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

Lorenzo Bretscher† Lukas Schmid‡ Tiange Ye§

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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 and 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, passive fund demand shocks spill over to the primary market, causing lower issuing yield spreads, and firms engaging in debt market timing by substituting expensive bank debt with cheaper bond financing. We provide causal evidence that non-fundamental demand shocks can have real effects in that constrained firms use issuance proceeds to fund investment. Our findings inform the ongoing debate about the regulatory treatment of cross-trades between funds by the SEC.

Keywords: demand shifts, corporate bonds, passive funds, price pressure, securities lending, demand elasticity, capital structure, debt financing.
JEL Classification: G11, G12, G22, G23

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†University of Lausanne, Swiss Finance Institute, and CEPR, Email: lorenzo.bretscher@unil.ch

‡USC Marshall School of Business and CEPR, Email: lukas@marshall.usc.edu

§USC Marshall School of Business, Email: tiange.ye@marshall.usc.edu

1 Introduction

The rise of passive investing is one of the most pervasive developments in financial markets over the past thirty years. Rather than trying to exploit potential mispricing, passive funds track various market indices and charge lower fees instead. Flows into such investment vehicles thereby create passive demand for index constituents. In US stock markets, for example, assets managed by passive funds rose from \$ 23 billions in 1993 to \$ 8.4 trillions in 2021, which amounted to 16% of the stock market. Among economists and policymakers alike, this surge in passive demand raises concerns about its effects on market volatility, fragility, competition, and price informativeness[1], for example. Providing direct evidence on any such effects remains challenging, however, in the absence of well-identified shocks to passive demand. While numerous empirical studies use changes in index membership to examine the impact of demand shocks in equity markets[2], concerns regarding omitted and confounding factors remain in these settings.[3]

In this paper, we turn to the corporate bond market to provide novel evidence regarding passive demand shocks. Notably, passive funds have played an increasingly important role in the corporate bond market as well, comparable to that in stock markets. The total amount of investment-grade (IG) corporate bonds held by passive funds has increased from \$50 billion to over \$450 billion between 2010 and 2021, for example. In this context, we introduce and identify 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 then put our empirical design to work to address two research questions using a comprehensive dataset of institutional investors' holdings. First, how do non-fundamental demand shifts by

[1]See Ben-David, Franzoni, and Moussawi (2018), Bhattacharya and O'Hara (2018), Haddad, Huebner, and Loualiche (2021), Sammon (2023) among others.

[2]See Chang, Hong, and Liskovich (2015), Appel, Gormley, and Keim (2016), **?** among others

[3]See Wei and Young (2019), Appel, Gormley, and Keim (2020) and Heath, Macciocchi, Michaely, and Ringgenberg (2022) for example.

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 features in the corporate bond market: passive funds' preference for maturity and their fixed mandates. Indeed, most passive funds exhibit maturity mandates in that they track corporate bond indexes based on maturity categories, namely long-term, intermediate-term, and short-term funds. These maturity categories are defined consistently: long-term funds invest in bonds with time-to-maturity longer than 10 years, intermediate-term funds focus on maturities from 5 to 10 years, while short-term funds choose bonds with either 1 to 5 years or 1 to 3 years maturity. Hence, there are three maturity cutoffs: 10-, 5-, and 3-year time-to-maturity. In this context, we find that passive fund demand for corporate bonds displays discontinuity around the maturity cutoffs separating long, intermediate, 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-term funds, and long-term funds exhibiting the smallest AUM. We show that the order and gap for the three maturity categories persist over time. 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 examining a passive fund demand shock.

Leveraging these three maturity cutoffs, we introduce a number of empirical specifications that allow us to examine the effects of passive demand shocks. In particular, we first apply a regression discontinuity design (RDD) approach to test the discontinuity of passive ownership around the maturity cutoffs. This serves as a validation test that there is indeed an abnormal jump in passive ownership after a bond crosses the maturity cutoff. We then treat the crossing event as an exogenous shock to examine the dynamic effects of demand shocks using local projection, as in Jordà (2005). This allows us to consider the full dynamics surrounding the passive demand shock and examine the effects' persistence. Additionally, we develop an instrumental variable (IV) approach and introduce a novel instrument for passive fund demand. This new instrument is designed to capture the exogenous variation in passive fund demand caused solely by crossing maturity categories. This IV helps us establish causality when we have to rely on the cross-sectional variation, such as when we examine the effects of passive demand on the primary market offering price. We think that the value of our instrument extends beyond our paper. It is applicable in a variety of settings in the context of passive fund ownership in the corporate bond market as well as in the recent demand-based asset pricing literature started by Koijen and Yogo (2019). Indeed, our instrument is closely related to the mandate-based instrument introduced in Koijen and Yogo (2019), but in a setting where the mandate is effectively observable. All three approaches are complementary to each other and are based on the same underlying mechanism. In our empirical analysis, we apply the most suitable approach for each test, and whenever possible, we cross-validate our findings with the other methods.

Using our empirical framework, we first show that there is indeed a significant jump in passive ownership after a bond crosses a maturity cutoff. On average, crossing maturity cutoffs lead to a 0.4% increase in passive ownership. The magnitude of this effect is substantial given that average passive ownership is only 5.5%. We next examine how non-fundamental demand shocks by passive funds affect prices and liquidity in secondary markets. Regarding price effects, we find that positive demand shocks by passive funds lead to a statistically significant reduction in yield spreads, after controlling for all bond characteristics, which starts to slowly reverse only five months after the crossing event. The magnitude of the spread reduction is around three bps relative to the pre-crossing level, which is economically meaningful given that we exclusively focus on IG bonds. Regarding liquidity, we find a significant improvement in the crossing bond's liquidity after the demand shock, and no evidence of reversal, suggesting persistent liquidity improvements. Moreover, we find that trading volume spikes around the crossing events, which is consistent with rebalancing activity, but it quickly reverses to the pre-crossing level, suggesting no long-run effect.

The positive price effect is consistent with downward-sloping demand curves as suggested by Shleifer (1986), and supports the notion that markets are inelastic and demand shifts may have long term price effects (Gabaix and Koijen, 2021). Our paper provides causal evidence in the corporate bond market. Indeed, under the efficient market hypothesis there should be no price effect as assets are perfectly substitutable and any demand changes by one group of investors will be immediately picked up by other investors. 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), and alleviates concerns that ETF arbitrage could lead to adverse selection (Foucault, Kozhan, and Tham, 2017).

Our finding of significant price effects of passive demand shocks is remarkable in view of the fact that the crossing event is fully predictable, so that arbitrageurs should be able to eliminate yield reductions. Indeed, we show that 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. While this is consistent with slow moving capital and inelastic demand, it raises the question regarding the sources of the limits to arbitrage. Here it is important to note that with high transaction costs passive corporate bond funds apply a sampling strategy that allows them to only hold parts of the relevant index portfolio. Thus, most, but not all eligible bonds crossing a maturity cutoff end up being purchased by passive funds. For potential arbitrageurs, therefore, it is uncertain which bonds and when they will purchase[4]. Additionally, our trading strategy is not profitable when round-trip transaction costs are taken into account, as the portfolio rebalances fully every month. Another way arbitrageurs can exploit temporary price pressure is by short-selling treated bonds. We also explore the security lending behavior around the maturity cutoffs, and demonstrate a notable increase in short loan quantity and a minor decrease in total lendable shares after crossing the maturity cutoff. Additionally, we find that bonds with a higher short-selling capacity exhibit weaker price impact and much quicker price reversal. This suggests that investors actively trade against demand-driven temporary price pressure by short-selling bonds to the extent that they are lendable.

While we document significant demand-driven price pressure, the price response is likely muted due to cross-trading. Cross-trading refers to the practice that funds run by the same investment advisor trade securities among each other at plausibly mutually beneficial prices rather than on the market place. For example, a Vanguard long-term fund may sell a crossing bond to a Vanguard intermediate-term fund, rather than having them transacting at bid and ask prices on the market place, thereby saving transaction costs. Such cross-trading is regulated by the SEC under rule 17a-7 of the Investment Company Act of 1940, which mandates these transactions to be effected at the independent current market price of the security, which are often hard to come by in fixed income markets. While historically the SEC has been quite lenient in the implementation of this rule in bond markets, rendering cross-trades common practice, it has, as announced in 2020, and effective in September 2022, adopted a much firmer stance recently, known as the 'Valuation rule.' [5] As a result, certain bonds that may have previously viewed as having readily available market quotations and being available to cross trade under rule 17a-7 may not meet the definition in the Valuation Rule and thus would not be available for such trades after the compliance date

[4]We show below, in figure A7, that there are no significant differences in characteristics between crossing bonds that are purchased ex-post versus those that are not, except for the former tending to be larger in size, thereby alleviating concerns regarding selection.

[5]See the statement from SEC here.

of the Valuation Rule. The SEC's move forward has triggered a widespread response from the industry amidst concerns regarding adverse effects on bond markets and higher trading costs.[6] Our results suggest that such higher trading costs would plausibly amplify price movements in secondary markets upon maturity-mandate based rebalancing, and thus inform the current debate. This is relevant in view of real effects of demands shocks that we turn to next. Our findings thus strongly suggest that the regulatory changes spearheaded by the SEC significantly affect the execution of passive trading strategies in bond markets.

We next ask whether passive fund demand shocks and price pressure in secondary markets spill over to the primary market and affect firms' financing policies, and thereby potentially real activity. To examine firm-level outcomes, we thus aggregate bond-level passive demand shocks at the firm level. Intriguingly, we find that passive demand shocks cause lower offering yields in the primary corporate bond market. In other words, firms experiencing passive demand shocks in secondary markets face favorable conditions in primary issuance markets. Notably, using an event study framework, we document that firms take advantage of lower financing costs by issuing, and thereby actively supplying, more bonds, both in terms of dollar amounts outstanding and numbers of bonds outstanding. At the same time, they reduce bank debt, suggesting that firms engage in debt market timing by substituting expensive bank debt with cheaper bond financing. Moreover, we show that average firms mostly use the issuance proceeds to increase their cash buffers, and increase payout. In contrast, however, we find evidence that financially constrained firms reduce payout instead and increase investment. This is an important result in our view as it shows how non-fundamental demand shocks can have real effects in the presence of financial constraints. Importantly, these results only pertain to firms who have crossing bonds outstanding that end up being purchased by passive funds ex-post. Indeed, in placebo tests we demonstrate that there are no discernible effects on firms whose crossing bonds are not purchased according to passive funds' sampling strategies, giving further credence to the notion that price pressure

[6] See e.g.https://www.sec.gov/investment/engaging-investment-company-cross-trading.

in secondary markets causes responses in firm policies. Overall, 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).

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 et al. 2015, among others). Pavlova and Sikorskaya (2023) 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.[7] In the corporate bond market, Holden and Nam (2017) and Marta (2022) find that 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. Closely related to, and independently from us, they also utilize a discontinuity design with bonds crossing maturity cutoffs, but focus on the 10 year cutoff exclusively and liquidity effects, while we consider primary market effects and spillovers. Similarly, Bai, Li, and Manela (2023) use that design to provide causal

[7]See Appel et al. (2016), Ben-David et al. (2018), Appel, Gormley, and Keim (2019), Heath et al. (2022), among others.

evidence that investor composition affects the value of data in the corporate bond market. 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), which highlights the importance of the inelastic demand by institutional investors (e.g., Basak and Pavlova, 2013; Gabaix and Koijen, 2021). Haddad et al. (2021) study how other investors change their behavior in response to the rise of passive investing. Bretscher, Schmid, Sen, and Sharma (2020) apply this demand system approach in the corporate bond market. Yu (2020) examines 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 effects of corporate bond mutual funds holdings on credit risk. Zhu (2021) shows mutual fund flows affect firms' bond issuance decisions. Kubitza (2021) finds that the demand shocks caused by insurance companies significantly impact firm debt issuance and investment. Ben-Rephael, Choi, and Goldstein (2021) find bond fund flows predict credit and business cycle. Adelino, Cheong, Choi, and Oh (2023) show that the supply of capital from mutual funds have significant effects on municipal bond financing and local government spending. Closely related to our work, Kashyap, Kovrijnykh, Li, and Pavlova (2021) argue that the inelastic demand caused by index benchmarking creates a "benchmark inclusion subsidy" that benefits the constituent firms. Our paper shows that frequently occurring exogenous demand shocks by passive funds significantly affect secondary market prices and improve liquidity. Additionally, we provide evidence that passive fund demand shocks spill over to the primary market and affect firms' financing cost and debt issuance.

The remainder of this paper is organized as follows: Section 2 explains the data sources and summarizes the sample. Section 3 introduces the institutional background. Section 4 elaborates on the identification strategy and empirical specification. Section 5 documents passive fund demand shifts around maturity cutoffs. Section 6 presents empirical results on the secondary market effects. Section 7 provides evidence on the effect of passive fund demand on primary market offering prices, capital structure, and investment. Finally, section 8 concludes.

2 Data and Summary Statistics

We draw on a variety of data sources for our analysis. Specifically, our 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), and (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.[8] 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.[9] 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 did not impose any restrictions on fund types, our sample includes holdings by all passive funds, not just pure corporate bond funds.

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

[8]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.

[9]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.

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 539,309 bond-month observations. The average passive fund ownership is 5.5%. Looking at each maturity category, the average passive ownership for the 10Y+, 5-10Y, 3-5Y, and 1-3Y maturity category are 3.96%, 5.6, 6.25%, and 6.53%, respectively. In untabulated statistics, we also show that, within the investment-grade category, the passive fund ownership is quite stable across different rating groups. The average yield spread is 1.29%. The median amount outstanding is $500 million and the average bid-ask spread is 43 bps. 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.

[Insert Table 1]

3 Institutional Background

In this section, we provide institutional background 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 their portfolios. For example, total market funds typically invest around 30% of their AUM in corporate bonds. Figure 1 illustrates 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 of 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. Such maturity-mandated funds are very popular. Nine of the ten largest corporate bond ETFs track maturity-mandated indices. Take 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 long-term (intermediate-term) indexes and will become eligible to intermediate-term (short-term) indexes.

Table 2 provides a snapshot for all maturity-constrained passive funds with AUM larger than $1 billion in June 2022.[10] Consistent with the 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) funds will have to purchase from other investors, which creates a positive demand shock.

[10] 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.

[Insert Table 2]

Figure 2 illustrates 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 increases since 2015, however the per bond demand gap remains 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 features. 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]

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 exclude 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.

[**Insert Figure 3**]

4 Empirical Framework

Based on the observed passive demand shifts around maturity cutoffs documented in Section 4, we now introduce a number of empirical specifications that allow us to examine the effects of passive demand shocks on secondary, and then, primary corporate bond market activity. In particular, we first apply a regression discontinuity design approach to test the discontinuity of passive ownership around the maturity cutoffs. We then treat the crossing event as an exogenous shock to study the dynamic effects of demand shocks using local projection, as in Jordà (2005). Additionally, we develop a instrumental variable approach and introduce a novel instrument for passive fund demand, which we label as $IV\_PassiveDemand$. This new instrument is designed to capture the exogenous variation in passive fund demand caused solely by bonds switching maturity categories. All three approaches are complementary to each other and share the same underlying mechanism. In our empirical analysis, we apply the most suitable approach for each test, and whenever possible, we cross-validate our findings using the other methods.

4.1 Regression discontinuity design

We first apply 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 category. Since the eligibility rule is deterministic, we employ a sharp RDD.[11] Each bond has a different crossing date, so bonds are staggered over time-to-maturity. Essentially, RDD allows us to compare the same bond before and after crossing the maturity cutoff. Specifically, we estimate the following model:

$$Passive_{it} = \beta I(PassX)_{it} + f(TTM_{it} - X) + Controls + \alpha_i + \lambda_t + \epsilon_{it}, \tag{1}$$

The dependent variable, $Passive_{it}$, is the percentage share of bond i held by passive funds at time t. In some tests, we also look at the ownership by other investor types. $I(PassX)_{it}$ is a dummy variable equal to one if the bond has passed the cutoff X. The running variable is $TTM_{it} - X$, which measures the distance between time-to-maturity and the maturity cutoff X. $f(TTM_{it} - X)$ is a function of the running variable, which we use to control for time-to-maturity. We use three functional forms: (1) linear function, (2) linear function with different slopes on both sides of the cutoff, and (3) a cubic polynomial function to control for any non-linear relationships. As a non-parametric control, we restrict the sample to observations whose time-to-maturity is within the ± 6 month bandwidth.[12] Unlike the typical RDD approach, we add bond fixed effects to exploit the within bond variation. This converts a pooled cross-sectional estimation into a panel estimation. We also include year-month time fixed effect. We control for time-varying bond characteristics such as 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. Standard errors are clustered at the bond and year-month levels to address intra-group correlations for the same bond and within the same month.

[11] 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.

[12] We did not apply the bandwidth selection methods such as the one suggested by Calonico, Cattaneo and Titiunik (2014) because the selected bandwidth may overlap with the other maturity cutoffs. Our bandwidth selection is based on the empirical evidence and institutional knowledge that most passive funds complete their portfolio rebalancing within six months. In untabulated tests, we show that our results are robust to alternative bandwidth selection such as ± 12 months.

The advantage of RDD is that we can restrict our sample to observations around the maturity cutoff, which avoids the bias caused by data far away from the cutoff. However, the problem of using RDD in our setting is that passive funds rebalance their portfolio gradually. Our empirical results suggest that most passive funds usually take around three months to fully rebalance their portfolios. Since RDD compares the average passive fund ownership before and after crossing the cutoff, it cannot fully capture the full dynamics of the passive demand shock and will underestimate the effect. Additionally, it is almost impossible to use RDD to study the primary market effect due to the nature of the data. Hence, we next treat the crossing event as an exogenous shock and apply local projection to study the dynamic effects of passive demand shocks.

4.2 Local projection

We apply local projection, as in Jordà (2005), to examine the full dynamics of the passive fund demand shifts around the maturity cutoffs. We estimate the following specifications:

$$\Delta Outcome_i^{t-1\rightarrow t+h} = \beta_h SwitchX_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \tag{2}$$

where $\Delta Outcome_i^{t-1\rightarrow t+h}$ are the cumulative changes of the outcome variable for bond i from $t-1$ to $t+h$. Here, the benchmark period is $t-1$. A positive coefficient means the level of the outcome variable at period $t+h$ is higher than period $t-1$, and vice versa. We look at outcome variables such as passive fund ownership, yield spreads, trading volumes, and bid-ask spreads. $SwitchX_{it}$ is an indicator variable equal to one if bond i crosses maturity cutoff X at month t, and 0 otherwise. In addition to the 10-year, 5-year, and 3-year maturity, we also combine all three cutoffs. 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 are the same as before. Standard errors are clustered at both bond and year-month levels.

The advantage of the local projection technique is its ability to capture the full dynamics of the effect. This is especially valuable given that passive funds adjust their holdings gradually. Additionally, different outcome variables may display heterogeneous dynamics. For instance, trading volume may spike during the crossing month, whereas the liquidity improvement may only start after one month.

Further, local projection allows us to examine the persistence of the effect, which is critical to our understanding of passive demand shocks. Finally, local projection helps us observe any front-running activity prior to the crossing event, if there is any. Unlike other event study approaches, such as difference-in-difference, we are not concerned about having significant coefficients before the shock. This is because we are interested in the fully dynamic effect of the passive demand shock. Additionally, since we are comparing the same bond before and after crossing the cutoff, anticipation does not undermine the exogeneity of our setting. In fact, we should expect to observe some pre-shock effects, given the fact that the crossing event is fully predictable.

4.3 Instrumental variable approach

Both previous approaches utilize the time-series variation before and after a bond crosses the maturity cutoff, which requires continuous observations around the crossing event. However, we need to use the cross-sectional variation in some tests because we do not have continuous observations. For example, we have to rely on the cross-sectional variation when studying the effect of passive fund demand on the primary market offering price because new bond issuance is discrete in nature. Both RDD and local projection are inapplicable in this case. Here, we introduce a new instrument based on bonds exogenously switching maturity categories. We label our instrument as $IV\_PassiveDemand$.

To construct our instrument, we first manually collect benchmark information for all maturity-mandated passive funds and then calculate the aggregate amount of assets benchmarked to each maturity range at each period. We then divide by the number of bonds within each maturity range, which gives us a proxy for per-bond passive demand in each maturity category.[13] Finally, we assign bonds with corresponding per-bond demand based on their time-to-maturity in each period. The mathematical form of our instrument is inspired by the investment universe instrument proposed by Koijen and Yogo (2019). Formally:

$$IV\_PassiveDemand_{it} = \log\left(\sum_{h=1}^{4} \frac{A_{ht}}{N_{ht}} \cdot \mathbb{1}_{ith}\right) \tag{3}$$

where A_{ht} is the aggregate amount of assets benchmarked to maturity category h in month t. There are four maturity categories: $h = 1, 2, 3, 4$ corresponding to 10+Y, 5-10Y, 3-5Y, and 1-3Y. The indicator function $\mathbb{1}_{ith}$ equals one if bond i falls into the maturity category h at time t. The denominator, N_{ht}, captures the total number of bonds outstanding for each maturity category. Since a bond can only belong to one maturity category at each time, for a specific bond at a specific time, $\mathbb{1}_{ith}$ can only equal one for one maturity category. Hence, the summation here just helps us assign bonds to the maturity category it belongs to. We take logs to be consistent with the demand-system approach as in Koijen and Yogo (2019).[14]

Similar to the investment universe instrument proposed by Koijen and Yogo (2019), our instrument reflects the investment mandate by maturity-mandated funds. The advantage of our instrument is that the investment mandates for passive funds are observable and exogenous. Specifically, there are three sources of variation in our instrument: (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) most importantly, bond crossing maturity cutoffs (e.g., switch from A_1 to A_2). If the demand gap between two maturity categories is larger (the difference between A_1 and A_2), the value of our instrument will increase more.

Figure 4 illustrates our instrument. Subfigure (a) shows how values of our instrument for each maturity category evolves over time. Note that the pattern of evolution of our

[13]Alternatively, we can weight by book value. The results are robust to this alternative specification.
[14]In untabulated tests, we show that our results remain unchanged if we use levels instead.

instrument closely maps to the pattern in figure 2, which demonstrates that our instrument successfully captures the variation in maturity-mandated passive fund demand. Subfigure (b) plots the average value over time-to-maturity for three sub-sample periods. Note that our instrument is almost flat except around the 10-year, 5-year, and 3-year cutoffs. Noticeably, the jump at the three-year cutoff becomes significantly smaller for the 2018-2022 sub-sample. This reflects the change of maturity mandate by IGSB. Hence, the jump size at each cutoff successfully maps to demand shifts by maturity-mandated passive funds.

[**Insert Figure 4**]

The value of our instrument extends beyond our paper. First, our IV is applicable to many studies about passive fund ownership in the corporate bond market. Having an IV that satisfies the exclusion restriction reasonably well is of great value to establish causality. Additionally, our instrument can be applied to the recent demand-based asset pricing literature. Our IV can help solve the endogeneity problem where the price and investor demand are jointly determined. Using our IV, it is possible to isolate the price change caused by exogenous demand shift by maturity-mandated passive funds and study the price elasticity by other investors.

5 Maturity Cutoffs and Passive Fund Demand

In this section, we provide formal evidence on the passive fund demand shift around maturity cutoffs separating long-term, intermediate-term, and short-term bonds. We then perform placebo tests using other maturity cutoffs and other investor types.

5.1 Passive fund demand around maturity cutoffs

In table 3, we perform regression of discontinuity tests controlling for other bond characteristics and fixed effects. All coefficients are significantly positive at 1% level, indicating that crossing maturity cutoffs significantly increase passive fund demand. The results are robust to which functional forms are used when controlling for the running variable. In untabulated test, we show our results are robust to alternative bandwidth selection.

[Insert Table 3]

Next, we examine the full dynamics of the passive fund demand shifts around the maturity cutoffs using local projection. Figure 5 plots the coefficient estimates from $h = -4$ to $h = 6$ using $t - 1$ as the benchmark. 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 increases by around 0.4% relative to the pre-crossing levels, which translates into $3 million in dollar terms. The magnitude of the effect is large given that the average passive fund ownership is 5.5%.

[Insert Figure 5]

5.2 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 (2) 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 6 summarizes the effects on passive fund holdings two month after the crossing event. The full dynamics of all placebo tests are reported in figure A2 and figure A3. Coefficients estimates for all placebo tests are close to zero and almost always insignificant. The RDD results for all placebo test are reported in table A1 and table A2. All coefficients are insignificant or even negative. Hence, the passive fund demand shift is unique to the three maturity cutoffs we choose.

[Insert Figure 6]

5.3 Demand from other institutional investors

One important requirement for crossing maturity cutoffs to be a valid setting to examine the impact of passive fund demand is that it should not confound with other investors' demand shift. Note that we do not 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 display 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 7 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, as we document in Table 4. 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 holdings gradually. Indeed, to avoid high transaction costs, other investors have an incentive to adjust their portfolios in such a more gradual manner. Hence, their revealed preference for maturity, measured by the average ownership over maturity, will be a smooth function as shown in figure 7.

[Insert Figure 7]

[Insert Table 4]

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

Figure 8, panel (a) illustrates the full dynamics of the yield spread changes around the crossing event using local projection. Relative to the benchmark period $t-1$, there is a significant reduction in yield spread of around 2 bps. Note that the positive price effect only starts reverting after about five months. This is consistent with slow moving capital and inelastic markets. Interestingly, the coefficients are significantly positive before the crossing event, which suggest that the yield spreads are already reduced by about 1 bp at period $t=-1$ relative to the period $t=-2$. This is not surprising given that the crossing event is fully predictable and there may be some front-running trading happening before the actual crossing day. If we choose period $t=-2$ as the benchmark period, the total spread reduction is around 3 bps. This price effect is economically meaningful in view of our exclusive focus on IG bonds, which exhibit an average yield spread of 129 bps in our sample.

[Insert Figure 8]

To better understand the corporate bond price elasticity in face of the passive fund demand shift, we estimate a two-stage least-squares (2SLS) regression, where in the first-stage, changes in passive ownership are instrumented by a dummy variable equal to one for the crossing month only. The detailed specification is as follows:

$$\Delta YieldSpread_{it}^{t-h\rightarrow t+h} = \beta\Delta\widehat{Passive}_{it}^{t-h\rightarrow t+h} + Controls + \alpha_i + \lambda_t + \epsilon_{it}$$
$$\Delta Passive_{it}^{t-h\rightarrow t+h} = \gamma SwitchX_{it} + Controls + \eta_i + \delta_t + u_{it}$$

Essentially, this 2SLS regression scales the cumulative changes in the yield spread by the cumulative changes in passive ownership, which informs us about the price effect given one percentage change in passive ownership, i.e., the price elasticity. Table 5 reports the results. In view of the dynamic pattern illustrated in Figure 9, the horizon h matters for estimating price elasticity. We look at three horizons, $h = 1, 2, 3$. Additionally, we examine the elasticity estimates when we combine all cutoffs and each cutoff separately, respectively. If we combine all cutoffs, for a one percentage increase in passive ownership, the spread reduction is around 6 bps. The estimated effect is smaller for $h = 1$, which suggests $h = 1$ is too short to capture the full price effect. Looking at each cutoff separately, the 10 year cutoff exhibits the largest yield reduction but becomes insignificant for $h = 2$ and $h = 3$. The 5 year cutoff shows the smallest yield reduction, suggesting it exhibits the highest price elasticity. A natural explanation comes from the fact that many intermediate-term passive funds sell at the 5 year cutoff, while for the 10 year and 3 year cutoff, the buying activity dominates. Overall, the results suggest that there is heterogeneity in terms of price elasticity across different maturity cutoffs.

[Insert Table 5]

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 A9 plots the cumulative return on this trading strategy. Table A4 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. The results remain significantly positive at 1% level, suggesting that the abnormal return cannot be absorbed by common factors in the corporate bond market.

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 against passive funds will thus be costly and difficult. Further, 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. Lastly, frictions such as transaction and opportunity costs may also make such trade not profitable.

Figure 9 illustrates the relevance of passive funds' sampling strategies regarding the effects of ex-post purchases of crossing bonds. To capture funds' ex-post purchasing behavior, we define indicator variables $HighPurchase_{it}$ and $LowPurchase_{it}$, respectively, that equal one if a bond's three-month cumulative net passive fund purchase (from $t-1$ to $t+2$) is above or below the median, respectively. To estimate the effect on outcomes variables, we estimate local projections for $h \in [-4, 6]$:

$$\Delta Outcome_i^{t-1\to t+h} = \beta_{h,high} Switch_{it} \times HighPurchase_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

$$\Delta Outcome_i^{t-1\to t+h} = \beta_{h,low} Switch_{it} \times LowPurchase_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}.$$

Figure 9 illustrates the coefficient estimates for changes in passive ownership, as well as yield spread changes. While clearly, passive ownership does not substantially change in case of low ex-post purchases, the effects on yield spreads are substantially muted in this case. This illustrates the risks arbitrageurs face when purchasing bonds ahead of an impending crossing event, as these may not be purchased ex-post. Importantly, in figure A7 we document that the distribution of bond characteristics do not materially differ between high and low purchases, other than the former exhibiting somewhat larger size, thereby making predicting ex-post purchases difficult.

[Insert Figure 9]

Another way arbitrageurs can exploit temporary price pressure is by short-selling treated bonds. Therefore, we also explore the security lending behavior around the maturity cutoffs, as short-selling capacity is a key factor in arbitrage limits (Duffie, Gârleanu, and Pedersen, 2002; Saffi and Sigurdsson, 2011). Following Sikorskaya (2023), we examine changes in supply (lendable shares), demand (short loan quantity), and cost (lending fee) for bonds crossing the maturity cutoffs. The results in figure A10 show a notable increase in short loan quantity and a minor decrease in total lendable shares after crossing the maturity cutoff. Interestingly, we do not observe any significant changes in the lending fee. Furthermore, we analyze price impacts for bonds with different short-selling capacities in figure A11. We split bonds into two groups based on their short-selling capacities six months ago. We find that bonds with more short-selling capacity have weaker price impact and much quicker price reversal. This suggests that investors actively trade against demand-driven temporary price pressure by short-selling bonds to the extent that they are lendable. Our findings are thus consistent with the idea that a higher short-selling capacity reduces market frictions and improves price efficiency.

6.2 Trading volume and liquidity

Figure 8, panel (b) plots the dynamics of trading volume around maturity cutoffs using a similar local projection specification. The dependent variable $\Delta Volume_i^{t-1\to t+h}$ 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 magnitudes, relative to the benchmark period, the trading volume increases by around 10% in the crossing month and 5% in the following month. Additionally, the effects on trading volume quickly revert back to the pre-crossing level after two months, suggesting passive fund demand increases do not necessarily lead to a permanent increase in trading volume. We report the results on trading volume using an RDD specification in the appendix. Consistent with the previous results, the coefficients are only significantly positive for the 10-year cutoff.

Figure 8, panel (c) plots the dynamics of liquidity around the maturity cutoffs. Liquidity is measured using volume-weighted bid-ask spreads. Negative coefficients therefore imply liquidity improvements. Coefficients are significantly negative since the crossing month t.

Further, there is no evidence of reversal. Hence, the results suggest that there are persistent liquidity improvements one month after the passive fund demand shift. In terms of magnitudes, the effect size is around 2 bps, which is substantial given that our sample average bid-ask spread is around 43 bps. We report the results on liquidity using an RDD specification in the appendix. 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.

7 Primary Markets and Firm Policies

In this section, we examine whether the secondary market effects of passive fund demand shifts spill over to the primary market and affect firms' decisions. In other words, we ask whether firms whose bonds experience price pressure in the secondary market through passive demand shocks face different primary market conditions, and whether firms' policies respond to such changes. We first investigate the effects on offering prices and then consider the effects on capital structure, payout, and investment policies. While our analysis was at the bond level thus far, we now aggregate bond-level passive demand shocks at the firm level to examine firm-level outcomes.

7.1 Primary market offering price

We start by examining the effects of passive demand shocks on offering prices in the primary corporate bond market. To do so, we need an instrument for passive fund demand shifts at the firm level. Hence, we construct $IV\_PassiveDemand\_firm$, which is the average of $IV\_PassiveDemand$ for firm i, weighted by the amount outstanding. This captures the firm level passive fund demand shifts caused by bonds switching maturity buckets. We consider the following 2SLS specification:

$$
\begin{aligned}
IssueSpread_{it} &= \beta \widehat{Passive\_firm}_{it} + Controls + FEs + \epsilon_{it} \\
Passive\_firm_{it} &= \gamma IV\_PassiveDemand\_firm_{it} + Controls + FEs + e_{it}
\end{aligned}
\tag{4}
$$

where $IssueSpread_{it}$ 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 $IV\_PassiveDemand\_firm_{it}$. 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 6 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. In the second stage, the coefficients on $Passive\_firm$ are significantly negative across all specifications, which suggests that exhibiting higher passive fund demand leads to lower issuing yield spreads. In other words, firms experiencing passive demand shocks in secondary markets face favorable conditions in primary issuance markets. This result is consistent with the hypothesis that positive secondary demand shifts spill over to the primary market and lead to lower financing costs. In terms of magnitude, for a one percentage increase in total firm-level passive demand, there is about a 20 bps reduction in the primary market issuance spread. Given that the median firm in our sample has five outstanding bonds, the spread reduction for one percentage increase in bond-level passive demand is about 4 bps. Combined with the 6 bps spread reduction in the secondary market, this roughly translates into 66% transmission rate from the secondary market to the primary market.

[**Insert Table 6**]

7.2 Implications for firm policies

It is natural to conjecture that firms facing favorable conditions in primary markets in response to passive demand shocks will take advantage of those and respond by adjusting their policies. We next provide formal empirical evidence to these effects.

To zoom in on the effects of demand shocks at the firm level, we adopt an event study framework to link demand shocks to firm level outcomes. For firm i in quarter t, we define a passive fund demand shock (captured by an indicator variable $PassiveShock_{it} = 1$) if there is at least one bond outstanding that crosses the 10Y, 5Y, or 3Y cutoffs ($Switch = 1$), and the change of passive fund holding is above the median ($HighPurchase = 1$). We then estimate the following regression model:

$$\Delta Outcome_{it} = \beta PassiveShock_{it} + Controls_{it} + FirmFE + TimeFE + \epsilon_{it}.$$

We focus on bonds with high net passive fund purchases because including bonds with low net passive fund purchases will underestimate our effect. Only firms with high ex-post passive fund purchases experience passive demand shocks. This will not affect the exogeneity of our setting as long as passive funds' purchase decisions are not made based on the prediction of future firm outcomes. Our previous empirical evidence suggests that passive funds decide which bond to purchase mainly based on the past trading volume, which is mostly exogenously determined by bond characteristics and uncorrelated with future firm performance (see figure A7).

Table 7, panel (a) reports the results. The coefficients on the dollar amount of bonds outstanding and the number of bonds outstanding are significantly positive, suggesting that firms who experience positive passive demand shock take advantage of the lower issuance cost and issue more bonds. In that sense, passive bond demand triggers active bond supply.

Moreover, the increase in the number of outstanding bonds suggests that firms issue more bonds instead of just rolling over existing ones. The coefficients on long-term debt and leverage are all significantly positive, suggesting that the passive demand shock has real effects on firms' capital structure. Notably, firms facing positive passive demand shocks reduce their bank debt. In view of the existing evidence that bank loans are usually more expensive (Schwert, 2022), our findings suggest that firms take advantage of the higher demand in the corporate bond market and use the proceeds to substitute expensive bank debt with cheaper bond debt.

[Insert Table 7]

To illustrate, we also test the dynamic effects using a regression model similar to the multiperiod difference-in-difference specification used in Hotchkiss, Sun, Wang, and Zhao (2022). We estimate the following specification:

$$Outcome_{it} = \sum_{j=-4}^{j=4} \beta_j PassiveShock_{i,t+j} + Controls_{it} + FirmFE + TimeFE + \epsilon_{it}$$

Period $t = -4$ is omitted as a benchmark, i.e., all effects are relative to the period $t = -4$. Those results are presented in figure 10.[15] To further stress the importance of ex-post purchases of crossing bonds by passive funds, we also run 'placebo-like' tests using the corresponding empirical designs with firms (captured by the indicator variable $PlaceboShock_{it} = 1$) that have at least one bond outstanding that crosses the 10Y, 5Y, or 3Y cutoffs ($Switch = 1$), and whose change of passive fund holding is below the median ($LowPurchase = 1$). In other words, in these tests, we focus on firms that had crossing bonds outstanding, but that mostly did not end up being purchased by passive funds ex-post. We should expect to see significantly weaker or no effects as these firms face weak or no passive demand shock. The corresponding results are in table 7, panel (b) and figure 11.

[15]Results on the firm-level passive ownership are reported in figure A8

Figure 10 documents a number of notable patterns. We find that firms experiencing a passive demand shock, that is, firms whose outstanding crossing bonds are materially purchased in secondary markets, respond by significantly increasing both the value and the number of bonds, predominantly in the longer end of the maturity spectrum, resulting in a significant increase in leverage (upper panel). These effects do not reverse in the short run. At the same time, intriguingly, these firms experience a significant reduction in bank debt (lower panel, leftmost figure). Additionally, there is no evidence of reversal four quarters after the demand shock, indicating that the change in debt structure is persistent. This pattern is consistent with firm policies exploiting favorable financing conditions in bond markets to substitute bank debt with 'cheaper' bond financing. The remaining figures in the lower panel shed light on the question of what firms do with the resulting proceeds. The cash holdings spike at period 0 and quickly revert after two quarters. The coefficients for the payout ratio become weakly significant one quarter following the passive demand shock. These results suggest that firms significantly increase their cash holdings in the short run, and then use parts of the proceeds to increase payout. On the other hand, there is no discernible effect on the average firm's investment. Our results thus suggest that for the average firm, passive demand shocks in secondary markets mostly lead to restructuring of their capital and debt structures' away from bank debt. In that sense, our results suggest that firms engage in debt market timing.

[Insert Figure 10]

Intriguingly, our 'placebo' tests in figure 11 illustrate that firms with crossing bonds that do not end up being bought by passive funds, do not respond materially to crossing events. Indeed, none of the corresponding estimates are statistically significant. This suggests, therefore, that price pressure through passive fund buying in secondary markets causes treated firms' responses.

[Insert Figure 11]

These results are paralleled in table 7 panel (b). Indeed, we confirm significant changes in debt structures towards long-term bonds away from bank debt for firms experiencing passive demand shocks. In turn, firms experiencing a placebo shock, show no significant changes.

Our results thus far address policies of the average firm experiencing passive demand shocks, and show that they respond to the ensuing favorable financing conditions. It is natural to conjecture that firms facing financial constraints may benefit more from lower offering yields. In table 8, we document some evidence to that effect. We define firms to be constrained if they exhibit lagged Whited-Wu (WW) indexes (Whited and Wu, 2006) in the top tercile of the overall distribution and estimate the effects of financial constraints on firm outcomes in our event study framework by interacting $PassiveShock$ with an indicator variable for financial constraints. The results are in Table 8. Indeed, in line with the above reasoning, constrained firms are especially prone to take advantage of favorable financing conditions in the corporate bond market and significantly increase their bond debt while reducing their bank debt, above and beyond the patterns documented for average firms. Interestingly, for the number of bonds outstanding, the coefficient of the interaction term is significantly negative. This indicates that despite a higher increase in total dollar amount outstanding, constrained firms issue fewer new bonds than unconstrained firms. One potential explanation is that it may be harder for constrained firms to issue additional new bonds. Instead, constrained firms are more likely to refinance the existing bonds with larger bonds. Another possible explanation is that when constrained firms have the chance to issue new bonds, they tend to issue larger ones. Notably, however, for constrained firms, we find no effect on total leverage, so that these results mostly amount to a restructuring of the debt structure towards temporarily cheaper bond financing, in the spirit of debt market timing.

[Insert Table 8]

Our previous results do not show any discernible effects of passive demand shocks on firms' investment. If anything, average firms use the proceeds of bond issuance to repay bank debt, increase their cash buffers, and increase their payouts. However, unless financial constraints prevent firms from undertaking investment projects, there are no obvious reasons why firms' investment policies should respond to favorable financing conditions in bond markets. In table 9, we show that firms' responses are significantly shaped by financial constraints. Indeed, the positive significant interaction terms of $PassiveShock$ with the financial constraints indicator shows that relative to the unconstrained firms, constrained firms increase their investment and cash holdings more in response to passive demand shocks. Interestingly, the interaction term coefficient is significantly negative for the payout ratio, suggesting that constrained firms are less likely to use the proceeds to increase payout. Overall, our results thus provide causal evidence that non-fundamental demand shocks have more substantial real effects in the presence of financial constraints.

[**Insert Table 9**]

8 Conclusion

This paper introduces 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, as well as persistent liquidity improvements. Second, passive fund demand shocks spill over to the primary market, causing lower issuing yield spreads, and firms engaging in debt market timing by substituting expensive bank debt with cheaper bond financing. We provide causal evidence that non-fundamental demand shocks can have real effects in that constrained firms use issuance proceeds to fund investment.

Our empirical framework provides a novel identification strategy that allows to assess the impact of passive demand on financial markets. Understanding the effects of passive demand is important in view of the prominent rise in capital allocated to passive funds in recent years and in view of ongoing regulatory changes related to the activity of passive funds in fixed income markets. Indeed, the SEC's move to adopt a firmer stance on cross-trading in bond markets may, in light of our findings, exacerbate price pressure that investors take advantage of when loanable bonds are available for short-selling. Our findings thus strongly suggest that the regulatory changes spearheaded by the SEC significantly affect the execution of passive trading strategies in bond markets.

Panel A: Market size

Panel B: Average ownership by institution

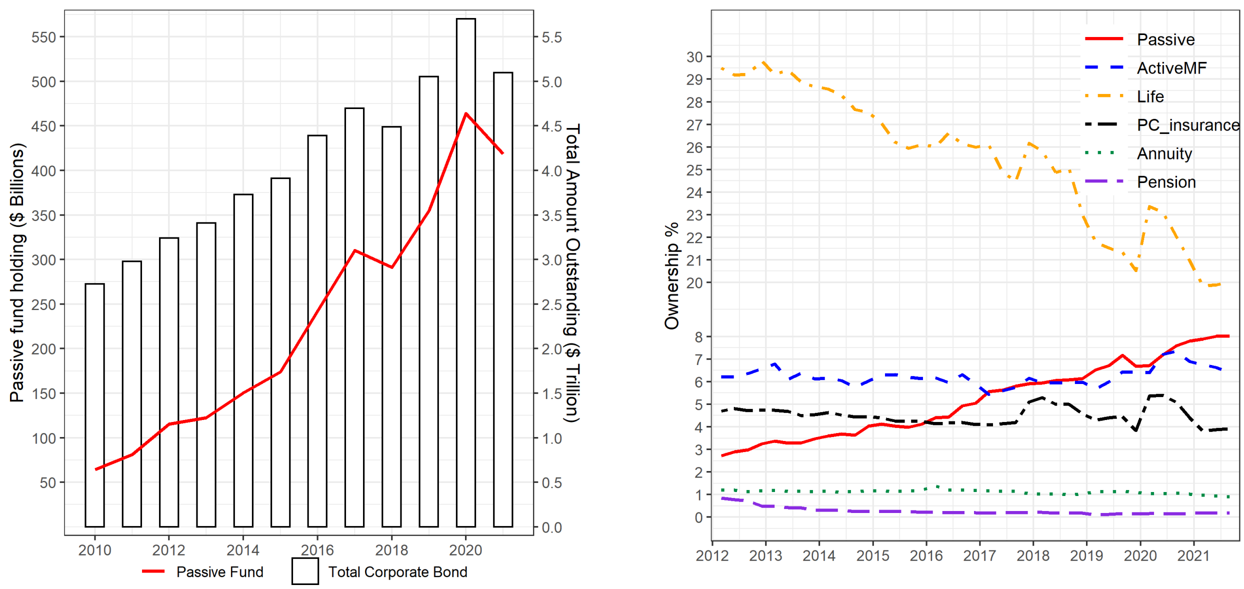


Figure 1: Evolution of the corporate bond market

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 of shares 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

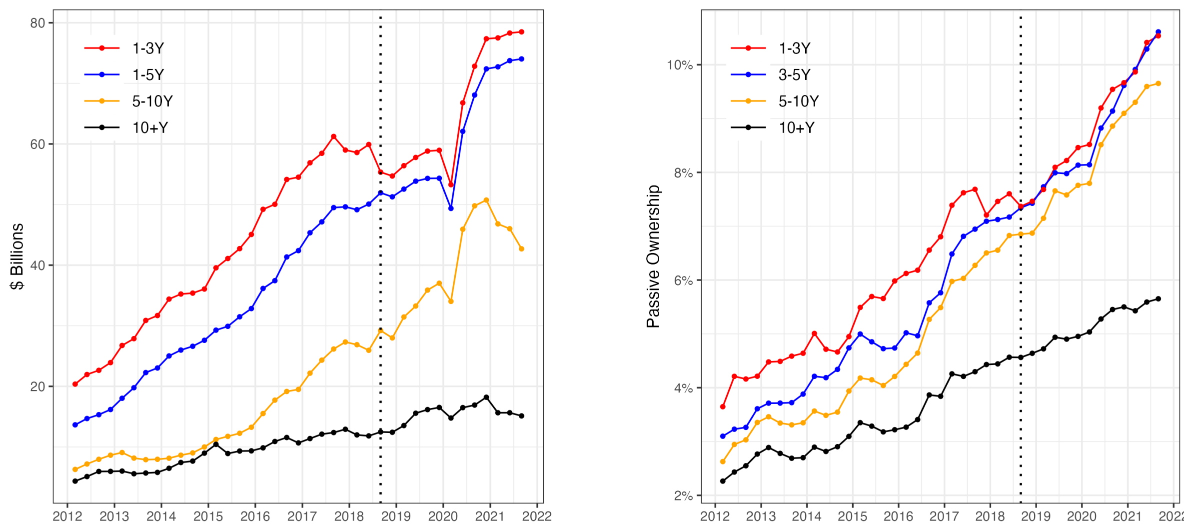
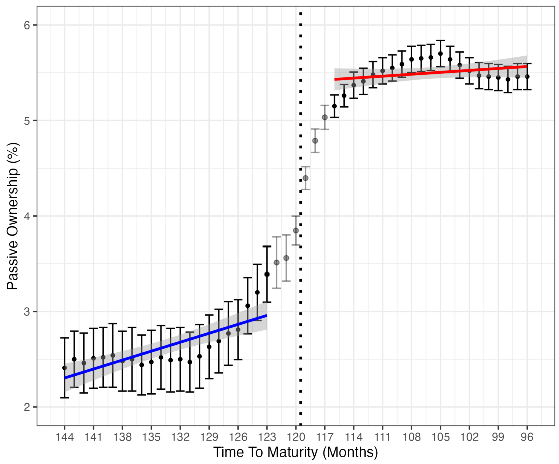


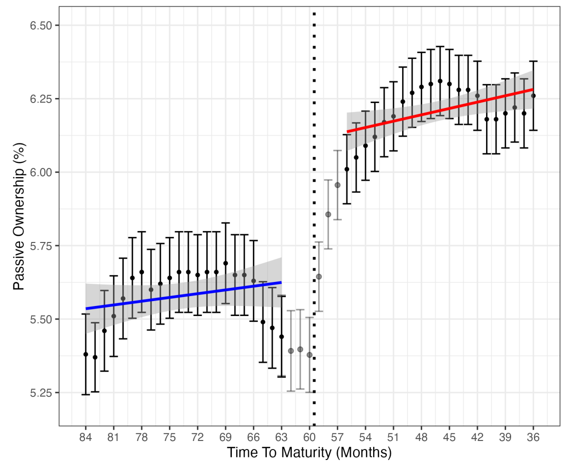
Figure 2: Maturity-mandated passive funds

Panel A plots the time series of the aggregate corporate bond holdings by passive funds that track each maturity category. There are four maturity categories: 10+Y, 5-10Y, 1-5Y, and 1-3Y. Panel B plots the average passive fund ownership over time for each maturity bucket. The vertical line marks September 2018, when a major corporate bond ETF (IGSB) changed its maturity mandate from 1-3 years to 1-5 years.

(a) 10 Year



(b) 5 Year



(c) 3 Year

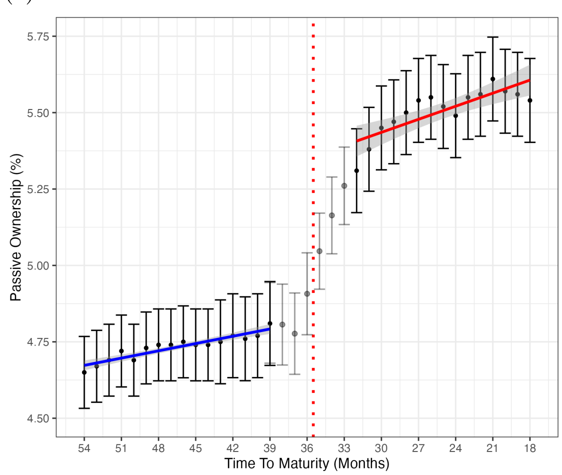
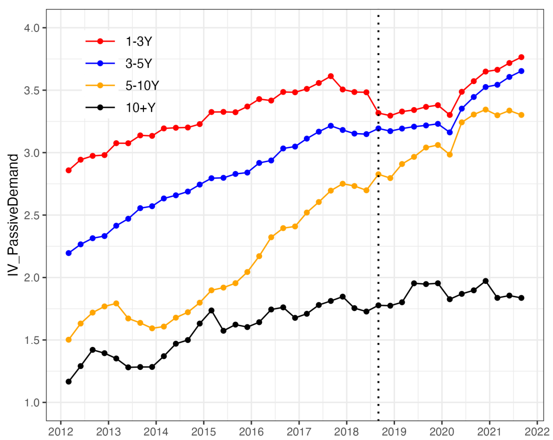


Figure 3: Passive fund ownership around maturity cutoffs

These figures plot the passive fund ownership around the three maturity cutoffs. Sub-figures (a) to (c) correspond to the 10-year, 5-year, and 3-year maturity cutoffs, respectively. The y-axis is the average passive ownership for bonds for every time-to-maturity. The error bars represent the 95% confidence interval. The dotted vertical lines indicate the three maturity cutoffs. The x-axis is the time-to-maturity in months, decreasing from left to right. The linear trends are estimated using the samples on the left and right of the cutoff, excluding the six months surrounding the cutoff.

(a) $IV\_PassiveDemand$ over time



(b) $IV\_PassiveDemand$ over maturity

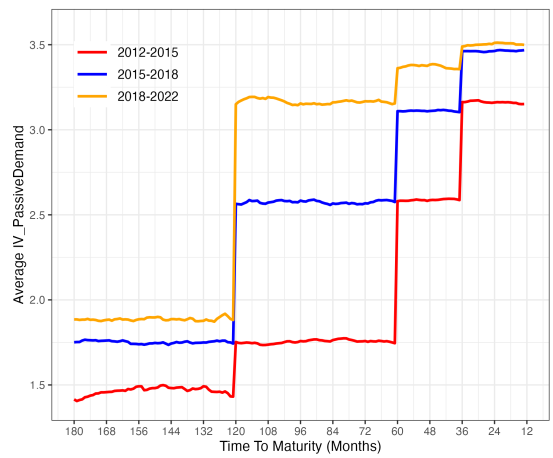


Figure 4: Instrumental variables for passive demand

Subfigure (a) plots the $IV\_PassiveDemand$ over time for each maturity bucket. The vertical line marks September 2018, when IGSB changed its maturity mandate from 1-3 years to 1-5 years. Subfigure (b) plots the average $IV\_PassiveDemand$ over time-to-maturity for three sub-sample periods: 2012-2015, 2015-2018, 2018-2022.

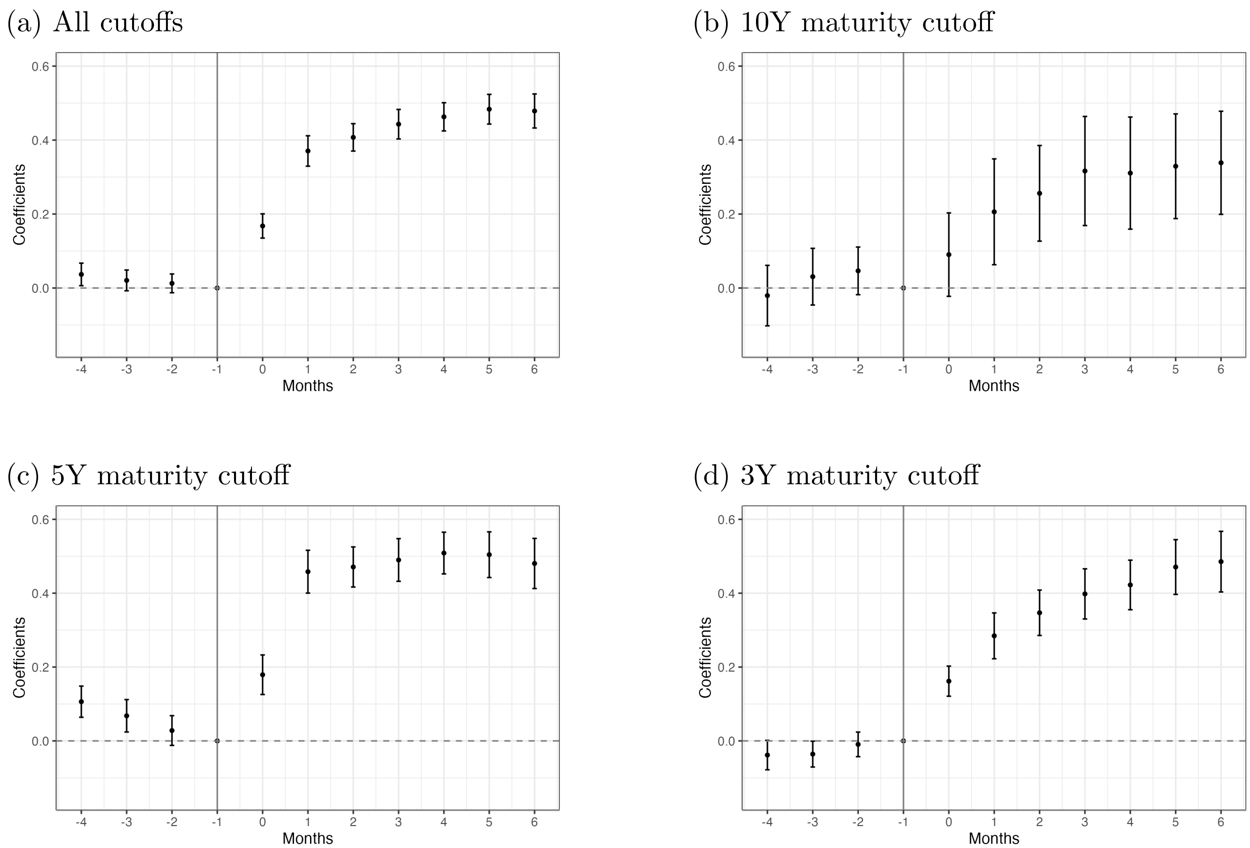


Figure 5: Passive fund ownership dynamics and crossing maturity cutoffs

This figure plots β_h estimated 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 change of passive fund ownership for bond i from $t-1$ to $t+h$. The vertical line represents the benchmark, which is one month before the crossing event, $t-1$. $SwitchX_{it}$ 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 95% confidence interval, where standard errors are clustered at both the bond and year-month levels.

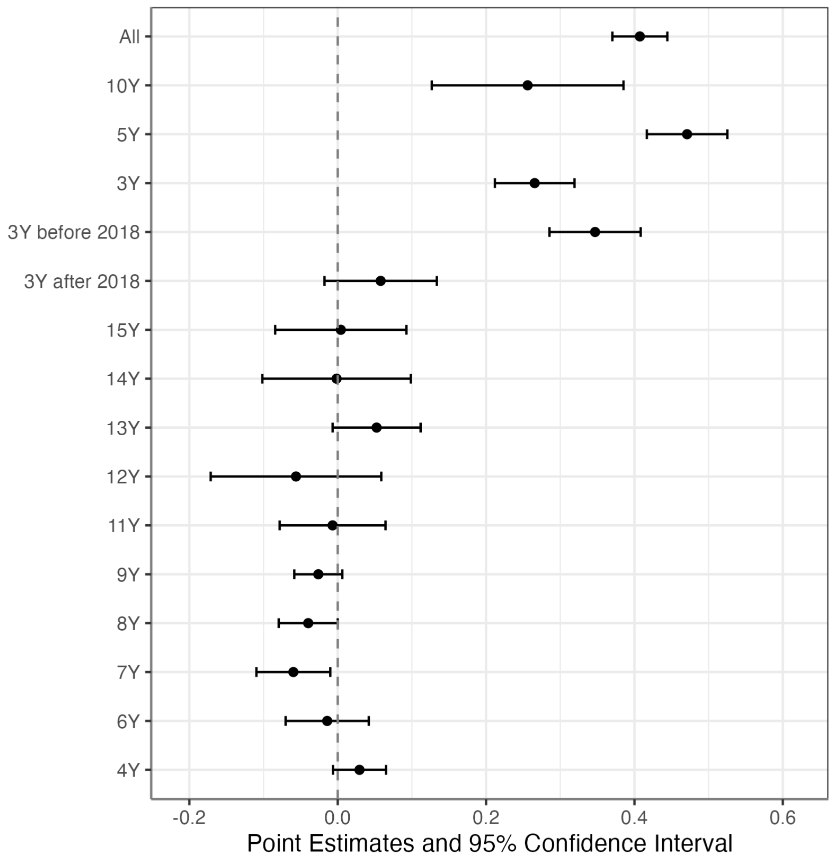


Figure 6: Summary of point estimates for all maturity cutoffs

This figure summarizes the effects of crossing different maturity cutoffs on passive fund demand. The figure plots point estimates β_X 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 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 95% confidence interval, where standard errors are clustered at both the bond and year-month levels.

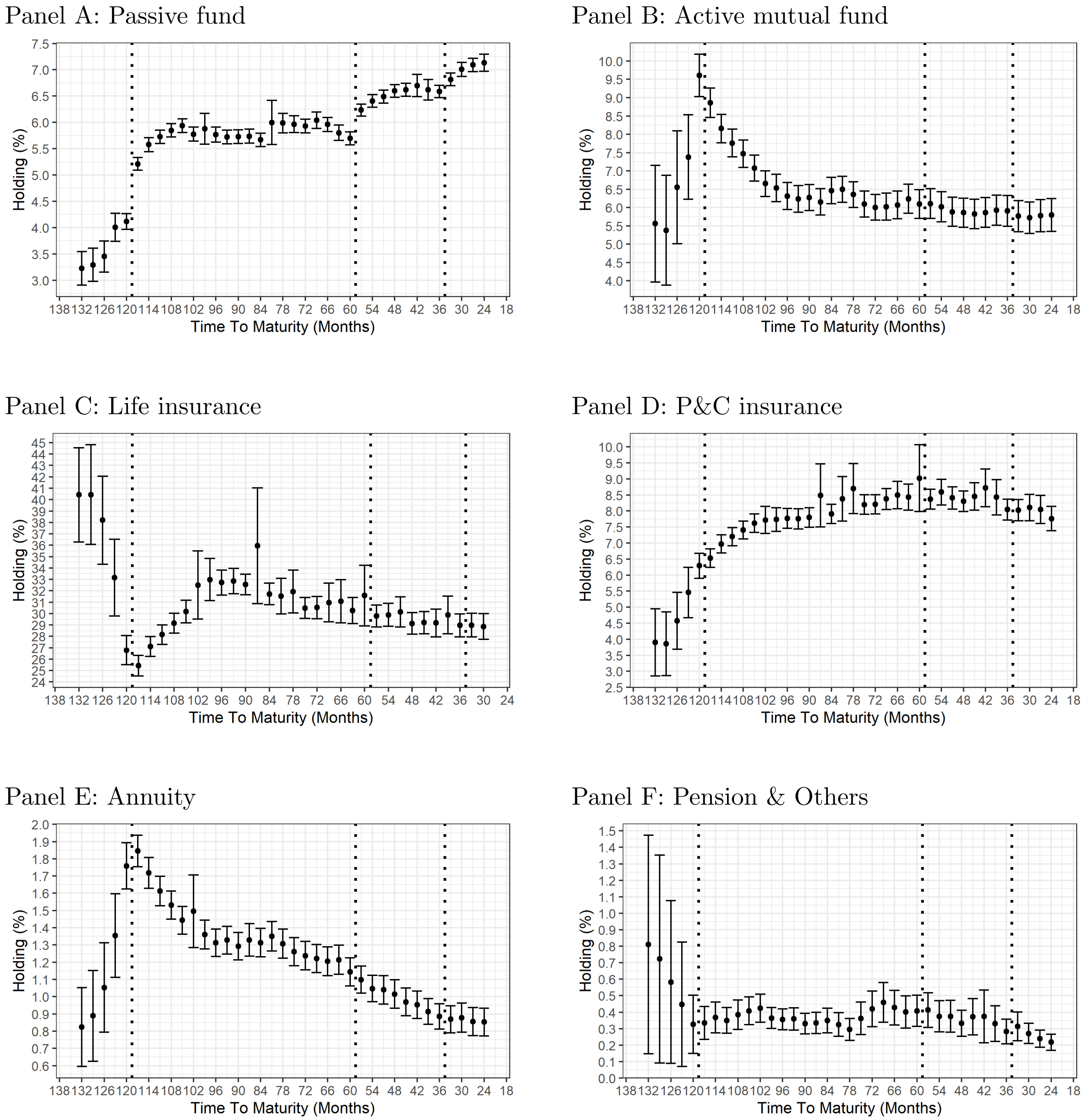
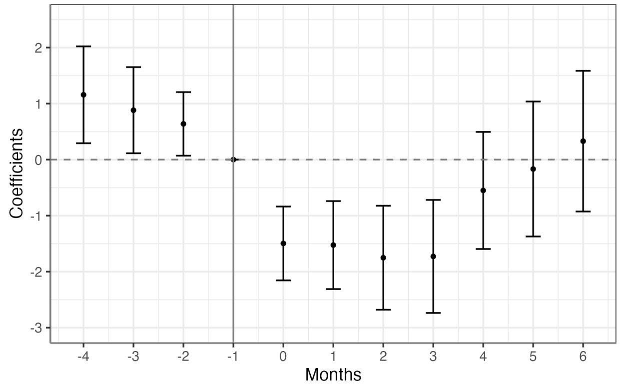


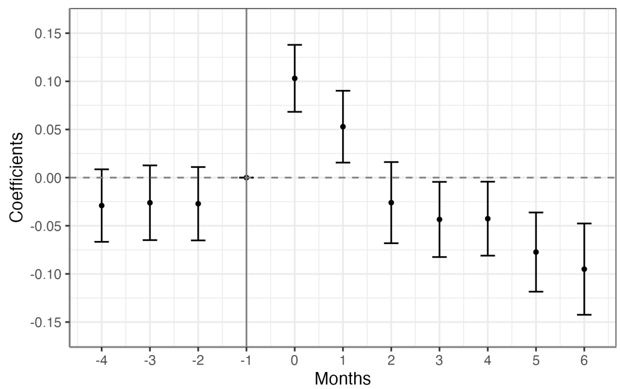
Figure 7: Corporate bond ownership over maturity by investor types

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 months. 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. Panel A to F correspond to passive funds, active mutual funds, life insurance, P&C insurance, variable annuity, and pension funds.

(a) Yield Spread



(b) Trading Volume



(c) Bid-Ask Spread

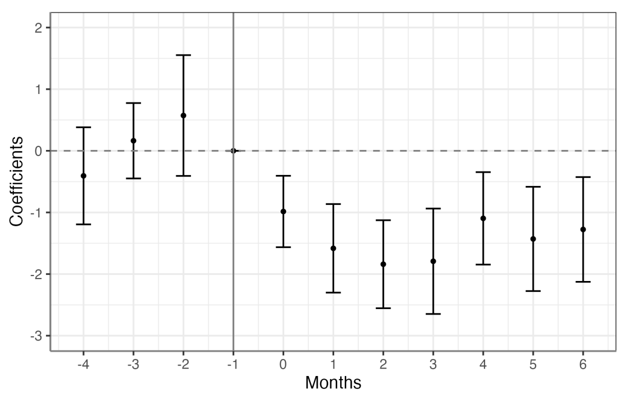


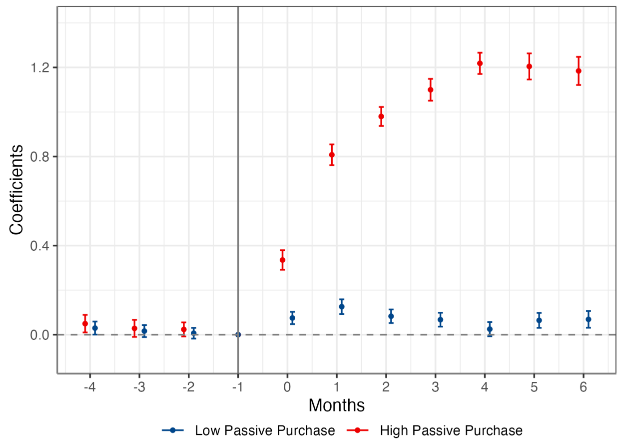
Figure 8: Secondary market activities and passive fund demand

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

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

where $\Delta Outcome_i^{t-1 \to t+h}$ is the change of outcome variables for bond i from $t-1$ to $t+h$. Outcome variables for subfigures (a) to (c) correspond to yield spread, trading volume, and bid-ask spread. Error bars represent the 90% confidence interval.

(a) Passive fund ownership



(b) Yield spread

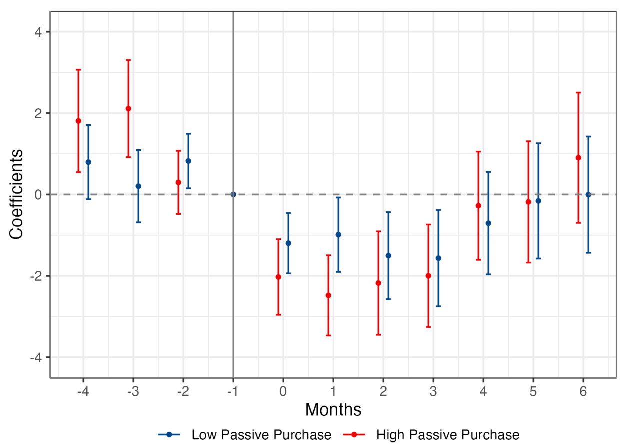


Figure 9: High vs. low passive fund purchase

This figure plots the coefficient estimates $\beta_{h,high}$ and $\beta_{h,low}$ from the following regression for $h \in [-4, 6]$:

$$\Delta Outcome_i^{t-1 \to t+h} = \beta_{h,high} Switch_{it} \times HighPurchase_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

$$\Delta Outcome_i^{t-1 \to t+h} = \beta_{h,low} Switch_{it} \times LowPurchase_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

$HighPurchase_{it}$ is an indicator variable equals to one if the three-month cumulative net passive fund purchase (from $t-1$ to $t+2$) is above the median. $LowPurchase_{it}$ is an indicator variable equals to one if the three-month cumulative net passive fund purchase (from $t-1$ to $t+2$) is below the median. $\Delta Outcome_i^{t-1 \to t+h}$ is the change of outcome variables for bond i from $t-1$ to $t+h$. Outcome variables for subfigures (a) to (b) correspond to passive ownership and yield spread. Error bars represent the 90% confidence interval.

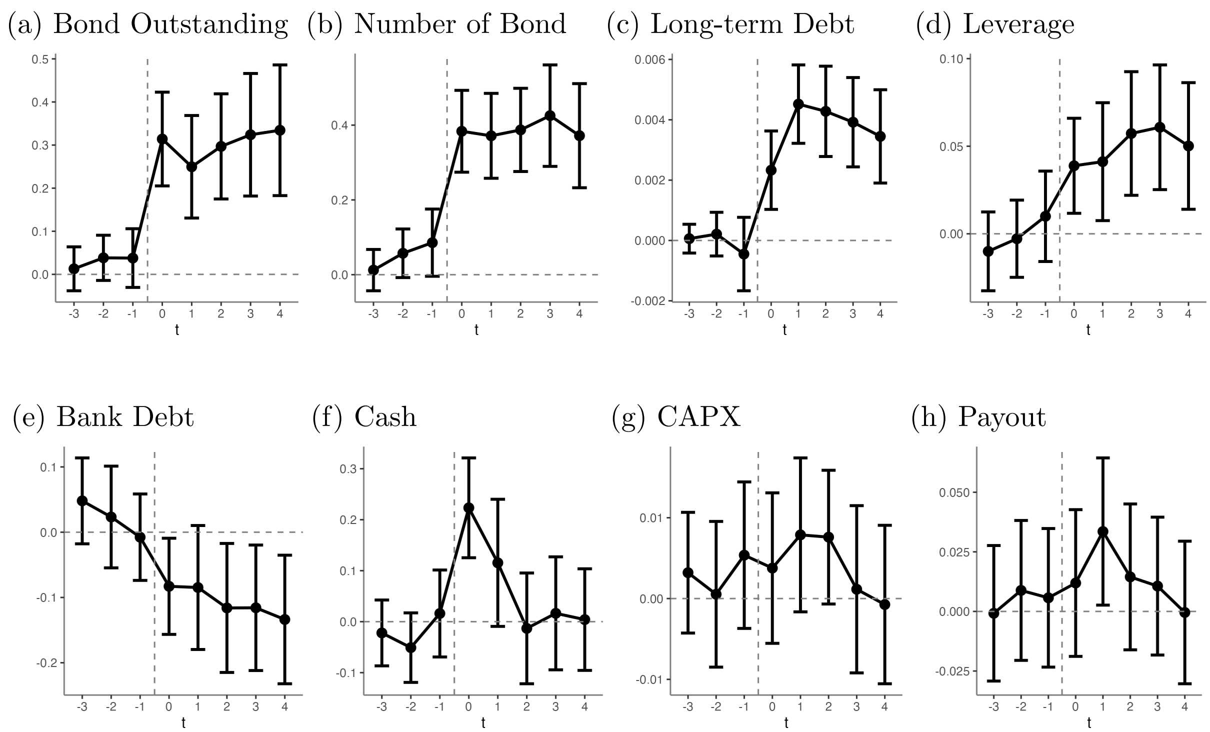


Figure 10: Real effects of passive fund demand shock

This figure plots the dynamic effect of passive fund demand shock on the capital structure. For firm i at quarter t, we define a passive fund demand shock ($PassiveShock_{it} = 1$) if (1) there is at least one bond crosses the 10Y, 5Y, or 3Y cutoffs ($Switch_{it} = 1$) and (2) three-month cumulative passive fund net purchase is above the median ($HighPurchase = 1$). We then estimate the following specifications:

$$Outcome_{it} = \sum_{j=-4}^{j=4} \beta_j PassiveShock_{i,t+j} + Controls_{it} + FirmFE + TimeFE + \epsilon_{it}$$

The benchmark period is $t = -4$. Subfigure (a) to (f) plots β_j for total bond outstanding, number of bonds outstanding, all long-term debt, leverage ratio, bank debt, cash holdings, CAPX, and payout ratio. Firm fixed effects and industry-by-time fixed effects are used for all specifications. Standard errors are clustered at time and firm levels. Error bars represent 90% confidence interval.

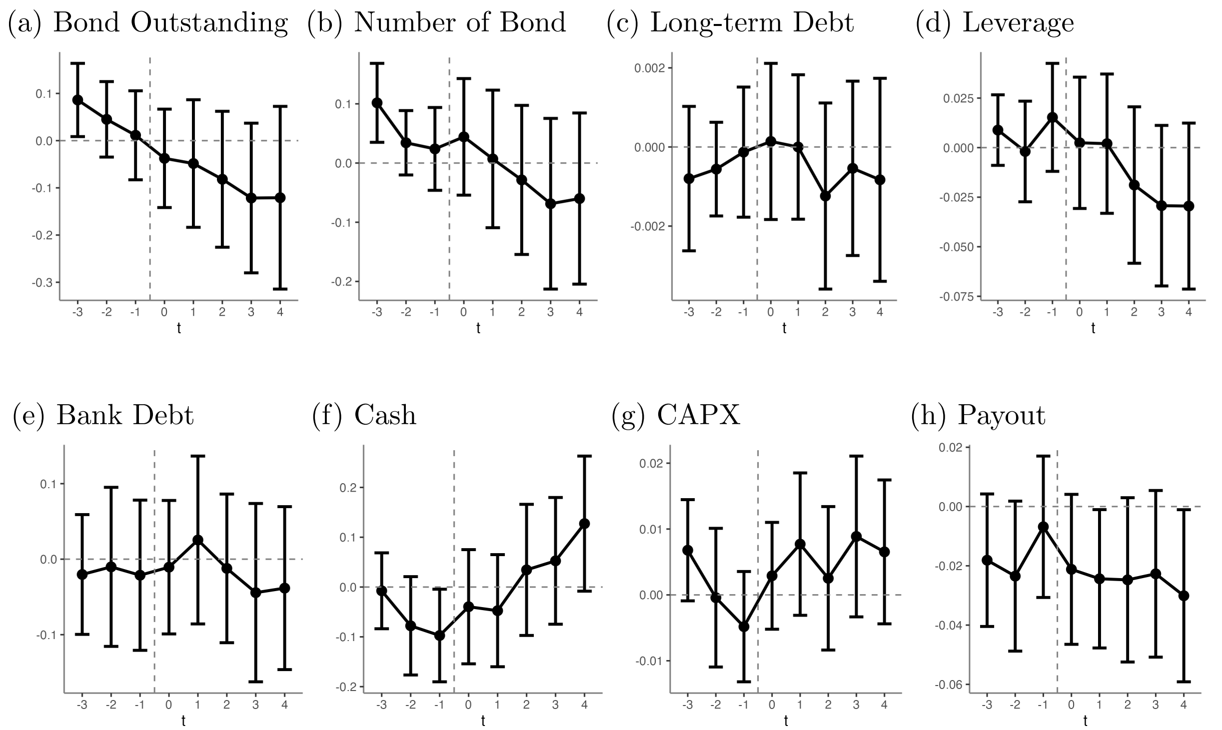


Figure 11: Placebo tests on capital structure

This figure plots the placebo test results on capital structure. For firm i at quarter t, we define a placebo shock ($PlaceboShock_{it} = 1$) if (1) there is at least one bond crosses the 10Y, 5Y, or 3Y cutoffs ($Switch_{it} = 1$) and (2) the change of passive fund holding is below the median ($LowPurchase_{it} = 1$).

$$Outcome_{it} = \sum_{j=-4}^{j=4} \beta_j PlaceboShock_{i,t+j} + Controls_{it} + FirmFE + TimeFE + \epsilon_{it}$$

The benchmark period is $t = -4$. Subfigure (a) to (f) plots β_j for total bond outstanding, number of bonds outstanding, all long-term debt, leverage ratio, bank debt, cash holdings, CAPX, and payout ratio. Firm fixed effects and industry-by-time fixed effects are used for all specifications. Standard errors are clustered at time and firm levels. Error bars represent 90% confidence interval.

Table 1: Summary Statistics

Panel A reports summary statistics for the monthly corporate bond sample. Panel B reports the summary statistics for corporate bond ownership by different investor types from the quarterly bond-level sample. Panel C reports the summary statistics for firm characteristics from the quarterly firm-level sample.

Variable	N	Mean	SD	P25	Median	P75
Panel A: Monthly bond-level sample						
Passive (%)	539309	5.52	3.6	2.61	4.96	7.60
10+Y	184556	3.96	2.70	1.81	3.90	5.82
5-10Y	161089	5.60	3.56	2.91	5.21	8.07
3-5Y	92934	6.25	3.91	3.31	6.01	8.97
1-3Y	100730	6.53	3.97	3.49	6.41	9.26
$\Delta Passive$ (%)	12464	0.71	1.23	0.01	0.47	1.18
10+Y to 5-10Y	3036	0.86	1.09	0.01	0.54	1.40
5-10Y to 3-5Y	4360	0.78	1.28	0.02	0.56	1.29
3-5Y to 1-3Y	5068	0.55	31.25	0.01	0.38	0.96
Yield spread (%)	539309	1.29	0.85	0.65	1.15	1.73
10+Y	184556	1.87	0.75	1.34	1.71	2.23
5-10Y	161089	1.29	0.74	0.78	1.12	1.59
3-5Y	92934	0.88	0.68	0.45	0.71	1.08
1-3Y	100730	0.60	0.58	0.23	0.46	0.76
Ratings	539309	7.39	1.95	6.00	8.00	9.00
Outstanding ($M)	539309	713.58	640.92	339.67	500.00	850.00
Log trading volume	539309	16.08	1.96	14.99	16.39	17.47
Bid-ask spread (bps)	539309	42.7	44.9	15.5	30.36	55.04
Time-to-maturity	539309	133.22	122.21	43.00	84.00	230.00
Panel B: Quarterly bond-level sample						
Active MF (%)	144655	4.64	6.33	1.71	4.37	8.74
Life insurance (%)	147549	23.59	28.49	11.94	23.36	36.46
PC insurance (%)	145779	4.69	6.08	1.83	4.59	8.12
Annuity (%)	143529	0.77	1.36	0.27	0.69	1.58
Pension fund (%)	110508	0.18	0.82	0.05	0.16	0.40
Panel C: Quarterly firm-level sample						
Passive_firm (%)	20715	4.88	2.67	3.11	4.53	6.66
Total bond ($M)	20715	6352.22	11657.07	900	2350	6383.75
Number of bond	20715	8.72	10.3	2	5	11
Long-term debt ($M)	20715	20.32	61.47	2.1	5.07	13.39
Leverage	20715	3.82	3.02	2.01	2.56	3.97
Bank debt ($M)	8240	551.76	1101.12	0.75	3.61	550
CAPX	20715	0.84	0.87	0.09	0.56	1.34
Cash	20715	9.29	10.84	2.03	5.56	12.54
Payout	20715	0.97	1.89	0.00	0.34	1.26

Table 2: Maturity-mandated passive funds

This table lists the maturity-mandated ETFs and index mutual funds that invest in the corporate bond market. 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 ETF and mutual fund share class. Column (5) reports the aggregate AUM that tracks 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: RDD tests on Passive fund ownership around maturity cutoffs

This table compares the passive fund ownership before and after a bond crosses the maturity cutoff. We report the results for the following RDD specifications:

$$Passive_{it} = \beta I(PassX)_{it} + f(TTM_{it} - X) + Contrls + \alpha_i + \lambda_t + +\epsilon_{it}.$$

We compare passive fund ownership before and after 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 X at the time t. $TTM - X$ is the distance between time-to-maturity and the cutoff X. $f(TTM - X)$ is a function of the distant variable: columns (1), (4), and (7) use linear function, columns (2), (5), (8) allow different slopes before and after the cutoff, columns (3), (6), and (9) use cubic function. Control variables include the contemporaneous bid-ask spread, credit rating, and the log amount outstanding in par value. Time fixed effects and bond fixed effects are included in all regressions. The bandwidth is ±6 month. 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.

	10Y			5Y			3Y		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$I(Pass10Y)$	0.265***	0.129**	0.184***						
	(0.048)	(0.057)	(0.056)						
$I(Pass5Y)$				0.453***	0.368***	0.336***			
				(0.027)	(0.025)	(0.025)			
$I(Pass3Y)$							0.127***	0.067***	0.070***
							(0.021)	(0.023)	(0.019)
Bandwidth	±6	±6	±6	±6	±6	±6	±6	±6	±6
Functional Forms	Linear	Diff Slopes	Cubic	Linear	Diff Slopes	Cubic	Linear	Diff Slopes	Cubic
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,103	6,103	6,103	40,105	40,105	40,105	51,402	51,402	51,402
Adjusted R^2	0.962	0.963	0.963	0.951	0.951	0.952	0.952	0.952	0.952

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

Table 4: RDD tests on ownership by different investor types

This table compares the corporate bond ownership of different investor types before and after a bond crosses the maturity cutoffs. We report the results for the following RDD specifications:

$$Ownership_{it} = \beta I(PassX)_{it} + f(TTM_{it} - X) + Controls + \alpha_i + \lambda_t + \epsilon_{it}.$$

We compare ownership by different investor types before and after crossing the 10Y, 5Y, and 3Y maturity cutoffs. The dependent variable, $Onwership_{it}$, is the total percentage share of bond i owned by each investor type: active mutual funds, life insurance, PC insurance, variable annuity, and pensions & others. $I(PassX)_{it}$ is a dummy variable equal to one if bond i has crossed the respective maturity cutoff X at the time t. $TTM - X$ is the distance between time-to-maturity and the cutoff X. $f(TTM - X)$ is a function of the distant variable. Control variables include the contemporaneous bid-ask spread, credit rating, and the log amount outstanding in par value. Time fixed effects and bond fixed effects are included in all regressions. The bandwidth is ±6 month. 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.

	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)
Bandwidth	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6	± 6
Functional Forms	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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 5: Price elasticity

This table studies the price elasticity of corporate bonds that crosses the maturity cutoffs. We report the results for the following 2SLS regression:

$$\Delta YieldSpread_{it}^{t-h\to t+h} = \beta \Delta \widehat{Passive}_{it}^{t-h\to t+h} + Controls + \alpha_i + \lambda_t + \epsilon_{it}$$
$$\Delta Passive_{it}^{t-h\to t+h} = \gamma SwitchX_{it} + Controls + \eta_i + \delta_t + u_{it}$$

In the first stage, we use $SwitchX_{it}$ to instrument the change of passive ownership from period $t-h$ to $t+h$, $\Delta Passive_{it}^{t-h\to t+h}$, where $SwitchX_{it}$ is an indicator variable equals to one if bond i cross the maturity cutoff X at month t. Maturity cutoffs include 10 years, 5 years, 3 years, and combinations of all three cutoffs. In the second stage, we regress the change of yield spread from period $t-h$ to $t+h$ on the instrumented change of passive ownership. Columns (1) to (4) correspond to $h=1$, columns (5) to (8) correspond to $h=2$, and columns (9) to (12) correspond to $h=3$. Control variables include the contemporaneous bid-ask spread, credit rating, and the log amount outstanding in par value. Time fixed effects and bond fixed effects are included in all regressions. Both Cragg-Donald F-Statistics and Kleibergen-Paap F-Statistics are reported. Standard errors clustered at the bond and month levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	Second Stage: $\Delta YieldSpread_{it}^{t-h\to t+h}$											
	$t-1\to t+1$				$t-2\to t+2$				$t-3\to t+3$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	10Y	5Y	3Y	All	10Y	5Y	3Y	All	10Y	5Y	3Y
$\Delta Passive$	-4.130^{***}	-20.943^{**}	-1.930	-6.742^{***}	-6.045^{***}	-17.289	-3.920^{**}	-8.435^{***}	-6.218^{***}	-12.350	-4.278^{**}	-8.189^{***}
	(1.325)	(10.322)	(1.463)	(2.203)	(1.543)	(15.261)	(1.839)	(2.259)	(1.767)	(12.210)	(2.041)	(2.259)
	First stage: $\Delta Passive_{it}^{t-h\to t+h}$											
	$t-1\to t+1$				$t-2\to t+2$				$t-3\to t+3$			
	All	10Y	5Y	3Y	All	10Y	5Y	3Y	All	10Y	5Y	3Y
$SwitchX$	0.369^{***}	0.391^{***}	0.406^{***}	0.201^{***}	0.186^{***}	0.194^{***}	0.459^{***}	0.441^{***}	0.420^{***}	0.281^{***}	0.351^{***}	0.405^{***}
	(0.021)	(0.018)	(0.023)	(0.073)	(0.059)	(0.068)	(0.030)	(0.024)	(0.034)	(0.032)	(0.034)	(0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cragg-Donald F-Statistic	939.9	15.6	739.5	240.4	664.1	7.3	430.3	239.1	544.1	5.8	297.3	244.1
Kleibergen-Paap F-Statistic	310	7.6	240.2	79	484.1	10	326.7	103.4	313.2	8	148.8	106.4
Observations	517,432	517,432	517,432	517,432	495,807	495,807	495,807	495,807	474,419	474,419	474,419	474,419

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

Table 6: Primary market offering spread

This table studies how passive demand affects bond offering yield spread in the primary market. We report the results from the following 2SLS specifications:

$$IssueSpread_{it} = \beta \widehat{Passive\_firm}_{it} + Controls + FEs + \epsilon_{it}$$

$$Passive\_firm_{it} = \gamma IV\_PassiveDemand\_firm_{it} + Controls + FEs + e_{it}$$

$IssueSpread_{it}$ is the offering yield spread of bond i at quarter t. $Passive\_firm$ is the average percentage of passive fund ownership for firm i's outstanding corporate bonds, weighted by the amount outstanding. In the first stage, $Passive\_firm$ is instrumented using $IV\_PassiveDemand\_firm_{it}$, which is the average of $IV\_PassiveDemand_{it}$, 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 absorbs any industry-specific trend, rating-by-year FE absorbs time-varying differences in yield spreads across different rating categories (rating categories are defined as AAA-AA, A, and BBB), maturity-by-year FE absorbs 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: $IssueSpread_{it}$					
	(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)
$IV\_PassiveDemand\_firm_{it}$	0.574^{***}	0.576^{***}	0.566^{***}	0.571^{***}	0.566^{***}	0.561^{***}
	(0.118)	(0.118)	(0.119)	(0.115)	(0.119)	(0.116)
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
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
Observations	3,314	2,936	3,314	2,936	3,314	2,936

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

Table 7: Real effects of passive demand on firm capital structure

This table studies the effect of passive fund demand shock on the firms' capital structure. For firm i at quarter t, we define a passive fund demand shock ($PassiveShock_{it} = 1$) as (1) at least one bond crosses the 10Y, 5Y, or 3Y cutoffs ($Switch = 1$) and (2) the change of passive fund holding is above the median ($HighPurchase = 1$). We then estimate the following specifications:

$$\Delta Outcome_{it} = \beta PassiveShock_{it} + Controls_{it} + FEs + \epsilon_{it}$$

where $\Delta Outcome_{it}$ are capital structure variables, including: total bonds outstanding, the number of bonds outstanding, long-term debt, leverage, and bank debt. In panel B, we replace $PassiveShock$ with $PlaceboShock$, where placebo shock is defined as (1) at least one bond crosses the 10Y, 5Y, or 3Y cutoffs ($Switch = 1$) and (2) the change of passive fund holding is below the median ($LowPurchase = 1$). Firm fixed effects are used for all specifications. Columns (1), (3), (5), (7), and (9) use year-quarter fixed effects, while columns (2), (4), (6), (8), and (10) use the industry-by-time fixed effect to further control for industry-specific time-varying trend. Standard errors clustered at the time and firm levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Passive Demand Shock

	$\Delta Bond$		ΔN_Bond		$\Delta Debt$		$\Delta Leverage$		$\Delta BankDebt$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$PassiveShock$	0.102***	0.104***	0.510***	0.508***	0.025***	0.025***	0.031*	0.026*	−0.081*	−0.099**
	(0.023)	(0.023)	(0.066)	(0.065)	(0.005)	(0.005)	(0.016)	(0.015)	(0.041)	(0.045)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Ind-by-Time FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	19,832	19,832	19,832	19,832	19,832	19,832	19,832	19,832	7,668	7,668
Adjusted R^2	−0.001	0.015	0.034	0.039	0.057	0.072	0.016	0.058	−0.029	−0.036

Panel B: Placebo Shock

	$\Delta Bond$		ΔN_Bond		$\Delta Debt$		$\Delta Leverage$		$\Delta BankDebt$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$PlaceboShock$	0.019	0.012	−0.014	−0.005	0.001	0.0002	−0.008	−0.010	−0.016	−0.028
	(0.029)	(0.037)	(0.037)	(0.037)	(0.005)	(0.005)	(0.009)	(0.010)	(0.048)	(0.051)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Ind-by-Time FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	19,832	19,832	19,832	19,832	19,832	19,832	19,832	19,832	7,668	7,668
Adjusted R^2	−0.001	0.015	0.017	0.022	0.054	0.070	0.016	0.058	−0.030	−0.037

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

Table 8: The impact of financial constraints on firms' responses to passive demand shock

This table studies how financial constraints affect firms' capital structure decisions following the passive demand shock. We measure financial constraints using the WW-index. We defined a firm as financially constrained, $I(Constrained) = 1$, if its lagged WW-index is in the top tercile. Firm fixed effects are used for all specifications. Columns (1), (3), (5), (7), and (9) use year-quarter fixed effects, while columns (2), (4), (6), (8), and (10) use the industry-by-time fixed effect to further control for any industry-specific time-varying trend. Standard errors clustered at the time and firm levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	$\Delta Bond$		ΔN_Bond		$\Delta Debt$		$\Delta Leverage$		$\Delta BankDebt$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$PassiveShock$	0.063**	0.076***	0.573***	0.577***	0.018***	0.017***	0.036*	0.029	−0.046	−0.050
	(0.027)	(0.025)	(0.081)	(0.080)	(0.004)	(0.004)	(0.018)	(0.017)	(0.052)	(0.058)
$PassiveShock \times I(Constrained)$	0.194***	0.152***	−0.157*	−0.160*	0.028*	0.030**	−0.040	−0.038	−0.220	−0.320**
	(0.051)	(0.051)	(0.087)	(0.087)	(0.015)	(0.015)	(0.039)	(0.037)	(0.150)	(0.139)
$I(Constrained)$	−0.042*	−0.015	0.041	0.063**	0.027***	0.032***	0.028	0.038*	−0.204	−0.185
	(0.023)	(0.015)	(0.026)	(0.027)	(0.009)	(0.010)	(0.021)	(0.020)	(0.161)	(0.173)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Ind-by-Time FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	19,832	19,832	19,832	19,832	19,832	19,832	19,832	19,832	7,668	7,668
Adjusted R^2	−0.002	0.008	0.039	0.041	0.062	0.076	0.017	0.054	−0.026	−0.026

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

Table 9: The effect of passive demand on investment, cash, and payout

This table studies how firms use the proceeds they get from the higher bond issuance. We focus on three outcome variables: CAPX, changes in cash holdings, and payout ratio. We measure financial constraints using the WW-index. We defined a firm as financially constrained, $I(Constrained) = 1$, if its lagged WW-index is in the top tercile. Firm fixed effect and industry-by-time fixed effect are used for all specifications. Standard errors clustered at the time and firm levels are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	$CAPX$		$\Delta Cash$		$Payout$	
	(1)	(2)	(3)	(4)	(5)	(6)
$PassiveShock$	0.007	−0.0004	0.637**	0.015	0.014	0.041
	(0.007)	(0.007)	(0.290)	(0.042)	(0.028)	(0.031)
$PassiveShock \times I(Constrained)$		0.038*		2.065**		−0.146*
		(0.022)		(1.016)		(0.074)
$I(Constrained)$		0.035**		−0.206		−0.109*
		(0.016)		(0.600)		(0.056)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,832	19,832	19,832	19,832	19,832	19,832
Adjusted R^2	0.872	0.854	0.086	0.080	0.333	0.333

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

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A Additional figures and tables

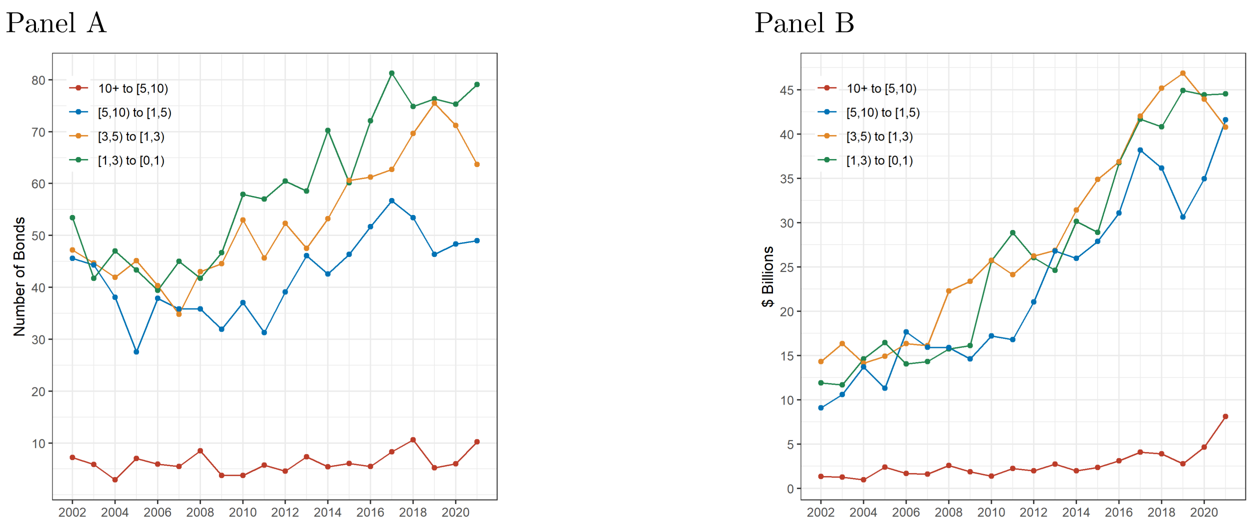


Figure A1: Bonds that switch maturity buckets per month

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.

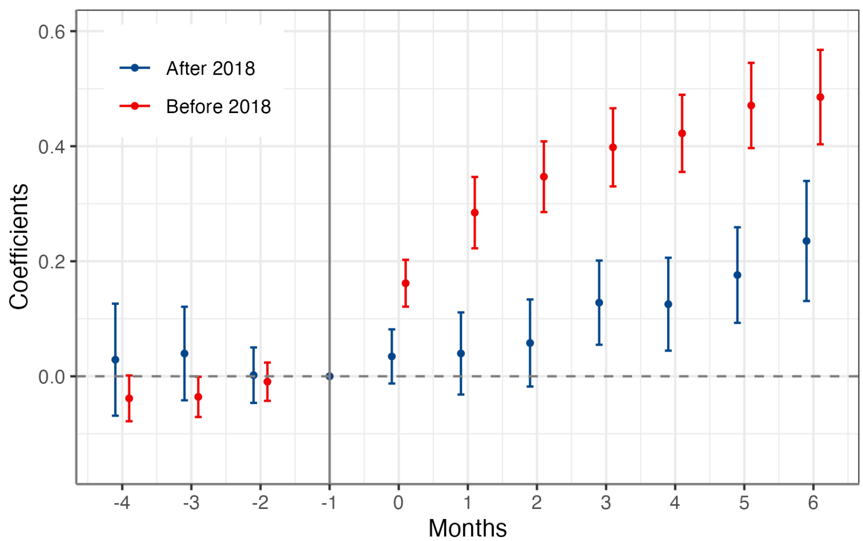


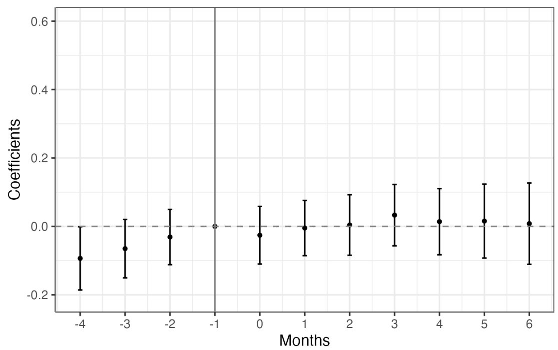
Figure A2: Compare 3Y maturity cutoff before and after 2018

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

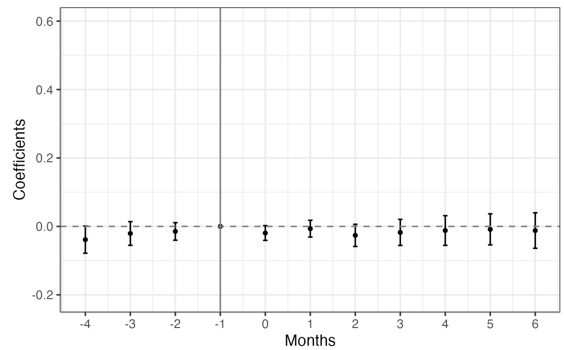
$$\Delta Passive_i^{t-1 \to t+h} = \beta_h SwitchX_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

where $\Delta Passive_i^{t-1 \to t+h}$ is the change of passive fund ownership for bond i from $t-1$ to $t+h$. $SwitchX_{it}$ is an indicator variable equal to one if bond i crosses a maturity cutoff X in month t, and 0 otherwise. 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.

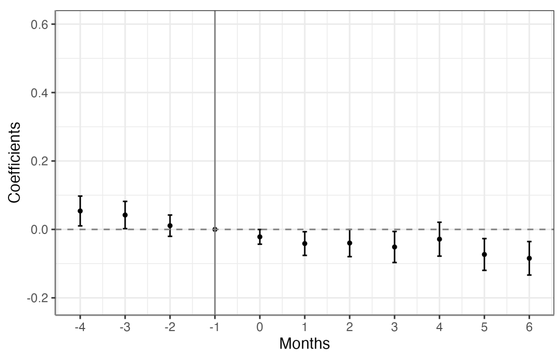
(a) 15Y maturity cutoff



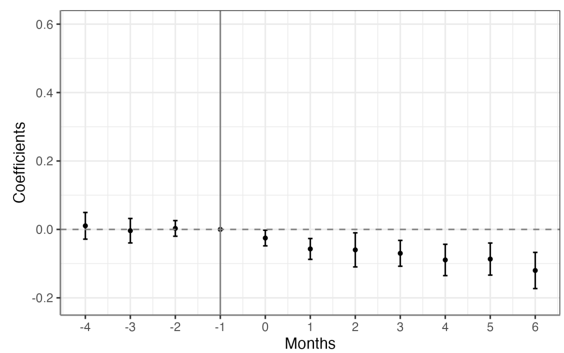
(b) 9Y maturity cutoff



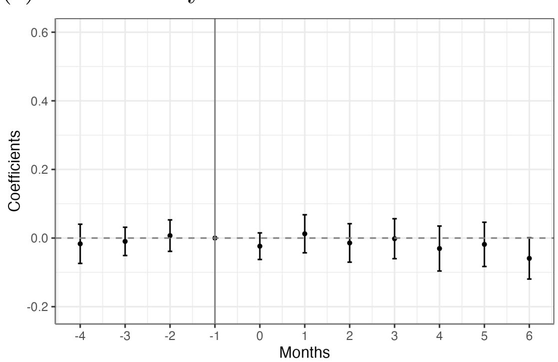
(c) 8Y maturity cutoff



(d) 7Y maturity cutoff



(c) 6Y maturity cutoff



(d) 4Y maturity cutoff

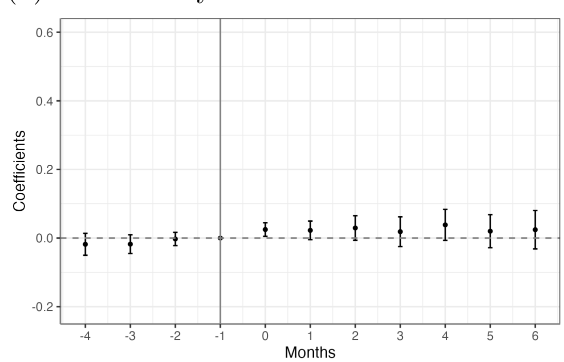


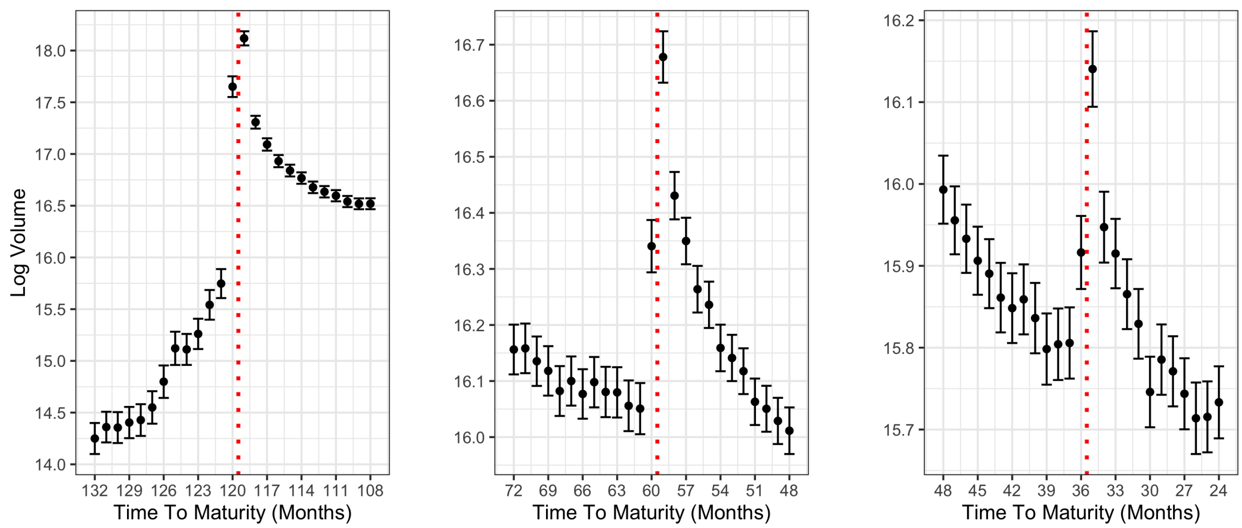
Figure A3: Placebo tests on passive fund holding

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

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

where $\Delta Passive_i^{t-1 \to t+h}$ is the change of passive fund ownership for bond i from $t-1$ to $t+h$. $SwitchX_{it}$ 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.

Panel A: Trading volume



Panel B: Bid-Ask spread

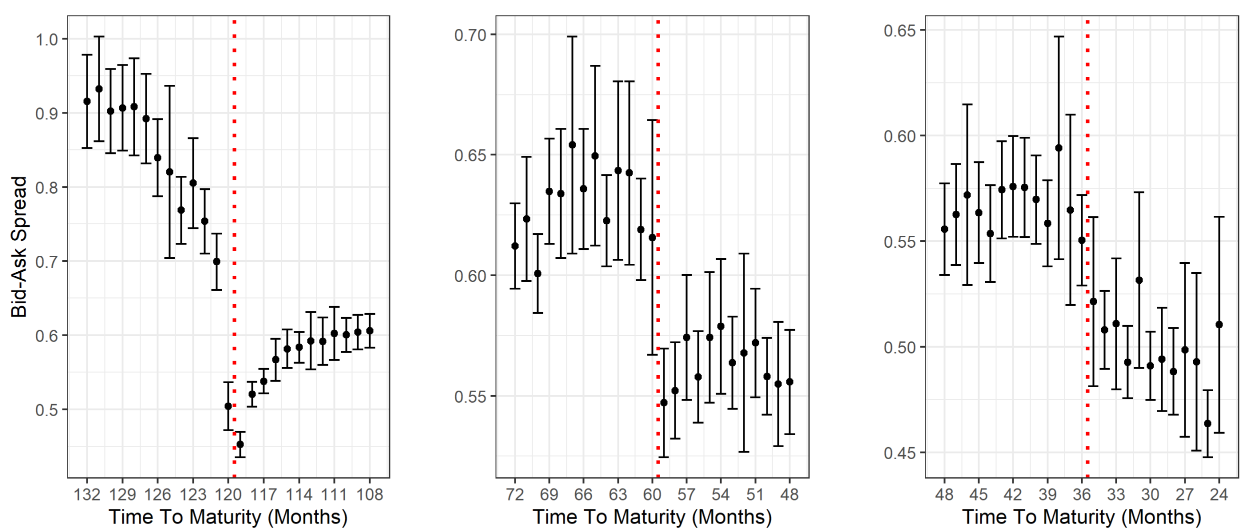


Figure A4: Trading volume and liquidity around maturity cutoffs

These figures plot the trading volume and bid-ask spreads around the maturity cutoffs. The x-axis is the time-to-maturity measured in months. 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.

Panel A: 10 year cutoff Panel B: 5 year cutoff Panel C: 3 year cutoff

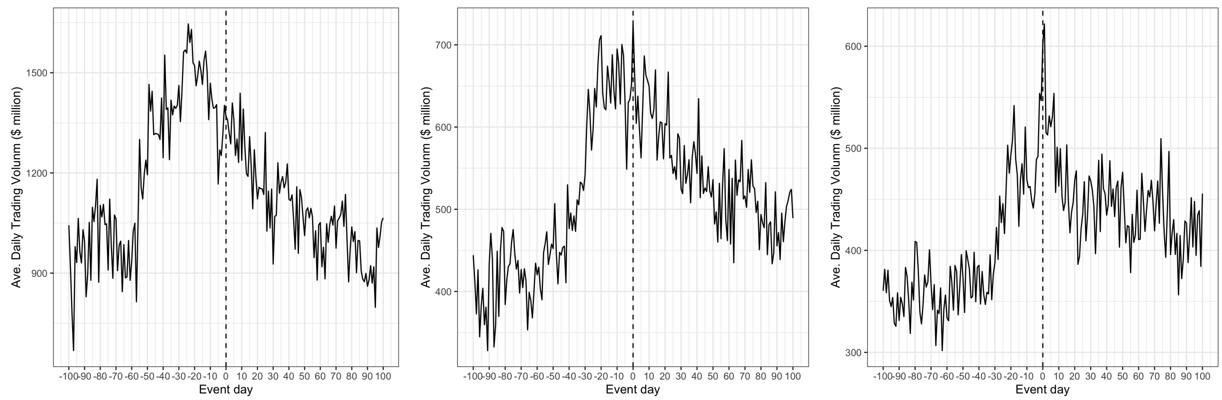


Figure A5: Average daily trading volume around maturity cutoffs

These figures plot the daily trading volume around maturity cutoffs.

Panel A: 10 year cutoff Panel B: 5 year cutoff Panel C: 3 year cutoff

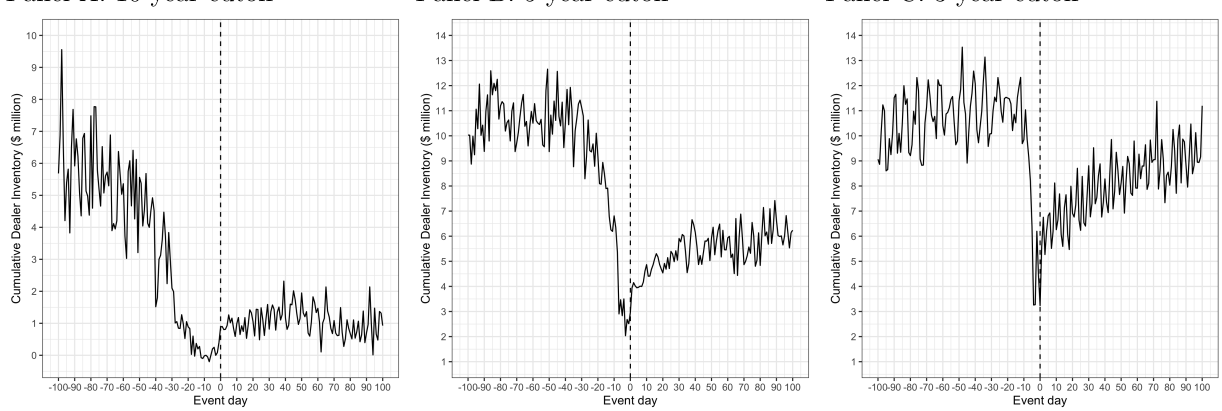
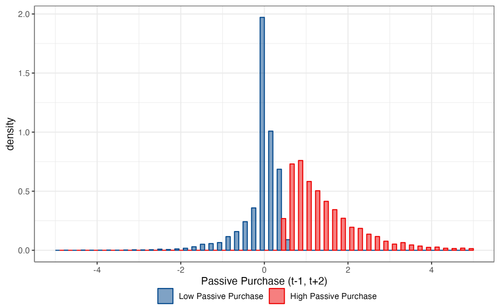


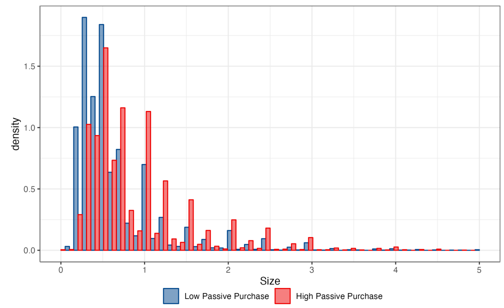
Figure A6: Cumulative dealer inventory around maturity cutoffs

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

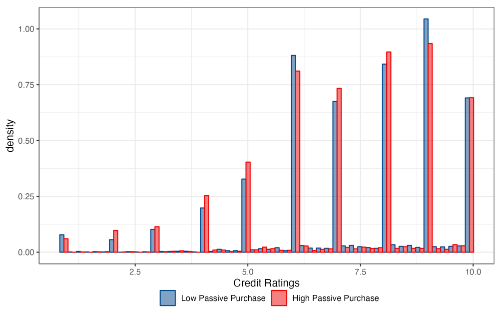
(a) Passive fund net purchase



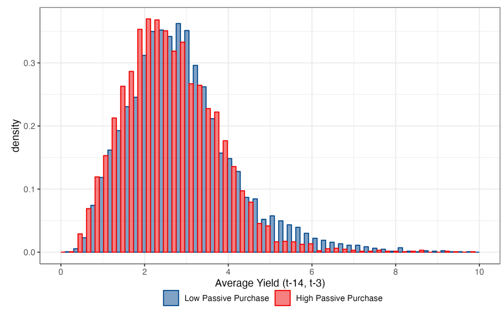
(b) Size



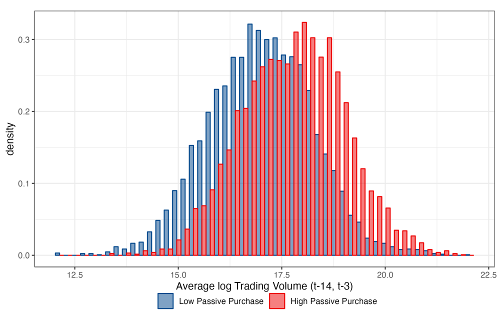
(c) Credit ratings



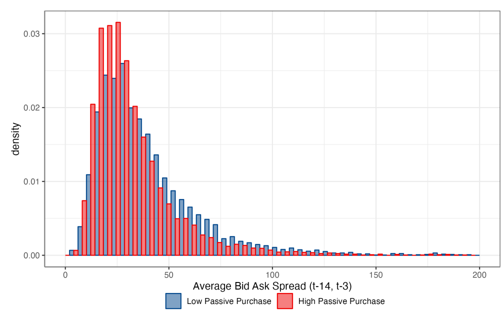
(d) Past yield spread



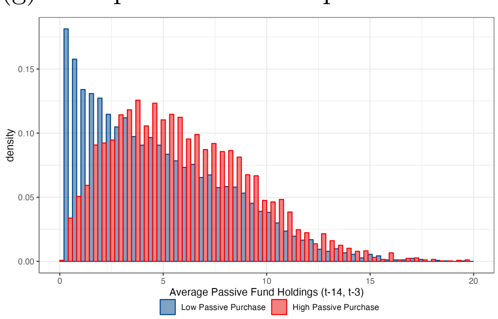
(e) Past trading volume



(f) Past bid-ask spread



(g) Past passive ownership



(h) Past number of passive fund

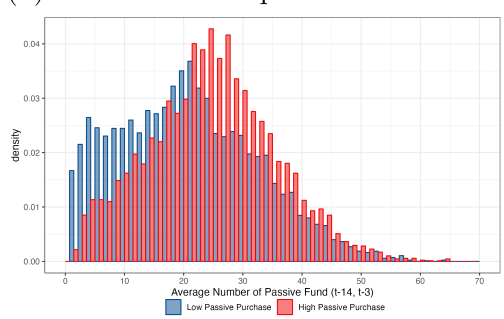
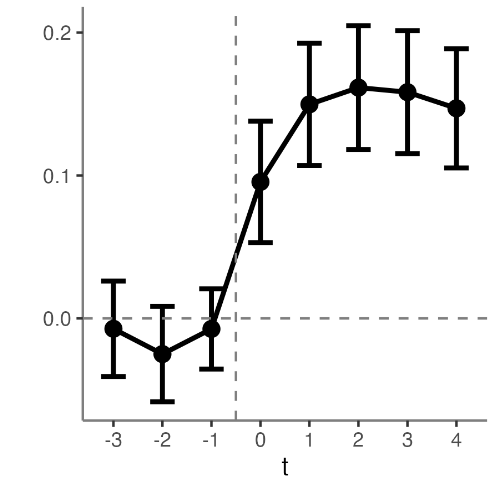


Figure A7: Difference between high and low passive purchase

This figure plots the distribution of bond characteristics between high and low passive purchases. Bond characteristics include: size, credit ratings, past yield spread, past trading volumes, past bid-ask spread, past passive fund ownership, and the past number of passive funds. All past variables are calculated as the average between $t-14$ to $t-3$.

(a) Passive demand shock



(b) Placebo shock

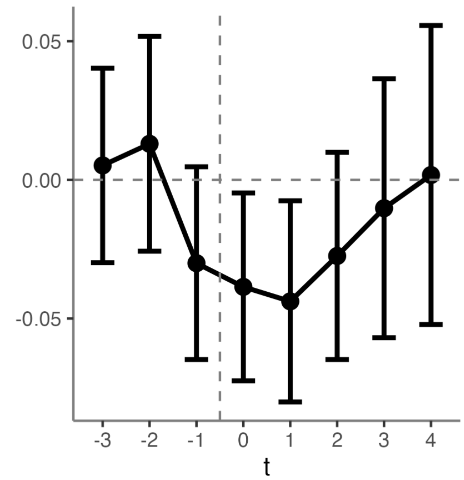
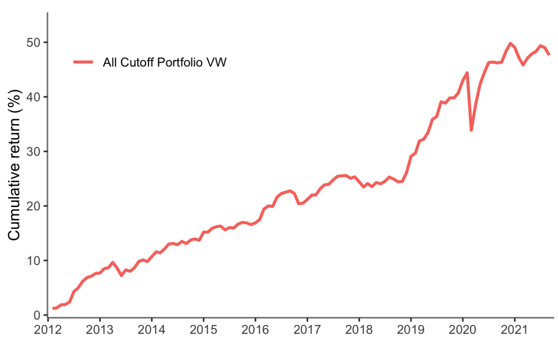


Figure A8: Firm average passive ownership

These figures plot the dynamics of firm average passive fund ownership for the passive fund demand shock and placebo shock.

(a) All cutoffs



(b) Each maturity cutoff

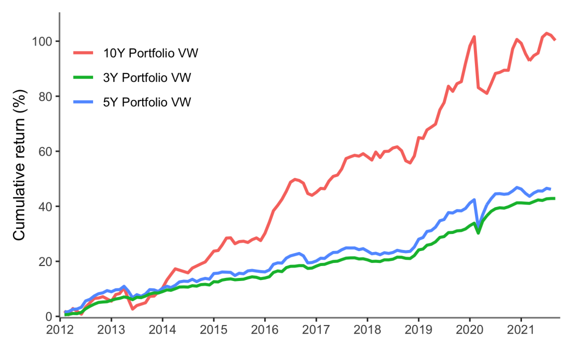
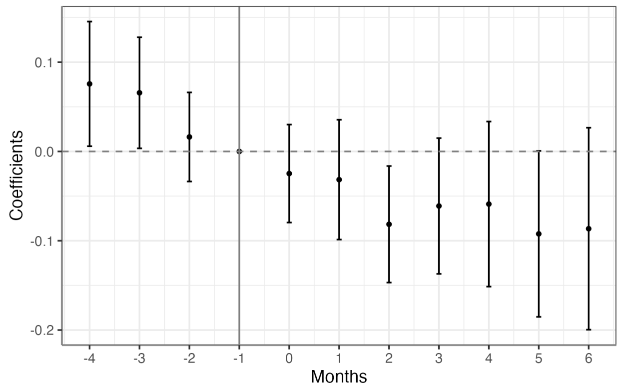


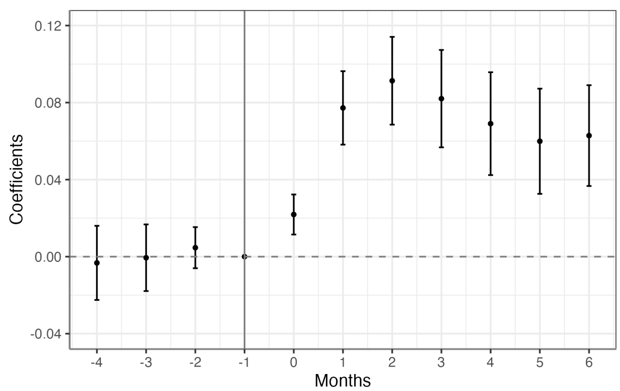
Figure A9: Profitability of Trading Strategies

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) Lendable shares



(b) Short loan quantity



(c) Lending fee

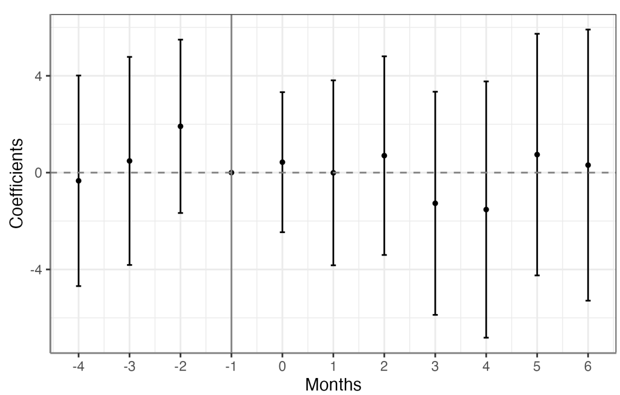


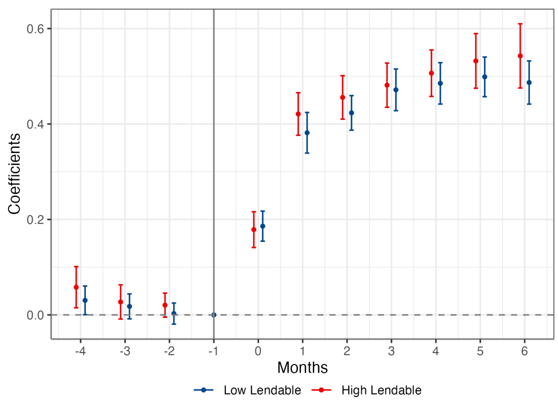
Figure A10: Security lending around the cutoff

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

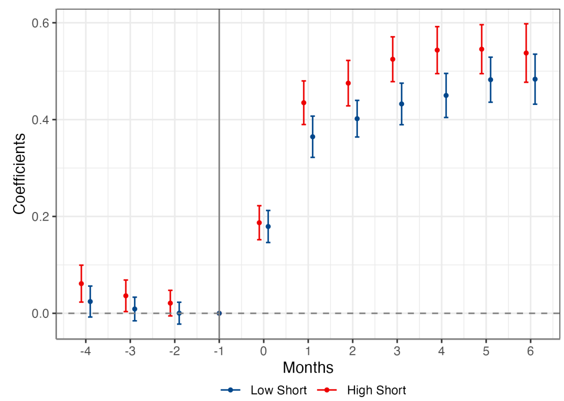
$$\Delta Outcome_i^{t-1 \to t+h} = \beta_h Switch_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

where $\Delta Outcome_i^{t-1 \to t+h}$ is the change of the security lending variable for bond i from $t-1$ to $t+h$. Outcome variables for subfigures (a) to (c) correspond to lendable shares, short loan quantity, and indicative lending fees. Error bars represent the 90% confidence interval.

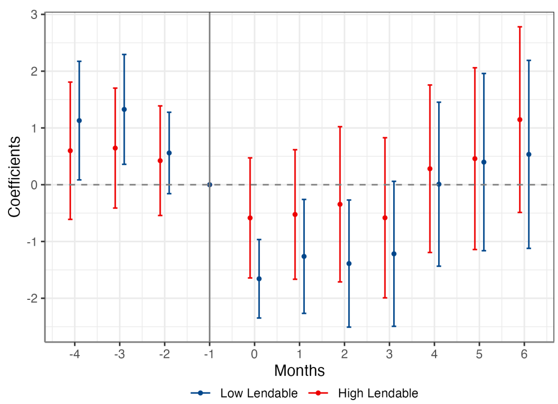
(a) Passive Holdings: lendable shares



(b) Passive Holdings: short loan quantity



(c) Yield Spread: lendable shares



(d) Yield Spread: short loan quantity

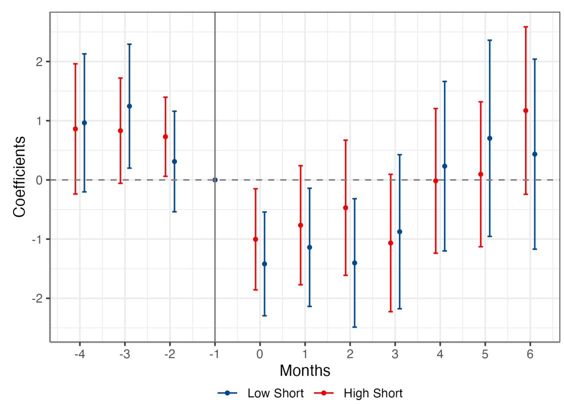


Figure A11: High vs. low short selling activity

This figure plots the coefficient estimates $\beta_{h,high}$ and $\beta_{h,low}$ from the following regression for $h \in [-4, 6]$:

$$\Delta Outcome_i^{t-1\rightarrow t+h} = \beta_{h,high} Switch_{it} \times High_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

$$\Delta Outcome_i^{t-1\rightarrow t+h} = \beta_{h,low} Switch_{it} \times Low_{it} + Controls_{it} + \alpha_i + \lambda_t + \epsilon_{it}$$

$High_{it}$ is an indicator variable equals to one if the lagged six month lendable shares or the lagged six month short loan quantity are above the median . Low_{it} is an indicator variable equals to one if the lagged six month lendable shares or the lagged six month short loan quantity are below the median. $\Delta Outcome_i^{t-1\rightarrow t+h}$ is the change of outcome variables for bond i from $t-1$ to $t+h$. Error bars represent the 90% confidence interval.

Table A1: RDD tests on the 3-year maturity cutoff before and after 2018

This table compares the passive fund ownership before and after a bond crosses the maturity cutoff. We report the results for the following RDD specifications:

$$Passive_{it} = \beta I(PassX)_{it} + f(TTM_{it} - X) + Contrls + \alpha_i + \lambda_t + +\epsilon_{it}.$$

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 X at the time t. $TTM - X$ is the distance between time-to-maturity and the cutoff X. $f(TTM - X)$ is a function of the distant variable. Control variables include the contemporaneous bid-ask spread, credit rating, and the log amount outstanding in par value. Time fixed effects and bond fixed effects are included in all regressions. The bandwidth is ±6 month. 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.

	Before 2018			After 2018		
	(1)	(2)	(3)	(4)	(5)	(6)
$I(Pass3Y)$	0.160***	0.100***	0.100***	0.058	−0.017	0.006
	(0.024)	(0.026)	(0.021)	(0.036)	(0.043)	(0.035)
Bandwidth	±6	±6	±6	±6	±6	±6
Functional Forms	Linear	Diff Slopes	Cubic	Linear	Diff Slopes	Cubic
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,452	34,452	34,452	16,950	16,950	16,950
Adjusted R^2	0.945	0.945	0.945	0.946	0.946	0.946

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

Table A2: Placebo tests for other maturity cutoffs

This table compares the passive fund ownership before and after a bond crosses the maturity cutoff. We report the results for the following RDD specifications:

$$Passive_{it} = \beta I(PassX)_{it} + f(TTM_{it} - X) + Contrls + \alpha_i + \lambda_t + +\epsilon_{it}.$$

We compare passive fund ownership before and after 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 X at the time t. $TTM - X$ is the distance between time-to-maturity and the cutoff X. $f(TTM - X)$ is a function of the distant variable. Control variables include the contemporaneous bid-ask spread, credit rating, and the log amount outstanding in par value. Time fixed effects and bond fixed effects are included in all regressions. The bandwidth is ±6 month. 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					
	(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)
Bandwidth	± 6	± 6	± 6	± 6	± 6	± 6
Functional Forms	Linear	Linear	Linear	Linear	Linear	Linear
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time 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 A3: Additional Summary Statistics for Issuance

	N	Mean	SD	P25	Median	P75
Maturity						
10Y	681	117.27	113.79	33.00	84.00	144.00
3Y	409	119.19	112.44	42.00	84.00	121.00
5Y	690	96.89	98.76	24.00	60.00	120.00
Rest	12915	114.99	114.38	36.00	84.00	121.00
Issuance Size						
10Y	681	274.86	522.14	1.93	6.12	1000.00
3Y	409	371.58	624.28	2.60	15.19	1000.00
5Y	690	254.53	461.32	1.99	6.40	800.00
Rest	12915	410.91	632.17	2.55	150.00	1000.00
Credit Ratings						
10Y	681	7.04	1.66	6.00	7.00	8.00
3Y	409	7.11	1.86	6.00	7.00	8.00
5Y	690	7.46	1.49	6.00	7.00	9.00
Rest	12915	7.29	2.00	6.00	7.00	9.00
Spread						
10Y	681	2.61	2.78	0.89	1.44	3.24
3Y	409	2.63	2.93	0.77	1.33	3.11
5Y	690	2.67	3.15	0.76	1.34	3.27
Rest	12915	2.61	2.88	0.87	1.52	3.02

Table A4: 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 A5: 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 **??**. 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 A6: 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 **??**. 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

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.