ISSN 0956-8549

Corporate Bond Multipliers: Substitutes Matter

By

Manav Chaudhary
Zhiyu Fu
Jian Li

FINANCIAL MARKETS GROUP DISCUSSION PAPER NO. 955

June 2026

Corporate Bond Multipliers: Substitutes Matter*

Manav Chaudhary† Zhiyu Fu‡ Jian Li§

Abstract

Many economic questions require estimating the price effect of demand shifts (multipliers) in the bond market. Corporate bonds have salient characteristics that distinguish close versus distant substitutes. We show that accounting for the heterogeneous substitutability between bonds is critical for estimating multipliers correctly. By allowing for heterogeneous substitution, we find that security-level multipliers are very small—an order of magnitude smaller than the estimate ignoring heterogeneous substitutability. Nonetheless, portfolio multipliers are substantially larger and monotonically increase with the aggregation level. Furthermore, we find that the multiplier is larger for high-yield bonds, longer-maturity bonds, and bonds with greater arbitrage risks.

Keywords: Corporate bonds, inelastic demand, mutual funds, demand-based asset pricing

JEL codes: G10, G12, G23

*We thank Brendan Berthold, Giulia Brancaccio, Anna Cieslak, Kent Daniel, Olivier Darmouni, Valentin Haddad, Lars Peter Hansen, John Heaton, Jean Helwege, Ralph Koijen, Erik Loualiche, Aytek Malkhozov, Stefan Nagel, Varun Sharma, Paul Tetlock, Vivian Yue and seminar participants at the AFFECT 2023 mentorship workshop, AFA 2024, the Bank of Canada-Queen's workshop on financial intermediation and regulation, Columbia Business School, David Backus Memorial Conference on Macro-Finance, Economic Dynamics and Financial Markets Working Group at the University of Chicago, EFA, EPFL, FIFI conference, HBS Junior Finance Conference, HKUST, NBER Summer Institute, Purdue University, University of Minnesota, TADC at LBS, and the Yiran Fan Memorial Conference at the University of Chicago for helpful comments. This research was funded in part by the Fama-Miller Center for Research in Finance at the University of Chicago Booth School of Business.

†Department of Economics and Booth School of Business, University of Chicago. Email: mchaudhary@chicagobooth.edu

‡Washington University in St. Louis, Olin Business School. Email: z.fu@wustl.edu

§Columbia Business School. Email: jl5964@columbia.edu

1 Introduction

Our paper studies the ability of the corporate bond market to absorb demand-driven price pressures. This question is critical for a wide range of policy issues, including the impact of quantitative easing or tightening, the equilibrium implications of regulations on insurance companies, and market stability concerns related to mutual fund runs (e.g., Bernanke 2010; Vissing-Jorgensen and Krishnamurthy 2011; Koijen et al. 2017; Goldstein et al. 2017).

Textbook theory tells us that the impact of demand shifts on prices crucially depends on the availability of substitute assets and how investors substitute between them. When an asset has close substitutes, idiosyncratic demand shocks will have smaller direct effect on prices, as investors can easily hedge risks and trade against these shocks. However, this same mechanism causes demand shocks to spillover across close substitutes. The substitutability of assets varies substantially in practice: Apple's 10-year bond is a good substitute for Google's 10-year bond (both bonds are AA+ rated), whereas it is a poor substitute for bonds issued by Bed Bath & Beyond, which are in default. Hence, this heterogeneity in substitutability should affect how demand shocks impact corporate bond prices.

While the existing literature has made substantial progress using both reduced-form and structural methods (e.g., Ellul et al. 2011; Manconi et al. 2012; Bretscher et al. 2022) to study the effect of demand shifts, it often overlooks the role of substitutes or makes overly restrictive assumptions about substitutability across assets. Reduced-form approaches abstract from substitution patterns, producing estimates that are not readily generalizable because they depend on the types of shocks used in the study. In contrast, structural approaches attempt to directly estimate parameters that do not depend on the type of demand shock; however, to do so they must explicitly specify substitution patterns. They often assume homogeneous substitutability across securities, which contradicts real-world patterns and, as we show, can lead to biased estimates.

This paper demonstrates that accounting for heterogeneous substitution patterns across assets is crucial for understanding how demand shocks impact prices. The corporate bond market provides an ideal setting to study substitution patterns because salient characteristics such as credit rating and maturity make identifying close substitutes relatively straightforward. In addition, the heterogeneity in substitution is likely pronounced along these dimensions. We show that accounting for these heterogeneous substitution patterns reduces the price effect estimated at the security level by an order of magnitude compared to models that overlook this heterogeneity. However, shocks at the portfolio level still induce significant price movements, and the effect on price increases monotonically with the aggregation level, consistent with fewer available substitutes at higher aggregation levels.

Specifically, we measure demand-driven price pressure using multipliers (Gabaix and Koijen, 2021).[1] If we assume homogeneous substitution among all bonds, we get a positive significant multiplier around 0.34 at the security level, consistent with the magnitudes found in existing studies. However, once we allow bonds to have a different cross-elasticity for bonds with similar versus different characteristics, our estimate for the multiplier drops to 0.06 and becomes insignificant.[2] Our results demonstrate that ignoring heterogeneous substitution patterns leads to a considerable upward bias.

In addition, we estimate the "substitute passthrough" of close substitutes, which is defined as the percentage increase in an asset's price due to its close substitutes' prices rising by 1%. This parameter is important for understanding how shocks are transmitted across assets. At the security level, we find that the substitute passthrough is around 1, implying a significant spillover effect among close substitutes.

Our findings suggest that individual bonds are highly substitutable and that the market is quite good at absorbing security-specific demand shocks. With that said, the market is not as good at absorbing demand shocks at more aggregated levels, such as demand shocks

[1]The multiplier captures the direct price effect of the demand shock holding the prices of all other assets fixed. Multiplier is approximately the inverse of the own price elasticity of demand—when investors' demand is less elastic, a given unit of demand shock induces larger price adjustments to clear the market.

[2]Assuming inelastic supply, our multiplier implies a market demand elasticity of 16.6.

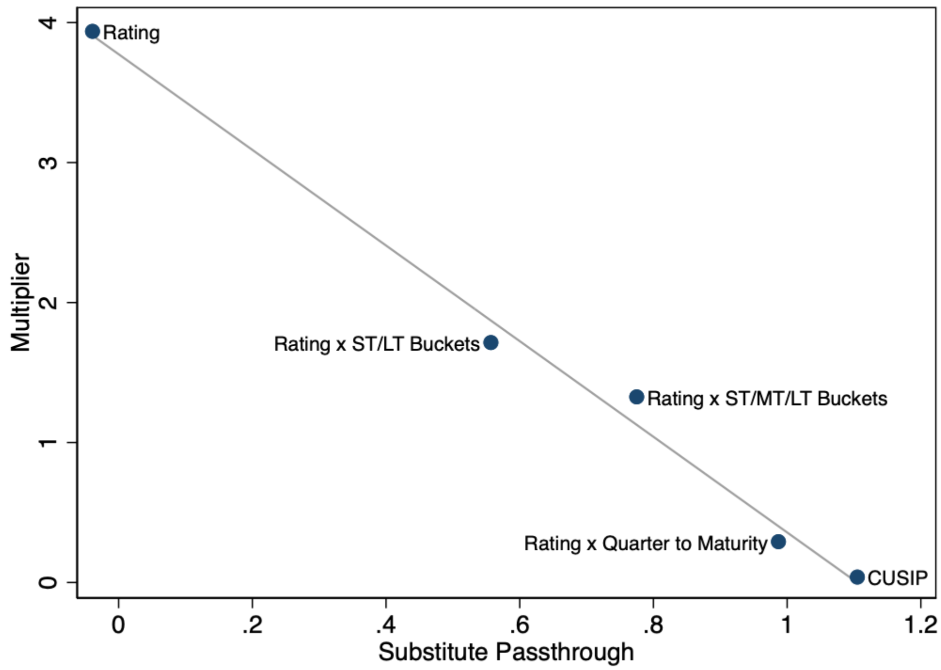
for a rating category. As Figure 1 shows, the more aggregated the demand shock, the higher the multiplier and the lower the substitute passthrough. The considerable difference in the multiplier between the security level and the more aggregated portfolio level highlights the double-edged nature of substitutability: while high substitutability reduces the price effect of direct demand shocks, it increases the spillover effect from indirect demand shocks to substitutes. This result also speaks to the optimal implementation of quantitative easing policies in order to achieve the maximum price impact.

Finally, we investigate the persistence of the price effect and its heterogeneity along various portfolio characteristics. We find that the price effect reverts after a quarter and that the multiplier is larger for high-yield bonds, longer-maturity bonds, and bonds with greater arbitrage risks.

Our results have important implications for the growing literature estimating demand elasticities and price impacts. Recent work estimating price impact by directly regressing returns on demand shocks increasingly add detailed characteristic-time fixed effects for identification (e.g., Choi et al. 2020; Coppola 2022; Holm-Hadulla and Leombroni 2023). Our framework clarifies that these fixed effect specifications are fundamentally estimating a different parameter compared to those without fixed effects. The former estimates the multiplier at the individual security level, whereas the estimates from the latter specification are averages between portfolio-level and security-level multipliers. A second strand of the literature estimates bond demand elasticities using structural models (e.g., Bretscher et al. 2022; Fang 2022; Darmouni et al. 2023). Our findings suggest that allowing for heterogeneous cross-elasticities becomes particularly important in settings with strong heterogeneity in asset substitutability. In settings with distinct substitute clusters, nested logit models can address this issue. In settings with more continuous degrees of substitutability, cross-elasticities can be modeled as a function of asset similarity.

To provide an overview of our methodology, we construct exogenous demand shocks from flow-induced trading by mutual funds. Following the literature, we assume that mutual funds

Figure 1: Multipliers and substitute passthroughs for increasingly aggregated bond portfolios



The figure plots the multipliers and the substitute passthrough coefficients (the link between substitute and test asset returns) for different levels of portfolio aggregation. See Table 4 for descriptions of the aggregation and Section 4.2 for the exact specifications. The figure shows a negative relationship between multipliers and substitute passthroughs. It also shows that multipliers are monotonically increasing in aggregation, whereas the substitute passthrough coefficients are monotonically decreasing in aggregation.

invest their flows into their existing portfolios proportionally (Lou, 2012).[3] To quantify the demand shocks, we account for autocorrelations in fund flows, extract the flow innovation terms and calculate the cumulative trading predicted by the innovations. We construct bond-level shocks by summing up fund-level shocks weighted by the fund's lagged holding share for each bond.

We use these demand shocks to estimate price multipliers. We show that as long as *lagged* mutual fund holding shares are orthogonal to unobserved demand shocks in the cross

[3] In Appendix D.1, we relax this one-to-one passthrough assumption by directly looking at mutual fund rebalancing to estimate lower bounds for the demand passthrough and use this to find upper bounds for the multiplier. This exercise suggests that the security-level multiplier is at most 0.08, which is still much smaller than what is typically found in studies that assume homogeneous cross-elasticities.

section, we can use our constructed demand shocks to identify the multipliers, even if the flows are endogenous. Our identification strategy is an application of the Bartik instrument, where exogeneity of shares guarantees instrument validity (Goldsmith-Pinkham et al., 2020; Chaudhry, 2022). From this perspective, our identification strategy can be viewed as pooling multiple exogenous exposure research designs. Each bond is exposed to flows into a given mutual fund, but the degree of exposure is governed by how much this mutual fund held the bond in the previous period, which is plausibly exogenous conditional on controls.

To estimate multipliers for individual bonds, we regress bond returns on the constructed demand shocks, controlling for the relevant substitute portfolio's returns. Under the homogeneous cross-elasticity assumption, we just need to control for the market return, or equivalently, a time fixed effect. The estimated multiplier is significantly positive and around 0.34, similar to the estimates in the literature.

However, once we relax the homogeneous cross-elasticity assumption, we find a much smaller multiplier. To allow for heterogeneous cross-elasticity, we control for the return of a substitute portfolio formed by bonds with the same detailed rating category as the security of interest.[4] To deal with the endogeneity of prices, we instrument the return of the substitute portfolio with the demand shocks to bonds in this portfolio. Under this specification, we find that the multiplier is around 0.06 and statistically insignificant. In other words, the direct price effect of these demand shocks from mutual funds is very small at the security level. On the other hand, the substitute passthrough is close to one, indicating the spillover effect among close substitutes is almost one to one. We also run a specification where we directly control for substitute prices using substitute portfolio-time fixed effects rather than using instrumental variables, and the multiplier estimates are essentially unchanged.

To understand why ignoring close substitutes leads to biased estimates, note that the multiplier is defined as the direct effect of a demand shock on an asset's price while holding

[4] We refer to $AAA, AA+, AA - AA + ...$ as detailed rating categories and $AAA, AA, A, BBB...$ as coarse rating categories.

the prices of all substitutes fixed. Failing to control for close substitutes leads to an upward bias in the estimated multiplier through two channels. First, general equilibrium effects imply that when a bond experiences a demand shock, the prices of its close substitutes also rise to clear the market—especially when the substitutes are more similar. Second, many commonly used demand shocks, such as those driven by investor flows or mandates, tend to be correlated across similar assets. Both channels induce a positive correlation between the asset-specific demand shock and omitted prices of its close substitutes, causing the multiplier to be overestimated.

We then estimate the multipliers for portfolios of corporate bonds. While the multiplier for individual bonds is very small, we find that portfolios have significantly positive multipliers. Furthermore, the portfolio multiplier is monotonically increasing in the degree of aggregation, while the substitute passthrough is monotonically decreasing. For portfolios formed by bonds in the same rating category with the same quarter to maturity, the multiplier is 0.3, significantly larger than the 0.06 estimate at the bond level. In the meanwhile, the portfolio substitute passthrough is estimated to be slightly lower than that at the bond level. At the most aggregated level, where each portfolio is formed by bonds in the same coarse rating group, the portfolio multiplier is 3.94 and the passthrough coefficient drops effectively to 0.

These empirical patterns are a natural consequence of heterogeneous substitution across assets. When investors treat bonds within a narrow group (e.g., BB+ rated) as close substitutes but are less willing to substitute across broader categories, aggregation reduces spillovers from outside the portfolio while amplifying the impact of demand shocks internal to it. Thus, higher multipliers at more aggregated levels reflects the underlying structure of investor substitution behavior—consistent with our theoretical framework.

Consistent with demand being more elastic in the long run, we find that the price response to demand shocks is not permanent and seems to revert fully. For our baseline level of aggregation, we find that the price effect takes around two quarters to revert. This reversion rate is somewhat faster than the four-quarter reversion Li (2021) found for stock portfolios.

Finally, we provide suggestive evidence that arbitrage risk is a potential structural driver of multipliers. We compute the Sharpe ratio of a strategy that takes advantage of the price deviation between the testing asset and its substitute portfolio for one quarter. This strategy incurs risks as prices may not converge in the following quarter due to fundamental shocks and future flow shocks. We find that the annualized Sharpe ratios are generally small, suggesting that unhedged risk may impede arbitrage activities. Indeed, in the cross section of portfolios formed by detailed rating and maturity, portfolios with high arbitrage risks have significantly higher multipliers. A one-standard-deviation increase in arbitrage risk increases the multiplier by 0.43. Corroborating the role of arbitrage risk, we also find that bonds with lower credit ratings and longer maturities have higher multipliers and larger arbitrage risk.

In the remainder of this section, we discuss the literature. We explain our demand framework in Section 2. Section 3 describes our data, construction of demand shocks, and identification strategy. Section 4 presents the estimation results, and Section 5 focuses on arbitrage risk as a potential driver of our results. Section 6 concludes.

1.1 Literature Review

We contribute to the literature that studies the price impact of and spillover effects of demand shifts, which is a critical input for answering a wide range of policy questions. For example, the economic impact of unconventional monetary policy (Todorov, 2020; Nozawa and Qiu, 2021; Gilchrist et al., 2023; Selgrad, 2023). And also, the vulnerability of the bond market to demand shocks, which has come into focus since the bond market disruption of March 2020 (Hubbard et al., 2021; Falato et al., 2021; Haddad et al., 2021; Ma et al., 2022). Our work highlights the importance of and shows how to correctly account for heterogeneous substitution patterns when estimating multipliers, especially for assets with easy-to-identify close substitutes.

Given its importance, the literature has used both reduced form and structural methods to estimate the price impact. On the structural side, several recent papers have adapted the asset demand system developed by Koijen and Yogo (2019) for the equity market to study corporate bond demand.[5] Bretscher et al. (2022) focus on the heterogeneous demand elasticities of different investors and find the average corporate bond multiplier is around 0.26. Darmouni et al. (2023) adopt a two-layer framework to capture the interaction effect between fund flows and asset market inelasticity. Their multiplier estimate ranges from 0.5 to 1.25, depending on the time period. Siani (2022) estimates the multiplier of the primary market and finds it is between 0.29 to 0.53. Fang (2022) uses a nested logit structure to allow for more flexible substitution within and across IG and HY bonds and finds a lower multiplier of around 0.1. Compared to these studies, we find corporate bond markets are considerably more elastic, with a bond-level multiplier of around 0.05. Our method differs in several ways. First, our approach allows for greater flexibility in substitution patterns. Echoing our findings, Fuchs et al. (2023) argue theoretically that estimates in logit-demand systems are biased under heterogeneous substitution and Haddad et al. (2025) propose using observables to control for such heterogeneity. Second, our approach is relatively model-agnostic and does not require us to observe all market participants' holdings.[6] Finally, our top-down approach makes it more suitable for studying bond-specific heterogeneity in multipliers.

An early strand of the reduced form literature uses index inclusion to estimate the price impact, and shows that adding assets to indices results in significant positive abnormal returns. For example, see Shleifer (1986); Harris and Gurel (1986); Beneish and Whaley (1996); Wurgler and Zhuravskaya (2002); Chen et al. (2004); Chang et al. (2015); Pavlova and Sikorskaya (2022) for stocks and Calomiris et al. (2022) for bonds. Generally, they find

[5] Jansen (2021) has also used demand systems to estimate the elasticity of European government bonds and finds a multiplier of around 0.24 for maturity bucket portfolios. For other papers applying the method to equity markets see Haddad et al. (2022).

[6] In more data-rich settings where researchers observe all bidders' submissions of price-quantity orders across multiple assets, Allen et al. (2025) develop a non-parametric method to estimate own- and cross-price elasticities without relying on price instruments.

a significant and permanent price impact; the estimated multipliers are around three orders of magnitude larger than those implied by standard models (Petajisto, 2009). Among these index-inclusion papers, Wurgler and Zhuravskaya (2002) have the closest connection with our paper. They show that the price impact is smaller for stocks with smaller idiosyncratic risks upon index inclusion. We find that portfolios with large arbitrage risks also have larger multipliers, consistent with the fact that idiosyncratic risks are positively correlated with expected return in the corporate bond market (Chung et al., 2019). Overall, our demand shock and the setting of corporate bonds have several advantages for establishing the importance of close substitutes. First, it is relatively easy to identify close substitutes in the case of corporate bonds based on credit rating and maturity. Second, index inclusion (or deletion) only affects a handful of assets in any given year, whereas flow-induced trading shocks impact all assets to some extent. The broader exposure allows us to conduct our analysis at portfolio levels, for which arbitrage risks are likely to play a more significant role in limiting arbitrage.

Another strand of the reduced form literature uses mechanical portfolio rebalancing as a source of demand shocks, showing that trading by mutual funds and ETFs in response to flows has a significant price impact (Lou, 2012; Coval and Stafford, 2007; Jotikasthira et al., 2012; Edmans et al., 2012; Li, 2021; Dannhauser and Hoseinzade, 2021). In contrast, Choi et al. (2020) find little evidence for fire-sale price pressure in the corporate bond market once fundamental risks are controlled for. Our estimates confirm that bond multipliers are smaller than stock multipliers once we control properly for close substitutes' flows. Other variants of mechanical-trading-induced demand shocks include using dividend-payment-induced-trading (Hartzmark and Solomon, 2022; Schmickler and Tremacoldi-Rossi, 2022), reinvestment of stimulus payments by US households (Greenwood et al., 2022), and investing refunds from unsuccessful bids in Chinese IPOs (Li et al., 2021). Overall, these papers find a significant price impact as well. Li and Lin (2022) demonstrate that individual stock prices respond more to aggregate demand shocks—those correlated across multiple securities—compared to demand shocks idiosyncratic to the stock. Our framework and results reveal that the stronger response of aggregate demand shocks is a direct consequence of investors' heterogeneous substitution patterns. Our identification strategy directly builds on the mutual fund flow-induced trading literature, but relies on shares' exogeneity rather than shocks' exogeneity (Goldsmith-Pinkham et al., 2020; Chaudhry, 2022). More importantly, we take into account the close substitute portfolio's return in the estimation, which helps address the omitted variable bias generated by flow-induced demand shocks that are correlated across assets.

At more aggregated levels, Gabaix and Koijen (2021) find that the multiplier of the overall equity market is around 5. Hartzmark and Solomon (2022) and Li et al. (2021) also find relatively large market-level multpliers. Other papers have attempted to estimate equity portfolio-level multipliers and found them somewhere between the multiplier of individual stocks and the overall market (Peng and Wang, 2019; Li, 2021). Consistent with these studies, we show that more aggregated portfolios of individual bonds have larger multipliers and are less sensitive to changes in the prices of their close substitutes.

2 Demand Framework

In this section, we outline our demand framework. We begin by introducing a fully general demand system that, while infeasible to estimate, allows for complete flexibility in the cross-elasticities between bonds. We then outline the homogeneous cross-elasticity restriction typically made by existing methods. This restriction makes estimation feasible; however, it risks introducing positive omitted variable bias to the multiplier estimates. Finally, we outline our demand system, which relaxes the homogeneous cross-elasticity restriction by allowing for *heterogeneous* cross-elasticities between close and distant substitutes, where close and distant substitutes are identified using bond characteristics such as rating and maturity.[7] Our demand system brings us one step closer to the general demand system but remains feasible for estimation.

2.1 Fully General Demand System

For a fund i in our sample (denote the set as MF), we assume its demand for the N available assets is

$$\underbrace{\mathbf{q}_{i,t}}_{N\times 1} = \underbrace{\Gamma}_{N\times N}\underbrace{\mathbf{p}_t}_{N\times 1} + \underbrace{\boldsymbol{\omega}_{i,t}}_{N\times 1} + \underbrace{\boldsymbol{\epsilon}_{i,t}}_{N\times 1} \qquad \text{for } i \in MF, \tag{1}$$

where $\mathbf{q}_{i,t}$ is an $N \times 1$ by vector, where element $q_{i,j,t}$ denotes the log quantity for bond j demanded by fund i. Similarly, $\mathbf{p}_t$ is the $N \times 1$ price vector, where element $p_{j,t}$ denotes the log price of bond j. The term Γ is an $N \times N$ matrix that governs demand elasticities and substitution patterns among bonds. To simplify the notation, we assume Γ is homogeneous among investors, but this does not matter for our estimation.[8] The slope of the demand curve for asset j is $\frac{\partial q_j}{\partial p_j} = \Gamma_{j,j}$. Furthermore, $\frac{\partial q_j}{\partial p_k} = \Gamma_{j,k}$ is the cross-elasticity of asset j to asset k's price. The observed demand shock from flow-induced trading is captured by the $N \times 1$ vector $\boldsymbol{\omega}_{i,t}$, where element $\omega_{i,j,t}$ denotes fund i's demand for bond j due to flows. Finally, the vector $\boldsymbol{\epsilon}_{i,t}$ captures the unobserved demand shocks to fund i at time t, including the fund's expectation about future returns and risks.

The demand equation (1) can be viewed as a log-linearization of any generic portfolio choice problem. For instance, it nests the portfolio choice implied by maximizing mean-variance utility. This approach helps to preserve flexibility, and does not impose the restrictions that come from explicitly specifying the agents' utility functions.

For an investor whose portfolio allocation is not observed in our sample, we denote their

[7]In Appendix I, we show how our approach links to logit demand systems and nested logit demand systems, as in Koijen and Yogo (2019) and Koijen and Yogo (2020).

[8]If Γ is heterogeneous among investors, then the final expression for market multipliers should be the average of investor elasticities weighted by their assets under management (AUM) shares.

demand as,

$$\mathbf{q}_{i,t} = \Gamma \mathbf{p}_t + \boldsymbol{\epsilon}_{i,t} \qquad \text{for } i \notin MF. \tag{2}$$

The demand specifications here capture both investors who demand liquidity and those who supply liquidity in equilibrium. With constant supply of bonds, the market clearing condition gives,[9]

$$\Delta \left(\sum_i \exp \left(\mathbf{q}_{i,t} \right) \right) = 0. \tag{3}$$

Log-linearizing the market clearing condition around the last period values, we get the return for bond j $\Delta p_{j,t}$ is:

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_{j,t}^{sub} + \tilde{\nu}_{j,t}. \tag{4}$$

where each term is given by

$$u_{j,t} \equiv \sum_i S_{i,j,t-1} \omega_{i,j,t} \equiv \sum_i \frac{\exp(q_{i,j,t-1})}{\sum_{i'} \exp(q_{i',j,t-1})} \omega_{i,j,t}$$
$$M \equiv -\frac{1}{\Gamma_{j,j}} \qquad \tilde{M} \equiv -\frac{\sum_{k \neq j} \Gamma_{j,k}}{\Gamma_{j,j}}$$
$$\Delta p_{j,t}^{sub} \equiv \sum_{k \neq j} \frac{\Gamma_{j,k}}{\sum_{k' \neq j} \Gamma_{j,k'}} \Delta p_{k,t}$$

The term $u_{j,t}$ denotes the bond-level observed demand shock, defined as the average of investor-level shocks weighted by each investor's lagged market share in the bond. The term $M u_{j,t}$ captures the change in the asset's price in response to its own demand shock, holding prices of substitutes fixed. If investors have downward-sloping demand with respect to the

[9] We assumed that net supply is constant to simplify the exposition, but this can be relaxed to allow for elastic supply. In this case, the price impact will reflect both shifts in the demand curve and movements along the supply curve. As a result, the multiplier will be the inverse of a weighted average of supply and demand elasticities. The literature typically finds low supply elasticities (Siani, 2022), hence it does not impact our conclusion that security-level demand elasticity is large.

asset's own price, then the diagonal of Γ should be negative (i.e., $\Gamma_{j,j} < 0$), which implies $M > 0$. We refer to M as the asset's own multiplier.

The second part of equation (4) captures the change in price due to movements in other assets' prices. The term $\Delta p_{j,t}^{sub}$ denotes the return of the substitute portfolio for bond j, where the portfolio weight of a given bond k is proportional to the cross-elasticity between bond j and bond k. The coefficient $\tilde{M}$ captures the spillover effects from the substitute portfolio. If assets are, broadly speaking, substitutes with each other, then the off-diagonal terms are positive, and $\tilde{M}$ should be positive. If assets are complements with each other, then the off-diagonal terms are negative, implying a negative $\tilde{M}$. We refer to $\tilde{M}$ as the substitute passthrough.

The residual term $\tilde{\nu}_{j,t}$ in equation (4) is defined as $\tilde{\nu}_{j,t} \equiv \nu_{j,t}/(-\Gamma_{j,j})$, where $\nu_{j,t}$ is the lagged-market-share weighted average of demand from the fund-level unobserved demand shocks $\boldsymbol{\epsilon}_{i,t}$. With a slight abuse of notation, we keep using $\boldsymbol{\omega}_{i,t}$ (and $\boldsymbol{\epsilon}_{i,t}$) for shocks instead of $\Delta\boldsymbol{\omega}_{i,t}$ (and $\Delta\boldsymbol{\epsilon}_{i,t}$). For now, we assume that the observed demand shocks $u_{j,t}$ are orthogonal to the unobserved shocks $\nu_{j,t}$. We explain how we construct this shock and the identification assumption that guarantees its orthogonality in the next section.

Why separately estimate M and $\tilde{M}$? As equation (4) indicates, the total price change of a bond has two components: (i) the direct effect from its own demand shock (as measured by the multiplier M), and (ii) the spillover effect from other prices (measured by $\tilde{M}$). Hence, the total price impact of demand shocks ultimately depends on the structure of the shocks. For instance, if bonds with larger spillover effects among them experience similar demand shocks, then the spillover component may be a large driver of the total price impact. Whereas if the demand shock is idiosyncratic to a single bond, spillover effects may be considerably more muted.

Because the direct effect and the spillover effect are often structurally correlated, identifying them separately is empirically challenging. Traditionally, the literature has directly regressed asset returns on demand shocks in a particular episode, effectively estimating total price impact that combines the direct and spillover effects, specific to the structure of demand shocks in that episode. While these reduced-form estimates reveal episode-specific total price impact, it is difficult to generalize the findings to other cases where the structure of the demand shocks may be different. For instance, reduced-form estimates using mutual-fund flow shocks, which tend to be correlated, may not be very informative for understanding the price impact of index inclusion, which tends to be more idiosyncratic. Furthermore, these reduced-form estimates provide limited insight into how demand shocks affect prices at the bond, portfolio, or asset class level.

To understand more generally how demand shocks affect prices, and conduct counterfactual analysis, it is important to estimate the underlying parameters like M and $\tilde{M}$ that separate the direct and spillover effects,[10] which is why the burgeoning asset demand-based literature attempts to directly estimate multipliers (or its inverse, elasticities). The policy impact across a wide range of assets crucially depends on the relative magnitudes of M and $\tilde{M}$.

Infeasibility of estimating the fully general demand system. Equation (4) suggests that if we observe asset-specific demand shocks $u_{j,t}$ and asset-specific substitutes $\Delta p_{j,t}^{sub}$, we can run a regression to estimate M and $\tilde{M}$. However, the construction of $\Delta p_{j,t}^{sub}$ is infeasible without further restrictions on cross-elasticities. Asset j's $\Delta p_{j,t}^{sub}$ is a weighted average of the returns of other assets, where the weights depend on unobserved cross-elasticities; the closer an asset is as a substitute, the larger its weights in the substitute portfolio. Hence, we will need to impose some structure on the substitution pattern, which will allow us to construct (or control for) the substitute portfolio returns without knowing the exact magnitudes of the cross-elasticities $\Gamma_{j,k}$.

[10] Once estimated, these parameters can be inverted to obtain investors' demand elasticities Γ.

2.2 Demand Structure with Heterogeneous Cross-elasticity

Homogeneous substitution. For tractability, the literature commonly assumes homogeneous substitution patterns. These demand systems imply investors' elasticity matrix is characterized by: (i) common own-price elasticity (diagonal elements), and (ii) common cross-elasticities (off-diagonal elements).

To make the substitution patterns in these systems more explicit, homogeneous demand models such as logit imply the following structure for the elasticity matrix Γ,[11]

$$\Gamma_{j,k} = \begin{cases} -\gamma^o + \gamma^d w_k & j = k \\ \gamma^d w_k & j \neq k \end{cases} \tag{5}$$

where γ^o and γ^d are scalars and w_k is the market share of bond k. The demand for an asset decreases when its own price increases. Since the market share of each individual bond is very small, $w_k \approx 0$, the own demand elasticity is approximately $-\Gamma_{j,j} \approx \gamma^o$.[12] The demand for asset j increases if the price for a generic asset k increases; the degree of substitution is determined by the parameter γ^d and the portfolio weight of asset k. Applying market clearing, we can see that such a demand system implies the following relationship for bond j's returns,

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_t^m + \tilde{\nu}_{j,t} \tag{6}$$

where the multiplier $M = 1/\gamma^o$, the substitute passthrough $\tilde{M} = \gamma^d/\gamma^o$, and the substitute portfolio's return Δp_t^m is the market return.

[11]Logit demand system is a special case, as it imposes the additional parametric restriction $\gamma^d = \gamma^o$. See Appendix I for detailed derivation.

[12]We include the cross-elasticity $\gamma^d w_j$ as part of the own-elasticity for technical reasons. It simplifies matrix inversion, which we later use for analyzing shock propagation. Empirically, as each bond is small relative to the market, whether we include the cross-elasticity term has little impact on the own-elasticity estimates. This also enables us to map our demand system to a logit specification, facilitating straightforward comparison.

Imposing the homogeneous substitution structure Γ presents a couple of ways to estimate the multiplier M. One way is to directly estimate equation (6) by regressing bond returns on demand shocks and controlling for market returns using time-fixed effects,

$$\Delta p_{j,t} = M u_{j,t} + \text{Time fixed effects} + \tilde{\nu}_{j,t}. \tag{7}$$

This approach is commonly employed by the flow-induced trading literature when estimating the price impact of demand shocks (Lou, 2012). Hence, interpreting these estimates as the direct price impact of demand shocks implicitly relies on a homogeneous substitution assumption. Another way is to estimate investor-level logit demand using holdings data and then apply market clearing to recover M. This approach is used by papers applying the methodology developed in Koijen and Yogo (2019).

The success of these approaches ultimately rests on whether the homogeneous substitution assumption correctly captures substitution patterns. However, the homogeneous-substitution assumption is likely to be violated in the corporate bond market. If the price of a BBB+ bond increases, investors will probably substitute much more into another BBB+ bond than an AAA bond (all else equal). In addition, there will probably be very little substitution in the high-yield bond class.

Heterogeneous substitution. We impose a two-layer structure to capture the heterogeneous substitution patterns. We allow cross-elasticities to have two levels: a cross-elasticity for similar bonds (close substitutes) and a cross-elasticity for bonds that are less similar (distant substitutes). More formally, we extend the homogeneous demand case such that Γ

takes the following form,

$$\Gamma_{j,k} = \begin{cases} -\gamma^o + \gamma^c w_{k|g} + \gamma^d w_k & j = k \\ \gamma^c w_{k|g} + \gamma^d w_k & j \neq k, j, k \text{ in the close substitute group } g \\ \gamma^d w_k & \text{otherwise} \end{cases} \tag{8}$$

where w_k is the share of asset k in the whole market and $w_{k|g}$ is the conditional share of k in group g of close substitutes. Practically speaking, the demand elasticity is essentially γ^o because the weight of each bond is small in the market portfolio and in our definition of close substitute group.[13] Intuitively, the cross-elasticity is scaled by market share so that the substitution effect is in proportion to their relative sizes. Appendix I shows that a similar demand structure also arises in a nested logit demand system.

In our baseline analysis, for a given bond, we define the group of close substitutes as all other bonds in the same detailed rating category. For example, for a BB+ bond with 10 years to maturity, we define its close substitutes as all other BB+ bonds. In Section 4.1, we show that detailed rating categories effectively capture heterogeneous substitution patterns. Our results remain quantitatively similar whether we use coarser definitions of close substitutes (such as investment grade/high yield bonds) or more refined definitions (such as bonds with similar maturity and rating).

Under this demand structure, the substitute portfolios for each asset j can be decomposed into two components: the portfolio of bonds in the close substitute group and a market portfolio. For brevity, we call the former portfolio bond j's close substitute. Specifically, equation (4) can be rewritten as,

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_{g(j),t} + \tilde{M}^m \Delta p_t^m + \tilde{\nu}_{j,t}, \tag{9}$$

[13] Even when individual bond's weight is small, spillover effects from close substitutes can still be sizable, because they reflect the combined influence of the entire portfolio of similar bonds.

or alternatively as

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_{g(j),t} + \text{Time fixed effects} + \tilde{\nu}_{j,t}, \tag{10}$$

where $\Delta p_{g(j),t}$ is the portfolio return of assets in asset j's close substitute group, weighted by each asset's lagged market value, and Δp_t^m is the market return. We instrument portfolio returns with demand shocks to solve endogeneity issues, as will be explained in Section 3.3. As before, the multiplier $M = 1/\gamma^o$ measures the price response to a one-percentage-point increase in demand, conditional on other asset returns. The passthrough coefficient $\tilde{M} = \gamma^c/\gamma^o$ captures the comovement of the test asset's price with its close substitutes' prices, conditional on the market return. A passthrough close to 1 indicates a strong substitutability among assets within groups.

For the purpose of estimating the multiplier M alone, we can also simply absorb $\Delta p_{g(j),t}$ and Δp_t^m with group-time fixed effects, as in equation (11):

$$\Delta p_{j,t} = M u_{j,t} + \text{Fixed effects}_{g,t} + \tilde{\nu}_{j,t}. \tag{11}$$

This group-time fixed-effect specification is more straightforward, and does not rely on any instrument for the group-level portfolio return. However, the baseline specification in equation (10) allows us to estimate the substitute passthrough coefficients $\tilde{M}$, which is informative about the spillover effect among close substitutes. In our analysis, we estimate both specifications (10) and (11). We find that the choice of specification has little impact on the estimate of M, suggesting the IV estimation strategy for equation (10) successfully addresses the endogeneity issues.

Omitted variable bias. Failing to control for close substitute prices leads to a biased estimation of the multiplier and, consequently, of the elasticity.[14] Since bond return depends on the direct effect of demand shocks (the multiplier) and the spillover effect from substitute price changes, not controlling for substitute price changes correctly will introduce an omitted variable bias (OVB) if demand shocks and substitute prices are correlated.

If cross-elasticities are homogeneous, controlling for the market return (or time-fixed effects) effectively accounts for the spillover from other assets. However, with heterogeneous cross-elasticities, this fails to account for all of the spillover effects sufficiently. Suppose close substitutes exert strong spillover effects while distant substitutes contribute little. In this case, controlling for the market return only captures the weaker average spillover of the overall portfolio and misses the stronger influence of close substitutes. As a result, the specification in equation (6) incorrectly attributes too much of the observed price response to the bond's own demand shock, leading to an overestimation of the multiplier.

Empirically, bond j's demand shocks and its close substitute price changes are usually positively correlated. Hence, ignoring close-substitute's price movements results in a positive OVB, leading to an overestimation of the multiplier and an underestimation of the elasticity. This bias tends to be large, as we find that $\tilde{M}$, which captures the additional spillover from close substitutes relative to distant substitutes, is sizable.

The positive OVB in multiplier estimates can arise for two main reasons, one structural and one empirical: (i) general equilibrium effects and (ii) correlated demand shocks. First, general equilibrium effects imply that when bond j's price rises due to positive demand shocks, substitute assets' prices also rise for the market to clear. This effect is particularly strong for close substitutes, as their similar payoffs make investors more inclined to shift demand toward them. This general equilibrium adjustment of substitute prices induces a positive correlation between the demand shocks and the close substitute prices, conditional

[14] Like elasticity, the multiplier is defined as the direct effect of demand shocks on prices while holding all other substitute prices fixed. Intuitively, failing to control for close substitute prices is akin to not holding all other prices fixed.

on the market return. As a result, ignoring the close substitutes' returns leads to a positive OVB.

Second, commonly used demand shocks in the literature, such as flow-induced trading and investment mandates, are positively correlated across bonds with similar characteristics. Therefore, when there is a positive demand shock for bond j, its close substitutes are likely to experience similar positive demand shocks, driving up their prices as well. This induces a positive correlation between the demand shock and close-substitute prices. Therefore, failure to properly control for close substitutes will contaminate the bond-level multiplier, biasing the estimate upward.

As we show in Section 4, at the bond level the multiplier M is very small once the return of the close-substitute portfolio, formed by bonds with the same detailed ratings, is controlled. Our result suggests that the market is fairly elastic at the bond level.[15] Finally, with sufficient statistical power, one can easily extend our analysis to allow for multiple layers of substitution: same detailed rating category, the same investment rating (investment-grade versus high-yield), and maturity dimension. We verify that the estimation results are quantitatively very similar to the case with two different levels of cross-elasticities. So we will focus on only two levels of heterogeneity for most parts of the paper.

Aggregation. Beyond bond-level multipliers, it is often more relevant, both empirically and for policy, to understand how portfolios of bonds, grouped by characteristics such as rating or maturity, respond to demand shocks. For instance, quantitative easing (QE) programs typically target bonds with similar features, and mutual funds tend to hold portfolios concentrated in specific segments of the bond market.

The portfolio-level effects are shaped by investors' substitution patterns across individual

[15] We are implicitly assuming that the cross-elasticity between corporate bonds and other asset classes (such as Treasury securities, mortgage-backed securities) is small, or the cross-elasticity between a corporate bond and other assets is similar to the cross-elasticity between that bond and its far substitute within the corporate bond class.

bonds. When cross-elasticities are heterogeneous—stronger among close substitutes and weaker among distant ones—the aggregated portfolio will exhibit a higher multiplier relative to the individual bond level, and a lower passthrough from other portfolios' returns.

For example, if investors treat BB+ rated bonds as close substitutes for one another but not for other bonds, this creates high spillovers among BB+ rated bonds and low spillover from other bonds. Consequently, when a demand shock hits a single BB+ rated bond, investors can easily substitute to another one in the same portfolio, dampening the effect on prices. However, when a demand shock hits the entire market segment of BB+ rated bonds, investors are more reluctant to substitute to bonds of other rating categories, resulting in a larger direct effect on price. Similarly, the passthrough from other portfolios is correspondingly lower.

To see this more formally, suppose at the bond-level investors' demand has a two-layer substitution structure as in equation (8). As discussed before, in this case the bond-level demand is given by equation (9) with a multiplier of $M = 1/\gamma^o$ and a close substitute passthrough of $\tilde{M} = \gamma^c/\gamma^o$.

Assume there are G close-substitute groups. We consider the demand system for the aggregated G portfolios, where each portfolio consists of value-weighted bonds that are in the same close-substitute group. These are portfolios of assets investors view as similar. Treating each portfolio as one asset, we can describe the portfolio-level demand system using a $G \times G$ elasticity matrix Γ^G, obtained by aggregating the bond-level demand matrix Γ to the portfolio level. For each portfolio g, the portfolio return is the average return to all bonds $j \in g$, weighted by its share in the portfolio $w_{j|g}$, and the elasticity $\Gamma^G_{g,g'}$ is the value-weighted aggregation of $\Gamma_{j,k}$ for bonds in portfolio $j \in g$ and $k \in g'$ respectively.

Given the bond-level elasticity matrix Γ in equation (8), we show that the portfolio demand matrix Γ^G is given by (see Appendix B for detailed derivation):

$$\Gamma^G_{g,g'} = \begin{cases} -(\gamma^o - \gamma^c) + \gamma^d w_{g'} & g = g' \\ \gamma^d w_{g'} & g \neq g' \end{cases} \tag{12}$$

where $w_{g'}$ is the weight of portfolio g' in the market portfolio. The aggregated demand system becomes a one-layer system with the own elasticity controlled by $(\gamma^o - \gamma^c)$ and the cross-elasticity of γ^d. The portfolio multiplier is $M^G = \frac{1}{\gamma^o - \gamma^c}$ and the portfolio substitute passthrough is $\tilde{M}^G = \gamma^d/(\gamma^o - \gamma^c)$.

The difference between the portfolio- and bond-level multipliers is exactly the within-group cross-elasticity γ^c. Since the cross-elasticity is positive ($\gamma^c > 0$), when the price of a particular bond rises, investors partially substitute toward other bonds in the same portfolio, dampening the price effect at the individual bond level.[16] This substitution channel, however, is ineffective when the entire portfolio experiences a demand shock, and hence it is netted out in the portfolio-level multiplier, making the portfolio-level multiplier larger. In fact, the greater the passthrough to substitutes at the bond level (as measured by γ^c/γ^o), the larger the wedge between the bond-level and portfolio-level multipliers.

In our baseline portfolio specification, we treat each asset as a market-value weighted portfolio formed by bonds with the same detailed rating category and quarter to maturity. We also consider other levels of aggregation in our empirical analysis.

Shock propagation. A related question is how a demand shock to a bond propagates to other bonds. The inverse of elasticity matrix $-\Gamma^{-1}$ encodes the price impact of a demand shock on the entire system. With a two-layer substitution structure, the multiplier also features two layers, with the propagation effect stronger within the close-substitute group than across groups. With a fully estimated Γ, in principle we can always invert it to obtain the

[16]For the demand system to be well-behaved, we also need $\gamma^o > \gamma^c$, so at the group level the demand is downward sloping.

shock propagation matrix, though with the two-layer structure, the expression can be quite complicated. To gain intuition, let us consider the case where the within-group substitution dominates and the cross-group substitution is negligible, i.e., $\gamma^c \gg \gamma^d \approx 0$.

Consider a 1% demand shock to an Apple AA+ bond (bond k) and we want to understand the price impact on the Apple bond itself as well as the spillover to a Google AA+ bond (bond j) in the same close substitute group. By inverting the matrix Γ, we have:

$$-\left(\Gamma^{-1}\right)_{j,k} = \underbrace{\frac{\gamma^c}{\gamma^o} \times \frac{1}{\gamma^o - \gamma^c} w_{k|g}}_{\text{Group-level}} + \underbrace{\frac{1}{\gamma^o} \times \mathbf{1}\left\{j = k\right\}}_{\text{Bond-specific}} \tag{13}$$

The first term in equation (13) applies uniformly to all bonds in the same close substitute group. This has an intuitive interpretation: to calculate the price impact of a 1% demand shock to the Apple bond on the Google bond, we first scale the shock by the Apple bond's weight in the substitute group $w_{k|g}$, adjusting the shock size in terms of the substitute-group portfolio. This scaled shock is then multiplied by the portfolio-level multiplier $M^G \equiv \frac{1}{\gamma^o - \gamma^c}$ derived earlier and transmitted to the Google bond through the security-level passthrough coefficient $\tilde{M} \equiv \gamma^c/\gamma^o$. When bonds within the same close-substitute group are highly substitutable ($\gamma^c/\gamma^o \approx 1$), the portfolio-level multiplier M^G provides a good approximation of the spillover effect on other bonds $-\left(\Gamma^{-1}\right)_{j,k}$ for $j \neq k$.

The second term, $\frac{1}{\gamma^o}$, represents the additional price effect on the Apple bond itself beyond what affects its close substitute group. This is precisely the bond-level multiplier that we identify in our estimation.

The relative magnitude of the two components depends critically on the degree of substitutability among bonds within the same group. When within-group substitution is high—as our empirical findings suggest—the security level multiplier is low while the substitute passthrough is high. In this case, a shock to the Apple bond acts more like a portfolio-level demand shock, generating a uniform price response across the group but having little additional effect on the Apple bond itself. In contrast, when assets are less substitutable, the price impact is more concentrated on the shocked bond, with limited spillovers to others. Thus, the overall policy effect on different assets hinges crucially on the degree of asset substitutability. For instance, our findings suggest that which bonds the central bank buys matters less than what kind of bonds it buys. Because of high spillovers and low direct price effects, increased demand from central bank purchases spreads strongly to bonds with similar characteristics, regardless of whether they are being purchased directly or not.

Equation (13) further demonstrates that even when the econometrician has bond-level demand shocks that are orthogonal to each other, the total price impact is a reduced-form estimate that combines both the group-level price effect and bond-specific effect. In contrast, our approach allows us to identify the underlying parameters directly.

3 Empirical Strategy

In this section, we introduce the data sources and explain the construction of our demand shocks in detail. We then discuss our identification strategy and the assumptions needed. The main source of demand shocks we use in this paper is flow-induced trading (FIT) by mutual funds. Flow-induced trading has broad coverage of bonds and sufficient variations, allowing us to extensively test the demand structure and its heterogeneity across different market segments and levels of aggregations. To further corroborate our main findings, in Appendix H, we use alternative identification strategies, including a flow shock to PIMCO and demand shocks from index rebalancing, and find consistent results.

3.1 Data

Mutual fund data. We obtain detailed data on open-end mutual funds in the US from Morningstar Inc. Morningstar is one of the largest providers of investment research to the asset management industry. Detailed holdings and fund flows are collected from surveys of mutual fund managers and cross-validated by Morningstar against publicly available sources such as regulatory filings to ensure their accuracy. Most funds report at least once per quarter. In order to keep as many funds as possible in our sample, we conduct our analysis at the quarterly frequency. The Morningstar mutual fund coverage is quite extensive: the dataset's total asset under management (AUM) lines up closely with the flow of funds open-end mutual fund sector AUM (see Figure C.1 in Appendix C).

Since our identification relies on flow-induced trading in the US corporate bond market, we apply some additional filters to narrow in on domestic bond mutual funds. First, we restrict our sample to funds that report their portfolio value in US dollars and also to securities denominated in US dollars. Second, we focus on funds that have at least \$10 million of bonds under management and bonds make up 50% to 120% of their portfolio's AUM. The lower bound is to filter out non-bond funds, and the upper bound is to filter out potential misreporting. For all bond-level analyses, we use holdings classified as corporate bonds by Morningstar. Taken together, this database gives us coverage of 1,071 unique funds from 2002Q1 to 2021Q3, totaling around 4.8 million bond-fund-quarter observations.

Denote mutual fund i's net inflow by $f_{i,t}$. It is the dollar flows $F_{i,t}$ scaled by lagged assets under management, i.e.,

$$f_{i,t} \equiv \frac{F_{i,t}}{AUM_{i,t-1}}.$$

This is a key building block for constructing our demand shocks. We denote the set of investors for whom we observe flow data as MF.

Bond return and characteristics. We use the WRDS Bond Returns file for corporate bond returns and certain characteristics, which is constructed using transaction-level data from FINRA's TRACE (Trade Reporting and Compliance Engine) database.[17] Specifically, our quarterly return measure is the cumulative end-of-month returns of the months that fall in a given quarter. Given we are looking at quarterly returns, we drop bonds with remaining

[17] WRDS winsorizes the returns at top and bottom 1% to filter out extreme returns.

time to maturity less than one quarter. We further merge this dataset with Morningstar and Mergent FISD data for bond issue and issuer characteristics.

Additionally, we apply filters to ensure we are capturing corporate bonds with reliable return data. We restrict our sample to securities that WRDS classifies as corporate bonds, and we restrict our attention to corporate bonds that have at least a CCC- or higher rating by S&P. We exclude convertible, putable, and exchangeable bonds. Overall, we have $367,966$ bond-quarter observations.

3.2 Constructing Flow Shocks

Our shock measure builds on the flow-induced trading (FIT) measure proposed by Lou (2012). The measure exploits the fact that mutual funds tend to mechanically invest inflows/outflows according to their existing portfolio weights (Coval and Stafford, 2007). As we will show in Section 3.3, flow-induced demand shocks are essentially a Bartik instrument, where the key identifying assumption is the exogeneity of lagged mutual funds holding shares (Goldsmith-Pinkham et al., 2020; Chaudhry, 2022). With that said, several concerns arise when directly using FIT as a demand shock measure; hence, we need to apply adjustments to get from FIT to our demand shock (Gabaix and Koijen, 2022). Below, we walk through how we construct our bond-specific demand shock measure.

Step 1: Measuring flow-induced trading by mutual funds. We assume that fund i mechanically reinvests dollar flow F_{it} according to the fund's existing portfolio weight $\theta_{i,j,t-1}$. This implies that the dollar amount of the flow-induced trading of bond j from fund i will be $\theta_{i,j,t-1}F_{i,t}$, and the percentage change will be the same as the fund flow $f_{i,t}$.

Flow-induced trading (implicitly) assumes that the flows are fully passed through to the demand shocks to each bond one-to-one. If the average passthrough is less than one-to-one, we risk underestimating the multiplier since we overestimate the shock size. However, the potential limitations of the assumption do not significantly impact our overall findings. Firstly, in Appendix D.1, we show that we can use estimates on the passthrough to realized trading to provide upper bounds on the passthrough to demand shocks and hence the multipliers. The upper bounds are still considerably smaller than the micro multipliers typically found for stocks and bonds. Secondly, the one-to-one passthrough assumption is more likely to hold for larger shocks and non-crisis periods. When we restrict our analysis to large shocks or exclude crisis periods, our estimates are quantitatively similar to our baseline results. Finally, we are interested in comparing the estimated multipliers with and without considering heterogeneous substitution. We use the same demand shocks across all specifications. Hence, the bias in the demand shock size cannot explain our finding.

One may also be concerned about heterogeneous passthrough across bonds: For example, funds selectively trade more liquid bonds. In Appendix D.1, we do not find the passthrough to be correlated with measures of liquidity such as bid-ask spreads. However, passthrough does seem to be correlated with size. We conduct subsample analysis for large and small bonds, and we find the multiplier estimates to be similar across the two subsamples, suggesting limited bias introduced by heterogeneous passthrough (details in Appendix D.1).

Step 2: Adjusting for predictability in flows. Because of return chasing by households, mutual fund flows and flow-induced trading tend to be predictable (Lou, 2012). As a result, forward-looking investors will trade today in anticipation of future flows. Hence, the relevant demand shock is not just the flow-induced trading today, but rather, the total amount of flow-induced trading predicted by innovations in flows today (Gabaix and Koijen, 2021). To determine flow innovations, we estimate the autocorrelation coefficients of flows by fund i,

$$f_{i,t} = \rho_{i,0} + \sum_{k=1}^{L} \rho_{i,k} f_{i,t-k} + \delta_i t + f_{i,t}^{\perp}. \tag{14}$$

In the baseline, we include lags with three periods ($L = 3$) and a fund-specific time trend. Our results are robust to various specification of the AR process (see Appendix D.2).[18]

[18]Our main results are also robust to using the raw flows.

Assuming relatively little discounting by forward-looking agents at the quarterly level, the relevant quantity of the demand shock for each bond in fund i, i.e., $\omega_{i,t}$,[19] is the total cumulative trading predicted by the innovation,

$$\omega_{i,t} = \frac{1}{1 - \sum_{k=1}^{L} \rho_{i,k}} f_{i,t}^{\perp}.$$

Step 3: Aggregating fund-level shocks to bond-level shocks. To obtain bond-level demand shocks, we aggregate the fund-level shocks $\omega_{i,t}$ to the bond level using funds' lagged holding shares. We denote bond j's demand shock in quarter t as $u_{j,t}$. Specifically, $u_{j,t}$ is defined as

$$u_{j,t} = \sum_{i \in MF} S_{i,j,t-1} \omega_{i,t}, \tag{15}$$

where $S_{i,j,t-1}$ is the market share of bond j that is held by investor i in period $t-1$.

Figure A.1 in Appendix A.1 plots the 1st to 99th percentile range of the shocks for each quarter, along with its median. The shocks have a fat-tailed distribution centered around zero, with larger shocks being around 1% of the total outstanding amount. The magnitude is relatively similar over time with the exception of the two crisis episodes in 2008 and 2020. For robustness, we explore including and dropping the crisis periods from our estimation sample and find that are results are robust to this decision.

3.3 Identification

As outlined in Section 2.2, we want to identify asset's multiplier M and the substitute passthrough $\tilde{M}$ from the specifications in equation (10), referred to as the IV estimates, and equation (11), referred to as the fixed-effect (FE) estimates. We control for other bond

[19] Under the one-to-one passthrough assumption, the demand shocks for bonds within a given fund are the same. With a slight abuse of notation, we now use $\omega_{i,t}$ to denote the demand shock for each bond held by fund i.

characteristics $X_{j,t}$ that are commonly used in the literature to ensure unbiased estimates.[20]

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_{g(j),t} + \text{Time fixed effects} + \beta_X^\top X_{j,t} + \tilde{\nu}_{j,t}, \tag{IV}$$

$$\Delta p_{j,t} = M u_{j,t} + \text{Fixed effects}_{g,t} + \beta_X^\top X_{j,t} + \tilde{\nu}_{j,t}. \tag{FE}$$

Specifically for the IV specification, we instrument the substitute price $\Delta p_{g(j),t}$ using a portfolio-level demand shock $u_{j,t}^{sub}$, defined as,

$$u_{j,t}^{sub} \equiv \sum_{k \neq j, k \in g(j)} w_{k|g(j),t-1}^{j} u_{k,t}, \tag{16}$$

where $w_{k|g(j),t-1}^{j}$ is the lagged market share of bond k within group $g(j)$.[21] Below, we outline assumptions that provide sufficient conditions for recovering M and $\tilde{M}$ from the IV and FE specifications.

Starting with the FE specification, to identify M, we need our constructed shock $u_{j,t}$ to be orthogonal to the unobserved demand shock $\tilde{\nu}_{j,t}$. In Appendix A, we show that Assumption 1 is sufficient for orthogonality and, if satisfied, allows us to successfully recover the multiplier M using OLS to estimate the fixed effects specification.

Assumption 1. *For any mutual fund i in each period t, the mutual fund's lagged holding share in asset j, $S_{i,j,t-1} \equiv \frac{Q_{i,j,t-1}}{\sum_i Q_{i,j,t-1}}$ (where $Q_{i,j,t}$ is the number of bond i's shares held by fund i in period t), is orthogonal to its unobserved demand shocks, $\tilde{\nu}_{j,t}$:*

$$\mathbb{E}_{i,t}\left[\tilde{\nu}_{j,t} S_{i,j,t-1} \middle| X_{j,t}\right] = 0 \qquad \forall i, t.$$

This identification strategy uses the same insight as in Goldsmith-Pinkham et al. (2020)

[20] The exact characteristics we control for depends on whether we are estimating bond-level or portfolio level multipliers, which we will specify in Section 4.

[21] To be consistent, the close-substitute portfolio return is constructed as $\Delta p_{g(j),t} = \sum_{k \neq j, k \in g(j)} w_{k|g(j),t-1}^{j} \Delta p_{k,t}$.

that Bartik instruments can be viewed as exogenous share instruments. As a result, the strategy is similar to an exposure research design, where bonds have exogenous exposures to common shocks, and the degree of exposure depends on the lagged holding shares of mutual funds (Chaudhry, 2022). To make the pooled exposure design intuition more concrete, suppose households receive a preference shock that increases their demand for bonds (this shock may be correlated with the fundamental characteristics of the bond market). As a result, bond mutual funds receive inflows. Consider a mutual fund that held 10% of bond A and 5% of bond B before the shock. Suppose this mutual fund receives an inflow that is 10% of its assets under management (AUM), and mechanically invests these inflows according to its previous period's portfolio weights. In this case, bond A would experience a demand shock of 1%, whereas bond B would experience a demand shock of 0.5%. Suppose the previous period's holding shares of the mutual fund are orthogonal to the shocks. In that case, the increase in the demand for bond A relative to that for bond B will be as good as randomly assigned.[22] Hence, given the exogeneity of funds' lagged holding shares, flow-induced trading by a single mutual fund amounts to an exogenous exposure research design. Our identification strategy pools many such instances of flow-induced trading, and hence it can be viewed as a pooled exposure design.[23]

To recover the substitute passthrough $\tilde{M}$, we must estimate equation (10) using an IV estimator. As before, we need u_{jt} to be orthogonal to the unobserved demand shock $\tilde{\nu}_{j,t}$, but now we also need $u^{sub}_{j,t}$ to be orthogonal to $\tilde{\nu}_{j,t}$ for instrument validity. The former is guaranteed by Assumption 1, but for the latter, we need a slightly stronger Assumption 1′;

[22] If the fund has mandates restricting what types of bonds the fund can hold, then the part of the previous period's holding shares that is determined by mandates is naturally orthogonal to demand shocks.

[23] Overall, our constructed demand shock is essentially predicted trading based on flows and past holding shares. We assume the fund flows are passed through one-to-one to asset demand (holding fundamentals fixed). If, however, the passthrough is less than one-to-one, then we may risk overestimating the demand shock and underestimating the multiplier. The passthrough from flows to asset demand is not directly observable, but we can bound the bias using the passthrough of flows to changes in holdings. In Appendix D.1, we estimate the passthrough to holdings following Lou's (2012) exercise and show that the passthrough at the CUSIP level is close to one-to-one and hence the bias is small.

which is the group portfolio level counterpart of Assumption 1.[24] If both assumptions are satisfied, we can successfully recover the multiplier M and substitute passthrough $\tilde{M}$

Assumption 1′. *For any mutual fund i in each period t, the mutual fund's lagged holding share in portfolio g (where g is defined as groups of bonds that are close substitutes) is orthogonal to the average demand shocks for that group:*

$$\mathbb{E}_{i,t}\left[\tilde{\nu}_{g,t} S_{i,g,t-1} | X_{j,t}\right] = 0 \qquad \forall i, t$$

where

$$S_{i,g,t-1} \equiv \frac{\sum_{j \in g} Q_{i,j,t-1}}{\sum_i \sum_{j \in g} Q_{i,j,t-1}} \qquad \tilde{\nu}_{g,t} \equiv \mathbb{E}_{g,t}[\tilde{\nu}_{j,t} | j \in g]$$

As we only need Assumption 1 to identify the multiplier M using the OLS estimator, it is arguably more robust than the multiplier estimate recovered by the IV estimator. However, we will show in Section 4 that the OLS and IV specifications produce quantitatively similar estimates for M, suggesting that Assumption 1′ likely holds.

Robustness of Assumption 1 and Assumption 1′. One potential threat to our assumptions is market-timing skills by mutual fund managers. Suppose some mutual fund managers have superior information about bond idiosyncratic returns in the future and allocate their portfolio in advance to front-run the market; in this case, the share exogeneity will be violated. This issue can be addressed using longer lags for shares. In Appendix D.3, we show the results are robust if we aggregate shocks using shares with one-year lags. It is unlikely that mutual fund managers are able to predict bond-level *idiosyncratic* returns in one year and allocate assets accordingly.

[24] In most cases, Assumption 1′ holds when Assumption 1 is satisfied. However, when the unobserved demand shock is correlated with other bonds' lagged market shares within the same close substitute group, Assumption 1′ may be violated even though Assumption 1 is satisfied.

Another potential concern is factor loadings driving portfolio shares as well as bond returns. Bond returns can load on common factors, such as credit risks, and there are style-specialized funds that overweigh bonds with higher loadings on one particular factor. For example, suppose the unobserved shocks $\tilde{\nu}_{j,t}$ have the following factor structure:

$$\tilde{\nu}_{j,t} = \beta_j \eta_t + \check{\nu}_{j,t},$$

where η_t is the factor and $\check{\nu}_{j,t}$ is the true idiosyncratic shock. Also suppose one mutual fund i specializes in factor η, which means its market share in bond j is a function of the bond's factor loading β_j:

$$S_{i,j,t-1} = \xi_{i,t-1}\beta_j + \check{S}_{i,j,t-1}.$$

In this case, the share-exogeneity condition expressed in terms of $\tilde{\nu}_{j,t}$ will be violated:

$$\mathbb{E}_{i,t}\left[\tilde{\nu}_{j,t} S_{i,j,t-1} | X_{j,t}\right] = \mathbb{E}_{i,t}\left[\beta_j^2 | X_{j,t}\right] \xi_{i,t-1}\eta_t \neq 0.$$

There are two approaches to address this concern. First, we can explicitly control for common factors in the final regression, allowing for heterogeneous loadings:

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_{j,t}^{sub} + \beta_j \eta_t + \check{\nu}_{j,t}, \tag{17}$$

so that shares are exogenous to $\check{\nu}_{j,t}$. In Appendix E.2, we verify that our results are robust to controlling for common factors in the literature.

Second, such violations of share exogeneity will only lead to biased estimates when mutual-fund flows (and thereby demand shocks $u_{j,t}$) also load on common factors η_t, and hence the concern can be addressed by purging common factors from mutual fund flows. In Appendix IA.A.1, we find that mutual fund flows have a weak factor structure after controlling for time fixed effects, suggesting omitted common factors are unlikely to be a significant issue. In Appendix D.2 by reconstructing the shocks after removing common factor variation from fund flows. The resulting factor-purged shocks yield estimates that are closely aligned with those from our baseline specification.

4 Estimation Results

We present our main findings in this section. We first show that the multiplier at the CUSIP level drops from 0.4 to less than 0.06 once we account for the heterogeneity in substitution patterns. Second, when we form bonds into our baseline portfolios, the portfolio multiplier becomes significantly larger, indicating demand is more inelastic at the portfolio level. Furthermore, the multiplier monotonically increases as we form increasingly more aggregated portfolios, whereas the substitute passthrough monotonically decreases. Finally, we investigate the dynamics of the price effect at the portfolio level and find the effect almost fully reverts after two quarters, suggesting demand is more elastic in the long run.

4.1 Baseline Estimates

CUSIP level. Table 1 presents our baseline estimates treating each CUSIP as one asset. The close substitute group is defined as bonds with the same detailed rating. We include the bid-ask spread, size, maturity, age, coupon rate and rating and industry fixed effects as additional controls in all the regressions. The first column corresponds to assuming homogeneous cross-substitution. Under this assumption, every asset has the same substitute portfolio, which is simply the market portfolio. This is equivalent to including time fixed effects in the regression. Hence, we can simply run the regression specified by equation (7). Under this assumption, we get a significant CUSIP multiplier of 0.41, indicating that a 1% increase in demand leads to a 0.41% increase in the bond's price. This implies that the average elasticity for a bond is around 2.4. The magnitude of the average elasticity is in line with the estimate in the literature using a standard logit demand system (Bretscher et al., 2022; Siani, 2022).

Once we relax the homogeneous cross-substitution assumption and allow certain groups of bonds to be closer substitutes compared to others, the CUSIP multiplier becomes close to zero, implying very elastic demand at the individual bond level. Columns (2)-(4) in Table 1 present results using the specification in equation (11). We include a group time fixed effect to control for the returns of the substitute portfolios, where groups are defined as bonds within the same detailed rating group. Furthermore columns (5)-(6) show the results from running the regression in equation (10), where we include the returns of a substitute portfolio, $\Delta p_{j,t}^{sub}$. The substitute portfolio is defined as the market-value weighted portfolio formed by all bonds within the same detailed rating category (excluding the asset itself).[25] We instrument the substitute portfolio's return ($\Delta p_{j,t}^{sub}$) with the market-value weighted demand shocks for all bonds in the substitute portfolio $u_{j,t}^{sub}$, defined in equation (16).[26] We also include a time fixed effect in all the regressions to control for the market portfolio return (the distant substitute) as well. Effectively, we are allowing the cross-elasticity to be different for bonds within the same rating category relative to all the other bonds.

Using the point estimate of the multiplier at 0.06 from Column (4), we compute the implied demand elasticity at the CUSIP level around 16.6, much larger than the current estimates in the literature. Among the elasticity estimates in the literature, Fang (2022)'s estimate of 10 is the closest to ours. Compared to other demand systems used for estimating corporate bond elasticities, Fang (2022) uses a more flexible nested logit structure, allowing for differential substitution within and across IG and HY categories. Overall, our result emphasizes the importance of explicitly modeling the rich heterogeneous substitution patterns in the corporate bond market.

In Appendix E.1, we conduct a range of robustness checks for the CUSIP-level estimates.

[25] We exclude crisis periods to ensure that our findings are not driven by unusually large return movements during those episodes. We also confirm that the results are robust when estimated using Fama–MacBeth regressions. That said, we cannot rule out the possibility that multipliers differ in crisis periods.

[26] The correlation between bond-specific shocks $u_{j,t}$ and close-substitute shocks $u_{j,t}^{sub}$ is 0.38.

Table 1: Security-level multipliers: homogeneous vs. heterogeneous substitutability

	Homo. OLS	OLS			First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.41***	0.01	0.04	0.06		0.04
	(0.06)	(0.05)	(0.04)	(0.04)		(0.05)
Substitute return						1.11***
						(0.06)
Group shock					2.89***	
					(0.28)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Group x Quarter FE	No	Yes	Yes	Yes	No	No
ST/LT x Quarter FE	No	No	No	Yes	No	No
Drop Crisis	No	No	Yes	Yes	Yes	Yes
N	301,775	301,775	284,323	284,323	284,323	284,323
R^2	0.22	0.40	0.37	0.41	0.64	0.34
First-stage F-statistic						102.36

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the multiplier estimates for individual securities. Across all specifications, we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by Fama-French 48 industries. Column (1) shows the estimates from regressing bond returns on the demand shock, controlling for time fixed effects, as in equation (7). This specification corresponds to a model in which we assume homogeneous cross-elasticity with all other bonds. Columns (2)-(4) show results from running the regression in equation (11) with different definitions of close substitutes. Columns (2) and (3) directly control for close-substitute prices using detailed rating x time fixed effects. Column (4) additionally controls for maturity (long-term/short-term) x quarter fixed effects to control for a potentially omitted time-varying maturity factor in holding shares. Columns (5) and (6) relate to the IV specification in equation (10). We regress bond returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to the substitute portfolio. Column (2)-(6) correspond to the model that allows for heterogeneous cross-elasticities between close and distant substitutes. Standard errors are clustered at the substitute group x time level.

We consider size weighting to focus more on the large representative bonds, and exclude bonds issued by financial firms. We find that the estimated effects increase modestly when we exclude bonds issued by financial firms, in part because most of financial-sector bonds are investment-grade, which tend to exhibit smaller price impacts. The overall magnitudes remain broadly comparable.

As mentioned in Section 3.2, in the case when the passthrough from fund flows to security-level flows is less than one to one, we can use the estimated passthrough coefficient to provide an upper bound for the multiplier. Appendix D.1 shows that the upper bound is approximately 0.08. Furthermore, the bias introduced by imperfect passthrough should be the same in all the specifications; hence, it cannot explain the difference in the estimates between column (1) (homogeneous cross-substitution) and columns (2)-(4) (heterogeneous cross-substitution). Finally, the one-to-one passthrough assumption is more likely to hold when shocks are larger. Appendix IA.A.3 shows that our estimates are stable when we only use large shocks (above median in absolute size).

In addition to a very small CUSIP multiplier, the substitute passthrough ($\tilde{M}$) is highly significant and quantitatively close to 1. This implies that within the detailed rating groups, bonds are effectively perfect substitutes with each other. Furthermore, when we include market return instead of time fixed effect, we find that the coefficient in front of the market return is almost 0, as shown in Table G.1 in Appendix G. This implies that the spillover effect among far substitutes is small. Furthermore, our point estimates are stable whether or not we exclude crisis periods or include additional fixed effects. Finally, we verify that our results are not driven by maturing bonds. Appendix IA.B shows our main results hold even if we drop bonds with less than one year to maturity.

As Zhu (2021) shows that bond mutual funds experiencing inflows tend to buy bonds issued by the same firms, we repeat the analysis at the issuer level, where we group bonds issued by the same firm into a portfolio and estimate the portfolio-level multiplier and substitute passthrough. We use the same definition of close substitutes as before. In Table F.1, we find that the firm-level multiplier tends to be larger than the security level.[27]

Our results imply that ignoring the substitute portfolio's return in the regression leads to a significant overestimation of the multiplier. Intuitively, when we observe a demand shock to bond j, it is likely that other similar bonds are also experiencing demand shocks. The price of bond j is higher not only because of its own demand shock but also because all of its substitutes now have higher prices. Hence, ignoring the substitute portfolio will lead to an overestimation of the multiplier from its own demand shock. Furthermore, in the case when certain bonds are closer substitutes than others, we need to overweight the close substitutes in constructing the substitute portfolio, or alternatively, allow the close substitutes to have a different coefficient from the other bonds.

In Appendix IA.D, we estimate the equity market multiplier at the stock level, following the identical procedure. We define close substitutes as stocks with similar factor loadings or stocks in the same industry group. We find that allowing for heterogeneous cross-substitution reduces the multiplier estimated, as in the corporate bond case. However, quantitatively, the difference is much smaller than that in the bond market, suggesting that heterogeneous substitution patterns are a particularly special feature of the bond market. Li et al. (2026) also find modest heterogeneity in substitution in the equity market by comparing the results from simple logit and nested logit. Perhaps because rating and maturity play a significant role in investors' demand, accounting for heterogeneous substitution is much more important in the bond market than in the equity market.

Portfolio level. Next, we form portfolios of bonds based on detailed rating and quarter to maturity, and estimate the multiplier at the portfolio level. In other words, we treat asset j in equations (10) and (11) as a portfolio of bonds with the same detailed rating and quarter to maturity. In addition to the market portfolio (which is taken care of by the time

[27] We aggregate returns and flow shocks to the issuer level defined by unique "gvkey", following Mota and Siani (2025).

effect), we include the return of a substitute portfolio that is formed by all bonds in the same detailed rating category as before. We also include the value-weighted average bid-ask spreads, amount outstanding, maturity, age and coupon rate of bonds in the portfolio, as well as the portfolio rating as controls in all the specification.

Table 2: Detailed rating × Quarter-to-maturity portfolio multiplier: homogeneous vs. heterogeneous substitutability

	Homo. OLS	OLS			First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.96***	0.27**	0.28**	0.30**		0.29**
	(0.12)	(0.10)	(0.09)	(0.09)		(0.10)
Substitute return						0.99***
						(0.05)
Group shock					3.18***	
					(0.34)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Group x Quarter FE	No	Yes	Yes	Yes	No	No
ST/LT x Quarter FE	No	No	No	Yes	No	No
Drop Crisis	No	No	Yes	Yes	Yes	Yes
N	76,521	76,521	72,217	72,217	72,217	72,217
R^2	0.24	0.50	0.45	0.47	0.51	0.41
First-stage F-statistic						86.69

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the multiplier and substitute passthrough coefficients estimated for portfolios formed by bonds with the same quarter to maturity and detailed rating. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. Column (1) shows the estimates from regressing portfolio returns on the demand shock, controlling for time fixed effects, as in equation (7). This specification corresponds to a model in which we assume homogeneous cross-elasticity with all other bonds. Columns (2)-(4) show results from running the regression in equation (11) with different definitions of close-substitutes. Columns (2) and (3) directly control for close-substitute prices using detailed rating x time fixed effects. Column (4) additionally controls for maturity (long-term/short-term) x quarter fixed effects to control for a potentially omitted time-varying maturity factor in holding shares. Columns (5) and (6) relate to the IV specification in equation (10), in which we regress portfolio returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to the substitute portfolio. Column (2)-(6) correspond to the model that allows for heterogeneous cross-elasticities between close and distant substitutes. Standard errors are clustered at the substitute group x time level.

The results are presented in Table 2. As before, column (1) corresponds to the result using the specification in equation (7), assuming homogeneous substitution. We find that the multiplier is 0.96 in this case. Columns (2)-(4) report results using the specification in equation (11), assuming heterogeneous substitution with different definitions of close substitutes. Furthermore, columns (5)-(6) relate to the IV strategy with the specification in equation (10).[28] Accounting for heterogeneous substitution brings down the multiplier estimate to 0.30. In other words, a 1% demand shock leads to 30 bps increase in price. This estimate is stable across various specifications. Similar to the security-level estimates, only including the market portfolio as the substitute significantly overestimates the portfolio multiplier. Once we include additional substitute portfolios, the multiplier estimated is considerably lower.

In the rest of the paper, unless specified otherwise, equation (10) is our baseline specification, where we instrument $\Delta p_{j,t}^{sub}$ with $u_{j,t}^{sub}$, since it allows us to estimate and interpret the coefficient in front of the substitute portfolio returns.

A priori, we expect the portfolio-level multiplier to be larger than the CUSIP multiplier. Intuitively, the substitutability among portfolios with different maturities should be smaller compared to the substitutability among CUSIPs with the same maturity. Indeed, Table 2 shows the multiplier on portfolios is significantly larger than the multiplier for individual CUSIPs in Table 1. Additionally, the substitute passthrough at the portfolio level is also smaller than that at the CUSIP level, consistent with the intuition that more aggregated portfolios are less substitutable.

To verify whether our demand specification sufficiently accounts for important cross-substitution heterogeneity, we allow further heterogeneity in cross-elasticities for bonds in the same investment-grade (IG) or high-yield (HY) group versus bonds that are not. We implement such specification by including an additional substitution portfolio formed by all the IG or HY bonds (excluding the own asset and close substitute's returns). The result

[28] At the baseline portfolio level, the correlation between asset-specific shocks $u_{j,t}$ and close-substitute shocks $u_{j,t}^{sub}$ is 0.44.

Table 3: Robustness with respect to alternative definitions of close substitutes

	(1)	(2)	(3)	(4)
Shock	0.29**	0.29**	0.27**	0.24*
	(0.10)	(0.10)	(0.10)	(0.10)
Detailed rating substitute return	0.99***	0.90***		
	(0.05)	(0.16)		
IG substitute return		0.12		
		(0.19)		
Coarse rating substitute return			1.07***	
			(0.08)	
Det rating x ST/LT substitute return				0.89***
				(0.06)
Quarter FE	Yes	Yes	Yes	Yes
Drop Crisis	Yes	Yes	Yes	Yes
N	72,217	72,217	72,217	72,164
First-stage F-statistic	86.69	3.89	148.28	39.81

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table shows that estimates for the baseline portfolio (formed by bonds with the same quarter to maturity and detailed rating) are robust to the exact definition of the close substitute. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. Column (1) is our baseline specification in which the close substitute is defined as all other bonds in the same detailed rating category. In column (2), the close substitute includes the detailed rating substitute and all bonds with the same investment rating as an additional substitute. Column (3) includes all other bonds in the same coarse rating category as substitutes. Column (4) includes all bonds in the same detailed-rating group and maturity bucket (short-term versus long-term) as close substitutes. Standard errors are clustered at the detailed rating x quarter level.

is shown in Table 3 column (2). The own multiplier does not change quantitatively. In addition, the substitution passthrough is much larger for bonds within the same rating category compared with bonds not in the same rating category but in the same IG/HY group. Columns (3) and (4) of Table 3 further confirm that our result is not sensitive to the choice of the specific substitute portfolio. Column (3) uses all bonds in the same coarse rating group to form the substitute portfolio (i.e., using a broader definition of the set of close substitutes).[29] We can also group bonds into two maturity groups based on the partition: $\{[0, 10), [10, \infty)\}$. Column (4)'s close substitute portfolio includes all bonds in the same maturity group and detailed rating category (i.e., a more narrow definition of the set of close substitutes). Across all the different alternative specifications, the estimated own multiplier is similar to that in the baseline case. Finally, in Appendix IA.C we consider substitute groups formed by other characteristics, and we find the estimates are stable once we control for the returns of the portfolios formed by the same detailed rating category.

4.2 Aggregated Portfolios

Motivated by the difference in the CUSIP and the portfolio multiplier, we repeat our analysis for portfolios with various aggregation levels, using the specification in equation (10). We find that the more aggregated the portfolio is, the larger the portfolio multiplier, consistent with the prediction in Section 2.2. Furthermore, as we move to more aggregated portfolios, they become less substitutable with each other, and hence the substitute passthrough becomes smaller.

Specifically, we estimate the multiplier and substitute passthrough for all the portfolios specified in Table 4. The second column specifies at which level we form the portfolios, and the third column specifies the substitute portfolio included in the regression in addition to the market portfolio. We control for the same set of portfolio characteristics as before. To

[29]For example, for 11-year BBB-rated bonds, the substitute portfolio includes all the BBB-rated bonds.

ensure our results are not driven by tail aggregate shocks, we exclude the crisis periods for all regressions.

Table 4: Aggregated portfolios and their substitute portfolio compositions

	Asset	Substitute Portfolio
Single security	Individual bonds	Other bonds in the same detailed rating category
Detailed rating × Quarter-to-maturity portfolios	Portfolios formed by detailed rating and quarter to maturity	Other bonds in the same detailed rating category
Rating × Short/Medium/Long-term maturity portfolios	Portfolios formed by coarse rating and three maturity groups ($\{[0,4),[4,10),[10,\infty)\}$)	Other bonds in the same coarse rating category
Rating × Short/Long-term maturity portfolios	Portfolios formed by coarse rating and two maturity groups ($\{[0,10),[10,\infty)\}$)	Other bonds in the same coarse rating category
Rating portfolios	Portfolios formed by coarse rating categories	Other bonds in the same investment grade category

This table presents all levels of portfolios for which we estimate multipliers and substitute passthroughs. The left two columns specify at which level the portfolio is formed. All bonds are weighted by their market-value inside the portfolio. The last column specifies the additional substitute portfolio included in the regression in addition to the time fixed effect.

Figure 1 visualizes our findings, and Table 5 presents the exact estimates. From Figure 1, we see that as we move from the CUSIP-level estimate to the most aggregated portfolios formed by ratings, the asset's own multiplier increases from 0.04 to 3.94, implying the demand elasticity drops from 25 to less than 0.25. Intuitively, it is easy to find substitutes for an individual bond, whereas it is much more difficult to find substitutes for the entire portfolio of BBB bonds. Hence, demand is much more elastic for individual CUSIPs compared with more aggregated portfolios. Furthermore, the substitute passthrough decreases from close to 1 to essentially 0. At the rating portfolio level, assets are much weaker substitutes with each other compared to those at the CUSIP level.

A similar pattern arises along other dimensions of aggregation. For instance, when we group bonds into issuer-level portfolios, we again find that issuer-level multipliers tend to be larger than security-level multipliers (see Table F.1 in Appendix F). This result aligns with the intuition that bonds issued by the same firm are highly substitutable (Choi et al., 2020; Zhu, 2021).

Our aggregation results highlight the connection between micro and macro multipliers. Demand elasticities naturally depend on what we define as an asset. Micro multipliers typically refer to the multiplier on an individual security, whereas macro multipliers refer to the multiplier when we treat a whole asset class as one.[30] They are at the two ends of a spectrum, and our results show that depending on the portfolio definition, the multiplier estimated can lie anywhere in between. In fact, inelastic demand at the portfolio level is what allows us to estimate the multipliers at more micro levels: the significance in the first stage of all the IV regressions relies on portfolio prices responding to demand shocks.

Finally, the difference in elasticities and spillover effects across portfolios with different aggregation levels also has interesting implications for unconventional monetary policy implementation. For example, at the bond level, we find low multiplier and high substitute passthrough, suggesting that the type of bonds the central bank purchases matters more than the specific bonds it selects. At the baseline portfolio level, the multiplier is significant, indicating that the maturity and rating of bonds that the central bank chooses to purchase matter for the distribution of price impact. Our estimates of M and $\tilde{M}$ at different aggregation level serve as important inputs to this analysis. We leave a proper quantitative investigation to future research.

[30] Our identification strategy does not allow us to uncover the macro elasticity for the corporate bond market as an asset class.

Table 5: Multiplier and substitute passthrough for increasingly aggregated bond portfolios

	CUSIP	Rat x Q to Mat	Rat x 3 Mat	Rat x 2 Mat	Rat
	(1)	(2)	(3)	(4)	(5)
Shock	0.04	0.29**	1.33*	1.71*	3.94***
	(0.05)	(0.10)	(0.63)	(0.84)	(0.93)
Substitute return	1.11***	0.99***	0.77***	0.56**	-0.04
	(0.06)	(0.05)	(0.13)	(0.17)	(0.30)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Drop Crisis	Yes	Yes	Yes	Yes	Yes
N	284,323	72,217	1,407	938	469
First-stage F-statistic	102.36	86.69	43.21	21.86	21.32

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table shows the multiplier and substitute passthrough estimates for various levels of portfolio aggregation (see Table 4 for descriptions of the aggregation). All the results are estimated using the IV specification in equation (10). Specifically, we instrument the substitute's return using demand shocks to the assets in the substitute portfolio. In all specifications, we exclude crisis periods and we control for the (average) bid-ask spreads, amount outstanding (log), maturity, age, coupon rate, and rating fixed effects. In Column (1), we also control for industry fixed effects, defined by the Fama-French 48 industries. Standard errors are clustered at the substitute group x time level.

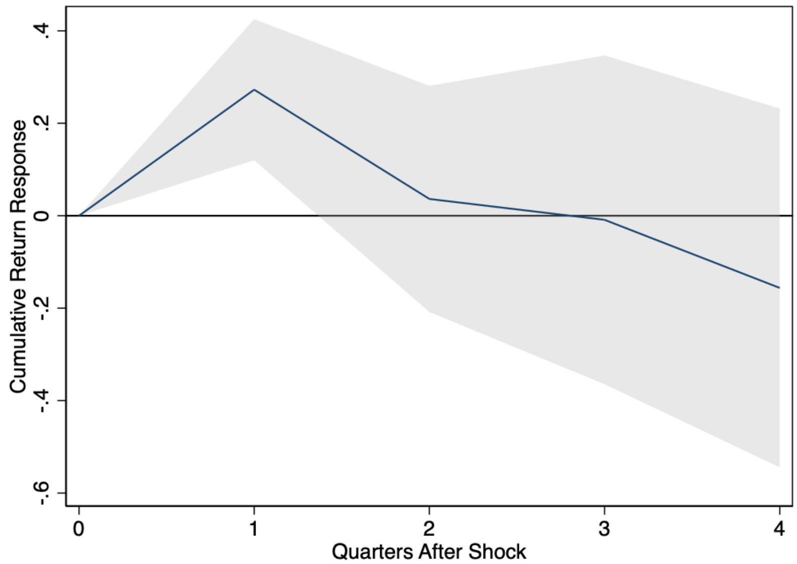
4.3 Dynamic Effects

Finally, we study the dynamic effects of price response to demand shocks in this section. We focus on the baseline portfolio specification in Section 4.1 (i.e., portfolios are formed by bonds with the same detailed rating and quarter to maturity). To see the dynamic effects, we regress portfolios' cumulative returns on lagged demand shocks. Specifically, we run the following regression:

$$\Delta p_{j,t:t+h} = M_h u_{j,t} + \text{Fixed effects}_{g,t+h} + \varepsilon_{j,t+h} \quad \text{for} \quad h = 0, 1, \ldots \tag{18}$$

Figure 2 plots the response of cumulative returns to demand shocks. Consistent with our previous result, there is a significant on-impact price increase upon positive demand shocks. The effect almost fully reverts in the following quarter, and the estimate is statistically

Figure 2: Baseline portfolio price effect dynamics



The graph plots the dynamic price effect estimates of the demand shock from equation (18). The estimates are for the detailed rating × quarter to maturity level (our baseline level of aggregation). Specifically, we regress various leads of the return of the portfolio in excess of its close substitute return on the demand shock. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. The shaded region denotes the 95% confidence interval.

indistinguishable from zero. In other words, the cumulative effect drops to 0 after $T + 1$. The reversal in return after six months is consistent with the hypothesis that long-term demand is more elastic than short-term demand. Table 6 shows the exact estimates.

Table 6: Baseline portfolio price effect dynamics

	T	T+1	T+2	T+3
	(1)	(2)	(3)	(4)
Shock	0.27**	0.04	-0.01	-0.16
	(0.10)	(0.14)	(0.20)	(0.19)
Group x Quarter FE	Yes	Yes	Yes	Yes
N	76,521	59,278	51,262	46,247
R^2	0.50	0.54	0.54	0.54

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the dynamic cumulative price effect estimates of the demand shock from equation (18). The estimates are for the detailed rating × quarter to maturity level (our baseline level of aggregation). Specifically we regress the cumulative return on the demand shock while controlling for substitute group x time fixed effects. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. Standard errors are clustered at the substitute group x time level.

5 Arbitrage Risk

To better understand the quantitative implications of the multipliers we find in the previous section, we look at the Sharpe ratio of a strategy that takes advantage of the price deviation between the test asset and its substitute portfolio at the one-quarter horizon. Specifically, we consider a strategy that sells the more expensive one between asset j and its close-substitute asset and buys the cheaper one. We unwind this position in the following period, given that we find the price gap disappears by the end of the next period on average.[31] For example, if portfolio A's price is too high relative to its substitute portfolio, arbitrageurs could make money by selling portfolio A and purchasing its substitute. However, if substitute returns do not fully replicate asset A's returns, arbitrageurs face risks and potentially losses. In other words, this is a near-arbitrage opportunity as the trade contains some risk.

The expected return of this strategy is $M \times Mean(|u_{j,t}|)$, where M is the multiplier

[31]The Sharpe ratios are calculated under the implicit assumption that different bonds and portfolios are segmented, and the arbitrageur buys and sells one bond/portfolio at a time. In other words, we are not considering the diversification benefit if the arbitrageur operates across multiple submarkets.

estimated in Section 4 and $|u_{j,t}|$ is the size of demand shocks in absolute terms. The volatility of this return is the arbitrage risk, defined as

$$ArbRisk_j \equiv std(\tilde{\nu}_{j,t} + Mu_{j,t}). \tag{19}$$

The arbitrage risk comes from non-flow shocks as well as the next period (observable) demand shocks ($u_{j,t}$). Since we have removed all the predictable components in constructing u, the future period u is unknown to the arbitrageur when carrying out the strategy and should be considered as part of the arbitraging risk.

The average Sharpe ratio of this arbitrage activity is then given by

$$SR = \frac{M \times Mean(|u_{j,t}|)}{Mean(ArbRisk_j)}. \tag{20}$$

We find the annualized Sharpe ratios across different aggregation levels are generally small.[32] While the multipliers are larger for more aggregated portfolios, the arbitrage risks also tend to be larger. Hence, even the maximum Sharpe ratio is small, and it is before considering potential shorting costs.[33] Our results reveal that the risks of engaging in these arbitrages are high relative to the average gain, which potentially explains why we observe these price deviations exist in the data.

[32]If we subset to large shocks only, the Sharpe ratios for portfolios at different aggregation levels are also small. The main reason is that the large shocks are accompanied by large noises as well.

[33]Other papers have found strategies that predict bond returns with much bigger Sharpe ratios (see, e.g., Bartram et al. 2020).

Table 7: Arbitrage risk and portfolio multipliers

	M	Arb. risk	Sharpe ratio
1. Det. Rating × quarter-to-maturity	0.29	0.06	0.02
2. Rating × ST/MT/LT Buckets	1.33	0.05	0.11
3. Rating × ST/LT Buckets	1.71	0.07	0.11
4. Rating	3.94	0.34	0.04

The table presents the estimated multipliers, the average arbitrage risk (as defined in equation (19)) and the implied annualized Sharpe ratio (as defined in equation (20)) for portfolios at different aggregation levels. Crisis periods (2008Q3–2008Q4 and 2020Q1–2020Q2) are dropped.

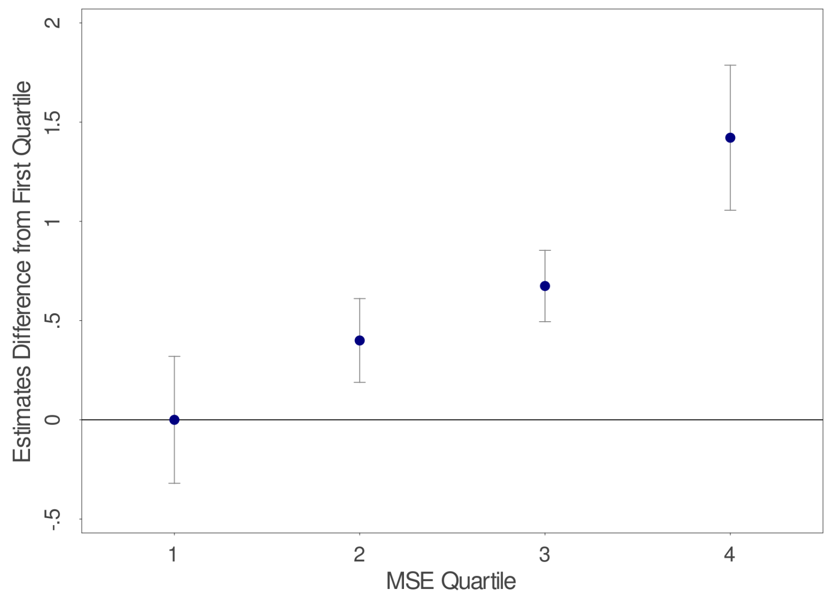
5.1 Multipliers and Arbitrage Risk

Motivated by the low Sharpe ratios, we explore to what extent arbitrage risk limits investors to substitute across assets. Our arbitrage risk is the part of the risk that cannot be hedged away by constructing the substitute portfolio, and hence it acts as a limit to arbitrage (Wurgler and Zhuravskaya, 2002). Intuitively, the higher the arbitrage risk, the less arbitrageurs are willing to substitute to alternative portfolios and hence higher multipliers. In Appendix IA.E, we provide a simple two-asset case illustrating this intuition.

We use our baseline portfolio (formed by bonds with the same detailed rating group and quarter to maturity) for analysis in this section. We first sort our portfolios into four groups based on the size of their arbitrage risk defined in equation (19): group 1 includes portfolios with the lowest arbitrage risk, and group 4 includes portfolios with the highest arbitrage risk. We run the baseline specification in Section 4.1 including interaction terms of group indicators and demand shocks ($u_{j,t}$). In other words, we allow the portfolio multiplier M to differ by group. We plot the relative magnitudes of the estimates for each group in Figure 3.

We indeed find that portfolios with higher arbitrage risk have higher portfolio multipliers and more inelastic demand. We obtain an almost monotone pattern of multipliers across groups. Groups with higher arbitrage risk have significantly higher portfolio multipliers. Wurgler and Zhuravskaya (2002) find similar patterns in the stock market using index inclusion and exclusion events. We verify that such pattern exists more broadly outside of the

Figure 3: Baseline portfolio's heterogeneous arbitrage risk and multipliers



The graph shows the detailed rating × quarter to maturity multiplier estimates in different arbitrage risk quartiles. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects. The estimates are presented relative to the lowest arbitrage risk quartile. The bars reflect 95% confidence intervals. As the estimates suggest, we can reject the null of no heterogeneity at the 95% level.

index-related events.

The relationship between arbitrage risks and portfolio multipliers is also verified in a regression specification. We add an interaction term between $ArbRisk_j$ and demand shock $u_{j,t}$ in the baseline regression specification,

$$\Delta p_{j,t} = M_0 u_{j,t} + M_1 u_{j,t} \times ArbRisk_j + \tilde{M} \Delta p^{sub}_{j,t} + \epsilon_{j,t} \tag{21}$$

Table 8 presents the results. The coefficient in front of the interaction term is significantly positive. A one-standard-deviation increase in arbitrage risk increases the portfolio multiplier by 0.43. We also find that the effect is particularly strong among the high-yield bonds, which have higher overall risks and also higher idiosyncratic risks.

Table 8: Benchmark portfolio's heterogeneous arbitrage risk and multipliers

	(1)	(2)
Shock	0.29**	0.18
	(2.75)	(1.66)
ArbRisk x Shock		0.43*
		(2.13)
Quarter FE	Yes	Yes
N	76,521	76,521
First-stage F-statistic	68.10	68.17

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents estimates for how the detailed rating × quarter to maturity multiplier estimates depend on the arbitrage risk of the portfolio. We standardized the arbitrage risk measurement by subtracting the mean and dividing it by the cross-sectional standard deviation of the arbitrage risk. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects. Column (1) estimates our baseline specification for the post-winsorized sample. Column (2) includes an interaction term between the demand shocks and arbitrage risk. Robust standard errors are clustered at the substitute group × time level.

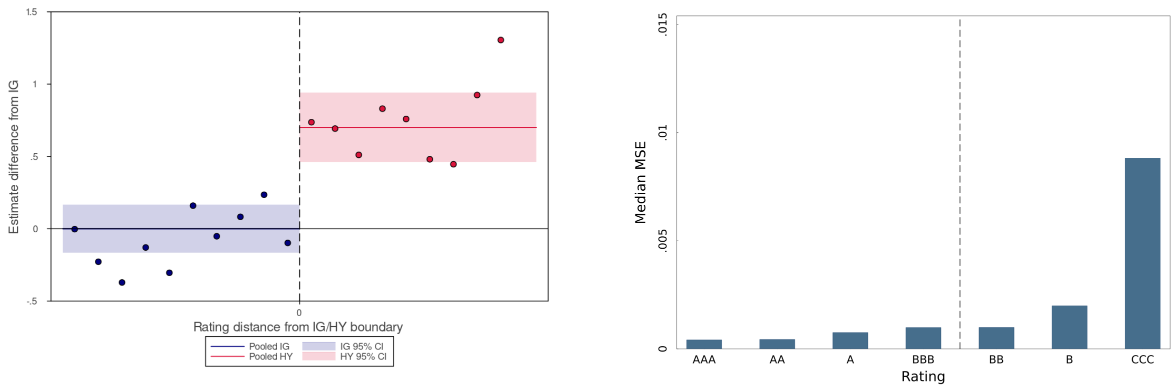
5.2 Rating and Maturity Heterogeneity

Finally, we look at how multipliers vary across different types of bonds, and explore whether the differences are consistent with arbitrage risks. We focus on the heterogeneity in multipliers for bond portfolios with different maturities and ratings. As before, we use our baseline portfolio specification.

We first estimate portfolio multipliers for IG versus HY bonds. We pool all the IG portfolios together and find the portfolio multiplier is close to 0. For the pooled HY portfolios, the estimated multiplier is around 0.6, much higher than that for IG portfolios. The overall estimate of 0.3 masks significant heterogeneity among portfolios with different ratings. We also estimate the portfolio multipliers for each rating category. The results are shown as scattered dots in Figure 4a. On average, riskier portfolios have higher portfolio multipliers. Furthermore, in Figure 4b, we find that riskier portfolios have higher arbitrage risk. This is consistent with what we find in Section 5.1, assets with higher arbitrage risk should have

Figure 4: Rating Heterogeneity

(a) Benchmark portfolio multiplier (b) Arbitrage risk



The left panel shows the multipliers for portfolios with different ratings. Portfolios are formed by bonds with the same detailed rating and quarter to maturity. In all regressions, we control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects. The estimates are plotted relative to the pooled investment-grade multiplier estimate. The blue and red dots are the heterogeneous estimates for IG and HY detailed rating categories, respectively. The red line represents the relative estimate for HY bonds. The blue and red shaded areas represent the 95% confidence interval for the IG and HY pooled estimate, respectively. The right panel shows the median arbitrage risk for the baseline portfolio by rating categories. Crisis periods (2008Q3–2008Q4 and 2020Q1–2020Q2) are dropped.

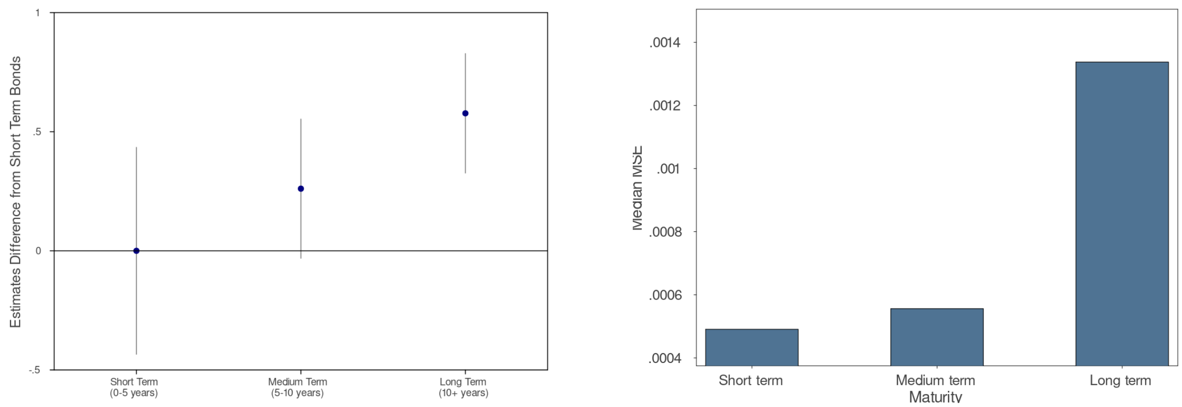
higher multipliers. HY bonds tend to be riskier with larger idiosyncratic risks. As a result, it may be more difficult to substitute to other assets, which leads to higher portfolio multipliers.

In addition to ratings, we also investigate heterogeneity along the maturity dimension. Specifically, we group portfolios into short, medium, and long maturity groups using 0-5, 5-10, and 10+ year bins. Figure 5a shows longer maturity portfolios have slightly higher portfolio multipliers, although the difference is not statistically significant. Short-term portfolios have a multiplier close to 0; medium-term and long-term portfolios have a higher multiplier around 0.3-0.5. Consistent with arbitrage risk affecting portfolio multipliers, Figure 5b shows that longer maturity portfolios have weakly higher arbitrage risk.

In addition to arbitrage risks, other factors likely also contribute to the heterogeneity of multipliers across rating and maturity. For example, investor segmentation implies the

Figure 5: Maturity Heterogeneity

(a) Benchmark portfolio multiplier (b) Arbitrage risk



The left panel shows the multipliers for portfolios with different maturity. Portfolios are formed by bonds with the same detailed rating and quarter to maturity, then grouped into short, medium, and long maturity portfolios using 0-5, 5-10, and 10+ year bins. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. The estimates are presented relative to the short-term maturity multiplier. The bars reflect 95% confidence intervals. The right panel shows the median arbitrage risk for the baseline portfolio by maturity group. Crisis periods (2008Q3–2008Q4 and 2020Q1–2020Q2) are dropped.

amount of arbitrage capital available in the investment-grade universe differs from that in the high-yield universe, at least in the short run. The heterogeneous multipliers for portfolios with different maturities could also be due to the clientele effects and segmentation along the yield curve (Vayanos and Vila, 2021; Kekre et al., 2022).

6 Conclusion

Our results underscore the importance of taking into account the correct substitute assets when estimating the multipliers. To this end we focus on the corporate bond market because their salient characteristics allow us to identify the close substitutes easily. We show that ignoring the heterogeneity in cross-elasticities leads to overestimation of the multiplier. At the bond CUSIP level, the multiplier estimated reduces significantly by an order of magnitude when we allow for certain bonds to be closer substitutes than others. While individual bond demand is quite elastic, demand for portfolios of bonds tend to be more inelastic. As the portfolio becomes more aggregated, the portfolio-level multiplier increases and the substitute passthrough decreases, suggesting reduced substitutability at higher aggregation levels.

More broadly, our findings suggest the need for developing methods to measure the relative substitutability of assets. Unlike corporate bonds, most asset classes do not have salient characteristics for identifying near substitutes. Recent work by Gabaix et al. (2023) shows a promising path forwards for measuring such latent characteristics leveraging investors' holding data.

This paper also sheds light on the plausible frictions generating inelastic demand by exploring how the price multiplier varies with observed bond characteristics. Our findings suggest that arbitrage risk may contribute to inelastic demand at the portfolio level; we leave the quantification of this channel to future research. In terms of persistence, we find that the price effect almost disappears after a quarter. For future work, it would be valuable to link the demand elasticities at different horizons to different arbitrage theories.

References

Allen, Jason, Jakub Kastl, and Milena Wittwer, "Estimating Demand Systems with Bidding Data ," 2025.

Bai, Jennie, Turan G. Bali, and Quan Wen, "Retracted: Common risk factors in the cross-section of corporate bond returns," *Journal of Financial Economics*, 3 2019, *131* (3), 619–642.

Bartram, Söhnke M., Mark Grinblatt, and Yoshio Nozawa, "Book-to-Market, Mispricing, and the Cross-Section of Corporate Bond Returns," *Working paper*, 12 2020.

Beneish, Messod D. and Robert E. Whaley, "An Anatomy of the "S & P Game": The Effects of Changing the Rules," *The Journal of Finance*, 12 1996, *51* (5), 1909.

Bernanke, Ben S., "The Economic Outlook and Monetary Policy - Federal Reserve Board," Technical Report 2010.

Bretscher, Lorenzo, Lukas Schmid, and Tiange Ye, "Passive Demand and Active Supply: Evidence from Maturity-Mandated Corporate Bond Funds," February 2023.

_ , _ , Ishita Sen, and Varun Sharma, "Institutional Corporate Bond Pricing," *SSRN Electronic Journal*, 1 2022.

Calomiris, Charles W., Mauricio Larrain, Sergio L. Schmukler, and Tomas Williams, "Large international corporate bonds: Investor behavior and firm responses," *Journal of International Economics*, 7 2022, *137*, 103624.

Chang, Yen-Cheng, Harrison Hong, Inessa Liskovich, Yen-Cheng Chang, Harrison Hong, and Inessa Liskovich, "Regression Discontinuity and the Price Effects of Stock Market Indexing," *Review of Financial Studies*, 1 2015, *28* (1), 212–246.

Chaudhry, Aditya, "Do Subjective Growth Expectations Matter for Asset Prices?," *SSRN Electronic Journal*, 9 2022.

Chen, Honghui, Gregory Noronha, and Vijay Singal, "The Price Response to S&P 500 Index Additions and Deletions: Evidence of Asymmetry and a New Explanation," 2004.

Choi, Jaewon, Saeid Hoseinzade, Sean Seunghun Shin, and Hassan Tehranian, "Corporate bond mutual funds and asset fire sales," *Journal of Financial Economics*, 11 2020, *138* (2), 432–457.

Chung, Kee H., Junbo Wang, and Chunchi Wu, "Volatility and the cross-section of corporate bond returns," *Journal of Financial Economics*, 8 2019, *133* (2), 397–417.

Coppola, Antonio, "In Safe Hands: The Financial and Real Impact of Investor Composition Over the Credit Cycle," 2022.

Coval, Joshua and Erik Stafford, "Asset fire sales (and purchases) in equity markets," *Journal of Financial Economics*, 11 2007, *86* (2), 479–512.

Dannhauser, Caitlin D. and Saeid Hoseinzade, "The Unintended Consequences of Corporate Bond ETFs: Evidence from the Taper Tantrum," *The Review of Financial Studies*, 12 2021, *35* (1), 51–90.

Darmouni, Olivier, Kerry Y Siani, and Kairong Xiao, "Nonbank Fragility in Credit Markets: Evidence from a Two-Layer Asset Demand System *," 2023.

Davis, Steven J. and John Haltiwanger, "Gross job creation, gross job destruction, and employment reallocation," *Quarterly Journal of Economics*, 1992, *107* (3), 819–863.

Dick-Nielsen, Jens and Marco Rossi, "The Cost of Immediacy for Corporate Bonds," *The Review of Financial Studies*, July 2019, *32* (1), 1–41.

Dick-Nielsen, Jens, Peter Feldhütter, Lasse Heje Pedersen, and Christian Stolborg, "Corporate Bond Factors: Replication Failures and a New Framework," *Working Paper*, 2023.

Dickerson, Alexander, Philippe Mueller, and Cesare Robotti, "Priced Risk in Corporate Bonds," *Journal of Financial Economics*, 2023, *150*, article 103707.

Edmans, Alex, Itay Goldstein, and Wei Jiang, "The Real Effects of Financial Markets: The Impact of Prices on Takeovers," *The Journal of Finance*, 6 2012, *67* (3), 933–971.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T Lundblad, "Regulatory pressure and fire sales in the corporate bond market $," 2011.

Falato, Antonio, Itay Goldstein, and Ali Hortaçsu, "Financial fragility in the COVID-19 crisis: The case of investment funds in corporate bond markets," *Journal of Monetary Economics*, 10 2021, *123*, 35–52.

Fang, Chuck, "Monetary Policy Amplification through Bond Fund Flows," *Working paper*, 2022.

Fuchs, William, Satoshi Fukuda, and Daniel Neuhann, "Demand-System Asset Pricing: Theoretical Foundations," December 2023.

Gabaix, Xavier and Ralph S J Koijen, "In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis," NBER Working Paper 28967, National Bureau of Economic Research 2021.

__ **and** __ , "Granular Instrumental Variables," 2022.

__ **, Ralph S. J. Koijen, and Motohiro Yogo**, "Asset Embeddings," *SSRN Electronic Journal*, 9 2023.

Gilchrist, Simon, Bin Wei, Vivian Z. Yue, and Egon Zakrajsek, "The Fed Takes on Corporate Credit Risk: An Analysis of the Efficacy of the SMCCF," *SSRN Electronic Journal*, 10 2023.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 8 2020, *110* (8), 2586–2624.

Goldstein, Itay, Hao Jiang, and David T. Ng, "Investor flows and fragility in corporate bond funds," *Journal of Financial Economics*, 12 2017, *126* (3), 592–613.

Greenwood, Robin, Nber Toomas Laarits, and Jeffrey Wurgler, "Stock Market Stimulus," 2022.

Haddad, Valentin, Alan Moreira, and Tyler Muir, "When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fed's Response," *The Review of Financial Studies*, 10 2021, *34* (11), 5309–5351.

— , **Paul Huebner, and Erik Loualiche**, "How Competitive is the Stock Market? Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing," 2022.

— , **Zhiguo He, Paul Huebner, Peter Kondor, and Erik Loualiche**, "Causal Inference for Asset Pricing," March 2025.

Harris, Lawrence and Eitan Gurel, "Price and Volume Effects Associated with Changes in the S&P 500 List: New Evidence for the Existence of Price Pressures," *The Journal of Finance*, 9 1986, *41* (4), 815.

Hartzmark, Samuel M and David H Solomon, "Predictable Price Pressure," 2022.

Holm-Hadulla, Fédéric and Matteo Leombroni, "Heterogeneous Intermediaries and Bond Characteristics in the Transmission of Monetary Policy *," 2023.

Hubbard, Glenn, Donald Kohn, Laurie Goodman, Kathryn Judge, Anil Kashyap, Ralph Koijen, Blythe Masters, Sandie O'connor, and Kara Stein, "Task Force on Financial Stability," Technical Report 6 2021.

Jansen, Kristy A.E., "Long-term Investors, Demand Shifts, and Yields," *SSRN Electronic Journal*, 8 2021.

Jotikasthira, Chotibhak, Christian Lundblad, Tarun Ramadorai, John Campbell, Cam Harvey, Donghui Li, Ludovic Phalippou, Michael Schill, Ajay Shah, and Dimitri Vayanos, "Asset Fire Sales and Purchases and the International Transmission of Funding Shocks," *The Journal of Finance*, 12 2012, *67* (6), 2015–2050.

Kashyap, Anil K, Natalia Kovrijnykh, Jian Li, and Anna Pavlova, "Is There Too Much Benchmarking in Asset Management?," *American Economic Review*, April 2023, *113* (4), 1112–41.

Kekre, Rohan, Moritz Lenel, and Federico Mainardi, "Monetary Policy, Segmentation, and the Term Structure *," 2022.

Koijen, Ralph S. J. and Motohiro Yogo, "Exchange Rates and Asset Prices in a Global Demand System," Working Paper 27342, National Bureau of Economic Research June 2020.

Koijen, Ralph S.J. and Motohiro Yogo, "A Demand System Approach to Asset Pricing," *Journal of Political Economy*, 8 2019, *127* (4), 1475–1515.

_ , François Koulischer, Benoît Nguyen, and Motohiro Yogo, "Euro-Area Quantitative Easing and Portfolio Rebalancing," *American Economic Review*, 5 2017, *107* (5), 621–27.

Koont, Naz, Yiming Ma, Lubos Pastor, and Yao Zeng, "Steering a Ship in Illiquid Waters: Active Management of Passive Funds," August 2024.

Li, Jennifer, Neil D Pearson, and Qi Zhang, "Impact of Demand Shocks on the Stock Market: Evidence from Chinese IPOS *," 2021.

Li, Jiacui, "What Drives the Size and Value Factors?," *SSRN Electronic Journal*, 6 2021.

_ and Zihan Lin, "Prices Are Less Elastic For Less Diversifiable Demand," *SSRN Electronic Journal*, 6 2022.

Li, Yizhang, Stanislav Sokolinski, and Andrea Tamoni, "Which investors drive anomaly returns and how?," *Journal of Financial Economics*, 2026, *179*, 104257.

Lou, Dong, "A Flow-Based Explanation for Return Predictability," *The Review of Financial Studies*, 12 2012, *25* (12), 3457–3489.

Ma, Yiming, Kairong Xiao, and Yao Zeng, "Mutual Fund Liquidity Transformation and Reverse Flight to Liquidity," *Review of Financial Studies*, 10 2022, *35* (10), 4674–4711.

Manconi, Alberto, Massimo Massa, and Ayako Yasuda, "The role of institutional investors in propagating the crisis of 2007–2008," *Journal of Financial Economics*, 6 2012, *104* (3), 491–518.

Mota, Lira and Kerry Siani, "Financially Sophisticated Firms," *Working Paper*, 2025.

Nozawa, Yoshio and Yancheng Qiu, "Corporate bond market reactions to quantitative easing during the COVID-19 pandemic," *Journal of Banking & Finance*, 12 2021, *133*, 106153.

Pavlova, Anna and Taisiya Sikorskaya, "Benchmarking Intensity," *The Review of Financial Studies*, 8 2022.

Peng, Cameron and Chen Wang, "Factor Demand and Factor Returns *," 2019.

Petajisto, Antti, "Why Do Demand Curves for Stocks Slope Down?," *Source: The Journal of Financial and Quantitative Analysis*, 2009, *44* (5), 1013–1044.

Schmickler, Simon and Pedro Tremacoldi-Rossi, "Spillover Effects of Payouts on Asset Prices and Real Investment," *SSRN Electronic Journal*, 10 2022.

Selgrad, Julia, "Testing the Portfolio Rebalancing Channel of Quantitative Easing," 2023.

Shleifer, Andrei, "Do Demand Curves for Stocks Slope Down?," *The Journal of Finance*, 7 1986, *41* (3), 579.

Siani, Kerry, "Raising Bond Capital in Segmented Markets," *SSRN Electronic Journal*, 10 2022.

Todorov, Karamfil, "Quantify the quantitative easing: Impact on bonds and corporate debt issuance," *Journal of Financial Economics*, 2 2020, *135* (2), 340–358.

Vayanos, Dimitri and Jean-Luc Vila, "A Preferred-Habitat Model of the Term Structure of Interest Rates," *Econometrica*, 1 2021, *89* (1), 77–112.

Vissing-Jorgensen, Annette and Arvind Krishnamurthy, "The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy," *Brookings working paper*, 2011.

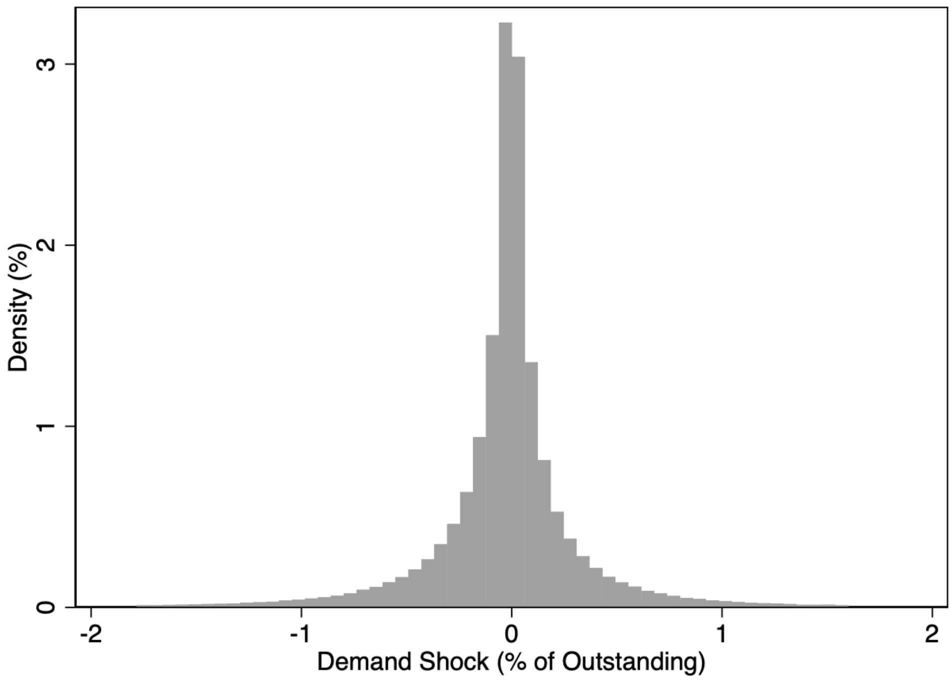
Wurgler, Jeffrey and Ekaterina Zhuravskaya, "Does Arbitrage Flatten Demand Curves for Stocks?," *Journal of Business*, 10 2002, *75* (4), 583–608.

Zhu, Qifei, "Capital Supply and Corporate Bond Issuances: Evidence from Mutual Fund Flows," *Journal of Financial Economics*, August 2021, *141* (2), 551–572.

A Data and Identification

A.1 Distribution of shocks

Figure A.1: Distribution of the constructed demand shocks ($N = 339,847$)



This graph plots the histogram the demand shock, for the values that fall between the 1st and 99th percentile. The shocks are represented as a percentage of the total outstanding amount.

A.2 Identification of Multipliers

We first consider the specification in equation (11), restated here:

$$\Delta p_{j,t} = M u_{j,t} + \text{Fixed effects}_{g,t} + \beta^\top X_{j,t} + \tilde{\boldsymbol{\nu}}_{j,t}.$$

To identify the coefficients correctly, we need the following moment conditions to be satisfied:

$$\mathbb{E}[u_{j,t}\tilde{\nu}_{j,t}|X_{j,t}] = 0. \tag{A.22}$$

We now prove that Assumption 1, i.e. $\tilde{\nu}_{jt} \perp S_{ij,t-1}$ for all fund i and time t, is a sufficient condition for satisfying these moment conditions. For clarity, we use the notation $\mathbb{E}_i^{(j)}$ to denote the expectation over dimension j conditional on dimension i.

Proof.

$$\begin{aligned}
\mathbb{E}\left[u_{j,t}\tilde{\nu}_{j,t}|X_{j,t}\right] &= \mathbb{E}\left[\mathbb{E}_{j,t}^{(i)}\left[S_{ij,t-1}\omega_{i,t}\right]\tilde{\nu}_{j,t}|X_{j,t}\right] && \text{(Definition of } u_{j,t}\text{)} \\
&= \mathbb{E}^{(i,j,t)}\left[S_{ij,t-1}\omega_{i,t}\tilde{\nu}_{j,t}|X_{j,t}\right] && \text{(L.I.E.)} \\
&= \mathbb{E}^{(i,t)}\left[\omega_{i,t}\mathbb{E}_{i,t}^{(j)}\left[S_{ij,t-1}\tilde{\nu}_{j,t}|X_{j,t}\right]|X_{j,t}\right] && \text{(conditional Exp.)} \\
&= \mathbb{E}^{(i,t)}\left[\omega_{i,t}0|X_{j,t}\right]. && \text{(I.D. assum.)}
\end{aligned}$$

□

The first equality is the definition of bond-level shocks as the aggregation across fund-level shocks. The second line directly follows through the law of iterated expectations. The third equality applies the law of iterated expectations again, and this time we take the expectations across bonds *within each fund*. As shocks $\omega_{i,t}$ are at the fund level, it can be pulled out of the expectations. This is the key property exploited in the exogenous-share design. Notice that here we do not assume orthogonal flows. The last equality uses the identification assumption.

A.3 Identification of Substitute Passthrough

We estimate the substitute passthrough according to the following equation:

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_{j,t}^{sub} + \text{Fixed effects}_t + \beta^\top X_{j,t} + \tilde{\nu}_{j,t},$$

where we instrument $\Delta p_{j,t}^{sub}$ with $u_{j,t}^{sub}$, constructed as the value-weighted group-level shocks:

$$u_{j,t}^{sub} \equiv \sum_k w_{k|g(j),t-1} u_{k,t},$$

where $g(j)$ is the group of close substitutes for bond j, and $w_{k|g(j),t-1} = \frac{\mathbb{I}_{k\in g(j)} w_{k,t-1}}{w_{g(j),t-1}}$ is the (lagged) market share of bond k within group $g(j)$. The required moment condition is:

$$\mathbb{E}[u_{j,t}^{sub} \tilde{\nu}_{j,t} | X_{j,t}] = 0.$$

The proof follows a similar strategy as before. We suppress the time subscript in the proof below for ease of notation.

Proof. Plug in the definitions and use the law of iterated expectations as before, we have:

$$\begin{aligned}
\mathbb{E}\left[u_j^{sub} \tilde{\nu}_j | X_{j,t}\right] =& \mathbb{E}^{(j)}\left[w_{k|g(j)} u_k \tilde{\nu}_j | X_{j,t}\right] && \text{(A.23)}\\
=& \mathbb{E}^{(j)}\left[w_{k|g(j)} \mathbb{E}_k^{(i)}\left[\omega_i S_{i,k} | X_{j,t}\right] \tilde{\nu}_j | X_{j,t}\right] && \text{(A.24)}\\
=& \mathbb{E}^{(i)}\left[\mathbb{E}_i^{(k)}\left[\mathbb{E}_{ik}^{(j)}\left[w_{k|g(j)} \tilde{\nu}_j\right] S_{i,k} | X_{j,t}\right] \omega_{i,t} | X_{j,t}\right]. && \text{(A.25)}
\end{aligned}$$

Notice that the inner expectation is essentially the group-level idiosyncratic shocks:

$$\mathbb{E}_{ik}^{(j)}\left[w_{k|g(j)} \tilde{\nu}_j\right] = \mathbb{E}_{ik}^{(j)}\left[\frac{\mathbb{I}_{k\in g(j)} w_k}{w_{g(j)}} \tilde{\nu}_j\right] = \frac{w_k}{w_{g(k)}} \underbrace{\mathbb{E}_{ik, j\in g(k)}^{(j)} \tilde{\nu}_j}_{\tilde{\nu}_g}.$$

Plug it back into equation (A.25), we have:

$$\mathbb{E}_i^{(k)}\left[\mathbb{E}_{ik}^{(j)}\left[w_{k|g(j)}\tilde{\nu}_j\right]S_{i,k}|X_{j,t}\right] = \mathbb{E}_i^{(k)}\left[\frac{w_k}{w_{g(k)}}S_{i,k}\tilde{\nu}_g|X_{j,t}\right]$$
$$= \mathbb{E}_i^{(g)}\left[\mathbb{E}_g^{(k)}\left[\frac{w_k}{w_{g(k)}}S_{i,k}\right]\tilde{\nu}_g|X_{j,t}\right].$$

furthermore, denote MV_k as the market value of asset k and MV_g as the market value of all assets in group g,

$$\mathbb{E}_g^{(k)}\left[\frac{w_k}{w_{g(k)}}S_{i,k}\right] = \sum_{k\in g}\frac{MV_k \times S_{i,k}}{MV_g} = S_{i,g}$$

where $S_{i,g}$ is the holding share of fund i of portfolio g. Hence

$$\mathbb{E}_i^{(k)}\left[\mathbb{E}_{ik}^{(j)}\left[w_{k|g(j)}\tilde{\nu}_j\right]S_{i,k}|X_{j,t}\right] = E_i^{(g)}\left[S_{i,g}\tilde{\nu}_g|X_{j,t}\right] = 0$$

Here we rely on the exogenous share assumption at the group level, i.e., $S_{i,g} \perp \tilde{\nu}_g$. □

B Derivations for the Aggregation Result

Assume a two-layer demand system as in equation (8). Suppose there are G close substitute groups, denoted by $g_1, g_2 ... g_G$. We order the bonds such that the bonds within the same close substitute group are next to each other, implying the following demand matrix Γ,

$$\Gamma = \begin{pmatrix} \Gamma_{g_1} & \Gamma_{g_1,g_2} & ... \\ \Gamma_{g_2,g_1} & \Gamma_{g_2} & ... \\ ... & & \\ .. & ... & \Gamma_{g_G} \end{pmatrix} \tag{B.26}$$

Γ takes a block matrix form. The blocks on the diagonal captures the demand elasticities and cross-elasticities of bonds within the same close substitute group, while the off-diagonal blocks feature the cross-elasticities of bonds across groups. Specifically, consider the on-diagonal matrix. For a given group g, suppose there are n bonds in this group. The elasticity matrix within the block is given by

$$\Gamma_g = \begin{pmatrix} -\gamma^o + \gamma^c w_{1|g} + \gamma^d w_1 & \gamma^c w_{2|g} + \gamma^d w_2 & \dots & \gamma^c w_{n|g} + \gamma^d w_n \\ \gamma^c w_{1|g} + \gamma^d w_1 & -\gamma^o + \gamma^c w_{2|g} + \gamma^d w_2 & \dots & \gamma^c w_{n|g} + \gamma^d w_n \\ \dots & & & \\ \gamma^c w_{1|g} + \gamma^d w_1 & \gamma^c w_{2|g} + \gamma^d w_2 & \dots & -\gamma^o + \gamma^c w_{n|g} + \gamma^d w_n \end{pmatrix} \tag{B.27}$$

where $w_{1|g}$ is the relative weight of bond 1 in this group and w_1 is the weight in the market portfolio. The element in the off-diagonal matrix Γ_{g_1,g_2} is simply equal to $\gamma^d w_{g_2(i)}$.

Consider the demand change of portfolio g, defined as the weighted average of demand changes across the bonds it contains, in response to its own price change. Suppose only the prices of bonds in portfolio g change, while the prices of other bonds are fixed:

$$q_g = \sum_{i \in g} w_{i|g} q_i \tag{B.28}$$

$$= \sum_{i \in g} w_{i|g} \left[-\gamma^o p_i + \sum_{j \in g} (\gamma^c w_{j|g} + \gamma^d w_j) p_j \right] \tag{B.29}$$

Substitute in portfolio return $p_g = \sum_{i \in g} w_{i|g} p_i$ and the identity $w_i = w_{i|g} w_g$, we get

$$q_g = -\gamma^o p_g + (\gamma^c + \gamma^d w_g) \sum_{j \in g} w_{j|g} p_j \tag{B.30}$$

$$= -(\gamma^o - \gamma^c - \gamma^d w_g) p_g \tag{B.31}$$

Now consider how demand of portfolio g_1 responds to the price change of portfolio g_2.

Suppose only the prices of bonds in portfolio g_2 changed.

$$q_{g_1} = \sum_{i \in g_1} w_{i_1|g_1} q_{i_1} \tag{B.32}$$

$$= \sum_{i \in g_1} w_{i_1|g_1} \sum_{j \in g_2} \gamma^d w_{j_2} p_{j_2} \tag{B.33}$$

Leveraging the identity that $w_{j_2} = w_{j_2|g_2} w_{g_2}$, we get

$$q_{g_1} = \sum_{i \in g_1} w_{i_1|g_1} \sum_{j \in g_2} \gamma^d w_{j_2|g_2} w_{g_2} p_{j_2} \tag{B.34}$$

$$= \sum_{i \in g_1} w_{i_1|g_1} \gamma^d w_{g_2} \sum_{j \in g_2} w_{j_2|g_2} p_{j_2} \tag{B.35}$$

$$= \sum_{i \in g_1} w_{i_1|g_1} \gamma^d w_{g_2} p_{g_2} = \gamma^d w_{g_2} p_{g_2} \tag{B.36}$$

Hence, the cross-elasticity of portfolio g_1's demand to portfolio g_2's price is $\gamma^d w_{g_2}$.

Therefore, the aggregated elasticity matrix Γ^G can be expressed as:

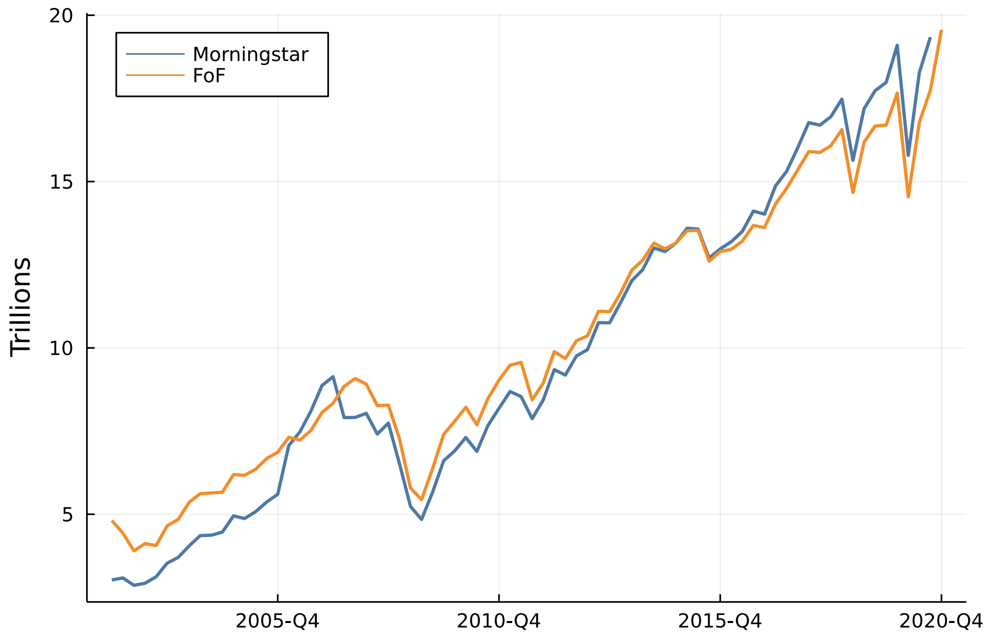
$$\Gamma^G_{g_1,g_2} = \gamma^d w_{g_2} - \mathbf{1}\{g_1 = g_2\} \times (\gamma^o - \gamma^c). \tag{B.37}$$

After aggregation, it becomes a one-layer demand system with the own elasticity $\gamma^o - \gamma^c$ and the cross-elasticity $\gamma^d w_{g_2}$ as in equation (5).

C Morningstar Data Coverage

We find that Morningstar mutual fund dataset coverage is quite extensive and closely lines up with the coverage of the Flow of Funds estimate of mutual fund holdings.

Figure C.1: Total assets of all mutual funds in flow of funds versus Morningstar



This figure plots the net total assets of all mutual funds reported to Morningstar (blue) against total mutual fund shares outstanding in the US, retrieved from Table L.244 from Financial Accounts (Flow of Funds).

D Robustness of Shock Construction

In this section, we explore the sensitivity of our results to various deviations from our baseline assumptions used in the shock construction process.

D.1 Assessing Passthrough of Fund Flows into Demand Shocks

In constructing our shocks, we assume that mutual funds mechanically reinvest inflows according to their existing portfolio weights. This assumption implies a one-to-one passthrough from inflows into demand shocks for the bonds in the portfolio. In this section, we test this assumption and find that it largely holds. To the extent that it is violated, the resulting bias in our estimates is relatively small.

Conceptually, there are two different concerns with the passthrough assumption. First, the passthrough may be less than one-to-one; second, the passthrough may be heterogeneous across bonds. We address each concern separately.

Passthrough less than one-to-one. If the true passthrough to corporate bonds is less than one-to-one, then assuming a one-to-one passthrough overestimates the size of the demand shock and hence underestimates the multiplier. To be concrete, suppose the passthrough from fund flow to bond level demand is $\beta \in [0, 1]$. Then the true demand shock at the bond level is scaled by β, and equation (4) becomes

$$\Delta p_{j,t} = \underbrace{M\beta}_{\hat{M}} u_{j,t} + \tilde{M}\Delta p^{sub}_{j,t} + \tilde{\nu}_{j,t} \tag{D.38}$$

By assuming a passthrough of 1, we are overestimating the size of the demand shock and hence underestimating the multiplier. If we have an estimate of β, we can adjust the estimated multiplier by $\frac{1}{\beta}$ to recover the true multiplier, $M = \frac{\hat{M}}{\beta}$. However, since the underlying demand shock is not observable, we do not have a direct estimate of β.

Nevertheless, we can use the passthrough of the fund flows to the *realized trading* to obtain a lower bound of β. Following Lou (2012), we regress the change in the fund holdings in bonds j on the fund flow f_{it}:[34]

$$\Delta q_{i,j,t} = \alpha + \tilde{\beta} f_{i,t} + \varepsilon_{i,j,t} \tag{D.39}$$

Because $\Delta q_{i,j,t}$ is the equilibrium change in holdings, the coefficient $\tilde{\beta}$ is a downward-biased estimate of the true passthrough β. Specifically, with a downward sloping demand

[34]To accurately measure the passthrough, here we define $\Delta q_{ijt} = 2\frac{Q_{ijt} - Q_{ij,t-1}}{Q_{ijt} + Q_{ij,t-1}}$ as the Davis and Haltiwanger (1992) change in mutual fund holdings, and f_{it} is here measured similarly to be consistent. Davis and Haltiwanger (1992) change is a second order approximation of the log difference, and has several desirable properties over the standard percentage change measure, for example, it is symmetric, and it does not generate outliers due to small base effects. The regression is also weighted by the lagged market value of fund holdings so that the passthrough estimates are representative in dollar terms.

curve, a positive demand shock pushes the bond's price higher, and the fund responds to the price change by decreasing the purchase of the bond relative to its demand shock. Hence, $\tilde{\beta}$ underestimates the true passthrough β, and as a result, $\frac{\hat{M}}{\tilde{\beta}}$ overestimates the true multiplier. In other words, we can use the estimated multiplier $\hat{M}$ and the estimated passthrough $\tilde{\beta}$ to bound the true multiplier M from both sides: $M \in [\hat{M}, \frac{\hat{M}}{\tilde{\beta}}]$. When $\tilde{\beta}$ is close to 1, the bound is tight.

Table D.1 reports the estimates of $\tilde{\beta}$ at the security (CUSIP) level.[35] In Column (1) we perform the regression without any controls, and in Column (2) we add quarter and fund fixed effects. The passthrough estimates $\tilde{\beta}$ are around 0.85 and 0.75, indicating that for a 1% flow, funds change their holdings in bonds on average by $0.75\% - 0.85\%$. Column (3) and (4) split the sample into inflows ($f_{it} > 0$) and outflows ($f_{it} < 0$), respectively. Both inflows and outflows are significantly passed through to the trading. For a 1% flow, funds increase their existing holdings by 0.59%; and for a 1% outflow, they sell their existing holdings by 1.13%. The passthrough is higher for outflows than inflows, echoing the findings in Lou (2012) for equities.

The estimated $\tilde{\beta}$ suggests that our estimated multipliers M are at most 25% lower than the true multipliers M. Our calculation suggests that the true CUSIP multiplier could be as high as 0.08, which is still much smaller than the estimates for equities and the estimates without controlling for substitution. Finally, the potential mis-measurement of passthrough applies to both specifications with and without close-substitute controls. Hence it cannot explain the difference between the two specifications.

Heterogeneity in passthrough. Another concern is that the passthrough may be heterogeneous across bonds—for example, when facing redemptions, funds may sell more liquid bonds first compared to less liquid bonds to minimize the price impact. This may result in

[35] By construction, passthrough increases with the level of aggregation as funds can pass the demand shock to other bonds within the same portfolio.

Table D.1: Estimating passthrough from flows into holdings

	Passthrough			
	(1)	(2)	(3)	(4)
Flows	0.846***	0.750***	0.584***	1.127***
	(0.055)	(0.038)	(0.061)	(0.096)
Time+Fund FE	No	Yes	Yes	Yes
Flow Type	All	All	Inflows	Outflows
N	4,094,225	4,094,221	2,412,401	1,681,809

This table presents estimates of the passthrough from fund flows to changes in holdings at the security (CUSIP) level using Equation (D.39). The dependent variable is the Davis-Haltiwanger growth rate in fund holdings of individual bonds. The independent variable is the fund's flow, also measured using the Davis-Haltiwanger growth rate. Column (1) shows the baseline specification without controls. Column (2) adds quarter and fund fixed effects. Columns (3) and (4) split the sample into positive flows (inflows) and negative flows (outflows) respectively. All regressions are weighted by the lagged market value of fund holdings. Standard errors are two-way clustered at the fund and quarter levels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

a tilt in demand shocks towards more liquid bonds.

Formally, suppose funds have bond-specific passthrough coefficients β_j, which can potentially depend on the bond's characteristics. Then at the fund level, the demand equation for bond j is given by

$$\Delta q_{i,j,t} = \alpha + \beta_j f_{i,t} + \mathbf{\Gamma}_{(j,:)} \Delta \mathbf{p}_t + \tilde{\varepsilon}_{i,j,t}. \tag{D.40}$$

Correspondingly, equation (4) becomes

$$\Delta p_{j,t} = M_j \beta_j u_{j,t} + \tilde{M} \Delta p_{j,t}^{sub} + \tilde{\nu}_{j,t} \tag{D.41}$$

In this case our estimated multiplier, $\hat{M} = \mathbb{E}^{(j)}[\beta_j]\mathbb{E}^{(j)}[M_j \frac{\beta_j}{\mathbb{E}^{(j)}[\beta_j]}]$, captures the cross-sectional average of multipliers weighted by the bond-specific relative passthrough $\frac{\beta_j}{\mathbb{E}^{(j)}[\beta_j]}$. When the passthrough is cross-sectionally uncorrelated with the multiplier M_j, the estimate simplifies to $\mathbb{E}^{(j)}[\beta_j]\mathbb{E}^{(j)}[M]$, i.e., we need only adjust for the average passthrough $\mathbb{E}^{(j)}[\beta_j]$

to recover the average multiplier $\mathbb{E}^{(j)}[M]$. The discussion in the previous section provides a bound.

When the passthrough is correlated with the multiplier across bonds, our estimator yields a weighted average multiplier, with weights proportional to $\frac{\beta_j}{\mathbb{E}^{(j)}[\beta_j]}$. In particular, if funds follow a liquidity pecking order and pass through flows disproportionately toward more liquid bonds (Choi et al., 2020; Ma et al., 2022), our pooled estimates will place greater weight on liquid bonds.

To obtain a more complete picture with the presence of heterogeneous passthrough and multipliers, we study the heterogeneity along different characteristics. First, we analyze how estimated passthrough varies with bond characteristics associated with liquidity. We modify equation (D.39) to include interaction terms with bond characteristics $X_{j,t}$:

$$\Delta q_{i,j,t} = \alpha + \left(\tilde{\beta} + \tilde{\beta}_X X_{j,t}\right) f_{i,t} + \beta_0 X_{j,t} + \varepsilon_{i,j,t}. \tag{D.42}$$

We consider three bond characteristics that are most associated with liquidity: the average bid-ask spread, the numerical credit rating, and the size of the bond, measured by the log of amount outstanding. We standardize the average bid-ask spread and the log of amount outstanding so the coefficients are associated with a one-standard-deviation change. The numerical rating starts at 0 for AAA bonds and increases by 1 for each notch downgrade.

Table D.2 reports the estimated passthrough coefficients $\tilde{\beta}$ and $\tilde{\beta}_X$ for the three bond characteristics. Consistent with the liquidity pecking order, passthroughs are significantly lower for bonds with lower credit ratings: each one-notch downgrade reduces the estimated passthrough by 0.018. Passthroughs are also significantly higher for larger bonds: a one-standard-deviation increase in log amount outstanding raises the passthrough by 0.072. The point estimate for the bid-ask spread is negative but not statistically significant.[36]

[36]Because these coefficients are estimated from realized trades, they do not map one-to-one to the passthrough from flows into demand shocks. For example, a bond with a higher bid-ask spread may have lower realized passthrough due to greater price impact, even if the fund intends to pass through the same

Given this heterogeneity in passthrough, we next examine to what extent multipliers also vary across these dimensions. Section 5.2 discusses multiplier heterogeneity across credit ratings in detail. Here, we split the sample at the median bond size and estimate multipliers separately for each half. Table D.3 shows that the estimated multipliers are similar across both subsamples, for both CUSIP-level and portfolio-level estimates, suggesting that passthrough-based weighting has limited impact on our pooled estimates.

Table D.2: Estimating passthrough heterogeneity from flows into holdings

	Passthrough		
	(1)	(2)	(3)
Flows	0.910***	0.740***	0.757***
	(0.084)	(0.038)	(0.039)
Flows × Rating (num.)	-0.018*		
	(0.008)		
Flows × Log(Amount Outstanding) (std.)		0.072**	
		(0.024)	
Flows × BidAsk (std.)			-0.009
			(0.027)
Time+Fund FE	Yes	Yes	Yes
Flow Type	All	All	All
N	4,094,221	4,094,079	3,940,110

This table presents estimates of the passthrough from fund flows to changes in holdings at the security (CUSIP) level and how this passthrough varies with bond characteristics using Equation (D.42). The dependent variable is the Davis-Haltiwanger growth rate in fund holdings of individual bonds. The independent variables are the fund's flow, also measured using the Davis-Haltiwanger growth rate, and its interactions with three bond characteristics: average bid-ask spread, numerical credit rating (larger numerical values denote worse credit ratings / higher credit risk), and log of amount outstanding. The average bid-ask spread and log of amount outstanding are standardized. All regressions include quarter and fund fixed effects and are weighted by the lagged market value of fund holdings. Standard errors are two-way clustered at the fund and quarter levels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

demand shock.

Table D.3: Multiplier by Size

	Cusip		Portfolio	
	(1)	(2)	(3)	(4)
	Small	Large	Small	Large
Shock	0.07	-0.00	0.32**	0.30*
	(0.04)	(0.07)	(0.10)	(0.15)
Group x Quarter FE	Yes	Yes	Yes	Yes
N	138124	146194	34970	37228
R^2	0.37	0.42	0.44	0.56

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the multiplier estimates for the smaller half of the bonds and the larger half of bonds in our sample respectively, following the specification in equation (11). Across all specifications, we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by Fama-French 48 industries for CUSIP-level estimates. We drop crisis periods. Standard errors are clustered at the substitute group x time level.

D.2 Sensitivity of Multiplier Estimation to Shock Construction Specifications

Table D.4 examines the sensitivity of our multiplier estimates to alternative choices in the shock construction process. Overall, our estimates do not seem to change much if we (i) control for additional factors as described in IA.A.2, (ii) use different specifications for our AR regressions in step 2 of the shock construction process, including controlling past fund returns.

D.3 Lagging Market Shares for Shock Construction

Another potential concern to the exogenous share condition is that some mutual fund managers have superior information and therefore can front-run the market, leading to a positive correlation between market share and bond returns. This issue can be addressed with further lagging the market share used in aggregating fund flow shocks: it is highly unlikely for a mutual fund manager to predict *idiosyncratic* returns at the bond level in one year and

Table D.4: Shock robustness

	Bench.	Robustness							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Shock	0.27^{**}	0.31^{**}	0.33^{**}	0.31^{**}	0.21^{**}	0.22^{**}	0.17^{***}	0.20	0.27^{**}
	(0.10)	(0.10)	(0.12)	(0.11)	(0.08)	(0.08)	(0.05)	(0.21)	(0.10)
AR lags	3	3	1	2	1	2	3	No	3
Time Trend	Yes	Yes	Yes	Yes	No	No	No	No	No
Factors	No	Yes	No	No	No	No	No	No	No
Past ret.	No	No	No	No	No	No	No	No	Yes
Group-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	76,521	76,521	80,073	76,521	76,521	76,521	76,521	76,521	76,521
R^2	0.50	0.50	0.48	0.50	0.50	0.50	0.50	0.50	0.50

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table summarizes the estimates for the portfolio multipliers when we use different specifications to extract demand shocks. All estimates are for portfolios formed by detailed rating and quarter-to-maturity as in Section 4.1. "AR lags" refers to how many lagged flows we control for when adjusting for the flow predictability in equation (14). "Time Trend" indicates whether we include a linear time trend in the flow predictability regression in equation (14). "Factors" refer to whether we remove the common factors from the flows using the parametric estimation explained in Appendix IA.A.2. "Past ret." refers to whether one-period lagged fund return is controlled for in equation (14). We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications.

allocate their portfolio in one year to benefit from it.[37] For this exercise, we drop bonds with maturity less than one year.

Table D.5 and D.6 report our baseline results using shocks aggregated with one-year-lag market shares. The results remain largely unchanged.

E Additional Robustness

E.1 Bond-level Estimates

Table E.1 presents additional robustness checks for the CUSIP-level estimates. We vary the type of close substitutes used in the regression, including controlling for industry-time fixed effects defined by the Fama-French 48 industries. We also consider size weighting to focus more on the large representative bonds, and exclude bonds issued by financial firms. The estimate becomes slightly larger when we exclude bonds issued by financial firms, in part because most of financial-sector bonds are investment-grade, which tend to exhibit smaller price impacts. Overall the results remain quantitatively similar.

E.2 Common Factors in Returns

In this section, we verify that our results are robust to including common factors in returns from the literature. Specifically, we run the following regression,

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_{j,t}^{sub} + \beta_j^\top \eta_t + \beta_X^\top X_{j,t} + \check{\nu}_{j,t} \tag{E.43}$$

where η_t represents the factor structure in returns. We consider three sets of factors for the bond market: (1) the reconstructed Bai et al. (2019) (BBW) factors from Dickerson et al.

[37] It might be more plausible if they are able to predict the dynamics of some systematic factors in one year and trade accordingly—the common factor issue is addressed in Section IA.A.1 by removing the common factors from flows.

Table D.5: Security level specifications lagging holding shares by one-year

	Homo. OLS	OLS			First-stage
	(1)	(2)	(3)	(4)	(5)
Shock	0.38***	-0.04	0.00		0.00
	(0.08)	(0.06)	(0.05)		(0.06)
Substitute return					1.10***
					(0.06)
Group shock				4.09***	
				(0.44)	
Quarter FE	Yes	Yes	Yes	Yes	Yes
Group x Quarter FE	No	Yes	Yes	No	No
ST/LT x Quarter FE					
Drop Crisis	No	No	Yes	Yes	Yes
N	252,202	252,202	237,258	237,258	237,258
R^2	0.22	0.41	0.38	0.64	0.17
First-stage F-statistic					83.63

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table shows the multiplier estimates from repeating the baseline CUSIP level specification for shocks constructed by lagging holdings shares by one-year. We control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by the Fama-French 48 industries. We drop observations with maturity less than one year. Column 1 is the OLS estimates from regressing bond returns on the demand shock, controlling for time fixed effects, as in equation (7)—this specification corresponds to a model in which we assume homogeneous cross-elasticity with all other bonds. Columns 2-4 show results from running the regression in equation (11) with different definitions of close-substitutes. Columns 2 and 3 directly control for close-substitute prices using detailed rating x time fixed effects. Column 4 additional controls for maturity (long-term/short-term) x quarter fixed effects to control for potentially omitted time-varying maturity factor in holding shares. Column 5 and 6 relate to the IV specification specified in equation (10). We regress bond returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to substitute assets. The IV specification corresponds to the model that allows for heterogeneous cross-elasticities between close and distant substitutes. The parentheses contain standard errors clustered at the substitute group x time level.

Table D.6: Baseline portfolio lagging holding shares by one-year

	Homo. OLS	OLS			First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	1.03***	0.26*	0.27*	0.30**		0.28*
	(0.15)	(0.11)	(0.11)	(0.11)		(0.12)
Substitute return						1.03***
						(0.05)
Group shock					4.28***	
					(0.52)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Group x Quarter FE	No	Yes	Yes	Yes	No	No
ST/LT x Quarter FE	No	No	No	Yes	No	No
Drop Crisis	No	No	Yes	Yes	Yes	Yes
N	76,521	76,521	72,217	72,217	72,217	72,217
R^2	0.24	0.50	0.45	0.47	0.49	0.24
First-stage F-statistic						66.75

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the quarter-to-maturity × detailed rating level multiplier estimates for demand shocks constructed by lagging holdings shares by one-year. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. We drop observations with maturity less than one year. Column 1 is the estimates from regressing portfolio returns on the demand shock, controlling for time-fixed effects, as in equation (11). This specification corresponds to a model in which we assume homogeneous cross-elasticity with all other bonds. Columns 2-4 show results from running the regression in equation (11) with different definitions of close-substitutes. Columns 2 and 3 directly control for close-substitute prices using detailed rating x time fixed effects. Column 4 additional controls for maturity (long-term/short-term) x quarter fixed effects to control for potentially omitted time-varying maturity factor in holding shares. Columns 5 and 6 relate to the IV specification in equation (10), in which we regress portfolio returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to substitute assets. The IV specification corresponds to the model that allows for heterogeneous cross-elasticities between close and distant substitutes. The parentheses contain standard errors clustered at the substitute group x time level.

Table E.1: Additional Robustness for CUSIP-level estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shock	0.08	0.08*	0.01	0.06	0.16**	0.14**	0.15*	0.14*
	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)
Det. rating x Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LT x Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. x Time	No	Yes	No	Yes	No	Yes	No	Yes
Size weighted	No	No	Yes	Yes	No	No	Yes	Yes
Finance excluded	No	No	No	No	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table summarizes the estimates for the CUSIP level multiplier under alternative specifications. Across all specifications, we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by the Fama-French 48 industries. Standard errors are clustered at the substitute group x time level.

(2023); (2) the bond market and the term structure factor from Dick-Nielsen et al. (2023); (3) bond age, market value, duration, value, equity momentum, market and term structure factors from Dick-Nielsen et al. (2023).[38] For each set of factors, we allow each security to have a different loading on the factors. We find both our CUSIP-level and baseline portfolio-level multiplier estimates are robust to including various sets of factors as controls. The results are shown in Table E.2.

F Firm-level Estimates

Motivated by the findings in Zhu (2021), we also estimate the multiplier and the substitute passthrough coefficient at the issuer level (defined by unique "gvkey"), where we group bonds issued by the same issuer into portfolios. The definition of close substitutes is the same as in the case of security-level estimates. The results are presented in Table F.1. In general, the multiplier estimates are larger than that at the security-level.

[38]Since our regression is at the quarterly frequency, we aggregate the monthly factor returns to quarterly returns.

Table E.2: Robustness with respect to factor controls

	(1)	(2)	(3)	(4)	(5)	(6)
	return	return	return	return	return	return
shock	0.277***	0.286**	0.199**	0.035	0.083*	0.033
	(0.078)	(0.093)	(0.067)	(0.042)	(0.042)	(0.034)
Security	Portfolio	Portfolio	Portfolio	Cusip	Cusip	Cusip
Group x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Factors	BBW	MRKT + TERM	Stolborg	BBW	MRKT + TERM	Stolborg
N	76437	76437	76437	299918	300832	300832
R^2	0.784	0.640	0.757	0.844	0.661	0.810

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table summarizes the estimates for the CUSIP and the baseline portfolio multipliers when we include different factor structures in the return regression. "BBW" refers to the reconstructed Bai et al. (2019) (BBW) factors from Dickerson et al. (2023), "Mkt + Term" refers to the bond market and the term structure factor from Dick-Nielsen et al. (2023), and "Dick-Nielsen et al." refers to the bond age, market value, duration, value, equity momentum, market and term structure factors from Dick-Nielsen et al. (2023). Across all specifications, we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by the Fama-French 48 industries for CUSIP-level estimates. Standard errors are clustered at the substitute group x time level.

Table F.1: Firm-level multipliers and passthrough estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shock	0.19**	0.18**	-0.01	-0.12	0.31***	0.27***	0.17	0.25
	(0.06)	(0.06)	(0.14)	(0.20)	(0.08)	(0.08)	(0.11)	(0.18)
Substitute return				1.06***				1.08***
				(0.08)				(0.10)
Det. rating x Time	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Ind. x Time	No	Yes	Yes	No	No	Yes	Yes	No
Size weighted	No	No	Yes	Yes	No	No	Yes	Yes
Finance excluded	No	No	No	No	Yes	Yes	Yes	Yes
First-stage F-statistic				71.67				69.43

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the multiplier estimates for portfolios formed by bonds issued by the same company (defined by the same "gvkey"). Across all specifications, we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by the Fama-French 48 industry. Columns (4) and (8) relate to the IV specification in equation (10). We regress portfolio returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to the substitute portfolio. Standard errors are clustered at the substitute group x time level.

G Alternative Specifications

In this section we explore other specification to estimate equation (9) i.e.,

$$\Delta p_{j,t} = M u_{j,t} + \tilde{M} \Delta p_{g(j),t} + \tilde{M}^m \Delta p_t^m + \tilde{\nu}_{j,t}$$

Our objective was to estimate for M, hence our baseline specification was a fixed effect regression, which directly controls for $\Delta p_{g(j),t}$ and Δp_t^m by including group × quarter fixed effect. While this specification is most robust, we lose economic content by not being able to estimate $\tilde{M}$. Hence, we additionally explored an IV specification, where we include $\Delta p_{g(j),t}$ (instrumenting it with $u_{g(j),t}$) and controlling for Δp_t^m using time-fixed effects. In the interest of brevity we left a third specification where we also estimate $\tilde{M}^m$ for the appendix. In this specification we can directly include $\Delta p_{g(j),t}$ and Δp_t^m, which we instrument with $u_{g(j),t}$ and $u_{m,t}$ respectively.

Table G.1 presents the estimates for all three specification. The own multiplier estimates are unchanged across the three specifications. The (near) substitute passthrough is close to one, where as the distant substitute passthrough is close to zero. These estimates are in line with what we would economically expect—a securities price is more closely tilted to near substitutes than distant substitutes.

Table G.2 presents similar estimates for the baseline level of aggregation. The own multiplier estimates are extremely similar across the three specifications. The (near) substitute passthrough is close to one, where as the distant substitute passthrough is significant but smaller than the near substitute. Overall, $\tilde{M}^m$ being larger for this more aggregated portfolio, compared to the CUSIP $\tilde{M}^m$ is also in line with what we would economically expect.

Table G.1: Security-level multipliers: alternative specifications

	OLS	2SLS	
	(1)	(2)	(3)
Shock	0.04	0.04	0.04
	(0.04)	(0.05)	(0.05)
Substitute return		1.11***	1.11***
		(0.06)	(0.06)
Mkt return (far sub.)			-0.06
			(0.09)
Quarter FE	Yes	Yes	No
Group x Quarter FE	Yes	No	No
Drop Crisis	Yes	Yes	Yes
N	284,323	284,323	284,323
R^2	0.37	0.17	0.33
First-stage F-statistic		102.36	46.13

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents CUSIP level multiplier estimates from an alternative instrumental variable specification. As before, we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by Fama-French 48 industries. As in the baseline, column 1 corresponds to directly controlling for close-substitute prices using detailed rating x time fixed effects. Similarly, as before, Column 2 corresponds to the IV specification in which we regress bond returns on the demand shock and substitute returns, while controlling for market returns using time fixed effects. We instrument for substitute returns using demand shocks to substitute assets. Column 3, is the alternative specification, that directly includes market returns, which we instrument for using demand shocks to the bond market as a whole. The parentheses contain standard errors clustered at the substitute group x time level.

Table G.2: Baseline portfolio multipliers: alternative specifications

	OLS	2SLS	
	(1)	(2)	(3)
Shock	0.28**	0.29**	0.30**
	(0.09)	(0.10)	(0.10)
Substitute return		0.99***	0.93***
		(0.05)	(0.06)
Mkt return (far sub.)			0.31*
			(0.12)
Quarter FE	Yes	Yes	No
Group x Quarter FE	Yes	No	No
Drop Crisis	Yes	Yes	Yes
N	72,217	72,217	72,217
R^2	0.45	0.23	0.39
First-stage F-statistic		86.69	23.49

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the quarter to maturity × detailed rating level multiplier estimates from an alternative instrumental variable specification. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. As in the baseline, column 1 corresponds to directly controlling for close-substitute prices using detailed rating x time fixed effects. Similarly, as before, Column 2 corresponds to the IV specification in which we regress bond returns on the demand shock and substitute returns, while controlling for market returns using time fixed effects. We instrument for substitute returns using demand shocks to substitute assets. Column 3, is the alternative specification, that directly includes market returns, which we instrument for using demand shocks to the bond market as a whole. The parentheses contain standard errors clustered at the substitute group x time level.

H Alternative Identifications

In this section, we explore two alternative identification strategies to further support our analysis: First, following Zhu (2021), we examine the price effect of a bond market demand shock triggered by Bill Gross' resignation from PIMCO. Second, following Koont et al. (2024), we analyze price pressures resulting from corporate bond index rebalancing. Both approaches yield results that are consistent with our baseline estimates.

H.1 PIMCO Shock

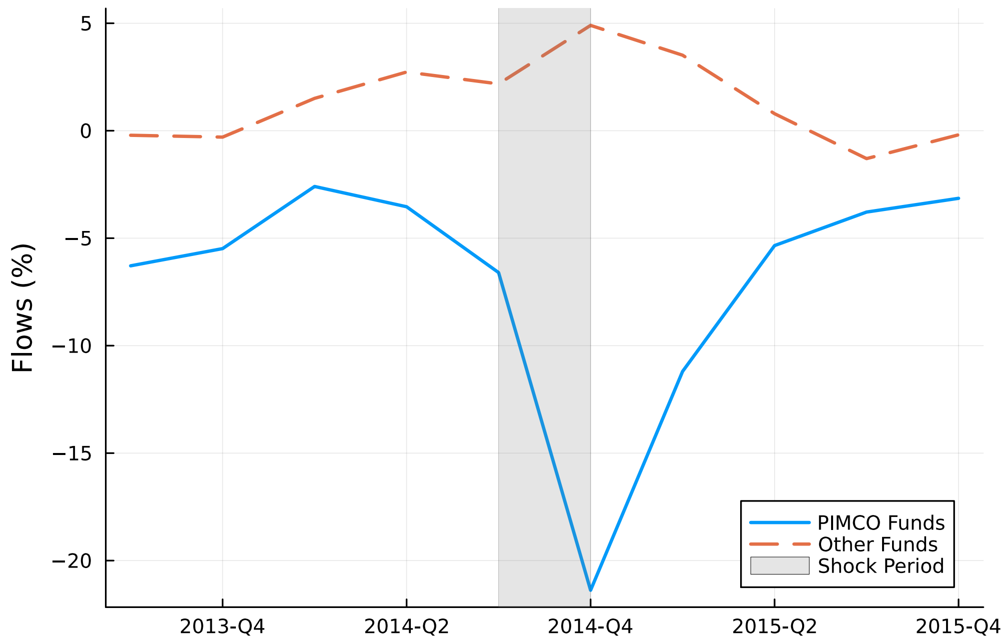
Following Zhu (2021), we use the outflows following the abrupt departure of Bill Gross from the Pacific Investment Management Company (PIMCO) as a shock to the corporate bond market. Complementing our baseline identification that relies on the share exogeneity, this event provides a quasi-natural experiment where the flows are plausibly exogenous.

As of late 2013, PIMCO held over $240 billion in corporate bonds, making it one of the most influential players in U.S. fixed-income markets. On September 26, 2014, its founder and chief investment officer, Bill Gross — widely known as the "Bond King"— abruptly left the firm.[39] In the aftermath, PIMCO experienced dramatic capital outflows across its entire fund family, including both funds directly managed by Gross and those under other portfolio managers. Figure H.1 illustrates the magnitude of this capital exodus. In the last two quarters of 2014, more than 25% of PIMCO's total assets under management departed following Gross' exit. This substantial and rapid outflow provides an ideal quasi-natural experiment to examine the price effect of selling pressure in corporate bond markets.

Our empirical design is akin to a difference-in-difference approach with continuous treatments. Because the resignation of Bill Gross happened in the last several days of 2014Q3, most investors did not promptly react to the shock until 2014Q4. As shown in Figure H.1,

[39] Although industry insiders had noted tensions between Gross and PIMCO executives in preceding months, the abruptness of his departure created a significant market event.

Figure H.1: PIMCO Shock



in Q4 PIMCO funds saw the largest outflows. Hence, we include one period before the shock (2014Q2) as the pre-treated period and two periods after the shock (2014Q3 and 2014Q4) as the treated periods. We consider bonds held by PIMCO funds as the treated group, with exposure proportional to their ownership share by PIMCO funds. We construct the shock at the bond level similar to equation (15) in the baseline specification, but further interact it with the treated indicator (held by a PIMCO fund):[40]

$$u_{j,t}^{\text{PIMCO}} = \sum_i S_{i,j,t-1} f_{i,t} \times \mathbf{1}_{i \in \text{PIMCO}}. \tag{H.44}$$

where $S_{i,j,t-1}$ is the lagged ownership share and $f_{i,t}$ is the fund flow. In other words, only bonds held by PIMCO funds are exposed to the shock, and the magnitude of the shock is proportional to the ownership share and the magnitude of the outflows. We first estimate

[40] As the PIMCO shock is not anticipated, we use the raw flows directly in constructing the shock rather than the innovations to the flows. Using innovations yields virtually identical results.

the multiplier with only time fixed effects,

$$\Delta p_{j,t} = M u_{j,t}^{\text{PIMCO}} \times \mathbf{1}_{\text{Post}} + \text{Time FE}_t + \beta_X X_{j,t} + \delta_j + \tilde{\nu}_{j,t}, \tag{H.45}$$

We then estimate the multiplier with group-time fixed effects to allow for potential heterogeneity in substitutability:

$$\Delta p_{j,t} = M u_{j,t}^{\text{PIMCO}} \times \mathbf{1}_{\text{Post}} + \text{Fixed effects}_{g,t} + \beta_X X_{j,t} + \delta_j + \tilde{\nu}_{j,t}, \tag{H.46}$$

In both cases, we interact the shock with the post-treatment indicator. We include CUSIP fixed effect to control for the pre-treatment differences. Substitute group g is defined as the detailed-rating group as in the main text, and control variables $X_{j,t}$ are the same as in the main text.

Table H.1 presents the effect of the PIMCO shock on bond returns. In Column (1), we only include the time fixed effect but do not control for substitute groups' returns. Column (1) shows that a one percentage point increase in the demand shock due to the PIMCO outflows is associated with a 0.512 percentage point increase in bond return, similar to the estimate in Table 1. Similarly to the exercise in the main text, after adding Quarter $\times$ Group fixed effects to control for close substitutes in Column (2), the coefficient drops substantially to 0.118 and becomes statistically insignificant. Columns (3) and (4) add bond characteristics as additional controls, and the results remain largely unchanged.

H.2 Index Rebalancing

Following Dick-Nielsen and Rossi (2019) and Koont et al. (2024), we also study the price effect of non-fundamental flows due to monthly rebalancing of corporate bond indices. To minimize tracking errors, passive funds buy and sell bonds as their weights in the indices change, providing another source of plausibly exogenous variation in demand for bonds.

Table H.1: Multiplier Estimates from PIMCO Shock

	ret			
	(1)	(2)	(3)	(4)
PIMCO Flows × Post	0.512**	0.118	0.480**	0.049
	(0.178)	(0.161)	(0.186)	(0.168)
Quarter FE	Yes	Yes	Yes	Yes
Quarter × Group FE	No	Yes	No	Yes
CUSIP FE	Yes	Yes	Yes	Yes
Control	No	No	Yes	Yes
N	15,688	15,688	14,232	14,232

This table reports multiplier estimates from the PIMCO shock on corporate bond returns. The demand shock is constructed as $u_{j,t}^{\text{PIMCO}}$ in equation (H.44), which captures the flow-induced demand from PIMCO funds after Bill Gross's departure. The specification follows equations (H.45) and (H.46). We include 2014Q2 as the pre-treated period and 2014Q3 and 2014Q4 as the treated periods. Fixed effects include time fixed effects (Quarter), Quarter × Group fixed effects where Group is defined as detailed-rating groups, and bond (CUSIP) fixed effects. In Columns (3)-(4) we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate, and detailed rating fixed effects. Standard errors are clustered at the bond levels. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We focus on the most tracked corporate bond index, Bloomberg US Corporate Index.[41] We retrieve the history of the weights of this given index from September, 2017 to January, 2021.[42] The index is rebalanced at the end of each month. Changes in index weights can arise from several sources: shifts in bond characteristics, adjustments to the index composition, or modifications to the index construction methodology. Importantly, due to the month-end rebalancing rule, there is a delay between the event that triggers the index weight change (which is during the month), and the actual weight change (at the end of the month). The timing difference allows us to identify the price effect due to demand shocks, separately from

[41] This index is formerly known as the Bloomberg-Barclay corporate bond index, Barclay Capital corporate bond index, etc.

[42] Bloomberg has a family of fixed-income indices, covering different segments of the market, among which the Bloomberg US Corporate Index is the component that covers the U.S. investment-grade corporate bond market. Together they are the most tracked indices in the fixed-income market measured by the total assets under management (AUM) of the funds that track these indices. It includes investment-grade USD-denominated corporate bonds that meets certain criteria, such as the minimum par amount outstanding and minimum maturity. See https://assets.bbhub.io/professional/sites/27/US-Corporate-Index.pdf for the details of the index methodology as of 2023.

the fundamental news. Koont et al. (2024) report that the changes in index weights are not fully predictable ex ante. Even if the rebalancing were fully anticipated, passive funds would not want to adjust their portfolio too much ahead of the rebalancing date, as such adjustments would create tracking error. Indeed, they show that the deviation of ETFs' portfolio from the index weights spikes at each index-rebalancing date.

We study the corporate bond price response in the month following the index weight changes. The total demand from passive investors can be approximated by the sum of asset under management of all passive funds that tracks the index, multiplied by the weight of the bond in the index, $AUM_{passive,t}w_{j,t}$. As the index weight changes, the demand from passive investors also changes. Denote $u_{j,t}^{weight}$ as the demand shock due to the change in index weight in terms of the total market value of the bond, it can be expressed as:

$$\begin{aligned} u_{j,t}^{weight} &= \frac{AUM_{passive,t-1}\Delta w_{j,t}}{MV_{j,t-1}} \\ &= \underbrace{\frac{AUM_{passive,t-1}w_{j,t-1}}{MV_{j,t-1}}}_{\text{Passive Ownership}_{j,t-1}} \frac{\Delta w_{j,t}}{w_{j,t-1}} \end{aligned}$$

That is, the total demand shock due to index weight changes is approximately the percentage change in index weight times the passive ownership share of the bond.

The challenge of using index rebalancing to identify the multiplier M is that the passive ownership is difficult to measure precisely. Active funds that are benchmarked to the same index may also have mechanical demand for bonds in the index (Kashyap et al., 2023). Therefore, we estimate the multiplier directly using the percentage change in index weight, using the fixed effect specification restated below, at the monthly frequency. We first include only time fixed effects:

$$\Delta p_{j,t} = \beta \frac{\Delta w_{j,t}}{w_{j,t-1}} + \text{Time FE}_t + \beta_X X_{j,t} + \delta_j + \tilde{\nu}_{j,t}, \tag{H.47}$$

We then include group-time fixed effects to capture potential heterogeneity in substitution:

$$\Delta p_{j,t} = \beta \frac{\Delta w_{j,t}}{w_{j,t-1}} + \text{Fixed effects}_{g,t} + \beta_X X_{j,t} + \delta_j + \tilde{\nu}_{j,t}, \tag{H.48}$$

where β captures the effect on price due to a 1% index weight change in each case.

The estimates are presented in Table H.2. Column (1) we regress the price change on the index weight change only controlling for time fixed effects and bond fixed effects. The direct price effect of a 1% weight change is around 1.1 basis points. In Column (2) we add in time-group fixed effects to control for close substitutes. Group is defined as bonds with the same detailed ratings. Similar to the results reported in the baseline, the estimated effect drops to 0.7 basis points after close substitutes are controlled for. In Column (3) and (4) we add in controls for bond characteristics. The estimated coefficient is slightly lower, but mostly consistent.

The implied magnitude of the multiplier is also consistent with the baseline estimates. Specifically, we can use the average passive ownership in the bond market to obtain a back-of-envelope estimate of the multiplier,

$$\hat{M} \approx \frac{\beta}{\text{Average Passive Ownership}}. \tag{H.49}$$

Bretscher et al. (2023) report that the passive funds account for around 5% of the investment-grade corporate bond market over this sample period. Combining this with our estimate in Column (4), the implied price multiplier is around $0.006/0.05 = 0.12$, at a similar scale as the baseline CUSIP-level results in Table 1. One may notice that the difference in multiplier estimates with and without controlling for close substitutes is not as large as that in the baseline case in Table 1. This may be due to the fact that changes in index weights are often bond-specific with low correlation across bonds, so the omitted variable bias discussed in Section 2.2 is attenuated.

Table H.2: Multiplier Estimates from Index Rebalancing

	ret (%)			
	(1)	(2)	(3)	(4)
ΔWeight (%)	0.011***	0.007***	0.010***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Month FE	Yes	Yes	Yes	Yes
CUSIP FE	Yes	Yes	Yes	Yes
Month × Group FE	No	Yes	No	Yes
Control	No	No	Yes	Yes
N	187,548	187,547	176,999	176,998

This table reports the effect of index weight changes on corporate bond returns. The independent variable is the percentage change in index weight, and the dependent variable is the percentage change in bond price, at the monthly frequency. The specification follows equations (H.47) and (H.48). Fixed effects include time fixed effects (Month), bond (CUSIP) fixed effects, and Month × Group fixed effects where Group is defined as detailed-rating groups. In Columns (3)-(4) we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate, and detailed rating fixed effects. Standard errors are clustered at the bond level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

I Interpretations Based on Logit Demand Systems

In this section, we show how our reduced form approach is linked to a nested logit demand system. Specifically, we derive the elasticity matrix Γ from a nested logit demand system and show that it yields a specification similar to that used in the main text.

Following Koijen and Yogo (2020), consider the demand structure for a representative investor as follows:

$$\begin{aligned} w(j \mid g) &= \frac{exp(\delta(j,g))}{\sum_{j\in g} exp(\delta(j,g))} \\ w(g) &= \frac{(\sum_{k\in g} exp(\delta(k,g)))^{\lambda}}{1+\sum_{g'}(\sum_{k\in g'} exp(\delta(k,g')))^{\lambda}} \qquad (I.50) \\ \delta(j,g) &= \beta_g p_j + \beta X + u_j, \end{aligned}$$

where $w(j \mid g)$ is the conditional share of asset j in group g, $w(g)$ is the share of group g in the whole portfolio. The unconditional share of asset j is therefore $w(j) = w(j \mid g)w(g)$. The parameter λ controls the substitution at the group level. When $\lambda = 1$, this system is reduced to the simple logit system as

$$w(j) = w(j \mid g)w(g) = \frac{exp(\delta(j,g))}{1 + \sum_{g'}(\sum_{k \in g'} exp(\delta(k,g')))}.$$

Taking the derivative of $w(j)$ with respect to p_k, we have:

$$\frac{\partial w(j)}{\partial p_k} = \begin{cases} \beta_g w(j)\left(1 - \lambda w(j) - (1-\lambda)w(j \mid g)\right) & j = k \\ -\beta_g w(j)\left(\lambda w(k) + (1-\lambda)w(k \mid g)\right) & j \neq k,\ j\&k \in g \\ -\beta_{g'} \lambda w(j)w(k) & j \in g, k \in g' \neq g \end{cases} \tag{I.51}$$

Log linearize the system (I.50) with the partial derivatives above, reorganize, we have:

$$\log \Delta w(j) = \beta_g \Delta p_j - \beta_g(1-\lambda)\sum_{k \in g} w(k \mid g)\Delta p_k - \lambda \sum_{g'}\sum_{k \in g'} \beta_{g'} w(k) \Delta p_k + u_j$$

Applying market clearing condition $\log \Delta w(j) = p(j)$, we can derive the equation for estimation:

$$\Delta p_j = \underbrace{\frac{1}{(1-\beta_g)}}_{M} u_j + \underbrace{\frac{\beta_g}{(\beta_g - 1)}(1-\lambda)}_{\tilde{M}} \underbrace{\sum_{k \in g} w(k \mid g)\Delta p_k}_{\Delta p_j^g} + \underbrace{\lambda \frac{1}{(\beta_g - 1)} \sum_{g'}\sum_{k \in g'} \beta_{g'} w(k)\Delta p_k}_{\text{Time FE}} + \tilde{\nu}_j \tag{I.52}$$

This equation can be mapped directly to our empirical specification, where the multiplier is pinnned down by the elasticity coefficient β_g, while the substitute passthrough is further pinned down by the group substitution coefficient λ.[43] When $\lambda = 1$, the nested system is

[43]Note that our reduced-form approach is more flexible than nested logit, as we do not impose the coefficient restriction on the substitute passthrough from close substitutes Δp_j^g and remote substitutes.

reduced to standard logit demand, and $\tilde{M} = 0$. In this case, we do not need to control for price changes for close substitutes. Our estimates of $\tilde{M}$ strongly reject this assumption. Therefore, when specifying demand for corporate bonds, a nested system is preferred over the standard logit demand.

Online Appendix for
"Corporate Bond Multipliers: Substitutes Matter"

IA.A Additional Robustness

IA.A.1 Non-parametric Estimation of Flow Factor Structure

In this section, we implement the factor models for flow shocks. We first show that flow shocks have weak factor structures in this section; in the next section we explicitly remove the common factors and show our results are robust.

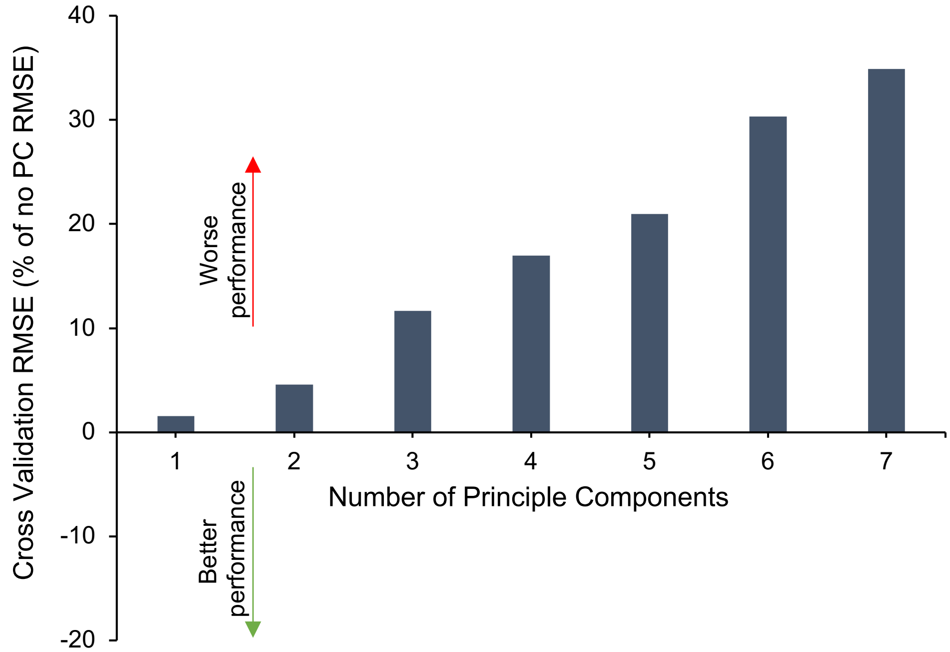
We first implement the non-parametric approaches to estimate common factors. Due to missing values in our data, we estimate the factor model using alternating least squares (ALS). We find the data exhibits a relatively weak factor structure, with the first factor only explaining around 8% of the variation in mutual fund flows.

With that said, non-parametric factor estimation methods are known to have poor finite sample performance when there are a lot of missing value. In our context, due to mutual fund entry and exit, we have a highly unbalanced panel of flow data—relative to a fully balanced panel we are "missing" 49.8% of observations. Hence, there is a risk that the factor model is simply fitting noise rather than identifying actual factors.

To assess this overfitting risk, we run a five-fold cross-validation exercise. The procedure splits the sample into five subsamples, estimates the factor model on one of them, and then assess the models performance on the four subsamples left out. It then repeats this five times and calculates the average performance of the method.

Figure IA.A.1 shows the average root mean-squared errors from the five-fold cross-validation exercise. The results suggests the factors are likely being fit on noise. In fact, adding more factors seems to make the out-of-sample performance even worse. While this finding does not suggest that there is a strong factor structure in flows, it does suggest

Figure IA.A.1: Cross-validation of non-parametric factor estimation



This figure shows the average out-of-sample root mean-squared errors from the five-fold cross-validation exercise, relative to the average out-of-sample root-square error for a model with no principle components. The exercise is repeated for models with a larger number of principle components.

that non-parametric factor estimation may not be able to extract it in our setting with a highly unbalanced panel. Due to this concern, in the next subsection we explore a parametric approach to estimating factors—the additional structure should help reduce the risk of overfitting.

IA.A.2 Parametric Estimation of Flow Factor Structure

Due to the poor performance of the non-parametric method in estimating factors, in this section we follow a parametric approach below. Specifically, let the data-generating process of innovation be:

$$f_{i,t}^{\perp} = \delta_t + \Lambda_{i,t}\eta_t + u_{i,t}, \tag{IA.A.1}$$

where δ_t is the time fixed effects, $\Lambda_i \eta_t$ is the contribution from common factors, and $u_{i,t}$ is the desired idiosyncratic demand shocks.

Following the common approach in asset pricing, we assume the factor loading are a linear function of characteristics, $\Lambda_{i,t} = C'_{i,t}\lambda$, where $C_{i,t}$ is a vector of observable characteristics of fund i, including (lagged) log AUM of the firm, the share in high-yield bonds, and the average duration in the portfolio, and λ is a constant vector. The data generating process of $f^{\perp}_{i,t}$ under this parameterization is then:

$$f^{\perp}_{i,t} = \delta_t + C'_{i,t}(\lambda \eta_t) + u_{i,t}. \tag{IA.A.2}$$

Notice (IA.A.2) can be estimated by running a panel regression of $f^{\perp}_{i,t}$ on $C_{i,t}$ with time-varying coefficients and time fixed effects. In the baseline where no additional factors are controlled, we simply regress $f^{\perp}_{i,t}$ on time fixed effects. The estimated residual is recovered as:

$$\tilde{u}_{i,t} = f^{\perp}_{i,t} - \hat{\delta}_t - C'_{i,t}(\widehat{\lambda \eta_t}) \tag{IA.A.3}$$

To minimize noise due to extreme outliers and volatile funds, we winsorize innovations $f^{\perp}_{i,t}$ at the 5% level before estimating (IA.A.2). Importantly, the winsorized innovations are only used in the estimation of coefficients. In (IA.A.3) we use the original $f^{\perp}_{i,t}$ to recover the demand shock $\tilde{u}_{i,t}$, as outliers are also valid idiosyncratic shocks to demand.

IA.A.3 Multipliers and shock sizes

In this section, we estimate the magnitudes of the bond-level and portfolio-level multipliers for bonds that experienced large shocks. There are two reasons why this might be interesting. First, the effect of the demand shocks may be non-linear, and one might expect large shocks generate larger price responses than small shocks. Second, the bonds with large demand shocks are likely to belong to funds that experienced large fund flows, in which case the passthrough assumption is more likely to hold. The CUSIP-level results are presented in Table IA.A.1, and the portfolio-level results are presented in Table IA.A.2. The estimates are quantitatively similar to what we have in the main text.

Table IA.A.1: Security-level multipliers from large shocks

	Homo. OLS	OLS			First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.38***	0.06	0.04	0.04		0.04
	(0.05)	(0.04)	(0.04)	(0.04)		(0.04)
Substitute return						1.21***
						(0.06)
Group shock					2.79***	
					(0.27)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Group x Quarter FE	No	Yes	Yes	Yes	No	No
ST/LT x Quarter FE	No	No	No	Yes	No	No
Drop Crisis	No	No	Yes	Yes	Yes	Yes
N	152,908	152,905	144,059	144,059	144,061	144,061
R^2	0.21	0.41	0.38	0.40	0.63	0.17
First-stage F-statistic						106.80

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table summarizes the estimates for the CUSIP multipliers when we only consider the subset of bonds with shocks that are above-median shock in size. We control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by the Fama-French 48 industries. Column 1 is the OLS estimates from regressing bond returns on the demand shock, controlling for time fixed effects—this specification corresponds to a model in which we assume homogeneous cross-elasticity with all other bonds. Columns 2 and 3 directly control for close-substitute prices using detailed rating x time fixed effects. Column 4 additional controls for maturity (long-term/short-term) x quarter fixed effects to control for potentially omitted time-varying maturity factor in holding shares. Column 5 and 6 relate to the IV specification in which we regress bond returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to substitute assets. The IV specification corresponds to the model that allows for heterogeneous cross-elasticities between close and distant substitutes. The parentheses contain standard errors clustered at the substitute group x time level.

Table IA.A.2: Baseline portfolio multipliers from large shocks

	Homo. OLS	OLS			First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.89***	0.29**	0.25**	0.25**		0.27**
	(0.11)	(0.10)	(0.10)	(0.09)		(0.10)
Substitute return						1.02***
						(0.06)
Group shock					3.03***	
					(0.34)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Group x Quarter FE	No	Yes	Yes	Yes	No	No
ST/LT x Quarter FE	No	No	No	Yes	No	No
Drop Crisis	No	No	Yes	Yes	Yes	Yes
N	40,036	40,033	37,024	37,024	37,026	37,026
R^2	0.25	0.53	0.48	0.50	0.52	0.26
First-stage F-statistic						76.09

Standard errors in parentheses

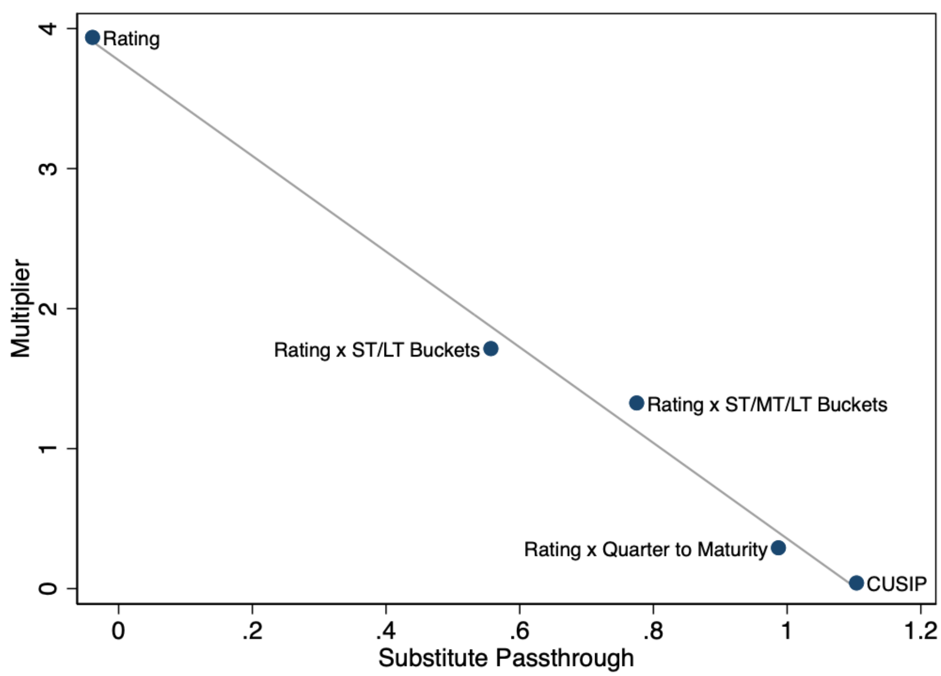
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the quarter to maturity × detailed rating level multiplier estimates using the subset of portfolios that experienced shocks that are above-median in absolute size. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. Column 1 is the OLS estimates from regressing bond returns on the demand shock, controlling for time fixed effects—this specification corresponds to a model in which we assume homogeneous cross-elasticity with all other bonds. Columns 2 and 3 directly control for close-substitute prices using detailed rating x time fixed effects. Column 4 additional controls for maturity (long-term/short-term) x quarter fixed effects to control for potentially omitted time-varying maturity factor in holding shares. Column 5 and 6 relate to the IV specification in which we regress bond returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to substitute assets. The IV specification correspond to the model that allows for heterogeneous cross-elasticities between close and distant substitutes. The parentheses contain standard errors clustered at the substitute group x time level.

IA.B Maturing Bonds

In this section, we show that our baseline results are not driven by bonds that are maturing soon by excluding bonds that have less than one year to maturity. Table IA.B.1 shows that once we control for the close substitute return, the multiplier for individual bonds drops significantly. Table IA.B.2 presents the results for the portfolio level estimates, with and without controlling for close substitute return. The results are quantitatively similar to the main text. Furthermore, Figure IA.B.1 and Figure IA.B.2 show that the aggregation results and dynamic responses hold if we exclude bonds with less than one year to maturity.

Figure IA.B.1: Multipliers and substitute passthroughs for increasingly aggregated bond portfolios (excluding maturing bonds)



The figure plots the multipliers and the substitute passthrough coefficients (the link between substitute and test asset returns) for different levels of portfolio aggregation, excluding bonds with less than one year to maturity. See Table 4 for descriptions of the aggregation and Section 4.2 for the exact specifications. The figure shows a negative relationship between multipliers and substitute passthroughs. It also shows that multipliers are monotonically increasing in aggregation, whereas the substitute passthrough coefficients are monotonically decreasing in aggregation.

Table IA.B.1: Security-level multipliers (excluding maturing bonds)

	Homo. OLS	OLS			First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.41***	0.01	0.04	0.06		0.04
	(0.06)	(0.05)	(0.04)	(0.04)		(0.05)
Substitute return						1.11***
						(0.06)
Group shock					2.89***	
					(0.28)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Group x Quarter FE	No	Yes	Yes	Yes	No	No
ST/LT x Quarter FE	No	No	No	Yes	No	No
Drop Crisis	No	No	Yes	Yes	Yes	Yes
N	301,775	301,775	284,323	284,323	284,323	284,323
R^2	0.22	0.40	0.37	0.41	0.64	0.17
First-stage F-statistic						102.36

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the multiplier estimates for individual securities, excluding bonds with less than one year to maturity. Across all specifications, we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects, defined by Fama-French 48 industries. Column (1) shows the estimates from regressing bond returns on the demand shock, controlling for time fixed effects, as in equation (7). This specification corresponds to a model in which we assume homogeneous cross-elasticity with all other bonds. Columns (2)-(4) show results from running the regression in equation (11) with different definitions of close substitutes. Columns (2) and (3) directly control for close-substitute prices using detailed rating x time fixed effects. Column (4) additionally controls for maturity (long-term/short-term) x quarter fixed effects to control for a potentially omitted time-varying maturity factor in holding shares. Columns (5) and (6) relate to the IV specification in equation (10). We regress bond returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to the substitute portfolio. Column (2)-(6) correspond to the model that allows for heterogeneous cross-elasticities between close and distant substitutes. Standard errors are clustered at the substitute group x time level.

Table IA.B.2: Detailed rating × Quarter-to-maturity portfolio multiplier (excluding maturing bonds)

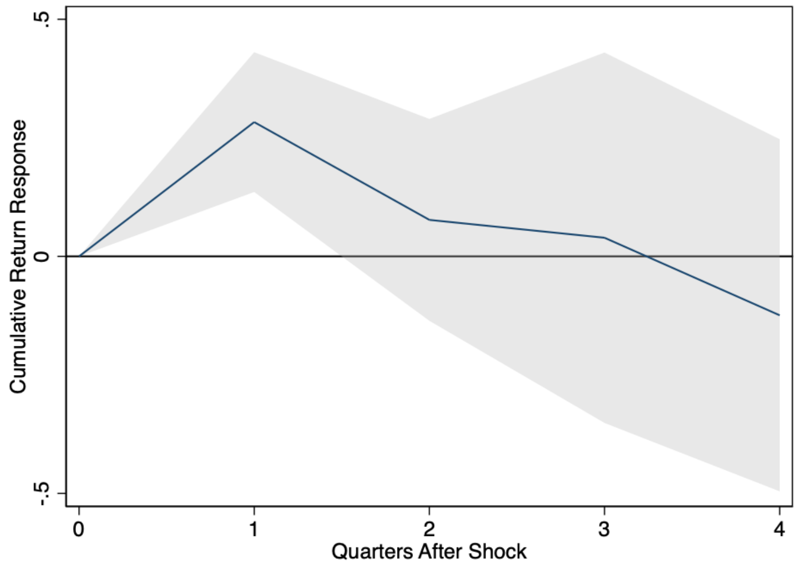
	Homo. OLS	OLS			First-stage	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.96***	0.27**	0.28**	0.30**		0.29**
	(0.12)	(0.10)	(0.09)	(0.09)		(0.10)
Substitute return						0.99***
						(0.05)
Group shock					3.18***	
					(0.34)	
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Group x Quarter FE	No	Yes	Yes	Yes	No	No
ST/LT x Quarter FE	No	No	No	Yes	No	No
Drop Crisis	No	No	Yes	Yes	Yes	Yes
N	76,521	76,521	72,217	72,217	72,217	72,217
R^2	0.24	0.50	0.45	0.47	0.51	0.23
First-stage F-statistic						86.69

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the multiplier and substitute passthrough coefficients estimated for portfolios formed by bonds with the same quarter to maturity and detailed rating, excluding bonds with less than one year to maturity. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. Column (1) shows the estimates from regressing portfolio returns on the demand shock, controlling for time fixed effects, as in equation (11). This specification corresponds to a model in which we assume homogeneous cross-elasticity with all other bonds. Columns (2)-(4) show results from running the regression in equation (11) with different definitions of close-substitutes. Columns (2) and (3) directly control for close-substitute prices using detailed rating x time fixed effects. Column (4) additionally controls for maturity (long-term/short-term) x quarter fixed effects to control for a potentially omitted time-varying maturity factor in holding shares. Columns (5) and (6) relate to the IV specification in equation (10), in which we regress portfolio returns on the demand shock and substitute returns, while controlling for time fixed effects (and additional controls depending on the specification). We instrument for substitute returns using demand shocks to the substitute portfolio. Column (2)-(6) correspond to the model that allows for heterogeneous cross-elasticities between close and distant substitutes. Standard errors are clustered at the substitute group x time level.

Figure IA.B.2: Baseline portfolio price effect dynamics (excluding maturing bonds)



The graph plots the dynamic price effect estimates of the demand shock from equation (18), excluding bonds with less than one year to maturity. The estimates are for the detailed rating × quarter to maturity level (our baseline level of aggregation). Specifically, we regress various leads of the return of the portfolio in excess of its close substitute return on the demand shock. We control for the portfolio average bid-ask spreads, amount outstanding (log), maturity, age and coupon rate, as well as rating fixed effects in all specifications. The shaded region denotes the 95% confidence interval.

IA.C Multiple Substitute Groups

In this section, we explore multiple potential close substitute groups and let the data inform us the most important ones. In Table IA.C.1, we run the IV regression in equation (10), including different and multiple close substitute groups' returns. Specifically, we consider bonds with the same detailed rating, year to maturity, industry and similar amount outstanding as potential close substitutes. We find that for both the CUSIP and the baseline portfolio, the passthrough coefficient on the return of the substitute portfolio defined by the same detailed rating is consistently significant, suggesting other bonds with the same rating indeed serve as close substitutes. In addition, we find that for the baseline portfolio, the passthrough coefficient with respect to bonds in the same maturity group is also significant.

However, the own-multiplier estimate remains quantitatively similar as long as we control for the substitute return based on ratings.

IA.D Substitutions in the Equity Market

In the main text of our paper, we focus on the corporate bond market. A priori, there are clear close substitutes in the bond market, which helps mitigate the effect of demand shocks. Ignoring close substitutes leads to biased multiplier estimates. Our estimates further validate this prior. Stocks, however, do not have clear close substitutes, and therefore it is harder to accommodate demand shocks without large price impacts. Assuming homogeneous substitution when estimating the multiplier is also not far off.

In this section, we confirm this prior on the equity market. Using the same Morningstar fund data, we follow identical procedures in shock construction and identification as in our baseline estimation. We estimate the stock multiplier with and without controlling for its close substitutes—defined in terms of loading on Fama-French three factors, or its industries. We find that controlling for close substitutes does reduce the estimated multiplier, but only very slightly, suggesting that substitutions are way less influential in the equity market than in the bond market.

Table IA.D.1 reports the estimates of the equity multipliers at the stock level. The shocks are constructed in the same way as in the baseline specification for corporate bonds, and the sample covers the CRSP universe of the U.S. listed stocks from 2003Q1 to 2020Q4. In the first column, we regress stock returns on stock level shocks, controlling for the time-fixed effect only. This specification assumes homogeneous substitution patterns across stocks. The point estimate is 0.38, indicating a one-percent demand shock to a single stock leads to a 38 basis points increase in the stock price.

In Column (2), we add group-time fixed effects to control for the close substitutes. The group here is defined as the stocks with similar factor loading as the test stock. Specifically,

Table IA.C.1: Robustness with respect to multiple substitutes

	(1) return	(2) return	(3) return	(4) return	(5) return	(6) return	(7) return
Shock	0.04	0.04	0.04	0.05	0.29**	0.34**	0.34**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.10)	(0.12)	(0.12)
Rating sub	1.11***	1.02***	1.01***	0.99***	0.97***	0.95***	0.98***
	(0.06)	(0.09)	(0.14)	(0.12)	(0.05)	(0.06)	(0.06)
Mat. sub		1.09	1.09	0.97		1.19***	1.26***
		(0.86)	(0.88)	(0.85)		(0.35)	(0.37)
ret_sub_8			0.03	0.09			
			(0.31)	(0.26)			
Size sub				1.04			-0.33
				(0.70)			(0.22)
Security	Cusip	Cusip	Cusip	Cusip	Portfolio	Portfolio	Portfolio
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drop Crisis	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	284323.00	284323.00	284219.00	284219.00	73160.00	73160.00	73160.00
R^2	0.17	0.22	0.22	0.23	0.22	0.25	0.24

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The table presents the multiplier and substitute passthrough estimates for individual bonds (Column 1-4) and benchmark portfolios (Column 5 - 7). Across all specifications, we control for bid-ask spreads, log amount outstanding, maturity, age, coupon rate and detailed rating fixed effects. We also include industry fixed effects for CUSIP-level estimates, defined by Fama-French 48 industries. We include multiple close substitutes' returns, and instrument each with the corresponding portfolio level demand shock. "Rating sub" is the return of portfolios formed by bonds with the same detailed rating. "Mat. sub" is the return of portfolios formed by bonds with the same year to maturity. "Ind. sub" is the return of portfolios formed by bonds in the same industry measured by the 2-digit SIC code and "Size sub" is the return of portfolios formed by bonds in the same size quartile. Standard errors are clustered at the substitute group x time level.

Table IA.D.1: Multiplier estimates for individual stocks

	Stock Return		
	(1)	(2)	(3)
Shock	0.380***	0.254***	0.252***
	(0.086)	(0.040)	(0.072)
Group x Quarter FE	None	FF3	Industry
Quarter FE	Yes	Yes	Yes
N	144,768	136,270	135,201
R^2	0.188	0.332	0.263

This table reports estimates of the multipliers for the stock market at the security level, using the specification in (11). Column (1) reports the multiplier estimate *without* controlling for heterogeneous substitution patterns. Columns (2)-(3) control for group-time fixed effects. In Column (2), the close substitute group is defined as $3 \times 3 \times 3$ bins sorted by loadings on Fama-French three factors. In Column (3), the close substitute group is defined as industry groups following the Global Industry Classification Standard (GICS), with 27 groups in total. The parentheses contain standard errors clustered at the substitute group x time level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

we compute the loading of each stock on Fama-French three factors, and then triple-sort them into $3 \times 3 \times 3$ groups. The total group numbers (27) are comparable with the detailed rating groups in the bond market (21). Controlling for the group-time fixed effects does reduce the point estimate, suggesting that the equity market also exhibits heterogeneous substitution patterns. Nevertheless, the reduction in the multiplier is much less dramatic than the bond market counterpart as reported in 1. After controlling for close substitutes, the multiplier is still around 0.25, only 34% smaller than the univariate regression. To put it into perspective, in the bond market we see an almost 90% drop in the multiplier once controlled for the close substitutes. The multiplier is also much larger than the point estimate in corporate bonds, indicating much inelastic demand in the equity market. This is also consistent with the prior that it is harder to substitute away in the stock market than the bond market. In Column (3) we define the close substitutes in terms of the Global Industry Classification Standard (GICS) industry groups (27 groups in total). The estimate is very close.

In conclusion, we find that the force of heterogeneous substitution is at work in the equity market as well, but it is much weaker than the bond market, consistent with our prior.

IA.E Arbitrage Risk

Consider a two-period economy populated with measure 1 of homogeneous investors. Investors have CARA utility, with absolute risk aversion coefficient γ. There are two risky assets with normally distributed payoff in period 2

$$\begin{pmatrix} D_A \\ D_B \end{pmatrix} \sim N(\mu, \Sigma) \tag{IA.E.4}$$

$$\Sigma = \begin{pmatrix} \sigma_A^2 & \rho\sigma_A\sigma_B \\ \rho\sigma_A\sigma_B & \sigma_B^2 \end{pmatrix} \tag{IA.E.5}$$

In addition, there is a risk-free asset with total return normalised to 1. Investors choose portfolio x to maximize expected utility,

$$x = \frac{\Sigma^{-1}}{\gamma}(\mu - p) \tag{IA.E.6}$$

$$x_A = \frac{\gamma\sigma_B^2(\mu_A - p_A) - \rho\gamma\sigma_A\sigma_B(\mu_B - p_B)}{|\gamma\Sigma|} \tag{IA.E.7}$$

where $|\cdot|$ denotes matrix determinant. Apply market clearing, we get

$$x + u + \nu = \bar{x} \tag{IA.E.8}$$

where u is the observed exogenous demand and ν is the unobserved demand shocks. Focusing on asset A, we can express its price as

$$p_A = \underbrace{\gamma\sigma_A^2(1 - \rho^2)}_{=M} u_A + \frac{\rho\sigma_A}{\sigma_B} p_B + \text{constant} + \underbrace{\gamma(\sigma_A^2\nu_A + \rho\sigma_A\sigma_B\nu_B)}_{\text{error term}} \tag{IA.E.9}$$

The micro multiplier maps to the term $\gamma\sigma_A^2(1-\rho^2)$ in this case, which is determined by both the risk aversion coefficient as well as asset A's residualized risk. To understand the term $\sigma_A^2(1-\rho^2)$, regress asset A's price on its substitute, asset B's price,

$$p_A = \beta_0 + \beta_1 p_B + \epsilon \tag{IA.E.10}$$

the variance of ϵ captures the risk in asset A that cannot be hedged by holding asset B, which is equal to $\sigma_A^2(1-\rho^2)$.

Hence we have shown that the multiplier M is increasing in both the risk aversion coefficient and the residualized risk that cannot be hedged by the substitute portfolio.