Passive Demand and Active Supply: Evidence from Maturity-mandated Corporate Bond Funds*

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February 2023

Abstract

We identify a novel and common exogenous demand shock caused by passive funds in the corporate bond market. Specifically, passive fund demand for corporate bonds displays discontinuity around the maturity cutoffs separating long-term, intermediate-term, and short-term bonds. Passive funds' demand increases significantly upon a bond's crossing of 10-, 5-, and 3-year time-to-maturity cutoffs. We develop a novel identification strategy to study the impact of passive fund demand in the corporate bond market. First, we find that these non-fundamental demand shifts lead to a significant and lasting decrease in yield spreads, as well as persistent liquidity improvements. Second, we find that passive fund demand shocks spill over to the primary market, causing lower issuing yield spreads and actively higher net debt issuance, thereby impacting firms' financing and investment activities.

Keywords: demand shifts, passive funds, corporate bonds, demand elasticity, ETFs, mutual funds, insurance companies.
JEL Classification: G11, G12, G22, G23

*We thank Kenneth Ahern, Constantin Charles, Christopher Jones, Kristy Jansen, Mete Kilic, Arthur Korteweg, Wenhao Li, Rodney Ramcharan as well as seminar participants at USC Marshall for helpful comments and discussions.

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1 Introduction

In this paper, we introduce a novel and common exogenous demand shock caused by passive funds in the corporate bond market. Leveraging these non-fundamental demand shocks, we develop an empirical strategy to causally identify the impact of passive funds demand shifts. We aim to address two research questions using a comprehensive dataset of institutional investors' holdings. First, how do non-fundamental demand shifts by passive funds affect secondary market trading, and how persistent are such effects? Second, do passive fund demand shocks spill over to the primary market and affect firms' financing policies and thereby real activity?

Our demand shock results from two institutional details: passive funds' preference for maturity and their fixed mandates. Specifically, we find that passive fund demand for corporate bonds displays discontinuity around the maturity cutoffs separating long-term, intermediate-term, and short-term bonds. This discontinuity arises because of the sizeable gap in total assets under management (AUM) across funds that invest in different maturity categories. Short-term funds have the highest total AUM, followed by intermediate-fund funds, and long-term funds have the smallest AUM. We show that the order and gap for the three maturity categories persist over time. Additionally, maturity categories are defined consistently: long-term funds have time-to-maturity longer than 10 years, intermediate-term funds have 5 to 10 year maturity, and short-term funds have two definitions: 1 to 5 years or 1 to 3 years. Hence, there are three maturity cutoffs: 10-, 5-, and 3-year time-to-maturity. Take the 10-year cutoff as an example. Once a bond crosses the 10-year cutoff, it will switch from the long-term to the intermediate-term category. As a result, long-term funds will sell the bond, and intermediate-term funds will buy. Since intermediate-term funds have larger total AUM, the aggregate net demand will increase for the crossing bond. Since it is reasonable to assume that, on average, bonds' fundamentals remain unchanged before and after crossing the maturity cutoff, the crossing event is suitable for studying the passive fund demand shock.

Leveraging these three maturity cutoffs, we develop two empirical strategies: the first uses a regression discontinuity design (RDD), and the second uses an instrumental variable (IV) panel regression. The RDD method is efficient at assessing the treatment effects within a narrow bandwidth, while the IV panel regression allows us to estimate the dynamics of the effects and long-term impacts. We apply both methods in our empirical analysis and show both results whenever possible. Our empirical design has advantages over the methods used by the existing literature. Most common identification strategies rely on one-time changes to index inclusion rules that happened before 2012, which leads to concerns about external validity. In contrast, the frequently occurring nature of our demand shocks allows us to utilize the entire sample and estimate how the effects evolve. Further, existing methods usually require matching treatment bonds with control bonds, which may introduce omitted variable bias. Our empirical method alleviates omitted variable and selection bias by comparing the same bond before and after crossing maturity cutoffs. Additionally, since the bond remains in the main index before and after crossing the cutoffs, our empirical strategy can isolate the effects of passive fund demand from the index effect, which is usually impossible for most empirical settings that rely on index inclusion.

Using our empirical framework, we first study how non-fundamental demand shocks by passive funds affect secondary market trading. We start with a price effect. According to the efficient market hypothesis there should be no price effect. The reason is that assets are perfectly substitutable and any demand changes by one group of investors will be immediately picked up by other investors. Meanwhile, some researchers argue that there may be a short-term price effect, which reflects the cost of immediacy, but the price should reverse quickly (Harris and Gurel, 1986). Recent studies find the market is very inelastic and demand shifts may have long term price effect (Gabaix and Koijen, 2021). Our paper provides causal evidence in the corporate bond market. Using both the RDD and the IV approach, we find that positive demand shocks by passive funds lead to a statistically significant reduction in yield spreads, after controlling for all bond characteristics. This positive price effect is consistent with downward-sloping demand curves as suggested by Shleifer (1986). Additionally, the price effect starts to slowly reverse only three month after the crossing event. The cumulative effects become insignificant five months after the crossing event. The slow price reversal is consistent with slow moving capital and inelastic demand. Further, the magnitude of the price effect is economically meaningful. A simple trading strategy that buys the crossing bond right before the crossing month and sells the bond right after the crossing month earns significant excess returns and positive alphas after controlling for common corporate bond factors.

One critical question is why there may be limits to arbitrage. Since the crossing event is fully predictable, arbitrageurs should be able to eliminate the price effect. First, passive corporate bond funds apply a sampling strategy that allows them to only hold parts of the index portfolio. For potential arbitrageurs, it is uncertain which bonds passive funds will purchase and when they will buy, and passive funds may react once they observe the front-run price increase. Additionally, it is important to note that our trading strategy does not account for transaction costs. As the portfolio rebalances fully every month, the strategy is not profitable when round-trip transaction costs are taken into account. In addition, after controlling for common factors, the alpha is half the size of the excess return. This suggests this strategy has significant risk exposure, and the arbitrage is therefore not risk-free. Overall, corporate bond passive fund design, high transaction costs, and risk exposure contribute to the limits to arbitrage.

The next secondary market phenomenon we examine is liquidity. The theoretical predictions on the effects of passive funds on liquidity are mixed. Some argue that passive funds improve market efficiency, while some believe that ETF arbitrage could lead to adverse selection (Foucault, Kozhan, and Tham, 2017). We find that trading volume spikes around the crossing events, which is consistent with rebalancing activity. However, the trading volume quickly reverses to the pre-crossing level, suggesting no long-run effect. Using both RDD and

IV methods, we find a significant improvement in the crossing bond's liquidity, measured by volume-weighted bid-ask spreads, one month after the demand shock. Further, there is no evidence of reversal, suggesting a persistent liquidity improvement. In terms of magnitude, a 1% increase in passive fund ownership leads to around a 5% relative reduction in the bid-ask spreads. The fact that passive fund demand shocks have a lasting effect on liquidity but not trading volume indicates that some unique features of passive funds contribute to the liquidity improvement. This is consistent with the empirical finding that ETF arbitrage leads to liquidity improvement for the underlying bonds (Koont, Ma, Pastor, and Zeng, 2022).

Critically, we investigate whether passive fund demand shocks spill over to the primary market and affect firms' financing policies, and thereby real activity. Using the IV approach, we find that higher passive fund demand leads to lower issuing yield spreads. This result is consistent with the hypothesis that positive secondary demand shifts spill over to the primary market and reduce firms' financing costs. We then find evidence that a positive demand shift by passive funds leads to more net debt issuance. Two interpretations are consistent with this empirical evidence. First, firms time the issuance to exploit the lower financing cost caused by positive secondary market demand shocks. Second, firms decide to issue more debt after observing lower financing costs caused by positive secondary market demand shocks. Overall, our evidence is consistent with the idea that a positive demand shock by passive funds in the secondary market spills over to the primary market, causing lower offering yield spreads and higher net debt issuance. Since many studies have shown that financing cost and capital structure are critical for firms' real activity, such as investment and R&D, such passive fund demand shocks may have important real effects. These results supplement the growing literature on real effect of secondary market price fluctuations, such as Ma (2019); Dathan and Davydenko (2020); Chen, Chen, and Li (2021); Kubitza (2021).

Finally, we investigate how other institutional investors react to the demand shift by passive funds. To that end, we link investors' portfolio holdings with bond characteristics using the demand-based asset pricing framework proposed by Koijen and Yogo (2019). To address the endogeneity problem, we instrument yields using a measure based on the heterogeneous passive fund demand for bonds within different maturity buckets. The instrument is valid as the price changes caused by the passive fund demand shock are likely exogenous to other investors. This instrument is inspired by the investment universe instrument by Koijen and Yogo (2019). Our instrument reflects the investment mandate by maturity-constrained funds, which has the advantage that the investment mandates for passive funds are observable. The demand system estimation captures the different investors' demand elasticity in response to the price change caused by passive fund demand shifts. The results reveal significant heterogeneity among investors. Notably, active mutual fund has relatively high demand elasticity, suggesting that they act as arbitrageurs. In contrast, insurance companies have low demand elasticity, which is consistent with the fact that insurance companies are buy-and-hold investors. The coefficients for other bond characteristics also have significant heterogeneity among investors and are consistent with Bretscher, Schmid, Sen, and Sharma (2020).

Related Literature This paper is related to several strands of literature. First, our paper contributes to the literature that studies the impact of demand shocks on asset prices. In equity markets, extensive empirical studies use changes in index membership to estimate the demand elasticity (See Shleifer 1986, Harris and Gurel 1986, Kaul, Mehrotra, and Morck 2000, Chang, Hong, and Liskovich 2015, among others). Pavlova and Sikorskaya (2022) provides a micro-foundation for the index effect through benchmarking behavior. Li, Fu, and Chaudhary (2022) study demand elasticities in the corporate bond market using mutual fund flows. Closely related to our paper, Jansen (2021) finds that sector-specific demand shock caused by regulatory reform significantly impacts the yield curve. Hartzmark and Solomon (2021) also find that predictable and pre-announced dividend payments lead to significant and persistent price pressure. Our paper focuses on the effects of frequently occurring demand shocks by passive funds in the corporate bond market.

Our paper also relates to the fast-growing literature on passive funds. Numerous studies have examined the impact of passive fund ownership in the equity market.[1] In the corporate bond market, Holden and Nam (2017) and Marta (2022) find ETF ownership has a positive effect on liquidity, while some studies find that ETF ownership leads to fragility and flow-induced selling pressure (Dannhauser, 2017; Pan and Zeng, 2019; Dannhauser and Hoseinzade, 2022). Li and Yu (2021) find that higher a short-term investor composition increases the liquidity component in yield spreads. Recently, Koont et al. (2022) find that bond ETFs actively balance index-tracking against liquidity transformation. Our paper provides a new identification strategy to isolate the effect of passive fund ownership.

Our paper also links to the recent literature about the demand-based asset pricing framework proposed by Koijen and Yogo (2019). Haddad, Huebner, and Loualiche (2021) study how other investors change their behavior in response to the rise of passive investing. Bretscher et al. (2020) apply this demand system approach in the corporate bond market. Yu (2020) examine the duration hedging behavior of insurance companies. We contribute to this literature by proposing a new instrument: the observable investment mandate by maturity-constrained funds.

Lastly, our paper belongs to the rapidly growing literature on non-bank financial intermediaries and their implications for asset prices and real activity. Ma (2019) shows that firms actively respond to the price difference between their equity and debt by changing the supply of equity and debt. Dathan and Davydenko (2020) shows that aggregate passive debt demand affects firms' financing activity. Similarly, Chen et al. (2021) show that the debt-equity spread predicts firms' financing activities. Choi, Dasgupta, and Oh (2020) study the impacts of corporate bond mutual funds holding on credit risk. Kubitza (2021) finds that the demand shocks caused by insurance companies significantly impact firm debt issuance and investment. Adelino, Cunha, and Ferreira (2017) and Adelino, Cheong, Choi, and Oh

[1] See Appel, Gormley, and Keim (2016), Ben-David, Franzoni, and Moussawi (2018), Appel, Gormley, and Keim (2019), Heath, Macciocchi, Michaely, and Ringgenberg (2022), among others.

(2023) show the supply of capital from mutual funds have significant impact of municipal bond financing and local government spending. Our paper shows that frequently occurring exogenous demand shocks by passive funds significantly affect the secondary market price and improve liquidity. Additionally, we provide evidence that passive fund demand shock spillovers to the primary market and affects firms' financing cost and debt issuance.

The remainder of this paper is organized as follows: Section 2 explains the data sources and summarize the sample. Section 3 introduces the institutional background. Section 4 documents the passive fund demand shifts around maturity cutoffs. Section 5 elaborates the identification strategy and empirical specification. Section 6 presents the empirical results on the secondary market effects. Section 7 provides evidence on the effect of passive fund demand on primary market offering price and net debt issuance. In section 8, we estimate the demand elasticity for other institutional investors. Finally, section 9 concludes.

2 Data and Summary Statistics

The sample is compiled from multiple databases: (1) CRSP Mutual Fund database for mutual fund and ETF holdings, (2) Morningstar Direct for additional holding data for ETFs and index funds, (3) the Thomson Reuters eMAXX database for quarterly holdings data of other institutional investors, e.g. insurance companies and pension funds, (4) the Trade Reporting and Compliance Engine (TRACE) Enhanced database for daily corporate bond transactions data, (5) the Wharton Research Data Services (WRDS) bond return database for monthly pricing data and credit rating, (6) the corporate bond and issuer characteristics data come from the Fixed Income Securities Database (FISD), (7) CRSP and Compustat for firm characteristics.

We start with the U.S. corporate bond universe by merging FISD and the WRDS bond return database. Following the literature, we exclude all bonds that are floating-rate, sinking fund, perpetual, convertible, preferred, asset-backed, foreign currency, Yankee, or Rule 144A securities. We further restrict our sample to investment-grade bonds as the market share of passive funds in the high-yield market is small. We exclude bonds that were issued less than 6 months ago. Additionally, bonds with a maturity of less than 18 months are excluded to avoid the close-to-maturity bias. WRDS provides corporate bond prices at a monthly frequency as measured by the last transaction price of the month.[2] Then, the yield-to-maturity is calculated using this month-end price, and the yield spread is yield-to-maturity minus the maturity matched treasury rate. We estimate the treasury yield curve using cubic splines as in Collin-Dufresne, Goldstein, and Martin (2001). When daily transactions data is needed, we follow Dick-Nielsen (2009) and Dick-Nielsen (2014) to clean up the TRACE enhanced database. Specifically, we correct for cancelled, corrected or reversed trades, and remove double-counting for agency trades. We also remove transactions with less than $100,000 in par value as in Bao and Pan (2013).

Passive fund holdings data are available from multiple data sources. However, the coverage rate and reporting frequency vary, particularly in the early period. As our empirical framework relies on accurate holdings data, we carefully compare different data sources and compile the most accurate holdings data at a monthly frequency. We mainly rely on CRSP but also complement it with Morningstar when Morningstar has a higher reporting frequency.[3] The order of choice if multiple data sources are available is: (1) Morningstar, (2) CRSP. When monthly holdings are unavailable, we impute them using the nearest available observations. We then aggregate the holdings at the bond level and divide it by the market capitalization to get the total passive fund ownership. As we didn't impose any restrictions on fund types, our sample includes holdings by all passive funds, not just pure corporate bond funds.

[2] Alternatively, one can also restrict the observation to transaction prices in the last 5 trading days of the month. Since we focus on IG bonds and the sample starts after 2012, the problem of not having a transaction is small.

[3] Morningstar Direct should have the most comprehensive data among these three sources, but we can only use it as a supplement because of the download restriction.

The holdings data for other institutional investors are from Thomson Reuters eMAXX database at a quarterly frequency. The database mainly covers the holdings of insurance companies, mutual funds, and pension funds (Becker and Ivashina, 2015). The investor types absent from eMAXX are government agency, banks, foreign investors, and households. The pension fund coverage rate is low since pension fund holdings are disclosed voluntarily. eMAXX provides investor type classification codes. Following Bretscher et al. (2020), we group investors into the following categories: life insurance, P&C insurance, variable annuity funds, and pension funds & others. Though eMAXX also has mutual fund holdings, it does not separate active and passive mutual funds. Hence, we get active mutual fund holdings data from the CRSP mutual fund database.

Table 1 reports the summary statistics. The monthly bond-level sample gives 444,893 bond-month observations. The average passive fund ownership is 5.5%. Notably, within the investment-grade category, the passive fund ownership is quite stable across different rating groups. The average yield spread is 1.13%. It is worth noting that the yield spread for BBB bonds is significantly higher than the rest of investment-grade bonds. The average amount outstanding is around $600 million and the average bid-ask spread is 33 bps. The quarterly sample has 147,549 bond-quarter observations. The average ownership for active mutual fund, life insurance, P&C insurance, variable annuity, and pension funds are 4.64%, 23.59%, 4.69%, 0.77%, and 0.18% respectively. Finally, the bond-investor-quarter level sample has over 570 thousand and 44 million observations for active mutual fund and other institutional investors.

[Insert Table 1]

3 Institutional Background

In this section, we introduce institutional details about passive funds in the corporate bond market. In particular, we discuss maturity-mandated funds, which are the key for our empirical design.

3.1 Passive corporate bond funds

Passive fixed income funds were first introduced around 2002. The market is dominated by large players such as Vangaurd, Blackrock, and State Street. Most funds from Vanguard have both ETF share and index mutual fund share classes. In addition to pure corporate bond funds, there are other funds that hold corporate bonds as part of the portfolio. For example, total market funds typically invest around 30% of their AUM in corporate bonds. Figure 1 shows the evolution of the market. The left panel shows that the total holdings of IG corporate bonds by passive funds has increased rapidly since 2010, from around $50 billion to over $450 billion. Notably, the growth of passive funds over the last 10 years is aligned with the expansion of the corporate bond market, which has grown from $3 trillion to over $5 trillion. The right panel shows the average ownership structure over time. There are six investor types: passive funds, active mutual funds, life insurance, P&C insurance, annuity, and pension funds. Despite still being the largest investor in the corporate bond market, the average ownership by life insurances has declined significantly over the last decades from 30% to 20%. On the contrary, the average ownership of passive funds has increased rapidly, from 3% to 8%. Notably, the ownership of active mutual funds has not changed much over the last ten years.

[Insert Figure 1]

One distinguishing feature of passive fixed income funds is that, unlike passive equity funds that replicate the index exactly, passive fixed income funds employ a sampling strategy and hold only part of the index. This is because the size of fixed income indices and high transaction costs make full replication impractical (Dannhauser, 2017). Fund prospectuses typically state that the sampling strategy aims to minimize tracking errors and match the index cash flow, duration, industry, and credit rating. Hence, passive funds can both choose not to buy bonds that are added to the index as well as to hold bonds that are excluded from the index. Though it is unlikely that passive fund managers actively select bonds that will outperform the rest of the index, it is possible that bonds held by passive funds are more liquid and less likely to be downgraded to HY. Therefore, although the goal of this market design is to have a sufficient buffer against redemption, it introduces selection bias for empirical tests. Part of the concerns could be alleviated by the fact that passive funds are constrained by tracking error, as deviations from the index will increase tracking error, negatively affecting fund flows. Nevertheless, the complex market structure makes it challenging to identify the impact of passive fund ownership.

3.2 Corporate bond indices and maturity categories

Fixed income and equity indices have very different eligibility requirements. While most equity indices, such as S&P 500 and Russell 1000, select constituents based on market capitalization, the most common eligibility requirements for fixed income indices are a minimum credit rating and a minimum time-to-maturity. For example, most corporate bond indices require a minimum time-to-maturity of one year, and investment-grade indices require a minimum rating of BBB. Hence, the membership for a general fixed income index usually changes for two reasons: (1) a major upgrade or downgrade of credit rating; (2) a time-to-maturity less than one year.

Another unique feature of fixed income funds is that there are sub-indices based on different maturity categories. The most common grouping is long-term, intermediate term, and short-term funds. These sub-indices are usually called maturity-enhanced indices or maturity-mandated indices. These maturity-mandated funds are very popular. Nine of the ten largest corporate bond ETFs track maturity-mandated indices. Taking the Vanguard corporate bond fund family as an example. Vanguard has three maturity-mandated ETFs: Vanguard long-term corporate bond ETF (VCLT) tracks the Bloomberg US Corporate (10+Y) index, Vanguard intermediate-term corporate bond ETF (VCIT) tracks the

Bloomberg US Corporate (5-10Y) index, and Vanguard short-term corporate bond ETF (VCSH) tracks the Bloomberg US Corporate (1-5Y) index.

Further, maturity categories are defined consistently across different indexes. The most common definitions are as follows: long-term indexes include bonds with time-to-maturity longer than 10 years, intermediate-term indexes consist of bonds with 5 to 10 year maturity, and short-term indexes include bonds with 1 to 5 year maturity. In some cases, short-term bonds are defined as bonds with 1-3 year maturity. While some indexes offer more granular maturity ranges, such indexes are rarely used by passive funds. One reason for passive funds not to chose more granular maturity ranges is higher transaction cost and tracking errors due to more frequent index rebalancing. Based on the definition of the maturity categories, there are three cutoffs: 10-, 5-, and 3-year time-to-maturity. Once a bond crosses the 10-year (5-year/3-year) maturity cutoff, it will switch from the long-term (intermediate-term) maturity category to the intermediate-term (short-term) maturity category. As a result, this bond will be excluded from the long-term (intermediate-term) indexes and will become eligible to the intermediate-term (short-term) indexes.

Table 2 is a snapshot for all maturity-constrained passive funds with AUM larger than $1 billion in June 2022.[4] Consistent with previous discussion, the maturity categories are defined consistently across funds. Hence, once a bond crosses the 10-year (5-year/3-year) maturity cutoff, long-term (intermediate-term) funds will sell and intermediate-term (short-term) funds will buy. If the buying demand is the same as the selling demand, then the transition would be smooth, i.e. no equilibrium demand changes. However, as shown by the last column of table 2, the total AUM for long-term funds, intermediate funds, and short-term funds are $18.7 billion, $104.7 billion, and $175.9 billion, respectively, indicating a sizeable demand gap across three maturity categories. Hence, in addition to buying all shares sold by the long-term (intermediate-term) funds, the intermediate-term (short-term)

[4]iShares iBoxx $ Investment Grade Corporate Bond ETF (LQD) invests in bonds with at least 3 year time-to-maturity. As LQD cannot be classified into the three categories, it is not listed in the table. For the rest of this paper, LQD has been taken into account in all analyses.

funds will have to purchase from other investors, which creates a positive demand shock.

[Insert Table 2]

Figure 2 shows the passive fund demand for each maturity bucket over time. The left panel plots the total AUM of maturity-mandated passive funds for every maturity bucket, which represents total demand in each maturity bucket. The right panel plots the average passive fund ownership for bonds within each maturity bucket, which captures the average per bond demand in each maturity bucket. The right panel addresses the concern that the difference in bond supply across maturity buckets may cancel out the demand difference. We can see the order is stable for both panels: 1-3Y maturity bucket have the highest demand, followed by 3-5Y , 5-10Y, and 10+Y. Though the order is unchanged, the size of the gap is changing over time. This time-varying gap is important because it determines the size of the demand shift. Later we develop a measure to capture this time-varying demand gap. There are two noticeable structure changes: (1) the total demand gap between 10+ and 5-10Y drastically increase since 2015, however the per bond demand gap remain stable; (2) both the total demand gap and per bond demand gap between 1-3Y and 3-5Y disappear almost entirely after 2018. Both structural changes are consistent with the institutional details. The first change is associated with the growth of Vanguard funds. The second change is because one large ETF (IGSB) switches from a 1-3Y index to a 1-5Y index. We will discuss the second structural change in more detail in the next section as it affects per bond demand.

[Insert Figure 2]

4 Maturity Cutoffs and Passive Fund Demand

This section first provides evidence on the passive fund demand shift around maturity cutoffs. We then perform placebo tests using other maturity cutoffs and other investor types.

4.1 Passive fund demand around maturity cutoffs

Figure 3 shows the unconditional average passive fund holdings around the maturity cutoffs. Sub-figure (a) to (c) corresponding to 10Y, 5Y, and 3Y cutoffs. The x-axis is the time-to-maturity measured in months. The bond is getting closer to its maturity date from left to right. The y-axis is the average total percentage share held by passive funds at each maturity. The vertical line represents the maturity cutoff. We excluded newly issued bonds to avoid potential bias. The error bar in panel A represents the 95% confidence interval. The discontinuities at all cutoffs are clearly visible. More specifically, the average passive fund ownership increase from 1.5% to 5%, 5.4% to 6%, 4.8% to 5.8% after crossing the 10 year, 5 year, and 3 year cutoffs. Both the relative increase and absolute increase are economically significant. In the table 3, we perform regression discontinuity tests controlling for other bond characteristics and fixed effects.[5] All coefficients are significantly positive at 1% level, indicating that crossing maturity cutoffs significantly increase passive fund demand.

[Insert Figure 3]

[Insert Table 3]

Next, we show the full dynamics of the passive fund demand shifts around the maturity cutoffs. We apply local projection, as in Jordà (2005). Specifically, we estimate the following regression:

$$\Delta Passive_i^{t-1\rightarrow t+h} = \beta_h SwitchX_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where $\Delta Passive_i^{t-1\rightarrow t+h}$ is the percentage change of passive fund ownership for bond i from $t-1$ to $t+h$ (from $t+h$ to $t-1$) if $h \geq 0$ ($h < 0$). Hence, the benchmark period is $t-1$. For $h \geq 0$ ($h < 0$), a positive β_h means that passive fund ownership has increased from

[5] Columns (1), (3), and (5) use indicator variables. Column (2), (4), and (6) use a measure PD that capture the per-bond demand change. The next section discusses more details about PD.

$t-1$ to $t+h$ (increase from $t+h$ to $t-1$). $SwitchX_{it}$ is an indicator variable equal to one if bond i crosses maturity cutoff X at month t, and 0 otherwise. The maturity cutoff X is defined at the 10-year, 5-year, 3-year maturity as well as combinations of all three cutoffs, respectively. Year-month fixed effects are included to absorb any aggregate trend, and bond fixed effects are used to absorb any time-invariant bond specific effects. $Controls_{it}$ includes time-to-maturity, credit rating, contemporaneous bid-ask spread, and the amount outstanding of the bond. Figure 4 plots the coefficient estimates β_h for $h \in [-4, 6]$. Subfigure (a) reports the results using all three cutoffs, and subfigures (b) to (d) correspond to the 10-year, 5-year, and 3-year cutoffs, respectively. We can see that for all cutoffs, the effects on passive fund ownership are large and significant at 1% level. The effects peak at around two months following the crossing event. There is no evidence on front-running and reversals. In terms of magnitude, the passive fund ownership increase by around 6% relative to the pre-crossing levels, which translate into roughly 0.5% in absolute total share outstanding and $3 million in dollar terms. The magnitude of the demand shift is consistent with the unconditional results.

[**Insert Figure 4**]

4.2 Other maturity cutoffs and placebo tests

We next perform placebo tests on other maturity cutoffs to make sure our results are unique to the three maturity cutoffs that are supported by institutional features. We run the same regressions as in equation (1) for the following maturity cutoffs: 15Y, 14Y, ..., and 4Y (except for the three selected cutoffs). We should see no significant effects. Additionally, we also compare the effects on the 3Y cutoff using pre-2018 and post-2018. As mentioned previously, in 2018, one large ETF (IGSB) switches from a 1-3Y index to a 1-5Y index. As a result, the demand gap around the 3Y cutoff almost disappeared. Hence, we should see a stronger effect using the pre-2018 sample and almost no effect using the post-2018 sample. Figure 5 summarizes the effects on passive fund holdings two month after the crossing event. The full dynamics of all placebo tests are reported in figure A3 and A4.[6] Coefficients estimates for all placebo tests are close to zero and almost always insignificant. Hence, the passive fund demand shift is unique to the three maturity cutoffs we choose.

[**Insert Figure 5**]

4.3 Demand from other institutional investors

One important requirement for crossing maturity cutoffs to be a valid setting to study the impact of passive fund demand is that it should not confound with other investors' demand shift. Note that we don't require the passive fund demand for maturity to be uncorrelated with all other investors' demand for maturity. What we require is that, around the month when bonds cross maturity cutoffs, other investors should, on average, not have significant shifts in their demand. Other investors such as active mutual funds and insurance companies can have their own preference for maturity. But as long as there are no discontinuities around the three maturity cutoffs, our setting is valid. Figure 6 plots the average ownership over time-to-maturity for all major institutional investors in the corporate bond market, including active mutual funds, life insurance, PC insurance, variable annuity funds, and pension funds. We can see that for all other investors, crossing the 5 and 3 year cutoffs is not associated with significant changes in ownership. In addition, the 10-year cutoff seems to be a turning point for active mutual funds, life insurance, and annuities. However, none of their ownership displays discontinuity around the 10-year cutoff. Additionally, formal RDD tests find no significant demand shifts for other institutional investors around the three maturity cutoffs (see table A8). Intuitively, passive fund demand display discontinuity because of their fixed mandate on maturity categories. Other investors are not restricted by such mandates and can adjust their holding gradually. Further, to avoid high transaction costs, other investors

[6] Results for placebo tests using RDD can be found in table A1.

have an incentive to adjust their portfolios gradually. Hence, their revealed preference for maturity, measured by the average ownership over maturity, will be a smooth function as shown by figure 6.

[Insert Figure 6]

5 Empirical Framework

This section first introduces the construction of a novel measure, which we label PD, that is designed to capture the exogenous time-varying per bond demand. We then develop two empirical specifications: the first one applies a regression discontinuity design (RDD), and the second one uses an instrumental variable approach. Finally, we discuss the difference between the two methods.

5.1 Construction of PD measure

Motivated by the discussion above, we develop a measure PD to better capture the time-varying per-bond demand shifts. First, we manually collect benchmark information for maturity-mandated funds, and then we calculate the aggregate amount of assets benchmarked to each maturity range. We then divide it by the number of bonds within each maturity range.[7] Finally, we assign bonds with corresponding PD based on their time-to-maturity. The mathematical form of PD is inspired by the investment universe instrument proposed by Koijen and Yogo (2019). Formally:

$$PD_{it} = PD_t(n) = \log\left(\sum_{h=1}^{4} A_{ht}\frac{\mathbb{1}_{ht}(n)}{1+\sum_{m=1}^{N}\mathbb{1}_{ht}(m)}\right) \tag{2}$$

where A_{ht} is the total par amount held for maturity bucket h in month t. There are four maturity buckets: $h = 1, 2, 3, 4$ corresponding to 10+Y, 5-10Y, 3-5Y, and 1-3Y. The indicator

[7] Alternatively, we can weight by book value. The results are robust to this alternative specification.

function $\mathbb{1}_{ht}(n)$ equals one if it falls into the maturity bucket h at time t. The denominator reflects the total number of bonds for each maturity range. Take the 10-year cutoff as an example. Before crossing the cutoff, $PD = \log(\frac{A_1}{1+N_1})$, where N_1 is the number of bonds in the 10+Y bucket. After crossing the cutoff, $PD = \log(\frac{A_2}{1+N_2})$. PD will increase by more if the difference between A_1 and A_2 is larger. We take logs to be consistent with the demand-system approach as in Koijen and Yogo (2019). Similar to the investment universe instrument proposed by Koijen and Yogo (2019), PD reflects the investment mandate by maturity-mandated funds. The advantage of PD is that the investment mandates for passive funds are observable and exogenous. There are three sources of variation in PD: (1) a change in assets benchmarked to maturity ranges (A_{ht}); (2) a change in the number of bonds within maturity ranges (supply effects); (3) bond crossing maturity cutoffs (switch from $A_{1,t}$ to $A_{2,t}$). If the demand gap between two maturity buckets is larger (the difference between $A_{1,t}$ and $A_{2,t}$), PD will increase more. See figure A2 for examples of PD over time-to-maturity.

The advantage of simple indicator variables is that they are easy to interpret, while the advantage of PD is that it captures the time-varying demand shifts. For most of our tests, we present both results using PD and simple indicator variables.

5.2 Regression discontinuity design

We first develop a regression discontinuity design (RDD) based on the demand shift around the maturity cutoffs. The treatment is being eligible for the index of the new maturity range. Since the eligibility rule is deterministic, we employ a sharp RDD.[8] The determinant variable is time-to-maturity. We use a linear function form to control for time-to-maturity. Each bond has a different crossing date, so bonds are staggered over time-to-maturity. As a non-parametric control, we restrict the sample to observations whose time-to-maturity is within the ±6 month bandwidth. Different from the typical RD approach, we add bond fixed

[8] Alternatively, treatment could be defined as being invested in maturity-mandated funds. As the probability of treatment is no longer deterministic, a fuzzy RD approach is required.

effects in order to only exploit the within bond variation. It converts a pooled cross-sectional estimation into a panel estimation. Essentially, it allows us to compare the same bond before and after crossing the cutoff. To ensure the estimate is not driven by the overall upward trend in passive fund holdings, we include time fixed effects. Specifically, we estimate the following equation:

$$Y_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it} \tag{3}$$

where Y_{it} is the variable of interest. We mainly focus on three outcome variables: $Passive\%_{it}$, which is the total percentage of shares of bond i held by passive funds at time t; $Yield\_Spread$, which is the yield-to-maturity minus the maturity-matched treasury yield; and $Bid\text{-}Ask$, which is the volume weighted bid-ask spread to proxy for bond liquidity. $I(PassX)_{it}$ is a dummy variable equal to one if the bond has passed the cutoff X. TTM_{it} is the time-to-maturity centered at the maturity cutoffs. X_{it} is a set of controls for time-varying bond characteristics, which include the log of the amount outstanding and the numerical average of credit ratings. We also control for the contemporaneous bid-ask spread to address the concern that the liquidity premium may drive the price effect. When estimating the effect on liquidity, we control for the lagged bid-ask spread. Finally, standard errors are clustered at the bond and month levels to address intra-group correlations for the same bond and within the same month. Note the timing in the estimation. For example, consider a bond that passes the maturity cutoff at the 15th of the month $t-1$. The index will rebalance at the last date of the month $t-1$. $I(PassX)$ turns to one, and PD increases at month t as most funds start buying at month t.[9]

In our setting, because bonds cross the maturity cutoff at different dates, we can stagger bonds around the maturity cutoffs. For the 5Y and 3Y cutoffs, we have enough bonds crossing the cutoff. Figure A1 plots the average number and amount of bonds that switch

[9] The forced selling caused by a bond being removed from the index is usually more urgent. Dick-Nielsen and Rossi (2019) find that most selling happens on the last day of the month.

maturity cutoffs per month. The average number of bonds crossing the 5-year and 3-year cutoff is around 50, which translates into around 40 $billion in the total amount outstanding. Since the crossing events happen frequently, we can directly compare the same bond before and after crossing the cutoff. However, for the 10-year cutoffs, we only have around 10 bonds crossing the cutoff every month. As a result, the estimate with the bond-fixed effect for the 10-year cutoff would be very noisy. Hence, we exclude bond-fixed effects in the RDD test for the 10Y cutoff, which allows us to explore richer cross-sectional variation.

The bandwidth selection may seem ad-hoc. However, it is hard to use the optimal bandwidth selection algorithm as in most RDD literature. The optimal bandwidth chosen by the algorithm tends to be large (around ± 30 months), resulting in overlap between two cutoffs. Our bandwidth selection is based on empirical evidence and institutional knowledge of passive fund trading patterns, that is, most passive funds would complete their portfolio rebalancing within about six months. Additionally, unlike RDD in other fields, the asset pricing literature provides well-established general patterns between yields and time-to-maturity both empirically and theoretically. Hence, the functional form is not as big a concern. In later robustness check, we show that the results are robust to using higher order polynomials of time-to-maturity, different slopes before and after the cutoff, as well as different bandwidths. Finally, our second method, IV panel regression, does not rely on bandwidth selection and thus provides additional robustness checks.

When estimating price elasticity, the RDD specification can be easily converted to a two stage least square (2SLS) approach as in Appel et al. (2016). Essentially, equation (3) is used as the first-stage. The detailed specification is as follows:

$$\begin{aligned} Passive\%_{it} &= \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it} \\ Y_{it} &= \eta_i + \delta_t + \gamma_1 \widehat{Passive}\%_{it} + \gamma_2 TTM_{it} + \gamma' X_{it} + u_{it} \end{aligned} \tag{4}$$

As discussed in Appel, Gormley, and Keim (2020), the 2SLS approach scales the discontinuity in the outcome variable by the discontinuity in the explanatory variable (passive fund demand).

5.3 IV panel regression

The second approach uses the crossing event as an instrument for the change in passive fund holdings in a panel regression setting. Because the crossing event is pre-determined and orthogonal to the fundamental, it naturally satisfies the exclusion restriction. As the first stage F-statistics are well above the Stock and Yogo (2005) critical value, it is not a weak instrument. Specifically, the IV panel regression specification is as follows:

$$\begin{aligned} \Delta Y_{it} &= \beta_h \Delta \widehat{Passive}\%_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it} \\ \Delta Passive\%_{it} &= \gamma_h SwitchX_{it} + Controls_{it} + \mu_i + \eta_t + e_{it} \end{aligned} \tag{5}$$

where ΔY_{it} is the change of outcome variables and $\Delta Passive\%^{it}$ is the change of passive fund holdings. $\Delta Passive\%^{it}$ is instrumented by $SwitchX_{it}$, which is an indicator variable equal to one if bond i crosses maturity cutoff X at month t, and 0 otherwise. Bond-fixed effects and time-fixed effects are included. This 2SLS panel regression can be performed in a way similar to equation (1) to capture the dynamics of the effects.

IV panel regressions have the advantage that they do not rely on bandwidth selection. Instead, it can capture the full dynamics of demand shocks' impact. Additionally, the advantage of RDD is that it restricts the sample around the maturity cutoff, so it avoids bias from observations far away from the cutoffs. However, RDD is not suitable in some cases due to the nature of the outcome variable. For instance, it is impossible to use RDD to study the impact on flow variables such as net issuance. Whenever possible, we provide evidence using both approaches so they can cross-validate each other.

6 Secondary Market Results

In this section, we put our empirical framework to work and ask whether shocks originating in passive fund demand shifts are reflected in secondary market prices, volume, and liquidity. Moreover, we examine a trading strategy designed to take advantage of such secondary market price effects.

6.1 Price effects

Table 4 reports the RD estimation results for yield spreads using 2SLS.[10]. Column (1), (3), and (5) instrument passive demand using indicator variables, while column (2), (4), (6) use PD as instrument.[11] The coefficients for yield spreads are significantly negative, which suggests that the yield spread decreases after crossing the maturity cutoffs. Since yield and price are inversely related, a reduction in yield spread indicates a positive price effect. Overall, the results suggest a positive price effect after the demand shift by passive funds. For the 10-, 5-, and 3-year cutoffs, a one percentage point increase in passive fund ownership results in roughly a 10, 6, and 8 basis point reduction in yield spreads. The coefficients for bid-ask spreads are significantly positive, suggesting the yield spread effect is higher for bonds with low liquidity. In unreported tests, the price effects are slightly larger if not controlling for the contemporaneous bid-ask spread. The results suggest that liquidity risk is priced in the corporate bond market. However, the positive price effect of crossing the maturity cutoff is not entirely driven by changes in liquidity risk. To address the concerns that the change of time-to-maturity may mechanically drive the price effect, we run the same specifications with other maturity cutoffs. Table A8 reports the results for the placebo tests. For all cutoffs, the coefficients are not significant.

[Insert Table 4]

[10] Direct RDD results are reported in table A6

[11] Table 3 is also the first stage results.

Figure 7 reports the full dynamics of the yield changes around the maturity cutoffs using an IV panel regression. The main explanatory variable is $Passive\%_i^{t-1\to t+2}$, which captures changes in passive fund ownership from $t-1$ to $t+2$. The reason to choose $h=2$ is based on the empirical observation that passive fund ownership peaks around 2 month following the crossing event (see figure 4). Subfigure (a) plots the coefficient estimates for bonds that cross any of the three cutoffs. Subfigures (b) to (d) correspond to the 10-year, 5-year, and 3-year cutoffs respectively. The coefficient estimates are all negative and statistically significant for t and $t+1$, which suggests a significant reduction in yield spreads. After translating the relative percentage effects to absolute effects, the magnitude of the peak effects is around 10 bps, which is consistent with the effects found using RDD. From $t+2$ onwards, the coefficients start slowly to revert to zero, suggesting slow price reversal. The prices fully revert back to the pre-crossing level around 5 months after the crossing event.

[Insert Figure 7]

6.1.1 Trading strategy

Based on the passive fund demand shift around maturity cutoffs, we build a simple trading strategy. The strategy is as follows: (1) buy bond i at month $t-1$ if bond i is going to cross a maturity cutoff in month t; (2) sell bond i at the end of month t. The portfolio rebalances at the end of each month. The return is calculated using the month end price reported in TRACE. Figure 8 plots the cumulative return on this trading strategy. Table 5 reports excess returns and alphas after controlling for BBW factors (Bai, Bali, and Wen, 2019) and FF factors (Fama and French, 1993). Newey-West adjusted standard errors are reported in parentheses. Panel A reports the results for portfolios weighted by the amount outstanding. Panel B reports the results for equally weighted portfolios. We also separately report return results for each individual cutoff. We also compare the alphas for the 3Y cutoff before and after 2018.

[**Insert Figure 8**]

[**Insert Table 5**]

6.1.2 Limits to arbitrage

One crucial question is why the market may not arbitrage away the price effect ex-ante. Since the crossing event can be fully anticipated, the EMH would suggest there will be no price effect. Our simple trading strategy of purchasing bonds one month before they cross the maturity cutoff and selling them one month after they cross the maturity cutoff generates positive alpha. One reason for the limits to arbitrage is that the sampling strategy allows passive funds to rebalance their portfolios flexibly. As a result, even though the demand shift is fully predictable, it is still difficult to profit from it ex-ante. Potential arbitrageurs are uncertain which bonds passive funds will purchase and when they will begin buying them. Passive funds can also decide not to purchase a bond if its price rises before crossing the cutoff. In addition, passive funds are dominated by large companies such as BlackRock and Vanguard. Ex-ante betting with passive funds will be costly and difficult. Last, such a trade is not risk-free, as one needs to hold the assets for extended periods of time, which will decrease investors' willingness to take the arbitrage opportunity. The slow reversal ex-post could be attributed to inelastic demand. Many investors in the corporate bond market are buy-and-hold investors, so there may not be sufficiently many investors willing to sell the bonds. Further, frictions such as transaction and opportunity costs may also make such trade not profitable.

6.2 Trading volume and liquidity

Figure 9 plots the dynamics of trading volume around maturity cutoffs using a IV panel regression. The dependent variable $\Delta Volume_i^{t-1\rightarrow t+h}$ is the percentage change of trading volume in par amount) for bond i from $t-1$ to $t+h$. We can see that trading volume spikes at the crossing month (t), which is consistent with passive funds' rebalancing activities. In terms of the magnitude, for all three cutoffs, the trading volume increases by around 10% at the crossing month. Additionally, the effects on trading volume quickly revert back to the pre-crossing level after two month, suggesting passive fund demand increases do not necessarily lead to a permanent increase in trading volume. Table 6 panel B reports the results on trading volume using RDD. Consistent with the previous results, the coefficients are only significantly positive for the 10-year cutoff.

[Insert Figure 9]

[Insert Table 6]

Figure 10 plots the dynamics of liquidity around the maturity cutoffs. Liquidity is measured using volume-weighted bid-ask spreads. So a negative coefficient implies a liquidity improvement. Except for the 10Y cutoff, coefficients are first insignificant at the crossing month t, and then become significantly negative starting one month after the crossing event. Further, there is no evidence on reversal. Hence, the results suggest that there are persistent liquidity improvements one month after the passive fund demand shift. In terms of the magnitude, a 1% increase in passive fund ownership leads to around 5% relative reduction in bid-ask spreads. The coefficients are insignificant for the 10Y cutoff, which could be due to too much noise and too few crossing events. Table 6 panel A reports the RDD results on liquidity. The coefficients for all maturity cutoffs are almost always significantly negative, indicating a liquidity improvement. Overall the results suggest that passive fund ownership improves liquidity but does not necessarily permanently increase trading volumes.

[Insert Figure 10]

7 Primary Markets and Firm Financing

This section examines whether the secondary market effects of passive fund demand shifts spill over to the primary market and affect firms' financing decisions. We first study the effects on offering prices and then investigate the effects on net debt issuance.

7.1 Primary market offering price

To study firm-level outcomes, we need an instrument for passive fund demand shifts at the firm level. Hence, we construct PD_firm, which is the average of PD for firm i, weighted by the amount outstanding. This captures the firm level passive fund demand shifts caused by bonds switching maturity buckets. We estimate the following 2SLS regressions:

$$\begin{aligned} YieldSpread_{it} &= \beta \widehat{Passive\_firm}\%_{it} + Controls + FEs + \epsilon_{it} \\ Passive\_firm\%_{it} &= \gamma PD\_firm_{it} + Controls + FEs + e_{it} \end{aligned} \tag{6}$$

where $YieldSpread_{it}$ is the offering yield spread. $Passive\_firm\%$ is the average percentage of passive fund holdings for firm i's outstanding corporate bonds, weighted by the amount outstanding. $Passive\_firm\%$ is instrumented using PD_firm_{it}. Issue level controls include issue size, credit rating, and initial maturity. Firm level controls include firm size, tangible asset, firm age, market-to-book ratio, leverage ratio, cash, lagged cash growth, lagged 12 month sales, lagged net income, and lagged CapEx. Three fixed effects are used: industry-by-year FE absorbs any industry specific trend, rating-by-year FE absorb time-varying differences in yield spreads across different rating category (rating categories are defined as AAA-AA, A, and BBB), maturity-by-year FE absorb time-varying differences in yield spreads across different initial maturity bucket (initial maturity buckets are defined as (0,3], (3,5], (5,10], (10,15], (15,∞]). Standard errors are clustered at year and firm levels.

Table 8 reports the results. F-Statistics for the first stage are significantly above the critical value suggested by Stock and Yogo (2005), suggesting the instrument is not weak. The coefficients on $Passive\_firm\%$ are significantly negative across all specifications, which suggest that higher passive fund demand leads to lower issuing yield spreads. This result is consistent with hypothesis that positive secondary demand shifts spillover to the primary market and lead to lower financing costs.

[Insert Table 8]

7.2 Net debt issuance

Next we study whether the passive fund demand shift affects firms' financing activities. Because firm's net debt issuance data is at quarterly level, we first aggregate monthly passive fund data to the quarterly level by taking the last observation within the quarter. We run the following 2SLS regressions:

$$\begin{aligned} \Delta Debt_{it} &= \beta \Delta \widehat{Passive\_firm}\%_{it-1} + Controls + FEs + \epsilon_{it} \\ \Delta Passive\_firm\%_{it-1} &= \gamma \Delta PD\_firm_{it-1} + Controls + FEs + e_{it} \end{aligned} \tag{7}$$

where $\Delta Debt_{it}$ is the net change of firm i's long term debt, scaled by lagged total assets. $\Delta Passive\_firm\%_{it-1}$ is the lagged change of average percentage of passive fund holding for firm i's outstanding corporate bonds, weighted by the amount outstanding. $\Delta Passive\_firm\%_{it-1}$ is instrumented using ΔPD_firm_{it-1}. Firm level controls include credit rating, lagged firm size, firm age, market-to-book ratio, leverage ratio, lagged cash holding, lagged 12 month sales, net income, CapEx, and lagged asset growth. Four fixed effects are used: firm FE absorbs any time-invariant firm specific variation, year FE takes out any time trend, industry-by-year FE absorbs any time-varying differences across industries, rating-by-year FE absorb any time-varying differences across different rating category (rating categories are defined as AAA-AA, A, and BBB). Standard errors are clustered at year and firm levels.

[**Insert Table 9**]

Table 9 reports the results. F-Statistics for the first stage are again significantly above the critical value suggested by Stock and Yogo (2005), suggesting the instrument is not weak. The coefficients on $\Delta Passive\_firm\%_{it-1}$ are significantly positive across all specifications, which suggest that a positive demand shift by passive funds leads to more net debt issuance. Two interpretations are consistent with the empirical evidence. First, firms time the issuance to exploit the lower financing cost caused by the positive secondary market demand shock. Second, firms decide to issue more debt after observing the lower financing cost caused by the positive secondary market demand shock. Overall, our evidence is consistent with the notion that a positive demand shock by passive funds in the secondary market spills over to the primary market, causing lower offering yield spreads and higher net debt issuance. Since many studies have shown that financing costs and capital structure are critical for firms' real activity, such as investment and R&D, we conclude that passive fund demand shocks may have important real effects. We end our analysis with the primary offering price and debt issuance because the power of our identification is diminishing along the causal chain.

8 Demand System Estimation

From the previous sections, we show that the bond price will increase as the demand by passive investors increases, suggesting that the aggregate demand curve is downward sloping. To investigate how different investors respond to the demand shift by passive investors, we use the characteristics-based demand system approach developed by Koijen and Yogo (2019) to estimate the price elasticities of demand. Specifically, we use the demand shift by passive investors as an exogenous shock to prices.

8.1 Characteristics-based demand system approach

Let investors be indexed by i, time is indexed by t, and bonds be indexed by n. Investor i's investment in bond n at time t be denoted as $B_{it}(n)$. Outside assets include all non-corporate bond assets, such as cash and treasuries, denoted as $n = 0$. Investor i's outside asset holding is then $B_{it}(0)$. Let $w_{it}(n)$ be the investor i's portfolio weight of corporate bond n at time t, which can be expressed as:

$$w_{it}(n) = \frac{B_{it}(n)}{B_{it}(0) + \sum_{m=1}^{N} B_{it}(m)}$$

The weight on the outside asset can be expressed as $w_{it}(0) = 1 - \sum_{m=1}^{N} w_{it}(m)$. Then, the investors' relative weight on bond n is the ratio between $w_{it}(n)$ and $w_{it}(0)$: $\delta_{it}(n) \equiv \frac{w_{it}(n)}{w_{it}(0)}$. Koijen and Yogo (2019) derive an empirically tractable equilibrium model of $\delta_{it}(n)$ from portfolio theory based on three assumptions: (1) investors have mean-variance preferences for returns (Markowitz (1952)); (2) returns have a factors structure; (3) the expected returns and factor loading depend only on asset's own prices and characteristics. The first and third assumptions are commonly used for empirical asset pricing studies. For the second assumption, as in the equity market, numerous studies have shown that common factors or bond characteristics can explain the cross-section of expected corporate bonds returns.[12] Under these assumptions, $\delta_{it}(n)$ can be written as a logit function of price and a vector of characteristics:

$$\ln \frac{w_{it}(n)}{w_{it}(0)} = \ln \delta_{it}(n) = \alpha_{it} + \beta_{0,i} y_t(n) + \beta_{1,i}' X_t(n) + \epsilon_{it}(n) \tag{8}$$

where $y_t(n)$ is the yield to maturity for bond n at time t, and $X_t(n)$ is a vector of bond characteristics, which captures the observable sources of risks that are known to explain

[12]See Fama and French (1993), Gebhardt, Hvidkjaer, and Swaminathan (2005), and Bai et al. (2019), among others.

investor's demand. The choice of bond characteristics closely follows Bretscher et al. (2020). We include the bond's bid-ask spread to proxy for the liquidity risk, as numerous studies have shown that liquidity is an important determinant of corporate bond risk.[13] We also include the amount outstanding as the literature has documented that mutual funds and insurance companies have special preference over the size of bonds (Sen and Sharma, 2020). We also include time-to-maturity and credit rating as they are important sources of risk. The error term $\epsilon_{it}(n)$ is referred to as the latent demand by Koijen and Yogo (2019), which captures the investor's unobserved demand on bond n that price and other bond characteristics cannot explain. We include fund-quarter fixed effects to only exploit the within bond and quarter variation. Note that because of the fund-quarter fixed effects, the choice of the outside asset does not matter for the estimation as any choice of $w_{it}(0)$ will be absorbed by α_{it}.[14] Following Bretscher et al. (2020), we restrict $\epsilon_{it}(n) \geq 0$ so that the portfolio weights are nonnegative.

The identification assumption for equation (8) is $\mathbb{E}\left[\epsilon_{it}(n) \mid y_t(n), x_t(n)\right] = 0$. As in the previous literature, we assume that bond characteristics other than yields are exogenous, that is, $\mathbb{E}\left[\epsilon_{it}(n) \mid x_t(n)\right] = 0$. However, it is not plausible to assume that the bond yields are orthogonal to the latent demand as institutional investors are clearly not price-takers. To address this endogeneity problem, Bretscher et al. (2020) and Yu (2020) use the investment universe instrument proposed by Koijen and Yogo (2019).[15] One weakness of the investment universe instrument is that we cannot precisely measure the investment universe as it is usually not explicitly stated or not publicly available. Our measure PD can address this problem since it can be regarded as the true investment mandate for maturity-mandated

[13]See Chen, Lesmond, and Wei (2007), Bao, Pan, and Wang (2011), Lin, Wang, and Wu (2011), among others.

[14]The choice of the outside asset will matter if one wants to do counterfactual simulation as in Koijen and Yogo (2019) and Bretscher et al. (2020).

[15]Specifically, the yield of bond n is instrumented as follow:

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

where $\mathbb{1}_{j,t}(n)$ equals one if bond n at time t is being held or ever held in the previous 11 quarters by investor j, i.e., it belongs to the investment universe of investor j.

passive funds. Since PD captures the demand shift by passive investors when a bond crosses a maturity cutoff, we know exactly where the demand shock is originating, which helps assess whether the instrument satisfies the exclusion assumptions of the IV approach. Specifically, crossing maturity cutoffs provide a plausible exogenous demand shift by passive funds, which are uncorrelated with the demand shocks of other investors. Therefore, crossing maturity cutoffs only affect the demand of other investors through its effect on the price, which allows clear identification of investor's demand elasticity.[16] Hence, we instrument the yield of bond n at time t using $PD_t(n)$:

$$\widehat{\mathrm{y}}_{i,t}(n) = PD_t(n) = \log\left(\sum_{h=1}^{4} A_{ht}\frac{\mathbb{1}_{ht}(n)}{1+\sum_{m=1}^{N}\mathbb{1}_{ht}(m)}\right) \tag{9}$$

where $\mathbb{1}_{ht}(n)$ equal one if bond n belongs to the maturity bucket h at time t and A_{ht} is the total AUM for passive funds constrained to maturity bucket h at month t. Intuitively, after a bond crosses a maturity cutoff, it has a larger exogenous component of demand as it is now eligible for a larger pool of maturity-mandated funds, which generates higher prices that are orthogonal to latent demand of other investor types.

8.2 Implementation and results

Because many institutions have small portfolios, it may be hard to accurately estimate the cross-section of investors i at each time t. Following Bretscher et al. (2020), we pool all investors with the same type and estimate the demand elasticity for each investor type in panel regression. We define five investor types: active mutual funds, life insurance, P&C insurance, variable annuities, and pension funds & others. This investor-type panel regression method allows me to quickly evaluate the heterogeneity in the demand elasticity across investor types. Additionally, to account for the heterogeneity in the investor size within

[16] We can only estimate the demand system for investors other than passive funds. However, the demand for passive funds should be rather straightforward as they track the index passively.

each group, we weight by investors' AUM as in Bretscher et al. (2020).

In addition to using fund-quarter fixed effect as in Bretscher et al. (2020), we also estimate the demand system using fund-bond fixed effect. While the fund-quarter fixed effect explores how funds allocate capital in each quarter, the fund-bond fixed effect examines how a fund adjusts the holdings according to bonds' characteristics. The two fixed effects have different implications. The fund-quarter fixed effect reveals the preference over each bond characteristic, and the fund-bond fixed effect speaks to the sensitivity of holdings in responses to the changes in bond characteristics. For instance, buy-and-hold investors may strongly prefer certain characteristics but may be insensitive to changes over time, possibly due to benchmarking, high adjustment costs, or inattention.

Table 7 presents the demand estimation for each investor type. Panel A reports the results using the fund-quarter fixed effect, and panel B reports the results using the fund-bond fixed effect. The results highlight significant heterogeneity of demand elasticities among investors, particularly between active mutual funds and insurance companies. The coefficients on yields are significantly positive for active mutual funds. It implies a downward-sloping demand curve. The fund-bond fixed effect coefficient is also significantly positive, suggesting that active mutual funds decrease holdings after bond price increases. The results suggest that active mutual funds serve as arbitrageurs in response to the demand shift by passive funds. For life insurance and P&C insurance, the coefficients on yield are not significant, which suggests that insurance companies have a very inelastic demand for price. It is consistent with the fact that insurance companies are mostly buy-and-hold investors. The yields' coefficients are neither significant for other investor types, implying an overall inelastic demand in the corporate bond market. Interestingly, with fund-bond fixed effects, variable annuity funds have a significant negative coefficient on yield.

[Insert Table 7]

For other characteristics, the coefficients on the bid-ask spread are significantly negative for active mutual funds but significantly positive for life insurance. Active mutual funds prefer more liquid bonds, while insurance companies tilt their portfolios towards illiquid bonds. Notably, in contrast to the cross-sectional results, the time-series results suggest that insurance companies do not adjust their holdings to changes in liquidity conditions. Active mutual funds tend to hold more short-term bonds, while insurance companies tend to reduce their holdings as the maturity date of the bond approaches. All investors prefer larger bonds, and the loading for active mutual funds is much higher than for insurance companies. Lastly, the cross-sectional results indicate that active mutual funds have no significant preference for credit ratings, while insurance companies hold more bonds with high credit ratings. Interestingly, the time-series results find that active mutual funds significantly reduce their holdings after a bond gets downgraded, while the insurance companies are insensitive to credit deterioration. Overall, the cross-sectional results are consistent with prior literature, and the time-series results indicate that active mutual funds frequently adjust their portfolios, while insurance companies are mainly buy-and-hold investors.

Finally, we explore the evolution of the demand elasticity for different investor types. Figure 11 reports the evolution of coefficients for each characteristics. The estimations use fund-quarter fixed effects. The coefficients are relatively stable over time, and the ranking among investor types is consistent with the pooled estimation. Two notable patterns emerge. First, the coefficients on maturity for active mutual funds increase steadily, implying that the preference for short-term bonds becomes weaker. Second, the coefficients on size for active mutual funds also increase over time, suggesting that the preference for large bonds becomes stronger. Most estimates vary significantly in 2020 due to Covid-19. In March 2020 corporate bond markets suffered a liquidity crisis. Following the market turmoil, the Fed announced the Secondary Market Corporate Credit Facility (SMCCF) plan, which is unprecedented as it allows the fed to purchase corporate bonds for the first time directly. As anecdotal evidence, there are two interesting observations. First, the coefficients for yields turn negative for all investor types, meaning that investors suddenly prefer bonds with a high price. Second, the credit rating coefficient surges drastically and turns positive for active mutual funds and variable annuity funds, implying a preference for risky bonds.

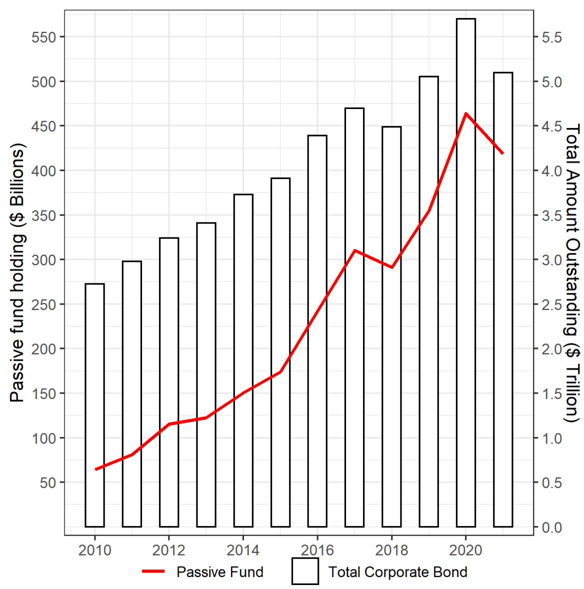
[Insert Figure 11]

9 Conclusion

This paper documents a novel and common exogenous demand shock caused by passive funds in the corporate bond market. Specifically, passive fund demand for corporate bonds displays discontinuity around the maturity cutoffs separating long-term, intermediate-term, and short-term bonds. Once a bond crosses the 10-, 5-, and 3-year time-to-maturity cutoffs, demand from passive funds increases significantly. Using this exogenous demand shock, we develop a novel identification strategy to examine the impact of passive fund demand in the corporate bond market. First, we find that these non-fundamental demand shifts lead to a significant and lasting decrease in yield spreads, suggesting a positive price effect. A simple trading strategy can earn a significantly positive alpha before transaction costs. Additionally, trading volume spikes around demand shifts and then almost fully reverses. We also find persistent liquidity improvements following the demand shocks. We then provide evidence that the effects of passive fund demand shocks spill over to the primary market, causing lower issuing yield spreads and higher net debt issuance.

Our empirical framework provides a novel identification strategy that allows to assess the impact of passive demand on financial markets. Critically, we show that passive corporate bond demand triggers active supply in that non-fundamental demand shocks cause firms to issue more corporate debt, thereby affecting firms' real decisions. Given the prominent rise in capital allocated to passive funds in recent years, these effects may become more prominent over time.

Panel A: Market size



Panel B: Average ownership by institution

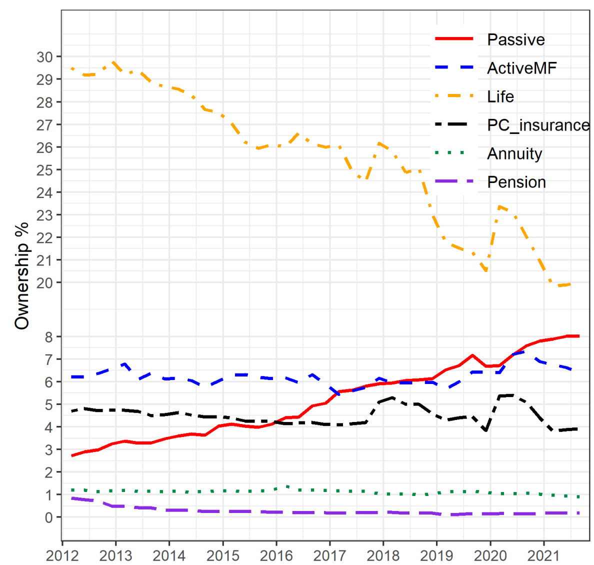
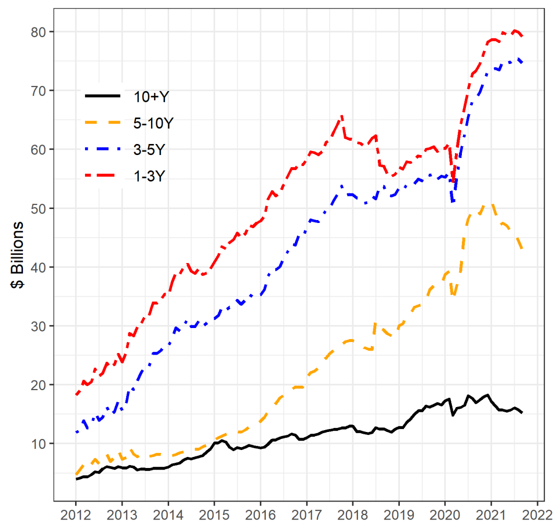


Figure 1: Evolution of the corporate bond market

The red line of panel A plots the evolution of passive fund holdings of IG corporate bonds (left y-axis). The bar shows the total amount outstanding of the IG corporate bond market (right y-axis). Panel B plots the average percentage ownership of IG corporate bonds for each investor type. The ownership is calculated as the percentage share outstanding owned by each investor type. There are six investor types: passive funds, active mutual funds, life insurance, P&C insurance, variable annuity, and Pension funds.

(a) Total demand for each bucket



(b) Average per bond demand for each bucket

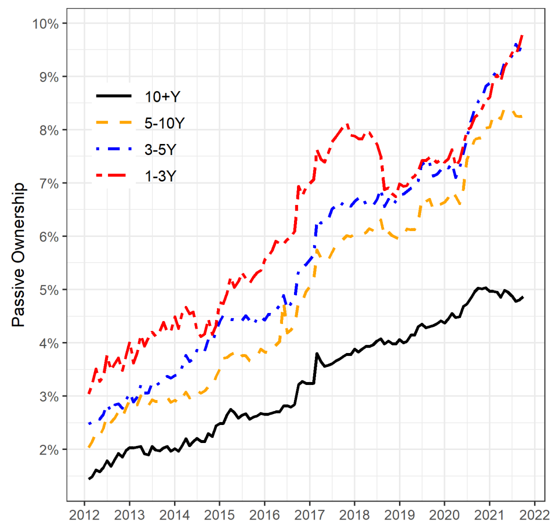


Figure 2: Maturity-constrained passive funds

Panel A plots the time series of the aggregate corporate bond holdings by passive funds that track each maturity bucket. There are four maturity buckets: 10+Y, 5-10Y, 1-5Y, and 1-3Y. Panel B plots the average passive fund ownership over time for each maturity bucket

(a) 10 Year (b) 5 Year (c) 3 Year

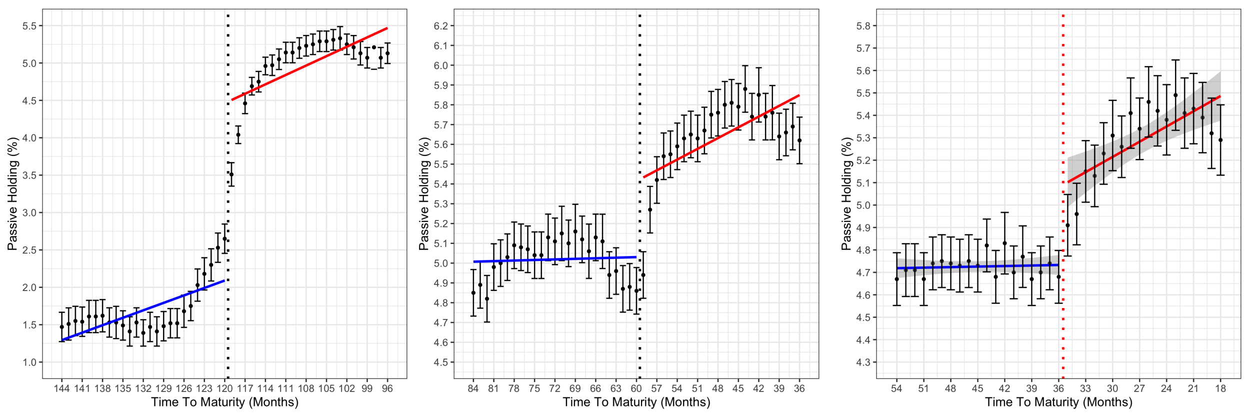
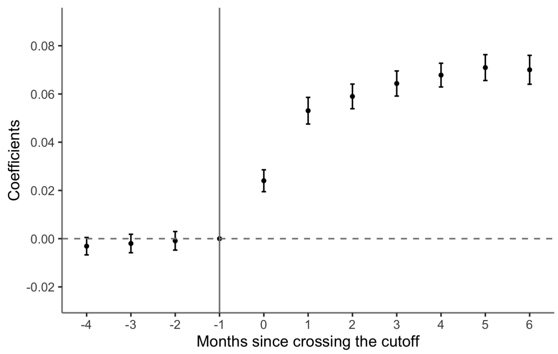


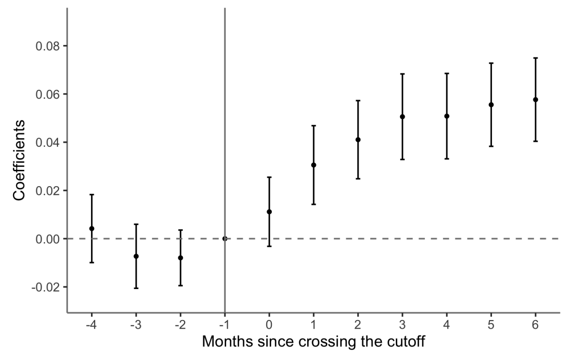
Figure 3: Passive fund ownership around maturity cutoffs

These figures plot the passive fund ownership around the three maturity cutoffs. The y-axis is the average passive ownership for bonds with a specific time-to-maturity. The x-axis is the time-to-maturity measured in month. From left to right, the bond is getting closer to its maturity date. The error bars represent the 95% confidence interval. The dotted vertical lines are maturity cutoffs. Thus, to the left of the vertical line is pre-cutoff and to the right of the vertical line is post-cutoff. The linear trends are estimated using the samples on the left and right of the cutoff. Sub-figures (a) to (c) correspond to the 10 year, 5 year, and 3 year maturity cutoffs, respectively. Sub-figure (c) uses the pre-2018 sample.

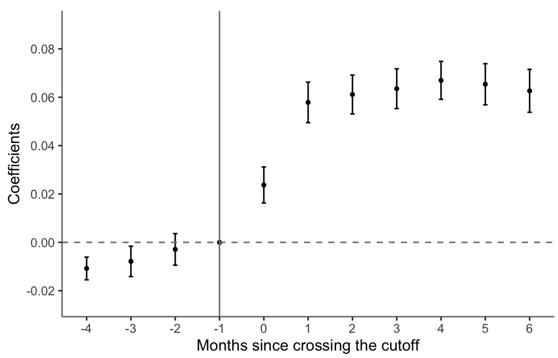
(a) All cutoffs



(b) 10Y maturity cutoff



(c) 5Y maturity cutoff



(d) 3Y maturity cutoff

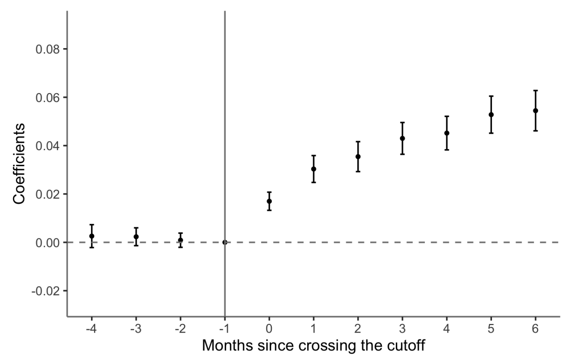


Figure 4: Passive fund holding dynamics and crossing maturity cutoffs

This figure plots the coefficient estimates β_h from the following regression for $h \in [-4, 6]$:

$$\Delta Passive_i^{t-1\rightarrow t+h} = \beta_h SwitchX_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

where $\Delta Passive_i^{t-1\rightarrow t+h}$ is the percentage change of passive fund ownership for bond i from $t-1$ to $t+h$ (from $t+h$ to $t-1$) if $h \geq 0$ ($h < 0$). The vertical line represents the benchmark, which is one month before the crossing event, $t-1$. For $h \geq 0$ ($h < 0$), a positive β_h means that passive fund ownership has increased from $t-1$ to $t+h$ (from $t+h$ to $t-1$). $SwitchX_{it}$ is an indicator variable equal to one if bond i crosses maturity cutoff X in month t, and 0 otherwise. Maturity cutoffs X are defined at the 10-year, 5-year, and 3-year time-to-maturity. Subfigure (a) plots the coefficient estimates for bonds that cross any of these three cutoffs. Subfigures (b) to (d) correspond to the 10-year, 5-year, and 3-year cutoffs respectively. Year-month fixed effects and bond fixed effects are included. $Controls_{it}$ includes time-to-maturity, credit rating, contemporaneous bid-ask spread, and the amount outstanding of the bond. Error bars represent the 90% confidence interval, where standard errors are clustered at both the bond and year-month levels.

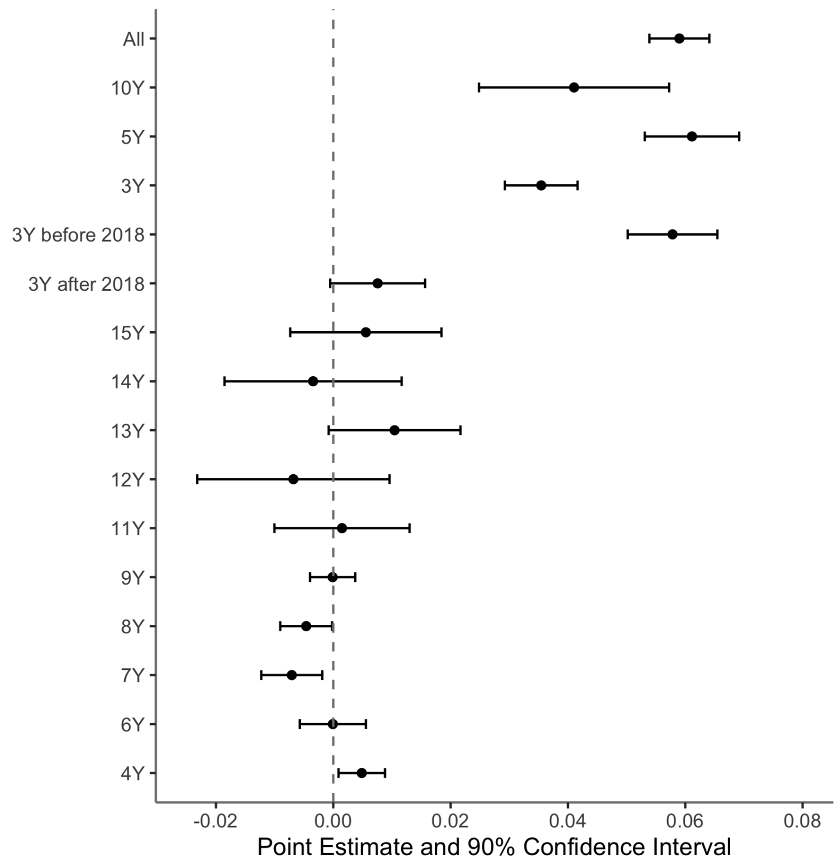


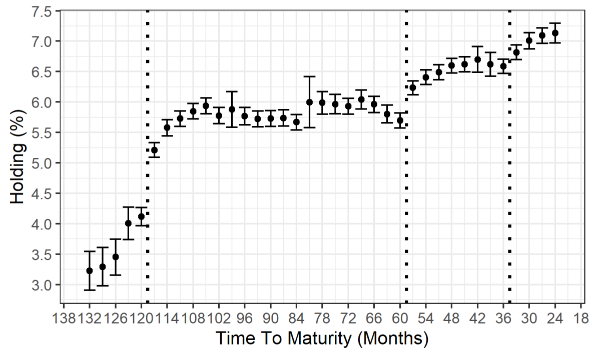
Figure 5: Summary of point estimates for all maturity cutoffs

This figure summarizes the effects of crossing different maturity cutoffs on passive fund demand. The figure plots point estimates β_X and 90% confidence intervals for cutoff X from the following regressions:

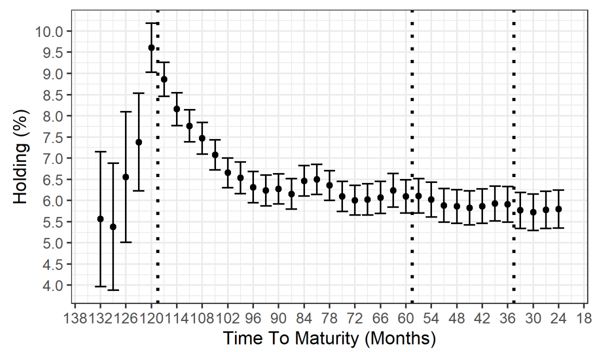
$$\Delta Passive_i^{t-1 \to t+2} = \beta_X SwitchX_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

where $\Delta Passive_i^{t-1 \to t+2}$ is the three-month cumulative percentage change of passive fund ownership for bond i from $t-1$ to $t+2$. $SwitchX_{it}$ is an indicator variable equal to one if bond i crosses maturity cutoff X in month t, and 0 otherwise. Maturity cutoffs X include: All (10Y, 5Y, and 3Y_before2018), 10Y, 5Y, 3Y, 3Y_before2018, 3Y_after2018, 15Y, 14Y, 13Y, 12Y, 11Y, 9Y, 8Y, 7Y, 6Y, and 4Y. Year-month fixed effects and bond fixed effects are included. $Controls_{it}$ includes time-to-maturity, credit rating, contemporaneous bid-ask spread, and the amount outstanding of the bond. Error bars represent the 90% confidence interval, where standard errors are clustered at both the bond and year-month levels.

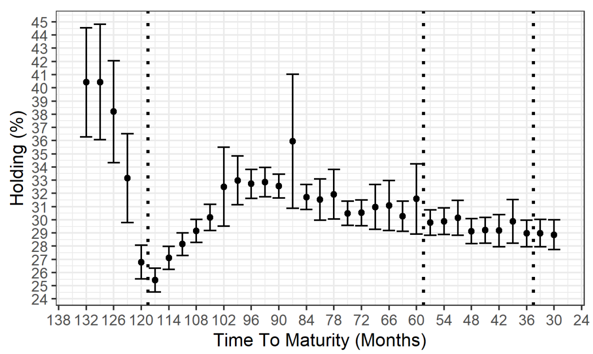
Panel A: Passive fund



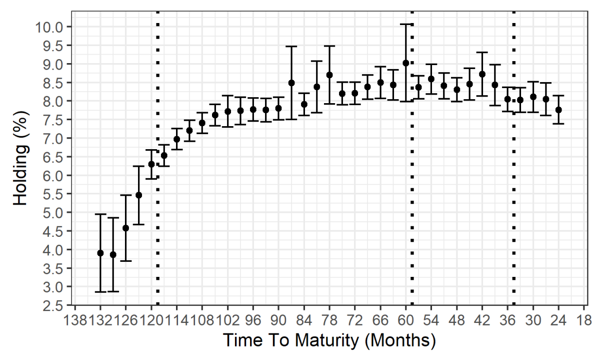
Panel B: Active mutual fund



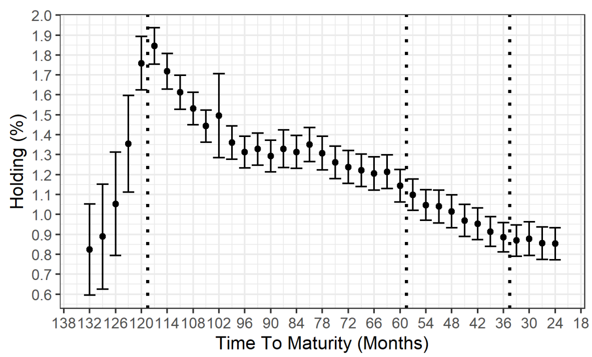
Panel C: Life insurance



Panel D: P&C insurance



Panel E: Annuity



Panel F: Pension & Others

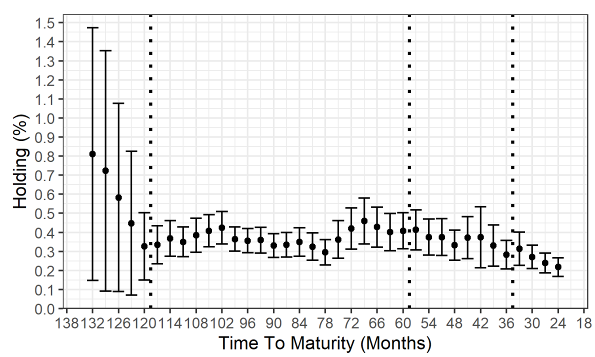
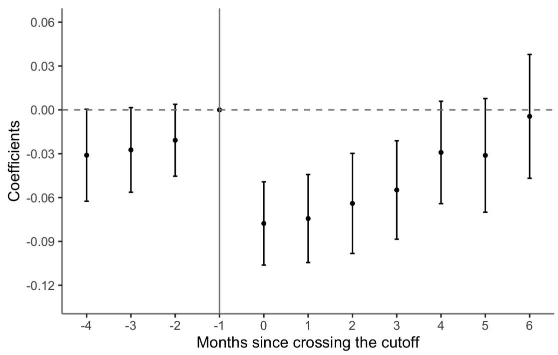


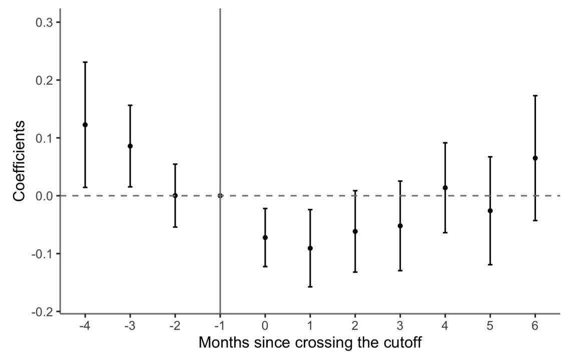
Figure 6: Corporate bond ownership over maturity by investor types

These figures plot the passive fund ownership over time-to-maturity for each investor type. The x-axis is the time-to-maturity measured in month. From left to right, the time-to-maturity decreases, i.e., the bond is getting closer to its maturity date. The y-axis is the average passive ownership for bonds with a specific time-to-maturity. The error bar is the 95% confidence interval. The three vertical dashed lines correspond to the 10 year, 5 year, and 3 year maturity cutoffs, respectively. Panel A to F correspond to passive funds, active mutual funds, life insurance, P&C insurance, variable annuity, and pension funds.

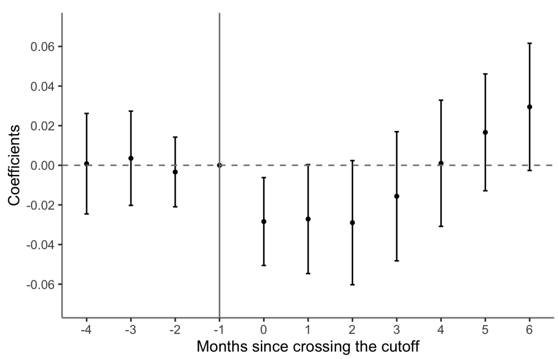
(a) All cutoffs



(b) 10Y maturity cutoff



(c) 5Y maturity cutoff



(d) 3Y maturity cutoff before 2018

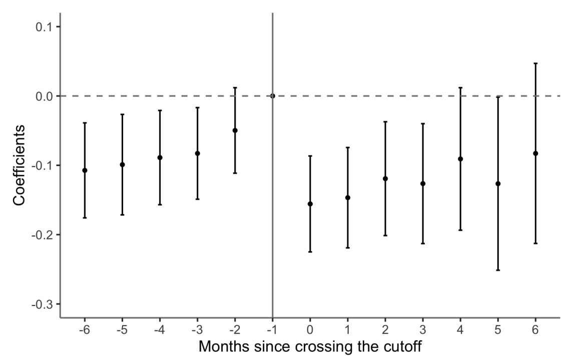


Figure 7: Yield spread dynamic and passive fund demand

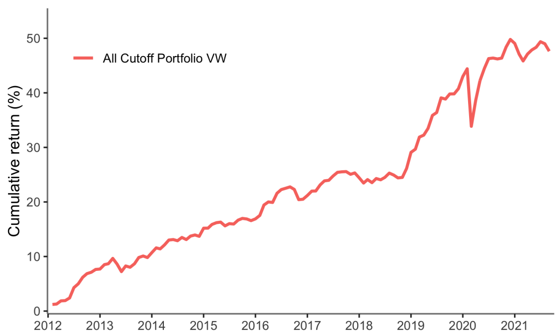
This figure plots the coefficient estimates β_h from the following 2SLS regression for $h \in [-4, 6]$:

$$\Delta YieldSpread_i^{t-1\to t+h} = \beta_h \Delta \widehat{Passive\%}_i^{t-1\to t+2} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

$$\Delta Passive\%_i^{t-1\to t+2} = \gamma_h SwitchX_{it} + Controls_{it} + \mu_i + \eta_t + e_{it}$$

where $\Delta YieldSpread_i^{t-1\to t+h}$ is the percentage change in yield spreads for bond i from $t-1$ to $t+h$ (from $t+h$ to $t-1$) if $h \geq 0$ ($h < 0$). Yield spreads are calculated using maturity-matched treasury rates. $Passive\%_i^{t-1\to t+2}$ is the change in passive fund ownership from $t-1$ to $t+2$. $Passive\%_i^{t-1\to t+2}$ is instrumented by $SwitchX_{it}$, which is an indicator variable equal to one if bond i crosses a maturity cutoff X in month t, and 0 otherwise. Subfigure (a) plots the coefficient estimates for bonds that cross any of the three cutoffs. Subfigures (b) to (d) correspond to the 10-year, 5-year, and 3-year cutoffs (before 2018), respectively. Year-month fixed effects and bond fixed effects are included. $Controls_{it}$ includes time-to-maturity, credit rating, contemporaneous bid-ask spread, and the amount outstanding of the bond. Error bars represent the 90% confidence interval, where standard errors are clustered at both the bond and year-month levels.

(a) All cutoffs



(b) Each maturity cutoff

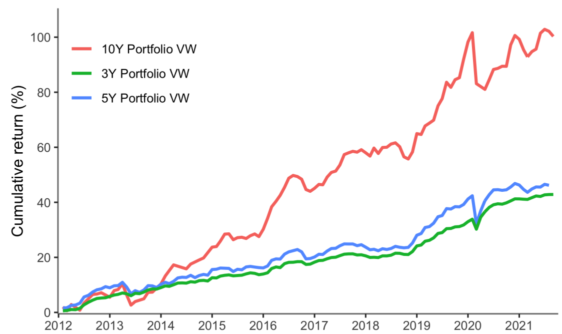
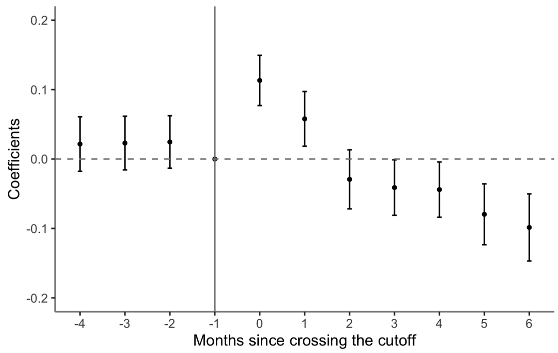


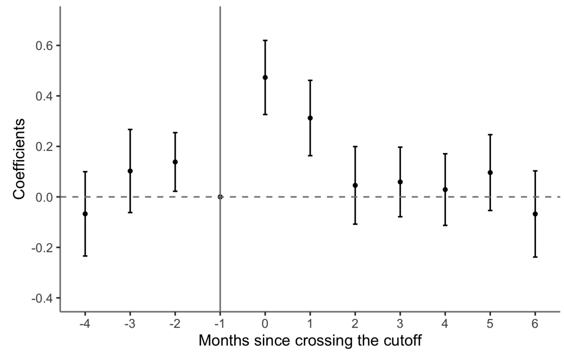
Figure 8: Profitability of Trading Strategies

This figure plots the cumulative returns of a simply trading strategy based on the passive fund demand shift around maturity cutoffs. The simple trading strategy is as follows: (1) buy bond i at the end of month $t-1$ if bond i is going to cross a maturity cutoff in month t; (2) sell bond i at the end of month t. The portfolio rebalances at the end of each month. Portfolios are weighted by the amount outstanding. Returns are calculated using the month end price reported in TRACE. Subfigure (a) plots the cumulative returns for a strategy using all maturity cutoffs (10Y, 5Y, and 3Y before 2018). Subfigure (a) plots the cumulative returns for strategies using 10Y, 5Y, and 3Y cutoffs before 2018 separately.

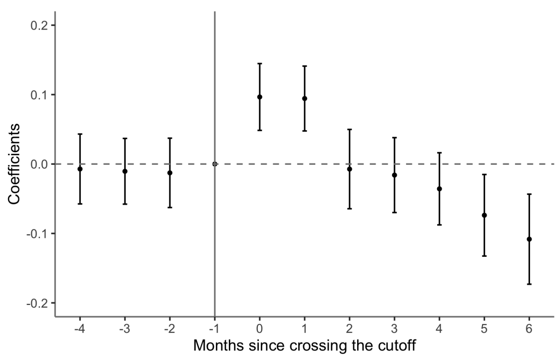
(a) All cutoffs



(b) 10Y maturity cutoff



(c) 5Y maturity cutoff



(d) 3Y maturity cutoff before 2018

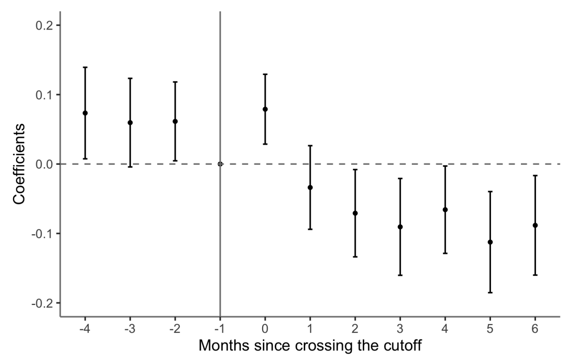


Figure 9: Trading volume dynamics and crossing maturity cutoffs

This figure plots the coefficient estimates β_h from the following regression for $h \in [-4, 6]$:

$$\Delta Volume_i^{t-1 \to t+h} = \beta_h SwitchX_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

where $\Delta Volume_i^{t-1 \to t+h}$ is the percentage change of trading volume (par amount) for bond i from $t-1$ to $t+h$ (from $t+h$ to $t-1$) if $h \geq 0$ ($h < 0$). $SwitchX_{it}$ is an indicator variable equal to one if bond i crosses a maturity cutoff X in month t, and 0 otherwise. Subfigure (a) plots the coefficient estimates for bonds that cross any of the three cutoffs. Subfigures (b) to (d) correspond to the 10-year, 5-year, and 3-year cutoffs, respectively. Year-month fixed effects and bond fixed effects are included. $Controls_{it}$ includes time-to-maturity, credit rating, contemporaneous bid-ask spread, and the amount outstanding of the bond. Error bars represent the 90% confidence interval, where standard errors are clustered at both the bond and year-month levels.

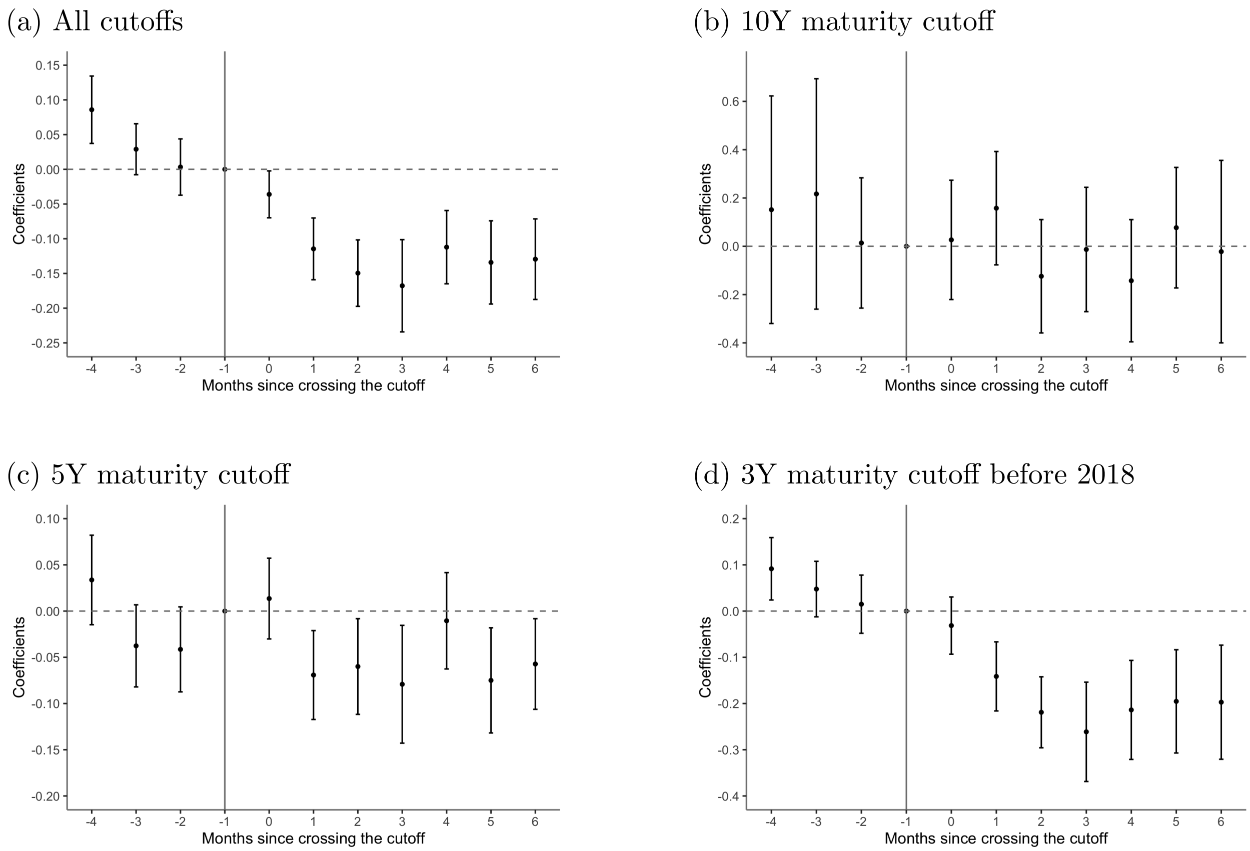


Figure 10: Liquidity dynamics and passive fund demand

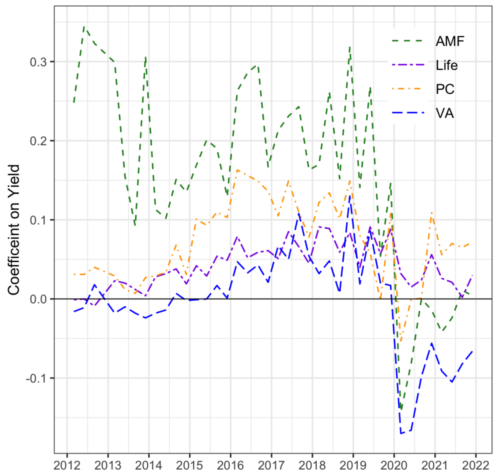
This figure plots the coefficient estimates β_h from the following 2SLS regression for $h \in [-4, 6]$:

$$\Delta Illiquidity_i^{t-1\to t+h} = \beta_h \Delta \widehat{Passive\%}_i^{t-1\to t+2} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

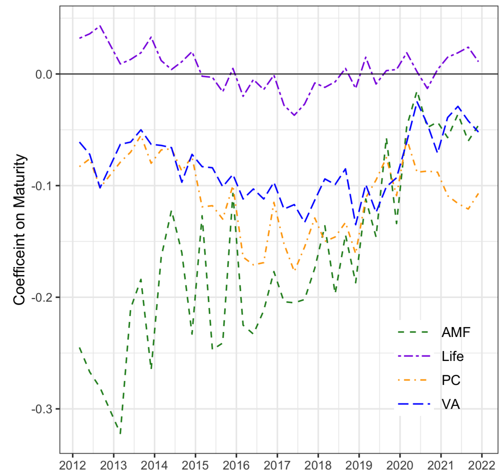
$$\Delta Passive\%_i^{t-1\to t+2} = \gamma_h SwitchX_{it} + Controls_{it} + \mu_i + \eta_t + e_{it}$$

where $\Delta Illiquidity_i^{t-1\to t+h}$ is the percentage change of the monthly volume-weighted bid-ask spread for bond i from $t-1$ to $t+h$ (from $t+h$ to $t-1$) if $h \geq 0$ ($h < 0$). $Passive\%_i^{t-1\to t+2}$ is the change in passive fund ownership from $t-1$ to $t+2$. $Passive\%_i^{t-1\to t+2}$ is instrumented by $SwitchX_{it}$, which is an indicator variable equal to one if bond i crosses a maturity cutoff X in month t, and 0 otherwise. Subfigure (a) plots the coefficient estimates for bonds that cross any of the three cutoffs. Subfigures (b) to (d) correspond to the 10-year, 5-year, and 3-year cutoffs (before 2018), respectively. Year-month fixed effects and bond fixed effects are included. $Controls_{it}$ includes time-to-maturity, credit rating, lagged bid-ask spread, and the amount outstanding of the bond. Error bars represent the 90% confidence interval, where standard errors are clustered at both the bond and year-month levels.

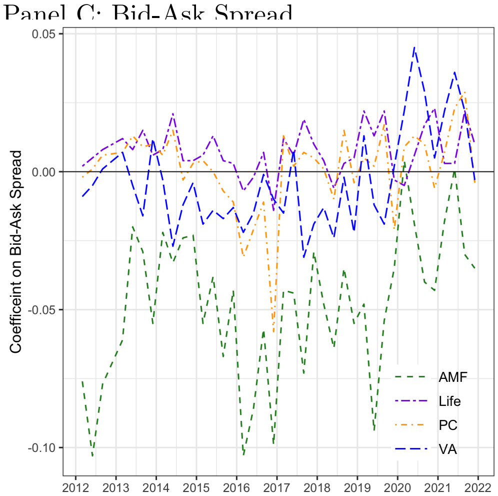
Panel A: Yield



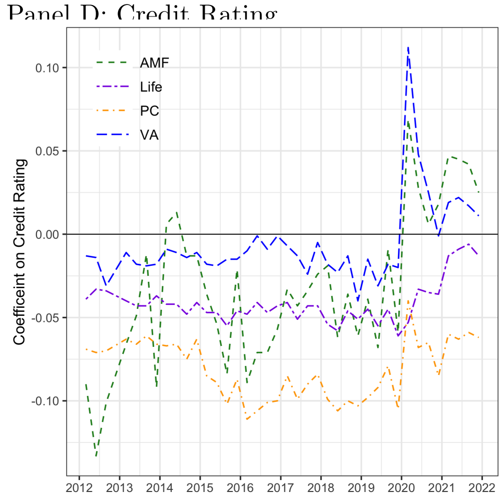
Panel B: Time-to-Maturity



Panel C: Bid-Ask Spread



Panel D: Credit Rating



Panel E: Size

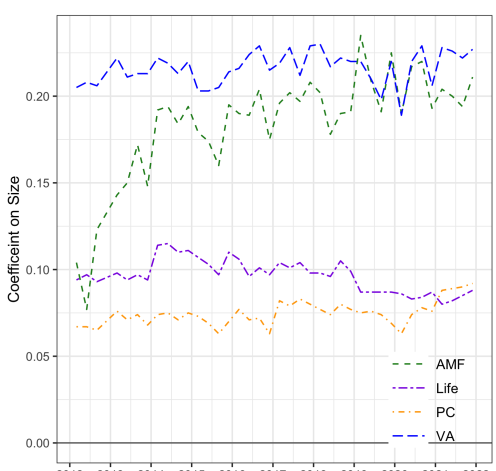


Figure 11: Demand elasticity over time

These figures plot the estimated coefficients for each characteristic over time. Panel A to E plot coefficients on yield, maturity, bid-ask spread, credit rating, and size.

Table 1: Summary Statistics

This table reports summary statistics for corporate bond characteristics and institutional ownership variables. The bond characteristic and passive fund ownership sample is at the monthly frequency, while the other institutional ownership variables are at the quarterly frequency. Panel A reports the monthly sample, which is composed of 444,893 bond-month observations for sample period January 2012 to September 2021. Panel B reports the quarterly aggregate institutional ownership. Panel C reports the quarterly investor holdings sample for active MF and eMAXX. *Passive fund* is the total ownership by all ETFs and index mutual funds. Yield spread is the yield minus the maturity matched treasury rate. *Return* is the monthly return computed using the latest transaction price. PD is defined as in equation (2). *Rating* is the numeric average of credit ratings by S&P, Moody's and Fitch. *Duration* is the modified duration.

Variable	N	Mean	SD	P25	Median	P75
Panel A: Monthly bond-level sample						
Passive funds (%)	444893	5.52	4.30	3.33	5.45	7.96
AAA	5973	5.42	2.95	3.42	5.40	7.50
AA	30974	5.89	5.27	3.98	5.88	8.01
A	170996	5.40	3.98	3.30	5.34	7.72
BBB	236950	5.55	4.40	3.26	5.48	8.13
Yield spread (%)	444893	1.13	0.86	0.72	1.11	1.63
AAA	5973	0.60	0.43	0.30	0.62	0.88
AA	30974	0.61	0.42	0.37	0.59	0.92
A	170996	0.89	0.53	0.59	0.88	1.24
BBB	236950	1.43	0.96	0.98	1.41	2.00
Yield (%)	444893	3.05	1.33	2.12	3.05	3.98
Return (%)	444893	0.35	2.44	-0.36	0.30	1.23
PD	444893	16.40	0.93	15.68	16.40	17.51
Rating	444893	7.63	2.00	6.00	8.00	9.00
Outstanding ($M)	444893	625.08	683.07	400.00	600.00	1000.00
Log trading volume	444893	16.85	1.61	15.77	16.88	17.82
Bid-ask spread	444893	0.33	0.40	0.17	0.31	0.54
Duration	444893	6.27	4.86	3.60	6.01	11.48
Time-to-maturity	444893	91.59	117.36	46.85	83.48	216.97
Panel B: Quarterly bond-level sample						
Active MF (%)	144655	4.64	6.33	1.71	4.37	8.74
Life insurance (%)	147549	23.59	28.49	11.94	23.36	36.46
PC insurance (%)	145779	4.69	6.08	1.83	4.59	8.12
Annuity (%)	143529	0.77	1.36	0.27	0.69	1.58
Pension fund (%)	110508	0.18	0.82	0.05	0.16	0.40
Panel C: Quarterly investor-level sample						
Active MF	5703940					
eMAXX	44272964					

Table 2: Maturity-constrained passive funds

This table lists the maturity-mandated ETFs and index mutual funds for corporate bonds. Column (1) shows the fund name with an AUM exceeding $1 billion. Column (2) lists the fund ticker. Column (3) reports the respective maturity ranges. Column (4) reports the fund AUM as of February 2022. Total AUM is reported if a fund has both ETFs and mutual funds. Column (5) reports the aggregate AUM that track each maturity bucket.

Fund Name	Ticker	Maturity	AUM ($B)	Total ($B)
Short-Term Maturity				
Vanguard Short-Term Bond Index Fund (incl. ETF)	VBIRX/BSV	1-5Y	$70.90	
Vanguard Short-Term Corporate Bond Index Fund (incl. ETF)	VSCSX/VCSH	1-5Y	$49.60	
iShares Investment Grade Corporate Bond ETF	IGSB	1-5Y	$21.25	
SPDR® Portfolio Short Term Corporate Bond ETF	SPSB	1-3Y	$7.53	
iShares Core USD Bond ETF	ISTB	1-5Y	$6.00	
iShares Investment Grade Corporate Bond ETF	SLQD	0-5Y	$2.35	
Fidelity® Short-Term Bond Index Fund	FNSOX	1-5Y	$2.30	
Schwab Short-Term Bond Index Fund	SWSBX	1-5Y	$2.10	
TIAA-CREF Short-Term Bond Index Fund	TTBHX	1-3Y	$1.30	
iShares ESG Aware USD Corporate Bond ETF	SUSB	1-5Y	$1.00	**$175.88**
Intermediate-Term Maturity				
Vanguard Interm-Term Corporate Bond Index Fund (incl. ETF)	VICSX/VCIT	5-10Y	$48.60	
Vanguard Interm-Term Bond Index Fund (incl. ETF)	VBILX/BIV	5-10Y	$37.00	
iShares Investment Grade Corporate Bond ETF	IGIB	5-10Y	$10.67	
SPDR® Portfolio Interm Term Corporate Bond ETF	SPIB	1-10Y	$5.48	
iShares Interm Government/Credit Bond ETF	GVI	5-10Y	$2.50	**$104.72**
Long-Term Maturity				
Vanguard Long-Term Bond Index Fund (incl. ETF)	VBLAX/BLV	10+Y	$10.30	
Vanguard Long-Term Corporate Bond Index Fund (incl. ETF)	VLCIX/VCLT	10+Y	$5.40	
iShares Investment Grade Corporate Bond ETF	IGLB	10+Y	$1.59	**$18.66**

Table 3: Crossing maturity cutoffs and passive fund ownership

This table reports the results for the following regression:

$$Passive\%_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it}.$$

The goal is to examine the change of passing ownership after crossing the 10Y, 5Y, and 3Y maturity cutoffs. The dependent variable, $Passive\%_{it}$ is the total percentage share of bond i owned by passive funds. $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoff at time t. PD is passive demand defined as in equation (2). TTM is the distance from the cutoff measured as time-to-maturity minus cutoff c. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, credit rating, the log amount outstanding in par value. Year-month fixed effects are added to control the time trend. Bond fixed effects are included in all regressions except the 10Y cutoff. The bandwidth is 6 month. Column (5) and (6) exclude post 2018 observations due to astructural change of the 3Y cutoff. Standard errors clustered at the bond and year-month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Passive%					
	10Y		5Y		3Y	
	(1)	(2)	(3)	(4)	(5)	(6)
$I(Pass10Y)$	0.659***					
	(0.095)					
$I(Pass5Y)$			0.423***			
			(0.027)			
$I(Pass3Y)$					0.156***	
					(0.024)	
PD		1.207***		0.293***		0.450***
		(0.116)		(0.024)		(0.054)
TTM	−0.145***	−0.120***	−0.014	−0.027	0.039	0.033
	(0.014)	(0.013)	(0.059)	(0.060)	(0.046)	(0.046)
Bid-Ask	−0.283**	−0.316***	0.006	0.007	−0.033	−0.033
	(0.116)	(0.116)	(0.020)	(0.020)	(0.024)	(0.024)
Rating	0.023	0.027	−0.052	−0.052	−0.107*	−0.108*
	(0.027)	(0.027)	(0.050)	(0.050)	(0.060)	(0.060)
Size	1.109***	1.108***	0.433	0.434	1.696***	1.697***
	(0.098)	(0.097)	(0.391)	(0.391)	(0.498)	(0.498)
Bandwidth	±6	±6	±6	±6	±6	±6
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	No	No	Yes	Yes	Yes	Yes
Observations	14,807	14,807	43,178	43,178	34,834	34,834
R^2	0.447	0.455	0.955	0.955	0.949	0.949
Adjusted R^2	0.443	0.451	0.949	0.949	0.943	0.943
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 4: Passive fund demand and yield spread

This table reports the following 2SLS results:

$$Passive\%_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it}$$

$$Yield\_Spread_{it} = \eta_i + \delta_t + \gamma_1 \widehat{Passive}\%_{it} + \gamma_2 TTM_{it} + \gamma' X_{it} + u_{it}$$

The goal is to quantify the effect of passive ownership on yield spreads. The dependent variable, $Yield\_Spread$ is the bond's yield-to-maturity minus the maturity-matched treasury yield. The first stage results are reported in table 3. The TTM is the distance from the cutoff measured as time-to-maturity minus cutoff c. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, credit rating, the log amount outstanding in par value. Year fixed effects are added to control the time trend. Bond fixed effects are included in all regressions except the 10Y cutoff. The bandwidth is 6 month. Column (5) and (6) exclude post-2018 observations. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Yield_Spread					
	10Y		5Y		3Y	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Passive}\%$	-0.241^{***}	-0.094^{***}	-0.056^{***}	-0.059^{***}	-0.073^{*}	-0.085^{**}
	(0.049)	(0.026)	(0.012)	(0.013)	(0.039)	(0.040)
TTM	-0.044^{***}	-0.012^{**}	-0.045^{**}	-0.045^{**}	-0.024^{*}	-0.033^{**}
	(0.009)	(0.006)	(0.020)	(0.019)	(0.013)	(0.015)
Bid-Ask	0.308^{***}	0.354^{***}	0.098^{***}	0.098^{***}	0.094^{***}	0.149^{***}
	(0.042)	(0.034)	(0.026)	(0.026)	(0.021)	(0.051)
Rating	0.220^{***}	0.217^{***}	0.124^{***}	0.124^{***}	0.068^{***}	0.054^{**}
	(0.009)	(0.007)	(0.020)	(0.020)	(0.015)	(0.022)
Size	0.307^{***}	0.144^{***}	-0.026	-0.025	0.091	0.131
	(0.055)	(0.033)	(0.030)	(0.031)	(0.097)	(0.103)
Bandwidth	±6	±6	±6	±6	±6	±6
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	No	No	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic	51.1	266.6	687.6	580.3	92.3	106.9
Observations	14,807	14,807	43,178	43,178	34,834	34,834

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Excess Returns and Alphas of Trading Strategies

This table reports the excess returns and alphas for a simple trading strategy based on the passive fund demand shift around maturity cutoffs. The simple trading strategy is as follows: (1) buy bond i in month $t-1$ if bond i is going to cross a maturity cutoff in month t; (2) sell bond i at the end of month t. The portfolio rebalances at the end of each month. The return is calculated using the month end price reported in TRACE. The first row reports the monthly portfolio returns in excess of the one-month treasury rate. The second and third rows report estimates of alpha after controlling for BBW factors (Bai et al. (2019)) and FF factors (Fama and French (1993)). Newey-West adjusted standard errors are reported in the parentheses. Panel A reports the results for portfolios weighted by the amount outstanding. Panel B reports the results for equally weighted portfolios. Column (1) to (7) reports results for all cutoffs (10Y, 5Y, and 3Y before 2018), 10Y, 5Y, 3Y, 3Y before 2018, and 3Y after 2018. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Panel A: Value-Weighted Portfolio					
	All	10Y	5Y	3Y	3Y before 2018	3Y after 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Excess return	0.310***	0.715***	0.299***	0.239***	0.254***	0.461***
	(0.075)	(0.193)	(0.088)	(0.051)	(0.052)	(0.071)
BBW alpha	0.132***	0.261**	0.079**	0.124***	0.152***	−0.017
	(0.035)	(0.128)	(0.036)	(0.033)	(0.044)	(0.014)
BBW+FF alpha	0.137***	0.324**	0.087***	0.124***	0.143***	−0.008
	(0.034)	(0.126)	(0.034)	(0.029)	(0.029)	(0.007)
	Panel B: Equal-Weighted Portfolio					
	All	10Y	5Y	3Y	3Y before 2018	3Y after 2018
	(1)	(2)	(3)	(4)	(5)	(6)
Excess return	0.328***	0.699***	0.324***	0.244***	0.257***	0.468***
	(0.074)	(0.190)	(0.083)	(0.048)	(0.051)	(0.073)
BBW alpha	0.151***	0.225*	0.117***	0.128***	0.149***	0.056***
	(0.034)	(0.122)	(0.033)	(0.034)	(0.042)	(0.010)
BBW+FF alpha	0.156***	0.292**	0.122***	0.132***	0.149***	0.064***
	(0.032)	(0.133)	(0.031)	(0.028)	(0.032)	(0.023)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Effects on liquidity and trading volume

This table reports the following 2SLS results:

$$Passive\%_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it}$$

$$Y_{it} = \eta_i + \delta_t + \gamma_1 \widehat{Passive}\%_{it} + \gamma_2 TTM_{it} + \gamma' X_{it} + u_{it}$$

For panel A, the dependent variable is the volume-weighted bid-ask spread. For panel B, the dependent variable is the monthly trading volume. The first stage is reported in table 3. TTM is the distance from the cutoff. X_{it} is the set of control variables that include the bid-ask spread (lagged for panel A), credit rating, the log amount outstanding in par value. Year fixed effects are added to control the time trend. Bond fixed effects are included in all regressions except the 10Y cutoff. The bandwidth is 6 month. Column (5) and (6) uses the pre-2018 sample. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Panel A: Bid-Ask Spread					
	10Y		5Y		3Y	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Passive}\%$	-0.071^{***}	0.005	-0.033^{***}	-0.042^{***}	-0.117^{***}	-0.112^{***}
	(0.021)	(0.007)	(0.011)	(0.013)	(0.030)	(0.028)
TTM	-0.008^{*}	0.009^{***}	-0.005	-0.005	0.009	0.009
	(0.004)	(0.002)	(0.015)	(0.015)	(0.015)	(0.015)
Lagged Bid-Ask	0.353^{***}	0.378^{***}	0.056^{**}	0.056^{**}	0.060^{***}	0.060^{***}
	(0.020)	(0.018)	(0.028)	(0.028)	(0.015)	(0.015)
Rating	0.008^{***}	0.006^{***}	0.015	0.015	-0.006	-0.005
	(0.002)	(0.002)	(0.012)	(0.012)	(0.009)	(0.009)
Size	0.009	-0.075^{***}	-0.068^{**}	-0.064^{**}	0.149^{*}	0.142^{*}
	(0.023)	(0.009)	(0.031)	(0.032)	(0.078)	(0.073)
Bandwidth	±6	±6	±6	±6	±6	±6
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	No	No	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic	49.1	265.4	687.3	580	92.3	107.2
Observations	14,807	14,807	43,178	43,178	34,834	34,834

	Panel B: Trading Volume					
	10Y		5Y		3Y	
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Passive}\%$	1.019^{***}	0.291^{***}	0.014	0.034	-0.352^{**}	-0.265^{*}
	(0.184)	(0.062)	(0.055)	(0.063)	(0.159)	(0.148)
TTM	0.161^{***}	0.001	0.075	0.077	-0.063	-0.065
	(0.034)	(0.016)	(0.078)	(0.078)	(0.081)	(0.080)
Bid-Ask	0.109	-0.133^{*}	0.030	0.030	0.078^{*}	0.083^{*}
	(0.138)	(0.070)	(0.025)	(0.025)	(0.045)	(0.045)
Rating	0.070^{***}	0.087^{***}	0.021	0.022	0.080	0.090^{*}
	(0.025)	(0.011)	(0.035)	(0.035)	(0.050)	(0.048)
Size	0.907^{***}	1.714^{***}	1.076^{***}	1.067^{***}	1.664^{***}	1.517^{***}
	(0.194)	(0.079)	(0.110)	(0.107)	(0.406)	(0.362)
Bandwidth	±6	±6	±6	±6	±6	±6
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	No	No	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic	49.1	265.4	687.3	580	92.3	107.2
Observations	14,807	14,807	43,178	43,178	34,834	34,834

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Demand system estimation

This table reports the estimates of demand elasticities for different institutional investors:

$$\ln \frac{w_{i,t}(n)}{w_{i,t}(0)} = \ln \delta_{i,t}(n) = \alpha_{it} + \beta_{0,i}\hat{y}_t(n) + \beta'_{1,i}X_t(n) + u_{i,t}(n).$$

, where $\hat{y}_t(n)$ is instrumented using PD. X_{it} is the set of bond characteristics, including time-to-maturity, bid-ask spread, credit rating, and log size. Panel A includes fund $\times$quarter fixed effects and panel B includes fund$\times$bond fixed effects. The first-stage results are reported in table A10. All bond characteristics are standardized. The estimates are weighted by fund's AUM to account for the heterogeneity in size. Standard errors clustered at the fund level are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: within fund-quarter variation					
	$\ln \delta_{i,t}(n)$				
	Active MF	Life	P&C	Annuity	Pension & Others
	(1)	(2)	(3)	(4)	(5)
$\widehat{Yield}$	0.179**	−0.022	0.011	0.014	−0.193
	(0.091)	(0.016)	(0.058)	(0.018)	(0.160)
Time-to-Maturity	−0.137**	0.007	−0.059*	−0.099***	−0.057
	(0.058)	(0.021)	(0.035)	(0.014)	(0.061)
Bid-Ask	−0.058***	0.020***	0.001	−0.006	0.036
	(0.018)	(0.005)	(0.009)	(0.004)	(0.044)
Rating	0.023	−0.032***	−0.072***	−0.011	0.028*
	(0.055)	(0.005)	(0.018)	(0.007)	(0.014)
Size	0.309***	0.041***	0.099***	0.216***	0.241***
	(0.022)	(0.008)	(0.009)	(0.020)	(0.028)
Fund×Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,663,318	5,841,847	3,753,947	1,484,867	434,036
Panel B: within fund-bond variation					
	(1)	(2)	(3)	(4)	(5)
$\widehat{Yield}$	0.419**	−0.095	−0.120	−0.451***	−0.001
	(0.165)	(0.169)	(0.132)	(0.174)	(0.138)
Time-to-Maturity	0.092	0.456*	0.421**	1.610***	0.565
	(0.483)	(0.262)	(0.196)	(0.423)	(0.427)
Bid-Ask	−0.138***	0.011	0.027	0.070***	−0.011
	(0.053)	(0.034)	(0.035)	(0.026)	(0.027)
Rating	−0.111***	0.018	0.023	0.067*	−0.002
	(0.030)	(0.018)	(0.023)	(0.035)	(0.023)
Size	0.444***	0.029***	0.047	0.459***	0.095***
	(0.054)	(0.011)	(0.029)	(0.046)	(0.017)
Fund×bond Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,663,318	5,841,847	3,753,947	1,484,867	434,036
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 8: Passive fund demand and primary market yield spread

This table summarizes the estimated effect of passive fund demand on the primary market offering yield spreads. Each column reports the coefficient estimates from the following 2SLS regressions:

$$\text{Yield Spread}_{it} = \beta \widehat{Passive\_firm}\%_{it} + Controls + FEs + \epsilon_{it}$$

$$Passive\_firm\%_{it} = \gamma PD\_firm_{it} + Controls + FEs + e_{it}$$

Yield Spread_{it} is the offering yield minus the maturity-matched treasury yield. $Passive\_firm\%$ is the average percentage of passive fund holdings for firm i's outstanding corporate bonds, weighted by the amount outstanding. $Passive\_firm\%$ is instrumented using PD_firm_{it}, which is the average of PD for firm i, weighted by the amount outstanding. Issue level controls include issue size, credit rating, and initial maturity. Firm level controls include firm size, tangible assets, firm age, market-to-book ratio, leverage ratio, cash, lagged cash growth, lagged 12 month sales, lagged net income, and lagged CapEx. Three fixed effects are used: industry-by-year FE absorb any industry specific trend, rating-by-year FE absorb time-varying differences in yield spreads across different rating categories (rating categories are defined as AAA-AA, A, and BBB), maturity-by-year FE absorb time-varying differences in yield spreads across different initial maturity buckets (initial maturity buckets are defined as (0,3], (3,5], (5,10], (10,15], (15,∞]). Standard errors clustered at year and firm levels are presented in parentheses. Cragg-Donald and Kleibergen-Paap F-Statistics are reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Second Stage: *Offering Yield*					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Passive\_firm}\%$	-0.212^{**}	-0.236^{**}	-0.201^{**}	-0.222^{**}	-0.201^{**}	-0.137^{*}
	(0.064)	(0.075)	(0.064)	(0.078)	(0.064)	(0.065)
	First stage: *Passive_firm%*					
	(1)	(2)	(3)	(4)	(5)	(6)
PD_firm	0.574^{***}	0.576^{***}	0.566^{***}	0.571^{***}	0.566^{***}	0.561^{***}
	(0.118)	(0.118)	(0.119)	(0.115)	(0.119)	(0.116)
Cragg-Donald F-Statistic	171.5	160.4	166.5	157.9	166.5	149.9
Kleibergen-Paap F-Statistic	23.7	24	22.5	24.9	22.5	23.5
Issue Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes	No	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Year FE	No	No	Yes	Yes	Yes	Yes
Maturity-by-Year FE	No	No	No	No	Yes	Yes
Observations	3,314	2,936	3,314	2,936	3,314	2,936

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: Passive fund demand and net debt issuance

This table reports the estimated effects of passive fund demand on net bond issuance. The following 2SLS regressions are performed:

$$\Delta Debt_{it} = \beta \Delta \widehat{Passive\_firm}\%_{it-1} + Controls + FEs + \epsilon_{it}$$

$$\Delta Passive\_firm\%_{it-1} = \gamma \Delta PD\_firm_{it-1} + Controls + FEs + e_{it}$$

$\Delta Debt_{it}$ is the net change of firm i's long term debt, scaled by lagged total assets. $\Delta Passive\_firm\%_{it-1}$ is the lagged change of average percentage of passive fund holding for firm i's outstanding corporate bonds, weighted by the amount outstanding. $\Delta Passive\_firm\%_{it-1}$ is instrumented using ΔPD_firm_{it-1}, which is the change of average of PD for firm i, weighted by the amount outstanding. Firm level controls include credit rating, lagged firm size, firm age, market-to-book ratio, leverage ratio, lagged cash holding, lagged 12 month sales, net income, CapEx, and lagged asset growth. Four fixed effects are used: firm FE absorbs any time-invariant firm specific variation, year FE takes out any time trend, industry-by-year FE absorbs any time-varying differences across industries, rating-by-year FE absorb any time-varying differences across different rating category (rating categories are defined as AAA-AA, A, and BBB). Standard errors clustered at year and firm levels are presented in parentheses. Cragg-Donald F-Statistics are reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Second Stage: $\Delta Debt_t$				
	(1)	(2)	(3)	(4)	(5)
$\Delta \widehat{Passive\_firm}\%_{t-1}$	1.928*	2.029*	2.056*	2.224**	2.255**
	(0.888)	(0.931)	(0.943)	(0.971)	(0.982)
	First stage: $\Delta Passive\_firm\%_{t-1}$				
	(1)	(2)	(3)	(4)	(5)
ΔPD_firm_{t-1}	0.223***	0.214***	0.212***	0.204**	0.203**
	(0.063)	(0.065)	(0.064)	(0.065)	(0.064)
Cragg-Donald F-Statistic	41.9	38.5	37.9	34.9	34.2
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	No	No
Rating-by-Year FE	No	No	Yes	No	Yes
Industry-by-Year FE	No	No	No	Yes	Yes
Observations	14,279	14,279	14,279	14,161	14,161

Note: *p<0.1; **p<0.05; ***p<0.01

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A Additional figures and tables

Panel A

Panel B

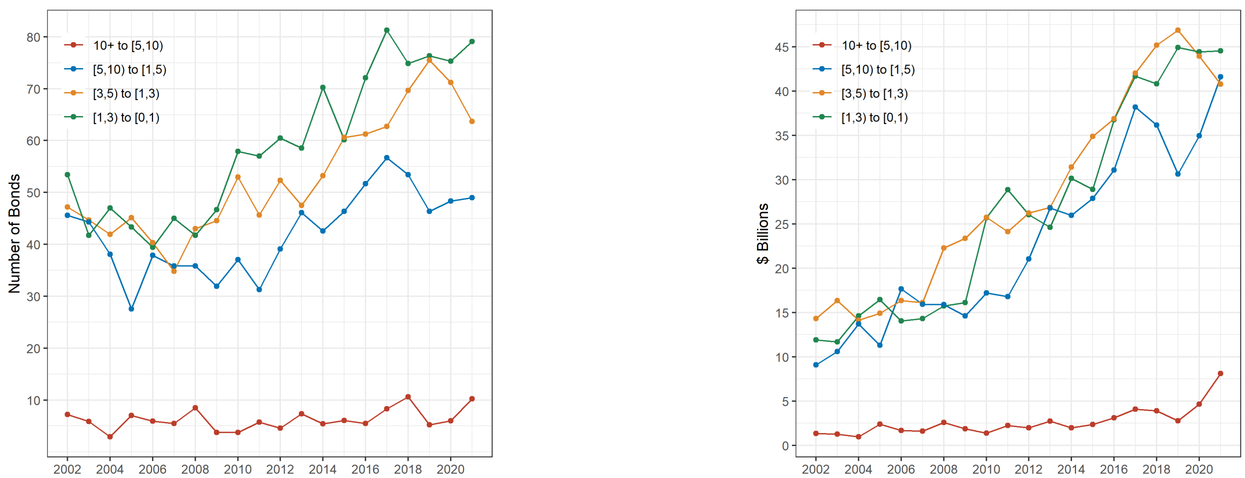


Figure A1: Bonds that switch maturity buckets per month

Panel A plots the average number of bonds that switch maturity buckets per month for each maturity bucket. Panel B plots the average amount outstanding that switch maturity buckets per month for each maturity bucket.

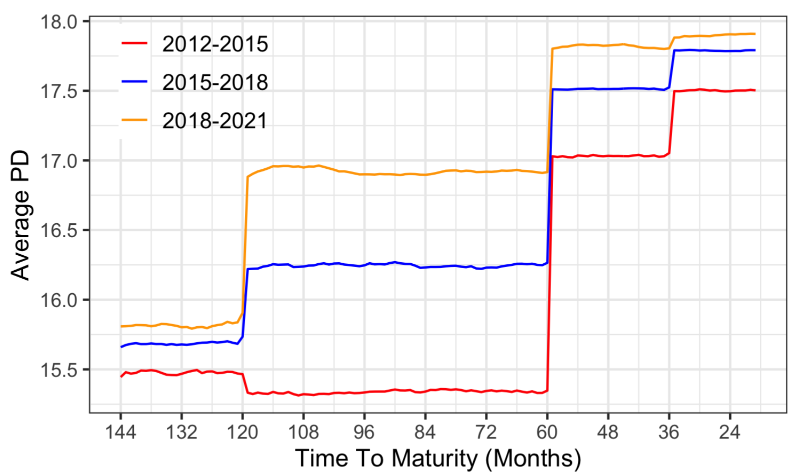
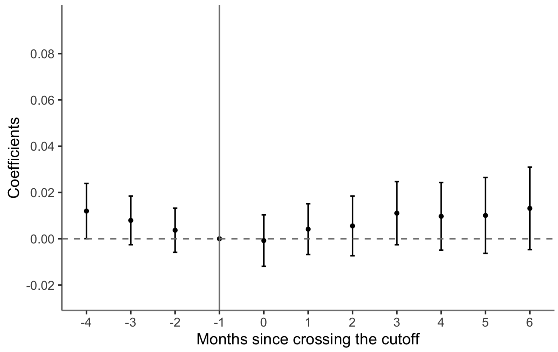
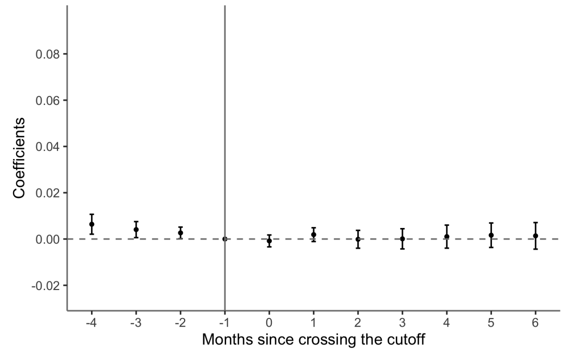


Figure A2: PD measures over maturity

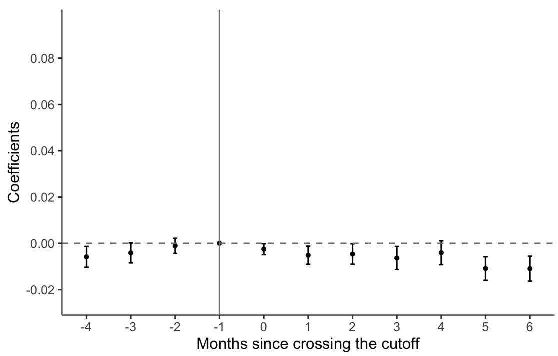
(a) 15Y maturity cutoff



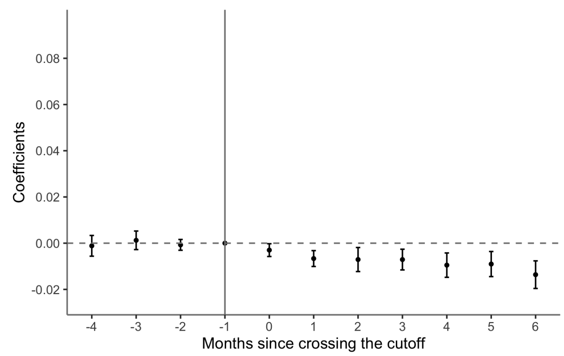
(b) 9Y maturity cutoff



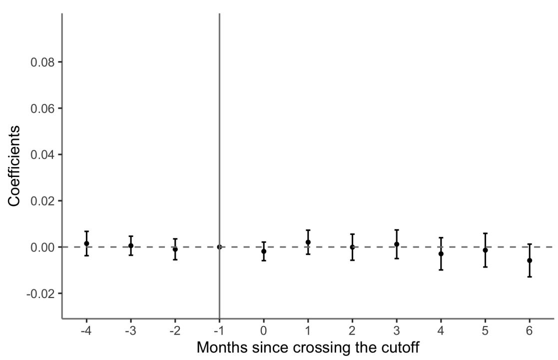
(c) 8Y maturity cutoff



(d) 7Y maturity cutoff



(c) 6Y maturity cutoff



(d) 4Y maturity cutoff

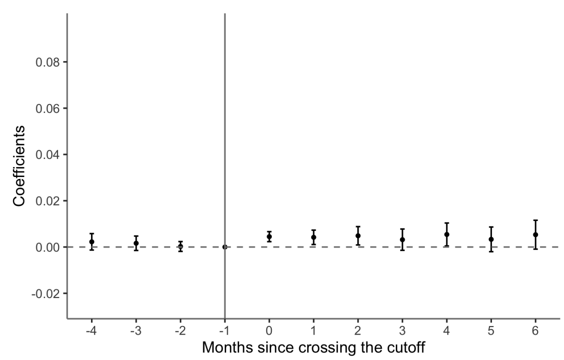


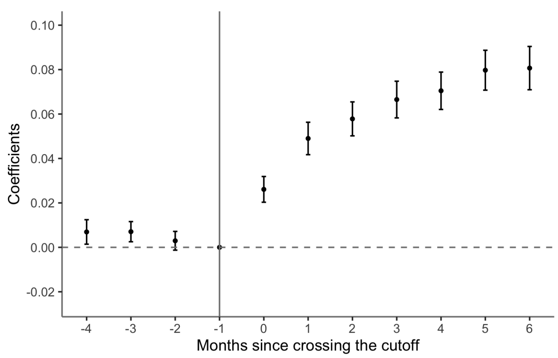
Figure A3: Placebo tests on passive fund holding

This figure plots the coefficient estimates β_h from following regression for $h \in [-4, 6]$:

$$\Delta Passive_i^{t-1 \rightarrow t+h} = \beta_h SwitchX_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

where $\Delta Passive_i^{t-1 \rightarrow t+h}$ is the percentage change of passive fund ownership for bond i from $t-1$ to $t+h$ (from $t+h$ to $t-1$) if $h \geq 0$ ($h < 0$). $SwitchX_{it}$ is an indicator variable equal to one if bond i crosses a maturity cutoff X in month t, and 0 otherwise. Subfigures (a) to (f) correspond to the 15-, 9-, 8-, 7-, 6-, and 4-year maturity cutoffs, respectively. Year-month fixed effects and bond fixed effects are included. $Controls_{it}$ includes time-to-maturity, credit rating, contemporaneous bid-ask spread, and the amount outstanding of the bond. Error bars represent the 90% confidence interval, where standard errors are clustered at both the bond and year-month levels.

(a) 3Y maturity cutoff before 2018



(b) 3Y maturity cutoff after 2018

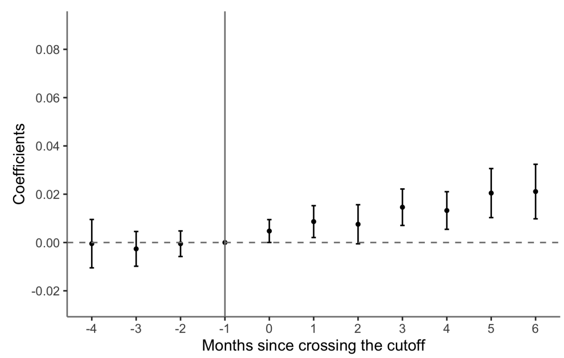


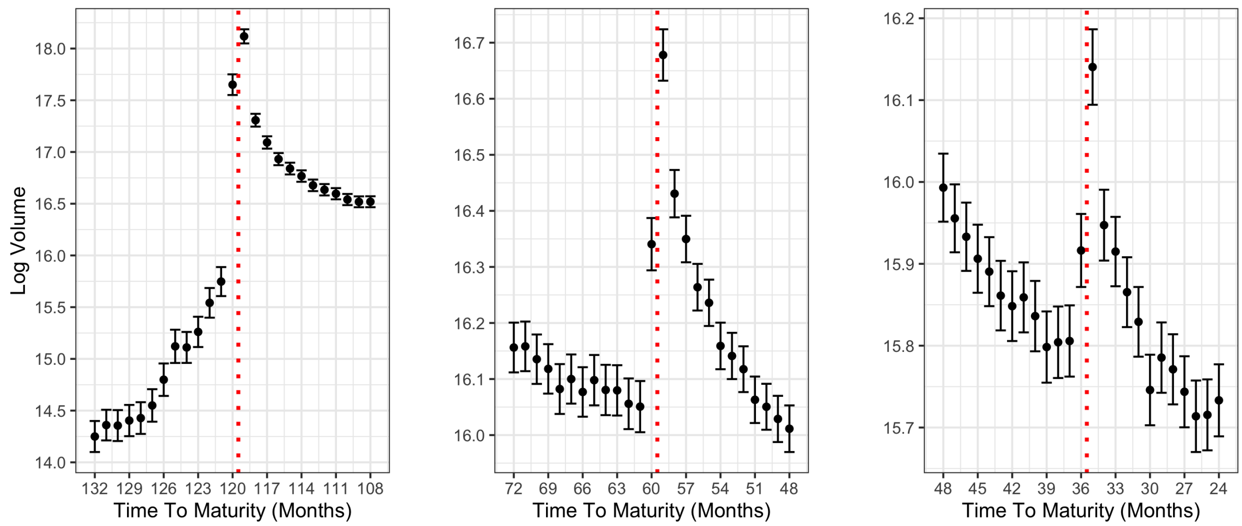
Figure A4: Compare 3Y maturity cutoff before and after 2018

This figure plots the coefficient estimates β_h from the following regression for $h \in [-4, 6]$:

$$\Delta Passive_i^{t-1 \to t+h} = \beta_h SwitchX_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

where $\Delta Passive_i^{t-1 \to t+h}$ is the percentage change of passive fund ownership for bond i from $t-1$ to $t+h$ (from $t+h$ to $t-1$) if $h \geq 0$ ($h < 0$). $SwitchX_{it}$ is an indicator variable equal to one if bond i crosses a maturity cutoff X in month t, and 0 otherwise. Subfigures (a) and (b) correspond to the the 3Y maturity cutoff before and after 2018 respectively. Year-month fixed effects and bond fixed effects are included. $Controls_{it}$ includes time-to-maturity, credit rating, contemporaneous bid-ask spread, and the amount outstanding of the bond. Error bars represent the 90% confidence interval, where standard errors are clustered at both the bond and year-month levels.

Panel A: Trading volume



Panel B: Bid-Ask spread

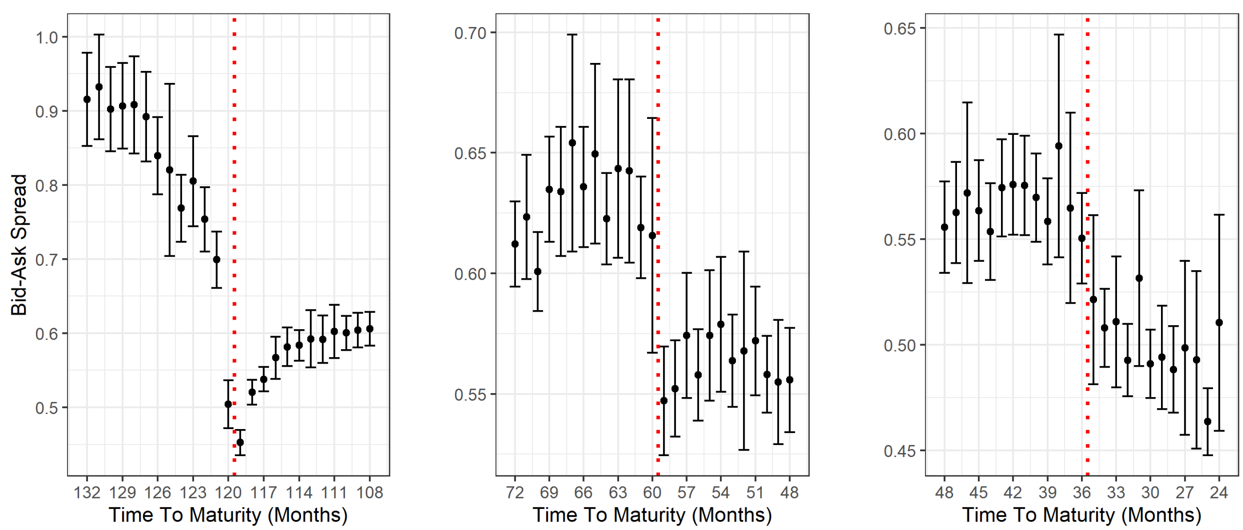


Figure A5: Trading volume and liquidity around maturity cutoffs

These figures plot the trading volume and bid-ask spreads around the maturity cutoffs. The x-axis is the time-to-maturity measured in month. From left to right, the time-to-maturity decreases, i.e., the bond is getting closer to its maturity date. For panel A, the y-axis is the average trading volume for bonds with specific time-to-maturity. For panel B, the y-axis is the average bid-ask spread for bonds with specific time-to-maturity. The error bar is the 95% confidence interval. The three sub-figures in each panel correspond to the 10 year, 5 year, and 3 year maturity cutoffs, respectively.

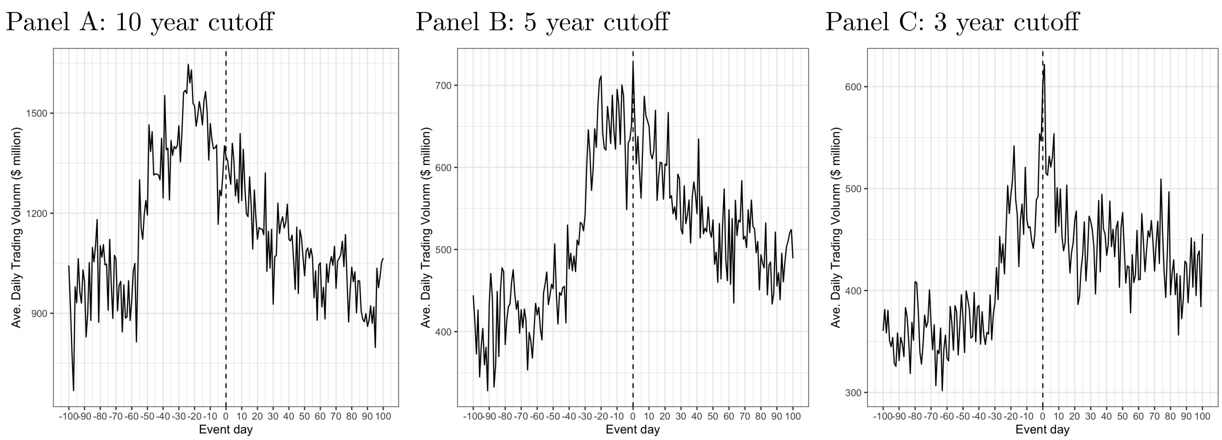


Figure A6: Average daily trading volume around maturity cutoffs

These figures plot the daily trading volume around maturity cutoffs.

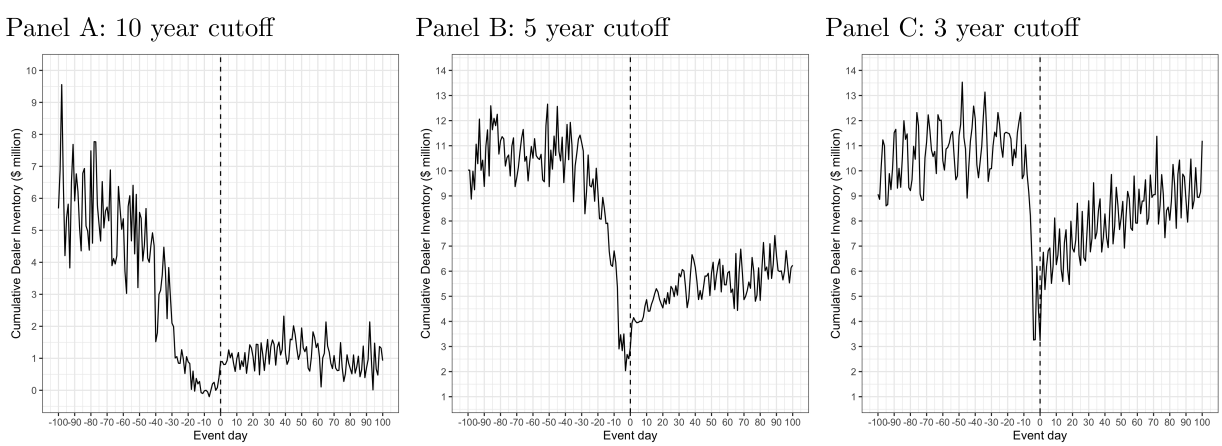


Figure A7: Cumulative dealer inventory around maturity cutoffs

These figures plot the daily cumulative dealer inventory around maturity cutoffs. The dealer inventory is computed by subtracting dealer sells from dealer buys.

Table A1: Placebo test for other maturity cutoffs: Passive Holdings

This table reports the results for the following regression:

$$Y_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it}.$$

The goal is to examine the change of passing ownership or yield spreads after crossing other maturity cutoffs. Panel A reports the effect on passive ownership and panel B reports the effects on yield spreads. $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoff at time t. TTM is the distance from the cutoff measured as time-to-maturity minus cutoff c. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, credit rating, the log amount outstanding in par value. Year fixed effects and bond fixed effects are included in all regressions. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Passive fund ownership%					
	(1)	(2)	(3)	(4)	(5)	(6)
$I(Pass2Y)$	0.023					
	(0.016)					
$I(Pass4Y)$		−0.008				
		(0.012)				
$I(Pass6Y)$			0.010			
			(0.022)			
$I(Pass7Y)$				−0.109***		
				(0.022)		
$I(Pass8Y)$					0.001	
					(0.018)	
$I(Pass9Y)$						−0.004
						(0.015)
TTM	−0.060***	−0.068***	−0.070***	−0.060***	−0.056***	−0.087***
	(0.008)	(0.007)	(0.011)	(0.008)	(0.009)	(0.009)
Bid-Ask	−0.201***	−0.145**	−0.147***	−0.113***	−0.107***	−0.106***
	(0.055)	(0.058)	(0.044)	(0.021)	(0.023)	(0.035)
Rating	0.010	−0.012	0.020	0.013	0.047	−0.067
	(0.054)	(0.048)	(0.054)	(0.050)	(0.050)	(0.050)
Size	2.049***	1.224*	1.109***	0.734	0.758*	0.429
	(0.479)	(0.677)	(0.404)	(0.546)	(0.393)	(0.612)
Bandwidth	± 6	± 6	± 6	± 6	± 6	± 6
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bond Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,588	48,276	35,045	32,000	29,841	31,192
R^2	0.954	0.958	0.952	0.957	0.951	0.954
Adjusted R^2	0.950	0.954	0.947	0.951	0.946	0.949

(Continued)

Table A2: Other investor holdings around maturity cutoffs

This table reports the results for the following regression:

$$Ownership\%_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it}.$$

The goal is to examine the change of ownership by other institutional investors after crossing other maturity cutoffs. $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoffs at time t. TTM is the distance from the cutoff measured as time-to-maturity minus cutoff c. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, credit rating, the log amount outstanding in par value. Year fixed effects and bond fixed effects are included in all regressions. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Active Mutual Funds			Life Insurance			PC Insurance			Variable Annuity			Pension & Others		
	10Y	5Y	3Y	10Y	5Y	3Y	10Y	5Y	3Y	10Y	5Y	3Y	10Y	5Y	3Y
$I(pass10Y)$	0.258*			−0.022			0.040			−0.129**			−0.025**		
	(0.137)			(0.348)			(0.131)			(0.050)			(0.010)		
$I(pass5Y)$		0.033			−0.125			−0.159			−0.016			−0.013	
		(0.073)			(0.395)			(0.140)			(0.010)			(0.009)	
$I(pass3Y)$			−0.008			−0.278*			−0.055			0.008			0.009
			(0.045)			(0.163)			(0.056)			(0.010)			(0.007)
TTM	0.189***	0.060***	0.004	−0.419***	0.124	0.131***	−0.112***	−0.014	0.051**	−0.001	0.020***	0.016***	−0.010***	0.002	0.006
	(0.034)	(0.019)	(0.015)	(0.078)	(0.097)	(0.047)	(0.026)	(0.030)	(0.022)	(0.008)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Bid-Ask	−0.097	−0.080	0.152	0.052	−1.319*	−0.133	0.073	−0.292	−0.099	0.018	−0.010	0.010	0.016	−0.016	−0.015
	(0.142)	(0.064)	(0.115)	(0.299)	(0.670)	(0.231)	(0.083)	(0.175)	(0.122)	(0.033)	(0.012)	(0.016)	(0.010)	(0.010)	(0.016)
Rating	0.234	0.190	0.208	0.031	−0.470	0.423	0.184	0.064	0.078	0.203*	−0.023	0.079**	−0.028	−0.034	0.010
	(0.259)	(0.140)	(0.177)	(0.384)	(1.145)	(0.778)	(0.168)	(0.276)	(0.299)	(0.111)	(0.037)	(0.031)	(0.027)	(0.026)	(0.017)
Size	−0.327	−3.528	−6.565	−38.781	−108.762***	−28.573**	−4.242**	−31.994***	−9.662**	0.470	−0.395	−0.450	−0.008	−1.308***	−0.338***
	(0.850)	(4.056)	(7.300)	(23.354)	(28.732)	(10.673)	(2.007)	(10.034)	(4.511)	(0.386)	(0.453)	(0.359)	(0.034)	(0.469)	(0.090)
Bandwidth	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,664	13,065	15,934	4,601	13,190	16,084	4,617	13,213	16,092	4,569	12,961	15,720	4,757	13,325	16,200
R^2	0.965	0.952	0.927	0.972	0.824	0.923	0.963	0.836	0.923	0.935	0.937	0.950	0.933	0.950	0.863
Adjusted R^2	0.923	0.928	0.895	0.937	0.736	0.889	0.919	0.755	0.890	0.856	0.906	0.929	0.854	0.925	0.803

Note: *p<0.1; **p<0.05; ***p<0.01

Table A3: PD around maturity cutoffs

This table reports the results for the following regression:

$$PD_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it}.$$

The goal is to examine the change of PD after crossing the 10Y, 5Y, and 3Y maturity cutoffs, which can help interpret the results. The dependent variable, PD is defined as in equation (2). $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoff at time t. TTM is the distance from the cutoff measured as time-to-maturity minus cutoff c. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, credit rating, the log amount outstanding in par value. Year fixed effects are added to control the time trend. The bandwidth is 6 month. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	PD		
	(1)	(2)	(3)
$I(Pass10Y)$	0.530^{***}		
	(0.066)		
$I(Pass5Y)$		1.358^{***}	
		(0.035)	
$I(Pass3Y)$			0.280^{***}
			(0.017)
TTM	-0.018^{***}	-0.021^{***}	-0.013^{***}
	(0.003)	(0.002)	(0.002)
Bid-Ask	-0.023^{*}	-0.017^{*}	-0.033^{***}
	(0.012)	(0.010)	(0.008)
Rating	0.034	-0.021^{**}	-0.009^{**}
	(0.025)	(0.008)	(0.004)
Size	−0.088	−0.005	0.010
	(0.054)	(0.022)	(0.008)
Year Fixed effects	Yes	Yes	Yes
Observations	14,624	40,514	48,864
R^2	0.954	0.976	0.954
Adjusted R^2	0.944	0.973	0.948
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A4: Robustness check: different slopes

This table reports the results for the following regression:

$$Passive\%_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 I(PassX)_{it} \times TTM + \beta_3 TTM_{it} + \beta' X_{it} + \epsilon_{it}.$$

It is a robustness check for passive fund ownership if our slope is different before and after the cutoff. $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoff at time t. PD is passive demand defined as in equation (2). TTM is the distance from the cutoff measured as time-to-maturity minus cutoff. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, and the log amount outstanding in par value. Year fixed effects are added to control the time trend. Bond fixed effects are included in all regressions except the 10Y cutoff. The bandwidth is ±6 month. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Passive%						
	10Y		5Y		3Y		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$I(Pass10Y)$	0.987***						
	(0.109)						
$I(Pass10Y) \times TTM$	−0.012						
	(0.019)						
$I(Pass5Y)$			0.192***				
			(0.034)				
$I(Pass5Y) \times TTM$			−0.062***				
			(0.006)				
$I(Pass3Y)$					0.049*	0.107***	
					(0.028)	(0.030)	
$I(Pass3Y) \times TTM$					−0.030***	−0.026***	
					(0.004)	(0.005)	
PD		1.611***		0.145***			0.608***
		(0.132)		(0.026)			(0.089)
$PD \times TTM$		−0.031**		−0.038***			−0.047***
		(0.012)		(0.004)			(0.007)
TTM	−0.076***	0.446**	−0.049***	0.611***	−0.065***	−0.055***	0.811***
	(0.017)	(0.209)	(0.006)	(0.064)	(0.006)	(0.007)	(0.137)
Bid-Ask	−0.422***	−0.393***	−0.109**	−0.096***	−0.180***	−0.070**	−0.139***
	(0.088)	(0.087)	(0.042)	(0.035)	(0.040)	(0.029)	(0.029)
Rating	0.001	0.007	−0.039	−0.044	−0.031	−0.078*	−0.034
	(0.023)	(0.023)	(0.046)	(0.045)	(0.045)	(0.043)	(0.045)
Size	0.958***	0.975***	1.368***	1.374***	2.517***	2.030***	2.527***
	(0.085)	(0.085)	(0.317)	(0.317)	(0.278)	(0.402)	(0.279)
Bandwidth	± 12	± 12	± 12	± 12	± 12	± 12	± 12
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond Fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Observations	30,021	30,021	79,006	79,006	94,752	63,251	94,752
R^2	0.474	0.490	0.927	0.927	0.930	0.924	0.930
Adjusted R^2	0.474	0.490	0.922	0.922	0.926	0.919	0.926

Note: *p<0.1; **p<0.05; ***p<0.01

Table A5: Robustness Check: smaller bandwidth and nonlinear control

This table reports the results for the following regression:

$$Passive\%_{it} = \alpha_i + \lambda_t + \beta_1 PD_{it} + \beta_2 TTM_{it} + \beta_2 TTM2_{it} + \beta_2 TTM3_{it} + \beta' X_{it} + \epsilon_{it}.$$

The goal is to examine the effect of passive ownership with smaller bandwidth and nonlinear controls . The dependent variable, $Passive\%_{it}$ is the total percentage share of bond i owned by passive funds. PD is passive demand defined as in equation (2). TTM is the distance from the cutoff measured as time-to-maturity minus cutoff c. $TTM2$ and $TTM3$ is TTM to the power of two and three. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, credit rating, the log amount outstanding in par value. Year fixed effects are added to control the time trend. Bond fixed effects are included in all regressions except the 10Y cutoff. Column (1), (3), and (5) use 6 month bandwidth. Column (2), (4), and (6) use 3 month bandwidth. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Passive%					
	10Y		5Y		3Y	
	(1)	(2)	(3)	(4)	(5)	(6)
PD	1.354***	1.015***	0.068**	0.050*	0.365***	0.281***
	(0.125)	(0.134)	(0.027)	(0.027)	(0.085)	(0.067)
TTM	−0.108***	−0.010	−0.127***	−0.146***	−0.070***	−0.072***
	(0.024)	(0.047)	(0.009)	(0.013)	(0.009)	(0.010)
Bid-Ask	−0.412***	−0.485***	−0.056	−0.053	−0.126***	−0.120***
	(0.109)	(0.153)	(0.042)	(0.034)	(0.034)	(0.031)
Rating	0.005	0.002	−0.065	−0.002	−0.072	−0.059
	(0.025)	(0.027)	(0.048)	(0.056)	(0.071)	(0.065)
Size	0.955***	0.913***	0.063	−0.767	1.371***	1.634***
	(0.095)	(0.103)	(0.488)	(0.573)	(0.398)	(0.506)
TTM2	0.006**	0.022***	0.010***	0.030***	0.003***	0.006***
	(0.002)	(0.005)	(0.001)	(0.003)	(0.001)	(0.002)
TTM3	−0.0001	−0.014***	0.001***	0.0004	−0.0002	−0.001
	(0.001)	(0.004)	(0.0002)	(0.001)	(0.0002)	(0.001)
Bandwidth	± 6	± 3	± 6	± 3	± 6	± 3
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bond Fixed effects	No	No	Yes	Yes	Yes	Yes
Observations	14,624	6,826	40,514	21,226	48,864	25,942
R^2	0.453	0.413	0.952	0.969	0.954	0.969
Adjusted R^2	0.452	0.411	0.946	0.962	0.949	0.962

Note: *p<0.1; **p<0.05; ***p<0.01

Table A6: Crossing maturity cutoffs and yield spread

This table reports the results for the following regression:

$$Yield\_Spread_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it}.$$

The goal is to examine the change in yield spreads after crossing the 10Y, 5Y, and 3Y maturity cutoffs. The dependent variable, $Yield\_Spread$ is the bond's yield-to-maturity minus the maturity-matched treasury yield. $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoff at time t. PD is passive demand defined as in equation (2). TTM is the distance from the cutoff measured as time-to-maturity minus cutoff c. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, credit rating, the log amount outstanding in par value. Year fixed effects are added to control the time trend. Bond fixed effects are included in all regressions except the 10Y cutoff. The bandwidth is ± 6 month. Column (5) and (6) exclude post-2018 sample. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	$Yield\_Spread$					
	10Y		5Y		3Y	
	(1)	(2)	(3)	(4)	(5)	(6)
$I(Pass10Y)$	-0.159^{***}					
	(0.023)					
$I(Pass5Y)$			-0.024^{***}			
			(0.005)			
$I(Pass3Y)$					-0.011^{**}	
					(0.006)	
PD		-0.114^{***}		-0.017^{***}		-0.027^{*}
		(0.031)		(0.004)		(0.016)
TTM	-0.010^{***}	-0.001	-0.044^{**}	-0.043^{**}	-0.027^{**}	-0.026^{*}
	(0.002)	(0.003)	(0.021)	(0.021)	(0.013)	(0.013)
$Bid-Ask$	0.376^{***}	0.383^{***}	0.098^{***}	0.098^{***}	0.096^{***}	0.096^{***}
	(0.032)	(0.032)	(0.026)	(0.026)	(0.021)	(0.021)
Rating	0.215^{***}	0.214^{***}	0.127^{***}	0.127^{***}	0.076^{***}	0.076^{***}
	(0.007)	(0.007)	(0.020)	(0.020)	(0.015)	(0.015)
Size	0.040^{**}	0.039^{**}	-0.050^{**}	-0.050^{**}	-0.033	-0.033
	(0.017)	(0.017)	(0.023)	(0.023)	(0.050)	(0.050)
Bandwidth	±6	±6	±6	±6	±6	±6
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	No	No	Yes	Yes	Yes	Yes
Observations	14,807	14,807	43,178	43,178	34,834	34,834
R^2	0.569	0.569	0.916	0.916	0.895	0.895
Adjusted R^2	0.566	0.565	0.905	0.905	0.883	0.883

Note: *p<0.1; **p<0.05; ***p<0.01

Table A7: Price effect and credit rating

This table reports the results for the following regression:

$$Yield\_Spread_{it} = \alpha_i + \lambda_t + \beta_1 I(PassX)_{it} \times Rating_{it} + Rating_{it} + \beta_2 TTM_{it} + \beta' X_{it} + \epsilon_{it}.$$

The goal is to examine the change in yield spreads after crossing cutoffs for different rating groups. The dependent variable, $Yield\_Spread$ is the bond's yield-to-maturity minus the maturity-matched treasury yield. $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoff at time t. PD is passive demand defined as in equation (2). $Rating_{it}$ is the credit rating group. There are three groups: AAA-AA (represented by the indicator variable AA), A, BBB. The reference level is AAA-AA without interaction. TTM is the distance from the cutoff measured as time-to-maturity minus cutoff. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, and the log amount outstanding in par value. Year fixed effects are added to control the time trend. Bond fixed effects are included in all regressions except the 10Y cutoff. The bandwidth is ±6 month. Column (5) uses the pre-2018 sample to examine the impact of the IGSB switching index. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	$Yield\_Spread$					
	10Y		5Y		3Y	
	(1)	(2)	(3)	(4)	(5)	(6)
$I(PassX) \times AA$	0.002		0.002		0.018	
	(0.044)		(0.019)		(0.017)	
$I(PassX) \times A$	-0.142^{***}		0.013		-0.003	
	(0.037)		(0.010)		(0.011)	
$I(PassX) \times BBB$	-0.176^{***}		-0.048^{***}		-0.047^{***}	
	(0.033)		(0.010)		(0.013)	
$PD \times AA$		-0.090^{*}		0.006		-0.057
		(0.048)		(0.012)		(0.062)
$PD \times A$		-0.093^{**}		0.010		-0.122^{**}
		(0.037)		(0.006)		(0.060)
$PD \times BBB$		-0.116^{***}		-0.038^{***}		-0.270^{***}
		(0.035)		(0.007)		(0.055)
A	0.394^{***}	0.330	0.039	-0.022	0.024	1.145^{**}
	(0.054)	(0.514)	(0.060)	(0.196)	(0.037)	(0.474)
BBB	1.098^{***}	1.375^{**}	0.252^{***}	0.962^{***}	0.158^{***}	3.835^{***}
	(0.051)	(0.607)	(0.065)	(0.270)	(0.048)	(0.745)
TTM	-0.010^{***}	-0.001	-0.046^{**}	-0.045^{**}	0.009^{*}	0.002
	(0.003)	(0.004)	(0.021)	(0.021)	(0.005)	(0.007)
$Bid-Ask$	0.381^{***}	0.388^{***}	0.099^{***}	0.099^{***}	0.188^{***}	0.184^{***}
	(0.035)	(0.035)	(0.027)	(0.027)	(0.033)	(0.033)
$Size$	0.011	0.014	-0.042^{*}	-0.042^{*}	-0.065	-0.066
	(0.018)	(0.018)	(0.022)	(0.022)	(0.052)	(0.053)
Bandwidth	±6	±6	±6	±6	±6	±6
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	No	No	Yes	Yes	Yes	Yes
Observations	14,807	14,807	43,178	43,178	34,834	34,834
R^2	0.507	0.506	0.916	0.916	0.850	0.851
Adjusted R^2	0.503	0.502	0.905	0.905	0.832	0.834

Note: *p<0.1; **p<0.05; ***p<0.01

Table A8: Placebo test for other maturity cutoffs: Yield Spread

This table reports the effects on yield spreads. $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoff at time t. TTM is the distance from the cutoff measured as time-to-maturity minus cutoff c. X_{it} is the set of control variables that include the contemporaneous bid-ask spread, credit rating, the log amount outstanding in par value. Year fixed effects and bond fixed effect are included in all regressions. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Yield_Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
$I(Pass2Y)$	0.021					
	(0.014)					
$I(Pass4Y)$		−0.006				
		(0.011)				
$I(Pass6Y)$			0.010			
			(0.008)			
$I(Pass7Y)$				−0.012		
				(0.010)		
$I(Pass8Y)$					0.005	
					(0.010)	
$I(Pass9Y)$						0.013
						(0.013)
TTM	0.030***	0.030***	0.014**	0.008	0.008	0.024***
	(0.007)	(0.008)	(0.006)	(0.007)	(0.005)	(0.008)
Bid-Ask	0.929***	0.616***	0.356***	0.302***	0.252***	0.306***
	(0.223)	(0.172)	(0.096)	(0.078)	(0.058)	(0.090)
Rating	0.074**	0.096***	0.176***	0.146***	0.111***	0.097***
	(0.032)	(0.028)	(0.029)	(0.032)	(0.023)	(0.032)
Size	0.182***	0.031	−0.008	−0.047	−0.024*	−0.028
	(0.063)	(0.057)	(0.025)	(0.035)	(0.014)	(0.058)
Bandwidth	± 6	± 6	± 6	± 6	± 6	± 6
Year Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bond Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,588	48,276	35,045	32,000	29,841	31,192
R^2	0.954	0.958	0.952	0.957	0.951	0.954
Adjusted R^2	0.950	0.954	0.947	0.951	0.946	0.949

Note: *p<0.1; **p<0.05; ***p<0.01

Table A9: Passive fund demand and primary market yield

This table summarizes the estimated effect of passive fund demand on the primary market offering yields. Each column reports the coefficient estimates from the following 2SLS regressions:

$$\text{Yield}_{it} = \beta \widehat{Passive\_firm}\%_{it} + Controls + FEs + \epsilon_{it}$$

$$Passive\_firm\%_{it} = \gamma PD\_firm_{it} + Controls + FEs + e_{it}$$

Yield_{it} is the offering yield. $Passive\_firm\%$ is the average percentage of passive fund holdings for firm i's outstanding corporate bonds, weighted by the amount outstanding. $Passive\_firm\%$ is instrumented using PD_firm_{it}, which is the average of PD for firm i, weighted by the amount outstanding. Issue level controls include issue size, credit rating, and initial maturity. Firm level controls include firm size, tangible assets, firm age, market-to-book ratio, leverage ratio, cash, lagged cash growth, lagged 12 month sales, lagged net income, and lagged CapEx. Three fixed effects are used: industry-by-year FE absorb any industry specific trend, rating-by-year FE absorb time-varying differences in yield spreads across different rating categories (rating categories are defined as AAA-AA, A, and BBB), maturity-by-year FE absorb time-varying differences in yield spreads across different initial maturity buckets (initial maturity buckets are defined as (0,3], (3,5], (5,10], (10,15], (15,∞]). Standard errors clustered at year and firm levels are presented in parentheses. Cragg-Donald F-Statistics are reported. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Second Stage: *Offering Yield Spread*					
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{Passive\_firm}\%$	-0.208^{**}	-0.239^{**}	-0.196^{**}	-0.223^{**}	-0.196^{**}	-0.140^{*}
	(0.069)	(0.089)	(0.070)	(0.089)	(0.070)	(0.071)
	First stage: $Passive\_firm\%$					
	(1)	(2)	(3)	(4)	(5)	(6)
PD_firm	0.574^{***}	0.576^{***}	0.566^{***}	0.571^{***}	0.566^{***}	0.561^{***}
	(0.118)	(0.118)	(0.119)	(0.115)	(0.119)	(0.116)
Cragg-Donald F-Statistic	171.5	160.4	166.5	157.9	166.5	149.9
Issue Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	No	Yes	No	Yes	No	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating-by-Year FE	No	No	Yes	Yes	Yes	Yes
Maturity-by-Year FE	No	No	No	No	Yes	Yes
Observations	3,314	2,936	3,314	2,936	3,314	2,936

Note: *p<0.1; **p<0.05; ***p<0.01

Table A10: Demand system estimation: first stage

This table reports the first stage of the demand elasticity estimation for different institutional investors. For panel A, fund ×quarter fixed effects are included. For panel B, fund ×bond fixed effects are included. All bond characteristics are standardized. The estimates are weighted by fund's AUM to account for the heterogeneity in size. Standard errors clustered at the fund level are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: within fund-quarter variation					
	$y_t(n)$				
	Active MF	Life	P&C	Annuity	Pension & Others
	(1)	(2)	(3)	(4)	(5)
PD	−0.350***	−0.299***	−0.318***	−0.336***	−0.311***
	(0.014)	(0.006)	(0.009)	(0.003)	(0.014)
TTM_month	0.266***	0.425***	0.337***	0.324***	0.397***
	(0.016)	(0.017)	(0.018)	(0.005)	(0.070)
T_Spread	0.177***	0.196***	0.171***	0.151***	0.199***
	(0.007)	(0.006)	(0.012)	(0.004)	(0.006)
RATING_NUM	0.281***	0.217***	0.273***	0.268***	0.241***
	(0.005)	(0.004)	(0.008)	(0.003)	(0.010)
Size	0.019***	0.033***	0.016***	0.032***	0.045***
	(0.004)	(0.004)	(0.005)	(0.002)	(0.006)
Fund×Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,663,318	5,841,847	3,753,947	1,484,867	434,036
Panel B: within fund-bond variation					
	(1)	(2)	(3)	(4)	(5)
PD	−0.176***	−0.095***	−0.063***	−0.167***	−0.113***
	(0.015)	(0.006)	(0.004)	(0.027)	(0.008)
TTM_month	2.715***	1.098***	1.111***	1.482***	1.254***
	(0.191)	(0.053)	(0.078)	(0.082)	(0.132)
T_Spread	0.225***	0.200***	0.257***	0.159***	0.194***
	(0.010)	(0.008)	(0.007)	(0.014)	(0.011)
RATING_NUM	0.170***	0.155***	0.140***	0.154***	0.130***
	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)
Size	0.026*	0.022***	0.055***	0.053***	0.035***
	(0.014)	(0.007)	(0.010)	(0.007)	(0.005)
Fund×bond Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	1,663,318	5,841,847	3,753,947	1,484,867	434,036
Note:					*p<0.1; **p<0.05; ***p<0.01

B Comparison with Alternative Methods

The previous literature mostly relies on quasi-nature experiments to test the impact of passive ownership in the corporate bond market. Dannhauser (2017) exploits two changes in ETF eligibility. First, the Markit iBoxx High Yield Liquid Index changes from a 50 bonds equal-weighted index to a 3% capped valued-weighted index, which includes all bonds that satisfy the eligibility requirements. Thus, the passive ownership of the newly included bonds will increase. The second experiment focuses on the iShares iBoxx Investment Grade Corporate Bond ETF (LDQ). LDQ tracks the Markit iBoxx Liquid Investment Grade Index, which only includes bonds with time-to-maturity of at least three years. Hence, upon crossing the 3-year maturity cutoff, a bond will be removed from the index, and LDQ will sell its position. Using the propensity score matching (PSM) and difference-in-difference (DiD) setting, the author finds that bonds sold by LDQ due to maturity reasons have a higher yield spread compared to the matched bonds that LDQ does not sell. Dick-Nielsen and Rossi (2019) use the index exclusions as a natural experiment to study the cost of immediacy. Specifically, they focus on two exclusion events: downgrade from IG to HY and time-to-maturity less than one year. While these index exclusion events are ideal for studying the price pressure caused by force-selling, they are not suitable to identify the impact of passive ownership. Marta (2022) use the change of index by iShares Short-Term Corporate Bond ETF (IGSB). In August 2018, IGSB switched from the Bloomberg Barclays 1-3Y index to the ICE BofAML 1-5Y index. As a result, after the switch, bonds with time-to-maturity between 3 and 5 years become eligible for IGSB, which leads to an increase in passive fund ownership.

We discuss the second experiment by Dannhauser (2017) in more detail as it is closely related to our empirical design. Though both methods rely upon the 3-year maturity cutoffs, the two methods have different implications. While we focus on the increase of aggregate passive fund ownership after passing the cutoff, Dannhauser (2017) focus on the exclusion from LDQ. As a result, we predict that, after conditioning on time-to-maturity, the yield spread should decrease upon crossing the 3-year cutoff, while Dannhauser (2017) predict a higher yield spread for bonds sold by LDQ compared to the maturity-matched bonds that LDQ does not sell. In other words, we predict the yield will decrease discontinuously at the 3-year cutoff while Dannhauser (2017) predicts that the downward trend of yield over time-to-maturity will be less steep for bonds that are sold by LDQ. Hence, despite the seemingly opposite predictions, the two methods are comparing different objects. Additionally, the sample period of Dannhauser (2017) is from 2009 to 2013 and our sample is from 2012 to 2021.

Our identification strategy has the following advantages compared to existing methods. First, our method is much less likely to suffer from omitted variable bias by focusing on the same bond around the maturity cutoffs. Quasi-natural experiments usually exploit the cross-sectional differences between treatment and control groups. However, fixed income securities are much more complicated than equity. For example, bonds may have different types and different covenants. As a result, it is hard to compare bonds in the cross-section. Second, one common concern for using the index as an instrument is that the index effect may have confounding effects other than the change in demand. For instance, getting added to the S&P500 index may attract more attention from investors and analysts, which may be correlated with the outcome variables. In our setting, the bond switches from one sub-index to another, and it remains in the same main index. Take the Bloomberg corporate bond index family as an example. The main index is the Bloomberg Barclays US Corporate Bond Index. The sub-indices are the Bloomberg Barclays US Corporate 1-5 Years, 5-10 Years, and 10+ Years indexes. The sub-indices received much less attention than the main index, which makes the attention mechanism less plausible. Third, another concern is selection bias. For instance, as suggested by Marta (2022), ETFs may self-select into more liquid stocks. Our empirical design can address the concern by comparing the same bond before and after crossing maturity cutoffs. Moreover, since our method does not rely on one-time events, we can examine how the effects change over time by comparing results using different sub-samples. Lastly, having multiple discontinuities can serve as an additional robustness check.