	(-1.27)	(-0.07)	(0.34)	(-1.11)	(0.14)	(0.75)
Constant	1.220***	1.127***	2.007***	1.241***	1.122***	1.967***
	(5.87)	(11.90)	(8.35)	(5.98)	(11.67)	(8.07)
Observations	141,481	141,482	141,320	138,141	138,141	138,006
R-squared	0.541	0.405	0.620	0.543	0.402	0.618
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11 Shift-Share IV for HCI Ownership

Panel A reports 2SLS effects of instrumented HCI ownership on fragility (Column 2), within-HCI trading correlation (Column 3), within-REST correlation (Column 4), and illiquidity (Bid-Ask, Roll; Columns. 5–6). Column. 1 shows the first stage (DV = *HCIOwn*). Panel B tests moderation of shocks: Columns. 1–3 interact instrumented *HCIOwn* with *ΔTrsy2* (information shocks); Columns. 4–6 interact it with instrumented *ΔPassiveOwn* (demand shocks). All regressions include bond/firm controls and fixed effects for issuer, rating-by-maturity, and year–quarter; standard errors are clustered by issuer and year–quarter. ***, **, * denote 1%, 5%, 10% significance. Variable definitions in Appendix 1. Unit of observation: bond–quarter (Panel A), bond–month (Panel B).

Panel A Fragility and Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*HCIOwn*	$\sqrt{BFragility}$	$CorrTrade_{HCI}$	$CorrTrade_{REST}$	*Bid-Ask*	*Roll*
	1st stage	2nd stage	2nd stage	2nd stage	2nd stage	2nd stage
$\widehat{HCIOwn}$		0.051***	-0.469***	0.205**	-0.033*	-0.091***
		(4.09)	(-5.11)	(2.23)	(-1.67)	(-4.24)
$Z_{j,t}^{share}$	0.608***					
	(15.49)					
MFOwn	-0.221***	0.269***	-2.266***	-0.980***	-0.451***	-0.115*
	(-6.88)	(8.78)	(-15.62)	(-5.84)	(-6.27)	(-1.72)
Rating	0.004**	0.002	-0.005	-0.031**	0.020***	0.014**
	(0.15)	(0.95)	(-0.42)	(-2.52)	(4.62)	(2.54)
Duration	-0.001	-0.002*	-0.011**	0.004	0.011***	0.011***
	(-0.74)	(-1.85)	(-2.05)	(0.67)	(5.46)	(3.14)
Bid-Ask	-0.754*	-1.170**	-2.180	-1.749		
	(-1.67)	(-2.27)	(-0.77)	(-0.57)		
Bond Age	-0.001	-0.002***	0.016***	0.041***	0.005***	0.019***
	(-1.30)	(-2.88)	(4.95)	(4.59)	(3.78)	(12.25)
Log (Bond Amt)	-0.011***	0.102***	-0.502***	-0.276***	-0.073***	-0.137***
	(-2.89)	(17.28)	(-15.88)	(-7.65)	(-13.15)	(-17.06)
Log (Firm Size)	0.051	-0.048	-0.073	-0.531*	0.026	0.238*
	(1.27)	(-1.26)	(-0.25)	(-1.69)	(0.29)	(1.86)
Leverage	0.005	0.006	-0.268***	0.172	0.054*	0.128***
	(0.29)	(0.33)	(-2.68)	(1.46)	(1.76)	(2.88)
Profitability	0.045	0.097	1.564***	0.699	-1.618***	-1.737***
	(0.51)	(0.97)	(3.42)	(1.63)	(-6.61)	(-6.63)
Cash	0.033	0.051**	-0.071	0.015	-0.034	0.076
	(1.58)	(2.18)	(-0.55)	(0.11)	(-0.76)	(1.42)
Observations		71,293	64,143	63,092	78,478	78,438
R-squared		0.067	0.081	0.042	0.050	0.062
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic		40.145	38.419	40.062	41.550	41.531
Kleibergen-Paap Wald F statistic		239.913	209.656	303.458	269.784	271.176

Panel B Yield Spread Response to Market Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			ΔYS – 2nd Stage			
$\widehat{HCIOwn} \times \Delta Trsy2$	-0.573***	-0.570***	-0.588***			
	(-4.37)	(-4.32)	(-4.26)			
$\widehat{HCIOwn} \times \Delta \widehat{PassiveOwn}$				0.841*	0.763*	0.512
				(1.84)	(1.85)	(1.32)
$\widehat{HCIOwn}$	-0.013	-0.007	-0.008	-0.230**	-0.196*	-0.126
	(-0.49)	(-0.26)	(-0.27)	(-2.07)	(-1.93)	(-1.30)
$\Delta Trsy2$	-0.164***	-0.172***	-0.167***			
	(-2.94)	(-3.11)	(-3.05)			
$\Delta \widehat{PassiveOwn}$				-0.344***	-0.318***	-0.274**
				(-2.68)	(-2.81)	(-2.25)
Rating		-0.003	-0.003		-0.033***	-0.030***
		(-1.24)	(-1.27)		(-4.15)	(-3.03)
Duration		0.005***	0.005***		0.003*	0.003**
		(3.45)	(3.58)		(1.81)	(2.31)
Bid-Ask		-8.527***	-8.390***		-4.253***	-4.460***
		(-4.27)	(-4.55)		(-4.47)	(-4.03)
Bond Age		0.001	0.001		-0.006***	-0.006***
		(1.15)	(1.45)		(-4.40)	(-3.78)
Log (Bond Amt)		-0.007*	-0.008**		-0.018**	-0.017**
		(-1.79)	(-2.31)		(-2.53)	(-2.48)
Log (Firm Size)			0.021			0.088
			(0.20)			(0.78)
Leverage			-0.008			-0.186***
			(-0.28)			(-3.75)
Profitability			0.231			0.345
			(0.95)			(1.11)
Cash			-0.028			-0.252***
			(-0.71)			(-3.25)
Other Maro Controls	Yes	Yes	Yes	No	No	No
Observations	271,149	270,021	220,687	268,832	259,991	199,977
R-squared	0.278	0.285	0.288	-0.320	-0.266	-0.214
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	No	No	No	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	96.923	96.487	90.217	20.598	26.039	18.919
Kleibergen-Paap Wald F statistic	239.025	223.991	198.106	7.076	9.072	6.487

Table 12 Loan-Side Controls

This table tests whether loan covenant protections affect the relationship between bond complexity, investor specialization, and bond spread sensitivity. Firms are grouped into three categories based on syndicated loan data: no loan, covenant-light loan, and covenant-heavy loan. Panel A reports regressions of monthly bond spread changes on Treasury yield shocks. Panel B reports two-stage least squares regressions using predicted changes in passive ownership. All regressions include firm and rating-by-maturity fixed effects. Standard errors are clustered by issuer and time. ***, **, * denote 1%, 5%, 10% significance. Variable definitions in Appendix 1. Unit of observation: bond–month.

Panel A Credit Spread Sensitivity to Treasury Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			ΔYS			
BComp × Δ*Trsy2*	-0.087***	-0.065***	-0.076***			
	(-4.98)	(-4.51)	(-5.01)			
HCIOwn × Δ*Trsy2*				-0.520***	-0.438***	-0.427***
				(-5.42)	(-5.01)	(-4.60)
Loan_Cov_Group × Δ*Trsy2*	0.021	0.036**	0.017	0.018	0.032**	0.015
	(1.40)	(2.13)	(1.30)	(1.46)	(2.21)	(1.35)
Δ*Trsy2*	-0.314***	-0.464***	-0.276***	-0.242***	-0.380***	-0.222***
	(-6.47)	(-6.16)	(-6.06)	(-5.06)	(-5.28)	(-4.78)
BComp	-0.000	0.000	-0.000			
	(-0.03)	(0.17)	(-0.07)			
HCIOwn				-0.010	-0.006	-0.008
				(-0.69)	(-0.45)	(-0.58)
Loan_Cov_Group	-0.002	-0.001	-0.002	-0.002	-0.001	-0.002
	(-0.79)	(-0.46)	(-0.94)	(-0.77)	(-0.46)	(-0.95)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	392,251	367,297	392,251	392,251	367,297	392,251
R-squared	0.262	0.265	0.268	0.264	0.267	0.269
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	No	No	No	No	No	No
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B Credit Spread Sensitivity to Demand Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			ΔYS			
BComp × $\Delta \widehat{PassiveOwn}$	0.057*	0.041	0.073**			
	(1.68)	(1.42)	(1.99)			
HCIOwn × $\Delta \widehat{PassiveOwn}$				0.560**	0.511**	0.542**
				(2.30)	(2.20)	(2.14)
Loan_Cov_Group × $\Delta \widehat{PassiveOwn}$	-0.086	-0.063	-0.006	-0.062	-0.050	-0.004
	(-1.58)	(-1.26)	(-0.12)	(-1.18)	(-0.98)	(-0.08)
$\Delta \widehat{PassiveOwn}$	-0.107*	-0.089	-0.136*	-0.180**	-0.161**	-0.198**
	(-1.66)	(-1.52)	(-1.68)	(-2.21)	(-2.12)	(-2.13)
BComp	-0.015*	-0.010	-0.020**			
	(-1.66)	(-1.21)	(-2.00)			
HCIOwn				-0.129**	-0.112**	-0.111**
				(-2.54)	(-2.27)	(-2.03)
Loan_Cov_Group	0.017	0.012	0.003	0.012	0.009	0.003
	(1.25)	(0.92)	(0.18)	(0.86)	(0.66)	(0.22)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	458,847	443,493	336,889	451,040	436,672	332,153
R-squared	-0.083	-0.050	-0.112	-0.123	-0.094	-0.130
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes