

Multi-Security Complexity and Selective Pass-Through in Corporate Bonds

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Abstract

How does multi-security complexity affect the transmission of shocks into credit markets? Using U.S. corporate bond and mutual fund holdings data from 2006–2023, we document a habitat preference by investors specializing in complex multi-security issuers. Multi-security complexity and specialist ownership amplify the response of credit spreads to Treasury-rate and FOMC information shocks but dampen the effects of mechanically induced passive-demand shocks. Specialists respond more strongly to information and trade against non-fundamental flows, generating selective pass-through of shocks into bond prices. Their trades predict future returns in complex bonds. Specialist ownership is associated with greater ownership-based fragility and lower trading frictions in secondary markets.

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Introduction

Unlike equities, bond financing often leads to highly complex debt structures. For example, as of December 2023, AT&T had 171 bonds outstanding, ranging from fixed- and floating-rate securities to callable and non-callable bonds, covenant-protected and non-covenant issues, and both public and Rule 144A offerings. Investors therefore face not a single security, but a portfolio of heterogeneous claims on the same firm and the valuation of each claim depends on the value of the other claims as well.

Do investors understand the intricacies of complex bond structures and if so, how do they react to them? Does such “multi-security complexity” affect the transmission of macroeconomic shocks into credit markets? More broadly, can the contractual architecture of corporate debt influence not only price discovery but also the stability of the market itself? These questions sit at the intersection of financial contracting, asset pricing, and monetary-policy transmission, yet the existing literature has largely studied them separately. In this paper, we argue that multi-security complexity shapes the ownership composition of corporate bonds, and that ownership composition in turn determines how different shocks are transmitted into prices.

More specifically, corporate bond markets are distinctive in one underappreciated respect. Firms typically issue multiple bonds simultaneously, and those bonds interact through their contractual provisions. A covenant in one bond can protect — or expose — holders of another bond issued by the same firm. A call provision in a senior bond, once exercised, may alter the protection available to the subordinated claims. Willingness to monitor and enforce a covenant, as well as to exercise a call provision, often depends not only on the terms and market value of an individual bond but also on the *structure of the issuer's broader debt portfolio* and the *incentives of other claimholders*. As a result, valuing a single bond frequently requires understanding the architecture of the issuer's entire debt structure rather than the bond in isolation.

We refer to this feature as *multi-security complexity*, defined as the degree of contractual heterogeneity across an issuer's outstanding bonds. Unlike conventional *individual-security complexity* arising from exotic payoffs or structured products, the complexity we study emerges from the interaction of otherwise standard *contractual* features—including callability, putability, collateral, seniority, and covenant protections—across multiple securities issued by the same firm. Existing theories of individual-security complexity typically assume homogeneous investors and emphasize risk concentration, neglected tail risks, and market fragility (Coval, Jurek, and Stafford, 2009; Gennaioli, Shleifer, and Vishny, 2012; Caballero and Simsek, 2013; Carlin, Kogan, and Lowery, 2013). However, when processing contractual information is costly, investors may differ substantially in their ability and willingness to acquire such information, leading to endogenous specialization in information production and trading (Goldstein and Yang, 2015). In such a setting, the consequences of multi-security complexity may depend critically on the ownership structure it attracts.

The valuation challenges posed by contractual heterogeneity across bonds of the same firm create incentives for investor specialization. As multi-security complexity rises, understanding contractual interactions becomes increasingly costly, encouraging participation by investors with greater expertise in analyzing debt contracts and cross-bond contingencies. We refer to these investors as *High-Complexity Investors (HCI)*, our empirical proxy for specialist investors. Other investors, whom we collectively label as *REST*, are less specialized in processing multi-security complexity and place relatively less weight on contractual information. The resulting ownership composition reflects an equilibrium response to the informational demands created by contractual heterogeneity.

Our analysis builds on the multi-security complexity measure developed in Kim and Massa (2026), which shows that contractual heterogeneity across an issuer's outstanding bonds affects credit spreads and investor clientele. We use such a measure to examine how complexity-induced ownership composition influences shock transmission, trading behavior, return predictability, and market

functioning. In doing so, we bring the issue of multi-security complexity in the current debate of financial fragility (e.g., Goldstein, Jiang, and Ng, 2017; Falato, Goldstein, and Hortaçsu, 2021; Haddad, Moreira, and Muir, 2021) and monetary policy transmission (e.g., Kuong, O'Donovan, and Zhang, 2024; Dannhauser and Hoseinzade, 2022; Fang, 2025).

We argue that multi-security complexity affects ownership composition and specialization. If specialist investors are better equipped to interpret the implications of news for complex bond structures, differences in ownership composition should affect how prices respond to different types of shocks. When a shock contains information about economic fundamentals, specialist investors should facilitate its incorporation into prices. In contrast, when price pressure originates from non-fundamental demand shocks—such as passive rebalancing, benchmark migrations, or redemption-driven selling—specialists may be more likely to recognise the absence of fundamental information and absorb rather than propagate the demand imbalance. As a result, bonds with greater specialist (HCI) ownership should exhibit *selective pass-through*: stronger price responses to fundamental shocks and weaker responses to non-fundamental shocks. We refer to this mechanism—where multi-security complexity attracts specialist investors and the resulting ownership composition influences the incorporation of information and the transmission of shocks—as the *multi-security complexity channel*.

This prediction extends the standard view that informed investors improve price efficiency by accelerating the incorporation of information into prices (Grossman and Stiglitz, 1980; Kyle, 1985). Under such view, markets with a greater presence of informed investors should incorporate fundamental information more rapidly. Our argument is more specific. Ownership specialization should affect the transmission of shocks *asymmetrically* depending on their informational content. Complexity and specialist ownership should amplify the response of credit spreads to fundamental news while dampening the response to non-fundamental demand pressure. This distinction is particularly important in corporate bond markets, where flow-induced shocks from passive investing and mutual fund

redemptions are pervasive and economically significant (Goldstein, Jiang, and Ng, 2017; Bretscher, Schmid, and Ye, 2025).

We examine this channel through the lens of mutual funds, which are among the most active institutional investors in U.S. corporate bond markets. Mutual funds are particularly well suited for our analysis because they exhibit substantial heterogeneity in portfolio specialization, face frequent flow-induced demand shocks, and disclose bond holdings at a sufficiently granular level to measure ownership composition and trading behavior. Specifically, we construct a comprehensive panel of 593,909 bond-month observations covering 1,726 U.S. corporate issuers between 2006 and 2023. We measure *multi-security complexity* at the issuer-quarter level as the average pairwise contractual distance across an issuer's outstanding bonds. We classify HCI funds on the basis of the extent to which their prior-year portfolios tilt toward complex bonds (i.e., bonds issued by high multi-security complex issuers) relative to style peers. To further sharpen the identification, we complement our baseline analysis with a shift-share instrument (Bartik, 1991; Goldsmith-Pinkham, Sorkin, and Swift, 2020) for specialist ownership and exploit the decomposition of FOMC announcements into information and policy components.

We document several findings consistent with the multi-security complexity channel. First, we identify an ownership specialization effect. HCI and REST exhibit economically meaningful differences in their characteristics and investment behavior. Relative to REST funds, HCI funds are smaller (average AUM of \$587 million versus \$911 million) and allocate substantially more capital to bonds (12.7% versus 8.1). Their investment styles are also persistent: 68% of HCI funds remain classified as HCI in the following year. Return-based factor exposures provide a similar picture. HCI funds load nearly twice as strongly on the corporate-bond market factor (0.449 vs. 0.243) while exhibiting only one-fifth of the stock-market exposure of REST funds (0.129 versus 0.680), consistent with a specialist focus on bond-specific risks rather than broad market exposure.

Second, complexity and specialist ownership generate economically meaningful selective pass-through. For information shocks, a one-percentage-point increase in the 2-year Treasury yield is associated with a 27–45 basis-point decline in credit spreads. This estimate is broadly consistent with the range reported in Duffee (1998) who finds 20 to 42 bps. A one-standard-deviation increase in multi-security complexity amplifies this response by roughly 8 basis points (bps), with similar magnitudes obtained for specialist ownership (10 bps). These magnitudes are economically meaningful. For comparison, a one-standard-deviation increase in issuer default probability amplifies the spread response by approximately 15 bps. By contrast, for mechanically induced passive-demand shocks, a one-standard-deviation increase in complexity reduces the spread response by approximately 4–7 bps, while a comparable increase in specialist ownership attenuates the response by roughly 9–10 bps. Thus, the same ownership structure that strengthens the incorporation of macroeconomic information dampens the transmission of non-fundamental demand pressure. These results are robust across alternative specifications and remain economically and statistically significant after controlling for interactions with issuer credit quality.

Third, the multi-security complexity channel survives stronger identification tests. To address concerns that specialist investors sort themselves into bonds that are inherently more sensitive to information shocks or less sensitive to non-fundamental demand pressure, we employ a shift-share instrument (Bartik, 1991) based on predetermined specialist holdings and subsequent fund-level capital flows. The first stage is strong, with Kleibergen–Paap F-statistics exceeding 190 in the Treasury-shock specifications. Instrumented specialist ownership continues to amplify the pass-through of Treasury-rate shocks, with interaction coefficients between -0.125 and -0.129 compared with -0.094 to -0.114 in the corresponding OLS specifications. Likewise, instrumented specialist ownership attenuates passive-demand-shock pass-through, with coefficients between 0.087 and 0.143 compared with 0.088

to 0.097 in OLS. These estimates suggest that the ownership effects are not driven by endogenous ownership selection.

Using reactions to high-frequency FOMC announcements, we provide further evidence that the amplification effect operates through information processing rather than mechanical interest-rate sensitivity. In particular, we decompose Treasury-yield changes into policy and information components (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). The former reflects unexpected monetary-policy actions, while the latter captures information revealed by the Federal Reserve about economic fundamentals and future growth prospects. Over the three-day announcement window, a 10 bp increase in the 2-year Treasury yield is associated with an approximately 3.8 bp decline in corporate bond spreads, in line with the scaled monthly estimates reported earlier (2.7–4.5 bps). A one-standard-deviation increase in multi-security complexity amplifies this response by roughly 0.7 bps, while a comparable increase in specialist ownership amplifies it by approximately 1.2 bps. When announcement-window Treasury-yield surprises are decomposed, these amplification effects remain similar in magnitude for the information component but disappear for the policy component, whose interactions are economically small and statistically insignificant. These findings are difficult to reconcile with a mechanical interest-rate-sensitivity explanation, which would predict amplification for both policy and information shocks.

While the preceding results establish that complexity and specialist ownership are associated with selective pass-through, they do not reveal why these effects arise. The multi-security complexity channel rests on the idea that specialist investors process contractual and macroeconomic information differently from other investors and therefore trade differently in response to shocks. If this mechanism is correct, we should observe systematic differences in how HCI and REST investors react to fundamental and non-fundamental shocks, and these differences should help explain the selective pass-through patterns documented above. And indeed, we provide direct evidence of this by focusing on the

trading and information-incorporation mechanisms underlying the multi-security complexity channel. HCI investors respond significantly more strongly than other investors to fundamental shocks: a one-pp increase in the 2-year Treasury yield reduces HCI net holdings by 2.3 pp, more than four times the corresponding response among REST investors (0.5 pp). Moreover, specialist ownership affects the behavior of other investors. Among bonds with low HCI ownership, REST investors exhibit little response to Treasury-rate shocks. In contrast, among bonds with high HCI ownership, REST investors reduce their holdings by 1.7 pp in response to the same shock. Economically, the estimated response is approximately 5.6 times larger in high-HCI bonds than in low-HCI bonds. These results suggest that specialist investors influence how information is transmitted through the broader investor base.

The opposite pattern emerges for non-fundamental demand shocks. A one-pp increase in passive ownership is associated with an 8.4 pp reduction in HCI holdings but a 9.1 pp increase in REST holdings, indicating that specialists tend to absorb whereas other investors tend to propagate passive-flow pressure. However, this tendency weakens markedly when specialist ownership is high. The response of REST investors falls from +13.0 pp in low-HCI-ownership bonds to −3.4 pp in high-HCI-ownership bonds, implying that specialist ownership dampens the transmission of non-fundamental demand shocks. Together, these findings suggest that specialist ownership not only affects specialist trading itself but also shapes how other investors respond to information and demand shocks.

Consistent with specialists possessing valuable information, their trades also predict future bond returns. Purchases by HCI investors are followed by significantly higher subsequent returns in complex bonds, whereas REST trading generally has little predictive power. At the three-month horizon, a one-standard-deviation increase in HCI net buying predicts returns that are approximately 52 bps higher in the most complex bonds than in the least complex bonds; at the six-month horizon, the corresponding difference reaches 80 bps. Similar patterns emerge for factor-adjusted abnormal returns. However, this predictive content becomes substantially weaker as specialist ownership increases. These

findings suggest that specialist investors possess information that is not yet fully reflected in prices when specialist participation is limited, but that this informational advantage becomes increasingly incorporated into prices as specialist ownership expands.

Finally, we consider the general market implications in terms of financial fragility. We document that the multi-security complexity channel affects not only information incorporation but also market fragility and liquidity. Greater specialist ownership is associated with higher multi-security complexity-based fragility, reflecting more concentrated investor clienteles and greater exposure to correlated trading. At the same time, more complex bond structures exhibit better liquidity, including narrower bid-ask spreads and lower price-impact measures. These findings suggest that informational efficiency and resilience need not move together. The same ownership structure that facilitates information incorporation and improves liquidity may also increase vulnerability to ownership-driven shocks.

Taken together, these findings suggest that multi-security complexity affects market outcomes primarily through the investor clientele it attracts. Ownership composition influences how information and demand shocks are transmitted into prices, how quickly information is incorporated into bond valuations, and how liquidity and fragility evolve in equilibrium.

Our paper connects and contributes to three strands of literature that have largely evolved separately. First, we contribute to the bond market microstructure and price-discovery literature (Duffee, 1998; Collin-Dufresne, Goldstein, and Martin, 2001; Bongaerts, de Jong, and Driessen, 2017). We show that the effects of investor specialization are shock-dependent. Specialist ownership amplifies the incorporation of fundamental information while dampening the effects of non-fundamental demand pressure. Trading and return-predictability evidence further suggests that specialist investors contribute to price discovery when specialist ownership is limited. As specialist participation deepens, however,

the informational advantage embedded in specialist trading becomes increasingly incorporated into prices, reducing the predictive content of subsequent trades.

Second, we contribute to the investor-composition literature (Greenwood and Thesmar, 2011; Goldstein, Jiang, and Ng, 2017; Falato, Goldstein, and Hortaçsu, 2021; Coppola, 2025), which studies how ownership structure affects asset prices, liquidity, and fragility. We show that ownership composition is itself an endogenous consequence of contractual design. Specifically, multi-security complexity is associated with greater specialist ownership, and this ownership specialization serves as a transmission mechanism linking debt structure to market outcomes. In doing so, we identify multi-security complexity as a systematic determinant of investor specialization and provide evidence that ownership composition affects not only market functioning but also how shocks are incorporated into prices.

Third, we contribute to the financial complexity literature (Coval, Jurek, and Stafford, 2009; Gennaioli, Shleifer, and Vishny, 2012; Caballero and Simsek, 2013; Carlin, Kogan, and Lowery, 2013). Existing studies have largely emphasized the costs of complexity, including risk concentration, neglected tail risks, and financial fragility. Our results suggest a more nuanced view. The consequences of complexity depend critically on the investor clientele it attracts. Through its effects on ownership specialization, complexity can strengthen information incorporation and improve market liquidity even as it increases ownership-based fragility.

The remainder of the paper is organized as follows. Section 2 describes the data, introduces the multi-security complexity and HCI ownership measures, and characterizes the HCI and REST investor groups. Section 3 presents the selective pass-through results, trading evidence and return predictability. Section 4 presents identification including instrumental-variable estimates and high-frequency FOMC evidence. Section 5 discusses implications in terms of fragility and liquidity. Section 6 concludes.

2. Data, Measures, and Investor Specialization

This section describes the sample, introduces the multi-security complexity and specialist-ownership measures, and provides evidence that the HCI classification captures a persistent and economically meaningful dimension of investor specialization. Section 2.1 describes the data and sample construction. Section 2.2 introduces the multi-security complexity measure and the ownership variables. Section 2.3 further characterizes the HCI and REST investor groups by comparing observable fund characteristics, classification persistence, investment behavior, and return-based factor exposures.

2.1 Sample Construction

Our analysis combines data from TRACE, Mergent FISD, the WRDS Bond Returns database, CRSP Mutual Funds, CRSP stock returns, COMPUSTAT, and several external sources of interest-rate and monetary-policy shocks. Bond-level prices, yields, and transactions are obtained from TRACE and WRDS. Following standard practice, we exclude floating-rate, sinking-fund, perpetual, convertible, preferred, asset-backed, foreign-currency, Yankee, and Rule 144A bonds. We further restrict the sample to nonfinancial and non-utility issuers and exclude bonds with less than one year remaining to maturity. Bond characteristics, including covenant provisions, seniority, collateral status, embedded options, and maturity, are obtained from FISD. We compute yield spreads as the difference between a bond's yield to maturity and the maturity-matched Treasury yield, where Treasury rates are obtained from Liu and Wu (2021).

After merging all the data sources and applying the sample filters, the final sample contains 593,909 bond-month observations covering 10,357 bonds issued by 1,726 firms from July 2006 to June 2023. Aggregation to the quarterly level yields 195,360 bond-quarter observations. Depending on the empirical setting, we organize the data into monthly, quarterly, and daily panels. The empirical analyses are conducted at multiple frequencies. Monthly specifications are used for the shock-transmission,

trading, and return-predictability tests, quarterly specifications for the fragility and liquidity analyses, and daily specifications for the high-frequency FOMC event-study tests.

Panel A of Table 1 reports summary statistics. In the monthly sample, the average change in bond yield spreads is -0.6 basis points with a standard deviation of 30 basis points, while changes in the 2-year Treasury yield average 1.8 basis points with a standard deviation of 17 basis points. Treasury rates increase in approximately 53% of bond-month observations and decrease in the remaining 47%. Multi-security complexity has a mean of 0.44 ($SD = 0.16$), indicating substantial variation in contractual heterogeneity across issuers. HCI ownership averages 49% ($SD = 35\%$), suggesting considerable heterogeneity in specialist participation across bonds. Mutual funds hold approximately 14% of the average bond outstanding, consistent with prior studies. The typical bond in our sample is rated around BB+, has a duration of roughly seven years, and an age of approximately 4.5 years. Additional summary statistics for the quarterly and daily samples are reported in Table 1.

2.2 Key Variables

Multi-Security Complexity. We measure multi-security complexity using the issuer-level complexity index developed by Kim and Massa (2026).¹ The measure captures contractual heterogeneity across all bonds issued by a firm in a given quarter. Each outstanding bond is represented by an eleven-dimensional vector of contractual features drawn from FISD, including callability, putability, convertibility, collateral, covenant provisions, coupon structure, and maturity characteristics. Multi-security complexity (*MSComp*) is defined as the average pairwise Euclidean distance across these feature vectors and is scaled to lie between zero and one.² Higher values indicate greater contractual

¹ In Kim and Massa (2026), the measure is referred to as issuer term variability (*ITV*). We use the term multi-security complexity (*MSComp*) throughout this paper because our focus is on contractual heterogeneity and investor specialization rather than on the characteristics of the issuer's debt maturity structure per se.

² Specifically, each outstanding bond is represented as a K -dimensional vector of feature indicators from FISD, compute pairwise distances across all bonds of the same issuer, and define multi-security complexity (*MSComp*) as the average pairwise Euclidean distance:

heterogeneity within the issuer's debt structure and therefore a greater need for cross-security contractual analysis.

The choice of the complexity measure is particularly important for our setting because the mechanism we study operates through investor specialization. To generate incentives for specialized information acquisition, complexity must arise from contractual interactions that require investors to analyze an issuer's debt structure as a whole rather than individual securities in isolation. Prior research shows that contractual heterogeneity affects investor behavior and pricing, influencing both investors' choices among alternative credit instruments and the compensation they require for processing contractual information (Oehmke and Zawadowski, 2017; Kim and Massa, 2026). This differs from the standard complexity measures that focus on individual security-level opacity, structured payoffs, or informational uncertainty surrounding a single instrument. Our *multi-security complexity* measure captures contractual heterogeneity across multiple securities issued by the same firm and is therefore particularly well suited for examining how complexity shapes investor specialization, ownership composition, and the transmission of shocks through financial markets.

The measure is constructed at the issuer level because many contractual interactions arise across an issuer's outstanding securities rather than within a single bond. This focus also aligns naturally with the specialization mechanism studied in this paper, as investors acquire expertise in the contractual structure of issuers rather than in isolated securities.

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

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 , $\mu_k = \sum_{j=1}^N \omega_j \mathbb{I}_{jk}$, with ω_j equal to bond j 's share of the issuer's total outstanding amount.

Specialist Ownership. For each bond-month, we measure HCI ownership as the fraction of mutual-fund holdings accounted for by funds classified as high-complexity investors. We proceed in three steps.

First, we compute each fund's monthly exposure to complex issuers. We match CRSP mutual-fund bond holdings to the issuer-level complexity indicator and calculate, for each fund-month, the share of the fund's positive market-value bond holdings invested in complex issuers.³ We then adjust this exposure for fund style by subtracting the average exposure of funds in the same Lipper objective code and month.

Second, we classify funds annually based on their prior-year style-adjusted complexity exposure. Because the objective is to identify investors that specialize in analyzing complex debt structures, the classification is constructed within the universe of bond funds defined by Lipper objective codes.⁴ For each fund-year, we average monthly style-adjusted complexity exposure over all available months in the year. Within each year, bond funds are ranked into quintiles based on this annual exposure, and funds in the top quintile are classified as HCI funds. This classification is then applied to the fund's holdings in the following calendar year, ensuring that HCI status is predetermined relative to the bond-month outcomes analyzed in the regressions.

Importantly, HCI status is not intended to identify investors that merely hold complex bonds. Rather, it identifies investors that consistently tilt toward complex issuers relative to style peers. Many bond funds occasionally invest in complex securities, but specialization implies a persistent preference for issuers whose valuation requires extensive contractual analysis. Our classification therefore aims to capture accumulated expertise in evaluating complex debt structures rather than temporary portfolio

³ We define a complex issuer using a binary indicator constructed from the issuer-level bond-complexity measure. Specifically, within each quarter, issuers are ranked into terciles based on multi-security complexity (*MSComp*), and issuers in the highest tercile are classified as complex.

⁴ HCI status is defined only among bond funds because the objective is to identify investors that specialize in analyzing complex debt structures within the fixed-income universe. Consequently, REST includes both non-HCI bond funds and other mutual funds that hold corporate bonds but are not part of the HCI classification exercise. This design reflects our focus on specialist investors versus the broader bond-holding investor base rather than on differences among bond-fund styles.

positions. Because the objective is to identify a specialist investor clientele, the HCI classification is not intended to partition the mutual-fund universe into mutually exclusive investment styles. Accordingly, HCI ownership and trading are measured using funds classified as HCI, while REST represents all remaining mutual-fund investors holding the bond. Our objective is to compare the behavior of specialist investors against the broader bond-holding investor base.

Third, we aggregate holdings to the bond-month level. For each bond-month, we sum the market value held by HCI funds and divide it by the total market value held by all mutual funds in that bond. This gives our main ownership measure, *HCIOwn*. The complementary share held by all remaining investors is denoted by *RESTOwn*. Because the denominator is total mutual-fund holdings rather than total amount outstanding, *HCIOwn* captures the composition of the mutual-fund investor base holding the bond. It therefore captures the relative importance of specialist investors within the mutual-fund investor base rather than the overall fraction of the bond held by specialists.

2.3 Characteristics of HCI and REST Investors

The interpretation of our empirical results relies on HCI and REST representing distinct investor clienteles. Although HCI status is constructed using portfolio exposure to complex issuers, it is useful to examine whether the resulting groups differ systematically along other dimensions. We therefore compare HCI and REST investors in terms of observable fund characteristics, classification persistence, issuer-level investment behavior, and return-based factor exposures.

Fund Characteristics. Panel A of Table 2 compares the characteristics of HCI and REST funds. Several notable differences emerge. HCI funds are significantly smaller than REST funds in terms of assets under management. At first glance, this may appear counterintuitive, as larger funds generally possess greater resources for information production. The result suggests that investment in complex issuers is not simply a manifestation of scale or resources but reflects a distinct investment orientation.

Importantly, the smaller size of HCI funds works against a simple price-impact explanation for our later findings. If larger investors mechanically exert greater influence on prices, the stronger predictive power associated with HCI trading cannot be attributed solely to fund size. HCI funds also charge higher expense ratios and are disproportionately affiliated with bond-specialist fund families. These differences are consistent with the presence of a more specialized investor clientele.

Persistence of HCI Status. A second concern is that HCI classification may simply reflect temporary portfolio rebalancing rather than a persistent investment orientation. We therefore examine the stability of HCI status over time. Panel B of Table 2 reports annual transition probabilities. Approximately 68.1% of funds classified as HCI in year t remain HCI in year $t+1$, compared with an unconditional HCI membership probability of 20%. Similarly, 91.0% of funds classified as REST remain REST in the following year. These transition probabilities indicate that movements between the two groups are relatively infrequent and that complexity exposure is far from randomly assigned. Instead, HCI status appears to reflect a stable feature of fund investment behavior. The evidence therefore supports interpreting HCI as a durable investment orientation toward complex issuers rather than a temporary portfolio allocation.

Issuer-Level Investment Behavior. Panel C examines whether HCI and REST differ in the way they allocate attention across issuers. HCI funds exhibit significantly higher issuer-attention HHI, indicating that their investment activity is more concentrated among a recurring set of issuers even after controlling for fund tenure and investment breadth. HCI funds also maintain investment relationships with issuers for longer periods. Together, these patterns suggest that HCI investors repeatedly allocate attention and capital to a narrower set of issuers than REST investors. While not by themselves sufficient to establish expertise, the results are consistent with a more focused investment approach and complement the persistence evidence reported above.

Fund Alpha and Factor Exposures. Panel D compares the return characteristics of HCI and REST portfolios. HCI funds load primarily on the aggregate corporate bond market factor ($\beta_{\text{MKTB}} = 0.45$) and only modestly on the aggregate stock market factor ($\beta_{\text{MKTS}} = 0.13$). In contrast, REST funds exhibit substantially greater equity-market exposure ($\beta_{\text{MKTS}} = 0.68$) and a lower loading on the bond market factor ($\beta_{\text{MKTB}} = 0.24$). These patterns are consistent with HCI investors placing greater emphasis on bond-specific investment opportunities. Although some of the differences likely reflect the broader fund universe represented in REST, the factor loadings provide additional evidence that HCI and REST represent economically distinct investor clienteles. The alpha estimates provide little evidence that HCI funds outperform on a risk-adjusted basis, suggesting that any informational advantages associated with investing in complex issuers are not easily detected at the aggregate fund level. We return to this reconciliation in Section 3.4.

Taken together, the results in Table 2 indicate that HCI and REST represent economically distinct investor clienteles. Relative to REST investors, HCI funds exhibit greater persistence in their complexity exposure, maintain more concentrated and longer-lasting issuer relationships, and display return characteristics more closely tied to corporate bond markets. While these patterns do not by themselves establish contractual expertise, they are consistent with HCI capturing a persistent investment orientation toward complex issuers. This distinction provides the foundation for our subsequent analysis of ownership composition, trading behavior, and shock transmission.

3. Selective Pass-Through

This section examines how multi-security complexity and specialist ownership affect the transmission of shocks into credit spreads. Our central hypothesis is that complexity influences price dynamics through ownership composition. If specialist investors possess an informational advantage in processing

multi-security complexity, they should facilitate the incorporation of fundamental information into prices while attenuating the effects of non-fundamental demand pressure.

We test this prediction using two distinct shock environments. The first consists of Treasury-yield changes, which capture variation in macroeconomic conditions and monetary-policy expectations. The second consists of mechanically induced shifts in passive-fund demand arising from maturity-based benchmark reclassifications. These shocks differ in their informational content: Treasury-yield movements convey information relevant to corporate credit risk, whereas passive-fund rebalancing generates demand pressure unrelated to issuer fundamentals.

The analysis proceeds in three steps. Section 3.1 examines whether complexity and specialist ownership amplify the pass-through of Treasury-yield shocks, while Section 3.2 investigates whether they attenuate the effects of passive-demand shocks. Together, these tests evaluate whether ownership composition generates selective pass-through of information and demand shocks. Section 3.3 then turns to trading-level evidence and examines whether differences in the behavior of HCI and REST investors can account for the price-level results.

3.1 Information Shocks: Treasury Yield Changes

We begin by examining the response of corporate-bond yield spreads to Treasury-yield movements. Following Duffee (1998) and Collin-Dufresne, Goldstein, and Martin (2001), we use monthly changes in the 2-year Treasury yield ($\Delta Trsy2$) as a summary measure of variation in macroeconomic conditions and monetary-policy expectations. Treasury-yield changes are widely used in the corporate-bond literature because they capture information relevant for the valuation of corporate cash flows and credit risk. Our objective is not to isolate a particular source of macroeconomic news, but rather to examine whether the extent to which such information is incorporated into credit spreads depends on ownership

composition. Section 4.2 further sharpens the identification using high-frequency FOMC announcement windows and information-shock decompositions. We estimate:

$$\begin{aligned} \Delta YS_{j,t} = & \beta_1 (W_{j,t-1} \times \Delta Trsy2_t) + \beta_2 \Delta Trsy2_t \\ & + \beta_3 W_{j,t-1} + \beta' X_{j,t-1} + \alpha_{f(j)} + \gamma_{r(j),m(j)} + \varepsilon_{j,t}, \end{aligned} \quad (1)$$

where $\Delta YS_{j,t}$ is the month- t change in bond j 's credit spread; $W_{j,t-1}$ denotes the standardized moderating variable at $t-1$. We estimate the specification separately using *MSComp* (issuer-level multi-security complexity) and *HCIOwn* (issue-level specialist ownership) as the moderating variable. $\Delta Trsy2_t$ is the contemporaneous change in the 2-year Treasury yield. $X_{j,t-1}$ includes lagged bond controls (rating, duration, bid-ask spread, bond age, log amount outstanding) and issuer fundamentals (log assets, leverage, profitability, cash), as well as contemporaneous macro factors (ΔVIX , S&P 500 return, yield-curve slope), the change in the issuer's Merton (1974) default probability, and issuer equity returns. We absorb issuer fixed effects $\alpha_{f(j)}$ and rating-by-maturity fixed effects $\gamma_{r(j),m(j)}$, and double-cluster standard errors by issuer and year-month. Year-month fixed effects are excluded because $\Delta Trsy2_t$ is aggregate and would be absorbed. The specification is estimated separately using *MSComp* and *HCIOwn* as the moderating variable.

Table 3 reports the results. Consistent with the existing literature, increases in Treasury yields are associated with declines in credit spreads. More importantly, the interaction between Treasury-yield changes and both multi-security complexity and specialist ownership is negative and statistically significant. Bonds issued by more complex firms and bonds with greater specialist ownership exhibit stronger spread responses to Treasury-rate movements. The magnitude of the effect is economically meaningful: while a 1-pp increase in the 2-year Treasury yield is associated with a 22–45 bp decline in credit spreads, the interaction estimates imply that a one-standard-deviation increase in multi-security complexity amplifies this response by approximately 8 bps. Similar magnitudes emerge for specialist ownership, with a one-standard-deviation increase amplifying the response by roughly 10 bps. For

comparison, a one-standard-deviation increase in issuer default probability amplifies the spread response by approximately 15 bps. Thus, the effects of contractual complexity and ownership composition are economically meaningful relative to a conventional measure of credit risk.

A natural alternative interpretation is that complexity merely proxies for credit risk. If more complex issuers are inherently riskier, stronger spread responses may simply reflect greater sensitivity to changes in economic conditions rather than differences in information processing. Table 4 provides a more direct test of these competing explanations by allowing the effect of Treasury-yield changes to differ across rising-rate and falling-rate environments. If the amplification effect primarily reflects credit risk, it should be stronger when Treasury yields fall, a state typically associated with deteriorating economic conditions and heightened default-risk concerns.

The results do not support this prediction. The interaction between Treasury-yield changes and both multi-security complexity and specialist ownership remains negative and statistically significant both when Treasury yields rise and when Treasury yields fall. Moreover, the estimated amplification effects are similar across rising-rate and falling-rate environments. In contrast, conventional credit-risk controls (Altman's Z-score and Merton's default probability) exhibit markedly asymmetric loadings across the two interest-rate regimes, with substantially stronger effects when Treasury yields decline. This pattern is consistent with the close link between interest rates, default probabilities, and credit spreads documented in the literature (Longstaff and Schwartz, 1995; Duffee, 1998; Collin-Dufresne, Goldstein, and Martin, 2001). The amplification effect associated with complexity and specialist ownership therefore appears considerably more symmetric than the behavior of conventional credit-risk measures. While this evidence does not by itself rule out a role for credit risk, it suggests that complexity and specialist ownership capture more than variation in issuer credit quality and is consistent with differences in how macroeconomic information is incorporated into prices.

3.2 Non-Fundamental Demand Shocks: Passive-Fund Rebalancing

We now examine whether the same ownership characteristics affect the transmission of non-fundamental demand shocks. Our prediction is that specialist ownership should attenuate the price impact of demand shifts that are unrelated to issuer fundamentals. To identify such shocks, we follow Bretscher, Schmid, and Ye (2025) and exploit mandatory rebalancing by maturity-constrained passive corporate-bond funds. These funds move bonds across benchmark buckets when remaining maturity crosses predetermined thresholds. Because the resulting changes in passive ownership are mechanically induced and unrelated to contemporaneous issuer information, they provide a useful setting in which to study non-fundamental demand pressure.

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). We estimate a first stage over the six-month window centred on the switch:

$$\Delta PassiveOwn_{j,t-3 \rightarrow t+3} = \pi_1 Switch_{j,t} + \pi' X_{j,t} + \alpha_{f(j)} + \lambda_t + \gamma_{r(j),m(j)} + \varepsilon_{j,t-3 \rightarrow t+3}, \quad (2)$$

where $\Delta PassiveOwn_{j,t-3 \rightarrow t+3}$ is the change in passive-fund ownership of bond j across the six-month window; $X_{j,t}$ contains bond and issuer controls; and $\alpha_{f(j)}$, λ_t , and $\gamma_{r(j),m(j)}$ are issuer, year-month, and rating-by-maturity fixed effects. First-stage F -statistics comfortably exceed conventional weak-instrument thresholds (reported with Table 5). In the second stage, we relate cumulative spread changes around the switch to instrumented passive ownership, allowing the effect to vary with complexity and specialist ownership:

$$\begin{aligned} \Delta YS_{j,t-3 \rightarrow t+3} = & \beta_1 (W_{j,t} \times \widehat{\Delta PassiveOwn}_{j,t-3 \rightarrow t+3}) + \beta_2 \widehat{\Delta PassiveOwn}_{j,t-3 \rightarrow t+3} \\ & + \beta_3 W_{j,t} + \beta' X_{j,t} + \alpha_{f(j)} + \lambda_t + \gamma_{r(j),m(j)} + \varepsilon_{j,t-3 \rightarrow t+3}, \quad (3) \end{aligned}$$

where $\widehat{\Delta PassiveOwn}_{j,t-3 \rightarrow t+3}$ denotes fitted values from the first stage. $W_{j,t}$ denotes the standardized moderating variable at t , where the specification is estimated separately using *MSComp* and *HCIOwn*

as the moderating variable. $\Delta Trsy2_t$ is the contemporaneous change. Controls and fixed effects mirror the first stage; standard errors are clustered by issuer.

Table 5 reports the results. Instrumented passive inflows compress credit spreads, consistent with mechanical demand pressure increasing bond prices: the coefficient on $\Delta \widehat{PassiveOwn}$ is negative and significant across specifications (t -statistics between -1.76 and -2.06). More importantly, the interaction between passive ownership shocks and both multi-security complexity and specialist ownership is positive and statistically significant in most specifications. The positive interaction implies that bonds with greater complexity or specialist ownership exhibit a weaker spread response to passive-demand shocks. One-standard-deviation increase in multi-security complexity reduces the spread response by approximately 4–7 bps, while a one-standard-deviation increase in specialist ownership reduces the response by roughly 9–10 bps. These magnitudes offset a substantial portion of the baseline spread compression induced by passive inflows. The results therefore suggest that complexity and specialist ownership attenuate the transmission of non-fundamental demand pressure into bond prices.

The contrast with the Treasury-shock results is informative. Whereas multi-security complexity and specialist ownership amplify the response of credit spreads to Treasury-rate movements, they dampen the response to mechanically induced passive-demand shifts. Complexity and specialist ownership therefore do not uniformly increase price sensitivity. Instead, their effects depend on the informational content of the underlying shock: amplification for information-rich shocks and attenuation for non-fundamental demand shocks. This pattern is consistent with the selective pass-through mechanism proposed in the paper.

3.3 Mechanism: Trading and Information Incorporation

The evidence in Sections 3.1 and 3.2 shows that multi-security complexity and specialist ownership generate selective pass-through. We now examine the mechanism underlying these effects. Our

argument is that specialist investors process contractual and macroeconomic information differently from other investors and that these differences are reflected in both their trading behavior and the informational content of their trades. We therefore first examine how HCI and REST investors respond to information and demand shocks and then investigate whether specialist trading predicts future bond returns. Together, these analyses provide a micro-foundation for the selective pass-through effects documented above.

3.3.1 Trading Responses to Information and Demand Shocks

The price-level evidence establishes that multi-security complexity and specialist ownership affect the transmission of both information and demand shocks. We now examine the trading behavior underlying these results. The analysis serves two purposes. First, it tests whether HCI and REST investors respond differently to the same shocks. Second, it examines whether ownership composition influences how non-specialist investors trade, providing a more direct test of the multi-security complexity channel. If specialist investors facilitate information incorporation and absorb non-fundamental demand pressure, these mechanisms should be visible in the trading behavior of both HCI and REST investors.

To study the multi-security complexity channel at the trading level, we construct trading measures from monthly changes in mutual-fund bond holdings, following the holdings-based approach commonly used in the institutional ownership and mutual-fund literature (Coval and Stafford, 2007; Greenwood and Thesmar, 2011; Goldstein, Jiang, and Ng, 2017). For each fund-bond position, trading is measured as the change in holdings between months $t-1$ and t , scaled by the average holdings over the two months. This symmetric scaling measures trading intensity relative to position size while avoiding the asymmetry associated with scaling solely by beginning-of-period holdings. We then aggregate these position-level measures separately across HCI and REST investors. The resulting variables, *Trade_HCI* and *Trade_REST*, capture the intensity of net buying or selling by each investor group relative to the size of its existing position.

In all the trading specifications, the shock variables and trading measures are measured contemporaneously, while specialist ownership and other bond- and issuer-level characteristics are lagged. This timing convention is applied consistently across both the Treasury-shock and passive-demand-shock analyses.

Treasury-Yield Shocks. Panel A of Table 6 reports trading responses to Treasury-yield changes. Columns (1)–(3) show baseline trading responses for HCI funds, REST funds, and the HCI–REST differential. In Column (1), HCI significantly reduce their net positions when Treasury yields rise ($\beta = -0.023$, $t = -2.55$), equivalent to approximately 135% of mean monthly HCI trading for a one-standard-deviation Treasury shock. By contrast, REST investors exhibit little response on average. Consistent with this difference, Column (3) shows that the HCI–REST trading differential is statistically significant ($t = -1.94$). For our purposes, the key result is not the direction of the response but its magnitude: HCI investors react significantly to Treasury-rate information whereas REST investors do not. Overall, the evidence indicates that specialist investors respond more strongly to Treasury-rate information than the broader investor base.

The role of specialist ownership is examined in Columns (4)–(5), which interact Treasury shocks with a high-*HCIOwn* indicator. For HCI investors, the interaction is economically small and statistically insignificant (Column 4: $\beta = 0.016$, $t = 0.58$), suggesting that HCI respond to Treasury-rate information regardless of the existing concentration of specialist ownership. In contrast, the interaction for REST investors is negative and significant (Column 5: $\beta = -0.014$, $t = -2.64$), implying that REST investors respond more strongly to Treasury-rate shocks when specialist ownership is already high. Economically, the estimated response is approximately 5.6 times larger in high-HCI bonds than in low-HCI bonds.

This pattern helps reconcile the weak average response of REST investors. The absence of an unconditional effect does not necessarily imply that non-specialists ignore Treasury-rate information.

Rather, Treasury-yield movements may require interpretation before their implications for individual bonds become clear. If specialist investors are better equipped to map macroeconomic news into bond values, REST investors may respond only when specialist ownership is sufficiently high to reduce uncertainty about the valuation implications of the shock. Under this interpretation, specialist ownership facilitates the incorporation of public information without necessarily implying that REST investors possess the same informational advantage as HCI investors.

Passive-Demand Shocks. Panel B of Table 6 reports trading responses to mechanically induced passive-demand shocks. The pattern differs sharply from that observed for Treasury shocks. HCI investors trade *against* passive-flow pressure, whereas REST investors tend to trade in the same direction as the flow shock. Specifically, a one-percentage-point increase in passive ownership reduces HCI holdings by 8.4 percentage points (Column 1: $\beta = -8.41$, $t = -2.10$), while increasing REST holdings by 9.1 percentage points (Column 2: $\beta = 9.07$, $t = 3.80$). The difference between the two groups is economically large and statistically significant (Column 3: $\beta = -20.47$, $t = -3.39$), consistent with specialist investors absorbing, rather than propagating, non-fundamental demand shocks.

Specialist ownership also alters the trading behavior of other investors. Among bonds with low HCI ownership, REST investors increase their holdings by approximately 13.0 percentage points in response to a one-percentage-point increase in passive ownership. In contrast, among bonds with high HCI ownership, the estimated response falls to approximately -3.4 percentage points ($= 13.00 - 16.39$), implying that REST investors no longer follow passive-flow pressure when specialist ownership is high. The corresponding interaction for HCI investors is positive but only marginally significant, indicating that the primary adjustment occurs through the behavior of REST investors. Overall, these results suggest that specialist investors not only trade against non-fundamental demand shocks themselves but also dampen the tendency of other investors to propagate such shocks..

Discussion. Overall, the trading evidence mirrors the price-level results and provides a micro-foundation for the selective pass-through patterns documented in Sections 3.1 and 3.2. HCI investors respond more strongly to Treasury-rate information and are more willing to trade against mechanically induced passive-demand shocks. At the same time, the behavior of REST investors varies systematically with specialist ownership. In bonds with greater specialist ownership, REST investors become more responsive to Treasury-rate information and less likely to trade alongside non-fundamental demand pressure. These patterns suggest that ownership composition influences not only the trading activity of specialists but also the way public information and demand shocks are reflected in the behavior of the broader investor base.

3.3.2 Return Predictability and Information Incorporation

The pass-through results suggest that specialist investors play an important role in the transmission of information and demand shocks. However, the trading evidence alone does not reveal whether the investors driving these effects possess information relevant for bond valuation. We therefore examine whether specialist trading predicts future bond returns. This analysis serves two purposes. First, it allows us to assess whether HCI and REST trading differ in their informational content. Second, it provides a micro-foundation for the pass-through results by examining whether the investors that drive shock transmission are also the investors whose trades contain information relevant for bond valuation.

If HCI investors possess information or valuation expertise that is only partially reflected in prices at the time of trade, purchases by HCI should be followed by stronger subsequent returns, particularly among complex bonds where contractual analysis is most important. Moreover, if specialist ownership facilitates the incorporation of contractual information into prices, the predictive content of HCI trading should be strongest when specialist ownership is low and should weaken as specialist participation deepens. For each bond j and month t , we estimate:

$$\begin{aligned}
CumRet_{j,t+1 \rightarrow t+k} = & \beta_1 Trade_HCI_{j,t} + \beta_2 Trade_REST_{j,t} + \beta_3 (Trade_HCI_{j,t} \times MSCompQ_{j,t}) \\
& + \beta_4 (Trade_REST_{j,t} \times MSCompQ_{j,t}) + \beta_5 MSCompQ_{j,t} + \beta'Z_{j,t} + \alpha_j + \lambda_t + \varepsilon_{j,t+1 \rightarrow t+k} \quad (4)
\end{aligned}$$

where $CumRet_{j,t+1 \rightarrow t+k}$ is bond j 's cumulative return from $t+1$ through $t+k$ for $k \in \{3, 6\}$ months; $Trade_HCI_{j,t}$ and $Trade_REST_{j,t}$ are the net trading measures for HCI and REST funds in bond j during month t (constructed as in Section 2); $MSCompQ_{j,t}$ is the within-month complexity quintile, taking values from 1 (lowest complexity) to 5 (highest complexity) at t ;⁵ and $Z_{j,t}$ contains lagged controls (cumulative past return as a momentum control, credit rating, duration, bid–ask spread, bond age, and log amount outstanding).⁶ Bond fixed effects α_j absorb all time-invariant bond characteristics; year-month fixed effects λ_t absorb aggregate market-wide return variation. Standard errors are clustered by bond.

Table 7 reports the results for cumulative returns over three- and six-month horizons, for both raw returns (Panel A) and two-factor abnormal returns (Panel B). Three findings emerge.

HCI Trading Predicts Returns in Complex Bonds. The return-predictive content of HCI trading increases sharply with multi-security complexity. Across both return horizons and both return measures, the interaction between HCI trading and multi-security complexity is positive and statistically significant. In Panel A, the interaction coefficient equals 0.0013 ($t = 3.76$) at the three-month horizon (Column 1) and 0.0020 ($t = 2.38$) at the six-month horizon (Column 4). Economically, these estimates imply substantial differences across the complexity distribution. At the three-month horizon, the estimated predictive effect of HCI trading increases from approximately -0.08% in the lowest-complexity quintile to $+0.44\%$ in the highest-complexity quintile. This corresponds to a 52 bp increase in expected three-month returns across the complexity distribution. At the six-month horizon, the

⁵ We use within-month complexity quintiles to allow for potential non-linearities in the relation between complexity and trading informativeness. The main conclusions are unchanged when the continuous complexity measure is used.

⁶ The timing convention is designed to isolate the forward-looking content of trading. The dependent variable is measured from month $(t+1)$ onward, while trading occurs during month (t) and all bond characteristics are measured at the end of month $(t-1)$. As a result, all explanatory variables are observed before the return window begins.

corresponding spread widens to approximately 80 bps (from -0.20% to $+0.60\%$). Thus, the return-predictive content of HCI trading is strongest among the most complex bonds, where contractual analysis is likely to be most valuable. This pattern is consistent with specialist expertise in evaluating complex debt structures rather than a general forecasting advantage across all bonds.

Predictability Is Strongest When Specialist Ownership Is Low. The second finding concerns the role of specialist ownership. In the low-HCIOwn subsample, the interaction between HCI trading and multi-security complexity remains positive and strongly significant across both horizons. Economically, purchases by HCI investors predict returns that are approximately 56 basis points higher over the subsequent three months in the highest-complexity bonds than in the lowest-complexity bonds. At the six-month horizon, the corresponding difference reaches approximately 100 basis points. By contrast, the corresponding interactions in the high-HCIOwn subsample are no longer statistically distinguishable from zero. Thus, the complexity-dependent return predictability of HCI trading is evident primarily among bonds with limited specialist ownership. This pattern is consistent with the view that specialist investors contribute to the incorporation of contractual information into prices, reducing the informational content of subsequent trades as specialist participation deepens (Grossman and Stiglitz, 1980).

The Results Survive Risk Adjustment. The findings are robust to risk adjustment. Panel B replaces raw cumulative returns with two-factor abnormal returns, where factor loadings on the aggregate bond market (MKTB) and stock market (MKTS) are estimated from rolling sixty-month regressions.⁷ The interaction between HCI trading and multi-security complexity remains positive and significant in the full sample. Economically, purchases by HCI investors predict abnormal returns that are approximately 36 basis points higher over the subsequent three months in the highest-complexity bonds than in the

⁷ There is no consensus asset-pricing model for corporate bond returns. Following recent studies of corporate bond mutual funds, including Goldstein, Jiang, and Ng (2017), we adjust returns using aggregate bond-market (MKTB) and stock-market (MKTS) factors. Our objective is not to estimate abnormal performance per se, but to verify that the predictive content of HCI trading is not driven solely by exposure to broad bond- or equity-market risks.

lowest-complexity bonds. At the six-month horizon, the corresponding difference increases to approximately 72 basis points. The ownership split confirms the same pattern observed in Panel A. In the low-HCIOwn subsample, the corresponding differences equal approximately 48 basis points over three months and 88 basis points over six months, whereas the predictive content disappears in the high-HCIOwn subsample. These results suggest that the forecasting power of HCI trading is unlikely to be driven solely by exposure to broad bond- or equity-market risks.⁸

REST trading does not exhibit the same pattern of complexity-dependent return predictability. While several REST coefficients are statistically significant, the signs are not consistent across specifications and therefore do not support the view that REST trading systematically contains information about future bond values. The only notable exception is in Panel B, where the interaction between REST trading and multi-security complexity is negative and significant in the low-HCIOwn subsample at the three-month horizon. Economically, purchases by REST investors predict abnormal returns of approximately +0.15% in the lowest-complexity bonds but −1.29% in the highest-complexity bonds, a difference of roughly 144 basis points across the complexity distribution. This pattern suggests that, in complex bonds with limited specialist ownership, REST investors tend to buy securities that subsequently underperform. The sharp contrast with HCI investors is difficult to reconcile with a generic institutional-trading explanation and instead supports the view that specialist and non-specialist investors differ in the information they bring to complex bonds.

Taken together, the trading and return-predictability results provide a micro-foundation for the pass-through evidence in Sections 3.1–3.2. The investors that respond most strongly to information shocks and trade against non-fundamental demand shocks are also the investors whose trades predict future returns in complex bonds. Moreover, the predictive content of specialist trading is strongest when

⁸ This result also helps reconcile the absence of significant fund-level alpha in Panel D of Table 2. Although HCI investors appear to possess an informational advantage in complex bonds, that advantage is concentrated in a subset of securities and therefore need not translate into detectable abnormal performance at the aggregate fund level.

specialist ownership is limited and becomes weaker as specialist participation deepens. Viewed collectively, these findings are consistent with the interpretation that ownership composition affects shock transmission through its influence on the incorporation of contractual information into bond prices.

4. Identification

This section provides additional evidence on the multi-security complexity channel. Section 4.1 addresses endogeneity in specialist ownership using a shift-share instrumental-variables design. Section 4.2 uses high-frequency FOMC announcement windows to sharpen the distinction between information-driven and mechanical interest-rate effects.

4.1 Shift–Share Instrument for Specialist Ownership

A central concern for the pass-through specifications is endogenous investor sorting. Specialist investors may disproportionately hold bonds whose prices are inherently more sensitive to information shocks or less sensitive to non-fundamental demand shocks. In that case, the documented relation between HCI ownership and shock transmission could reflect unobserved bond characteristics rather than a causal effect of ownership composition. Conversely, changes in bond valuations, liquidity, or expected returns may themselves attract specialist investors, generating reverse causality. As a result, observed variation in HCI ownership may be correlated with unobserved determinants of pass-through.

To address these concerns, we construct a shift-share instrument that combines predetermined bond-level exposure to HCI investors with subsequent variation in fund-level capital flows. Following Bartik (1991), Goldsmith-Pinkham, Sorkin, and Swift (2020), Borusyak, Hull, and Jaravel (2022), Fang (2025), and Coppola (2025), the instrument predicts changes in specialist ownership by interacting baseline portfolio weights with subsequent fund flows while holding portfolio composition fixed.

Consequently, identification comes from investor-level capital flows rather than contemporaneous bond-level conditions.⁹ Because the portfolio weights are measured prior to the realization of subsequent fund flows, the identifying variation comes from investor-level flow shocks rather than contemporaneous changes in bond characteristics. Under the assumption that these flow shocks are orthogonal to bond-level innovations, the instrument isolates plausibly exogenous variation in specialist ownership.

Table 8 reports the 2SLS results. The first-stage relationship is strong in the Treasury-shock specifications, with Kleibergen–Paap rk Wald F-statistics exceeding 190, comfortably above conventional weak-instrument thresholds. The corresponding statistics for the passive-demand specifications are lower, ranging from 6.5 to 9.1, indicating a weaker but still informative first stage. Importantly, the second-stage estimates closely mirror the baseline OLS results. Instrumented specialist ownership ($\widehat{HCTOwn}$) continues to amplify the pass-through of Treasury-rate shocks, with interaction coefficients between -0.125 and -0.129 compared with -0.094 to -0.114 in the corresponding OLS specifications. Instrumented specialist ownership also attenuates the effects of passive-demand shocks. Although the passive-demand interaction is estimated less precisely and statistical significance weakens in the most saturated specification, the estimated effect remains economically meaningful and

⁹ Specifically, for each fund–bond pair (f, j) , let $Holdings_{f,j}^{t_0}$ denote the baseline dollar holding at t_0 and $\% \Delta AUM_{f,t}$ the cumulative percentage change in AUM from t_0 to t . The predicted HCI dollar exposure to bond j at time t is:

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

Converting to a predicted ownership share by dividing by the bond’s total mutual-fund dollar holdings at baseline (held fixed over time):

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

The instrument $Z_{j,t}^{share}$ varies across bonds and over time through two channels: cross-sectional variation in baseline HCI exposure (the “share”), and time-series variation in fund-level capital flows (the “shift”). Crucially, the portfolio weights are frozen at baseline, so the instrument is purged of contemporaneous bond-specific selection. We compute $\% \Delta AUM_{f,t}$ using return-adjusted net flows and take baseline holdings from the prior calendar year, consistent with the predetermined timing convention used throughout the paper.

comparable in magnitude to the baseline OLS results. Overall, the similarity between the OLS and IV estimates suggests that the multi-security complexity channel results are unlikely to be driven by endogenous ownership sorting or reverse causality.

4.2 Information versus Policy Shocks around FOMC Announcements

The evidence in Section 3 shows that complexity and specialist ownership amplify the response of credit spreads to Treasury-yield movements. While consistent with an information-incorporation channel, these results do not by themselves rule out a more mechanical explanation. In particular, bonds held by specialist investors may possess characteristics that make their spreads intrinsically more sensitive to interest-rate movements, irrespective of the information conveyed by those movements. To distinguish between these explanations, we exploit high-frequency FOMC announcement windows.

FOMC announcements provide a useful setting because they allow Treasury-yield changes to be decomposed into components associated with conventional monetary-policy shocks and components associated with information revealed by the central bank about economic fundamentals. A growing literature argues that financial markets interpret part of the announcement-window response as reflecting central-bank information about the economic outlook rather than policy actions alone (Gürkaynak, Sack, and Swanson, 2005; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). If the amplification documented in Section 3 reflects differences in how investors process and incorporate information into prices, it should be more pronounced for the information component of announcement-window yield changes than for the conventional policy component.

For each FOMC meeting, we measure bond-spread changes over the (-1,+1) trading-day window surrounding the announcement. We estimate specifications relating announcement-window spread changes to interactions between multi-security complexity and changes in the 2-year Treasury yield, controlling for bond and issuer characteristics as well as issuer, rating-by-maturity, and event-

date fixed effects. Standard errors are double-clustered by issuer and event date. To separate policy and information effects, we decompose announcement-window Treasury-yield changes using the high-frequency shock measures of Gürkaynak, Sack, and Swanson (2005) and Nakamura and Steinsson (2018), both obtained from the publicly available data provided by Acosta, Brennan, and Jacobson (2024). We then estimate separate interactions for the policy and information components and examine which component drives the amplification effect documented in Section 3.

Table 9 reports the results. The baseline specification confirms the monthly evidence in a tighter identification setting. In the three-day announcement window, a 10 bp increase in the 2-year Treasury yield is associated with an approximately 3.8 bp decline in corporate bond spreads, consistent with the scaled monthly estimates reported earlier (2.7–4.5 bps). A one-standard-deviation increase in multi-security complexity amplifies this response by roughly 0.7 bps (Column 1), while a comparable increase in specialist ownership amplifies it by approximately 1.2 bps (Column 4). When Treasury-yield surprises are decomposed, this amplification increases modestly to about 0.9 bps for the information component but disappears for the policy component (Columns 2 and 3). A similar pattern emerges for specialist ownership. A one-standard-deviation increase in specialist ownership amplifies the baseline announcement-window response by approximately 1.2 bps (Columns 5 and 6), and this effect is entirely driven by the information component of Treasury-yield surprises, while the corresponding policy-shock interactions are economically small and statistically indistinguishable from zero.

These results are difficult to reconcile with a purely mechanical sensitivity explanation. If the amplification effect reflected bond characteristics that mechanically magnify spread responses to Treasury-yield movements, amplification would be expected regardless of whether the yield change originated from conventional policy shocks or information revealed about economic fundamentals. Instead, amplification is concentrated in the information component of announcement-window shocks. This pattern is consistent with the view that the effects documented in Section 3 are linked to the

processing and incorporation of information rather than solely to mechanical exposure to interest-rate movements.

5. Fragility and Liquidity Implications

The preceding analysis shows that specialist ownership affects how information and demand shocks are transmitted to bond prices. An important question is whether these effects have broader implications for market functioning. Specialist ownership may improve the incorporation of information into prices and facilitate liquidity provision by attracting investors with greater expertise in complex securities. At the same time, concentrating ownership among a relatively specialized investor base may increase exposure to correlated trading and investor outflows, potentially increasing fragility. We examine both implications in this section.

Financial Fragility. We adapt the Greenwood and Thesmar (2011) fragility measure to the corporate-bond market. The measure captures the extent to which a bond is exposed to correlated trading by its investor base, reflecting both ownership concentration and commonality in investors' liquidity needs. We first examine whether complexity and specialist ownership are associated with greater ownership-based fragility. We then assess whether bonds with greater fragility exhibit the same shock-transmission patterns documented earlier in the paper. Panel A of Table 10 shows a robust positive relation between complexity and subsequent fragility (Column 1-2). Similar results emerge when complexity is replaced by specialist ownership (Column 3-4). Specifically, a one-standard-deviation increase in multi-security complexity increases the square root of bond fragility by approximately 0.004, while a comparable increase in specialist ownership increases it by roughly 0.005–0.006. Relative to the sample mean of 0.121, these estimates imply increases in fragility of approximately 3–5 percent. Economically, the findings suggest that complexity and specialist ownership are associated with investor bases whose trading is more concentrated and whose liquidity needs are more correlated, increasing ownership-based fragility.

We next examine whether ownership-based fragility is related to the pass-through patterns documented in Section 3. Consistent with the earlier results, bonds with greater fragility exhibit stronger responses to Treasury-yield shocks (Column 5) and weaker responses to passive-demand shocks (Column 6). We do not interpret these results as evidence that fragility itself causes these effects. Rather, they suggest that fragility captures an aspect of the underlying ownership structure associated with specialist participation. In this sense, the same ownership structure that gives rise to greater fragility also appears to be associated with stronger incorporation of information and weaker transmission of non-fundamental demand shocks.

Bond Liquidity. We next examine the implications of specialist ownership for secondary-market liquidity. We evaluate this possibility using three standard measures of bond illiquidity: bid-ask spreads, the Amihud (2002) price-impact measure, and Roll's (1984) effective-spread estimator. Panel B of Table 10 shows that greater complexity is associated with lower subsequent illiquidity across all three measures (Columns 1-3). Similar patterns emerge when complexity is replaced by specialist ownership (Columns 4-6). Specifically, a one-standard-deviation increase in complexity reduces bid-ask spreads by approximately 0.008, lowers the Amihud illiquidity measure by 0.004, and reduces Roll's effective-spread measure by 0.008. Relative to sample means, these effects correspond to reductions of approximately 1.7%, 2.6%, and 1.0%, respectively. Although these magnitudes are small in absolute terms, they are consistently negative across all three liquidity measures and indicate that bonds held by specialist investors tend to exhibit lower trading costs despite greater ownership-based fragility.

The liquidity results are noteworthy because they suggest that fragility and liquidity capture different dimensions of market functioning. Greater specialist ownership is associated with a more concentrated investor base and therefore greater exposure to correlated trading, yet these same bonds exhibit narrower bid-ask spreads and lower price-impact measures. While the results do not establish the precise mechanism underlying this relation, they are consistent with the view that specialist

participation is associated with more liquid secondary-market trading despite greater ownership concentration.

Overall, the evidence suggests that specialist ownership is associated with a distinctive trade-off. Bonds with greater specialist ownership exhibit stronger information incorporation and lower trading frictions, but also greater ownership-based fragility. These findings indicate that liquidity and fragility capture different dimensions of market functioning and may arise from the same underlying ownership structure. While specialist ownership appears to be associated with more efficient incorporation of information into prices, it may also increase vulnerability to correlated investor flows.

Conclusion

This paper examines how multi-security complexity affects the transmission of shocks into corporate-bond prices. We argue that the effects of complexity operate through ownership composition. Bonds issued by firms with more heterogeneous debt structures tend to have greater specialist ownership, and this ownership composition shapes how information and non-fundamental shocks are incorporated into prices.

Our central finding is that complexity and specialist ownership affect the pass-through of information and demand shocks in opposite ways. Bonds with greater complexity and specialist ownership respond more strongly to Treasury-rate movements and FOMC information shocks, but less strongly to mechanically induced passive-demand shocks. Trading-level evidence points to a similar pattern: specialist investors respond more strongly to information-based shocks and are more willing to trade against non-fundamental flow pressure. Specialist ownership also appears to influence the behavior of non-specialists, increasing their responsiveness to public information while reducing their tendency to reinforce demand-driven trading.

We further show that specialist trading predicts future returns in complex bonds, whereas non-specialist trading generally does not. This predictive content is strongest when specialist ownership is limited and weakens as specialist participation deepens, consistent with the view that specialist investors contribute to the incorporation of contractual information into prices. Finally, specialist ownership is associated with an interesting tension between liquidity and fragility: bonds with greater specialist ownership exhibit lower trading frictions but greater ownership-based fragility. These findings suggest that fragility and liquidity capture different dimensions of market functioning and may arise from the same underlying ownership structure.

Overall, our results highlight the importance of investor specialization and ownership composition in understanding how information and non-fundamental shocks are transmitted through corporate bond markets. More broadly, they suggest that the consequences of multi-security complexity depend critically on the investors who choose to hold complex securities.

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Appendix 1: Variables Description

Variable	Definition	Database
MSComp	Multi-security complexity, measured as the average pairwise Euclidean distance across contractual features of a firm's outstanding bonds, as described in Kim and Massa (2026).	FISD
HCIOwn	Ownership share of High Complexity Investors (HCI) in a bond's total amount held by bond mutual funds.	CRSP MF, FISD, TRACE
Trade_HCI (Trade_REST)	Monthly net trading intensities by HCI and REST investors, scaled by average beginning- and end-of-month holdings.	CRSP MF
BFraility	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
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)
$\Delta Trsy2$	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
ΔPD	Change in Probability of default, derived from Merton's (1974) model over a specified window.	CRSP, Compustat
$\widehat{\Delta Trsy2}^{(NS)}$	Predicted component of $\Delta Trsy2$ by monetary policy shocks from Nakamura and Steinsson (2018)	Acosta, Brennan, and Jacobson
$\Delta Trsy2^{(GSS)}$	Predicted component of $\Delta Trsy2$ by monetary policy shocks from Gürkaynak, Sack, and Swanson (2005)	(2024), Liu and Wu
$r_{\Delta Trsy2}^{(NS)}$	Residual component of $\Delta Trsy2$ by monetary policy shocks from Nakamura and Steinsson (2018)	(2021)
$r_{\Delta Trsy2}^{(GSS)}$	Residual component of $\Delta Trsy2$ 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
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, Schmid and Ye (2025).	CRSP MF, TRACE, FISD
$\widehat{\Delta PassiveOwn}$	Predicted components of PassiveOwn by Switch	
$\Delta PassiveOwn$	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 2.2 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

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). $\Delta Trsy2$ is the change in the 2-year U.S. Treasury yield (pp). $\widehat{\Delta Trsy2}^{(NS)}$ and $r_{\Delta Trsy2}^{(NS)}$ are the predicted and residual components of $\Delta Trsy2$ based on monetary policy shocks from Nakamura and Steinsson (2018); $\widehat{\Delta Trsy2}^{(GSS)}$ and $r_{\Delta Trsy2}^{(GSS)}$ are based on shocks from Gürkaynak, Sack, and Swanson (2005). *MSComp* is multi-security complexity (issuer level). *HCIOwn* is the ownership share held by High-Complexity Investors (HCI). *Trade_HCI* and *Trade_REST* are monthly net trading intensities by HCI and REST investors, scaled by average beginning- and end-of-month holdings. *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
$\Delta Trsy2$	593,909	.018	.167	-.33	.414
MSComp	593,909	.441	.158	0	.661
HCIOwn	593,906	.491	.346	0	.971
Switch	485,574	.02	.139	0	1
$\Delta \widehat{PassiveOwn}$	430,157	.003	.009	-.015	.023
Trade_HCI	88,641	.002	.097	-.463	.422
Trade_REST	92,261	.003	.057	-.229	.23
PD	545,853	.073	.197	0	.755
Zscore	482,473	1.856	1.157	.065	4.489
$\Delta Slope$	593,909	-.016	.157	-.302	.317
ΔVIX	593,909	-.072	4.645	-8.55	10.34
ΔPD	507,449	0	.012	-.038	.036
S&P500Ret	593,908	.008	.041	-.084	.079
StockRet	535,215	.009	.075	-.139	.157
Rating	593,909	-.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					
MSComp	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
Daily Sample					
ΔYS (bp)	258,785	-.308	14.873	-34	33
MSComp	384,554	.445	.161	0	.665
HCIOwn	331,045	.488	.344	0	.965
$\Delta Trsy2$ (bp)	258,785	-1.17	6.541	-16.282	11.726
$\widehat{\Delta Trsy2}^{(NS)}$ (bp)	384,554	-.672	1.583	-4.021	2.901
$r_{\Delta Trsy2}^{(NS)}$ (bp)	383,470	-.314	5.879	-13.226	11.185
$\widehat{\Delta Trsy2}^{(GSS)}$ (bp)	384,554	-.722	1.798	-4.55	3.2
$r_{\Delta Trsy2}^{(GSS)}$ (bp)	383,470	-.395	5.906	-14.046	10.951

Table 2 HCI and REST Fund Characteristics, Classification Persistence, and Return-Based Factor Exposures

This table characterizes the two investor groups. Panel A compares observable fund attributes between HCI funds (top-quintile style-adjusted multi-security complexity exposure) and REST funds (all remaining funds) using t-tests; the unit of observation is the fund-year. Panel B presents the year-on-year HCI classification transition matrix. Panel C reports fund-level cross-sectional regressions of issuer stickiness on the HCI indicator. Issuer-attention HHI measures the concentration of a fund's investment activity across issuers over its observed history, with higher values indicating repeated focus on the same issuers. Average quarters per issuer measures the average duration of issuer-level investment relationships. All specifications control for fund tenure and the number of issuers ever held. Robust standard errors in Panels A and C. ***, **, * denote significance at the 1%, 5%, and 10% levels. In Panel D, time-series regressions of equal-weighted monthly excess returns for HCI funds, REST funds, and the HCI–REST differential on two factors: MKTB (aggregate corporate bond market excess return) and MKTS (aggregate stock market excess return). Estimated over 156 months (2010–2022) using Newey–West standard errors with six lags. R² reported for OLS.

Panel A Fund Characteristics (fund-year observations)

	Mean (HCI)	Mean (REST)	Mean diff.	t-stat
Observations (fund-years)	30,312	125,427		
AUM (\$m)	586.5	910.7	−324.2	−13.40***
Expense ratio (%)	0.918	0.869	0.049	14.15***
Turnover ratio	1.355	1.336	0.020	1.50
Fund age (years)	10.69	11.81	−1.12	−19.05***
Equity allocation (%)	2.83	3.72	−0.88	−9.00***
Bond allocation (%)	12.72	8.05	4.68	23.67***
Family bond AUM share (%)	12.71	8.40	4.31	22.32***

Panel B Year-on-Year HCI Classification Transition Matrix

	Classified as REST in year t+1	Classified as HCI in year t+1
Classified as REST in year t	91.0%	9.0%
Classified as HCI in year t	31.9%	68.1%

Panel C Issuer-level Investment Behavior Regressions (fund-level cross-section)

	(1) Issuer HHI	(2) Avg qtrs per issuer
HCI indicator	0.050*** (0.003)	0.602*** (0.113)
Fund tenure (quarters)	−0.001*** (0.000)	0.173*** (0.003)
Issuers ever held	−0.000*** (0.000)	0.001*** (0.000)
N	15,462	15,462
R ²	0.118	0.323

Panel D HCI and REST Fund Factor Exposures and Alpha

Portfolio	α (bp/month)	t-stat	β _{MKTB}	β _{MKTS}	N	R ²
HCI funds	1.8	0.25	0.449***	0.129**	156	0.658
REST funds	−10.4	−2.65**	0.243***	0.680***	156	0.977
HCI minus REST	12.2	1.64	0.207***	−0.551***	156	0.882

**Table 3 Complexity, Specialist Ownership, and
Credit Spread Responses to Treasury-Rate Changes**

This table reports regressions of changes in credit spreads on interactions between multi-security complexity or HCI ownership and changes in 2-year Treasury rates. Multi-security complexity and HCI ownership are standardized variables with mean zero and unit standard deviation in the regression. Columns 1–3 focus on multi-security 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.

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	ΔYS					
$MSComp \times \Delta Trsy2$	-0.087*** (-4.97)	-0.066*** (-4.52)	-0.076*** (-5.00)			
$HCIOwn \times \Delta Trsy2$				-0.114*** (-5.42)	-0.097*** (-5.04)	-0.094*** (-4.60)
$\Delta Trsy2$	-0.306*** (-6.39)	-0.447*** (-6.11)	-0.269*** (-5.98)	-0.304*** (-6.45)	-0.423*** (-5.97)	-0.272*** (-6.10)
$Zscore \times \Delta Trsy2$		0.074*** (3.56)			0.062*** (3.23)	
$PD \times \Delta Trsy2$			-0.547*** (-3.63)			-0.075*** (-2.68)
$MSComp$	-0.000 (-0.04)	0.000 (0.18)	-0.000 (-0.09)			
$HCIOwn$				-0.002 (-0.69)	-0.001 (-0.46)	-0.002 (-0.59)
$Zscore$		0.007 (1.41)			0.007 (1.41)	
PD			-0.075*** (-2.66)			-0.075*** (-2.68)
$\Delta Slope$	-0.229*** (-4.01)	-0.222*** (-3.98)	-0.223*** (-4.08)	-0.230*** (-4.04)	-0.222*** (-4.00)	-0.225*** (-4.10)
ΔVIX	0.005* (1.73)	0.005* (1.78)	0.005* (1.73)	0.005* (1.72)	0.005* (1.77)	0.005* (1.72)
$S\&P500Ret$	-1.539*** (-4.44)	-1.485*** (-4.39)	-1.536*** (-4.50)	-1.548*** (-4.48)	-1.492*** (-4.42)	-1.543*** (-4.52)
ΔPD	1.077*** (2.90)	1.128*** (3.12)	0.927*** (2.61)	1.096*** (2.97)	1.143*** (3.16)	0.940*** (2.63)
$StockRet$	-0.681*** (-12.26)	-0.670*** (-11.74)	-0.678*** (-12.16)	-0.677*** (-12.13)	-0.667*** (-11.67)	-0.675*** (-12.05)
Constant	-0.021 (-0.09)	-0.029 (-0.12)	0.033 (0.14)	-0.021 (-0.08)	-0.029 (-0.12)	0.025 (0.10)
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 4 Treasury-Rate Increases versus Treasury-Rate Declines

This table examines whether the relation between Treasury-rate shocks and credit-spread responses differs between periods of rising and falling Treasury yields. The specification allows the interaction between Treasury-rate changes and either multi-security complexity (*MSComp*) or specialist ownership (*HCIOwn*) to vary across positive and negative Treasury-yield movements. Multi-security complexity and HCI ownership are standardized variables with mean zero and unit standard deviation in the regression. All regressions include issuer and rating-by-maturity fixed effects as well as the full set of bond, issuer, and macroeconomic controls used in Table 3. Standard errors are clustered by issuer and year-month. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix 1.

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	ΔYS					
$MSComp \times \Delta Trsy2^-$	-0.101*** (-3.54)	-0.055** (-2.29)	-0.078*** (-3.07)			
$MSComp \times \Delta Trsy2^+$	-0.067** (-2.52)	-0.066*** (-3.05)	-0.065*** (-2.78)			
$HCIOwn \times \Delta Trsy2^-$				-0.133*** (-3.63)	-0.085** (-2.51)	-0.095*** (-2.84)
$HCIOwn \times \Delta Trsy2^+$				-0.095** (-2.34)	-0.107*** (-2.94)	-0.094** (-2.40)
$Zscore \times \Delta Trsy2^-$		0.190*** (5.79)			0.182*** (5.68)	
$Zscore \times \Delta Trsy2^+$		-0.014 (-0.49)			-0.030 (-1.29)	
$PD \times \Delta Trsy2^-$			-1.036*** (-4.28)			-0.987*** (-4.22)
$PD \times \Delta Trsy2^+$			-0.066 (-0.26)			0.048 (0.19)
$\Delta Trsy2^-$	-0.498*** (-4.97)	-0.851*** (-7.29)	-0.426*** (-4.18)	-0.500*** (-4.98)	-0.837*** (-7.11)	-0.432*** (-4.24)
$\Delta Trsy2^+$	-0.162** (-2.32)	-0.137 (-1.22)	-0.155** (-2.47)	-0.158** (-2.34)	-0.102 (-1.00)	-0.157** (-2.53)
<i>MSComp</i>	-0.001 (-0.25)	0.002 (0.75)	-0.000 (-0.06)			
<i>HCIOwn</i>				-0.005 (-1.01)	-0.001 (-0.27)	-0.003 (-0.62)
<i>Zscore</i>		0.019*** (3.46)			0.019*** (3.59)	
<i>PD</i>			-0.138*** (-3.81)			-0.142*** (-4.01)
Constant	0.080 (0.33)	-0.014 (-0.06)	0.110 (0.48)	0.090 (0.37)	-0.007 (-0.03)	0.111 (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 5 Complexity, Specialist Ownership
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 multi-security complexity (Columns 1–3) or HCI ownership (Columns 4–6). Multi-security complexity and HCI ownership are standardized variables with mean zero and unit standard deviation in the regression. Instruments are based on maturity-driven fund flows; see Section 3.2 for instrument construction details. 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.

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	ΔYS					
$MSComp \times \Delta \widehat{PassiveOwn}$	0.056* (1.67)	0.041 (1.40)	0.073** (2.00)			
$HCIOwn \times \Delta \widehat{PassiveOwn}$				0.097** (2.34)	0.088** (2.24)	0.093** (2.15)
$\Delta \widehat{PassiveOwn}$	-0.126** (-1.96)	-0.103* (-1.76)	-0.139* (-1.76)	-0.134** (-2.06)	-0.117* (-1.90)	-0.141* (-1.84)
$MSComp$	-0.015* (-1.66)	-0.010 (-1.21)	-0.020** (-2.01)			
$HCIOwn$				-0.130** (-2.57)	-0.113** (-2.29)	-0.111** (-2.04)
$Rating$		-0.028*** (-5.48)	-0.028*** (-4.11)		-0.028*** (-5.30)	-0.029*** (-4.20)
$Duration$		0.003*** (3.74)	0.003*** (3.20)		0.003*** (2.83)	0.002** (2.31)
$Bid-Ask$		-2.688*** (-4.78)	-2.904*** (-4.04)		-2.693*** (-4.50)	-2.820*** (-3.84)
$Bond\ Age$		-0.004*** (-4.25)	-0.005*** (-3.32)		-0.005*** (-4.52)	-0.006*** (-3.73)
$Log\ (Bond\ Amt)$		-0.000 (-0.00)	0.000 (0.07)		-0.002 (-0.45)	-0.002 (-0.45)
$Log\ (Firm\ Size)$			0.118 (1.47)			0.108 (1.33)
$Leverage$			-0.080** (-2.20)			-0.088** (-2.33)
$Profitability$			0.014 (0.06)			0.086 (0.37)
$Cash$			-0.174*** (-3.19)			-0.156*** (-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 6 HCI and REST Trading Response to Market Shocks

OLS regressions of contemporaneous net trading on the contemporaneous change in the 2-year Treasury yield. Both dependent variable and shock are measured in month t . Columns 1–3 show baseline results for the full sample. Columns 4–5 add the interaction of ΔTrsy_2 with a top-quintile HCI ownership dummy (measured at $t-1$). All specifications include issuer and rating-by-maturity fixed effects. Year-month fixed effects are included in Panel B but excluded in Panel A because the Treasury-yield shock is an aggregate variable. Standard errors two-way clustered by issuer and year-month. Lagged controls ($t-1$): changes in Treasury yield curve slope, changes in VIX, changes in firm default probability, firm stock returns, stock market returns, credit rating, duration, credit spread, bond age, log issue amount, log firm assets, leverage, profitability, cash. ***, **, * = 1%, 5%, 10%. Observations at bond-month level.

Panel A Treasury Rate Shocks

	Baseline			With HCIOwn Interaction	
	HCI	REST	HCI–REST	HCI	REST
	(1)	(2)	(3)	(4)	(5)
ΔTrsy_2	–0.023** (–2.55)	–0.005 (–1.29)	–0.018* (–1.94)	–0.025** (–2.47)	–0.003 (–0.82)
High HCIOwn				–0.010*** (–3.98)	0.002** (2.18)
$\Delta\text{Trsy}_2 \times \text{High HCIOwn}$				0.016 (0.58)	–0.014** (–2.64)
Other Controls	Yes	Yes	Yes	Yes	Yes
Observations	66,215	68,821	66,157	66,215	68,821
Issuer FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	No	No	No	No	No
Rating $\times$ Maturity FE	Yes	Yes	Yes	Yes	Yes

Panel B Passive-Demand Shocks

	Baseline			With HCIOwn Interaction	
	HCI	REST	HCI–REST	HCI	REST
	(1)	(2)	(3)	(4)	(5)
$\Delta\text{PassiveOwn}$	–8.41** (–2.10)	9.07*** (3.80)	–20.47*** (–3.39)	–12.21** (–2.46)	13.00*** (3.94)
High HCIOwn				–0.03 (–1.56)	–0.01 (–1.15)
$\Delta\text{PassiveOwn} \times \text{High HCIOwn}$				20.95* (1.87)	–16.39** (–2.10)
Other Controls	Yes	Yes	Yes	Yes	Yes
Observations	49,409	49,409	49,409	49,409	49,409
Issuer FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Rating $\times$ Maturity FE	Yes	Yes	Yes	Yes	Yes
KP LM statistic	34.98	34.98	34.98	6.53	4.59
KP Wald F statistic	41.55	41.55	41.55	3.47	2.40

Table 7 HCI Trading Intensity and Bond Return Predictability

This table reports the results of OLS regressions of cumulative bond returns on lagged HCI and REST fund trading intensity, interacted with lagged multi-security complexity. multi-security complexity is measured using within-month complexity quintiles (*MSCompQ*; 1 = lowest complexity, 5 = highest complexity). Panel A uses raw cumulative returns; Panel B uses two-factor abnormal returns (*MKTB* and *MKTS*), where factor betas are estimated using rolling 60-month regressions with a minimum of 36 monthly observations. Columns split the sample by prior-month HCI ownership: Full Sample, Low HCI Ownership (bottom four quintiles at (t-1)), and High HCI Ownership (top quintile at (t-1)). All specifications include bond and year-month fixed effects and control for lagged cumulative return, rating, duration, bid-ask spread, bond age, log bond amount outstanding, log firm size, leverage, profitability, and cash holdings. Standard errors are clustered by bond. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Horizon: t+1 to t+3			Horizon: t+1 to t+6		
	<i>Full Sample</i>	<i>Low HCI Own</i>	<i>High HCI Own</i>	<i>Full Sample</i>	<i>Low HCI Own</i>	<i>High HCI Own</i>
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A Raw Returns						
<i>Trade_HCI</i>	-0.0021* (-2.00)	-0.0017 (-1.59)	-0.0059 (-1.67)	-0.0040 (-1.50)	-0.0027 (-1.50)	-0.0061 (-1.23)
<i>Trade_HCI</i> × <i>MSCompQ</i>	0.0013*** (3.76)	0.0014*** (4.04)	0.0017 (1.76)	0.0020** (2.38)	0.0025*** (4.18)	0.0020 (1.47)
<i>Trade_REST</i>	-0.0073** (-2.53)	-0.0019 (-0.61)	-0.0070 (-0.96)	-0.0071 (-1.21)	-0.0005 (-0.11)	-0.0207** (-2.19)
<i>Trade_REST</i> × <i>MSCompQ</i>	0.0011 (1.15)	-0.0010 (-0.98)	0.0023 (1.19)	0.0004 (0.23)	-0.0027 (-1.82)	0.0065** (2.41)
<i>MSCompQ</i>	0.0001 (0.37)	0.0001 (0.42)	-0.0001 (-0.16)	0.0001 (0.23)	0.0001 (0.14)	0.0000 (0.03)
Observations	346,495	279,147	66,751	182,182	266,773	63,107
Panel B Factor-Adjusted Abnormal Returns						
<i>Trade_HCI</i>	-0.0028** (-2.15)	-0.0034*** (-2.69)	-0.0039 (-0.83)	-0.0057** (-2.50)	-0.0067*** (-3.13)	-0.0054 (-0.85)
<i>Trade_HCI</i> × <i>MSCompQ</i>	0.0009** (2.01)	0.0012** (2.59)	0.0006 (0.45)	0.0018** (2.55)	0.0022*** (2.96)	0.0018 (1.04)
<i>Trade_REST</i>	0.0012 (0.29)	0.0051 (1.17)	-0.0069 (-0.84)	-0.0030 (-0.49)	0.0017 (0.27)	-0.0058 (-0.48)
<i>Trade_REST</i> × <i>MSCompQ</i>	-0.0017 (-1.25)	-0.0036** (-2.38)	0.0019 (0.86)	-0.0008 (-0.40)	-0.0030 (-1.43)	0.0020 (0.60)
<i>MSCompQ</i>	0.0000 (-0.13)	0.0003 (1.00)	-0.0017 (-1.73)	-0.0005 (-0.76)	0.0003 (0.51)	-0.0036 (-1.84)
Observations	176,852	140,450	35,988	166,831	132,888	33,544
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes
Momentum Controls	Yes	Yes	Yes	Yes	Yes	Yes
SE cluster	Bond	Bond	Bond	Bond	Bond	Bond

Table 8 Shift-Share IV Evidence on Specialist Ownership and Shock Transmission

This table reports two-stage least squares estimates using a shift-share instrument for specialist ownership ($HCI\widehat{Own}$). The instrument combines predetermined bond-level exposure to HCI investors with subsequent variation in fund-level capital flows. Columns (1)–(3) examine the pass-through of Treasury-rate shocks by interacting instrumented $HCI\widehat{Own}$ with changes in the 2-year Treasury yield. Columns (4)–(6) examine the pass-through of passive-demand shocks by interacting instrumented $HCI\widehat{Own}$ with instrumented changes in passive ownership. Instrumented HCI ownership are standardized variables with mean zero and unit standard deviation in the regression. All specifications include bond and issuer controls together with issuer and rating-by-maturity. Year-month fixed effects are included in Columns (4)–(6) but excluded from Columns (1)–(3) because $\Delta Trsy2$ is an aggregate variable. Standard errors are clustered by issuer and time period. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix 1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta YS - 2^{nd} \text{ Stage}$					
$HCI\widehat{Own} \times \Delta Trsy2$	-0.126*** (-4.37)	-0.125*** (-4.32)	-0.129*** (-4.26)			
$HCI\widehat{Own} \times \Delta Passive\widehat{Own}$				0.143* (1.84)	0.130* (1.85)	0.087 (1.32)
$HCI\widehat{Own}$	-0.003 (-0.49)	-0.002 (-0.26)	-0.002 (-0.27)	-0.039** (-2.07)	-0.033* (-1.93)	-0.022 (-1.30)
$\Delta Trsy2$	-0.239*** (-4.95)	-0.247*** (-5.17)	-0.244*** (-5.17)			
$\Delta Passive\widehat{Own}$				-0.253*** (-2.81)	-0.235*** (-2.87)	-0.219** (-2.31)
Rating		-0.003 (-1.24)	-0.003 (-1.27)		-0.033*** (-4.15)	-0.030*** (-3.03)
Duration		0.005*** (3.45)	0.005*** (3.58)		0.003* (1.81)	0.003** (2.31)
Bid-Ask		-8.527*** (-4.27)	-8.390*** (-4.55)		-4.253*** (-4.47)	-4.460*** (-4.03)
Bond Age		0.001 (1.15)	0.001 (1.45)		-0.006*** (-4.40)	-0.006*** (-3.78)
Log (Bond Amt)		-0.007* (-1.79)	-0.008** (-2.31)		-0.018** (-2.53)	-0.017** (-2.48)
Log (Firm Size)			0.021 (0.20)			0.088 (0.78)
Leverage			-0.008 (-0.28)			-0.186*** (-3.75)
Profitability			0.231 (0.95)			0.345 (1.11)
Cash			-0.028 (-0.71)			-0.252*** (-3.25)
Other Macro 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	96.293	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 9 Complexity, Specialist Ownership, and FOMC Shock Decomposition

This table presents event-study regressions using high-frequency monetary policy shocks, namely, Nakamura-Steinsson (NS) and Gürkaynak-Sack-Swanson (GSS). Columns 1–3 use multi-security 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. Multi-security complexity and HCI ownership are standardized variables with mean zero and unit standard deviation in the regression. Other control variables, included but not reported for brevity, are $\Delta Slope$, ΔVIX , $S\&P500Ret$, ΔPD , 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.

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	ΔYS					
$MSComp \times \Delta Trsy2$	-0.069** (-2.42)					
$MSComp \times \widehat{\Delta Trsy2}^{(NS)}$		0.075 (0.59)				
$MSComp \times r_{\Delta Trsy2}^{(NS)}$		-0.086** (-2.20)				
$MSComp \times \widehat{\Delta Trsy2}^{(GSS)}$			0.070 (0.65)			
$MSComp \times r_{\Delta Trsy2}^{(GSS)}$			-0.087** (-2.28)			
$HCIOwn \times \Delta Trsy2$				-0.120*** (-3.49)		
$HCIOwn \times \widehat{\Delta Trsy2}^{(NS)}$					-0.070 (-0.45)	
$HCIOwn \times r_{\Delta Trsy2}^{(NS)}$					-0.123*** (-2.81)	
$HCIOwn \times \widehat{\Delta Trsy2}^{(GSS)}$						-0.068 (-0.48)
$HCIOwn \times r_{\Delta Trsy2}^{(GSS)}$						-0.119*** (-2.84)
$MSComp$	0.269* (1.79)	0.403** (2.01)	0.399** (2.06)			
$HCIOwn$				-0.040 (-0.21)	0.030 (0.12)	0.020 (0.08)
Constant	-3.054 (-0.62)	-3.232 (-0.66)	-3.230 (-0.66)	-5.275 (-1.15)	-5.377 (-1.18)	-5.354 (-1.18)
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 10 Complexity, Specialist Ownership, and Market Functioning

This table examines broader implications of specialist ownership for market functioning. Panel A investigates ownership-based fragility. Columns (1)–(4) relate future bond fragility to multi-security complexity (*MSComp*) and specialist ownership (*HCIOwn*). Multi-security complexity and HCI ownership are standardized variables with mean zero and unit standard deviation in the regression. Columns (5)–(6) examine whether bonds with greater fragility exhibit different credit-spread responses to shocks, with Column (5) using OLS to examine Treasury-rate shock pass-through and Column (6) using IV to examine passive-demand shock pass-through. Panel B examines bond-market liquidity using future bid-ask spreads, Amihud (2002) illiquidity, and Roll (1984) effective-spread measures. Lower values indicate greater liquidity. All specifications include bond and issuer controls together with issuer, rating-by-maturity, and time fixed effects. Standard errors are clustered by issuer and time period. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Variable definitions are provided in Appendix 1.

Panel A Financial Fragility

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	$\sqrt{BFragility}$				ΔYS	$\Delta YS (IV)$
<i>MSComp</i>	0.004*** (2.97)	0.004** (2.25)				
<i>HCIOwn</i>			0.005*** (4.28)	0.006*** (4.21)		
$\sqrt{BFragility} \times \Delta Trsy2$					-0.119* (-1.67)	
$\sqrt{BFragility} \times \Delta PassiveOwn$						0.529* (1.74)
$\sqrt{BFragility}$					0.005 (0.43)	-0.218** (-1.97)
$\Delta PassiveOwn$						-0.292 (-1.64)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes	Yes	Yes
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

Panel B Bond Liquidity

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Bid-Ask_{t+1}</i>	<i>Amihud_{t+1}</i>	<i>Roll_{t+1}</i>	<i>Bid-Ask_{t+1}</i>	<i>Amihud_{t+1}</i>	<i>Roll_{t+1}</i>
<i>MSComp</i>	-0.008* (-1.86)	-0.004* (-1.80)	-0.008* (-1.76)			
<i>HCIOwn</i>				-0.007*** (-2.80)	-0.004*** (-3.45)	-0.016*** (-5.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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