Institutional Corporate Bond Pricing*

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Abstract

The corporate bond market, dominated by institutional players such as insurance companies, pension funds, and mutual funds, is a critical source of funding for U.S. corporations. We assess the impact of shocks to financial institutions on the costs of debt financing, such as credit spreads, by estimating an equilibrium demand-based corporate bond pricing model. To that end, we first compile a rich novel dataset connecting institutional investors' holdings to corporate bond characteristics and estimate their equilibrium demand functions. We find significant heterogeneity in demand elasticities across major institutional investors. With low interest rates, mutual funds increasingly seek liquidity in corporate bond markets, with short investment horizons and high demand elasticities, akin to a reaching for yield, which is provided by insurance companies with inelastic demand. In counterfactual equilibrium simulations, we evaluate the corporate bond pricing implications of i) mutual fund fragility and bond fire sales, ii) monetary policy tightening through rising rates, and iii) a tapering of the Fed's corporate credit facility, among others. While the latter's effects appear modest, our model predicts substantial disruptions in corporate bond prices for the former two scenarios through shifts in institutional demand. In equilibrium, such disruptions are reflected in the real economy through firms' financing decisions. Our model thus emphasizes 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 nine trillions 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. In particular, our approach recognizes the role of the various main players in the corporate bond market, as well as the dispersion in their investment mandates. Following the novel equilibrium framework proposed by Koijen and Yogo (2019), we implement this approach by estimating a demand system that allows us to match institutional corporate bond holdings covering a significant fraction of the overall universe of corporate bonds outstanding. To that end, we start by building 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. The estimation results then allow to relate corporate bond demand at an institutional level to bond characteristics. Specifically, we empirically recover institutional investors' bond demand elasticities with respect to movements in prices, as well as to proxies for liquidity, default risk, duration, and issuance size. These elasticities have wide implications for corporate bond pricing.

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 particular, we can

[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.

quantitatively assess the corporate bonds pricing implications of counterfactual redistributions of assets under management across investors, changes in demand functions, or changes in bond characteristics. Focusing on counterfactual credit spreads across rating classes, we consider i) the pricing implications of corporate bond mutual fund fragility and the associated possibility of corporate bond fire sales of mutual funds that can easily be captured by forced outflows from large mutual funds in our data; ii) the pricing implications of the recent rise of corporate bond mutual funds in a low interest rate environment by computing counterfactual credit spreads in a scenario in which market shares of mutual funds had remained at their 2006 level; iii) the pricing consequences of rising interest rates following a monetary policy tightening amidst concerns about rising inflation; (iv) the consequences of a tapering of the Federal Reserve's Corporate Credit Facility, which we can represent by a counterfactual redistribution of the Fed's corporate bonds across investors; and (v) the implications of a significant credit migration in which credit risk across bonds significantly rises, similar to a perceived overall deterioration of credit quality as in the recent financial crisis. In equilibrium, any pricing implications of such scenarios are reflected in the real economy through firms' financing decisions. Our model thus allows to shed some light on the consequences of policy changes that have the potential to affect the real economy through their effects on corporate bond markets.

More specifically, our first contribution is to construct a comprehensive dataset of holdings, yields, and bond characteristics by combining three major databases. We exploit quarterly holdings data of bonds from Thomson Reuters eMAXX and carefully match it 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 asset managers and institutional investors (insurance companies, mutual funds, and pension funds predominantly) 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. We note that by the end of sample period, the share of the market held reduces to 24% for insurance companies and increases to 23% for mutual funds, closely mirroring the shares reported in U.S. Flow of Funds account. Our definition of U.S. publicly traded corporate bond universe yields the total outstanding (by par value) of 6.5 trillion U.S. dollars in 2019.[2] On average, WRDS Bond Returns database provides us with the yields of around 90% of the bonds that are part of U.S. corporate bond universe.

[2]According to SIFMA, the total U.S. corporate bonds outstanding is $9 trillion as of 2019.

With our dataset in hand, we estimate a demand system at an intermediary 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 in the time series, 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. As an example, shocks to latent demand may capture unexpected changes in the regulatory environment. Our initial set of bond characteristics include yield, bond size, liquidity, default risk, time to maturity, and coupon.

While in the light of current empirical asset pricing it is natural to relate investors' demanded portfolio weights to bond characteristics, an endogeneity problem arises as any demand left unmodeled is likely correlated with weights and prices themselves. We find that the persistence of investors' investment mandates provides a reliable instrument that allows to isolate exogenous variation in prices and therefore provide unbiased coefficient estimates. Indeed, we find that corporate bond portfolio compositions are very persistent over time in line with the notion that long-term investors predominantly implement buy and hold strategies. This observation makes corporate bond investments an ideal environment to apply the demand based asset pricing approach.

Regarding demand elasticities, we uncover several empirical patterns that stress the importance of dissecting corporate bond demand at an institutional level. In particular, our results suggest substantial differences in corporate bond demand across institutional investors. Such patterns are challenging to rationalize in a representative agent framework. Specifically, we find that that insurance companies have less elastic demand than mutual funds consistently in most time periods. Moreover, while the demand for mutual funds is downward-sloping, demand for life insurers becomes upward-sloping during the recent low interest interest rate period. These facts line up with insurers' duration hedging motives. As insurers' hedging demand increases with declines in interest rates, demand for corporate bonds increases and the slope of the demand curve becomes upward-sloping. In contrast, mutual funds do not hedge duration mismatch in the same way as life insurers and the slope of the demand curve remains downward-sloping throughout. Similarly, we find significant differences in the demand for liquidity across these institutions. Mutual funds tilt their portfolios towards more liquid bonds, while, in contrast, insurance companies tilt their portfolios towards more illiquid bonds, as measured by their bid-ask spreads. Moreover, mutual funds tilt their portfolios toward bonds with shorter maturities. This finding is again consistent with the notion that insurance companies are more heavily invested in long-term bonds, which are likely less liquid.

We find that corporate bond demand of mutual funds and insurance companies differ across a host of additional key dimensions. Mutual funds tilt their portfolios toward bonds with higher offering amounts (large bonds). In contrast, insurance companies tilt their portfolios toward smaller bonds. Surprisingly, we find that the corporate bond market is less segmented along credit ratings as compared to other bond characteristics, such as maturity, liquidity, and bond size. Indeed, our results suggest that the corporate bond market is highly segmented along bond maturity. Mutual funds tilt their portfolios toward bonds with shorter maturities. In contrast, insurance companies tilt their portfolios toward bonds with longer maturities. We also investigate the latent demand of these investors, which is the demand originating due to investors' preferences, beliefs, and constraints that are not captured by the characteristics themselves. We find that cross-sectional variability in latent demand is fairly stable over time for most institutions.

In addition, the estimated demand system allows us to measure the price impact of idiosyncratic shocks to an investor's latent demand. We use this measure to study the evolution of liquidity in the corporate bond market over time, and in particular after the financial crisis and during the COVID-19 period. We find that the average price impact increased during the financial crisis and has remained high for most of the post-crisis period. Interestingly, the increase in the price impact is similar for all bonds across the distribution, i.e. price impact has increased not just for the most illiquid bonds, but also for the relatively more liquid bonds, 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 jumps up and remains high during this period, consistent with the results in Haddad, Moreira, and Muir (2020). The dynamics of the price impact after the financial crisis are also consistent 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 and have potentially undermined investors' ability to adjust their portfolios without impacting prices too much. We also investigate the heterogeneity in price impact across institutions and find that the price impact of an average insurance company is larger than the average mutual fund.

Finally, our counterfactual experiments provide a quantitative perspective on the effects of the recent macroeconomic environment on equilibrium corporate bond prices. In particular, 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 market participants with a preference for long-term bonds, primarily insurance companies. This effect has been diminishing over time as other mutual funds would have been better able to absorb large redemptions recently. 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 bonds. Similarly, our estimated model predicts significantly higher credit across all securities in a scenario of a large credit migration, such as an overall possibly perceived deterioration of credit quality, as observed at the onset of the recent Covid-19 crisis. 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 investor holding a bond matters for equilibrium bond prices, contrary to what would be suggested by the standard representative-agent based models of corporate bond pricing. Moreover, our findings suggest that such 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 corporate bond markets.

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.[3] 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

[3]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.

bonds. Second and crucially, this literature has not explored the role of liquidity providers (e.g., insurers) 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 pricing dynamics driven by shocks originating in the mutual funds sector.[4]

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. 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.

2. Institutional Corporate Bond Holdings Data

2.1. Data Sources and Sample Construction

Our sample combines data from three sources. We obtain monthly prices, yields, and ratings for 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, such as maturity, coupon rate, currency, issuer domicile, rule 144 classification, etc. 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. In addition to prices and yields, the database also provides bond ratings. As the holdings data are at a quarterly frequency, we convert the monthly time series to quarterly frequency by taking the last available yield and price of each bond in a given quarter. WRDS Bond Returns database uses the transactions reported in TRACE (Trade Reporting and Compliance Engine) to first compute bond prices, and subsequently use these prices to calculate bond yields.

[4]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.

Availability of prices and yields in the WRDS database is conditional on observing the transactions of a given bond in TRACE. As some bonds may not trade frequently and thus may not be present in the WRDS database, we check the quality of the coverage with respect 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 U.S., and are publicly traded. We exclude convertible bonds and only keep bonds that were outstanding in a given quarter. Our definition of U.S. publicly traded corporate bond universe yields the total outstanding (by par value) of 6.5 trillion US dollars in 2019.[5]

We merge the bonds that are in WRDS Bond Returns database with the U.S. corporate bond universe. Table A.1 provides the coverage of the WRDS Bond Returns database over the years. On average, WRDS Bond Returns database provides us with the yields of around 90% of the bonds that are part of U.S. corporate bond universe. The coverage improves over time from 77% in 2006 to around 93% in 2019. In addition, we classify the bonds that are in the WRDS Bond Returns database but are not part of our definition of U.S. publicly traded corporate bond as the *outside asset*.

Next, we merge the bonds in the WRDS Bond Returns database with Thomson Reuters eMAXX US to obtain bond holdings. eMAXX provides comprehensive coverage of fixed income holdings by asset managers and institutional investors at the security level.[6] The database predominantly covers the holdings of insurance companies, mutual funds, and pension funds (Becker and Ivashina (2015)).[7] To further substantiate our sample with holdings of US corporate bonds by foreign institutions, we also enrich our data set with the eMAXX Europe holdings data. Our final sample consists 20 million bond $\times$ institution $\times$ quarter observations of non-zero holdings.[8,9]

Table 1 provides an overview of the bond holdings in our final sample. Our sample period starts in quarter 1 of 2006 and ends in quarter 3 of 2019. 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 bond amount outstanding. The

[5]According to SIFMA total U.S. corporate bond outstanding is $9 trillion as of 2019.

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

[7]The database does not have the holdings of some institutional investors including hedge funds and banks.

[8]The number of observations is roughly 80 times larger when we include the zero holdings of institutions. This increase in observations is due to the large number of institutions as well as bonds in the cross-section.

[9]In the event eMAXX cannot obtain updated holdings for a given quarter from an institution, the previous quarter holdings are reported. We drop such stale holdings.

median (90th percentile) asset under management (AUM) for these financial intuitions is around \$65 million (\$630 million) at the start of the sample and it increases to \$74 million (\$1 billion) by the end of the sample period. The median (90th percentile) number of bonds held by the financial institutions in our sample ranges from 50 to 85 (160 to 375).

Market clearing requires that a bond's total outstanding equal the sum of the dollar holdings across all institutions. For each bond, we define the share held by the residual sector as the difference between bonds' outstanding amount and the total dollar holdings of all institutions observed in eMAXX. The residual sector represents holdings of institutions that are not currently captured by our sample such as banks, hedge funds, bond ETFs, 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, no bonds in the investment universe, or no outside assets.

2.2. Sample Representativeness and Coverage

To check whether our sample well represents the overall holding patterns in the corporate bond market, we plot the share of corporate bonds held by different types of institutions using flow of funds data from financial accounts of the United States. Figure 1 shows that insurance companies and mutual funds are the largest holders of corporate bonds and together they hold close to 60% of the total U.S. corporate bonds outstanding. Pension funds are the third largest investors in the U.S. corporate bond market. In line with this, the majority of financial institutions in our sample also consist of insurance companies and mutual funds. The remaining institutions in our sample predominantly consist of other long-term investors such as pension funds, endowments, and sovereign funds. In view of this, we classify the financial institutions in eMAXX into three types: i) insurance companies; ii) mutual funds; and iii) pension funds and other long-term investors (henceforth, pension funds).

Table A.2 provides the bond holdings by institution type. In terms of the share of the market held, 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 of increase in the number of bond mutual funds and their holdings post-crisis. Both the level of holdings and the trend in our sample across institution types mirror the ownership patterns we observe using the flow of funds data (see Figure 1). This gives us confidence that our sample is a fair representation of the holding patterns in corporate bonds and well captures the three main types of investors, which account for over 70% of the total holdings in the sector. Moreover, our sample also captures well the evolution of the holdings over time for these institutions.

To check if our sample fairly represents the portfolio composition of different type of financial institutions and that the sample is not skewed towards a certain type of bonds, we compare the rating and maturity distribution of holdings in our sample with the distribution of bonds that were outstanding during our sample period. Table 2 provides 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). A simple comparison between the distribution of the bonds outstanding with the distribution of bond holdings, show that the holdings in our sample are not skewed towards a particular rating category. During our sample period, 83.5% of the bonds belong to the investment grade category (BBB or above). In comparison, 85.5% of the total holdings in our sample belong to investment grade category. We also observe that insurance companies hold a very small proportion of bonds in the high yield category. This is consistent with the holdings of insurers obtained from their statuary fillings which show that insurers tend to hold a very small share of non-investment grade bonds (Sen and Sharma (2020)).

Table 3 provides the distribution of the total bond outstanding and total bond holdings, and holdings for each institution type across maturity buckets. Holdings in our sample constitutes of 45% of the bond with less than 5 years of maturity, 31% with maturity between 5 to 10 years, and 24% with maturity between 10 to 30 years. This matches quite closely with the distribution of the overall bonds outstanding during our sample period. During our sample period, around 35% of the bonds outstanding has less than 5 years of maturity, 37% has the maturity between 5 to 10 years, and 28% has the maturity greater than 10 years. We also find that around 80% of the bonds with maturity above 10 years are held by insurance companies.

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) and make one important change: we incorporate bond-specific features to the demand system, which can 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 owns asset $A_{i,t}$, which she allocates across bonds in her investment universe and an outside asset. 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 which are restricted by their investment mandates.

The portfolio weights of investor i are denoted by $w_{i,t}(n)$, where $\sum_{n=0}^{N} w_{i,t}(n) = 1$:

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

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 have 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. For example, liquidity has been shown to be an important determinant of corporate bond risk (see, for example, Dick-Nielsen, Feldhütter, and Lando (2012) or Chen, Lesmond, and Wei (2007)). In our analysis, we capture liquidity of a security by including the bond's bid ask spread.

Further, we additionally include the size of a bond, i.e., the initial offering amount which can be seen as another proxy for liquidity. Importantly, however, Sen and Sharma (2020) show that insurance companies care about the size after controlling for a bond's liquidity. Moreover, we follow Koijen, Koulischer, Nguyen, and Yogo (2020a) and include a bond's time to maturity. Finally, we follow Bali, Bai, and Wen (2019) and rely on Standard & Poor credit ratings to capture credit risk of a bond.

3.2. Market Clearing

We complete the asset pricing model with market clearing 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. That is, the market value of a bond must equal the wealth-weighted sum of portfolio weights across all investors. To ensure market clearing for all bonds at all times, we introduce a residual investor which accounts for all the holdings for each bond which we do not observe in our sample. Additionally, this residual investor also includes small institutions with with less than \$10 millions 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 from Koijen and Yogo (2019) as it makes use of investment mandates at the investor level.

An investment mandates defines the investment universe for a given investor, i.e., the group of securities in which an investor is allowed to invest. Institutional corporate bond investors are likely to have investment mandates. It is probably most transparently stated in the case of corporate bond indices. Similarly, insurance companies could also have investment mandates. Unfortunately, for most investors these investment mandates are not readily accessible. Consequently, we attempt to verify the that institutional investors indeed invest in a fixed subset of bonds by following Koijen and Yogo (2019) and, in particular, replicating their Table 1. That is, we define the investment universe for each institution at each date as bonds that are currently held or ever held in the previous 11 quarters. Thus, the investment universe includes a zero holding whenever a bond that was held in the previous 11 quarters is no longer in the portfolio. Table 4 reports the percentage of bonds held in the current quarter that were ever held in the previous one to 11 quarters. For the median institution in assets under management (AUM), 91 percent of bonds that are currently held were also held in the previous quarter. This percentage increases slowly to 98 percent at 11 quarters. That is, corporate bond portfolio compositions seem to be very persistent over time which is in line with long-term investors that predominantly implement buy and hold strategies. Put differently, the current holdings contain information of 91 percent of the holdings held in the past 11 quarters. Compared to bonds, similar percentages for stocks are not nearly as high. We follow Koijen and Yogo (2019) and define an investor's investment universe based on 11 quarters lookback period. That said, we could probably afford to have a slightly shorter lookback period given the very persistent holdings in corporate bonds.

To sum up, Table 4 provides supporting evidence for our initial claim. Put differently, institutions have investment mandates, as they invest in a relatively fixed subgroup of bond issuers over time. That is, in what follows we define the investment universe for each institution at a given date as the subset of bond issuers that are currently or were ever held in the previous 11 quarters.

Importantly, as the investment universes are pre-determined, they are exogenous to demand shocks. However, the validity of an instrument based on exogenous investment mandates also depends on the variation in the investment universe across investors. 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.

Importantly, corporate bonds are conceptually very different from stocks. That is, an investor might buy and sell and buy again a certain stock over and over again over the sample period. In contrast, however, corporate bonds have a predetermined expiry date. As a result, whenever a bond has 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, allow 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. Alternatively, we could follow Yu (2020) and define the investment universe at the issuer rather than at the bond level.

Having defined investment universes for each investor, we instrument the yield of bond n 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 i (i.e, $n \in N_{i,t}$). 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.

To make our instrument more robust, we only use institutions with steady firm-level investment universe. That is, in our calculations of the instrument, we only use observations where at least 95 percent of issuers of current bond holdings are included in the firm-level investment universe.

3.4. Implementation

Tables 1 and A.2 show 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 by two different methods.

First, we pool all financial institutions of the same type and estimate an investor group specific instrumental variable (IV) regressions. We distinguish between six different institution groups: life insurers, P&C insurers, traditional mutual funds, variable annuities, other US institutions & pension funds, and foreign institutions. Further, we 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 due to the fact that most corporate bonds pay non-zero coupons. While estimating characteristics-based demand functions with yield-to-maturities for coupon paying bonds is not an issue, things get more complicated when evaluating counterfactuals as we further discuss in section 6. To pre-empt these issues we calculate bond-specific pseudo zero-coupon yields based on yield-to-maturities. 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:

$$ln(P_t) = -y_t(T - t) \tag{4}$$

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:

$$\begin{aligned} P_t &= C/2e^{-y_t^1} + C/2e^{-2\times y_t^2} + ... + C/2e^{-2n\times y_t^{2n}} + Fe^{-2n\times y_t^{2n}} \\ &= Fe^{-n\times y_t^n} + C/2\sum_{i=1}^{n} e^{-i\times y_t^i} \end{aligned} \tag{5}$$

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 (5). Finally, we calculate bond specific pseudo zero yields according to equation (4). 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.

4. Estimation Results

This section documents the main findings of the estimation of the characteristics-based demand system in equation (2). We include a bond's time to maturity to capture duration risk. To proxy for bonds' default risk, we convert bonds' ratings into a numeric scale using the numerical ratings provided in the WRDS Bond Return database for each rating category. Numerical ratings range from 1 (AAA) to 21 (C-). To proxy for liquidity, we include the bond's bid-ask spread. We also include the initial offering amount of a bond, which can be seen as a proxy for a bond's liquidity, but it is also a measure of a bond's size and, to some extent, the size of the issuer.

4.1. Demand Heterogeneity

Table 5 shows the characteristics-based corporate bond demand by institution type estimated from an IV regression. We group our sample institutions into the following broad groups: insurance companies, mutual funds, other US institutions and pension funds, and foreign institutions. We further break insurance companies into life insurers and property and casualty (P&C) insurers. Also within mutual funds, we distinguish between traditional mutual funds, which also include bond ETFs, and variable annuity (VA) funds.[10] Further, we include Fund $\times$ Quarter fixed effects to exploit the variation in holdings within a fund and quarter. For all investor groups the Kleibergen-Paap F-statistic is substantially above the Stock and Yogo (2005) critical value of 10. That is, we reject the null of weak instruments.

The table reveals that institutions have vastly different demand elasticities and that preferences vary for different bond characteristics across institution types. Insurance companies have less elastic demand and mutual funds, pension funds, and foreign investors are significantly more elastic with respect to bond yields. We also estimate a negative (and statistically significant) coefficient on the instrumented yield for life insurers and a positive (but statistically insignificant) coefficient for P&C insurers. Thus, there is heterogeneity within insurance companies with life insurers being less elastic compared to P&C insurers.[11]

Notably, life insurers have a preference for long maturity bonds relative to other investors (P&C, mutual funds and foreign institutions), which have a preference for short maturity

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

[11] 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.

bonds. P&C, mutual funds, pension, and foreign institutions also have a preference for more liquid bonds, as can be seen from the negative coefficient on the bid-ask spread. In contrast, life insurers have a positive coefficient, suggesting, if anything, a preference for bonds with high bid-ask spreads. Mutual funds also appear to have a greater preference for bonds with greater issuance size relative to P&C and life insurers. Finally, the coefficient on rating is consistently negative across all institution types.

4.2. Demand Heterogeneity: Time-Series Dynamics

To explore the time-series dynamics we estimate the characteristics-based demand system at the institution and quarter level. We start by quantifying the strength of our instrument and run a first-stage regression of yields on the instrumented yield and the characteristics contained in the vector $\mathbf{x}_{i,t}$ for each institution at each quarter. Table 6 reports the distribution of the first-stage t-statistics by investor groups in Panel A and over time in Panel B. Naturally, the t-statistics are negative due to the inverse relationship between the investment universe of a bond and its yields. More importantly, the absolute value of the statistics are generally well above the critical value for rejecting the null of weak instruments at the 5% level (Stock and Yogo (2005)).[12] Notably, the first-stage holds up strongly even during the period which contains the financial crisis between 2008 and 2010.

Figure 2 plots the estimated coefficients for the three largest institution types over time.[13] Three key points stand out. First, the differences in the coefficients for different bond characteristics across institutions are persistent over time. Second, the starkest differences are present for life insurers and mutual funds. Third, there is substantial heterogeneity within the insurance sector, with the coefficient estimates of P&C insurers, for the most part, behaving differently compared to life insurers. To examine the heterogeneity across institutions more carefully, in what follows, we focus on the differences between life insurers and mutual funds, which are also the two largest institutional investors in corporate bonds.

4.2.1. Yield

To understand how the demand elasticities and preference for various bond characteristics vary across life insurers and bond mutual funds, Figure 3a plots the AUM weighted coefficients for the characteristics-based demand system along with the 95% confidence intervals on the right hand side panel. We document two main facts. First, Figure 3a shows that mutual funds have more elastic demand than life insurers consistently in most time periods.

[12] The only institutions for which we cannot reject right away the null of weak instruments concerns foreign institutions.

[13] Following Koijen and Yogo (2019), we report the cross-sectional average of the estimated coefficients for each institution type, which we weight by the assets under management of each institution.

Second, 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 4.3, we provide estimates of elasticities with respect to bond prices.

These facts line up with the main institutional differences between insurers and mutual funds. First, life insurers typically have a negative duration mismatch as their assets are relatively short-dated in comparison to their liabilities. As a result, insurers' hedging demand shifts with shifts in interest rates.[14] Our estimates suggest that as interest rates declined (particularly after 2011) demand for corporate bonds increased, suggesting that the slope of the demand curve became upward sloping, which is also consistent with the findings in Domanski et al. (2017) for German insurers. In contrast, mutual funds have short-dated liabilities and, as we will show below, they tilt asset selection toward short-dated bonds. Thus, mutual funds do not hedge duration mismatch in the same way as life insurers and the slope of the demand curve is downward-sloping throughout. Consistent with this, P&C insurers have downward-sloping demand throughout. Their liabilities are short-dated like mutual funds and unlike life insurers.

4.2.2. Time to Maturity

Figure 3c 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, mutual funds tilt their portfolios toward bonds with shorter maturities. In contrast, insurance companies tilt their portfolios toward bonds with longer maturities.

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 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 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

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

hedge short-dated deposit like liabilities. Overall, the time series patterns for life insurers are consistent with duration hedging. The estimated coefficients are positive (and statistically significant) and increase in magnitude after 2011 when interest rates declined substantially. This further corroborates the evidence in the previous section that demand curve becomes upward-sloping for life insurers after 2011.

4.2.3. Liquidity

Figure 3e shows the coefficient on bonds' bid-ask spreads, which is a proxy for a bond's liquidity. We find significant differences in the demand for liquidity across these institutions. Mutual funds tilt their portfolios toward bonds that have a lower bid-ask spread, i.e. more liquid bonds. In contrast, life insurers tilt their portfolios toward bonds that have a higher bid-ask spread, i.e. more illiquid bonds, especially in the more recent sample. Moreover, the coefficients are negative for most of the sample for mutual funds, implying that mutual funds demand liquidity in corporate bonds throughout. In contrast, insurers, driven by their preference for illiquid bonds, appear to act as liquidity providers.

These results complement the existing literature on bond mutual funds' and insurance companies' investment decisions. For example, Ellul, Jotikasthira, Kartasheva, Lundblad, and Wagner (2018) and Sen and Sharma (2020) explore potential reasons for why insurers may have a preference for illiquid assets. In contrast, we expect bond mutual funds to hold relatively more liquid bonds as they offer daily liquidity to investors. The literature has also studied the potential for fire sales originating from bond mutual funds as they engage in liquidity transformation by investing in corporate bonds, which are relatively speaking an illiquid asset class, and in turn providing liquidity to beneficiaries (Falato, Goldstein, and Hortaçsu (2020)). While it is true that corporate bonds are illiquid in general, our results imply that within corporate bonds, mutual funds do not select into the most illiquid bonds.[15] Crucially, the mutual funds literature does not explore the role of liquidity providers (e.g., insurers) when mutual funds might engage in fire sales. Our results show that accounting for this heterogeneity could be important to fully understand the equilibrium price dynamics for corporate bonds.

4.2.4. Bond Size

We next examine how demand varies by bonds' issuance size. Figure 3g shows the coefficient on log issuance amount. As our estimation controls for a bonds' liquidity, the coefficient on log issuance amount captures demand for bond size after factoring in liquidity.

[15] Choi, Hoseinzade, Shin, and Tehranian (2020), find no evidence of redemption driven price dislocation between 2009 and 2017. In contrast, the evidence in Falato, Goldstein, and Hortaçsu (2020) and Haddad, Moreira, and Muir (2020) together is consistent with the notion that redemptions could lead to asset price dislocations.

Three key results stand out. First, we find significant differences in demand for bond size for insurers and mutual funds. In general, mutual funds tilt their portfolios toward bonds with higher offering amounts (large 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, as we find above. Third, there is an increase in the demand for small bonds in the few quarters around the financial crisis for insurers, consistent with the evidence in Sen and Sharma (2020).[16] To the extent that a bond's size is a proxy for the issuing company's size, our results show that insurers are more likely than mutual funds to provide debt financing to smaller companies.

4.2.5. Default Risk

Figure 3i shows the coefficient on bonds' credit ratings, which captures a bond's credit risk. We convert ratings into a numerical scale, using the numerical ratings provided in the WRDS Bond Returns database. A negative coefficient implies that investors tilt selection toward higher rated (lower default probability) bonds. Both life insurers and mutual funds tilt selection toward higher rated bonds. Overall, we find that the corporate bond market is less segmented along credit rating as compared to other bond characteristics, such as maturity, liquidity, and bond size.

4.3. Demand Elasticities

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 7 (a) reports the summary statistics of the estimated demand elasticities by investor sector for the period 2006:1 to 2020:3. Consistent with the estimation results described above, mutual funds have the highest demand elasticities, followed by VA funds, Other and Pension funds, and Foreign funds. Crucially, insurance companies have significantly lower demand elasticities. In particular, demand for life insurers are inelastic, i.e. < 1 on average. In fact, for some life insurers and P&C insurers, we estimate negative demand elasticities implying upward-sloping demand curves. The AUM weighted elasticity for the corporate bond market

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

as a whole is 3.7. Overall, these estimates are in line with Koijen et al. (2020a) who present a similar ranking of investor-specific elasticities for EU government bonds.

In Panel (b), we report the summary statistics for the recent sample period 2010:1 to 2020:3. Demand elasticities for all investor groups are similar to the estimates of the overall sample. However, demand elasticities decreased further for life insurers, consistent with the time-series demand estimates shown in Figure 2. The overall AUM weighted elasticity for the market as a whole is also similar to the estimates of the overall sample at 3.8. However, this masks important time trends. On one hand, life insurers have become more inelastic over time, which puts a downward pressure on the market-wide elasticity. On the other hand, the share of mutual funds have risen, which puts an upward pressure on the overall market-wide elasticity because mutual funds have significantly more elastic demand. 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 close to 1.5, i.e. 60% lower than the actual elasticity of 3.8.

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 4 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

$$\begin{aligned}\frac{\partial \mathbf{p}_t}{\partial \log(\epsilon_{i,t})'} &= \left(\mathbf{I} - \sum_{j=1}^{I} A_{j,t}\mathbf{H}_t^{-1}\frac{\partial \mathbf{w}_{j,t}}{\partial \mathbf{p}_t'}\right)^{-1} A_{i,t}\mathbf{H}_t^{-1}\frac{\partial \mathbf{w}_{i,t}}{\partial \log(\epsilon_{i,t})'} \\ &= \left(\mathbf{I} - \sum_{j=1}^{I} A_{j,t}\beta_{0,j,t}\mathbf{H}_t^{-1}\mathbf{G}_{j,t}\right)^{-1} A_{i,t}\mathbf{H}_t^{-1}\mathbf{G}_{i,t}\end{aligned} \tag{6}$$

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 5 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 equation (6) 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 5 (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 6 (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 6 (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 explore potential sources of heterogeneity in liquidity demand across bonds, across institutions, and over time.

5.2.2. Cross-Institutions Trends

We next study the dynamics of price impact by institution type. We estimate the price impact for each bond and institution through the diagonal elements of matrix (6) and then average by institution type. Figures 5 and 6 (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 the implied corporate bond prices of hypothetical movements in perceived credit quality, 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.

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

Our primary interest in our counterfactual analysis 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 $\mathbf{A}_\mathbf{t}^{\mathbf{CF}}$ we calculate associated corporate bond price changes as

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

We calculate these counterfactual price vectors using the algorithm from Koijen and Yogo (2019).[17] Alternatively, we can calculate the changes in bond yields using the transformation discussed in Section 3.4.

6.1. Credit Migration

In our first counterfactual, we ask how would the bond market equilibrium shifts if there is a widespread credit migration. To implement this new equilibrium, we proceed by downgrading all bonds in the sample by one notch, e.g., AA+ rated bonds are downgraded to AA and BBB- are downgraded to BB etc. That is, we change the vector of bond characteristics by changing the bond ratings to $\mathbf{x}_\mathbf{t}^{\mathbf{CF}}$ and calculate the counterfactual equilibrium yields implied by $\mathbf{g}\left(\mathbf{s}_t, \mathbf{x}_\mathbf{t}^{\mathbf{CF}}, \mathbf{A}_t, \beta_t, \epsilon_t\right)$. For each bond, we then compute the counterfactual credit spreads and the difference between the counterfactual and the empirical (actual) credit spreads.

Figure 7 shows the evolution of the difference between the counterfactual and the empirical (actual) credit spreads over time. The following facts stand out. 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, the counterfactual credit spreads are countercyclical. They increase much more (relative to the actual credit spreads) in bad times, e.g. during the financial crisis and the COVID-19 crisis. This is natural because the impact of a widespread credit migration has a higher impact on spreads during market downturns. Third, there is substantial heterogeneity across bonds

[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.

in how much spreads shift when there is a widespread downgrade. As Figure 7 shows, the difference in spreads ranges from about 20bps for a bond in the 25th percentile to 80bps for a bond in the 75th percentile of the distribution during the COVID-19 crisis.

To understand what drives this heterogeneity, we split the sample by bond characteristics and by the predominant investor holding a bond. (i) *Bond characteristics*: Table 8 shows the shift in the credit spreads by rating and maturity. We observe that the shift in the spreads is higher for short-maturity bonds. (ii) *Predominant investors*: Table 9 shows the shift in the credit spreads by splitting bonds by their predominant holder. As the impact of a widespread rating migration is expected to affect bonds held by insurers more (because of rating-based capital requirements), we compute the proportion of a bond being held by the insurers as a whole. As the heterogeneity in changes in spreads across investors could simply be driven by differences in bond holdings, we control for bond characteristics. Overall, the shift in the spreads is heterogeneous across investor groups. In particular, Table 9 shows that the impact of a credit migration would be higher for bonds that are held by the insurance sector, all else equal. This is intutive as the selling pressure would be higher for insurers as the regulatory risk weights are ratings based. When downgrades occur, insurers' risk based capital constraints would be more likely to bind as capital requirements increase. This suggests that insurers may amplify the credit shocks as risk constraints bind.

6.2. Undoing the Rise of Bond Mutual Funds

There has been a substantial increase in the presence of bond mutual funds since the financial crisis. In the next counterfactual, we ask how the bond market equilibrium would be affected if mutual funds had remained small. To implement the new equilibrium, we keep the share of mutual funds constant at their 2006:Q1 level. That is, we keep the relative size of the mutual fund sector constant at the level of 2006Q1. 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 types of institutional investors 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 is 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. For each bond, we then compute the difference between the counterfactual and the empirical (actual) credit spreads.

Figure 8 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 not predominantly held by mutual funds (panel (b)).

Second, in Figure 9, 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 within our estimation framework. The remaining investor types (insurance companies predominantly) have a lower preference towards short-dated and high yield bonds (see Section 4). As a result, they have to be compensated more to be 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 held by mutual funds given the segmentation in the bond market that we document (see Section 4).

6.3. Run on Large Mutual Funds

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. In the next counterfactual, we test the impact of large-scale redemptions from bond mutual funds on the bond market equilibrium. We proceed as follows. First, we assume that the largest mutual funds 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 size corresponds to 1% of the corporate bond market. Note that the relative size of the shock is constant over time, unlike the previous counterfactual. As a result, any time trend in the magnitude of the credit spread changes is due to the change in the composition of the remaining corporate bond investors. Second, we implement the transfers 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.

Two main results stand out when we redistribute assets to <u>all</u> remaining investors that do not experience an outflow. First, Figure 10 shows that there would be a large impact on yields if bond mutual funds experienced large redemption requests. Moreover, unlike the previous counterfactual, the impact of bond mutual funds' outflows is declining over time. This is because 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) has increased over time. Unlike insurers whose preference tilts towards long-term bonds, the remaining mutual funds prefer short-term bonds and have to be compensated less than insurers to hold these bonds when large mutual funds sell their positions.

Second, we dig deeper into the heterogeneity across bonds. Figure 11 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.

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 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. Within each sector, we redistribute the assets in proportion of investors' own AUMs. Figure 12 shows that the effects would be larger if insurers provided liquidity instead of mutual 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 have a similar demand function. As a result, the remaining mutual funds can absorb these bonds at a lower compensation.

Overall, our results clearly demonstrate that the composition of investors would play a large role if market disruptions were to occur and this heterogeneity is important to understand to understand the equilibrium price dynamics.

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 (depicted in Figure 2) and measure the sensitivities of each estimated parameter 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.

(i) Table A.3 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 reflect an objective to exploit a higher term premium typically observed in a high rate environment.

(ii) Table A.4 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 11 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 would increase, bond yields (prices) would 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 would rise more for short-dated bonds relative to long-dated bonds. This is consistent with the evidence in Table A.3, which shows that when rates rise mutual funds' preference to hold long maturity bonds increases. This would suggest that the yields of long-term bonds should rise less than short-term bonds. Second, yields would rise more for high yield bonds relative to investment grade bonds. This is also consistent with the evidence in Table A.3 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 have to be higher. Panel (b) and (c) show these effects are further reinforced when we incorporate potential redistribution of AUMs.

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 its assets.[19]

Table 10 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 effective purchases themselves.

To relate the demand elasticities to the yield impact of a potential intervention in the corporate bond market, we consider a simple back-of-the-envelope calculation. In summer 2020, the Federal Reserve purchased 5 billion USD worth of corporate bonds while the overall market was 7,000 billions USD. The weighted average demand elasticity is 3.7, which implies a yield impact of $0.07/3.7 = 0.02\%$. Assuming an average duration of 1.5 years, the yield falls by 2 basis points, in line with our estimates in table 10.

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.

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

[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).

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 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 long-dated bonds, bonds with smaller issuance size, and supply liquidity. In contrast, mutual funds, with shorter investment horizons, have more elastic demand, preference for 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 particular, we evaluate the corporate bond pricing implications of i) mutual fund fragility and bond fire sales, ii) monetary policy tightening through rising rates, and iii) a tampering of the Fed's corporate credit facility, among others. While the latter's effects appear modest, our model predicts substantial disruptions in corporate bond prices for the former two scenarios through shifts in institutional demand. In equilibrium, such disruptions are reflected in the real economy through firms' financing decisions.

Overall, our 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 bond pricing. Moreover, our findings suggest that such 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 corporate bond markets.

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 exclude foreign owners of corporate bonds.

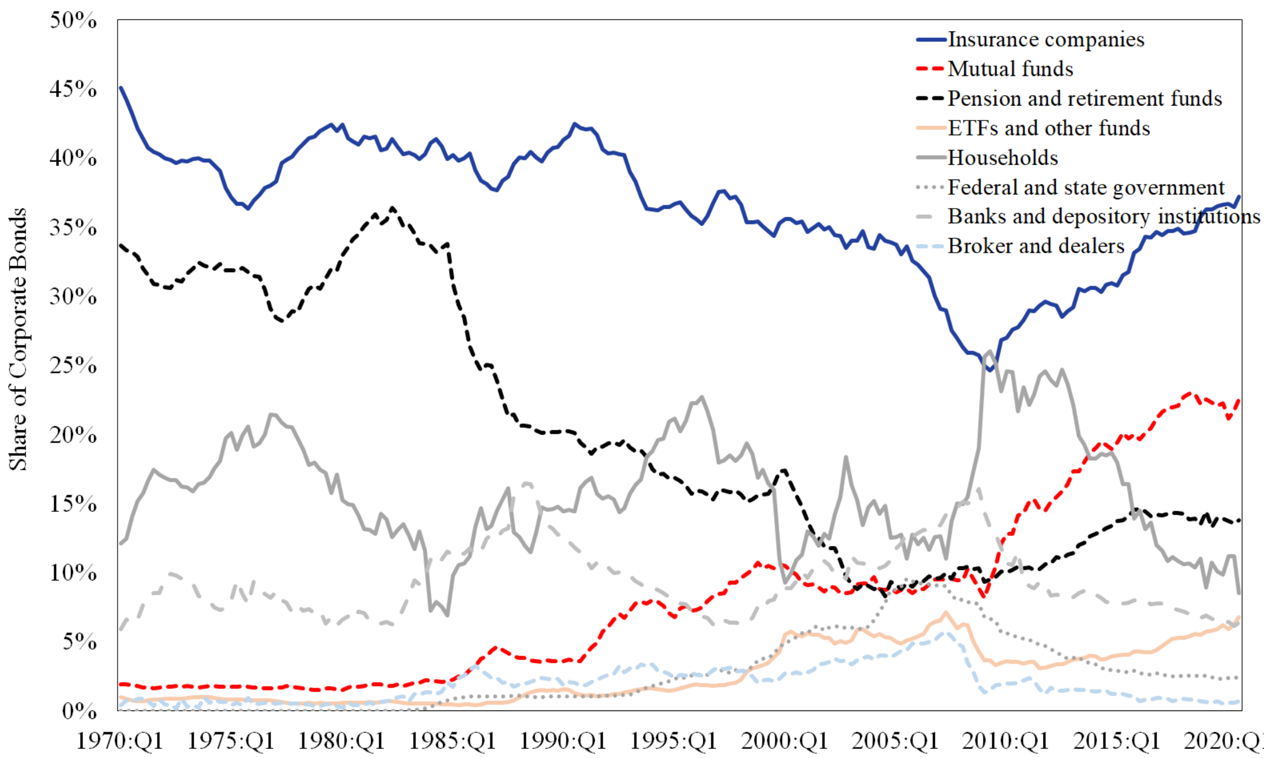


Figure 2: Evolution of the Estimated Demand-System Over Time

This figure plots the estimated coefficients of characteristics-based demand equation (2) for different institutions for each quarter-year. Characteristics-based demand equation is estimated in an AUM weighted panel regression setup. The quarterly sample period is from 2006:1 to 2020:3.

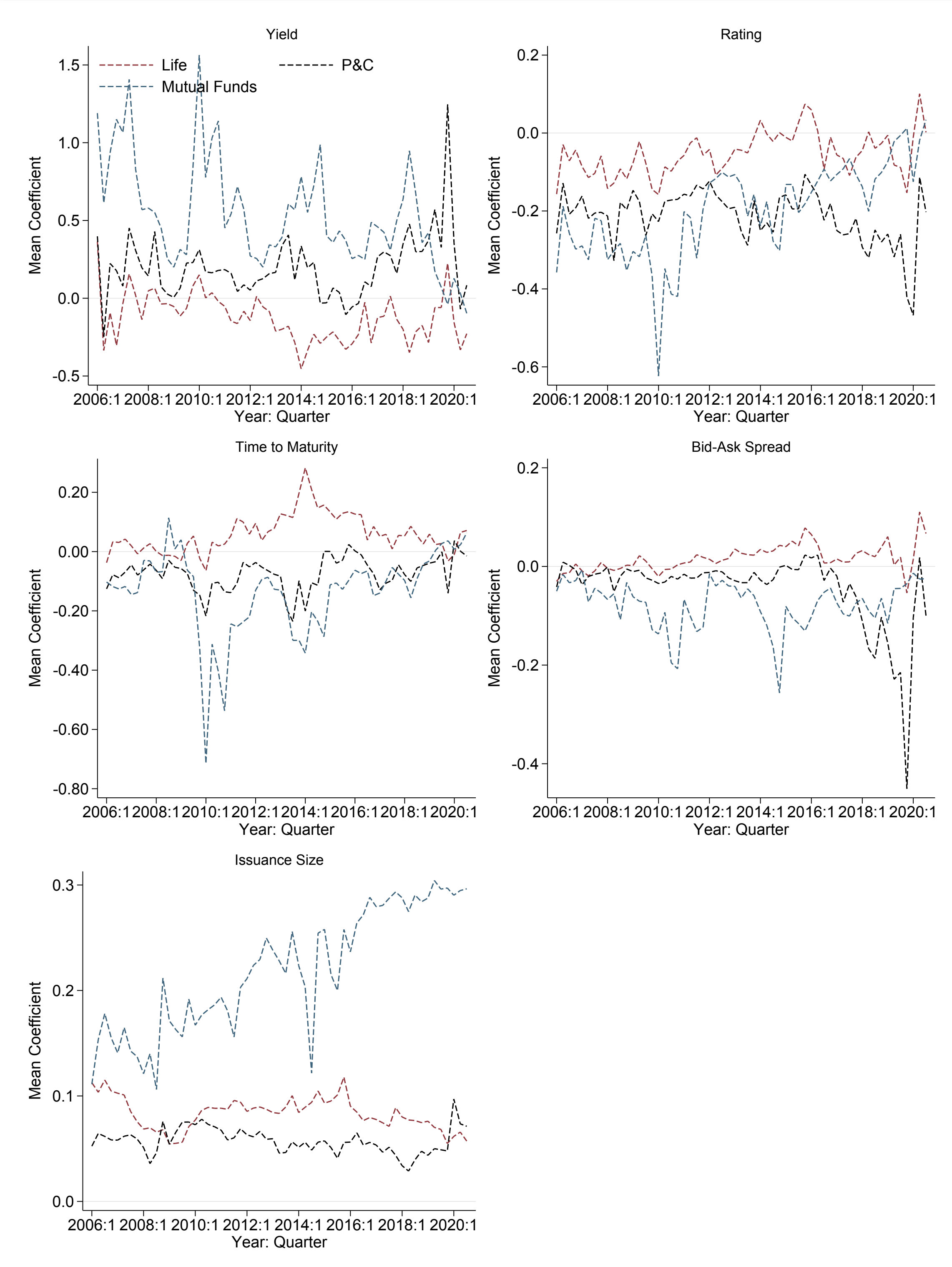
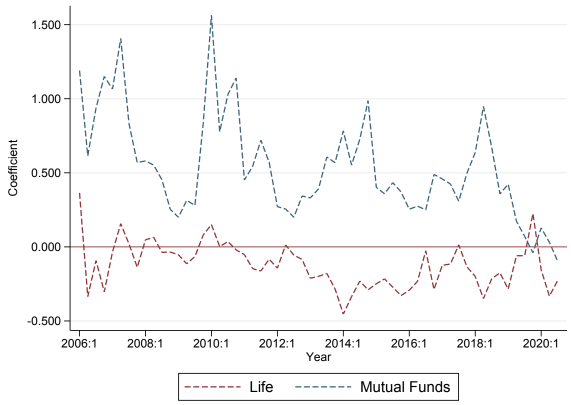
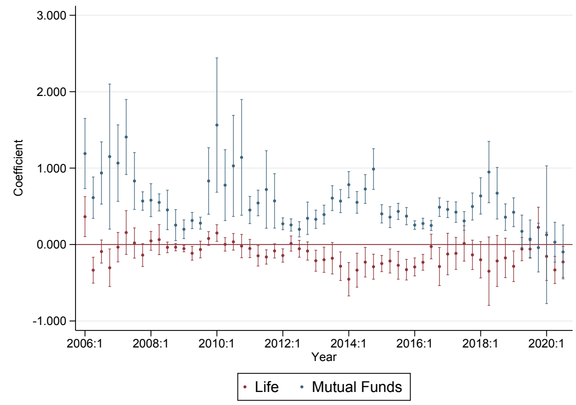


Figure 3: Evolution of the Estimated Demand-System - Life Insurers vs. Mutual Funds

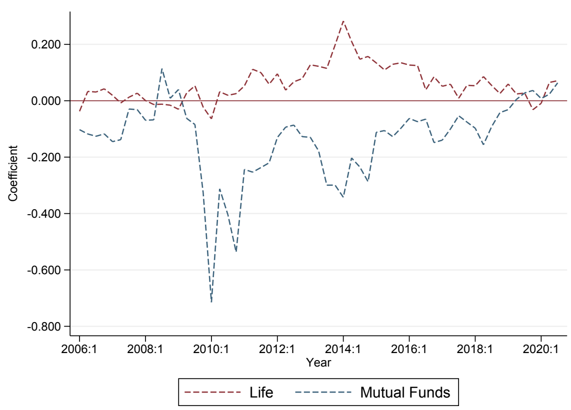
This figure plots the estimated coefficients on instrumented yield, time to maturity, bid-ask spreads, bond size and credit rating for life insurers and mutual funds for each quarter. The left panels plot the estimated coefficients and the right panels plot the estimated coefficients including the 5%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



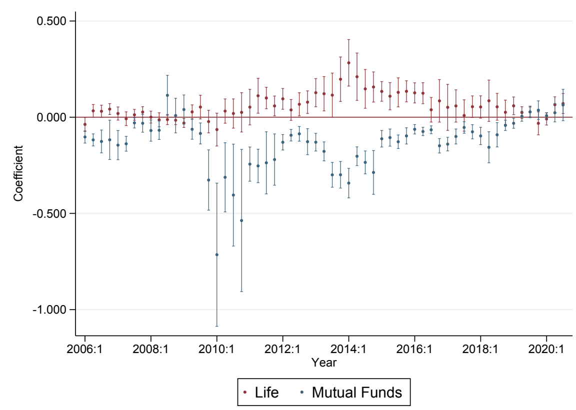
(a) Yield



(b) Yield - Confidence Bands

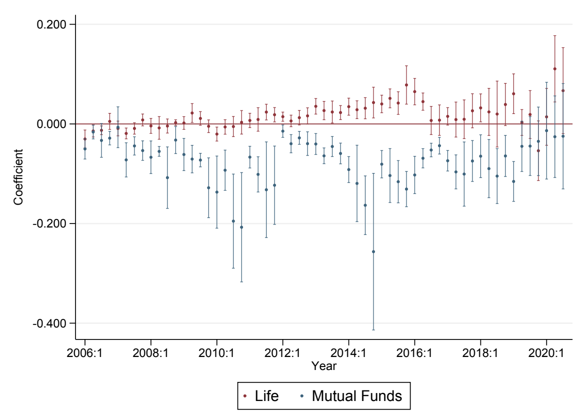


(c) Time to Maturity



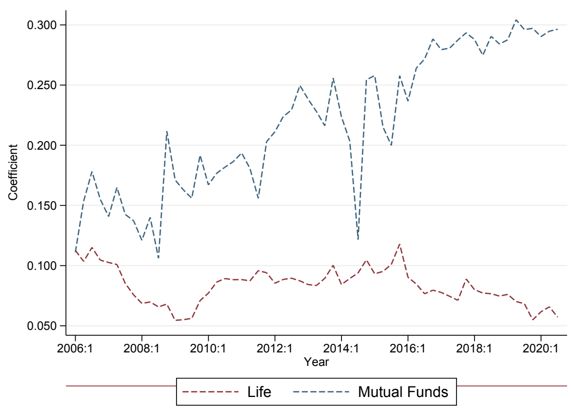
(d) Time to Maturity - Confidence Bands

(e) Bid-Ask Spread

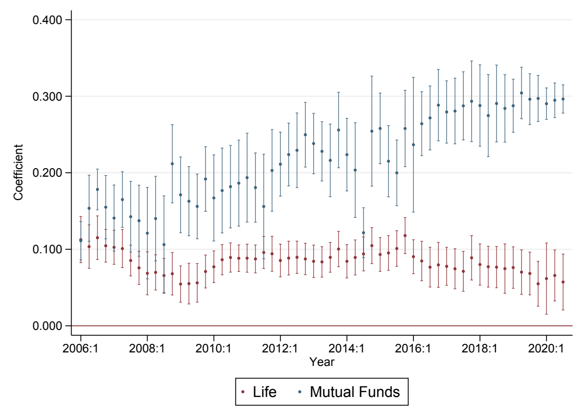


(f) Bid-Ask Spread - Confidence Bands

Figure 3: Evolution of the Estimated Demand-System - Life Insurers vs. Mutual Funds (contd...)

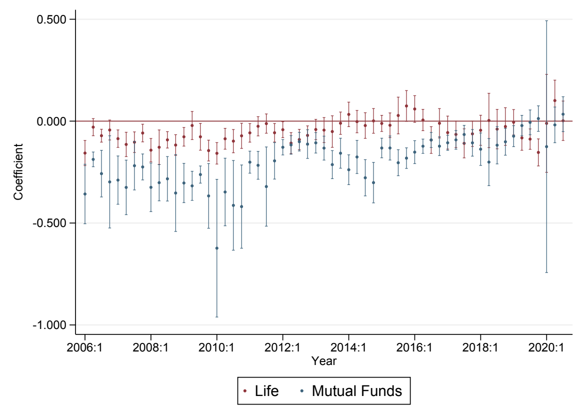


(g) Bond Size



(h) Bond Size - Confidence Bands

(i) Rating



(j) Rating - Confidence Bands

Figure 4: 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.

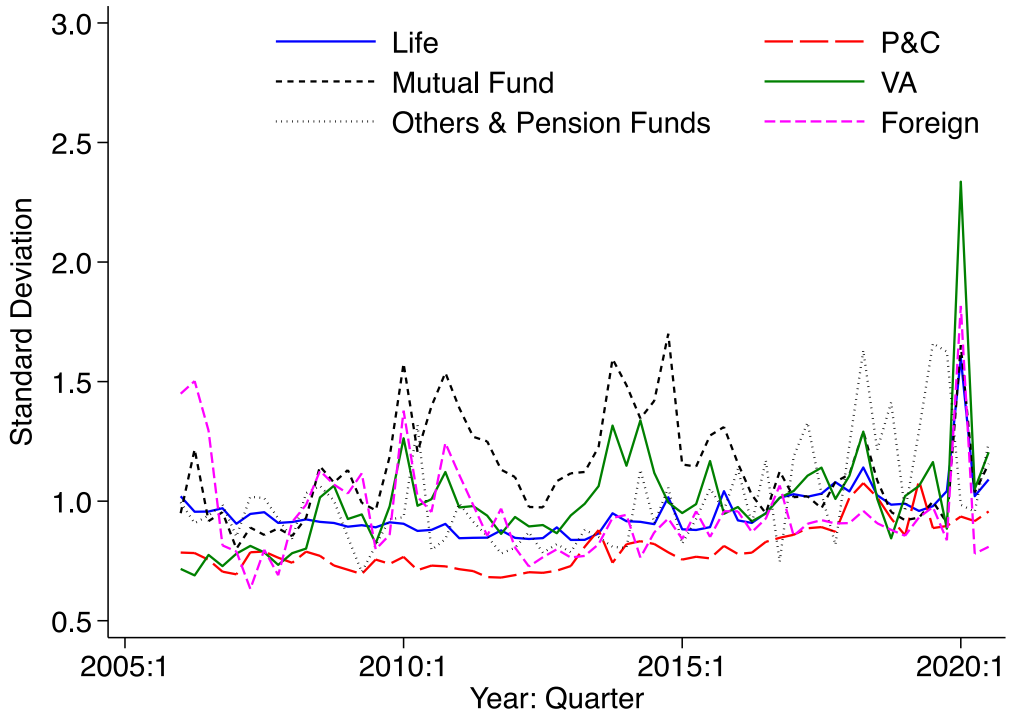
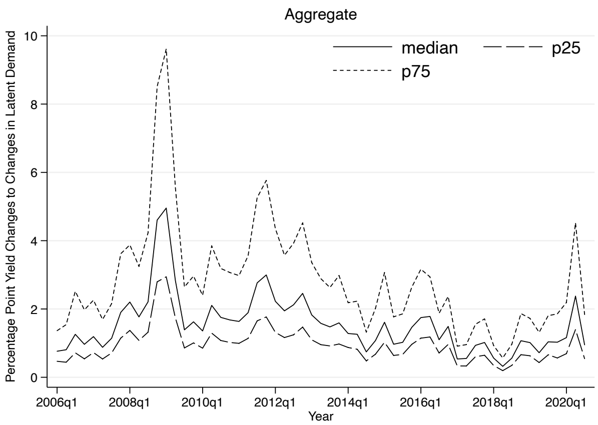


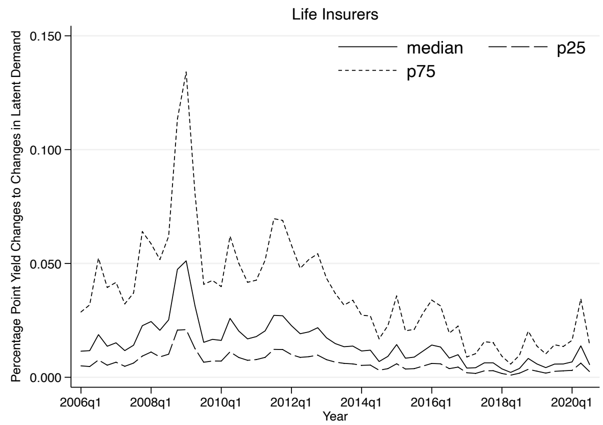
Figure 5: Price Impact - Yield Changes to Latent Demand

This figure plot 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.

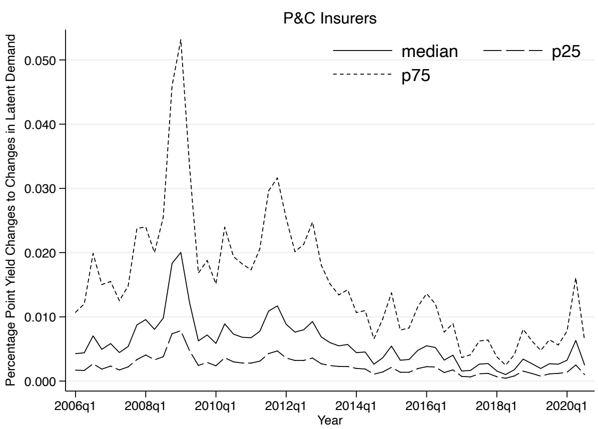
(a) Aggregate.



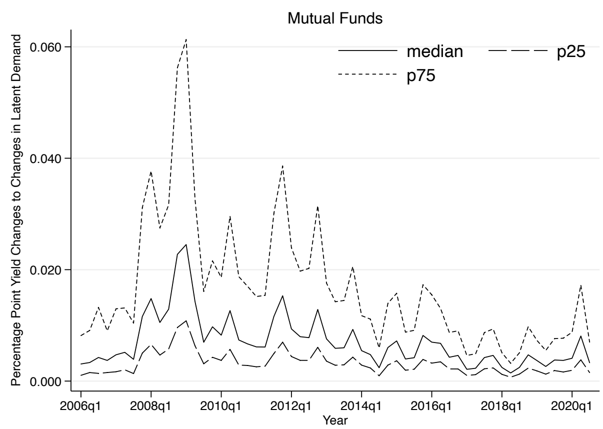
(b) Life Insurer.



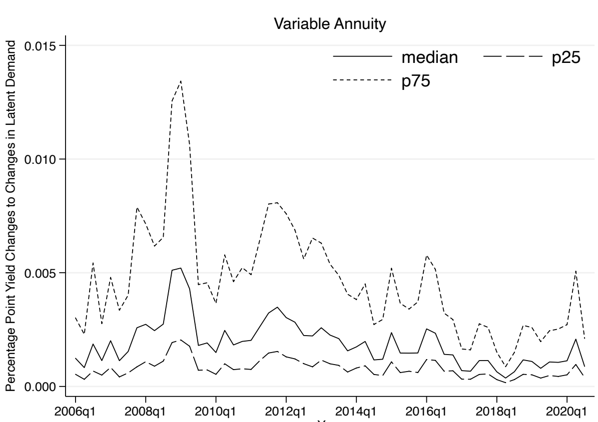
(c) P&C Insurer.



(d) Mutual Funds.



(e) Variable Annuities.



(f) Foreign Investors.

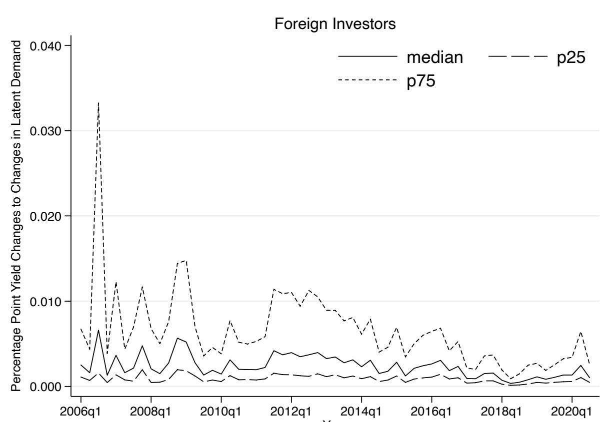
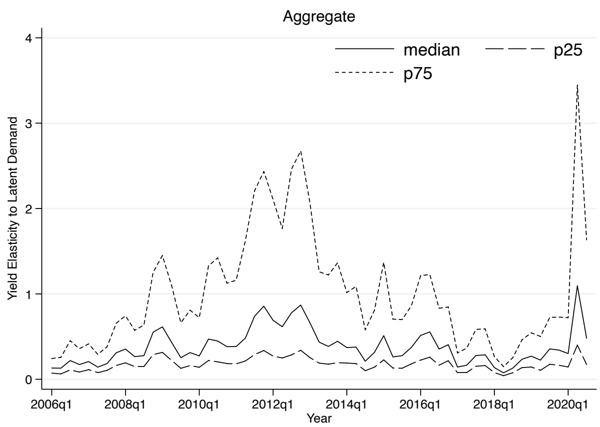


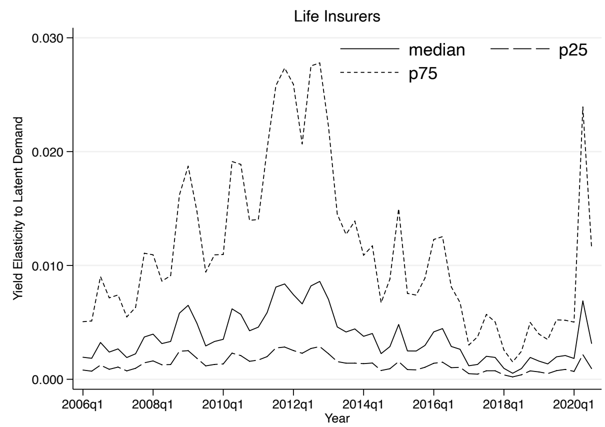
Figure 6: Price Impact - Yield Elasticity to Latent Demand

This figure plot 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.

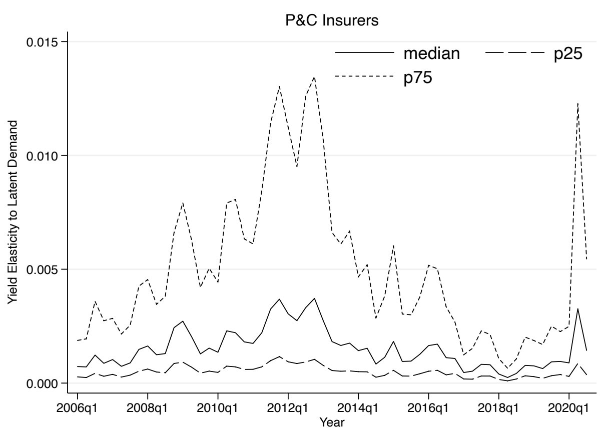
(a) Aggregate.



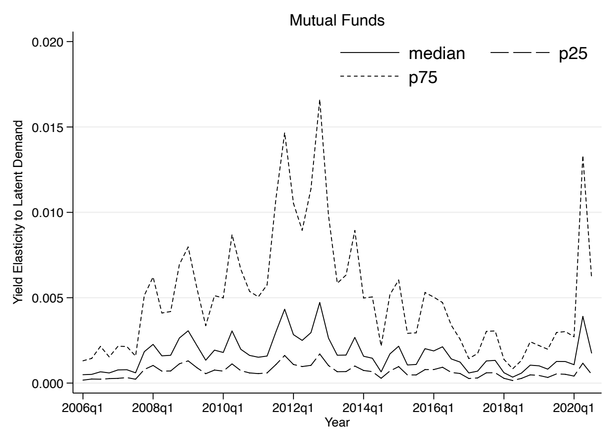
(b) Life Insurer.



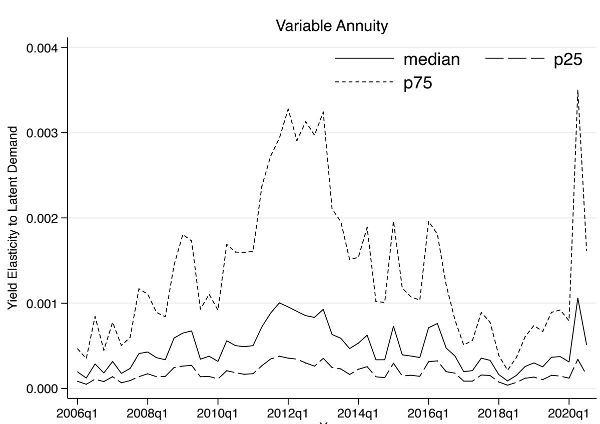
(c) P&C Insurer.



(d) Mutual Funds.



(e) Variable Annuities.



(f) Foreign Investors.

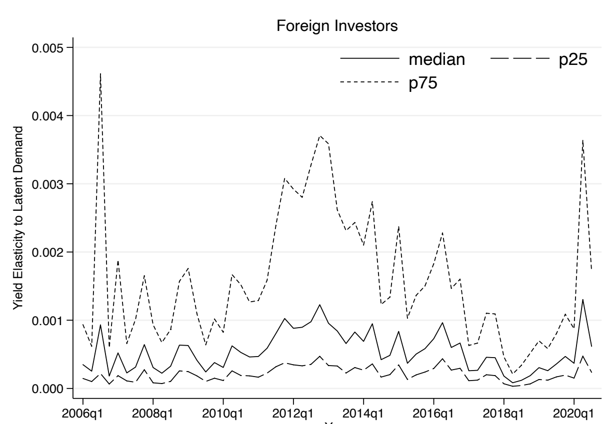


Figure 7: Widespread Credit Migration: Aggregate Effects

In this counterfactual all bonds are downgraded simultaneously by one step, for example from AA to AA-. The figure plots the market value-weighted median, the 25th, and the 75th percentiles of credit spread changes across all bonds. The quarterly sample period is from 2006:1 to 2020:3.

(a) Aggregate.

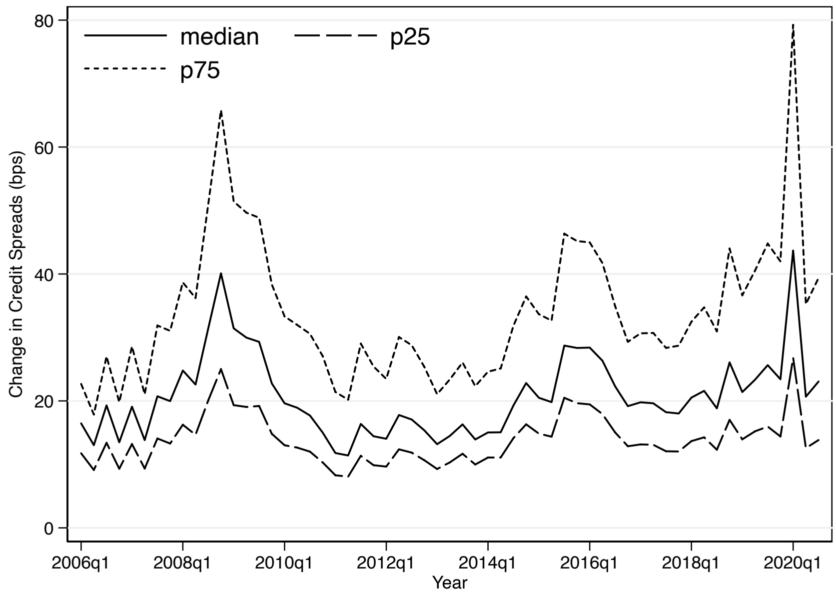
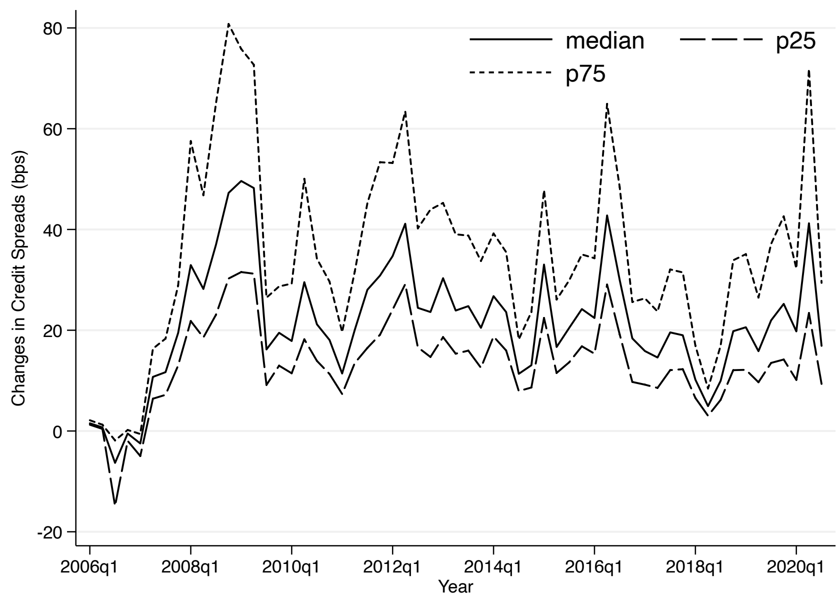


Figure 8: Undoing the Rise of Bond Mutual Funds: Aggregate Effects

This figure reports the counterfactual changes in credit spreads had the relative size of the mutual fund sector stayed constant since 2006:1. Panel (a) reports the counterfactual changes in credit spreads in basis points for all bonds held predominately 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.

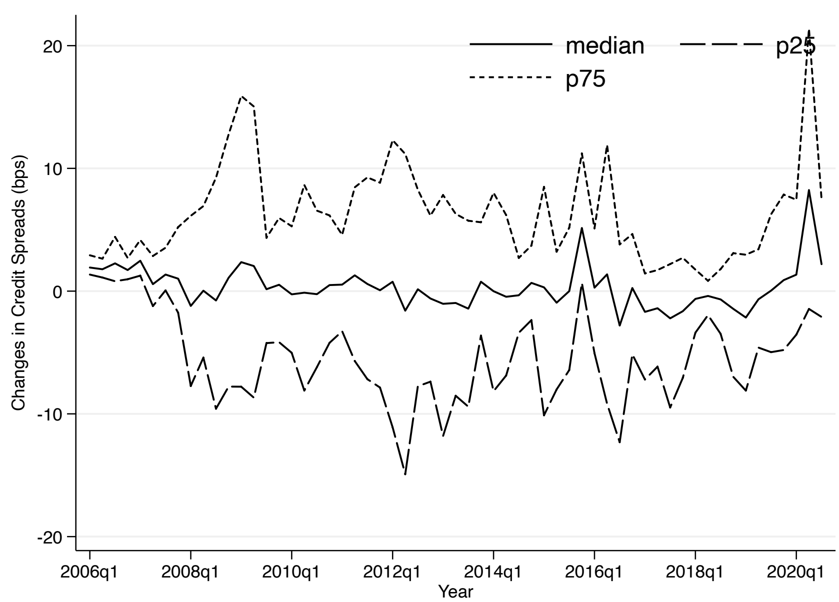
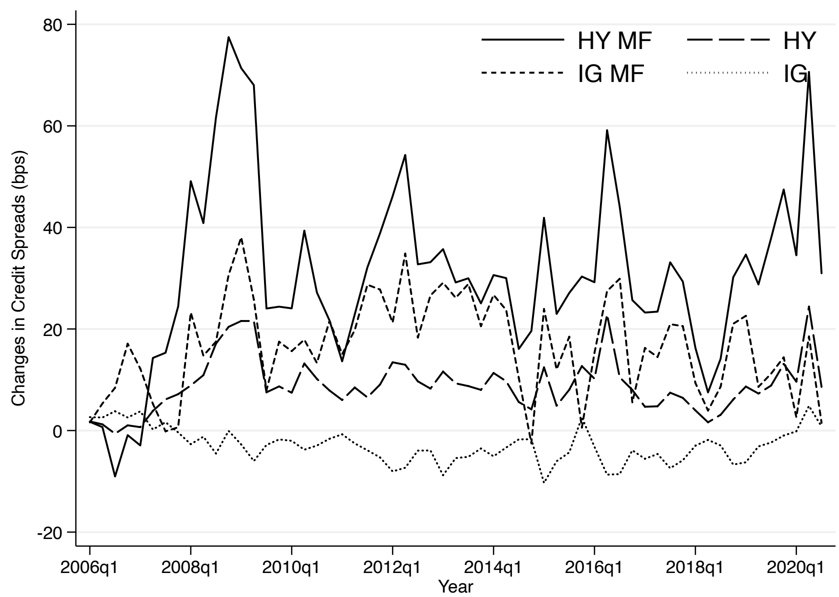


Figure 9: Undoing the Rise of Bond Mutual Funds: Heterogeneity of the Effects

This figure reports the counterfactual changes in credit spreads had the relative size of the mutual fund sector stayed constant 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 predominately by mutual funds, and high yield bonds held predominately by mutual funds. Panel (b) reports the counterfactual changes in credit spreads in basis points for short- and long-term bonds that are held predominately 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.

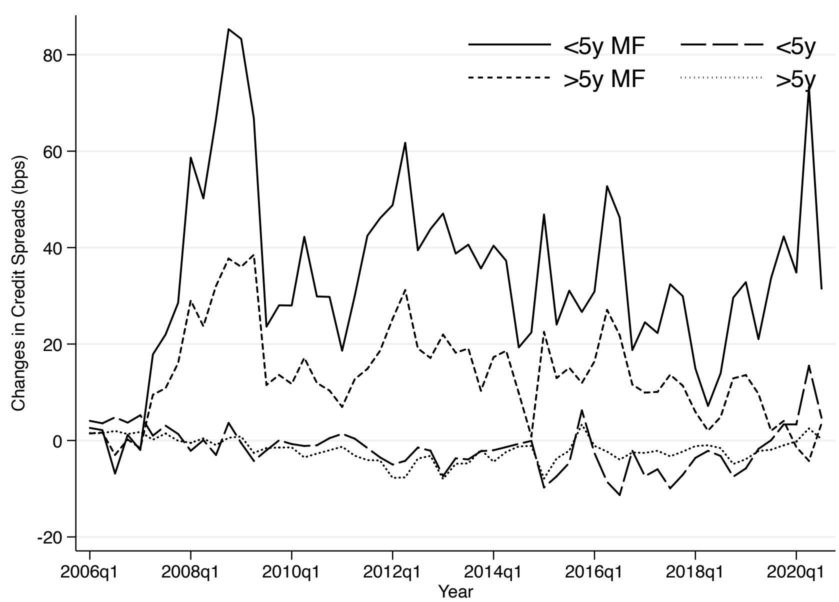


Figure 10: Run on Large Mutual Funds: Aggregate Effects

In this counterfactual the mutual fund sector experiences an outflow that corresponds to 1% of the total AUM in the sample. This figure reports 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.

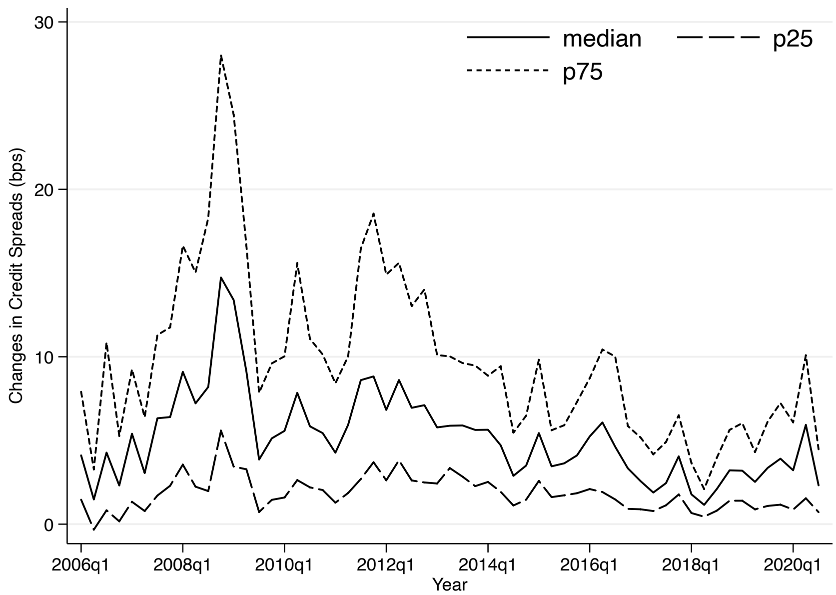
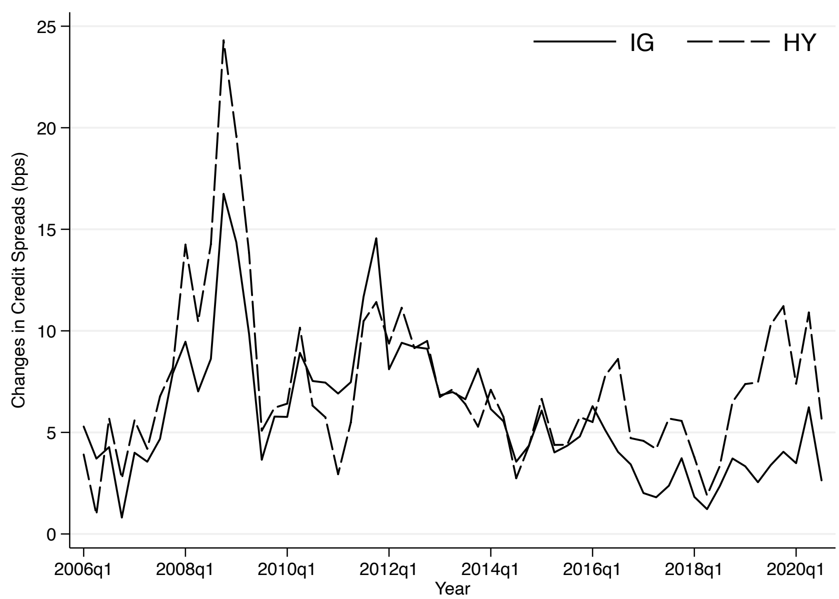


Figure 11: Run on Large Mutual Funds: Heterogeneity of the Effects

In this counterfactual the mutual fund sector experiences an outflow that corresponds to 1% of the total AUM in the sample. This figure reports 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.

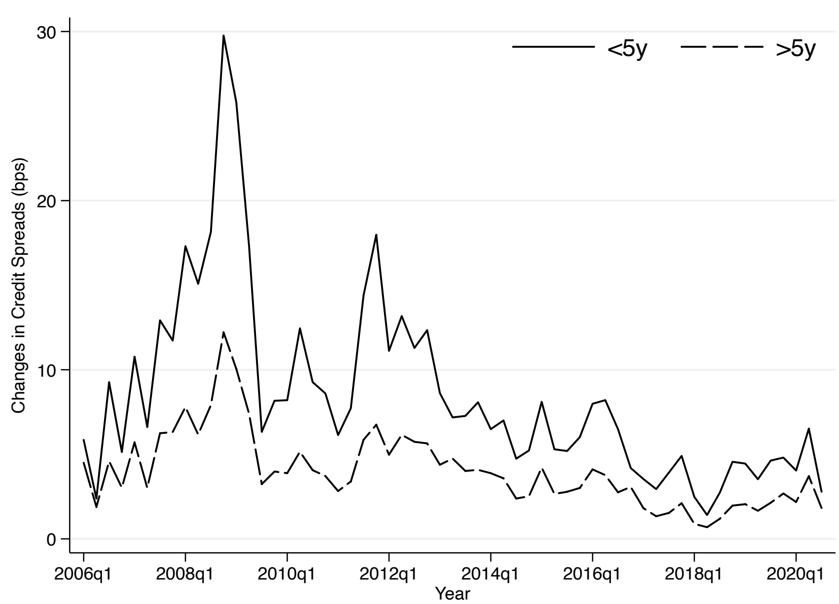
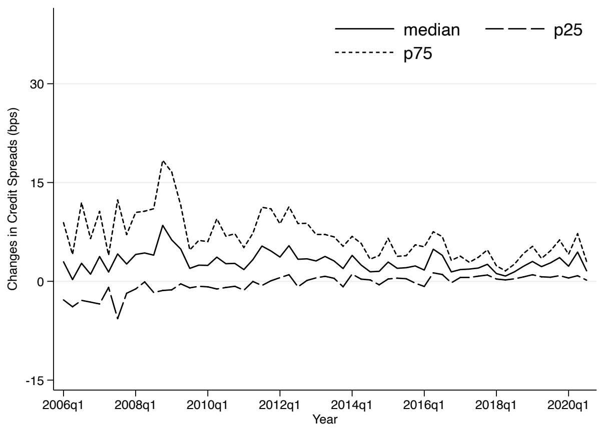


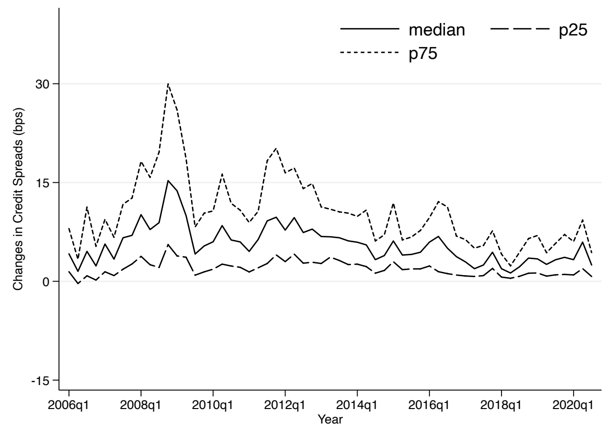
Figure 12: Run on Large Mutual Funds: Who Provides Liquidity?

In this counterfactual the mutual fund sector experiences an outflow that corresponds to 1% of the total AUM in the sample. This figure reports 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.

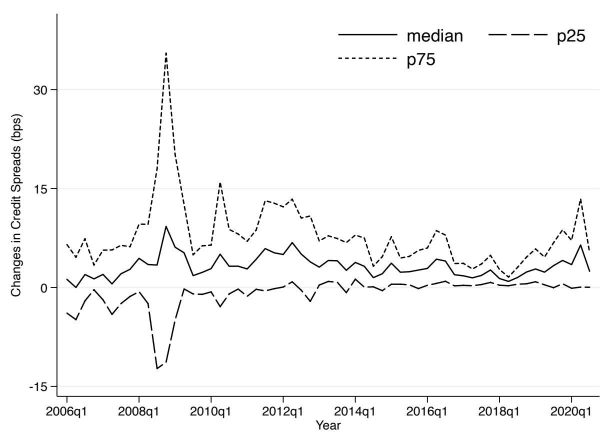
(a) Mutual funds buy.



(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 55 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: Institutional Holdings: Rating 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 PC insurance firms, Mutual funds include both traditional Mutual Funds and Variable Annuities, and Other include Foreign Funds, Pension Funds and all other remaining categories.

Rating	Total Outstanding	Total Holdings	Holdings By Financial 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 3: 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 PC insurance firms, Mutual funds include both traditional Mutual Funds and Variable Annuities, and Other include Foreign Funds, Pension Funds and all other remaining categories.

Maturity	Total Outstanding	Total Holdings	Holdings By Financial 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 4: 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 5: Bond Characteristics and Demand Heterogeneity: By Institution Types

The table shows the demand heterogeneity across institution types. We estimate the characteristics-based demand equation (2) in an AUM weighted panel regression setup. The dependent variable is 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. 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			
	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 6: First-stage t-statistics - Institution-level Estimation

This table reports the distribution of first-stage t-statistics on the instrument by investor groups in panel A and by time in panel B. For comparison, the absolute value of the critical value for rejecting the null of weak instruments at the 5 percent level by Stock and Yogo (2005) is 4.05.

Panel A: First-stage t-stats by Investor Groups						
	avg	median	p1	p5	p90	p99
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-stats by 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 7: Estimated Demand Elasticity by Investor Sector

The demand elasticity is estimated for each institution, bond, and date. The elasticities are then aggregated to the institution level by calculating a holdings-weighted average. This table reports summary statistics of the estimated demand elasticities (pooled over time) for the sample period from 2006:1 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 8: Widespread Credit Migration: Heterogeneity of the Effects

This table reports the counterfactual changes in credit spreads if there is a widespread credit migration. The table reports the changes between counterfactual and empirical credit spreads by letter rating and bond maturity. The sample period is from 2006:1 to 2020:3.

	Counterfactual Changes in Credit Spreads						
	AAA	AA	A	BBB	BB	B	CCC
<5 years	46	45	47	46	41	38	40
5 - 10 years	16	16	16	16	16	16	17
>10 years	7	7	7	7	8	7	8

Table 9: Widespread Credit Migration: Heterogeneity of the Effects by Investor Sector

The table reports panel regression results. In particular, we regress the counterfactual change in credit spreads due to credit migration for each bond on bond characteristics (controls) and variables that characterize the fraction of holdings of insurance companies for a given bond. That is, *% insurance* measures the fraction of total amount outstanding that is held by insurance companies. Similarly, the dummy variables, $\mathbb{1}_{\%insurance>\delta\%}$, equal one if insurance companies hold more than $\delta\%$ of the total amount outstanding of a bond. All regression specifications control for rating, time to maturity, bond size, and bid-ask spread and include quarter fixed effects. The standard errors are clustered by time and bond. The quarterly sample period is from 2006:1 to 2020:3.

	I	II	III	IV	V
% insurance	5.61***				
	(0.40)				
$\mathbb{1}_{\%insurance>20\%}$		0.41			
		(0.26)			
$\mathbb{1}_{\%insurance>40\%}$			1.71***		
			(0.22)		
$\mathbb{1}_{\%insurance>60\%}$				3.01***	
				(0.23)	
$\mathbb{1}_{\%insurance>80\%}$					5.25***
					(0.33)
Controls	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	214,764	214,764	214,764	214,764	214,764
Adjusted R-squared	0.79	0.78	0.78	0.78	0.79

Table 10: 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 sample period is from 2006:1 to 2020:3.

	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

Table 11: 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 tightening of monetary policy. The table reports the changes between counterfactual and empirical yields by letter rating and bond maturity. The counterfactual estimation is done assuming an initial starting point that mimics the holdings patterns and market conditions in 2020.

	Counterfactual Changes in Credit Spreads						
	AAA	AA	A	BBB	BB	B	CCC
A. Changes in Demand Functions							
< 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							
< 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 Functions & AuM							
< 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

A. Additional Figures and Tables

Table A.1: Coverage of Corporate Bonds Market in WRDS Bonds Return Database

The table reports the coverage of bonds in WRDS Bonds Retrun database with respect to the overall US publicly traded corporate bond 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	2013	2014	2015	2016	2017	2018	2019
Number of corporate bonds in FISD (K)	16.3	17.7	18.0	16.5	16.8	17.6	17.9	18.2	18.9	19.8	20.5	22.6	25.4	29.0
Number of corporate bonds in both WRDS and FISD (K)	8.2	9.1	9.8	10.4	11.5	12.6	13.9	15.0	16.1	17.4	18.4	20.7	23.7	22.9
Percent of FISD corporate bonds represented in WRDS (%)	50.6%	51.2%	54.3%	62.7%	68.4%	71.7%	77.6%	82.5%	85.4%	87.8%	89.5%	91.6%	93.3%	79.1%
Par value of corporate bonds in FISD (billions of $)	3369.0	3544.0	3729.8	4029.6	4264.3	4594.8	4871.9	5140.6	5449.3	5929.3	6378.0	6677.9	6822.5	6928.1
Par value of corporate bonds in both WRDS and FISD (billions of $)	2606.0	2849.3	3127.8	3527.2	3850.0	4227.7	4555.3	4853.9	5178.4	5661.9	6108.4	6429.9	6593.5	6470.3
Percent of FISD corporate bonds represented in WRDS (%)	77.4%	80.4%	83.9%	87.5%	90.3%	92.0%	93.5%	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 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.4: 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