Institutional Corporate Bond Pricing*

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Abstract

We estimate an equilibrium demand-based corporate bond pricing model linking institutional holdings to bond characteristics. Our estimates show heterogeneity in demand elasticities across institutions, with elastic mutual funds demanding liquidity, akin to reaching for yield, and inelastic insurance companies. Moreover, we document stark differences in preferences for maturity, credit risk, and liquidity across institutions. In counterfactuals, we evaluate the pricing implications of credit quality migration, mutual fund fragility, monetary policy tightening, and a tapering of the Fed's corporate credit facility. Our model predicts substantial disruptions in bond prices through shifts in institutional demand and identifies the composition of institutional demand as an important state variable for corporate bond pricing.

Keywords: Corporate Bond Pricing, Intermediary Asset Pricing, Demand Systems, Insurance Companies, Mutual Funds, Bond Market Fragility, ZLB, Interest Rate Liftoff, Fed Corporate Credit Facility.

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1. Introduction

The corporate bond market is one of the major sources of funding for U.S. corporations. With around $9 trillion worth of corporate bonds outstanding in total as of 2019, it also provides investors with critical investment opportunities. Yet, the pricing of these instruments is far from being well understood. Indeed, in an influential contribution, Huang and Huang (2012) document a "credit spread puzzle" in that standard structural models of corporate bond pricing predict credit spreads significantly lower than their counterparts in the data. Empirically, this observation suggests that even the most recent refinements of this class of models, based on a representative agent framework, do not realistically capture the tradeoffs that corporate bond investors face.[1] On the flip side, they do not adequately reflect the funding opportunities relevant for corporations. Notably, as opposed to stock markets, from an institutional viewpoint, the corporate bond market has been dominated by long-term investors such as insurance companies and pension funds, as well as, increasingly, mutual funds, but limited involvement by retails investors and hedge funds, for example.

In this paper, we re-evaluate corporate bond pricing by dissecting corporate bond demand at an institutional level. More specifically, following Koijen and Yogo (2019), we estimate an equilibrium demand-based corporate bond pricing model that explicitly recognizes the role of the various main players and their investment mandates in the corporate bond market. The institutional structure of the corporate bond market renders it an ideal environment to apply the demand based asset pricing approach. By carefully linking institutional investors' corporate bond holdings to bond characteristics, we empirically characterize institutions' demand functions and thereby recover estimates of their demand elasticities with respect to movements in prices, as well as to proxies for liquidity, default risk, duration, and issuance size. By aggregating bond demand across institutions and establishing market clearing by matching it with the total value of a bond outstanding, we can compute equilibrium bond

[1] See, e.g., the recent contributions of Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), Chen (2010), or Kuehn and Schmid (2014), who provide risk-based explanations of the credit spread puzzle.

pricing implications of counterfactual redistributions of assets under management across investors, changes in demand functions, or changes in bond characteristics.

The contribution of our paper is threefold. First, we compile a rich and novel dataset that links institutional corporate bond holdings to bond yields, returns, and characteristics. Our combined sample provides comprehensive coverage of insurance companies', pension funds', and mutual funds' corporate bond holdings. Second, we provide novel estimates of institutional investors' demand functions for corporate bonds with different characteristics. Critically, we document significant heterogeneity in demand elasticities across investors, especially with regards to prices, liquidity, credit risk, and maturity. Third, in counterfactual equilibrium simulations, we evaluate the corporate bond pricing implications of i) credit quality migration, ii) mutual fund fragility, iii) monetary policy tightening, and iv) a tapering of the Fed's corporate credit facility. We show that demand heterogeneity substantially shapes price movements in that our model predicts substantial disruptions in corporate bond prices through shifts in institutional demand. Our results thus highlight the composition of institutional demand as an important state variable for corporate bond pricing.

Our comprehensive dataset of holdings, yields, and bond characteristics is based on three major data sources. We exploit quarterly holdings data of bonds from Thomson Reuters eMAXX and carefully match it to monthly prices, yields, and ratings for corporate bonds from the WRDS Bond Returns database. In addition, we obtain bond and issuer characteristics from the Fixed Income Securities Database (FISD). eMAXX provides comprehensive coverage of fixed income holdings by institutional investors (predominantly insurance companies, mutual funds, and pension funds) at the security level. The institutions in our sample collectively hold roughly 50% of the total bond amount outstanding. In terms of the share of the market held, on average, insurance companies hold around 35% of the total amount outstanding, whereas mutual funds hold around 10% at the start of the sample. Notably, by the end of sample period, the share of the market held increases to 23% for mutual funds, mirroring the widely documented rise of corporate bond mutual funds.

With our dataset at hand, we estimate a demand system at an institutional level in equilibrium following Koijen and Yogo (2019). Empirically, the methodology provides us with estimates of investors' elasticities of demand with respect to a number of bond characteristics, as well as the price impact of shocks to latent demand in the aggregate and by different institution types. Latent demand captures investors' preferences, beliefs, and constraints not accounted for by the prevalent characteristics themselves such as unexpected changes in the regulatory environment. Specifically, we link investors' portfolio weights in a bond to the bond's yield, size, liquidity, default risk, time to maturity, and coupon. Given the joint endogeneity of an investor's portfolio weights in a bond and its yield, we instrument the latter with the remaining investors' holdings. These are plausibly exogenous to current demand shocks because corporate bond portfolios of institutions are very persistent over time. This implies that institutions have a relatively restricted and pre-determined investment universe, possibly because they follow a set of fixed investment mandates.

We document that the main investors in the corporate bond market exhibit vastly different demand elasticities. Moreover, preferences for different bond characteristics also vary starkly across institution types, implying that the corporate bond market is highly segmented. The starkest differences in demand parameters exist for the two largest institutional investors in corporate bonds: life insurers and mutual funds. Indeed, life insurance companies exhibit inelastic demand, tilt portfolios to investment grade bonds, consistent with a sharp discontinuity in capital requirements at the IG-HY threshold, long-dated bonds, and bonds with smaller issuance size. They are also willing to hold illiquid bonds. Notably, life insurers have become more inelastic over time. In contrast, mutual funds, with shorter investment horizons, have more elastic demand, preference for high yield and short-dated bonds, bonds with larger issuance size, and demand liquidity. At a more aggregated level, we find that the market-wide elasticity for the corporate bond market as a whole is around 3.7, larger than that of the U.S. stock market, suggesting that bonds may be closer substitute to each other than stocks. Regarding price impact, we find that it increased substantially during the financial crisis, and has remained high for a large part of the post-crisis period, consistent with the notion that higher bank capital requirements and the Volcker rule have limited banks' market making activities and thus potentially undermined investors' ability to adjust their portfolios without impacting prices too much.

Finally, our counterfactual experiments provide a quantitative perspective on the effects of the recent macroeconomic environment on equilibrium corporate bond prices. To begin with, our estimated model predicts significantly higher credit spreads in a scenario of a large credit quality migration, such as an overall perceived deterioration of credit quality, as observed at the onset of the recent Covid-19 crisis. The rise is most pronounced for investment grade bonds held by insurance companies that are downgraded, as in such a scenario insurers face sharply rising capital requirements. Similarly, the rising presence of mutual funds in the corporate bond market in the wake of falling interest rates have given rise to concerns about market fragility because of potential fire sales caused by large-scale redemptions from bond market funds. We find that the rise of mutual funds significantly lowered the costs of debt financing at the lower end of the maturity spectrum and for lower credit ratings. Similarly, a potential bond fire sale by large mutual funds would substantially increase the credit spreads for short-dated, high credit risk bonds, as those would have to be absorbed by market participants with a preference for long-term bonds, such as insurance companies. On the flipside, we estimate the significance of mutual funds to be shrinking in scenarios with rising interest rates in the context of a monetary tightening, perhaps due to concerns about a persistent rise in inflation, in line with the expectations of policymakers and academics who have conjectured that mutual fund sector may shrink in size going forward as interest rates begin to rise. Our model predicts significantly higher credit spreads surrounding an interest rate liftoff, especially with short-term and high-yield bonds. In the model, this arises as mutual fund outflows are absorbed by insurers, whose preferences are tilted towards long-term investment grade bonds. On the other hand, a tapering of the Federal Reserve's Corporate Credit Facility would only have negligible effects on credit spreads and the costs of debt through the lens of our model, primarily reflecting its modest size to begin with.

Overall, our findings suggest that the type of investors holding and demanding bonds affects equilibrium bond prices, in contrast to the implications of standard representative-agent based models of corporate bond pricing. Moreover, our findings suggest that disruptions would disproportionately affect the cost of financing of firms whose bonds are held by mutual funds given the segmentation in the bond market that we document. Our model thus emphasizes the composition of institutional demand as an important state variable for corporate bond pricing and allows to shed some light on the consequences of policy changes that have the potential to affect the real economy through their effects on the costs of debt financing.

Related literature: Our paper is related to several strands of the literature on corporate bonds pricing and liquidity. Motivated by the new demand-based asset pricing literature (Koijen and Yogo (2019)), we estimate a demand system for U.S. corporate bonds. The corporate bonds market makes for an ideal setting for a demand-based asset pricing approach as it is dominated by financial institutions that plausibly have significantly different preferences and constraints. From an asset pricing stand point, our work therefore provides a complementary perspective to structural models of credit risk based on Leland (1994) and expanded on more recently by Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), Chen (2010), and Kuehn and Schmid (2014).

Given the emphasis on the role of financial institutions, our work is also related to the growing literature that emphasizes the role of financial intermediaries in asset pricing. A number of critical contributions include the work by He and Krishnamurthy (2012), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Adrian, Etula, and Muir (2014), and He, Kelly, and Manela (2017), to name a few. Our findings suggest that considering the effects of investor heterogeneity could be of further help in improving the performance of these asset pricing models, at least in the context of corporate bonds.

Our paper also relates to the debate about whether the post-crisis changes in regulation, e.g. Volcker rule, led to a reduction in corporate bond market liquidity (Duffie (2012)).

While Trebbi and Xiao (2019) finds no evidence of liquidity deterioration during periods of regulatory intervention, Allahrakha, Cetina, Munyan, and Watugala (2019), using confidential supervisory data on dealer-identified corporate bond trading, find that Volcker rule has reduced the liquidity of corporate bonds.[2] Our estimation allows us to directly quantify the price impact of institutions' portfolio adjustments. Thus, we contribute to this debate in two ways. First, we show that price impact of of institutional trades have increased considerably after the financial crisis, consistent with the concerns that investors are unable to make large trades without impacting the prices. In addition, we can distinguish the price impact of portfolio adjustments at different times, for different institutions, and for different bonds, which can help shed light on the mechanisms by which liquiduty may have deteriorated in these markets.

Since the financial crisis, policymakers, practitioners, and academics have debated whether large redemption demand from bond mutual funds can create a potential for fire sales leading to dislocation of asset prices from fundamental values. Related to this, recent work argues that bond mutual funds engage in liquidity transformation by offering daily liquidity to holders but invest in illiquid assets (see, for example, Ben-Rephael, Choi, and Goldstein (2020) and Ma, Xiao, and Zeng (2020)). We contribute to this literature in two ways. First, we show that while it is true that corporate bonds are illiquid in general, our results imply that within the corporate bonds market, mutual funds do not select into the most illiquid bonds. Second , this literature has not explored the role of liquidity providers when mutual funds potentially engage in fire sales. We document the presence of two divergent investor classes who have heterogeneous preference and demand for liquidity. Our findings highlight the importance of taking account of this heterogeneity in order to fully understand the asset

[2] In addition, various policy reports also find conflicting evidence. 2015 Financial stability report by The Bank of England highlighted that the average size of a large trade in U.S. investment grade corporate bonds has declined by almost 30% since 2007. Also, see Anderson, Webber, Noss, Beale, and Crowley-Reidy (2015). However, Adrian, Fleming, Shachar, Stackman, and Vogt (2015) conclude that price-based liquidity measures (bid-ask spreads and price impact) are very low by historical standards, indicating ample liquidity. Bao, O'Hara, and Zhou (2018) show that bonds have become less liquid during times of stress due to the Volcker Rule and reduction in market-making activities by dealers regulated by the rule as not been offset by non-Volcker-affected dealers. Anderson and Stulz (2017), provide evidence that liquidity is lower after the crisis for extreme VIX increases but not for idiosyncratic stress events.

pricing dynamics driven by shocks originating in the mutual funds sector.[3]

Our results also complement the existing literature on insurance companies' investment decisions for corporate bonds. For example, Becker and Ivashina (2015) show that insurers invest in highly rated bonds, but controlling for regulatory risk weights select into more credit risky bonds. Choi and Kronlund (2018) examine the reaching for yield strategies of corporate bond mutual funds. Ellul, Jotikasthira, and Lundblad (2011) provide evidence of fire sale in downgraded corporate bonds. Ge and Weisbach (2020) show that Property and Casualty insurers invest in safe bonds following losses. In particular, Ellul, Jotikasthira, Kartasheva, Lundblad, and Wagner (2018) and Sen and Sharma (2020) explore potential reasons why insurers may have a preference for illiquid assets. Sen and Sharma (2020) also show that insurers increased the holdings of illiquid bonds (e.g. private placements and corner small bond issues) during and after the financial crisis. Koijen and Yogo (2022) show that insurers' large allocation to corporate bonds can be understood within the context of an asset pricing model with leverage-constrained households and institutional investors. Relatedly, Greenwood and Vissing-Jorgensen (2018) and Jansen (2021) examine the impact of insurers and pension funds' investment decisions on government bond yields.

Roadmap: We describe our data sources and detail the construction of our dataset in section 2. In section 3, we introduce our demand system for corporate bonds, and show how we implement it empirically. Section 4 reports the main estimation results. In section 5, we describe trends in price impact and liquidity. Section 6 provides a detailed examination of our counterfactual equilibrium simulations. Section 7 provides a few concluding remarks.

2. Institutional Corporate Bond Holdings Data

An important aspect of our approach is a dataset linking corporate bond holdings, yields, and characteristics. We start by describing our data sources and the construction of our rich

[3]Perhaps, unsurprisingly Choi, Hoseinzade, Shin, and Tehranian (2020) find no evidence of redemption driven price dislocation between 2009 and 2017, suggesting that it would take a much larger redemption shock for prices to get dislocated substantially. The evidence in Falato, Goldstein, and Hortaçsu (2020) and Haddad, Moreira, and Muir (2020) during the COVID-19 crisis would be consistent with this notion.

and comprehensive dataset.

2.1. Data Sources and Sample Construction

Our sample combines data from three sources. We obtain monthly prices, yields, and credit ratings of corporate bonds from the WRDS Bond Returns database. We obtain the quarterly holdings of bonds from Thomson Reuters eMAXX. In addition, we obtain bond and issuer characteristics, e.g., maturity, coupon, currency, issuer domicile, rule 144 classification, from the Fixed Income Securities Database (FISD).

We start the sample construction by obtaining the time series of corporate bonds' prices and yields at a monthly frequency from the WRDS Bond Returns database. The WRDS database collects the transactions reported in TRACE (Trade Reporting and Compliance Engine) to identify bond prices, which it uses to subsequently compute bond yields. As the holdings data are at a quarterly frequency, we convert the data from monthly to quarterly frequency by taking the last available price and yield of each bond in a given quarter.

The availability of prices in the WRDS database hinges upon observing a transaction of a given bond in TRACE. As some bonds may not trade frequently and therefore may not be present in the WRDS database, we check the quality of the coverage relative to the overall U.S. corporate bond universe. To construct the U.S. corporate bond universe, we follow an approach similar to Asquith, Au, Covert, and Pathak (2013) and identify corporate bonds in FISD that are denominated in U.S. dollars, are issued by firms domiciled in the U.S., and are publicly traded. We exclude convertible bonds and bonds that had no outstanding amount in a given quarter. This definition of the U.S. corporate bond universe, which we refer to as the publicly traded bond universe, yields a total outstanding of 6.5 trillion U.S. dollars in 2019 (by par value). We next merge the bonds that are in the WRDS database with the publicly traded bond universe. Table A.1 shows the coverage of the WRDS database over the years. On average, the WRDS database contains the prices and yields of around 90% of the bonds that are part of the publicly traded bond universe. The coverage improves over time from 77% in 2006 to about 93% in 2019.

Next, we merge the matched bonds in the WRDS database with the Thomson Reuters eMAXX database to obtain information on investors' bond holdings. eMAXX provides a comprehensive coverage of fixed income holdings of institutional investors at a security (CUSIP) level.[4] The database predominantly covers the holdings of insurance companies, mutual funds, and pension funds (Becker and Ivashina (2015)).[5] We include both the U.S. eMAXX, which covers the holdings of North American investors, and global eMAXX, which provides the holdings of foreign investors in Europe and Asia Pacific. We complement the U.S. database with the global database because foreign funds hold a non-trivial fraction of the corporate bond market. The eMAXX holdings data are quarterly and cover the period from quarter 1 2006 to quarter 3 2020. Our final sample consists 20 million bond $\times$ institution $\times$ quarter observations.[6,7]

Table 1 provides an overview of the bond holdings in our final sample. The number of financial institutions in our sample increases over time and ranges from around 1,300 at the start of the sample to around 3,400 at the end of the sample. On average, the institutions in our sample collectively hold roughly 45% to 50% of the total corporate bonds' amount outstanding. The median (90th percentile) institution by assets under management (AUM) holds \$55 million (\$630 million) of assets at the start of the sample, which increases to \$75 million (~\$1 billion) by the end of the period. The median (90th percentile) institution by number of bonds held holds 50 to 85 (160 to 375) unique bonds during the sample period.

2.2. Sample Representativeness and Coverage

We next examine whether our sample represents the overall institutional holding patterns and the composition of corporate bonds' outstanding well.

[4]Fixed income holdings in eMAXX also include government and municipal bonds. As the focus of the paper is corporate bonds we exclude these from our sample.

[5]The database does not cover the holdings of institutional investors including hedge funds and banks.

[6]We exclude zero holdings of institutions. The number of observations would be roughly 80 times larger if we had included the zero holdings of institutions, due to the inclusion of both a larger number of institutions and a larger number of bonds.

[7]In the event that eMAXX cannot obtain updated holdings in a given quarter from an institution, the previous quarter's holdings are reported. We drop such stale holdings.

By institution type: To check the distribution of holding patterns, we plot the share of the total bonds outstanding held by different types of institutions using the U.S. Flow of Funds (FoF) accounts. First, Figure 1 shows that insurance companies and mutual funds are the largest holders of corporate bonds, together accounting for close to 60% of the total bonds outstanding. Pension funds are the third largest class. Second, the share of the total bonds outstanding held by mutual funds has increased, especially after the financial crisis.

The ownership patterns in our sample closely mirror the ownership patterns we observe in the FoF data, both in levels and in trends. Consistent with the FoF data, the predominant institutions in our final sample consist of insurance companies and mutual funds. The remaining institutions include other long-term investors such as pension funds, endowments, and sovereign funds. Table A.2 provides a breakdown of the total outstanding by institution type. Life insurance companies hold around 35% of the total outstanding, whereas mutual funds hold around 5% at the start of the sample. Over time, we see an increase in the share of the total market held by mutual funds and, by the end of our sample, in 2020 they hold around 15% of the total outstanding. This is consistent with the broad trend observed in the FoF that the holdings of bond mutual funds have increased since the financial crisis. These patterns give us confidence that our sample is a fair representation of the holding patterns observed in the corporate bond market. In particular, our sample well captures the three main types of investors, who account for over 70% of the overall market.

By bond characteristics: To check the composition of corporate bonds' outstanding, we evaluate the distribution of the two main bond characteristics: (i) ratings and (ii) maturity. Table A.3 provides the distribution of credit ratings by total par value in the holdings data compared against the overall market. The distribution of bonds in the holdings data closely matches the overall market. On average in the holdings data, 85% of the bonds belong to the investment grade category (BBB or above) compared to 84% in the overall market. Moreover, the distribution in the holdings data does not skew towards any particular rating category. Table A.4 provides the distribution of total outstanding by maturity buckets. On average, in the holdings data, 35% of the bonds have less than 5 years remaining maturity, 37% have remaining maturity between 5 to 10 years, and 28% have remaining maturity greater than 10 years. Broadly speaking, this is comparable to the distribution present in the overall market. However, we note that our sample contains a slightly lower number of short-maturity bonds. We also observe that insurance companies hold a small proportion of bonds in the high yield category and a large proportion of long maturity bonds, which is consistent with the holdings of insurers obtained from their regulatory fillings.

3. A Demand System for Corporate Bonds

In this section we outline our characteristics-based demand system that describes investor demand in corporate bonds. We do so by building on the work of Koijen and Yogo (2019) and Koijen et al. (2020b). That is, we focus on bond-specific characteristics in our demand system, which capture expected returns and risk of corporate bonds.

3.1. Characteristic-Based Demand

We index investors by $i = 1, \ldots, I$. Further, we index corporate bonds by $n = 0, \ldots, N$, where $n = 0$ corresponds to the outside asset and, finally, time is denoted by t. Hence, the yield of bond n is denoted by $y_t(n)$. Each bond is associated with a vector of observed bond characteristics, $\mathbf{x}_t(n)$, which includes time to maturity, bond rating, initial offering amount, and the bid ask spread.

Investor i has total wealth $A_{i,t}$, which she allocates across bonds in her investment universe and an outside asset. The outside asset is comprised of all observed bonds that are not part of our definition of the U.S. corporate bond universe. Following Koijen and Yogo (2019), we assume that investors choose bonds only from their investment universe, denoted by $N_{i,t}$. The assumption that investors can only invest in bonds in their investment universe is motivated by the fact that investment managers hold very concentrated portfolios, likely restricted by their investment mandates.

The portfolio weights of investor i in bond n are denoted by $w_{i,t}(n)$, where $\sum_{n=0}^{N} w_{i,t}(n) =$

1:

$$w_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in N_{i,t}} \delta_{i,t}(m)} \tag{1}$$

where $\delta_{i,t}(n) = \frac{w_{i,t}(n)}{w_{i,t}(0)}$ and the portfolio weight in the outside asset is $w_{i,t}(0) = 1 - \sum_{m \in N_{i,t}} w_{i,t}(m)$.

Koijen and Yogo (2019) derive an empirically tractable model of portfolio weights from traditional portfolio theory, based on three assumptions. First, investors have preferences such that the optimal portfolio is a mean-variance portfolio (Markowitz (1952)). Second, returns follow a factor structure, which has been shown to be relevant in the context of corporate bond returns (among others, Bessembinder, Kahle, Maxwell, and Xu (2009) and Bali, Bai, and Wen (2019)). Third, both expected returns and factor loadings depend only on an asset's own prices and characteristics. Under these assumptions, we can write the portfolio weight from equation (1) as a logit function of the yield $y_t(n)$ and a vector of characteristics $\mathbf{x}_t(n)$:

$$\ln \frac{w_{i,t}(n)}{w_{i,t}(0)} = \ln \delta_{i,t}(n) = \alpha_i + \beta_{0,i} y_t(n) + \beta_{1,i}' \mathbf{x}_t(n) + u_{i,t}(n) \tag{2}$$

where $u_{i,t}(n) = \ln U_{i,t}(n)$ is the log of latent demand which captures investor i's demand that is not well explained by observed yields and characteristics.

The bond characteristics in $\mathbf{x}_t(n)$ are meant to capture key sources of risk. We include the following three key bond characteristics. (i) To capture credit risk, we follow Bali, Bai, and Wen (2019) and use Standard & Poor credit ratings obtained from the WRDS returns database. We convert bonds' ratings into a numeric scale using the numerical ratings provided in the WRDS database for each rating category. Numerical ratings range from 1 (AAA) to 21 (C-). (ii) Following Koijen, Koulischer, Nguyen, and Yogo (2020a), we include a bond's time to maturity to capture duration risk. (iii) Finally, liquidity is shown to be an important determinant of corporate bond risk (see e.g., Dick-Nielsen, Feldhütter, and Lando

(2012) and Chen, Lesmond, and Wei (2007)). We capture liquidity by including the bond's bid-ask spread. In addition, we include the size of a bond, i.e., the initial offering amount, which can be seen as another proxy for liquidity.

3.2. Market Clearing

We complete the asset pricing model by imposing market clearing for each bond. That is, the market value of a bond must equal the wealth-weighted sum of the portfolio weights across all investors. Hence, we impose for each bond n at time t

$$M_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n) \tag{3}$$

where $M_t(n)$ is the market value of bond n. For each bond, we define the share held by the residual sector as the difference between the bonds' outstanding amount and the sum of the dollar holdings across all institutions observed in eMAXX. The residual sector represents holdings of institutions that are not currently captured by our sample, e.g., banks, hedge funds, government agencies, and households. Moreover, we also include as part of the residual sector any institution that has less than $10 million in assets under management.

3.3. Identification Strategy

Estimating equation (2) implicitly requires $\mathbb{E}\left[u_{i,t}(n) \mid y_t(n), \mathbf{x}_t(n)\right] = 0$ to hold. As discussed above, we entertain the assumption that characteristics other than yields are exogenous, determined by an exogenous endowment process. Hence, this assumption takes care of the characteristics in $\mathbf{x}_t(n)$ in the previous expression. This leaves us with the orthogonality restriction of yields, $y_t(n)$. Usually, this is justified with investors being atomistically small, so that demand shocks have negligible price impact. However, even if individual investors are atomistic, correlated demand shocks could have price impact in the aggregate which rules out any factor structure in latent demand. As a result, latent demand, $u_{i,t}(n)$, is generally correlated with yields. Therefore, we need an instrumental variable for $y_t(n)$.

Our instrument is closely related to the instrument adopted by Koijen and Yogo (2019), which makes use of investment mandates at the institution level. Investment mandates restrict an institution's investment universe, i.e. the group of securities in which the institution may invest. It is plausible that institutional investors have investment mandates. For example, they may invest in a certain subset of bonds, e.g., investment grade bonds, or track a particular corporate bond index. For most investors, unfortunately, it is hard to directly observe their investment mandates. Consequently, we empirically verify whether institutions indeed invest in a fixed subset of bonds. To that end, we examine whether institutions' portfolios are persistent over time. Table 2 reports the percentage of bonds held in the current quarter that were also held in any of the previous 1 to 11 quarters. For the median institution by assets under management (AUM), 91% of bonds that are currently held were also held in the previous quarter. This fraction increases slowly to 98% at 11 quarters. This indicates that corporate bond portfolio compositions are very persistent over time and institutions invest in a relatively fixed subgroup of bonds over time. This is largely consistent with institutions having a restricted and pre-determined investment universe, possibly because they follow a set of fixed investment mandates. Importantly, the pre-determined investment universes are exogenous to demand shocks.

However, the strength of the instrument also depends on its cross-sectional variation, which is primarily driven by variation in the investment universes across institutions. Put differently, the instrument would have no variation if the investment universe were identical across institutions. Fortunately, from an identification perspective, Tables 1 and A.2 show that the investment universe is typically a relatively small set of bonds given that the median institution holds between 48 and 86 bonds. This implies substantial cross-sectional variation in the investment universe across institutions.

Based on the persistent holding patterns for corporate bond investors in the data, we define an institution's investment universe at each date, $N_{i,t}$, as the subset of bonds that are either held currently or were held at any point in the previous 11 quarters.[8] Based on this

[8]Importantly, corporate bonds have a predetermined expiry date. As a result, whenever a bond has

assumption, we instrument the yield of bond n at time t as follows

$$\widehat{\mathrm{y}}_{i,t}(n) = \log\left(\sum_{j\neq i} A_{j,t}\frac{\mathbb{1}_{j,t}(n)}{1+\sum_{m=1}^{N}\mathbb{1}_{j,t}(m)}\right)$$

where the indicator function $\mathbb{1}_{j,t}(n)$ equals one if bond n at time t belongs to the investment universe of investor j (i.e, $n \in N_{j,t}$). Hence, the instrument depends only on the investment universe of other investors, which are exogenous under our identifying assumptions. Intuitively, when a certain bond issue is included in the investment universe of more investors, particularly in the investment universe of large investors, it has a larger exogenous component of demand. A large exogenous demand component generates higher prices and, hence, lower yields that are orthogonal to latent demand.[9]

3.4. Implementation

Table 1 shows that many institutions have concentrated portfolios, so the cross-section of an institution's holdings may not be large enough to accurately estimate equation (2). To overcome this issue, we estimate the demand system with two different methods.

First, we pool all institutions of the same type and estimate investor group specific instrumental variable (IV) regressions. We group institutions into the following broad groups: (i) insurance companies, (ii) mutual funds, (iii) other US institutions and pension funds, and (iv) foreign institutions. Further, we break insurance companies into life insurers and property and casualty (P&C) insurers. Similarly, we break mutual funds into traditional mutual funds, which also include bond ETFs, and variable annuity (VA) funds.[10] Our

matured, there is no way an investor can buy again the very same bond. Hence, the concept of investment mandates cannot apply for matured bonds. Put differently, allowing for zero holdings of already matured bonds is non-sensual. Such a concern is particularly important in the presence of buy and hold investors. As a result, in our definition of the investment universe, we only consider bonds that have not matured yet, i.e., are still alive. Relatedly, Yu (2020) chooses a slightly different approach and defines the investment universe at the issuer rather than at the bond level.

[9] To make our instrument more robust, we exclude the residual sector and aggregate only over institutions with little variation in their investment universe. That is, we only rely on institutions where at least 95 percent of the current bond holdings are included in the investment universe.

[10] While variable annuities are administered by life insurance companies, they invest policyholder funds in mutual funds. Thus, we group variable annuities within mutual funds.

estimations use a weighted IV regression setup to account for the substantial heterogeneity in the size (i.e., total AUM) of institutions within a group.

Second, we estimate the demand functions at the institution level for each quarter. That is, we follow the approach of Koijen and Yogo (2019) and estimate the coefficients for each institution whenever there are more than 1,000 strictly positive holdings. For institutions with fewer than 1,000 holdings, we pool together similar institutions in order to estimate the demand coefficients. In particular, institutions are grouped by type and quantiles of AUM. The investor type specific panel regressions allow us to assess the cross-sectional heterogeneity in demand functions across broad investor groups. The estimations at the institution level are more granular and offer not only insights about cross-sectional differences in demand functions but also how these differences evolve over time.

Another challenge is that most corporate bonds pay non-zero coupons. While estimating the demand system with yield-to-maturities for coupon paying bonds is not intractable, the computations get more involved in conducting counterfactual equilibrium simulations, as we further discuss in Section 6. To preempt these issues, we calculate bond-specific pseudo zero coupon yields based on yield-to-maturities. Appendix B describes the main steps of our computations. Importantly, however, the estimates for the demand system do not change in any meaningful way if we use yield to maturities of the coupon bonds rather than the corresponding pseudo zero coupon yields.

4. Estimated Demand System for The Corporate Bond Market

This section documents the main results from estimating the characteristics-based demand system in equation (2). We first estimate the demand system using a pooled (AUM weighted) IV regression for each institution type for the full sample period from 2005:1 to 2020:3. In our estimations, we include Fund $\times$ Quarter fixed effects to exploit the variation in holdings across bonds but for the same fund and quarter. Next, to understand the time-series dynamics and how the demand parameters evolve over time, we estimate the demand system for each quarter separately.

First Stage Results: We start by presenting the first-stage results. Table 3 reports the distribution of the first-stage t-statistics and illustrates the strength of the instrument used in the IV estimation. Panel A shows the results by investor groups. The absolute value of the t-statistics are generally well above the critical value for rejecting the null of weak instruments at the 5% level (Stock and Yogo (2005)).[11] Panel B shows the results over time. Notably, the first-stage holds strongly even during the financial crisis (between 2008 and 2010). Note that the t-statistics are negative because there is a negative (positive) relationship between the shocks to the investment universe of a bond and its yields (prices). For the panel regressions, the Kleibergen-Paap F-statistic documents the strength of the first-stage regression. For all institution types, Table 4 shows that the Kleibergen-Paap F-statistic is substantially above the Stock and Yogo (2005) critical value of 10 for rejecting the null of weak instruments.

4.1. Estimated Demand Parameters

Table 4 shows the results from the panel regression. We find that the main investors in the corporate bond market exhibit vastly different demand elasticities. Moreover, preferences for different bond characteristics also vary starkly across institution types, implying that the corporate bond market is highly segmented. The starkest differences in demand parameters exist for the two largest institutional investors in corporate bonds: life insurers and mutual funds. In Figure 2, we plot the estimated coefficients over time and find that the differences in the demand parameters across insurers and mutual funds are persistent over time. We next discuss the estimates characteristic by characteristic below.

4.1.1. Yield

There are three main facts to note about institutions' demand elasticities with respect to bond yields. First, Table 4 shows that mutual funds, pension funds, and foreign investors

[11] The only institution type for which we cannot overwhelmingly reject the null of weak instruments are foreign institutions. However, note that even for foreign investors the t-statistics are above the Stock and Yogo (2005) critical value for a vast majority of investors.

are significantly more elastic with respect to bond yields.[12] In contrast, insurance companies have less elastic demand. Moreover, there is substantial heterogeneity within the insurance sector, with life insurers being less elastic compared to P&C insurers. Second, the differences between mutual funds and insurers, the two largest investor groups, are persistent over time. To understand how the demand elasticities evolve over time for these two investor types, Figure 2a plots the AUM weighted coefficients along with their 95% confidence intervals on the right hand side panel for each quarter. Figure 2a shows that mutual funds have more elastic demand than life insurers consistently in most time periods. Third, while demand is downward-sloping for mutual funds throughout the sample period, demand becomes upward-sloping with respect to bond prices after 2011 for life insurers. This can be seen from the negative coefficients on yield for life insurers: as yield decreases (price increases) demand increases for life insurers. In Section 4.2, we transform these estimates to price elasticities and discuss the institutional factors contributing to these trends.

4.1.2. Time to Maturity

Table 4 shows the coefficient on bonds' time to maturity, which captures preference for duration risk across institutions. We find that the corporate bond market is highly segmented along maturity. The coefficient on time to maturity is positive for life insurers, but it is negative for mutual funds. In other words, life insurers tilt their portfolios toward bonds with longer maturities. In contrast, mutual funds tilt their portfolios toward bonds with shorter maturities. Other investors (e.g., foreign and P&C insurers) also have a preference for short maturity bonds, similar to mutual funds. Finally, Figure 2c shows that the differences in preference for duration risk is highly persistent over time across the two main institution types (life insurers and mutual funds).

The heterogeneity in the preference for duration risk is consistent with the institutions' liability structure. Mutual funds have short-dated deposit like liabilities, which potentially

[12] Even though pension funds are long-dated investors like insurance companies, we find that pension funds are relatively more elastic and behave similar to mutual funds. This result might be driven by the fact that we observe relatively few pension funds in our data.

subject them to runs (Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017)). Life insurers, on the other hand, have long-dated liabilities. In addition, insurance products often also embed fees that make it costly for consumers to withdraw from these funds. Both these factors make the effective duration of insurance liabilities high (Domanski, Shin, and Sushko (2017)). Thus, consistent with duration hedging and models of preferred habitat (Vayanos and Vila (2009)), we observe that insurers have an inelastic demand for long maturity bonds to hedge long-dated liabilities, and mutual funds have a demand for short maturity bonds to hedge short-dated deposit like liabilities.

4.1.3. Liquidity

Table 4 shows the coefficient on bonds' bid-ask spreads, which captures preferences for liquidity across institutions. We find significant differences in the demand for liquidity across institutions. Mutual funds, pension, P&C insurers, and foreign institutions have a negative coefficient on the bid-ask spread, implying that they tilt their portfolios towards bonds that have a lower bid-ask spread, i.e. more liquid bonds. In contrast, life insurers have a positive coefficient on the bid-ask spread, i.e. they tilt their portfolios toward bonds that have a higher bid-ask spread, suggesting a preference for illiquid bonds.[13] Figure 2e shows that the differences across the two main institution types (life insurers and mutual funds) are persistent over time. This implies that mutual funds demand liquidity in the corporate bond market throughout, in line with the fact that they offer daily liquidity to investors.

These results shed new light on the existing literature on bond mutual funds. Bond mutual funds engage in liquidity transformation as they invest in corporate bonds, which are relatively speaking an illiquid asset class, and in turn provide daily liquidity to beneficiaries (Falato, Goldstein, and Hortaçsu (2020)). While it is true that corporate bonds are illiquid in general, our results demonstrate that within corporate bonds, mutual funds do not select into the most illiquid bonds. Our results thus indicate that the extent of liquidity transformation is less than previously suggested in the literature. This has consequences for the magnitude

[13] For example, Ellul, Jotikasthira, Kartasheva, Lundblad, and Wagner (2018) and Sen and Sharma (2020) offer reasons why insurers have a preference for illiquid assets.

of fire selling that should be expected from bond mutual funds' activities.

4.1.4. Bond Size

We next examine how demand varies by a bond's issuance amount by including the log issuance amount in our estimation. As the specification controls for bonds' liquidity, the coefficient on log issuance amount helps capture the demand for bond size after factoring in liquidity. Three results stand out. First, mutual funds have a preference for larger bonds relative to P&C and life insurers (Table 4). In particular, the differences in demand are significant for life insurers and mutual funds (Figure 2g). Throughout the sample, mutual funds tilt their portfolios toward larger bonds. In contrast, insurance companies tilt their portfolios toward smaller bonds. Second, we find that mutual funds' demand for large bonds has been increasing over time. As large bonds are also likely to be more liquid, this evidence is consistent with mutual funds' demanding more liquid bonds (see above). Third, there is an increase in the demand for small bonds in the few quarters around the financial crisis for insurers, consistent with Sen and Sharma (2020).[14] To the extent that a bond's size proxies for the issuing company's size, our results suggest that insurers are more likely than mutual funds to provide debt financing to smaller companies.

4.1.5. Default Risk

Table 4 shows the coefficient on bonds' credit rating score, which captures a bond's credit risk. Recall that we convert ratings into a numerical scale, using the numerical ratings provided in the WRDS Bond Returns database. The coefficient on the credit rating score is consistently negative across all institution types. However, the estimates vary considerably across institutions and, in particular, across life insurers and mutual funds (Figure 2i).

To understand how segmented is the bond market along the rating dimension, we conduct the estimation within investment grade (IG) and high yield (HY) buckets. In Table A.5, we include a dummy variable which takes a value of 1 for HY bonds and 0 for IG bonds. To understand how demand varies within each bucket, we also interact the rating bucket

[14] Sen and Sharma (2020) show that insurers corner small bond issues during and after the financial crisis.

dummies with the numerical rating scores.

Two facts stand out. First, the coefficient on the HY dummy is negative and statistically significant for life insurers and positive and statistically significant for mutual funds and foreign investors. Thus, on average, life insurers prefer IG bonds, while mutual funds and foreign investors prefer HY bonds. Second, within each bucket, the nature of the demand also varies considerably. Life insurers appear to mainly care about the IG-HY distinction and their demand is relatively insensitive to default risk within the IG and HY buckets, as seen from the statistically insignificant coefficients on the *Rating* interaction terms in Table A.5. This pattern is consistent with the fact that insurers face sharp discontinuity in capital requirements at the IG-HY threshold and that they have a tendency to reach for yield within rating buckets that have similar capital requirements (Becker and Ivashina (2015)). In contrast, mutual funds' demand is sensitive within IG and HY buckets, with demand tilting towards safer bonds within each bucket. Even so, they appear less sensitive to default risk within IG bonds than within HY bonds. These facts strongly suggest that different types of institutions appear to specialize in different parts of the credit spectrum, driven perhaps by institution specific considerations, e.g., investment mandates or capital requirements.

4.2. Demand Elasticities

In this Section, we compute the equilibrium demand elasticities for individual investor types and for the corporate bond market as a whole. Following Koijen and Yogo (2019), we define institution i's demand elasticity for bond n as

$$-\frac{\partial \log\left(Q_{i,t}(n)\right)}{\partial \log\left(P_{i,t}(n)\right)} = 1 + \frac{\beta_{0,i}}{m_t(n)}\left(1 - w_{i,t}(n)\right)$$

where $m_t(n)$ is the time to maturity of bond n and other variables are as defined in equations (1) and (2). A higher coefficient $\beta_{0,i}$ on the yield implies a higher demand elasticity with respect to price. Table 5 (a) reports the summary statistics of the estimated demand elasticities by investor sector for the period 2006:1 to 2020:3 and for the recent sample period 2010:1 to 2020:3. We note three main facts below.

4.2.1. Mutual funds are more price elastic than life insurers

Table 5 (a) shows that mutual funds have the highest demand elasticities (with mean elasticity of 11.6), followed by VA funds, Other and Pension funds, and Foreign funds. On the other end of the spectrum are life insurance companies who have the lowest demand elasticities. In particular, for life insurers, the demand curve is inelastic, i.e. < 1 on average. These elasticity estimates are in line with Koijen et al. (2020a) who present a similar ranking of investor-specific elasticities for EU government bonds. The differences in price elasticities suggest that mutual funds tend to do demand more liquidity in the bond market relative to life insurers as mutual funds are more responsive to small price movements.

4.2.2. Life insurers have become more inelastic over time

In Panel (b), we report the summary statistics for the post financial crisis sample period from 2010:1 to 2020:3. Demand elasticities are similar to the overall sample estimates in Panel (a) for all investor groups. However, elasticities of life insurers have decreased substantially from 0.5 to 0.1, consistent with the declining time-series estimates shown in Figure 2a.

The decline in elasticities for life insurers suggests that insurers have become more passive over time. There are two possible interpretations of this trend. One interpretation is that this is a result of increasing competition from mutual funds. As the presence of mutual funds increased, insurers have retreated from providing liquidity, consistent with the model in Haddad, Huebner, and Loualiche (2022). Another interpretation is that the trend is due to increased propensity to do duration hedging when interest rates decline. Life insurers typically have a negative duration mismatch as their assets are relatively short-dated in comparison to their liabilities. As a result, when interest rates decline, insurers' hedging demand increases.[15] This would lead to an increase in the demand for long-term bonds and this demand could become less responsive to price movements. Consistent with this idea,

[15] Consistent with this, Sen (2019) shows that insurers dynamically hedge duration mismatch as interest rates shift using interest rate derivatives.

we estimate negative demand elasticities, i.e. demand slopes upward, for many insurers in the later part of the sample. In other words, as rates declined (prices increased) the demand for bonds increased further due to a hedging motive.[16] Moreover, the elasticities for P&C insurers, who have short term liabilities like mutual funds, have remained mostly unchanged through time, further corroborating the duration hedging explanation.

4.2.3. Market-wide elasticity estimates are larger than the estimates for the stock market

We next compute the market-wide elasticity for the corporate bond market as a whole by weighting the investor specific elaticities by their AUMs. The market-wide elasticity in the overall sample is 3.7. In comparison, estimates for the U.S. stock market range from 0.3 (Koijen and Yogo (2019), Haddad, Huebner, and Loualiche (2022)) to slightly over 1 (Chang et al. (2015)). This suggests that bonds may be closer substitute to each other than are stocks. Indeed, consistent with our estimates, the elasticity for the EU government bond market is estimated to be about 3.2. (Koijen et al. (2020a)).

Interestingly, the market-wide elasticity in the recent sample is close to that in the overall sample despite the rise of mutual funds in the market. This is because the overall elasticity masks two opposing time trends. On one hand, life insurers have become more inelastic over time, as we discuss above. This puts a downward pressure on the market-wide elasticity. On the other hand, the share of mutual funds has risen, which puts an upward pressure on the overall market-wide elasticity because mutual funds are significantly more elastic. For example, we estimate that if the share of mutual funds had stayed the same at their 2006 level, the market-wide elasticity during the more recent sample period would have been closer to 1.5, i.e. 60% lower than the actual elasticity of 3.8, ignoring any competitive responses on part of insurers. This highlights the need to incorporate the full breadth of investor heterogeneity when studying pricing dynamics.

[16] Domanski et al. (2017) estimate upward sloping demand curves for German insurers during the recent low interest rate period.

5. Price Impact and Liquidity

In this Section, we use the estimated characteristics-based demand system to estimate the price impact of demand shocks (i.e. yield elasticity to latent demand) in the aggregate and by different institution types. We follow Koijen and Yogo (2019) and estimate the characteristics-based demand system in equation (2) at an institution-quarter level using GMM. The estimated demand system provides estimates of price impact of idiosyncratic shocks to an investor's *latent demand* (which we describe below), $\frac{\partial y_t(n)}{\partial u_{i,t}(n)}$, for all bonds and for all institutions. We use this measure to study the evolution of liquidity in the corporate bond market over time, and in particular, after the financial crisis.

5.1. *Latent Demand*

Given the estimated coefficients, we recover estimates of latent demand according to equation (2). Latent demand captures investors' preferences, beliefs, and constraints not accounted for by the characteristics themselves. Figure A.1 reports the cross-sectional standard deviation of log latent demand by institution type, weighted by assets under management. A higher standard deviation implies more extreme portfolio weights that are tilted away from observed characteristics. In general, the cross-sectional variability in latent demand is relatively fairly stable over time for most institutions.

5.2. *Price Impact and Liquidity*

The estimated demand system in section 3 allows us to estimate the price impact of demand shocks for all bonds. Following Koijen and Yogo (2019), we define the coliquidity matrix for investor i as

$$\begin{aligned} \frac{\partial \mathbf{p}_t}{\partial \log(\epsilon_{i,t})'} &= \left(\mathbf{I} - \sum_{j=1}^{I} A_{j,t}\mathbf{H}_t^{-1}\frac{\partial \mathbf{w}_{j,t}}{\partial \mathbf{p}_t'}\right)^{-1} A_{i,t}\mathbf{H}_t^{-1}\frac{\partial \mathbf{w}_{i,t}}{\partial \log(\epsilon_{i,t})'} \\ &= \left(\mathbf{I} - \sum_{j=1}^{I} A_{j,t}\beta_{0,j,t}\mathbf{H}_t^{-1}\mathbf{G}_{j,t}\right)^{-1} A_{i,t}\mathbf{H}_t^{-1}\mathbf{G}_{i,t} \end{aligned} \tag{4}$$

The (n, m) th element of this matrix is the elasticity of bond price n with respect to investor i 's latent demand for asset m. The coliquidity matrix measures the price impact of idiosyncratic shocks to an investor's latent demand. This expression implies a larger price impact for investors whose holdings are large relative to other investors that hold the asset. We estimate the price impact of demand shocks for the bond market in the aggregate and for each institution type. Figure 3 plots the distribution of yield changes to latent demand across all bonds from 2006:Q1 to 2020:Q3. Henceforth, we refer to the yield responses to negative demand shocks as *price impact* for brevity. Panel (a) shows price impact for bond market in the aggregate and panel (b)-(f) for each individual institution type.

5.2.1. Aggregate Trends

To calculate the aggregate coliquidity matrix, we aggregate equation (4) across all investors. We then estimate the aggregate price impact for each bond through the diagonal elements of aggregate coliquidity matrix. We then use the price changes to calculate corresponding yield changes. The following key facts stand-out from Figure 3 (a). First, negative shocks to latent demand lead to a rise (decline) in bond yields (prices). Second, price impact was low before the onset of the financial crisis, it increased substantially during the financial crisis, and has remained high for a large part of the post-crisis period. Third, the increase in price impact is pervasive across the distribution of bonds, i.e. price impact has increased not just for the most illiquid bonds (75th percentile), but also for the relatively more liquid bonds (25rd percentile), signalling a general decline in bond market liquidity. Finally, we observe a significant increase in the estimated aggregate price impact during the COVID-19 crisis. In particular, the price impact of most bonds, including the most liquid ones jump up and remain high during the first half of 2020.

To depict the evolution of price impact over time, in Figure 4 (a), we plot the yield elasticities (i.e. percentage change in yields) to negative demand shocks. This allows us to account for the general decline in interest rates during the sample period. Figure 4 (a) reinforces the pattern that price impact has risen substantially since the financial crisis. The time series dynamics of the price impact after the financial crisis lines up with what many academics and policymakers have increasingly argued - that higher bank capital requirements and the Volcker rule, two key initiatives taken in response to the financial crisis, have limited banks' market making activities has potentially undermined investors' ability to adjust their portfolios without impacting prices too much. To shed light on the mechanisms by which liquidity may have deteriorated in these markets, we next explore potential sources of heterogeneity in liquidity demand across bonds, across institutions, and over time.

5.2.2. Cross-Institutions Trends

To examine the dynamics of price impact by institution type, we estimate the price impact for each bond and institution through the diagonal elements of matrix (4) and then average by institution type. Figures 3 and 4 (b)-(f) provide the distribution of price impact across all bonds for the average institute within an institution type. The individual institution specific estimates of price impact exhibit similar time series patterns as the aggregate price impact.

Price impact increased in the post-crisis period for all institution types relative to the pre-crisis levels. We also find that the price impact of an average life insurer is larger than the average mutual fund and other investor types. This makes sense because life insurers are significantly less elastic with respect to yields than mutual funds (see Section 4.2). Thus, demand shocks result in greater price impact for insurers than mutual funds.

6. Counterfactual Equilibrium Simulations

In this section, we evaluate a number of counterfactual bond market equilibria. That is, based on our estimated demand system, we calculate bond prices and yields that would prevail under circumstances that differ from the existing market conditions. In particular, the estimated demand system allows us to trace out movements in implied corporate bond prices due to hypothetical changes in perceived credit quality of bonds, mutual fund selling pressure, short term interest rates, or the Federal Reserve's Corporate Bond Facilities.

The demand system introduced in equation (2) together with market clearing defined in equation (3) allows us to calculate the equilibrium price. That is, bond prices are fully determined by bond supply denoted by the vector $\mathbf{s}_t$, bond characteristics $\mathbf{x}_t$, the wealth distribution given by asset under management of all investors $\mathbf{A}_t$, the estimated coefficients on characteristics β_t, and latent demand ϵ_t.

$$\mathbf{p}_t = \mathbf{g}\left(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t\right)$$

The primary object of interest in the counterfactual simulations is to examine how corporate bond yields change when either the characteristics, the wealth distribution, or the estimated demand coefficient change. For example, to assess the effects of a change in the wealth distribution from $\mathbf{A}_t$ to $\mathbf{A_t^{CF}}$ we calculate associated corporate bond price changes as

$$\Delta\mathbf{p}_t = \mathbf{g}\left(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A_t^{CF}}, \beta_t, \epsilon_t\right) - \mathbf{g}\left(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t\right).$$

We calculate these counterfactual price vectors using the algorithm from Koijen and Yogo (2019), where we calculate the changes in yields exploiting the transformed pseudo zero coupon yields discussed in Section 3.[17]

6.1. *Credit Quality Migration*

In our first counterfactual, we ask how would the bond market equilibrium shift if a large subset of bonds experience a deterioration in credit quality akin to what happens during periods of crises. Our question is motivated by the fact that different institutions appear to specialize in different parts of the credit spectrum, perhaps because of investment mandates or capital requirements (see Section 4). Given the heterogeneity in demand functions, it is plausible that equilibrium bond prices may display patterns that cannot just be explained

[17] See their appendix C. Importantly, one can only prove convergence if investor demand curves are downward sloping. This is a potential issue given that some of insurance companies have upward sloping demand curves. Despite the presence of these institutions, we find that our algorithm generally converges. However, in our baseline results we restrict the coefficients such that the demand curves are downward sloping. Importantly, when we compare unrestricted to restricted results we find essentially no difference either qualitatively or quantitatively. This suggests that the heterogeneity in demand elasticities across investor sectors is more important compared to the relatively smaller heterogeneity within an investor sector.

by standard risk-return trade-offs and heterogeneity in investor composition may be an important state variable to consider. To implement this new equilibrium, we proceed by downgrading investment grade bonds in the sample by one notch, e.g., AA+ rated bonds are downgraded to AA and BBB- are downgraded to BB+ etc, and then compute the new equilibrium prices. Formally, we change the vector of bond characteristics by changing the bond ratings to $\mathbf{x_t^{CF}}$ and calculate the counterfactual equilibrium yields implied by $\mathbf{g}\left(\mathbf{s}_t, \mathbf{x_t^{CF}}, \mathbf{A}_t, \beta_t, \epsilon_t\right)$. For each bond, we then compute the counterfactual credit spreads and the difference between the counterfactual and the empirical (actual) credit spreads.

Table 6 shows the difference between the counterfactual and the actual credit spreads across different types of bonds and institutions. First, we observe that the difference is positive on average, i.e. spreads increase when bonds are downgraded, which is intuitive as investors have to be compensated to hold riskier bonds. Second, and more importantly, the extent to which the spreads increase varies in important ways across bonds and institutions. We observe a symmetric rise in spreads across all rating categories, except for the erstwhile BBB- bonds (which now becomes high yield) whose spreads rise by twice as much as the rise in spreads of other investment grade bonds. Crucially, though this disproportionate rise in spreads for the erstwhile BBB- bonds happens only when these bonds are predominantly held by insurance companies and not mutual funds.

To test these patterns formally, we regress the counterfactual changes in credit spreads on the fraction of the bond that is held by insurance companies (% insurance) in Table 7. We control for bond characteristics as the heterogeneity in changes in spreads across investors could simply be driven by differences in their bond holdings. Table 7 shows that % insurance has a positive but statistically insignificant coefficient, implying that a bond's holding pattern does not explain the rise in spreads on average. However, the interaction term (% insurance $\times$ $BBB-$) is positive and highly statistically significant. Thus, for BBB- bonds, the magnitude of the rise in spreads increases with the fraction being held by insurers. In fact, for BBB- bonds the gap in spreads between bonds held *only* by insurers vs. those that are not held by insurers at all is as much as 56bps.

These patterns are consistent with our estimated demand system (see Section 4.1), which shows that insurers' demand functions have a sharp discontinuity at the IG-HY threshold. However, their demand within investment grade bonds is less sensitive to default risk. This is consistent with the sharp discontinuity insurers face in capital requirements at the IG-HY threshold. As a result, bonds predominantly held by insurers, upon downgrade to HY, may experience a greater rise in spreads due to the rebalancing pressure insurers face to ease capital constraints. The same patterns do not hold for mutual funds to the same extent as mutual funds have a greater preference for HY bonds, as we document in Section 4. Furthermore, Table 6 shows that the changes in credit spreads are countercyclical and increase more in bad times, e.g. during the financial crisis. This suggests that insurers may amplify credit shocks when bond markets are fragile.

6.2. Undoing the Rise of Bond Mutual Funds

The next two counterfactual simulations focus on mutual funds. Since the financial crisis, there has been a dramatic increase in the presence of bond mutual funds. In view of this, we ask how the bond market equilibrium would be affected if mutual funds were to remain small? To implement the new equilibrium, we keep the relative size of the mutual fund sector constant at its level in 2006:Q1, i.e. before mutual funds experienced a rise. To this end, we introduce a transfer in assets under management as in Koijen et al. (2020b). For mutual funds, the amount of outflow is computed as

$$F_{i,t} = A_{i,t} \times \frac{\sum_{j \in \text{Mutual Fund}} A_{j,t} - \sum_{k \in \text{Mutual Fund}} A_{k,2006Q1}}{\sum_{j \in \text{Mutual Fund}} A_{j,t}}$$

whereas the other institution types receive an inflow of

$$F_{i,t} = \frac{A_{i,t}}{\sum_{l \notin \text{Mutual Fund}} A_{l,t}} \times \left(\sum_{j \in \text{Mutual Fund}} A_{j,t} - \sum_{k \in \text{Mutual Fund}} A_{k,2006Q1} \right).$$

The counterfactual assets under management are then simply calculated as $A_{i,t}^{CF} = A_{i,t} - F_{i,t}$ for mutual funds and $A_{i,t}^{CF} = A_{i,t} + F_{i,t}$ for other investors. As before, for each bond, we compute the difference between the counterfactual and the actual credit spreads.

Figure 5 shows the evolution of the difference in spreads over time. We split the sample of bonds into those that are predominantly held by the mutual funds sector and those that are not. Several notable patterns emerge. First, as expected, bonds predominantly held by the mutual funds sector would experience a greater rise in spreads in a world where mutual funds were to remain small (Panel (a)). For example, the median bond would experience an increase of close to 50bps, if we were to run this counterfactual during the financial crisis. In contrast to bonds predominantly held by mutual funds, we see a relatively smaller effect on bonds that are not predominantly held by mutual funds (Panel (b)).

Second, in Figure 6, we explore the heterogeneity of the effects across bonds. (i) We find that high yield bonds would experience a greater rise in spreads (Panel (a)). (ii) Such bonds would experience a greater rise in times of market downturns, e.g., during the COVID-19 crisis. (iii) We find that bonds that have a shorter maturity would be affected more (Panel (b)). In contrast, high yield and short-dated bonds not predominantly held by mutual funds are affected significantly less. The fact that we observe a greater shift in spreads for short-dated and high yield bonds can be rationalized given the estimated demand system in Section 4. The remaining investor types (insurance companies predominantly), who in the counterfactual simulation do not experience an outflow, have a substantially lower preference towards short-dated and high yield bonds (see Section 4). As a result, they have to be compensated more to make them willing to hold these bonds in equilibrium.

These findings suggest that the type of investor holding a bond matters for equilibrium bond prices, contrary to what would be suggested by the standard representative-agent based models of corporate bonds pricing. Policymakers and academics have conjectured that mutual fund sector may shrink in size going forward as interest rates begin to rise. Our findings suggest that such disruptions would disproportionately affect the cost of financing of firms whose bonds are predominantly held by mutual funds given the substantial market segmentation that we document.

6.3. Run on Large Mutual Funds

As mutual funds' importance has grown in the corporate bond market, policymakers, practitioners, and academics have debated whether mutual funds could make bond markets fragile. In particular, large redemption demand from bond mutual funds can create a potential for fire sales leading to dislocation of asset prices from fundamental values. In the next counterfactual, we test the impact of such large-scale redemptions from bond mutual funds on equilibrium spreads. We proceed as follows. First, we assume that the largest mutual funds would experience a 20% outflow in AUM each. In each quarter, we only shock the largest mutual funds whose combined assets under management account for 5% of the total corporate bond market AUM. Hence, the shock corresponds to 1% of the total corporate bond AUM in size. Note that the relative size of the shock is constant over time, unlike in the previous counterfactual. As a result, any time trend in the magnitude of the credit spread changes is solely due to the change in the composition of the remaining corporate bond investors. Second, we implement the transfers in AUMs similarly to the previous counterfactual. That is, we calculate the outflows for mutual funds and proportional inflows for other investors to compute $\mathbf{A_t^{CF}}$. Then, we solve for $\mathbf{g}\left(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A_t^{CF}}, \beta_t, \epsilon_t\right)$ and compute for each bond the difference between the counterfactual and the empirical (actual) credit spreads.

We discuss our results in two parts. First, in studying the equilibrium effects, we force *all* remaining investors to provide liquidity and we do so in proportion to their size (AUMs). Second, we force a set of institutions to stay out of the market and only allow a sub-group of institutions to provide liquidity. We do so to understand whether pricing dynamics would vary depending on the composition of institutions that remain in the market when mutual funds sell their holdings.

6.3.1. Bond market effects when all remaining investors provide liquidity

Two main results stand out when we redistribute assets to all remaining investors that do not experience an outflow. First, as expected, Figure 7 shows that there would be a large increase in spreads if bond mutual funds experienced large redemption requests. Moreover, different from the previous counterfactual, the impact on spreads is declining over time. To understand why this is the case note that the share of bond mutual funds has risen over time (see Figure 1). As a result, the assets of the remaining mutual funds who did not receive the counterfactual outflow (and could absorb the outflows of the funds that actually did receive the shock) have been increasing over time. Unlike insurers whose preferences tilt in the opposite direction to mutual funds, the remaining mutual funds (who do not experience the counterfactual outflow) tend to prefer high yield and short-term bonds and thus have to be compensated less than insurers to hold these bonds in equilibrium.

Second, we dig deeper into the heterogeneity across bonds. Figure 8 shows that the largest impact would be on short-dated bonds ($<$ 5 years remaining maturity). In contrast, there is very little effect on long-term bonds ($>$ 5 years remaining maturity). Similarly, we find a large effect on high yield bonds relative to investment grade bonds. These findings are consistent with our estimated demand system. Insurers have a greater preference for long-term and investment grade bonds. As a result, they demand a lower compensation to hold these bonds when large mutual funds sell their positions. In contrast, for short-term and high yield bonds, insurers would demand a higher compensation.

6.3.2. Does it matter who provides liquidity?

We next explore the equilibrium effects further by testing if the pricing implications would be different depending on which investors stepped in to provide liquidity when mutual funds sold their holdings. To do so, we conduct three variations of this counterfactual analysis where instead of redistributing to *all* remaining investors, we redistribute *only* to (i) remaining mutual funds who did not experience the shock; (ii) insurance companies only, and (iii) all other non-insurance and non-mutual funds (predominantly foreign funds). Thus, only remaining mutual funds, only insurance companies, and only foreign investors provide liquidity in (i), (ii), and (iii) respectively. Note that within each sector, we redistribute the assets in proportion of investors' own AUMs. Figure 9 shows that the effects would be larger if insurers provided liquidity instead of mutual funds and foreign funds. The stark differences in the demand functions across mutual funds and insurers can explain the heterogeneity in the pricing effects. Insurers would demand a greater compensation to hold the typical bond which the large mutual funds would sell. In contrast, the remaining mutual funds and foreign funds have relatively similar demand parameters. As a result, they can absorb these bonds at a lower compensation.

Overall, our results clearly demonstrate that the composition of investors would play a large role if bond market redemptions were to occur and this heterogeneity is important in order to understand the equilibrium price dynamics. Presence of foreign funds and other mutual funds that do not experience outflows would mute the pricing effects substantially.

6.4. Interest Rate Lift-off

The U.S. has witnessed historically unprecedented low interest rates for the past decade. In particular, rates have been near-zero since the COVID-19 pandemic began. However, concerns about rising inflation has prompted expectations about interest rate hikes in the near future. In this section, we test the pricing consequences of rising interest rates following a monetary policy tightening. In particular, we examine how the equilibrium would shift if rates were to rise by 100bps. To do so, we focus on two elements of the demand system that may be sensitive to interest rates: (i) the estimated demand parameters β_t and (ii) the composition of AUMs across investors. We exploit time-series variation in the estimated demand parameters (e.g., depicted in Figure 2) and measure the sensitivities of the estimated parameters to shifts in the Fed funds rate, which we then use to predict counterfactual demand parameters for a 100bps shift in rates. Similarly, we measure the sensitivities of the share of total AUM of an investor group to the Fed funds rate and use the estimated relationship to predict changes in the share of AUMs. Finally, we recompute the counterfactual equilibrium yields for a 100bps rise in the Fed funds rate in a world where the demand parameters would shift, AUM shares would shift, or both would shift. We then compare the counterfactual yields with the actual yields. More specifically, we measure the sensitivities to the Fed funds rate using quarterly data from 2006:1 to 2019:4. We implement the counterfactual equilibrium assuming the 2020 holdings and market conditions as our initial condition. We do so because we want to quantify the impact of a rise in Fed funds rate using initial conditions that closely reflect current holdings patterns and market conditions.

Estimated demand parameters: Table A.6 shows that mutual funds' demand parameters are highly sensitive to the Fed funds rate. In contrast though, life insurers' demand parameters are less affected by shifts in the Fed funds rate. In particular, regarding mutual funds, two points are notable. First, when rates rise, mutual funds' preference to hold higher credit quality bonds increases as seen from the negative coefficient on β_{Rating}. This shift in asset selection is in line with reaching for yield behavior in a low rate environment, as documented for mutual funds (Choi, Hoseinzade, Shin, and Tehranian (2020)), which suggests a greater tilt towards high yield (investment grade) bonds when rates are low (high). Second, when rates rise, mutual funds' preference to hold long maturity bonds increases as evident from the positive coefficient on $\beta_{Maturity}$. This reflects an objective to exploit a higher term premium typically observed in a high rate environment.

Composition of AUMs: Table A.7 shows the impact of the Fed funds rate on AUM composition across investor sectors. When rates would rise, we would observe a redistribution of AUMs away from all sectors and particularly from mutual funds. These AUMs would be redistributed to life insurers, suggesting outflows are absorbed by them.

Table 8 documents the new equilibrium yield changes resulting from the shifts in the demand parameters and AUM composition that we document above. Panel (A) shows that when Fed funds rate increases, bond yields (prices) rise (decline) given the changes in the demand parameters we estimate. In addition, consistent with the shifts in the demand parameters, we document that the yield changes are heterogeneous in two ways. First, yields rise more for short-dated bonds relative to long-dated bonds. This is consistent with the evidence in Table A.6, which shows that when rates rise mutual funds' preference to hold long maturity bonds increases. This suggests that the yields of long-term bonds should rise less than short-term bonds. Second, yields rise more for high yield bonds relative to investment grade bonds. This is also consistent with the evidence in Table A.6 that mutual funds move away from high yield and into safer bonds. In equilibrium, as the outflows are absorbed by life insurers (see above) who instead prefer investment grade and long-dated bonds, the compensation to hold high yield and short-dated bonds has to be higher. Panels (B) and (C) show these effects are further reinforced when we incorporate potential redistribution of AUMs. These findings again demonstrate the importance of taking account of investors' holding patterns when examining the impact of macro shocks.

6.5. *Impact of Fed Selling-off its Corporate Bond Holdings*

In this counterfactual, we aim to quantify the impact of the Fed selling off its corporate bond holdings that it has previously accumulated under the Secondary Market Corporte Credit Facility (SMCCF) on corporate bond spreads. To that end, we obtain data on Fed's SMCCF holdings from the Federal Reserve's SMCCF transaction specific disclosures at the end of 2020Q3. Our dataset contains both the bonds' CUSIPs as well as the amount purchased. In terms of implementation, we represent the SMCCF as a separate investor category in our demand estimation framework and re-estimate the demand curves. That is, we re-distribute holdings from the unobserved residual investor (which was introduced for market clearing) to the SMCCF. As the bond holdings of the SMCCF are small compared to the overall AUM of the residual investor, the estimated demand coefficients do not change materially.[18] Next, we proportionally re-distribute the holdings of the SMCCF to the other investors. That is, we estimate the counterfactual effects of a complete sell-off of the SMCCF. Notably, our counterfactual does not rely on any demand function of the SMCCF as we re-distribute all

[18] For example, the Fed held about $4.1 billion of total par value in corporate bonds as of 2020:Q3.

its assets.[19]

Table 9 reports the counterfactual credit spreads alongside the difference between the counterfactual and the empirical (actual) credit spreads. The table shows that the impact of a Fed sell-off on corporate bond spreads would be minimal. This is consistent with the recent evidence in Haddad et al. (2021), supporting the view that large price movements in the corporate bond market following the Fed announcement reflected anticipations of future purchases in bad states rather than the purchases themselves.

Overall, our findings closely align with the existing literature on mutual funds' and insurers' portfolio decisions, thus validating the estimation exercise. Our estimation offers an avenue to study the implications of policy changes on the corporate bond market equilibrium. We note, however, that our estimated characteristics-based demand model can be used for policy experiments only under the null that it is a structural model of asset demand that is policy invariant. The Lucas (1976) critique applies under the alternative that the coefficients on characteristics and latent demand ultimately capture beliefs or constraints that change with policy. Hence, any application of this model to a policy context implies the assumption of policy invariance. Moreover, we cannot answer welfare questions without making assumptions on preferences, beliefs and potential constraints. However, as our primary object of interest is the pricing of corporate bonds the latter matters less in our set-up.

7. Conclusion and Broader Implications

Based on the observation that the corporate bond market is dominated by a few key players, namely insurance companies, pension funds, and mutual funds, we estimate their demand for securities across characteristics in equilibrium. To that end, we build a rich new dataset linking corporate bond characteristics with detailed information about institutional investor level security level and estimate a demand system exploiting the restriction that holdings

[19] This is important as estimating a demand function for the SMCCF would not make sense as its holdings are supply- rather than demand-driven (effectively, the seller of a bond that meets the qualification criterion decides to sell to SMCCF and not vice versa).

need to match up with demand in equilibrium. Persistence in institutions' holdings provide us with a powerful instrument to isolate exogenous movement in prices. We find significant heterogeneity in demand elasticities across the main players in the corporate bond market, namely insurers, pension funds, and mutual funds. Insurance companies exhibit inelastic demand, tilt portfolios to investment grade and long-dated bonds, bonds with smaller issuance size, and are willing to hold illiquid bonds. In contrast, mutual funds, with shorter investment horizons, have more elastic demand, preference for high yield and short-dated bonds, bonds with larger issuance size, and demand liquidity.

In equilibrium, our estimated demand functions need to match up with supply. In other words, investors' portfolio weights reflecting their demands across securities have to add up their values outstanding. Following Koijen and Yogo (2019), this simple insight endows us with a powerful tool to compute counterfactual equilibrium prices. In counterfactuals, we evaluate the corporate bond pricing implications of i) credit quality migration, ii) mutual fund fragility, iii) monetary policy tightening, and iv) a tapering of the Fed's corporate credit facility. Our model predicts substantial disruptions in corporate bond prices through shifts in institutional demand and emphasizes the composition of institutional demand as a state variable for corporate bond pricing. In equilibrium, such disruptions are reflected in the real economic outcomes through firms' financing decisions. Our results thus allow to shed some light on the consequences of policy changes that have the potential to affect the real economy through their effects on debt pricing.

Our work suggests a number of directions for further research. From a corporate finance perspective, we can evaluate firms' optimal capital structure and bond issuance decisions taking as given investors' corporate bond demand and examine how the latter would affect corporate investment decisions, for example. From an investment perspective, it would be worthwhile examining the role of corporate bonds in households' portfolios given the presence and demands of large institutional investors in the corporate bond market. We leave these questions for future research.

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I. Figures

Figure 1: Institutional Share of Corporate Bonds

The chart shows share of institutional investors for the corporate bond market for the period 1970:1-2020:3. The data are quarterly and taken from the U.S. Federal Flow of Funds account. We compute institutional shares excluding foreign owners of corporate bonds, who account for roughly 11% of the market on average during the period 1970 to 2020.

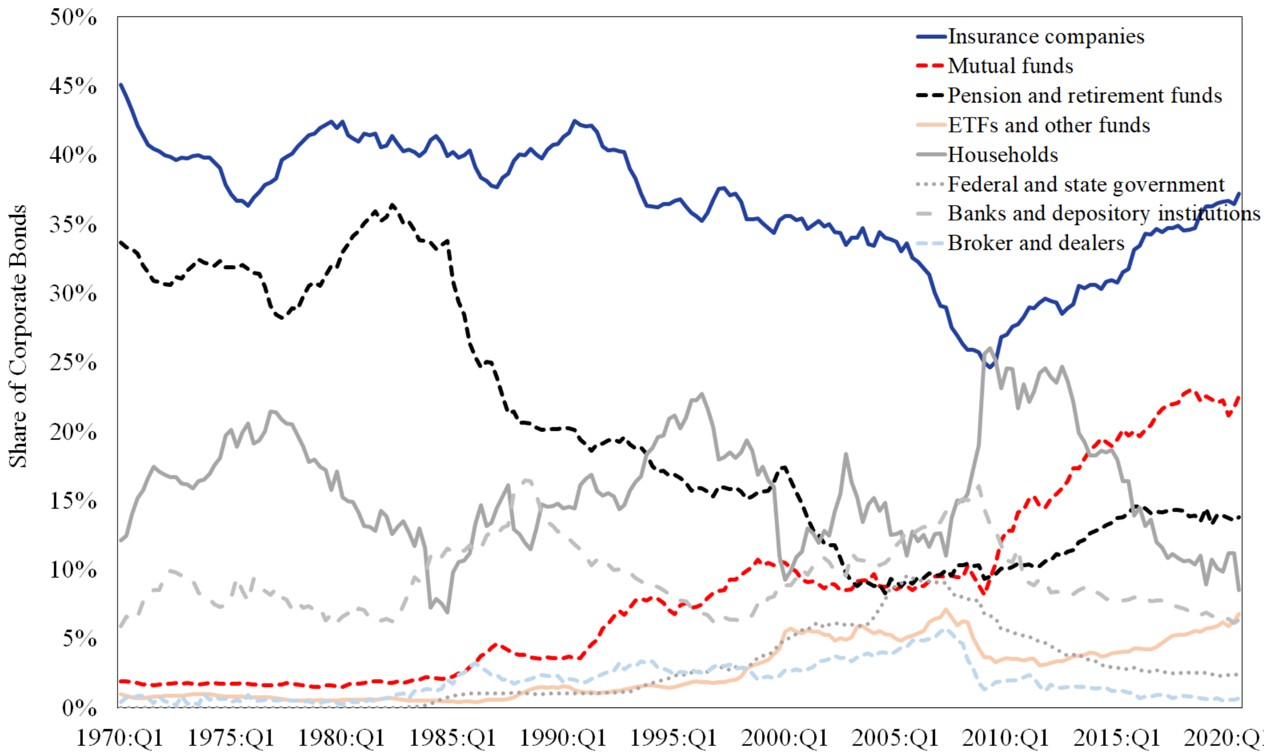
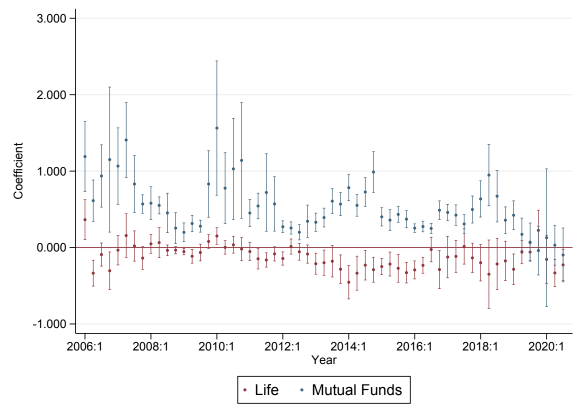


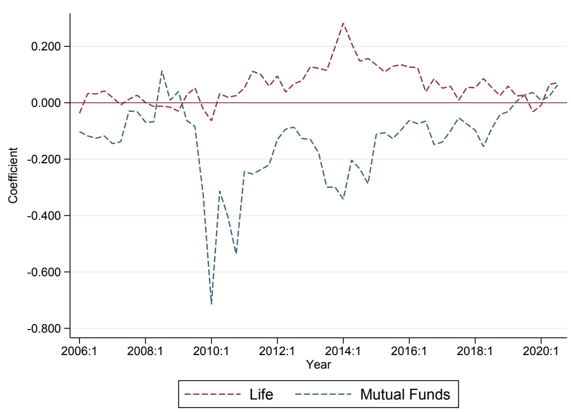
Figure 2: Evolution of the Estimated Demand-System - Life Insurers vs. Mutual Funds

This figure plots the estimated coefficients on instrumented yield, time to maturity, bid-ask spreads, bond size and credit rating for life insurers and mutual funds for each quarter. The left panels plot the estimated coefficients and the right panels plot the estimated coefficients including the 5% and 95% confidence bands. The quarterly sample period is from 2006:1 to 2020:3.

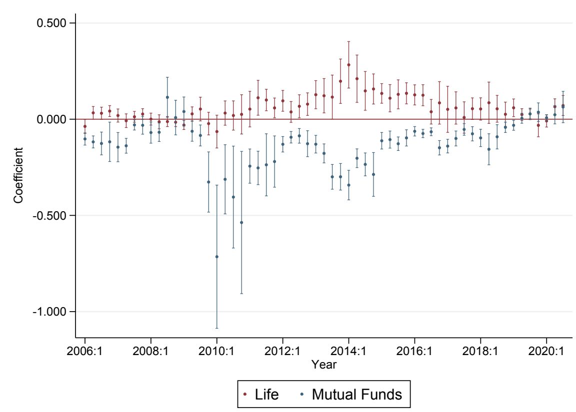
(a) Yield



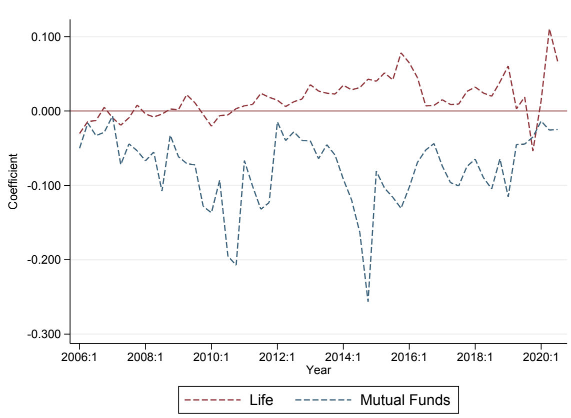
(b) Yield - Confidence Bands



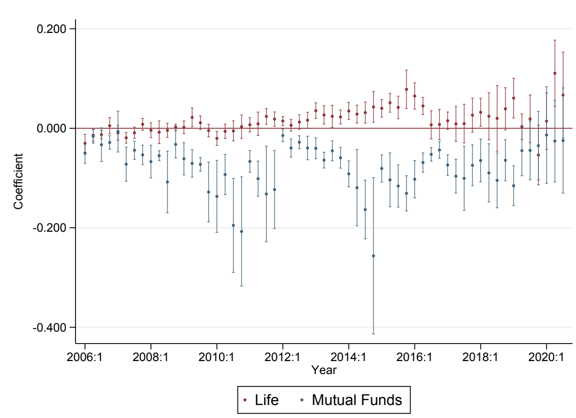
(c) Time to Maturity



(d) Time to Maturity - Confidence Bands

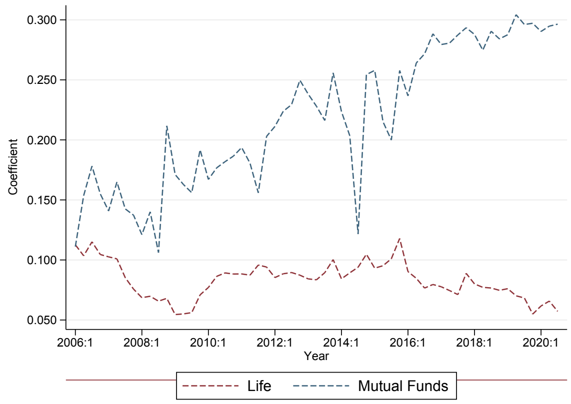


(e) Bid-Ask Spread

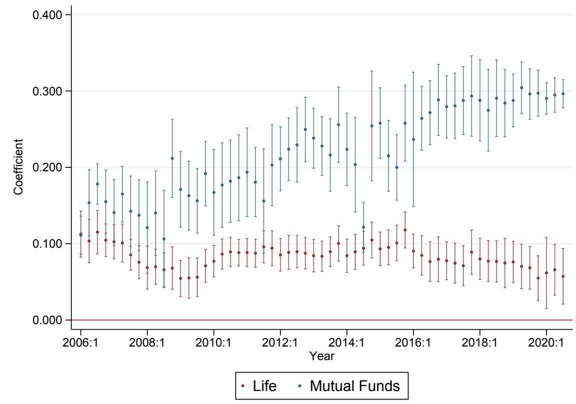


(f) Bid-Ask Spread - Confidence Bands

Figure 2: Evolution of the Estimated Demand-System - Life Insurers vs. Mutual Funds (contd...)

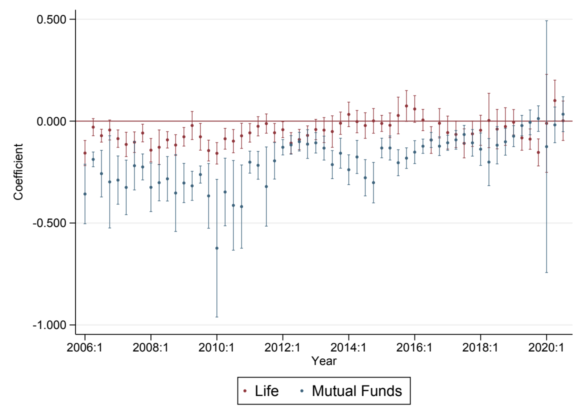


(g) Bond Size



(h) Bond Size - Confidence Bands

(i) Rating

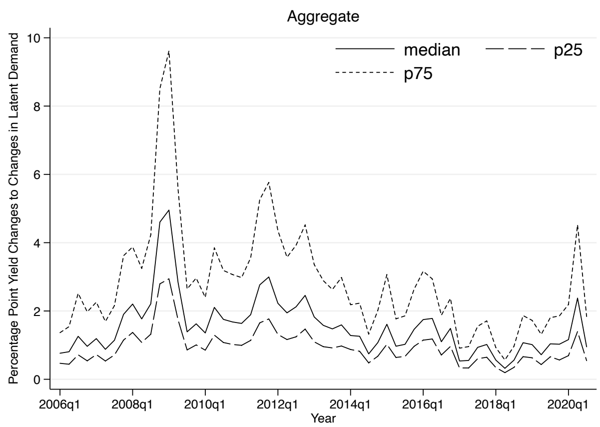


(j) Rating - Confidence Bands

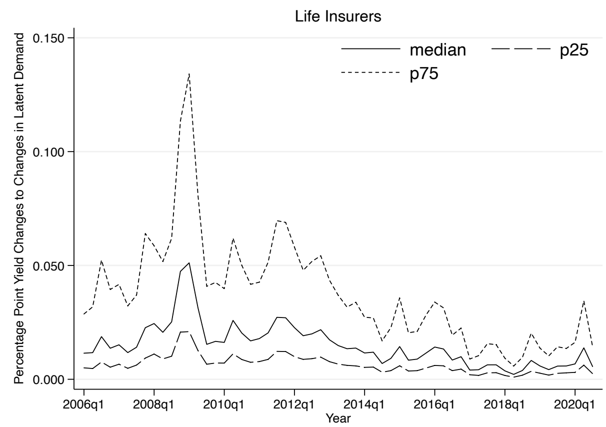
Figure 3: Price Impact - Yield Changes to Latent Demand

This figure plots the median, the 25th and the 75th percentiles of percentage point yield changes to changes in latent demand. Panels a)-f) plot the aggregate price impact and the average investor-specific impact. The quarterly sample period is from 2006:1 to 2020:3.

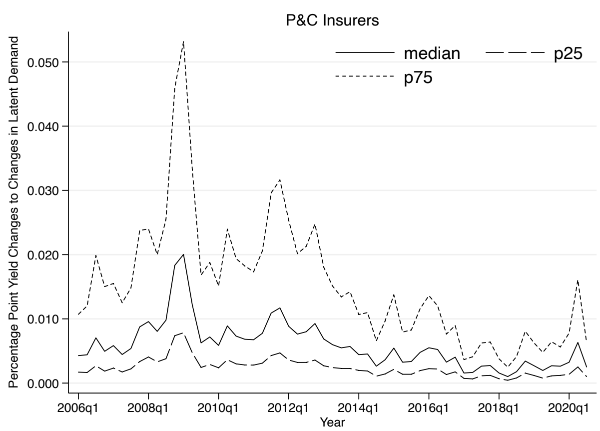
(a) Aggregate.



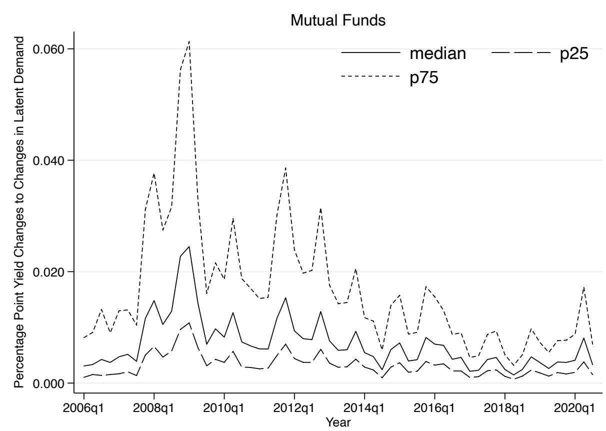
(b) Life Insurers.



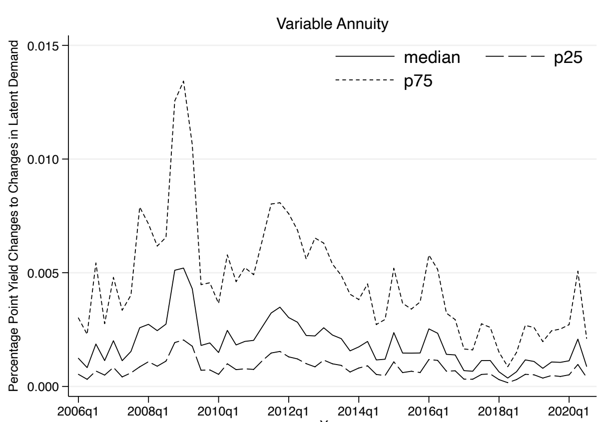
(c) P&C Insurers.



(d) Mutual Funds.



(e) Variable Annuities.



(f) Foreign Investors.

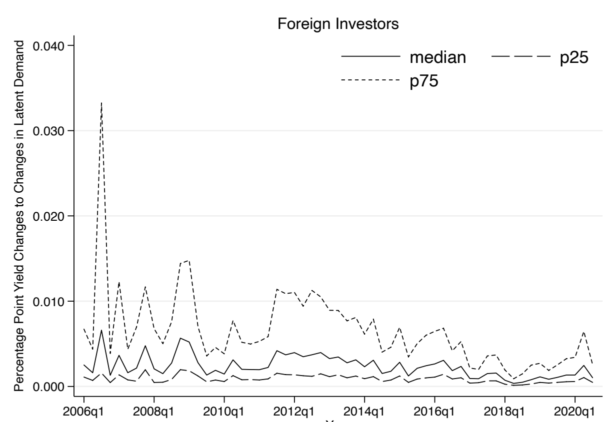
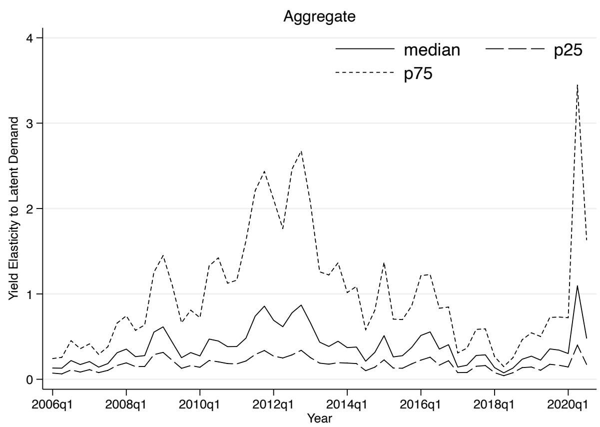


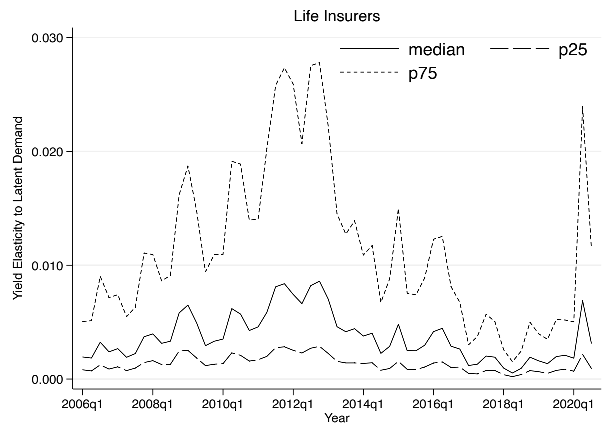
Figure 4: Price Impact - Yield Elasticity to Latent Demand

This figure plots the median, the 25th and the 75th percentiles of yield elasticities to changes in latent demand. Panels a)-f) plot the aggregate price impact and the average investor-specific impact. The quarterly sample period is from 2006:1 to 2020:3.

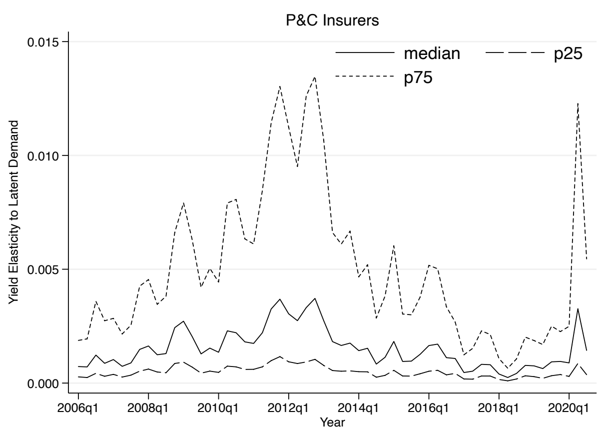
(a) Aggregate.



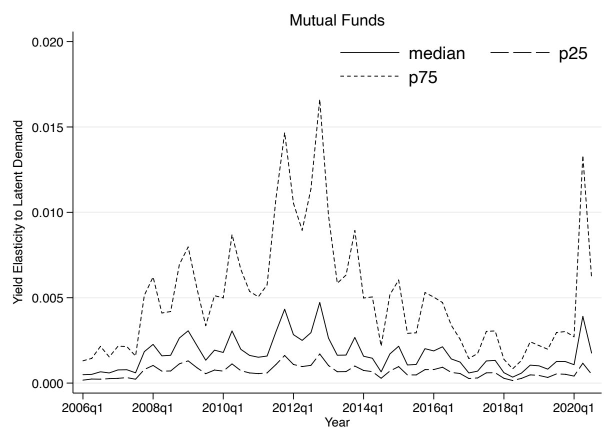
(b) Life Insurers.



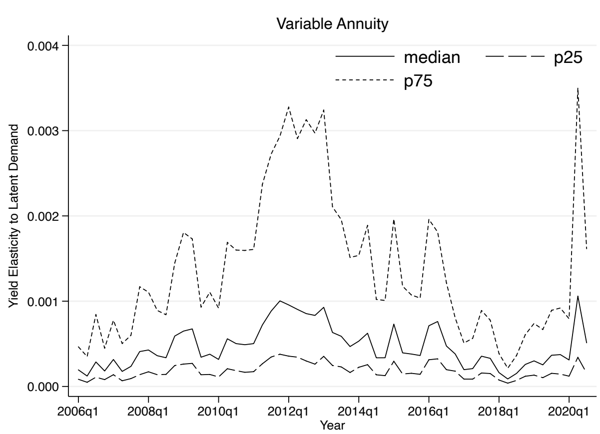
(c) P&C Insurers.



(d) Mutual Funds.



(e) Variable Annuities.



(f) Foreign Investors.

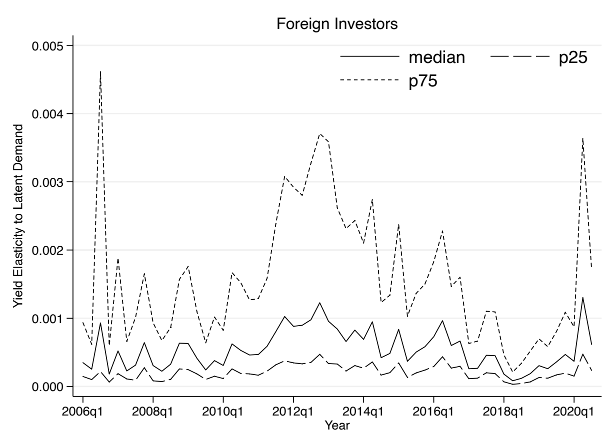
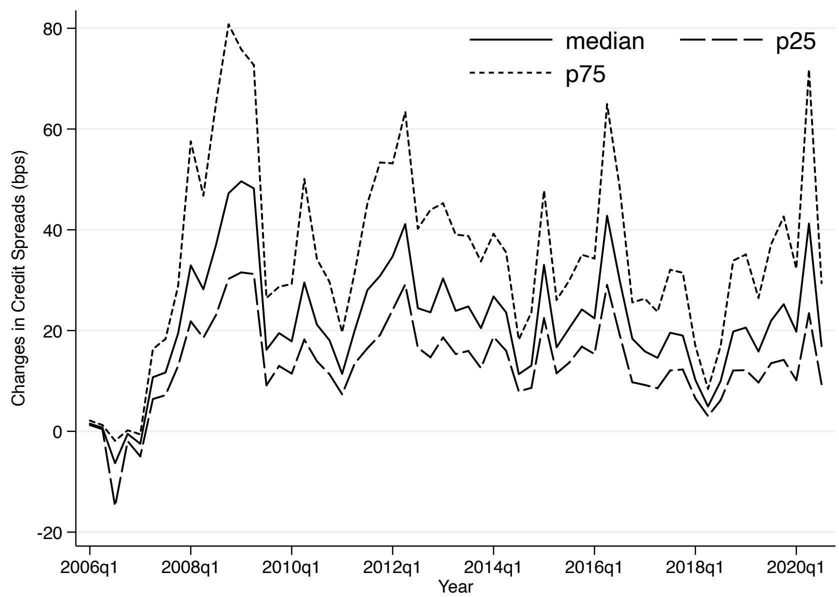


Figure 5: Undoing the Rise of Bond Mutual Funds: Aggregate Effects

This figure reports the counterfactual changes in credit spreads had the relative size of the mutual fund sector stayed unchanged since 2006:1. Panel (a) reports the counterfactual changes in credit spreads in basis points for all bonds held predominantly by mutual funds, i.e., when more than 50% of the total amount outstanding is held by mutual funds. Similarly, panel (b) reports the counterfactual changes in credit spreads for bonds that are *not* predominantly held by mutual funds. Both figures plot the market value-weighted median, the 25th, and the 75th percentiles of credit spread changes. The quarterly sample period is from 2006:1 to 2020:3.

(a) Bonds predominantly held by mutual funds.



(b) Other bonds.

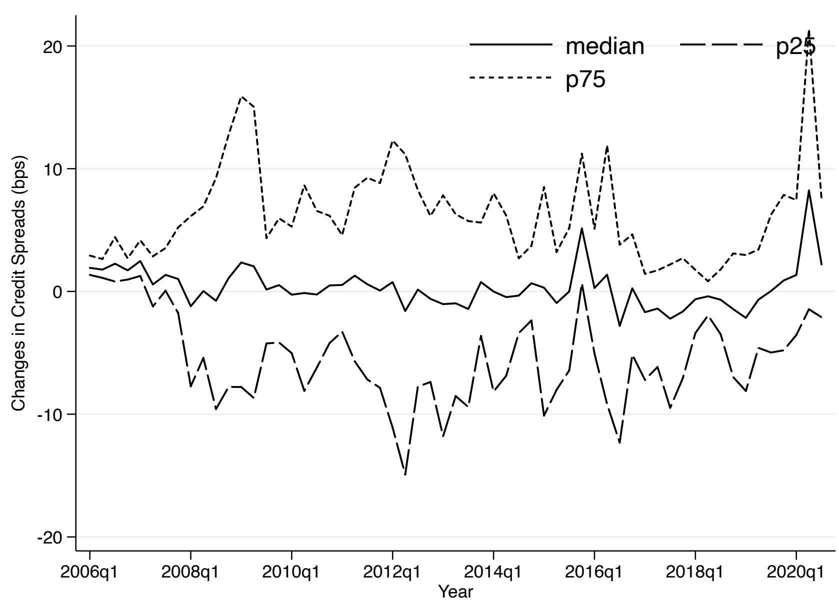
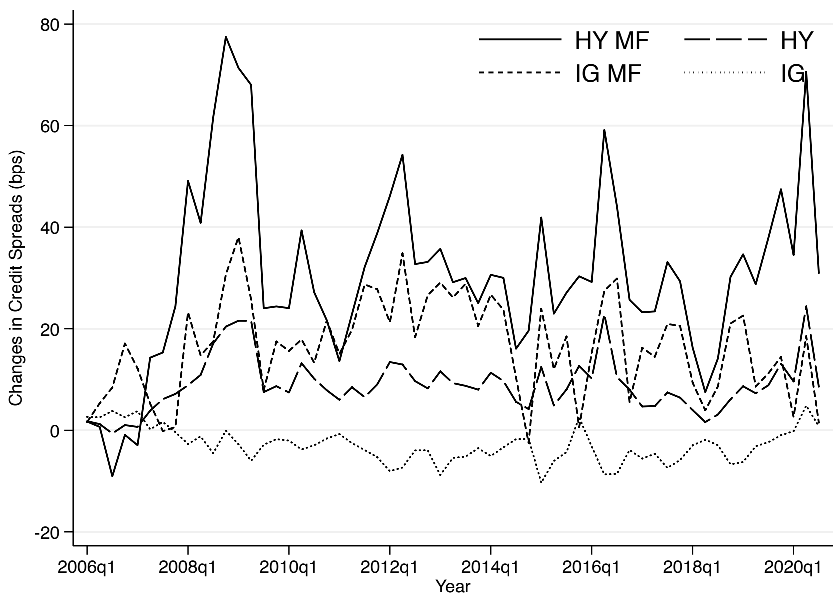


Figure 6: Undoing the Rise of Bond Mutual Funds: Heterogeneity of the Effects

This figure reports the counterfactual changes in credit spreads had the relative size of the mutual fund sector stayed unchanged since 2006:1. Panel (a) reports the counterfactual changes in credit spread in basis points for all investment grade bonds, all high yield bonds, investment grade bonds held predominantly by mutual funds, and high yield bonds held predominantly by mutual funds. Panel (b) reports the counterfactual changes in credit spreads in basis points for short- and long-term bonds that are held predominantly by mutual funds and bonds that are not. The sample period is from 2006:1 to 2020:3.

(a) High yield vs investment grade bonds.



(b) Short- vs long-term bonds.

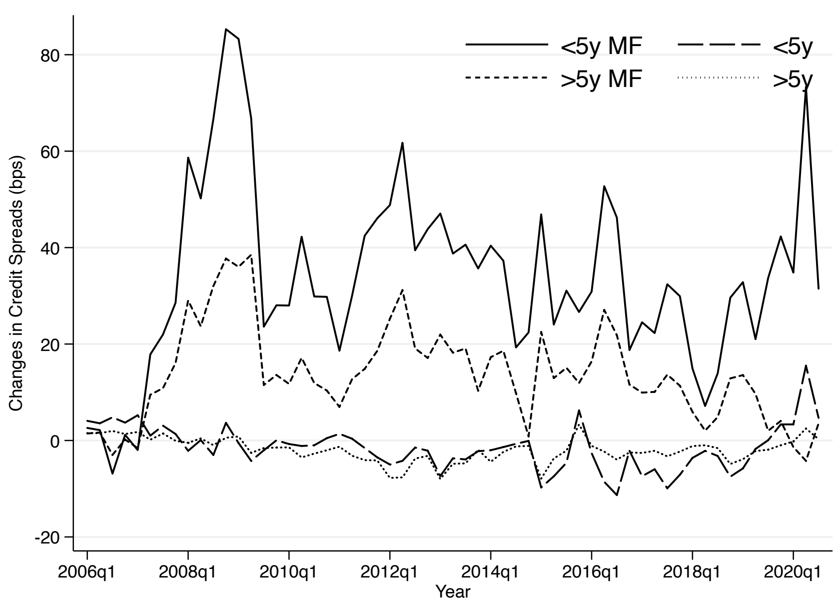


Figure 7: Run on Large Mutual Funds: Aggregate Effects

This figure reports the counterfactual changes in credit spreads had the mutual fund sector experienced an outflow that corresponds to 1% of the total AUM in the sample. We report the value-weighted median, the 25th, and the 75th percentiles of the difference in credit spread changes between bonds that are mainly held by mutual funds and other bonds. The quarterly sample period is from 2006:1 to 2020:3.

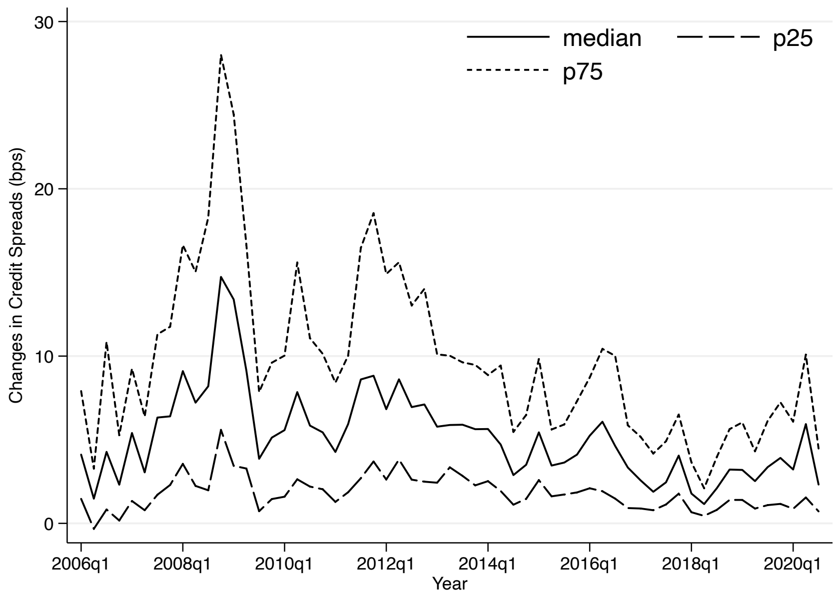
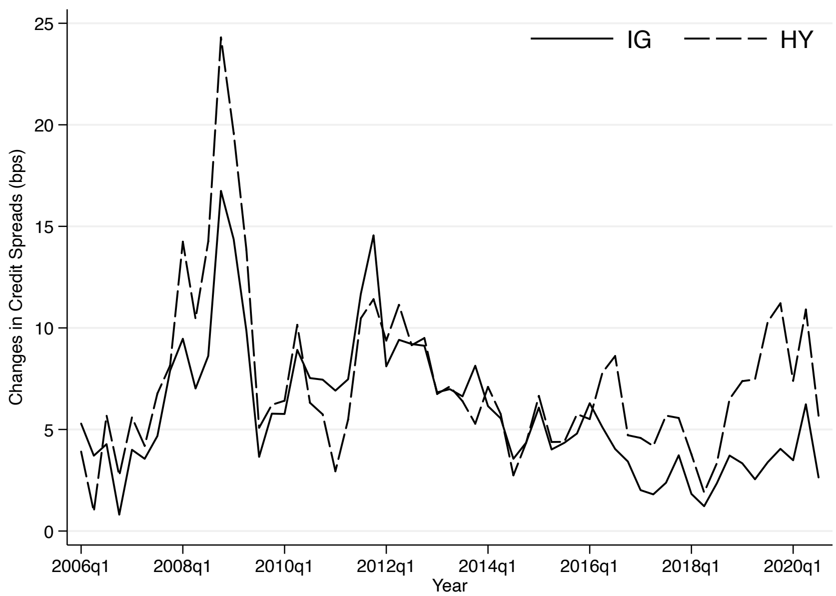


Figure 8: Run on Large Mutual Funds: Heterogeneity of the Effects

This figure reports the counterfactual changes in credit spreads had the mutual fund sector experienced an outflow that corresponds to 1% of the total AUM in the sample. We report the value-weighted mean of the difference in credit spread changes between bonds that are mainly held by mutual funds and other bonds. In particular, panel (a) plots this difference for high yield and investment grade bonds and panel (b) for short- and long-term bonds. The quarterly sample period is from 2006:1 to 2020:3.

(a) High yield vs investment grade bonds.



(b) Short- vs long-term bonds.

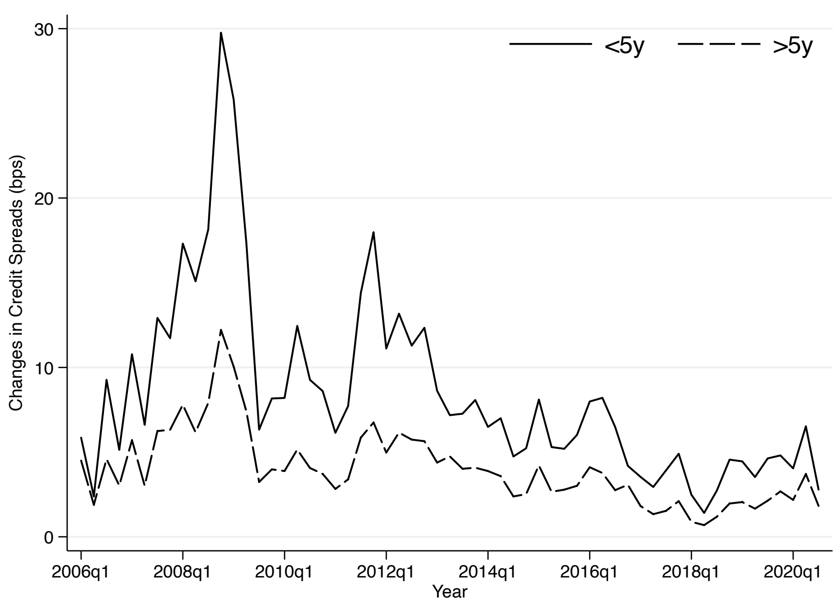
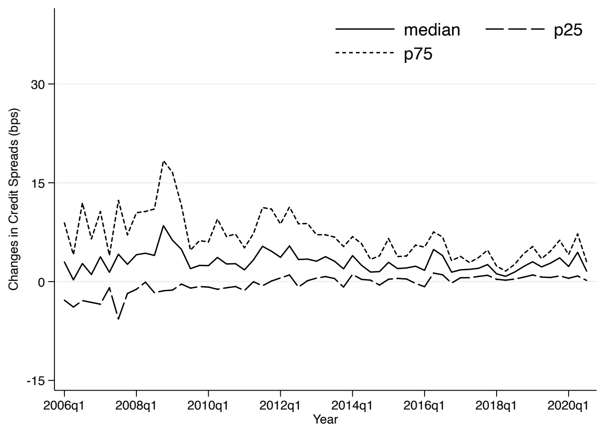


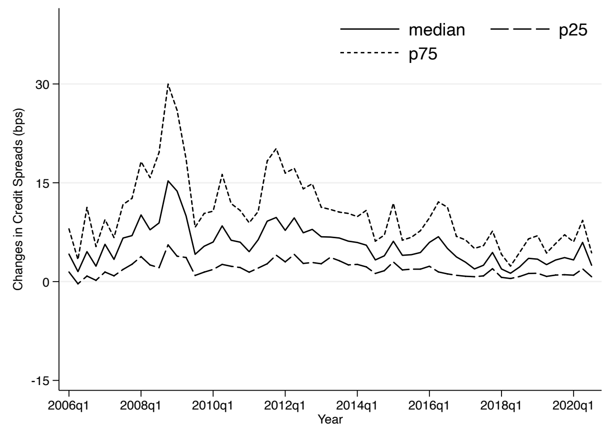
Figure 9: Run on Large Mutual Funds: Who Provides Liquidity?

This figure reports the counterfactual changes in credit spreads had the mutual fund sector experienced an outflow where we force a set of institutions to stay out of the market and only allow a sub-group of institutions to provide liquidity. The size of the outflow corresponds to 1% of the total AUM in the sample. We report the value-weighted median, the 25th, and the 75th percentiles of the difference in credit spread changes between bonds that are mainly held by mutual funds and other bonds. The quarterly sample period is from 2006:1 to 2020:3.

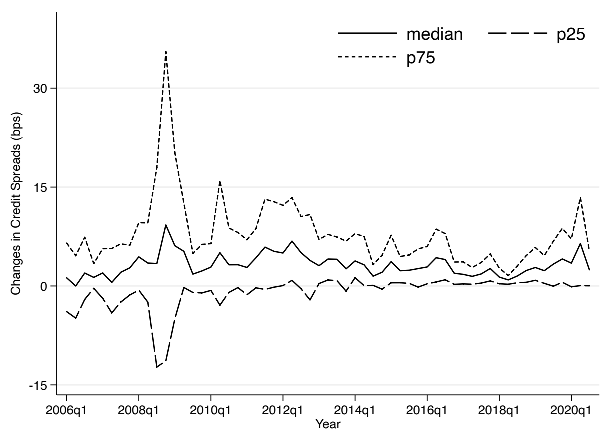
(a) Mutual funds buy.



(b) Insurance companies buy.



(c) Other investors buy.



II. Tables

Table 1: Summary of Institutional Holdings

The table reports the summary statistics of the institutional holdings in our sample. Each cell is the time-series mean of the quarterly summary statistic within the given year. The sample period includes 59 quarters from 2006:1 to 2020:3.

Year	Number of Funds	% of Market Held	Fund AUM (USD Million)		Number of Bonds in	
			Median	90th Percentile	Median	90th Percentile
2006	1281	49	54	629	48	162
2007	1360	45	55	623	51	168
2008	1570	45	55	618	53	182
2009	1972	46	59	639	57	212
2010	2036	50	63	726	58	216
2011	2172	48	65	757	60	229
2012	2444	49	68	770	64	236
2013	2486	48	71	831	68	252
2014	2622	47	70	853	67	258
2015	2676	46	70	872	69	278
2016	3260	45	67	792	68	282
2017	3666	48	69	848	74	305
2018	3297	45	72	879	79	331
2019	3960	45	68	806	78	328
2020	3478	44	76	983	86	377

Table 2: Persistence of the Set of Bonds Held

This table reports the percentage of bonds held in the current quarter that were ever held in the previous one to eleven quarters. Each cell is a pooled median across time and all institutions in the given assets under management (AUM) percentile. The quarterly sample period is from 2006:1 to 2020:3.

AUM percentile	Previous Quarters										
	1	2	3	4	5	6	7	8	9	10	11
1	92	95	95	96	97	97	97	98	98	98	98
2	91	94	95	96	96	97	97	98	98	98	98
3	91	93	94	95	96	96	97	97	97	98	98
4	91	94	95	95	96	96	97	97	97	98	98
5	91	94	95	95	96	96	97	97	97	98	98
6	91	94	95	96	96	96	97	97	97	98	98
7	91	94	95	96	96	97	97	97	98	98	98
8	91	94	95	96	96	97	97	97	98	98	98
9	91	95	96	96	97	97	97	98	98	98	98
10	91	95	97	97	98	98	98	98	98	98	99

Table 3: First Stage t-statistics - Institution Level Estimates

This table reports the distribution of the first stage t-statistics on the instrument, where we estimate a first stage regression of actual yields on the instrumented yields and all the characteristics for each institution at each quarter. We report the t-statistics by investor types in Panel A and by time in Panel B. For comparison, the absolute value of the Stock and Yogo (2005) critical value for rejecting the null of weak instruments at the 5 percent level is 4.05.

	Mean	Median	p1	p5	p90	p99
Panel A: First Stage t-statistics by Institution Types						
Life Insurers	-12.26	-11.54	-23.31	-21.44	-6.33	-4.92
P&C Insurers	-12.50	-12.06	-22.81	-20.38	-6.98	-5.05
Mutual Funds	-11.00	-10.56	-22.40	-19.31	-5.82	-4.29
Variable Annuities	-10.58	-10.00	-20.58	-17.92	-5.84	-4.67
Others & Pension Funds	-12.11	-10.54	-23.77	-20.73	-6.70	-5.00
Foreign Investors	-8.89	-8.83	-16.27	-15.06	-3.80	-2.42
Panel B: First Stage t-statistics Over Time						
2006 - 2008	-14.97	-15.28	-24.10	-22.36	-8.64	-7.37
2008 - 2010	-9.73	-9.40	-15.89	-14.50	-6.65	-5.96
2010 - 2012	-14.70	-14.90	-24.32	-22.31	-8.49	-5.26
2012 - 2014	-15.98	-16.41	-23.28	-22.01	-9.67	-8.53
2014 - 2016	-10.78	-10.74	-20.50	-16.90	-6.31	-5.42
2016 - 2018	-11.71	-11.56	-18.97	-16.91	-8.03	-6.99
2018 - 2020	-8.82	-8.76	-15.86	-13.19	-5.69	-4.80

Table 4: Heterogeneity in the Estimated Demand Parameters: By Institution Types

The table shows the heterogeneity in the estimated demand parameters across institution types. We estimate the characteristics-based demand equation (2) in an AUM-weighted panel regression setup. The dependent variable is the log of portfolio weight of institution i for bond b at time t, relative to the portfolio weight of the outside asset. $\overline{Yield}_{b,t}$ represents the instrumented yield of bond b at time t. The vector of characteristics include remaining maturity, bid-ask spread, initial offering amount (issuance size), and credit ratings, which we covert into a numeric scale. For ease of comparing the coefficients across characteristics, we standardise all the variables by dividing by their pooled standard deviations. Table shows standard errors in parentheses, clustered at the fund level. Significance: * 10%; ** 5%; *** 1%. The quarterly sample period is from 2006:1 to 2020:3.

	Insurance		Mutual Funds		Others	
	Life	P&C	Traditional	Variable Annuity	Others & Pension	Foreign
	I	II	III	IV	V	VI
$\overline{Yield}_{b,t}$	-0.134**	0.134	0.337***	0.379***	0.459**	0.277***
	(0.062)	(0.111)	(0.078)	(0.068)	(0.204)	(0.054)
$Maturity_{b,t}$	0.062**	-0.043	-0.065***	-0.096***	-0.094	-0.018*
	(0.025)	(0.027)	(0.018)	(0.012)	(0.059)	(0.009)
$Bid\text{-}Ask_{b,t}$	0.018*	-0.047	-0.065***	-0.092***	-0.081**	-0.113***
	(0.010)	(0.033)	(0.018)	(0.020)	(0.034)	(0.018)
$Issuance\ Size_{b,t}$	0.079***	0.057***	0.271***	0.169***	0.082***	0.159***
	(0.013)	(0.010)	(0.024)	(0.029)	(0.013)	(0.014)
$Rating_{b,t}$	-0.048*	-0.215***	-0.103***	-0.218***	-0.268***	-0.146***
	(0.026)	(0.044)	(0.033)	(0.038)	(0.056)	(0.041)
Fund × Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,873,182	3,314,272	5,044,257	1,354,470	364,796	1,754,718
Adjusted R-squared	0.04	0.05	0.11	-0.09	-0.19	-0.11
Kleibergen-Paap F-statistic	283.91	293.63	59.81	165.58	82.25	207.55

Table 5: Demand Elasticities by Institution Types

Demand elasticities are estimated for each institution, bond, and date. The elasticities are then aggregated to the institution level by calculating an AUM-weighted average. Panel A (panel B) of this table reports summary statistics of the estimated demand elasticities (pooled over time) for the sample period from 2006:1 to 2020:3 (2010:1 to 2020:3). The weighted average elasticity in the last row uses asset weights which are based on the average market values of the asset holdings of a sector.

	Mean	Median	p5	p95	sd
A. 2006:1 - 2020:3					
Life Insurers	0.50	0.49	-2.34	3.37	2.02
P&C Insurers	2.68	2.08	-0.81	6.29	3.37
Mutual Funds	11.62	9.85	5.74	19.78	5.49
Variable Annuities	7.24	7.02	3.38	12.26	4.16
Others & Pension Funds	7.51	5.75	1.73	16.38	5.50
Foreign Investors	4.76	3.65	0.30	10.58	4.73
AUM-weighted average	3.73				
B: 2010:1 - 2020:3					
Life Insurers	0.10	-0.01	-2.34	3.34	1.89
P&C Insurers	2.76	1.60	-1.19	8.29	3.89
Mutual Funds	11.50	10.39	6.16	18.31	5.26
Variable Annuities	8.11	8.10	4.31	12.28	4.46
Others & Pension Funds	8.06	5.72	1.73	18.24	6.32
Foreign Investors	3.42	3.13	0.30	7.60	2.61
AUM-weighted average	3.84				

Table 6: Credit Quality Migration

This table reports the counterfactual changes in credit spreads if a large subset of bonds experience a deterioration in credit quality. In particular, all investment grade bonds are downgraded by one notch, for example from AA+ to AA. The table reports the difference between the counterfactual and the actual credit spreads across different types of bonds and institutions. A bond is categorized as being predominantly held by a certain investor sector if more than 50% of the bond's outstanding is held by corresponding institutions combined. The sample period is from 2006:1 to 2020:3 (except in the last rows of panels A and B where we focus on the crisis sample period from 2008:3 to 2009:4).

A. Bonds predominantly held by insurance companies

	AAA	AA+	AA	AA-	A+	A	AA-	BBB+	BBB	BBB-
< 5 years	27	29	27	23	25	24	23	22	21	45
5 - 10 years	10	10	10	10	10	9	9	9	9	21
> 10 years	4	4	4	4	4	4	4	4	4	10
All maturities (Full sample)	10	13	10	11	11	11	10	11	10	22
All maturities (Financial crisis)	18	19	21	17	19	18	18	17	16	40

B. Bonds predominantly held by mutual funds

	AAA	AA+	AA	AA-	A+	A	AA-	BBB+	BBB	BBB-
< 5 years	32	26	37	31	27	31	32	34	33	26
5 - 10 years	11	12	16	15	11	11	12	11	11	11
> 10 years	4	9	5	7	4	2	3	4	3	4
All maturities (Full sample)	17	19	25	26	20	18	23	23	23	16
All maturities (Financial crisis)	24	70	35	47	19	22	20	24	20	12

Table 7: Credit Quality Migration: Heterogeneity of the Effects by Institution Types

The table reports panel regression results, where we regress the counterfactual changes in credit spreads due to credit quality migration for each bond on the fraction of total amount outstanding that is held by insurance companies (*% insurance*) and other dummy variables that characterize insurers' holdings for a given bond. For example, $\mathbb{1}_{\%insurance>\delta\%}$, equal one if insurance companies hold more than $\delta\%$ of the total amount outstanding of a bond. BBB^- is a dummy variable that takes a value of 1 for BBB- bonds and zero otherwise. We include bond characteristics as controls, including rating, time to maturity, bond size, bid-ask spreads, and the BBB^- dummy. We include quarter fixed effects so that the coefficient of interest is identified from variation across bonds. The standard errors are clustered by time and bond. The quarterly sample period is from 2006:1 to 2020:3. We restrict the sample to investment grade bonds as the conterfactual is conducted only on these bonds.

	I	II	III	IV	V
% insurance	2.15				
	(4.65)				
% insurance × BBB^-	55.64***				
	(18.96)				
$\mathbb{1}_{\%insurance>20\%}$		2.88			
		(1.56)			
$\mathbb{1}_{\%insurance>20\%} \times BBB^-$		6.58*			
		(11.13)			
$\mathbb{1}_{\%insurance>40\%}$			1.86		
			(1.31)		
$\mathbb{1}_{\%insurance>40\%} \times BBB^-$			7.40		
			(8.09)		
$\mathbb{1}_{\%insurance>60\%}$				1.23	
				(1.20)	
$\mathbb{1}_{\%insurance>60\%} \times BBB^-$				17.19***	
				(6.76)	
$\mathbb{1}_{\%insurance>80\%}$					1.80
					(1.14)
$\mathbb{1}_{\%insurance>80\%} \times BBB^-$					22.29***
					(6.05)
Controls	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	147,787	147,787	147,787	147,787	147,787
Adjusted R-squared	0.13	0.13	0.13	0.13	0.13

Table 8: Interest Rate Liftoff

This table reports the counterfactual changes in yields of U.S. corporate bonds if Fed Funds rates were to rise by 100bps due to a tightening of monetary policy. The table reports the difference between the counterfactual and empirical (actual) yields by letter rating and bond maturity. The counterfactual estimation is done assuming an initial starting point that mimics the holding patterns and market conditions in 2020.

	Counterfactual Changes in Credit Spreads						
	AAA	AA	A	BBB	BB	B	CCC
A. Changes in Demand Parameters							
$<$ 5 years	28	30	34	39	39	36	35
5 - 10 years	12	13	15	16	16	19	17
$>$ 10 years	4	6	7	7	5	6	4
B. Changes in AUM Composition							
$<$ 5 years	1	0	-1	0	3	4	2
5 - 10 years	0	0	-1	0	2	3	0
$>$ 10 years	-1	0	-1	-1	0	0	2
C. Changes in Demand Parameters & AUM composition							
$<$ 5 years	22	26	28	32	37	35	31
5 - 10 years	9	11	12	13	16	18	19
$>$ 10 years	2	5	4	4	4	4	6

Table 9: Impact of Fed Selling-off its Corporate Bond Holdings

This table reports the counterfactual changes in credit spreads had the Federal Reserve sold their entire Secondary Market Corporate Credit Facility (SMCCF) corporate bond holdings at the end of 2020:3. The table reports the counterfactual credit spreads as well as the changes between counterfactual and empirical credit spreads. The counterfactual estimation is done assuming an initial starting point that mimics the holding patterns and market conditions in 2020:Q3.

	Counterfactual Credit Spreads			
	AAA	AA	A	BBB
All	25	29	46	104
$<$ 3 years	23	25	42	94
$>$ 3 years	32	42	57	125
	Credit Spreads Changes			
	AAA	AA	A	BBB
All	2	2	2	2
$<$ 3 years	2	2	3	2
$>$ 3 years	2	1	1	1

A. Additional Figures and Tables

Figure A.1: Standard Deviation of Latent Demand

This figure displays the cross-sectional standard deviation of log latent demand by institution type, weighted by assets under management. The quarterly sample period is from 2006:1 to 2020:3.

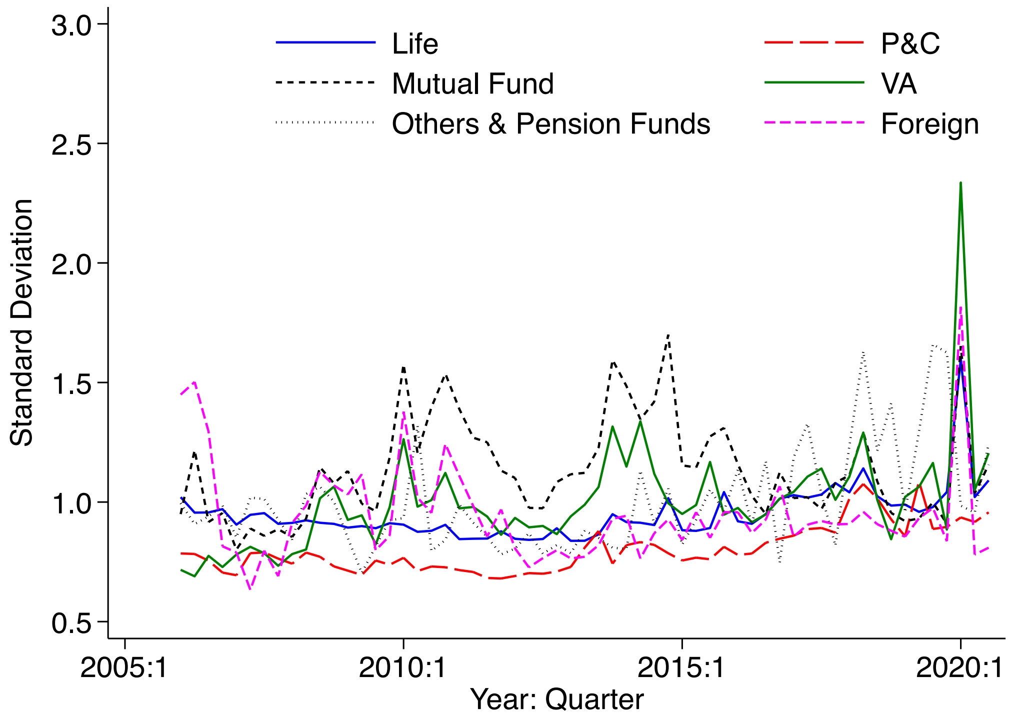


Table A.1: Coverage of Corporate Bonds in the WRDS Bond Returns Database

The table reports the coverage of bonds in WRDS Bonds Returns database with respect to the overall U.S. publicly traded corporate bonds' universe identified using FISD. The table reports the time-series mean of each quarterly summary statistic within the given year.

	Year						
	2006	2007	2008	2009	2010	2011	2012
Corporate bonds in FISD (*thousands*)	16.3	17.7	18	16.5	16.8	17.6	17.9
Corporate bonds in both WRDS and FISD (*thousands*)	8.2	9.1	9.8	10.4	11.5	12.6	13.9
FISD corporate bonds represented in WRDS (%)	50.6%	51.2%	54.3%	62.7%	68.4%	71.7%	77.6%
Par value of bonds in FISD (*billions*, $)	3369	3544	3730	4030	4264	4595	4872
Par value of bonds in both WRDS and FISD (*billions*, $)	2606	2849	3128	3527	3850	4228	4555
FISD corporate bonds represented in WRDS (%)	77.4%	80.4%	83.9%	87.5%	90.3%	92.0%	93.5%
	2013	2014	2015	2016	2017	2018	2019
Corporate bonds in FISD (*thousands*)	18.2	18.9	19.8	20.5	22.6	25.4	29
Corporate bonds in both WRDS and FISD (*thousands*)	15	16.1	17.4	18.4	20.7	23.7	22.9
FISD corporate bonds represented in WRDS (%)	82.5%	85.4%	87.8%	89.5%	91.6%	93.3%	79.1%
Par value of bonds in FISD (*billions*, $)	5141	5449	5929	6378	6678	6823	6928
Par value of bonds in both WRDS and FISD (*billions*, $)	4854	5178	5662	6108	6430	6594	6470
FISD corporate bonds represented in WRDS (%)	94.4%	95.0%	95.5%	95.8%	96.3%	96.6%	93.4%

Table A.2: Summary of Institutional Holdings by Institution Type

The table reports the summary statistics of the institutional holdings in our sample for each institution type. Each cell is the time-series mean of quarterly summary statistic within the given year. The sample period includes 55 quarters 2006:1 to 2020:3.

Year	Number of Funds	% of Market Held	Fund AUM (USD Million)		Number of Bonds Held	
			Median	90th Percentile	Median	90th Percentile
Panel A: Life Insurers						
2006	518	38	103	1733	74	247
2007	515	32	93	1643	75	255
2008	537	29	88	1486	78	272
2009	640	30	86	1645	86	310
2010	660	33	99	2021	88	333
2011	690	31	91	2020	89	347
2012	704	30	98	2073	94	374
2013	692	28	104	1967	98	396
2014	696	27	104	1963	98	416
2015	724	25	97	1970	96	424
2016	710	23	97	2104	102	429
2017	769	22	98	2269	110	464
2018	720	22	110	2362	119	508
2019	776	18	96	1964	112	477
2020	696	18	120	2694	135	545
Panel B: P&C Insurers						
2006	430	5	36	257	29	95
2007	441	5	36	266	30	98
2008	476	5	36	258	34	106
2009	598	5	39	277	38	118
2010	671	5	43	332	42	115
2011	722	5	43	341	42	116
2012	772	5	43	360	42	128
2013	763	5	42	380	44	146
2014	758	5	43	398	48	156
2015	784	5	45	391	50	168
2016	803	4	44	407	50	175
2017	850	4	45	448	58	210
2018	868	5	49	524	63	235
2019	868	4	50	519	68	234
2020	800	5	58	616	77	274
Panel C: Mutual Funds						
2006	196	4	46	320	43	104
2007	237	6	55	561	52	128
2008	320	8	59	602	55	134
2009	457	9	69	566	62	161
2010	432	9	79	712	59	157
2011	458	9	72	784	62	194
2012	611	11	79	798	67	212
2013	654	12	88	938	68	225
2014	640	11	90	1008	70	246
2015	671	12	99	1197	76	287
2016	849	13	90	1010	80	289
2017	994	15	97	1160	80	292
2018	849	13	103	1085	78	300
2019	1097	15	91	1020	82	342
2020	946	13	104	1199	88	388

Year	Number of Funds	% of Market Held	Fund AUM (USD Million)		Number of Bonds Held	
			Median	90th Percentile	Median	90th Percentile
			Panel D: Variable Annuities			
2006	69	1	38	193	56	113
2007	87	1	40	199	61	116
2008	103	1	49	167	62	128
2009	146	1	50	226	75	162
2010	120	1	55	243	72	148
2011	142	1	65	424	78	192
2012	174	1	67	416	83	204
2013	196	1	73	463	86	245
2014	176	1	91	483	94	254
2015	176	1	90	546	98	246
2016	234	1	93	523	107	294
2017	264	2	102	521	110	312
2018	230	1	101	548	111	332
2019	254	1	100	539	112	349
2020	201	1	84	496	113	339
			Panel E: Others & Pension Funds			
2006	59	1	74	582	43	155
2007	46	1	69	490	48	176
2008	85	1	57	549	47	156
2009	52	1	80	688	52	188
2010	65	1	88	743	62	217
2011	71	1	93	862	64	244
2012	80	1	108	816	68	240
2013	46	1	157	1365	80	315
2014	49	1	181	1644	88	318
2015	48	1	145	1778	80	309
2016	47	1	133	2215	77	337
2017	44	1	155	2482	88	373
2018	43	1	199	3029	112	395
2019	46	1	170	2667	105	339
2020	42	1	265	3490	134	516
			Panel F: Foreign			
2006	10	0	51	976	32	71
2007	33	0	43	479	39	95
2008	50	0	47	236	46	94
2009	78	0	40	187	58	108
2010	88	1	52	275	58	113
2011	87	1	57	453	63	121
2012	104	1	73	490	70	140
2013	136	1	70	513	74	159
2014	303	2	51	514	46	148
2015	273	2	43	374	36	154
2016	617	3	46	418	41	194
2017	745	4	49	425	47	201
2018	587	2	47	362	48	216
2019	919	6	44	433	43	221
2020	793	7	47	472	46	237

Table A.3: Institutional Holdings: Ratings Distribution

The table reports the rating distribution (by par value) of bonds outstanding (Column I), bond holdings (Column II), and holdings for each institution type (Column III to V). Each cell in column I is a pooled ratio of total outstanding of the bonds in a given rating category by total outstanding. Each cell in column II is a pooled ratio of total holdings of the bonds in a given rating category by total bond holdings. Each cell in column III to V is a pooled ratio of total holdings of the bonds in a given rating for all financial institutions that belong to a given type by total bond holding (by par value). Insurers include both Life and P&C insurers; Mutual funds include both traditional and variable annuities funds; and Others include foreign funds, pension funds, and other funds.

Rating	Overall Market	Holdings Data	Holdings By Institution Type		
			Insurers	Mutual Funds	Others
	I	II	III	IV	V
AAA	2.0%	1.4%	0.8%	0.3%	0.3%
AA	9.7%	7.7%	4.9%	1.9%	0.9%
A	34.1%	34.6%	25.0%	7.1%	2.5%
BBB	37.7%	41.8%	27.9%	10.8%	3.2%
BB	8.2%	7.7%	2.8%	3.8%	1.1%
B	5.7%	5.2%	1.0%	3.3%	0.9%
CCC	2.1%	1.4%	0.2%	1.1%	0.2%
CC	0.1%	0.1%	0.0%	0.1%	0.0%
C	0.1%	0.0%	0.0%	0.0%	0.0%
D	0.2%	0.1%	0.0%	0.1%	0.0%
Total	100.0%	100.0%	62.6%	28.4%	9.0%

Table A.4: Institutional Holdings: Maturity Distribution

The table reports the maturity distribution (by par value) of bonds outstanding (Column I), bond holdings (Column II), and holdings for each institution type (Column III to V). Each cell in column I is a pooled ratio of total outstanding of the bonds in a given maturity bucket by total outstanding. Each cell in column II is a pooled ratio of total holdings of the bonds in a given maturity bucket by total bond holdings. Each cell in column III to V is a pooled ratio of total holdings of the bonds in a maturity bucket for all financial institutions that belong to a given type by total bond holding (by par value). Insurers include both Life and P&C insurers; Mutual funds include both traditional and variable annuities funds; and Others include foreign funds, pension funds, and other funds.

Maturity	Overall Market	Holdings Data	Holdings By Institution Type		
			Insurers	Mutual Funds	Others
	I	II	III	IV	V
Less than 5 Years	44.6%	34.6%	20.0%	12.2%	2.5%
5 to 10 Years	30.9%	36.6%	22.4%	11.5%	2.7%
10 to 30 Years	23.5%	27.7%	19.6%	4.6%	3.5%
Greater than 30 Years	1.0%	1.0%	0.6%	0.2%	0.2%
Total	100.0%	100.0%	62.6%	28.4%	9.0%

Table A.5: Estimated Demand Parameters: By Institution Types - Ratings Segmentation

The table shows the heterogeneity in the estimated demand parameters across institution types. We estimate the characteristics-based demand equation (2) in an AUM-weighted panel regression setup. The dependent variable is the log of portfolio weight of institution i for bond b at time t, relative to the portfolio weight of the outside asset. $\overline{Yield}_{b,t}$ represents the instrumented yield of bond b at time t. The vector of characteristics include remaining maturity, bid-ask spread, initial offering amount (issuance size), a dummy variable that takes the value of 1 if a bond is a high yield bond and 0 otherwise, credit ratings, which we covert into a numeric scale, and interactions of credit ratings with dummies for investment grade (IG) and high yield (HY) bonds. For ease of comparing the coefficients across characteristics, we standardise all the variables by dividing by their pooled standard deviations. Table shows standard errors in parentheses, clustered at the fund level. Significance: * 10%; ** 5%; *** 1%. The quarterly sample period is from 2006:1 to 2020:3.

	Life	P&C	Mutual Funds	Variable Annuity	Others & Pension	Foreign
	I	II	III	IV	V	VI
$\overline{Yield}_{b,t}$	-0.005	0.568***	0.645***	0.829***	1.024***	0.660***
	(0.114)	(0.187)	(0.185)	(0.133)	(0.361)	(0.132)
$Maturity_{b,t}$	0.019	-0.136***	-0.137***	-0.192***	-0.243**	-0.066***
	(0.040)	(0.042)	(0.041)	(0.023)	(0.098)	(0.017)
$Bid\text{-}Ask_{b,t}$	-0.006	-0.160***	-0.113***	-0.186***	-0.173***	-0.224***
	(0.018)	(0.053)	(0.042)	(0.038)	(0.058)	(0.046)
$Issuance\ Size_{b,t}$	0.087***	0.060***	0.274***	0.170***	0.100***	0.159***
	(0.014)	(0.007)	(0.023)	(0.029)	(0.014)	(0.014)
$Investment\ grade_{b,t} \times Rating_{b,t}$	-0.003	-0.039***	-0.035***	-0.053***	-0.045***	-0.033***
	(0.005)	(0.008)	(0.010)	(0.005)	(0.017)	(0.008)
$High\ Yield_{b,t} \times Rating_{b,t}$	-0.008	-0.109***	-0.178***	-0.216***	-0.131***	-0.198***
	(0.021)	(0.039)	(0.058)	(0.037)	(0.048)	(0.040)
$High\ Yield_{b,t}$	-0.101*	0.053	0.335**	0.292***	-0.009	0.377***
	(0.059)	(0.115)	(0.140)	(0.101)	(0.091)	(0.132)
Fund × Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,873,182	3,314,272	5,044,257	1,354,470	364,796	1,754,718
Adjusted R-squared	0.06	-0.39	-0.12	-0.68	-0.78	-0.82
Kleibergen-Paap F-statistic	442.47	125.92	301.25	278.31	59.69	63.81

Table A.6: Institutional Investor Demand Functions and Interest Rates

The table shows the relationship between the standardized demand function coefficients of the institutional investors and the federal fund rate measured in percent. Hence, the regression coefficients measure by how many standard deviations the demand function coefficients of institutional investors change if the federal fund rate moves by one percentage point. Standard errors are reported in parentheses, clustered at the institution and quarter level. All regression specifications include institution fixed effects. Significance: * 10%; ** 5%; *** 1%. The quarterly sample period is from 2006:1 to 2019:4.

	Insurance		Mutual Funds			
	Life	P&C	Traditional	Variable Annuity	Others & Pension	Foreign
$\beta_{\overline{Yield},t}$	-0.049	-0.028	0.133	-0.034	0.129	0.003
	(0.036)	(0.036)	(0.107)	(0.178)	(0.122)	(0.136)
$\beta_{Maturity,t}$	0.043	0.006	0.182*	0.377	-0.124	0.455
	(0.036)	(0.022)	(0.101)	(0.442)	(0.214)	(0.390)
$\beta_{Bid-Ask,t}$	0.011	0.025***	-0.057	-0.079	0.034	-0.201
	(0.008)	(0.009)	(0.064)	(0.147)	(0.026)	(0.204)
$\beta_{Issuance\ Size,t}$	0.003	0.031***	0.120	0.101	0.186***	-0.120
	(0.029)	(0.008)	(0.078)	(0.170)	(0.062)	(0.104)
$\beta_{Rating,t}$	0.018	0.013	-0.028**	0.054	0.036	-0.226***
	(0.017)	(0.017)	(0.014)	(0.089)	(0.022)	(0.036)

Table A.7: Institutional Investor Market Share and Interest Rates

The table shows the relationship between the overall market share of institutional investors (in percent) and the federal fund rate measured in percent. Hence, the regression coefficient measure the percentage change in institutional investor market share of a one percentage point change in the federal fund rate. Standard errors are reported in parentheses. Significance: * 10%; ** 5%; *** 1%. The quarterly sample period is from 2006:1 to 2020:3.

	Insurance		Mutual Funds			
	Life	P&C	Traditional	Variable Annuity	Others & Pension	Foreign
ffr_t	1.099***	-0.027	-1.075***	-0.086***	-0.019**	-0.178*
	(0.373)	(0.020)	(0.193)	(0.018)	(0.009)	(0.104)
Observations	59	59	59	59	59	59
Adjusted R-squared	.104	-.001	.268	.153	.042	.008

B. Implementation Details

B.1. Pseudo Zero Coupon Yields

This Section describes the procedure for computing the pseudo zero coupon yields. The advantage of zero coupon bonds over coupon paying bonds is that there is a simple and direct mapping between the price and the yield of the bond. Effectively, the log of the bond price is simply equal to the negative of the zero-coupon yield multiplied by the time to maturity:

$$ln(P_t) = -y_t(T - t) \tag{B.1}$$

To calculate bond-specific zero-coupon yields for coupon paying bonds we make use of the following approximation. The price of a coupon paying bond with time to maturity of n years which pays semi-annually a constant coupon of $C/2$ is defined as follows:

$$\begin{aligned} P_t &= C/2e^{-y_t^1} + C/2e^{-2\times y_t^2} + ... + C/2e^{-2n\times y_t^{2n}} + Fe^{-2n\times y_t^{2n}} \\ &= Fe^{-n\times y_t^n} + C/2\sum_{i=1}^{n} e^{-i\times y_t^i} \end{aligned} \tag{B.2}$$

where y_t^x denotes the zero-yield for $x/2$-years and F is the face value of the bond. That is, $Fe^{-n\times y_t^n}$ equals the price of a corresponding zero coupon bond with the same time to maturity and face value as the original coupon bond. Hence, the first term is what we are looking for. The second term is increasing in the coupon C and the time to maturity and can be approximated as follows:

$$C/2\sum_{i=1}^{2n} e^{-i\times y_t^i} \approx C \times n \times e^{-n\times y_t^{ytm}/2}$$

That is, we assume the $n/2$-years zero yield equals the yield-to-maturity of the coupon paying bond. Conditional on this approximation, we can calculate the price of the zero coupon bond by taking the difference of the price of the coupon bond and the second term on the right hand side of equation (B.2). Finally, we calculate bond specific pseudo zero yields according to equation (B.1). Importantly, however, our results for the characteristics-based demand do not change if we use yield-to-maturities for the coupon bonds rather than corresponding pseudo zero yields.