The Impact of Benchmarking in Fixed Income Funds

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Abstract

I empirically study the asset pricing implications of corporate bond funds' performance concerns relative to a benchmark index. Benchmarking has a large impact on bond prices, as funds re-balance in response to index weight changes. On average, a long/short portfolio of bonds with an increase/decrease in index weights generates a monthly alpha of 40 bps. The direction and magnitude of this effect depend on past flows and cash levels of both passive and active funds holding the assets. The impact gets larger when more investors are benchmarked. My findings show that benchmarking is an important channel through which institutions affect the pricing of corporate bonds beyond fundamentals.

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1 Introduction

Open end mutual funds are key players in financial markets, with $40 trillion under management globally in 2016. The performance of most active and passive fund managers is evaluated against a benchmark index, either through explicit compensation or indirectly, through the flow-to-performance relation.[1] Recent papers show that benchmarking incentives affect institutions' trading strategies and distort prices in equity markets.[2]

The growing industry of corporate bond funds is evaluated against benchmarks which are much different from stock indexes.[3] Fixed-income benchmarks include many more assets, while also having a larger and more frequent turnover. Additionally, index constituents are less liquid, as corporate bonds are traded Over-the-Counter (OTC).[4] Whether benchmarking impacts portfolio allocation in fixed income funds and hence bond prices, is an open issue. If it does, are the effects related to mutual funds' liquidity management? Bond funds allow daily redemptions like equity funds, but differently from them hold illiquid assets. Such liquidity mismatch sparked a discussion on whether bond funds are exposed to runs.[5] Shedding light on the drivers of portfolio allocation of bond funds is a key contribution to the debate.

My paper tackles these questions by empirically studying the asset pricing implications of benchmarking incentives in the US corporate bond market, and how they relate to funds' liquidity management. First, I find that benchmarking has a large impact on corporate bond prices, as funds re-balance in response to mechanical weight changes in the benchmark index. On average, a long/short portfolio of bonds with index weight increases/decreases generates an α of 40 bps per month. Second, I show that the direction and magnitude of the price impacts critically depend on past flows and cash levels of *both* the active and passive bond funds holding the assets. Third, I provide evidence that the documented impact gets larger when a higher fraction of the institutions in the market are benchmarked. My findings show

[1]For example, in 2017 $16 trillion in assets were benchmarked to indexes offered by FTSE Russell.
[2]See Basak and Pavlova (2013), Chen, Noronha, and Singal (2005), Chang, Hong, and Liskovich (2015).
[3]AUM (investment in corporate bonds) from $1.5 ($0.52) trillion in 2008, to $3.6 ($1.6) trillion in 2016.
[4]These features do not allow bond funds to hold the index, and leads them to invest into a subset of it.
[5] See Goldstein, Jiang, and Ng (2017) and Zeng (2017).

that benchmarking is an important channel through which institutional investors affect the pricing of corporate bonds beyond fundamentals.

To guide my empirical tests, I propose a theoretically motivated re-balancing mechanism for bond funds in response to index weight changes. The mechanism works as follows. Risk-averse fund managers trade-off hedging demand for illiquid assets in the benchmark against holding cash in expectation of future redemptions.[6] Consider a fund manager with a portfolio of illiquid index assets and cash, facing unexpected changes in the benchmark. While the hedging demand changes proportionally to the variation in the index weights, the total effect on the portfolio allocation depends on the net fund flows. All else equal, if the fund experiences net inflows, the manager has additional cash to re-invest, which increases her demand for risky assets. Overall, the manager will buy more assets that increased the index weight and sell fewer of those that decreased it. If the liquidity discounts are large enough, the manager could end up only investing the inflows in bonds with weight increases, avoiding selling those with decreases. On the other hand, after meeting large redemptions, the manager will rebuild her cash holdings in expectation of future outflows.[7] In aggregate, the manager will sell more assets that decreased the index weight and buy fewer of those that increased it. The cash rebuilding motive can push the manager to sell more than what she would sell in a liquid market (e.g. equities). Intuitively, the aggregate amount of re-balancing and its effect on bond prices increases when a larger fraction of investors in the market is benchmarked.

In my empirical analysis, I use Bank of America/Merrill Lynch (BofA/ML) US High Yield Index and BofA/ML US Corporate Index monthly changes in constituents' weights as shocks to benchmarked investors' hedging demand. Using a sample from November 2004 to June 2016, I sort corporate bonds based on past index weight changes into quintile portfolios on a monthly basis, and analyze equally-weighted excess returns. First, I investigate the average

[6]The corporate bond market is illiquid due to its OTC structure. Trading an asset might lead to large discounts. Hence, in order to limit expected liquidation costs arising from future redemptions, managers hold larger cash buffers than what they would keep in a liquid market (e.g. equity funds). See Chermenko and Sunderam (2016), Choi and Shin (2018), Goldstein, Jiang, and Ng (2017).

[7]See Zeng (2017) for a detailed analysis of the cash rebuilding mechanism in a dynamic model.

effect across all assets. Going long into the bonds with the most positive index weight changes and short into those with the most negative, earns an average monthly excess returns of 39.87 bps, generating an α of 39.5 bps beyond stock and bond pricing factors. For high yield (HY) (investment grade, [IG]) bonds, the excess return is 88.97 (14.77) bps, with an α of 88.10 bps (13.43 bps). Importantly, the price effects are not coming from a symmetric reaction to positive and negative index weight changes. Bonds with large weight increases generate positive excess returns and are linked to excess buying activity. Those with decreases show no drop in prices, and have a trade order imbalance that is close to zero. Bonds in my sample are on average exposed to positive flows. Hence, my result is consistent with funds re-investing inflows and buying assets that increased the index weight while selling fewer of those that decreased it.

I rule out several alternative explanations. First, my findings are not driven by weight changes linked to variations in a bond's fundamental value, which are excluded from the sample.[8] Second, they are robust to multiple regression specifications wherein I control for bond characteristics, fund flows, past performance and time-issuer fixed effects. Third, I provide evidence that my findings cannot be explained by past month returns (i.e., institutions persistently buying bonds that performed best in the previous month). Fourth, the effects I document are unchanged when using value-weighted portfolio returns or including in the sample index inclusions and exclusions.

In an attempt to pin down the interaction between benchmarking and liquidity management in bond funds, I study how the price distortions relate to different levels of past fund flows. I do so by constructing a measure of bond-specific exposure to fund flows. In line with the cash rebuilding mechanism, I find that, after being exposed to large outflows, bonds with index weight decreases are sold more than those with weight increases are bought. This leads to large negative price impacts on the bonds that had the most negative index weight changes,

[8] I do not consider bonds that enter/exit the index, or those that experience any rating change. Index inclusions and exclusions are events that are easy to predict, and could be mixed with other trading motives. Rating changes reflect a variation in credit risk, which is linked to the fundamental value of the bond.

up to an average of -57.56 bps excess monthly returns. Consistent with the reinvestment channel, bonds exposed to inflows present instead stronger impacts (positive excess returns and excess buying activity) on assets with the most positive weight changes. The magnitudes of the effects are larger in the HY segment, where flows of active funds seem to be the main driver. In the IG segment, however, flows of index funds play a dominant role.

In addition, I focus on bonds exposed to outflows, and study how the price distortions vary according to the level of funds' cash holdings. In this case, I construct a measure of bond-specific exposure to fund cash holdings. Intuitively, I find that bonds exposed to high cash holdings exhibit effects in line with the reinvestment channel. Interestingly, bonds exposed to low cash holdings present price impacts that are consistent with cash rebuilding, with negative returns on the assets affected by index weight decreases. Taken together, my findings on flows and cash levels point at relative performance concerns as a potential channel for instability in fixed income markets. If many funds with low cash holdings are hit by large outflows at the same time, benchmarked asset managers will try to rebuild their cash buffer by selling the same assets. This could lead to widespread fire-sales and potentially more outflows and fund distress.

I provide evidence that the price impacts following index changes come indeed from benchmarked institutions. I analyze quarterly variations of par-amount bond holdings in the cross-section of investors and relate them to the changes in index weights. I show that active and passive bond funds, on average, buy bonds with the most positive weight changes, while they sell those with the most negative. In strong support of the proposed mechanism, insurance and pension funds, which are not explicitly tied to an index, show no such behavior.[9]

In additional analysis, I explore the time variation of the price distortions, dividing the sample into three sub periods. This exercise is particularly relevant since bond funds grew a lot in recent years. The price impacts are larger in the last part of the sample $(2012-2016)$ than

[9]In their prospectuses, insurance companies and pension funds often report their performance relative to a benchmark. However, their managers' compensation structure is not tied to an index explicitly, and there is no exposure to short-term investor flows.

pre-crisis ($2004-2007$). The effect is particularly strong for the IG segment, where mutual funds were substantially absent pre-crisis. Taken together, my findings support the idea that distortions arising from benchmarking are increasing when a larger fraction of investors are benchmarked.

Literature. My paper contributes to the growing literature on benchmarking and asset prices. Existing research has concentrated on equity markets, where investors can trade (almost) frictionlessly.[10] I am among the first to focus on the fixed income market, which is, due to its OTC nature, characterized by significant trading frictions that can change the way institutions shift their portfolios.[11] Moreover, the structure of fixed income benchmarks is extremely different from that of equity indexes. Bond benchmarks are impossible to hold entirely, and the large turnover on a monthly basis makes it much harder to predict how the index composition will change.

Furthermore, my work adds to the recent literature on fixed income mutual funds. Goldstein, Jiang, and Ng (2017) study flow patterns in corporate bond mutual funds, providing evidence of a concave flow-to-performance relationship. Choi and Shin (2018) study the fire-sale price impact of bond funds' investor redemptions, finding that fund manager absorb investor's redemptions with cash, and that mostly low-cash funds trigger a price impact. Jiang, Li, and Wang (2017) analyze the liquidity management policies of corporate bond funds in meeting redemptions. Zeng (2017) shows in a model that mutual funds' cash management can still generate shareholders' runs in illiquid markets. In my paper, I analyze an aspect of fixed income mutual funds incentives that has not received much focus (benchmarking), and show its interaction with funds' liquidity management.

More generally, my paper relates to the body of literature that analyzes fixed income

[10] Brennan (1993), Cuoco and Kaniel (2011), Basak and Pavlova (2013), Buffa, Vayanos, and Wooley (2014), Breugem and Buss (2018), Buffa and Hodor (2017), Chen, Noronha, and Singal (2005), Lines (2017), Chang, Hong, and Liskovich (2015), Coles, Heath, and Ringgenberg (2018)

[11] Dick-Nielsen and Rossi (2019) focus on index exclusions as a natural experiment to measure cost of immediacy in corporate bonds.

investors' trading behavior and the impact thereof in corporate debt markets[12], Chen and Choi (2018). I propose an additional channel (benchmarking) that can systematically impact fixed income investors' trading behavior, and can be used to explain part of the price distortions found in the market.

The remainder of the paper proceeds as follows. I provide institutional details on fixed income indexes and lay out the theoretical foundations of my analysis in Section 2. I describe data and main variables in Section 3. The empirical results are presented in Section 4. Section 5 concludes.

2 Institutional Details and Theoretical Foundations

2.1 Institutional Details: Benchmarks in Fixed Income Markets

In the US corporate bond market, there are two main providers of benchmark indexes: Bloomberg/Barclays (BB) and BofA/ML. Each of them has one index for the IG segment and one for the HY segment. BB has its US Corporate bond index and US Corporate High Yield bond index. BofA/ML has its US Corporate Index and US High Yield Index. All of those indexes have similar, publicly available rules for inclusion, and each asset that fulfills those rules is part of the index. For example, a bond is included in the index if it exceeds a minimum amount outstanding, has a fixed coupon rate, is rated by one of the main credit rating agencies, has at least one year to maturity, has not been partially called, and does not present any complex optionality.[13,14] The inclusion rules put no restriction on the number of assets that are in the index: the number of bonds included in the benchmark is therefore varying constantly.[15] Index constituents are market capitalization weighted, meaning that a

[12] Becker and Ivashina (2015), Choi and Kronlund (2018), Cai, Han, Li, and Li (2017), Timmer (2018)

[13] A ful list of the index inclusion rules for BB can be found at https://data.bloomberglp.com/indexes/sites/2/2016/08/Factsheet-US-Corporate-High-Yield.pdf and https://data.bloomberglp.com/indexes/sites/2/2016/08/2017-08-08-Factsheet-US-Corporate.pdf.

[14] A full list of the index inclusion rules for BofA/ML can be found at https://www.mlindex.ml.com/GISPublic/bin/getdoc.asp?fn=H0A0&source=indexrules and https://www.mlindex.ml.com/GISPublic/bin/getdoc.asp?fn=C0A0&source=indexrules.

[15] See Figure 3 for a time series on index constituents and turnover in the BofA/ML indexes.

bond gets a higher weight if it has a larger outstanding amount and/or has a higher return in the previous month.

Every index is re-balanced on the last calendar day of the month, and no changes are made to constituent holdings other than on month-end re-balancing dates.[16] Therefore, at the end of each month, investors know the index composition for the following month. All information about index constituents and weights is publicly available and easily accessible through Bloomberg. While index rules are known and it is easy to predict when a bond enters/exit the index, index constituents weights are harder to foresee. Every month there are bonds entering/exiting the index, and this constant turnover changes the weights of all the other assets in the benchmark. For example, a bond that had a positive return in month $t-1$, can still get its benchmark weight decreased if some bonds with a large amount outstanding are entering the index in month t. Furthermore, the number of securities included in the benchmark index is so large that it is almost impossible for an investor to hold the full index.[17] As described in Dick-Nielsen and Rossi (2019), fund managers who follow the index tend to use a sampling strategy, by holding a subset of bonds in the index, which matches some index characteristics (such as duration or callability). Therefore, even if the unlikely case of a month when no changes in the constituents of the index take place, a fund manager could still not replicate the index as she holds only a subset of it.

In my analysis, I will use data on constituents and weights of BofA/ML indexes, for which I have more detailed information. While the BB index is the most common in the IG segment of the market, BofA/ML is as used as BB in the HY segment.[18] However, choosing one index over the other does not make a difference, considering that BB and BofA/ML are really

[16] On the re-balancing date, BofA/ML uses information available up to and including the third business day before the last business day of the month, while BB uses information up to the last business day of the month.

[17] In July 2016, the BB (BofA/ML) HY and and IG indexes included 2,2179 (2,283) and 9,805 (9,311) securities, respectively. For more details on the differences in eligibility requirements across indexes, see http://docs.edhec-risk.com/mrk/000000/Press/EDHEC_Publication_Corporate_Bond_Indices.pdf.

[18] According to Robertson and Spiegel (2018), in the IG segment, 80% of the funds use BB as a benchmark, while only 9% refer to BofA/ML. In the HY segment, by comparison, 38% use BB and 37% BofA/ML. In general, BB and BofA/ML indexes (which are highly correlated) are used as benchmarks by the great majority of the bond fund universe. In general, BB and BofA/ML indexes (which are highly correlated) are used as benchmarks by the great majority of the bond fund universe.

similar in terms of index rules. In fact, I calculate the correlation between daily returns of the BofA/ML and BB indexes from January 2000 to March 2018 and obtain 96% for IG and 90% for HY.

2.2 Theoretical Foundations and Main Predictions

In this section, I lay out the theoretical foundations of my empirical predictions. I propose a re-balancing mechanism of bond funds in response to variations in the index. My arguments are formalized in a one period model with heterogeneous agents in Appendix A.

Typical models of benchmarking feature heterogeneous types of risk-averse investors, both maximizing terminal wealth. One type has standard CARA preferences, while the other is concerned also about the performance of an exogenous benchmark.[19] Risk-averse benchmarked institutions are penalized for tracking error variance and, in equilibrium, invest a higher amount of wealth, relative to standard investors, in assets that are part of (have higher weight in) the index. This excess demand results in higher equilibrium prices and volatilities for assets that are part of (have higher weight in) the benchmark index. An unexpected positive (negative) change in an asset's index weight, leads benchmarked investors to re-balance their portfolio, by increasing (decreasing) their investment in such security. In turn, the rebalancing causes an increase (decrease) in equilibrium prices. This modeling setup assumes that investors can trade frictionlessly, without any discounts arising from illiquidity.

When analyzing benchmarking in fixed income markets, one needs to take into account that securities are mostly exchanged OTC, and hence are subjected to significant trading frictions, which make the securities illiquid.[20] As a result, the trading strategies of open end fund managers are significantly affected. Outflows become costly, as selling assets in an illiquid

[19]The utility function of the benchmarked investor could be modeled as the differential in performance between the investor's portfolio and the benchmark as in Brennan (1993) and Lines (2017), or by adding a multiplicative factor that is positively correlated with the index value as in Basak and Pavlova (2013) and Basak and Pavlova (2016). The utility specifications could apply to both active and passive investors. In my paper, I consider both of them to be "benchmarked investors."

[20]For a complete overview of such frictions, see Friewald and Nagler (2018)

market implies potentially large discounts.[21] Therefore, compared to equity funds, bond fund managers have larger cash holdings, in order to limit the price impacts of outflows.[22] Taking this into account, how does a fund manager react to variations in the benchmark index?

Consider the simple case of an economy with two risky assets (x, y), both in the index, and a risk-free security with zero rate of return. As in equity models, a benchmarked investor's optimal asset demand has a hedging component that is correlated with the index weights. Differently from those models, the benchmarked investors keeps some additional cash in anticipation of future redemptions. The larger cash holdings are justified by the fact that selling illiquid assets to meet outflows is costly, and holdings more cash mitigates the expected costs arising from future redemptions.

Assume that a fund manager is faced with an exogenous variation in the index weights of the two risky assets, with asset x increasing and asset y decreasing their weights by the same amount.[23] In any case, the demand for asset x (asset y) will increase (decrease), due to the variation in the hedging component of the optimal portfolio. However, the manager's total reaction will depend on whether the fund has been subjected to net inflows (from investors or coupon/principal payments) or outflows (from investor's redemptions).[24] In the first case, the fund manager will have a lower cash demand and increase her investment in the illiquid risky assets. This results in an increase in the investment in x that is stronger than the drop in the investment in y, translating into a positive return in x, that is larger than the negative return in y. If the manager's liquidity concerns are large enough, she could buy more of asset x only through the inflows, and avoid selling asset y.

Conversely, if the fund has been subjected to outflows, the fund manager will need to re-

[21]See, for example, Ellul, Jotikasthira, and Lundblad (2011) for regulatory-induced fire sales or Choi and Shin (2018) for fire-sales linked to fund outflows.

[22]Extensive empirical evidence of this phenomenon can be found in Chermenko and Sunderam (2016), Morris, Shim, and Shin (2017), Goldstein, Jiang, and Ng (2017), and Choi and Shin (2018).

[23]This is the typical situation that occurs in the corporate bond market, due to the constant monthly turnover in the benchmark that leads to index weight changes. For details see 2.1.

[24]The following mechanism holds under the realistic assumption that inflows (outflows) do not increase (decrease) dramatically the optimal amount of cash of the fund. If, for example, the optimal cash amount of the fund increases (drops) after inflows (outflows), it can happen that the fund does not need to reinvest (rebuild cash buffer).

build her cash reserves in expectation of future redemptions. This results in the fund selling more of asset y than it buys of asset x. The negative price impact on y is therefore stronger than the positive impact on x. Intuitively, the aggregate amount of re-balancing and its effect on bond prices increases when a larger fraction of investors in the market is benchmarked. Based on these arguments, I formulate the following hypotheses, to be tested empirically.

H1: Reinvestment Channel: When in a portfolio of funds that experienced net inflows, bonds with index weight increases have positive excess returns that are larger (in absolute terms) than the negative returns on the bonds with index weight decreases. This is the result of bond funds re-investing the additional cash and buying bonds with index weight increases more than selling those with index weight decreases.

H2: Cash Rebuilding Channel: When in a portfolio of funds that experienced net outflows, bonds with index weight decreases have negative excess returns that are larger (in absolute terms) than the positive returns on the bonds with index weight increases. This is the result of bond funds rebuilding their cash reserves through selling bonds with index weight decreases more than buying those with index weight increases.

H3: Impact of More Benchmarked Investors. When a larger fraction of the investors in the economy is benchmarked, the impact on prices in response to index weight changes and/or fund flows is larger.

3 Main Variables and Data

3.1 Bond Returns and Asset Pricing Factors

Consistently with Lin, Wang, and Wu (2011), the return of bond i in month t is defined as:

$$R_{i,t} = \frac{(P_{i,t} + AI_{i,t} + C_{i,t}) - (P_{i,t-1} + AI_{i,t-1})}{(P_{i,t-1} + AI_{i,t-1})} \tag{1}$$

where $P_{i,t}$ is the volume-weighted average price of bond i on the last trading day of month t on which at least one trade occurs, P_{t-1} is the same price estimate in the previous month and $AI_{i,t}$ is the accrued interest of the bond. $C_{i,t}$ is the coupon paid between month-ends $t-1$ and t. I calculate monthly returns of bonds that have at least one trade in the last five days of the month. Throughout my analysis, I use corporate bond returns in excess of the benchmark index return in that month.

In my analysis, I also use standard stock and bond asset pricing factors. Specifically, I use market (MKT), size (SMB), book-to-market (HML), stock momentum (UMD) and default (DEF), term (TERM), liquidity (LIQ) and bond momentum (BMOM). For a detailed description on how each of the factors is constructed, see Table A1 in the Appendix.

3.2 Bond Liquidity and Order Imbalance

On each day with at least one trade, I calculate the liquidity of bond i on day t using the illiquidity measure of Bao, Pan, and Wang (2011). On trading day t, the measure is given by the auto-covariance between the returns generated from consecutive transaction prices over a pre-defined time window. $\gamma_t = -Cov(\Delta p_{s+1}, \Delta p_s)$, where p_s is the log transaction price of the bond. My time window includes the trading day and the previous 20 working days, which translates into a rolling window of approximately one month. I then average, in each month, the illiquidity measure of a bond, and obtain a monthly estimate of illiquidity for bond i. In my analysis, I always use illiquidity with a lag. In this way, my proxy for a bond's illiquidity is not affected by the trading activity taking place in the same month of the bond return.[25] In the regression tests, I use the illiquidity measure without any transformation. When reporting summary statistics instead, I transform the measure in an estimate of one way-transaction costs.[26]

I calculate the order imbalance (OIB) of bond i in month t as the difference between buy volume and sell volume, scaled by the amount outstanding of the bond.

3.3 Institutional Holdings Variables

I use two measures to analyze the cross-section of institutional investors' portfolio holdings in corporate bonds. All measures are at a quarterly level. First, I capture the level of institutional bond holdings, and calculate for each bond the percentage of the amount outstanding held by a certain type of investor. Second, I focus on the dynamics of portfolio holdings. I calculate, for each bond, the quarterly variation of holdings from an investor type, as a percentage of amount outstanding. It is noteworthy that portfolio holdings are observed in par-amount, and are therefore not linked to changes in portfolio values due to returns. A positive change in my variable means that an investor has bought a greater amount of a bond, and not that the value of this bond has increased in the portfolio due to past positive performance. I divide the portfolio holdings according to benchmarked and non benchmarked institutions. In the first group, I include active bond funds (ACT), bond index funds (INDF), and bond ETFs (ETF). The second group comprises insurance funds (INS) and pension funds (PENS).

3.4 Bond Fund Flows and Cash Holdings

Following Goldstein, Jiang, and Ng (2017), the net flow of fund j in month t is defined as

$$Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1 + R_{j,t})}{TNA_{j,t-1}} \tag{2}$$

[25] When observing a return in t, I consider the average illiquidity over $t-1, t-2, t-3$.

[26] Following Bao, Pan, and Wang (2011), I obtain the round trip cost estimate with $(2 \cdot \sqrt{\gamma_t})$. Similarly to Friewald, Jankowitsch, and Subrahmanyam (2012),when the illiquidity measure is smaller than 0, I consider it 0. I then divide the estimate in half, in order to obtain one-way transaction costs.

where $TNAj, t$ are total net assets of fund j at the end of month t and $R_{j,t}$ is the return of fund j from month-end $t-1$ to month-end t. As it is standard practice in the literature, $Flow_{j,t}$ is winsorized at the 1% and 99% level. Furthermore, I construct a bond-specific exposure to fund flows. $Flow_{i,t}$ for bond i in month t is the ownership-weighted average of the net flows in month t of its bond mutual fund owners.[27] I also obtain a quarterly measure of cash holdings at the fund level. Cash holdings information is only available at a quarterly frequency. $Cash_{j,q}$ is the percentage of the fund TNA invested in cash and government bonds.[28] I construct a bond-specific exposure to fund cash holdings. $Cash_{q,t}$ for bond i in quarter q is the ownership-weighted average of the cash holdings (as a percentage of TNA) of its bond mutual fund owners in that quarter.

3.5 Data

I rely on several databases to establish my findings. First, I use the Enhanced Trade Reporting and Compliance Engine (TRACE) database to obtain transactions data including prices, trade directions, and volumes of the underlying bonds.[29] I apply standard filters as described by Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) to clean the data. I use monthly bond returns from WRDS Corporate Bond Database.[30] I obtain bond characteristics from the Fixed Income Securities Database (Mergent FISD). I retrieve information on investors' quarterly holdings of corporate bonds from Lippers eMAXX fixed income database. eMAXX has complete coverage of the corporate bond portfolio holdings of mutual funds, insurance companies and pension funds in the United States.[31] I obtain information on mutual funds' characteristics and performance from the CRSP Survivorship-Bias-Free Mutual Fund

[27]The weights are based on the ownership at the end of the previous quarter.

[28]Similar measures are employed by Goldstein, Jiang, and Ng (2017) and Choi and Shin (2018).

[29]The Enhanced TRACE is available up to December 2014. I use standard TRACE in the last part of my sample (January 2015-June 2016).

[30]WRDS Corporate Bond Database is a novel data source that provides monthly bond returns calculated from cleaned TRACE data. I chose to report results obtained from returns of the WRDS Corporate Bond Database, in order to make the replication of my findings easier.

[31]For a detailed description of the eMAXX data, see Dass and Massa (2014), and Becker and Ivashina (2015).

database. I identify bond funds based on CRSP objective codes.[32] I manually match by name CRSP bond fund information with eMAXX holdings, ending up with $1,144$ unique bond funds. Furthermore, I obtain from Bloomberg the monthly list of index constituents and index weights for the BofA/ML US High Yield Index and BofA/ML US Corporate Index. Finally, I retrieve data on stock and some bond factors from Kenneth French's website.[33]

I construct a panel of monthly bond returns matched with bond characteristics, portfolio holdings, fund flows, and benchmark index weights from November 2004 until June 2016. A bond return is included in my final sample only if the bond has not entered/exited the index in that month. Moreover, I exclude returns of bonds that experienced rating changes in the current month, the previous month and the next one. The dataset contains $335,135$ bond-month observations, split into $109,693$ for HY and $225,442$ for IG bonds. The observations are attributable to $12,384$ bonds ($5,035$ that appear at least once in the HY segment and $8,108$ in the IG).

I provide descriptive statistics of the variables used in my analysis for the full sample in Table 1, panel A. The average bond in the sample has $713.32 million in amount outstanding, 5.73 years to maturity, a coupon rate of 5.79%, a rating of 9.27, a one-way transaction cost of 52.57 bps and an order imbalance close to zero. I compare bonds in the HY index versus those in the IG one in panels B and C. HY bonds have, on average, more volatile returns, larger benchmark weight changes, lower amount outstanding, lower time to maturity, higher coupon, and are more illiquid.

The statistics on portfolio holdings show that active bond funds hold a significant part of the bonds in the HY index, with 16% of the amount outstanding on average, and more than 27% in the upper quantile. They hold less in the IG index, with only 6% of amount outstanding on average, which reaches 11% in the upper quantile. Insurance companies

[32]As in Goldstein, Jiang, and Ng (2017), a mutual fund is defined as a bond fund if the Lipper objective code is among (A,BBB, HY, SII, SID, IID), or Strategic Insight objective code is among (CGN, CHQ, CHY, CIM, CMQ, CPR, CSM), or Wiesenberger objective code is among (CBD, CHY), or has IC as the first two characters of the CRSP objective code. Among the bond funds, I identify bond index funds and bond ETFs through index_fund_flag and et_flag.

[33]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

instead own a large portion of the corporate bonds in the IG index: 34% of the outstanding amount on average, which increases to over 50% in the upper quartile. On the other hand, they hold much less in the HY segment, with 12% of the amount outstanding on average, that is consistent with the regulatory constraint which forces them to have no more than 20% of their portfolio invested in speculative grade assets. Index funds hold generally more bonds in the IG index, but in a much lower quantity than active bond funds (on average 1% in HY and 3% in IG). Finally, pension funds and ETFs play a much smaller role, with approximately 1% and close to zero, respectively. Figures 1 and 2 display the time dynamics of bond holdings across investors. Fixed income active and index funds increase their investment in corporate bonds over the years. Interestingly, active bond funds' holdings of HY bonds were already considerably high before the crisis (on average 10% of amount outstanding). On the other hand, the presence of bond funds in the IG segment was negligible before 2008. Insurance companies have a rather constant level of holdings in corporate bonds over the sample, while pension funds decrease their investment significantly post-crisis.

The net flows of active bond funds are on average around zero, in all panels. The upper and lower quantile are close to symmetric, with values between −1.3% and 1.8%. The HY segment presents larger negative flows, amounting to −1.7% in the lower quantile. Net flows of bond index funds are generally more positively skewed, with the lower quantile being close to zero and the upper one between 1.8% and 2.7%. The positive flows of bond index funds are consistent with their increase in bond holdings over time, as shown in Figure 1.

The cash measures highlight some interesting stylized facts. First, on average, HY bonds are held by funds with less cash-like securities than those that hold IG bonds (6.5% versus 13.3% for active funds and 3.2% versus 25.9% for bond index funds). Second, index funds hold significantly more cash-like assets than active bond funds in the IG segment, while the opposite is true for HY, but with a lower magnitude. The stark difference in the IG segment could be explained by the fact that the benchmark index includes also some treasuries and index funds, that need to track the benchmark more closely and might choose to hold more government bonds.

4 Empirical Findings

4.1 Portfolio Sorts

I start my empirical analysis by assessing the pricing implications of benchmarking in the whole US corporate bond market. In each month, I sort corporate bonds based on index weight changes into quintile portfolios and calculate equally weighted excess returns. As described in more detail in Section 2.1, the benchmark index composition for month t is known at the end of month $t-1$. I am therefore interested in excess returns from month-end $t-1$ to month end t, of portfolios created with information available up to month-end $t-1$. I exclude from my portfolios bonds whose first (last) month in the index is month t ($t-1$). In this way, my findings are not capturing excess returns following index exclusions or inclusions. Those events are relatively easy to predict and often linked to heterogeneous trading motives that are not benchmarking.[34] Furthermore, I exclude all bonds that had rating changes in months $t-1$, t, and $t+1$. Rating changes can signal a variation in the issuer's credit risk, and returns around such events might incorporate that, independently from benchmarking. My final sample is hence capturing only changes of weights *within* the index and not surrounding rating changes.[35]

The results for the full sample are provided in Table 2.[36] The sort variable (index weight

[34]For example, bonds are excluded from the IG index and included in the HY index (excluded from the HY index and included in the IG index) when downgraded from IG to speculative grade and vice-versa. Events of this kind are relevant also for other non-benchmarked/regulatory-constrained investors such as insurance companies, which might need to sell those securities to meet their regulatory capital buffer. It is hard to disentangle benchmarking motives from regulatory-induced trading. I therefore decide to exclude such confounding events.

[35]It is important to note that I perform the sorting *before* removing index inclusions/exclusions and rating changes. I do so in order to capture variation in weights that are large with respect to the full spectrum of corporate bonds in the index, assuming this is the universe that investors are looking at when deciding how to re-balance their portfolio.

[36]Note that, even for the full sample, the sorts on index weight changes are performed *separately* across IG and HY index. P5 includes bonds with large positive weight increases *relative to their benchmark*. Pooling weight changes across indexes would make no sense, as the number of securities in the two indexes are structurally different, and therefore the variation in weights are not comparable.

change) presents significant heterogeneity across the five portfolios, with an average decrease of 14.24 bps/100 in P1 and an average increase of 12.04 bps/100 in P5. There is a strong positive relation between bond excess returns and past index weight changes. In line with the idea that investors re-balance their portfolios in response to variations in the benchmark composition, I find that corporate bond excess returns increase from the portfolio of bonds with lowest index weight changes (P1) to the portfolio of bonds with the highest (P5). The return differential between P5 and P1 is large (39.87 bps on a monthly basis) and highly significant, with a t-statistic of 2.8. Remarkably, the return in the following month drops to 9.23 bps, and becomes statistically insignificant. Such a pattern supports the view that the price effects are linked to immediate re-balancing of investors' portfolios in response to changes in the benchmark composition. Interestingly, while the bonds with the most positive weight changes realize a statistically (t-stat 2.98) and economically significant (31.80 bps) return, those with the most negative do not present a sizable reaction, with a statistically insignificant excess return of -8.07 bps. According to Table 1, the bonds in the sample are exposed to positive flows. Therefore, my result is consistent with the reinvestment mechanism proposed in H1 of Section 2.2. Fund managers need to re-invest the inflows and, overall, buy the assets that increased the index weight, more than they sell those that decreased it. This generates bonds with index weight increases having positive excess returns that are larger (in absolute value) than the negative returns on the ones with index weight decreases.

Portfolios characteristics in P1 and P5 are really similar, indicating that large weight changes are likely independent of standard bond characteristics such as size, credit rating, time to maturity, coupon and illiquidity. While the last four characteristics are similar across the other portfolios as well, size presents a U-shaped pattern. The larger bonds are concentrated in P5 and P1, while P2, P3, and P4 contain bonds of almost half the amount outstanding. Such a pattern is not surprising, considering that bigger bonds have larger weights to start with, and hence are more likely to experience larger weight changes. Active bond funds hold around 10% of the amount outstanding, on average, across all portfolios. Bond index funds hold much less, ranging between 1.9% and 2.5% of amount outstanding across the quintiles. This falls in line with what is observed in Table 1 and Figures 1 and 2. The only portfolio characteristic that presents a monotonic pattern with respect to the sort variable is the past month return, which increases with the weight change. The relation is mechanical, due to the market-value weighting scheme of the benchmark index: with no bonds entering/exiting the index from $t-1$ to t, the new weights would be determined *only* by the returns in $t-1$. Although the total absence of inclusions and exclusions never occurs, a significant correlation between weight changes and past month returns still remains. I will show in the robustness tests in Section 4.7 that this variable is not driving my results. Finally, the monthly order imbalance of the bonds in the portfolios strongly supports the direction of the excess returns. Corporate bonds that experienced large increases in the benchmark have, on average, a positive order imbalance of 21.67 bps, meaning that buy trades are in excess of approximately 0.2% of the outstanding amount. In line with the aforementioned asymmetry between large positive and negative index weight changes, the order imbalance of P1 is much smaller, amounting to -7.82 bps. Consistent with the excess returns, differences in order imbalance across portfolios almost disappear in the following month.

Asset Pricing in Table 2 presents regressions of monthly excess returns across quintiles on standard asset pricing factors for stocks (MKT, SMB, HML, and UMD) and bonds (TERM, DEF, LIQ, and BMOM). I find a an economically (39.51 bps) and statistically significant (4.42 t-stat) α for P5$-$P1, which is in line with the results on excess bond returns. The largest contribution to α comes from P5 while P1, not surprisingly, has an insignificant α that is close to zero. The massive decrease of α in the following month, supports the idea that the documented price distortions are linked to re-balancing in response to benchmark composition changes. The other stock and bond risk factors present no statistically significant pattern across the quintiles. Generally, there is a negative correlation with MKT, and a positive one with TERM and DEF, across all portfolios. Bond liquidity and bond momentum are positively correlated with the long-short portfolio returns, indicating that they share common variation with index re-balancing but do not subsume it.

In Table 3, I show the results of the univariate portfolio sorts for the HY and IG index separately in panels A and B, respectively. Generally, the direction of findings and the mechanism is really similar to what presented in Table 2 for the full sample. The only difference lies in the magnitudes, with the HY segments presenting larger effects than the IG one. P5-P1 generates a positive excess return of 88.98 bps (t-stat 2.73) for HY and 14.77 bps (t-stat 2.63) for IG, corresponding to an α of 88.10 bps and 13.43 bps, respectively. Similarly to the full sample results in Table 2, and in line with the mechanism proposed in H1, P1 does not present any negative returns that are statistically different from zero. As for the full sample, characteristics of the portfolios are similar. Moreover, the dynamics of the order imbalance across quintiles is consistent with the findings on excess returns.

The sources of a different magnitude in the effects among HY and IG are multiple. First, as pointed out in Section 2.1 and displayed in Figure 3, the HY index includes a smaller number of assets, which is reflected in a larger magnitude of the sort variables. The average index weight change in P1 (P5) is -38.71 bps/100 for HY versus -2.20 bps/100 for IG (27.86 bps/100 versus 1.30 bps/100). Intuitively, smaller weight changes should lead to smaller price distortions, all else equal. Another reason that can explain the smaller magnitude in the effects is the distribution of portfolio holdings across benchmarked and non-benchmarked investors. In the HY segment, active bond funds and bond index funds together hold around 19% of the outstanding amount, whereas they reach at most 9% in IG bonds. Intuitively, if benchmarked investors (mutual funds) are driving such distortions, the magnitude of the price impacts should be lower when those investors are less in the market. The latter argument is consistent with H3 in Section 2.2.

4.2 Regression-Based Tests

In order to further control for confounding factors when studying price distortions, I perform a regression based test, using the following model for bond i in month t

$$R_t^e = \alpha + \gamma X_{i,t} + \beta_1 \cdot P1_{it} + \beta_2 \cdot P5_{it} + FE_{i,t} + e_{it} \tag{3}$$

where R_t^e is the excess return, and X_{it} is a vector of controls including bond characteristics, past returns and fund flows.[37] P1 and P5 are dummies that equal 1 if the bond belongs to the respective quintile, according to a sort based on index weight changes. FE is a vector with month and issuer fixed effects. Note that the reference dummy includes bonds belonging to P2, P3 and P4. This specification allows for capturing the amount of difference among the returns of bonds with large positive (P5) or negative (P1) benchmark weight changes with respect to those that experience small variations in the index (P2,P3,P4). This specification also allows to identify potential asymmetric behavior of assets in P5 or P1. I cluster standard errors at the issuer level, following Petersen (2009).

Table 4 presents the results for both the full sample (first column) and IG/HY indexes (second and third column, respectively). The asymmetric reaction to benchmark weight changes documented in the portfolio sorts is confirmed. The P5 coefficient is always positive and significant, ranging between 14.28 bps for IG and 32.37 bps for HY. Moreover, the coefficient on P5 is always larger than that on P1, which amounts to -13.85 bps for HY and is close to zero otherwise. The results unambiguously suggest that large positive variations in the benchmark are associated with larger returns more than large negative variations, as in the re-balancing mechanism discussed in Section 2.2. The magnitudes of the coefficients are largely in line with what documented in Tables 2 and 3 with portfolio sorts.

As an alternative regression specification, I run the following model:

$$R_t^e = \alpha + \gamma X_{i,t} + \sum_{j=2}^{5} \beta_j \cdot P_{jt} + FE_{i,t} + e_{it} \tag{4}$$

[37] In the main specification, I do not include the 1-month lag return. Including it into the regression would strengthen the results even more. In fact, R_{t-1}^e enters with a negative coefficient and, in turn, the coefficient on P5 jumps up. However, the strong correlation between index weight changes and past month returns could lead to upward biased estimates of the P5 coefficient. I take a conservative approach and report the regressions tests without R_{t-1}^e. The results with the inclusion of this variable are in the Internet Appendix, in Table IA3.

where $\sum_{j=2}^{5} \beta_j \cdot P_j$ are dummies that equal 1 if the bond belongs to the respective quintile, according to a sort based on index weight changes. Note that the reference dummy is P1, and therefore the other dummies can be interpreted as return differentials between P_j and P1, with $j = 2, ...5$. All controls and standard errors are identical to those in the baseline model 3. The goal of this specification is to capture the return differential in the long-short portfolio P5-P1, and the monotonically increasing relation between excess returns and Δw documented in the portfolio sorts. The results are displayed in Table IA1, which is in the Internet Appendix. Again, the findings of the portfolio sorts are supported: there is a positive and monotonically increasing relation between portfolio excess returns and benchmark index weight changes. The magnitude of the differential P5-P1 is around 22.23 bps in the full sample, 46.62 bps in the HY yield segment and 11.85 in IG. All coefficients on P5$-$P1 are highly statistically significant.

In line with intuition, in all specifications bond excess returns are higher for bonds with higher credit risk and longer time to maturity. In the IG segment, bonds with larger size have lower returns. Overall, the regression-based tests confirm the findings on the portfolio sorts, establishing a strong link between index weight changes and *subsequent* excess returns. The empirical evidence presented so far, has concentrated on the average effect of benchmarking on bond prices, and has provided support for H1.

4.3 Benchmarking and Bond Fund Flows

In this section, I want to dig deeper into the interaction between benchmarking and liquidity management, aiming also to find support for the cash rebuilding mechanism proposed in H2. I do so by focusing on bonds exposed to large fund outflows right before index rebalancing, and check whether the assets with negative index weight changes indeed exhibit larger price drops and selling activity.

I first perform a sample-split based on the exposure of bonds to past month fund flows ($Flow_{i,t-1}^{ACT}$ and $Flow_{i,t-1}^{INDF}$). I create a sample of bonds exposed to large outflows, low flows and large inflows, based on the distribution quantiles of the flow variable.[38] The first group aims to find support for the cash rebuilding mechanism, exploring what happens to price distortions when fund managers re-balance after being hit by large negative flows. The samples of low flows and large inflows are meant to provide further support to the reinvestment hypothesis. I then repeat the analysis with portfolio sorts and regression-based tests for each of the new samples. I choose to focus on the two indexes separately, given the structural differences in the investors' pool between HY and IG, as shown in Table 1 and Figures 1 and 2.

Table 5 displays the results of the portfolio sorts and regression-based tests on the different subsample for both the HY and IG segments. Starting from panel A (HY), and focusing on active bond fund flows, an interesting pattern emerges. In line with cash rebuilding, when bonds are exposed to large outflows from active bond funds, there is a negative and significant price impact on assets that had large decreases in the benchmark weights. The magnitudes of the impacts are also large, with -57.78 bps (t-stat 2.55) in the portfolio sorts and -40.63 bps (t-stat 3.52) in the regression. The average order imbalance of the bonds in P1 is -21.10 bps (vs -13.80 bps in the baseline results in Table 3), confirming that the price drops are linked to a larger selling activity. Interestingly, the bonds in P5 still conserve positive order imbalance (17.10 bps) and price impacts (39.63 bps and 20.95. both statistically significant). However, they are smaller than what observed in P1. Taken together, my findings suggest active fund managers hit by outflows respond to index changes by selling more those assets that had weight decreases. This behavior is in line with fund managers trying to rebuild their cash buffers in expectation of future redemptions. Such trading activity exposes some assets to large price drops, which could lead to fire-sales and market instability. If many funds are hit by large outflows at the same time, managers with benchmark-related concerns will try to rebuild their cash buffer by selling the same assets. This could lead to a negative

[38] A bond belongs to the sample of *large outflows* (*large inflows*) whenever $Flow^{ACT}_{i,t-1} \leq -1.5\%$ ($Flow^{ACT}_{i,t-1} \geq 1.5\%$). *Low flows* include bonds where $-1.5\% < Flow^{ACT}_{i,t-1} < 1.5\%$. The cutoff value of 1.5% has been chosen since it corresponds roughly to the 15th and 85th percentile of the distribution of $Flow^{ACT}_{i,t}$, as shown in Table 1. However, the findings are robust to different cutoff levels. The same cutoff is applied to $Flow^{INDF}_{i,t}$.

spiral starting with large fire-sales discounts, which lead to negative fund performance and, potentially, more outflows.

Moving into the other subsample, both of them present asymmetric price impacts, with larger effects on bonds with index weight increases, in line with H1. Overall, I confirm the proposed mechanism of stronger buying pressure on bonds with large weight increases in the benchmark, in cases of net inflows. Interestingly, the low flows subsample presents results which are really similar to the large inflows. The flow measure I use in my analysis does not capture reinvestment of assets' cash flows (coupon and principal payments), which are included in the return of the fund.[39] My findings can be explained by managers re-investing bond cashflows in assets with large benchmark weight increases.[40]

The results of the samples based on bond index funds flows do not show any reaction to large outflows, and generally confirm the findings for low flows and large inflows. The lack of reaction to large outflows of bond index funds can be reconciled with the low ownership share of this class of investors in the HY segment, compared to active funds. As shown in Figure 1, bond index funds hold, on average, at most 2% of an HY bond, while active bond funds never go below a 10% ownership share.

panel B displays results on the IG segment. There is no strong negative reaction to the large outflows of active bond funds, while the effects for low flows and large inflows are confirmed here as well. Shifting the focus on bond index funds, low flows and large inflows confirm the asymmetric effects on excess returns proposed in H1, with a larger impact in presence of large inflows. Large outflows generally do not show statistically significant reactions. However, order imbalance (-17.33 bps), the sign of the portfolio sorts excess return (-4.03 bps), and the regression coefficient (-3.39 bps) on P1 suggest that there is larger selling activity on bonds with index weight decreases, in line with H2. Results in the IG segment provide support to the idea that relative performance concerns can lead to sizable

[39] See, for more details http://www.crsp.com/files/MF_Sift_Guide.pdf.

[40] Bond funds have a non-trivial cashflow components from the latter, as in a large bond portfolio assets mature and pay coupons on a regular basis.

impacts, only if the fraction of benchmarked institutions in the market is large enough.

There are four main take-aways from the analysis on the relation between bond fund flows and benchmarking. First, flows of active bond funds have a large impact on the HY segment, while flows of bond index funds play a bigger role into the IG segment. Second, large outflows of active bond funds in the HY segment are followed by stronger selling activity and negative price impacts on bonds with big index weight decreases. This result is in line with fund managers trying to rebuild their cash buffers after being hit by large redemptions. Similar effects can be found in relation to large outflows of bond index funds in the IG segment, but magnitudes and significance are much lower. Third, low flows and large inflows are generally associated with the stronger impacts on bonds with benchmark weight increases. This result is consistent with funds re-investing bond cash flows and investors' inflows to buy assets with positive index weight changes. My findings support the mechanism proposed in Section 2.2, and are, to the best of my knowledge, the first to highlight the tight link between benchmarking incentives and liquidity management in fixed income funds.

4.4 Benchmarking and Cash Levels of Bond Funds

The evidence presented so far supports H1 and H2, based on the interaction between index weight changes and bond exposure to fund flows. In this section, I am interested in studying the role played by funds' cash levels. While cash holdings might not be relevant when there are additional inflows, they could play a role when a fund is hit by outflows and needs to re-balance with respect to the benchmark. Facing the same amount of outflows and variation in the index, funds with higher cash holdings would require less cash rebuilding, and hence less selling of bonds with index weight decreases.

Similarly to what is described in Section 4.3, I first perform a sample-split based on the exposure of bonds to funds' cash holdings ($Cash_{i,q}$). I create a sample of bonds exposed to high and low cash holdings, based on the distribution quantiles of the cash variable. Measuring the relation between index variations and funds' cash holdings is challenging. Cash holdings are disseminated only quarterly, creating a time-mismatch with the monthly re-balancing in the benchmark. Moreover, one needs to take into account fund flows within the quarter. A fund might have particularly low cash levels at the beginning of the quarter, but receive large inflows in the first month of the quarter that could increase the cash level significantly. In order to alleviate such concerns, I include bond i in quarter q in the high (low) cash sample, if both $Cashgov_{i,q-1}$ and $Cashgov_{i,q}$ belong to the highest (lowest) quintile of the whole sample. This feature aims at removing bonds whose cash exposure changes significantly from quarter to quarter. Moreover, I focus only on bonds that are exposed to zero or negative flows.[41] Considering assets that are exposed to inflows, would make it hard to pin down the impact of *existing* cash holdings in the fund. Once the subsample are defined, I repeat the analysis with portfolio sorts and regression-based tests for each of the subsample.

The results are displayed in Table 6, with both portfolio sorts and regression-based tests on the different subsample for the HY and IG segments. Starting from HY bonds, the relation between active funds' cash holdings and price distortions is strong, and in line with the proposed mechanism. Bonds that had large negative index weight changes are sold more (-28.78 bps versus -17.67 bps) and exhibit larger negative price impacts (-46.58 bps versus -15.89 bps) if they are held in portfolios of funds with low cash holdings than in those of funds with high cash holdings. Consistently, bonds that had large weight increases in the benchmark are bought more and have larger positive price impacts if they are held by funds with high cash. The regressions confirm what displayed in the portfolio sorts, with a negative (positive) and significant coefficient for P1 (P5) in the sample of bonds exposed to low (high) cash funds. When focusing on index funds' cash holdings, I do not find any significant relation with reactions to benchmark changes, neither in portfolio sorts nor regression-based tests. This is consistent with index funds playing a smaller role than active investors in the HY segment, as shown in Table 5.

Moving to the IG segment in panel B, there is no significant relation between active funds'

[41] $Flow_{i,t-1}^{ACT} \leq 0$ or $Flow_{i,t-1}^{INDF} \leq 0$

cash holdings and price reactions to changes in the benchmark. Active funds' small role in the IG segment of the market is in line with the findings in Table 5. When looking at index funds' cash holdings, there is no significant effect for bonds exposed to low cash funds. On the other hand, bonds exposed to high cash index funds that had large positive (negative) index weight changes present significant increases in prices (no price reaction).

Overall, I provide novel evidence of a link, in fixed income markets, between benchmarking-driven price distortions and mutual funds' cash holdings. There are two main take-aways from this exercise. First, the cash rebuilding mechanism is particularly strong in assets held by funds hit by outflows *and* low cash holdings. Second, the reinvestment mechanism can apply to cases of assets exposed to outflows, but held by funds with particularly high cash buffers. Overall, higher cash holdings can mitigate the negative price impacts following the re-balancing of funds after variations in the benchmark.

4.5 The Dynamics of Portfolio Holdings

The evidence I have presented so far is consistent with the presence, in the US corporate bond market, of price distortions linked to index variations. To further support the idea that the documented effects come indeed from benchmarked institutions, I analyze quarterly changes in par-amount bond holdings in the cross-section of investors, and relate them to the variation of benchmark index weights. According to the mechanism discussed in 2.2, benchmarked institutions should increase their holdings in bonds with large positive index weight change and decrease them in those with large negative ones. As a placebo test, I also analyze variations in the portfolio holdings of non-benchmarked institutions for which I have data (insurance companies and pension funds). Since they are not tied to a benchmark, I should document no pattern in their holdings which is consistent with the effects on returns presented in Sections 4.1 and 4.2. The data on portfolio holdings are disseminated quarterly, hence I cannot observe the re-balancing of institutions at the same frequency of returns and index weight changes. The discrepancy in timing of observations does not allow me to capture the immediate re-balancing of the portfolios following monthly index weight changes. Nevertheless, I can study the link between the variation of index weights and portfolio re-balancing on a quarterly basis. For a given bond, in each quarter, I observe the variation (in percentage of outstanding amount) in the holdings of a specific type of investors. Note that the holdings are given in par-amount, and are therefore independent of returns. Their changes reflect investors buying or selling a specific security, not mechanical adjustments in portfolio values due to variations in market prices.

In my analysis, I first calculate for each bond, from quarter-end to quarter-end, the cumulative variation in portfolio holdings (as a percentage of amount outstanding) of a certain group of investors. Second, I sort corporate bonds based on cumulative quarterly index weight changes, making sure that the variation in portfolio holdings is not contemporaneous to the information on benchmark weight changes.[42] The average quarterly cumulative Δw for HY in P1 is -61.683, which is almost double the average in P5, which amounts to 32.687. The same applies for the IG segment (-2.96 versus 1.53).[43] When analyzing potential asymmetries in trading behavior, it is important to bear in mind that the negative weight changes are twice as large the positive ones. Third, I run the following regressions:

$$\Delta H_{ixq} = \alpha + X_{iq} + \beta_1 \cdot P1_{iq} + \beta_2 \cdot P5_{iq} + FE_{i,t} + e_{iq} \tag{5}$$

$$\Delta H_{ixq} = \alpha + X_{iq} + \sum_{j=2}^{5} \beta_{iq} \cdot P_{iq} + FE_{i,t} + e_{iq} \tag{6}$$

where ΔH_{ixq} is the variation in portfolio holdings of bond i by investor group x in quarter q.

[42] Assume w_t is the vector of index weights in month t. For the January-March quarter, I calculate cumulative index weight changes: $(w_{JAN} - w_{DEC}) + (w_{FEB} - w_{JAN}) + (w_{MAR} - w_{FEB})$. The information fo these weight changes is know at the end of December, January and February, respectively. Therefore, the cumulative variation of index weights uses information up to February-end. The variation in portfolio holdings is instead calculated by using the holdings observable at December-end and those at March-end. The earliest information I use about index weight is available to investors on the last day of December, and therefore it is unlikely that part of it is already incorporated in the holdings. The latest information I use instead is available one month before (February-end) than I observe the holdings again (March-end), allowing me to capture at least some response by institutions to variation in index weights.

[43] Such discrepancies are due to the fact that I perform the portfolio sorts on weight changes *before* removing index inclusions/exclusions and rating changes. I do so in order to capture variation in weights that are large with respect to the full spectrum of corporate bonds in the index, assuming this is the universe that investors are looking at when deciding how to re-balance their portfolios.

The explanatory variables are identical to those in equations 3 and 4, only at the quarterly level. I consider the following types of benchmarked investors: active bond funds (ACT), bond index funds (INDF), and bond ETFs (ETF). I also analyze the following non-benchmarked institutions: insurance funds (INS), and pension funds (PENS).[44]

Table 7 shows the results of the tests on portfolio holdings for HY in panel A and IG in panel B. I choose to focus on the two indexes separately, given the structural differences in the investors' pool between HY and IG, as shown in Table 1 and Figures 1 and 2. Starting with panel A, active bond funds and bond index funds are the institutions whose variation in holdings is consistent with the mechanism proposed in Section 2.2. For both investors groups, P1 and P5 are highly significant and with the expected sign. Benchmarked investors increase (decrease) their holdings in bonds with large positive (negative) benchmark weight changes, with relatively similar magnitudes.[45] The results on the second regression specification confirm the findings on active and index bond funds. $P5 - P1$ is positive, significant, and the one with the largest magnitude. Moreover, the pattern from $P2 - P1$ to $P5 - P1$ is generally increasing, consistent with what is documented for excess returns with the portfolio sorts. Not surprisingly, given their extremely low aggregate holdings, bond ETFs do not show any relation with index weight changes. When moving to non-benchmarked institutions, none of the patterns displayed in active and index bond funds are present. Insurance companies have a significant negative coefficient on P1, but P5 is close to zero and not significant. Additionally, there is no clear relation across the coefficients in the second regression specification, with $P5 - P1$ being smaller than both $P4 - P1$ and $P3 - P1$. Finally, pension funds show no relation with variation in the benchmark index weights.

Panel B (IG bonds) delivers a similar picture, with the difference being that only bond

[44] I do not consider insurance funds owned by an asset-management firm (e.g. Blackrock), since they could be affected by benchmarking concerns.

[45] As I can only analyze holdings quarterly, I do not make any statement as to whether investors buy more bonds in P5 (reinvestment) or sell more in P1 (cash rebuilding). The flows change every month, and it is hard to disentangle their overall effect on a quarterly frequency. However, if one wants to compare the magnitudes, coefficients are generally consistent with the average effect documented in Tables 2 and 3. The coefficients are similar (12.12 bps versus -15.99 bps and 1.9 bps versus -2.86 bps). Nevertheless, as the weight decreases in P1 are twice as large as the increases in P5, the relative response is stronger for the weight increases.

index funds seem to move their holdings in relation to variations in the benchmark, while active bond funds have no sensitivity. The coefficients of bond index funds are on the same order of magnitude of those observed for the HY segment, although slightly smaller. This can be explained by the lower magnitude of the index weight changes in the IG index, which has many more constituents than the HY index. As in panel A, the holdings of non-benchmarked institutions show no pattern which is consistent with the effects on returns presented in Sections 4.1 and 4.2.

Overall, I show that the variation in the portfolio holdings of benchmarked institutions is consistent with the price distortions. They buy bonds with large weight increases in the benchmark and sell those with large weight decreases. This creates a significant wedge in the portfolio holding dynamics between assets with positive index weight changes and those with negative ones, controlling for other confounding factors. I show that active bond funds (bond index funds) are the ones with the most sensitivity to variations in the HY (IG) yield index. To the best of my knowledge, this paper is the first to show that active funds trade consistently with benchmark-related concerns.[46] Finally, I provide a placebo test wherein I show that holdings of non-benchmarked institutions (insurance companies and pension funds) are not sensitive to variations in the index.

4.6 Are the Price Distortions Increasing over Time?

The sharp increase of fixed income funds' corporate bond holdings in recent years has drawn a lot of attention, both among academics and regulators.[47] Since the period of steep growth in fixed income funds is included in my sample, it is interesting to explore how the price distortions documented in Tables 2 and 3 vary over time. Based on H3, I should expect the effects to be larger in the latter part of the sample, when a larger fraction of benchmarked

[46] Dick-Nielsen and Rossi (2019) study liquidity provision in the bond market, using index exclusions as a natural experiment wherein index trackers require immediacy. However, they do not mention active funds and do not investigate the holding dynamics of the institutions with respect to the whole spectrum of variations in the benchmark.

[47] See for example Goldstein, Jiang, and Ng (2017), and Feroli, Kashyap, Schoenholtz, and Shin (2014) for a discussion.

institutions is present in the US corporate bond market.

I repeat the monthly portfolio sorts presented in Tables 2 and 3, and split the sample into three time periods of similar length: November 2004-December 2007, January 2008-December 2011 and January 2012-June 2016. I am particularly interested in the variation between the first and the last periods, where the differences in the holdings of fixed income funds are largest.[48] The results are reported in Table 8 for all bonds (panel A), HY (panel B) and IG (panel C). Panel A provides evidence that the price distortions are present in all the time periods (P5-P1 excess return positive and statistically significant), but are generally stronger in the last years of the sample than in the pre-crisis period (17.77 bps versus 39.96 bps). Long-short portfolios in the first and last period generate positive significant alphas, with the largest belonging to January 2012-June 2016 (40.82 bps, t-stat 2.57). The increase in active and index bond funds over time is highlighted in the portfolio characteristics. Active bond funds increase their average investment on a corporate bond, from around 7% of the outstanding amount pre-crisis, up to almost 11% in the last period of the sample. Bond index funds show an even stronger relative growth, going from 0.3% up to 3.5%.

The HY panel confirms the findings on the full sample, with larger magnitude. Notably, the price distortions are already strong in the pre-crisis period, which is consistent with an already large presence of active bond funds in the market (12% of amount outstanding on average). Moving to the IG index in panel B, an even more interesting pattern arises. The price distortions observed in the full sample for IG bonds are coming mainly from the last period (18.94 bps, t-stat 2.18), while being completely absent in the pre-crisis years (5.09 bps, t-stat 1.15). The pattern in excess returns pairs nicely with the statistics on holding levels. In 2004-2007, active bond funds and bond index funds hold, on average, 2.15% and 0.55% of amount outstanding, respectively. In 2012-2016, however, the holdings increase to 7.3% for active funds and 4% for index funds.

In Table IA8 in the Internet Appendix I display results for an extension of the regression

[48] The middle sub-period contains the financial crisis and the subsequent recovery, and therefore carries a lot of noise. I focus, therefore, on the comparison between the first and last periods.

specification in 4, where I add interaction terms between P5-P1 and dummies that identifies the different time periods. The results are really similar to what I observed in Table 8, with the interaction term between P5-P1 and the 2012-2016 dummy is positive (around 11-13 bps) and highly significant for both the full sample and the IG sample. In the HY sample, the coefficient is positive but not significant. I conclude that price distortions in HY bonds are already high pre-crisis, and remain as strong (but not statistically larger) after 2012.

Overall, the results presented in Tables 8 and IA8 provide strong evidence that the price effects arising from benchmarking increased when the share of benchmarked investors in the market got larger, in line with H3. The increase is particularly significant for the IG segment, where fixed income funds and price distortions were almost absent in 2004-2007. My findings support the idea that mutual funds' increased participation in the bond market might have contributed to an amplification of the price distortions that arise from variations in benchmark composition.

4.7 Robustness and Additional Results

In this section, I include a battery of robustness tests for my findings. First, I provide evidence that my results are not explained by past month returns, (i.e., investors consistently buying bonds that performed best in the previous month). Second, I show that my conclusions are un-affected if I use value weighted portfolios. Third, I show that my results are not changed when considering index exclusions-inclusions.

Controlling for Past-Month Returns. As the benchmark index is market-value weighted, index weight changes are highly correlated with past month returns. Therefore, my results could also be explained by investors persistently buying bonds that performed best in the previous month. I provide several tests in order to exclude this alternative explanation. First, I double-sort corporate bonds into five past month return (R^e_{t-1}) portfolios, and then into quintile portfolios based on index weight changes (Δw). The goal is checking whether the relation between variations in the benchmark holds also within bonds that had really similar returns in the previous month. Results are presented in Table 9 for the full sample (panel A), HY bonds (panel B) and IG bonds (panel C). In each of the 15 long-short portfolios displayed in the three panels, sorting on index weight changes after having conditioned on past month performance, generates statistically significant positive excess returns and alphas. Furthermore, the magnitudes of the effects are overall consistent with the baseline results. An interesting exception is represented by the portfolios that include the most negative index weight changes (P1.5-P1.1), where results are significant but the magnitudes are larger. In these portfolios, there is a decreasing monotonic relation between bond size and index weight changes, (i.e. the portfolio with most positive Δw includes smaller bonds). As a consequence, part of the effect is due to smaller bonds being less liquid and carrying larger returns on average.[49] As an additional test, I perform univariate sorts based on past month returns. The results are presented in Table IA2, and show that going long into the bonds with the most positive past month returns and short in those with most negative, leads to negative performance, consistent with a short-term reversal mechanism in the bond market. This test shows that, if anything, past month returns impose a lower bound on my results based on Δw. This view is supported in regression-based tests where R^e_{t-1} is included as a control variable, displayed in Table IA3. In all specifications, R^e_{t-1} enters with a negative coefficient, consistent with the reversal effect. While the P5 coefficient in the HY sample is basically unchanged (35.72 vs 32.37 bps), the other ones get substantially larger (34.20 bps versus 20.08 bps for all bonds and 31.99 bps versus 14.28 bps for IG), supporting the view that my baseline results are a lower bound. As the strong correlation between Δw and past month returns could also lead to upward biased estimates in P5, I take a conservative approach and report as main results the regressions tests without R^e_{t-1}. Overall, the alternative mechanism through which investors buy bonds that performed well in the previous month cannot explain my findings.

[49] See, for example Edwards, Harris, and Piwowar (2007) and Lin, Wang, and Wu (2011) about the relationship between bond size and illiquidity.

Value-Weighted Portfolios. Corporate bonds can have a large cross-sectional heterogeneity in their amount outstanding, as shown in the summary statistics in Table 1. As a consequence, using value-weighting instead of equal-weighting in portfolio sorts, might lead to significantly different results. I show that my findings are not affected by the weighting rule applied in the portfolio sorts, by repeating them with value-weighted portfolios. Results are displayed in Table IA5 for the full sample and Table IA6 for HY and IG segments, respectively. They are really similar to those presented in Tables 2 and 3, both in magnitude and statistical significance.

Including Bonds that Enter/Exit the Benchmark Index. My findings are based on a sample wherein index weight changes that are linked to inclusions and exclusions from the benchmark are not considered. Inclusions and exclusions from the index are highly predictable, since they are determined by mechanical rules, as explained in Section 2.1. Moreover, they are triggered by events that are linked to institutional trading unrelated to benchmarking, such as rating changes and bonds that are partially called. I show that my findings are not affected if index inclusions-exclusions are part of my sample. Table IA7 displays the results of portfolio sorts for a sample with index inclusions and exclusions. The results are really similar to the ones presented in Tables 2 and 3, both in terms of magnitude and statistical significance.[50]

5 Conclusion

This paper shows that benchmarking concerns of fixed income fund managers lead to significant distortions in corporate bond prices, as a consequence of portfolio re-balancing, in response to variations in the benchmark index. The direction and magnitude of the effects strongly depend on past flows and cash levels of *both* active and passive bond funds holding

[50]The fact that index inclusions and exclusions do not amplify the magnitude of my findings is consistent with institutions being able to predict such events, and trading in advance.

the assets.

I propose a mechanism wherein managers trade-off investment into illiquid benchmark assets, against holding cash in expectation of redemptions. In case of inflows, managers over-proportionally buy bonds with index weight increases. If hit by outflows, in an attempt to rebuild their cash buffer, they over-proportionally sell the bonds with index weight decreases.

Consistently, I show empirically that, when exposed to funds inflows, bonds with index weight increases have positive excess returns (excess buying activity) that are larger than the negative returns (excess selling activity) on the bonds with index weight decreases, which are mostly insignificant. Going long into the bonds with the most positive benchmark index weight changes and short into those with the most negative, generates a significant α of 39.5 bps (13.4 bps for IG and 88.1 bps for HY) beyond stock and bond pricing factors. In line with the cash rebuilding mechanism, I find that, when exposed to large outflows, bonds with index weight decreases are sold more than those with weight increases are bought. This leads to large negative price impacts (up to -57 bps monthly excess returns) on those assets. A similar effect can be found in bonds that are exposed to outflows and low funds' cash holdings. My findings support the idea that funds managers' benchmarking concerns, coupled with large outflows, give an incentive to sell the same assets quickly in order to rebuild a cash buffer. Hence, these concerns act as a potential channel of instability in fixed income markets.

Variations in portfolio holdings in line with the pricing results can only be documented among benchmarked institutions (active fixed income funds and bond index funds). On the other hand, I cannot find among non-benchmarked investors (insurance companies and pension funds) any pattern consistent with the variation in prices. My results provide first evidence of fixed income fund managers jointly considering liquidity management and relative performance incentives.

Overall, my paper highlights the interaction between benchmarking incentives and liquidity management in fixed income funds, documenting the price distortions arising from it. My work is only a first step towards understanding how the tension between liquidity provision and the investment objectives of fixed income funds shape trading strategies, asset prices and, ultimately, financial stability. More research is needed to shed light, for example, on the dynamic implications of funds' re-balancing policies, and on the design of benchmarks in illiquid markets.

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Figure 1: Portfolio Holdings of Benchmarked Investors. I plot, for the average index-eligible bond in the sample, the fraction of amount outstanding that is in the portfolio of active bond funds (on the left) and bond index funds (on the right). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), and bond holdings (from Lipper eMAXX) for the sample period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

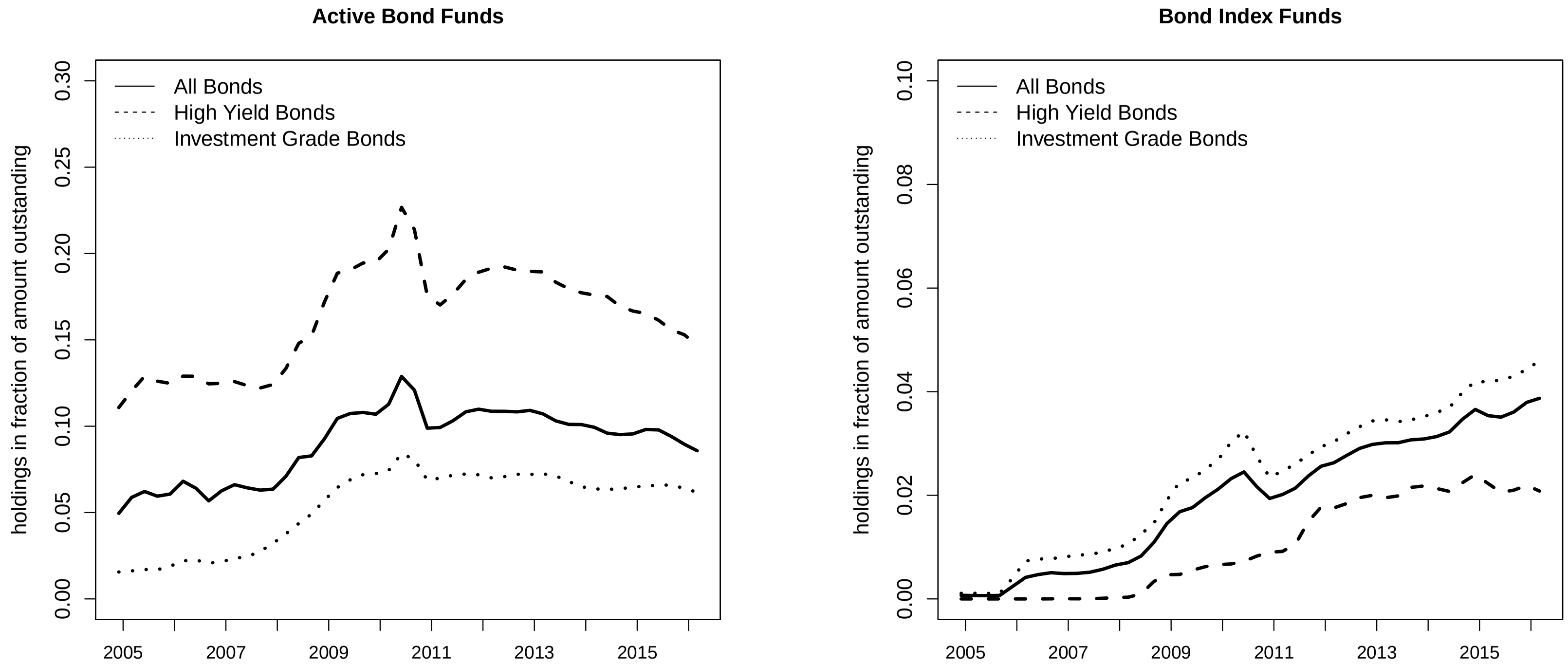

Figure 2: Portfolio Holdings of Non-Benchmarked Investors. I plot, for the average index-eligible bond in the sample, the fraction of amount outstanding that is in the portfolio of insurance companies (on the left) and pension funds (on the right). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), and bond holdings (from Lipper eMAXX) for the sample period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

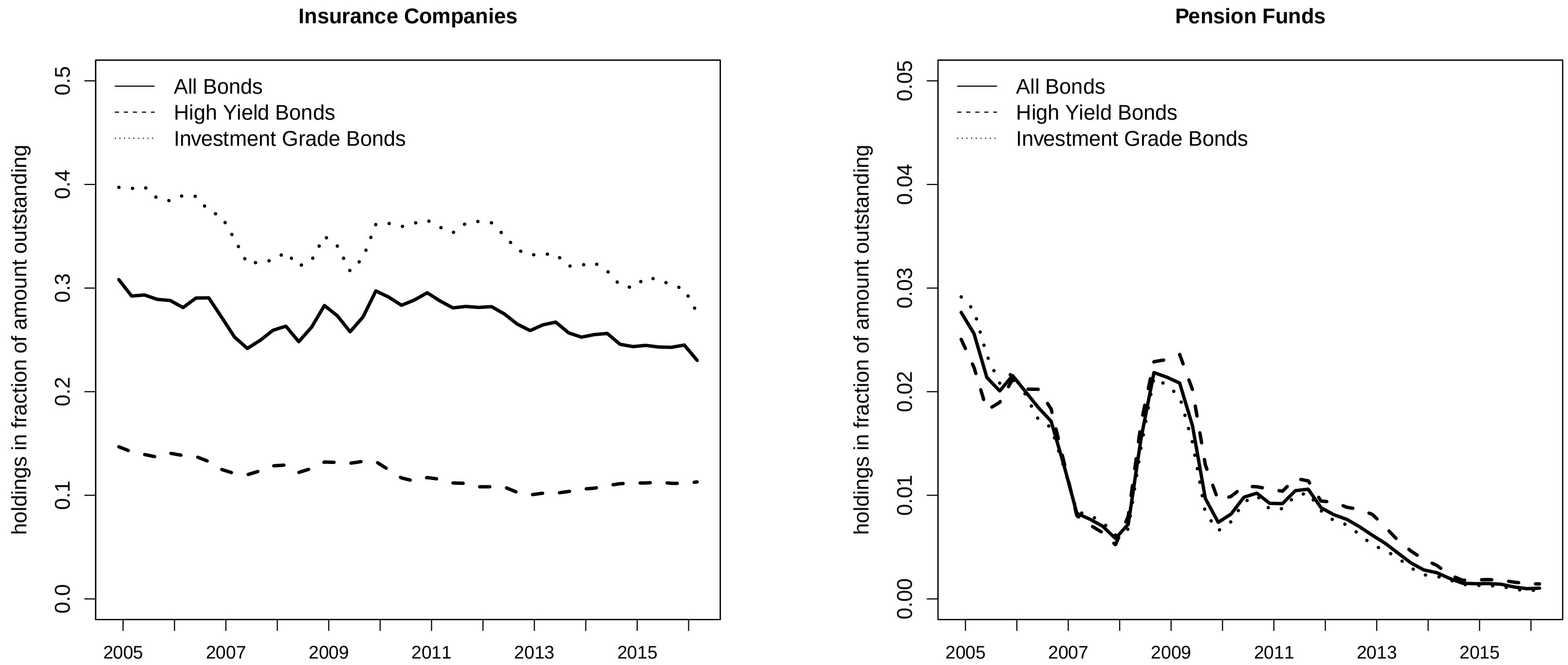

Figure 3: Turnover and Constituents of Bond Indexes I plot, for the average index-eligible bond in the sample, the fraction of amount outstanding that is in the portfolio of insurance companies (on the left) and pension funds (on the right). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), and bond holdings (from Lipper eMAXX) for the sample period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

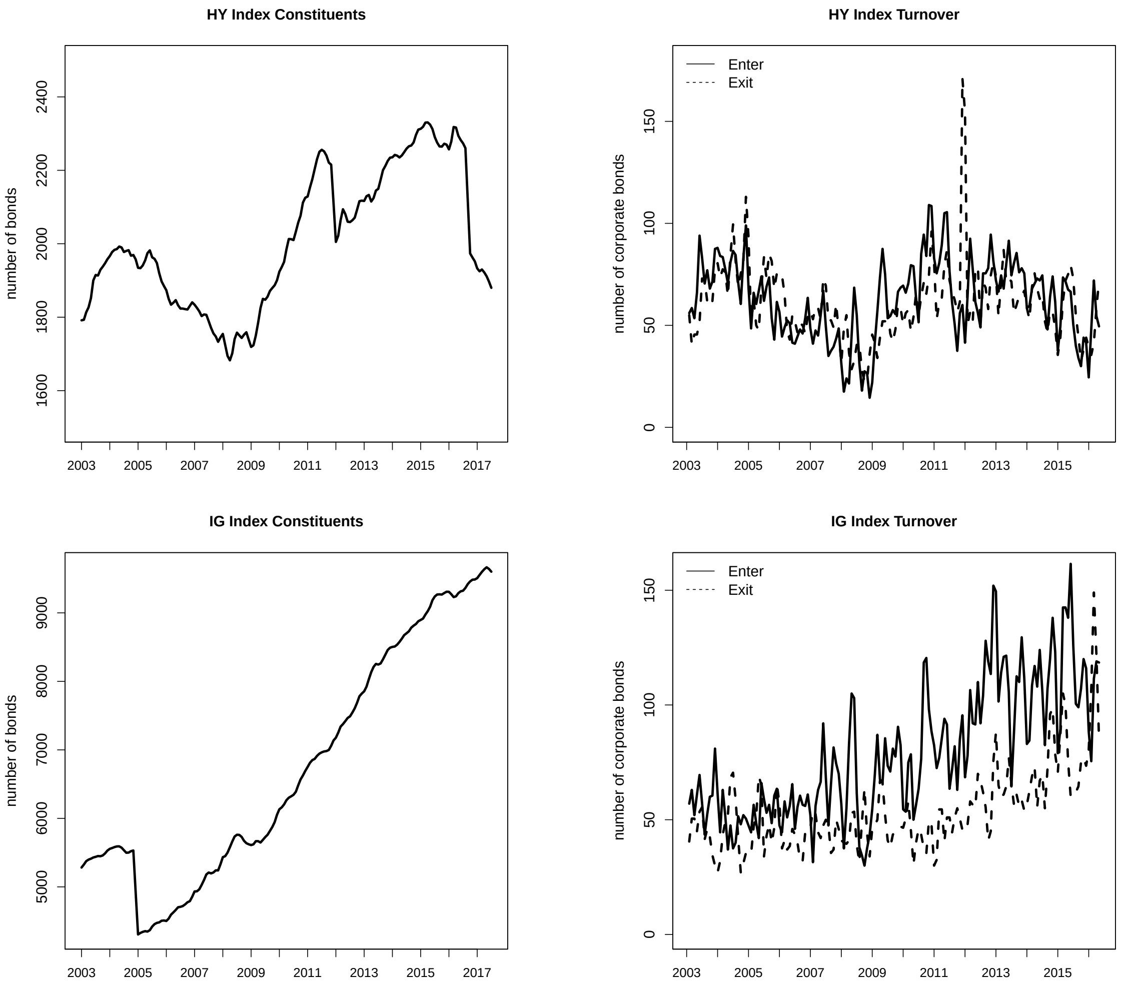

Table 1: Summary Statistics. I summarize descriptive statistics for the main variables used throughout the paper. R^e_{it} is the return of bond i from month-end $t-1$ to mont-end t, taking into account coupon payments and accrued interest. Δw is the variation in index weights of a specific bond from month t-1 to month t. Bond size is the amount outstanding if bond $i$in month t. Rating is obtained by assigning integer numbers to the ratings (i.e., AAA=1, AA+=2, ..., D=22) and calculate averages at the asset level at month-end. ACT, INDF, INS, and PENS are the fraction of amount outstanding held by bond active and index funds, insurance companies and pension funds, respectively. I report across all bonds the means, standard deviations, and the 15%, 50%, and 85% quantiles. Statistics for all bonds, HY bonds and IG bonds are displayed in panel A, B and C, respectively. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), and bond holdings (from Lipper eMAXX) for the sample period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

Variable	**Unit**	**Mean**	**SD**	**0.15**	**Median**	**0.85**
			Panel A: All Bonds			
R^e_t	[bp]	2.435	218.069	−138.962	−6.169	141.123
Δw	[bp/100]	−1.371	25.912	−3.900	−0.200	1.100
Bond Size	[$1 million]	713.319	597.059	275.000	500.000	1100.000
Rating	[integer]	9.266	3.928	6.000	9.000	14.000
Time to Maturity	[years]	5.726	3.985	2.330	5.200	8.710
Illiquidity	[bp]	52.574	41.108	22.001	43.062	79.513
Coupon	[percentage]	5.789	2.137	3.500	5.750	7.875
OIB_t	[bp]	1.453	193.683	−117.039	0.500	121.700
ACT	[percentage]	0.092	0.091	0.010	0.063	0.189
INDF	[percentage]	0.022	0.022	0.000	0.017	0.047
INS	[percentage]	0.266	0.201	0.056	0.224	0.500
PENS	[percentage]	0.009	0.030	0.000	0.002	0.017
ETF	[percentage]	0.000	0.001	0.000	0.000	0.000
$Flow^{ACT}_t$	[percentage]	0.001	0.037	−0.013	0.002	0.018
$Flow^{INDF}_t$	[percentage]	0.011	0.039	−0.001	0.003	0.027
$Cash^{ACT}_t$	[percentage]	0.111	0.100	0.027	0.085	0.215
$Cash^{INDF}_t$	[percentage]	0.216	0.173	0.005	0.256	0.406

Table 9 continued on next page.

Table 1 continued from previous page.

Variable	Unit	Mean	SD	0.15	Median	0.85
			Panel B: High Yield Bonds			
R_t^e	[bp]	11.307	351.168	−200.035	−3.376	229.568
Δw	[bp/100]	−3.386	45.083	−17.600	−1.700	10.700
Bond Size	[$1 million]	524.920	453.210	200.000	400.000	800.000
Rating	[integer]	13.907	2.335	11.000	14.000	16.000
Time to Maturity	[years]	6.948	5.597	3.220	5.960	9.032
Illiquidity	[bp]	63.739	55.557	25.002	50.035	98.318
Coupon	[percentage]	7.644	1.684	6.000	7.500	9.375
OIB_t	[bp]	1.475	221.242	−136.844	0.280	141.600
ACT	[percentage]	0.162	0.102	0.053	0.155	0.266
INDF	[percentage]	0.011	0.019	0.000	0.000	0.032
INS	[percentage]	0.118	0.117	0.015	0.085	0.223
PENS	[percentage]	0.010	0.032	0.000	0.004	0.019
ETF	[percentage]	0.000	0.002	0.000	0.000	0.000
$Flow_t^{ACT}$	[percentage]	0.000	0.031	−0.017	0.000	0.018
$Flow_t^{INDF}$	[percentage]	0.012	0.053	0.000	0.000	0.034
$Cashgov_t^{ACT}$	[percentage]	0.065	0.057	0.029	0.051	0.098
$Cashgov_t^{INDF}$	[percentage]	0.032	0.064	0.002	0.019	0.036
			Panel C: Investment Grade Bonds			
R_t^e	[bp]	−1.174	146.652	−118.953	−6.965	109.586
Δw	[bp/100]	−0.390	2.494	−1.100	−0.200	0.300
Bond Size	[$1 million]	804.987	635.861	300.000	600.000	1250.000
Rating	[integer]	7.008	2.170	5.000	7.000	9.000
Time to Maturity	[years]	5.132	2.698	2.070	4.690	8.550
Illiquidity	[bp]	47.315	33.135	20.798	40.404	71.511
Coupon	[percentage]	4.887	1.709	3.000	5.100	6.500
OIB_t	[bp]	1.442	178.750	−107.562	0.600	112.323
ACT	[percentage]	0.058	0.061	0.007	0.040	0.110
INDF	[percentage]	0.027	0.022	0.002	0.025	0.051
INS	[percentage]	0.339	0.194	0.124	0.322	0.554
PENS	[percentage]	0.008	0.028	0.000	0.002	0.016
ETF	[percentage]	0.000	0.000	0.000	0.000	0.000
$Flow_t^{ACT}$	[percentage]	0.001	0.040	−0.011	0.002	0.018
$Flow_t^{INDF}$	[percentage]	0.010	0.029	−0.001	0.008	0.027
$Cashgov_t^{ACT}$	[percentage]	0.133	0.111	0.026	0.134	0.239
$Cashgov_t^{INDF}$	[percentage]	0.259	0.162	0.006	0.298	0.418

Table 2: Portfolios Sorted by Index Weight Changes: All Bonds. I sort corporate bonds based on index weight changes into quintile portfolios and calculate equally-weighted excess returns. P1 contains bonds with the most negative index weight changes, P5 the most positive. P5−P1 presents results for going long P5 and short P1. Sort Variable presents means of the variable used in the sorts. Excess Bond Returns reports monthly means of excess returns in basis points. Portfolios Characteristics summarizes portfolio means of amount outstanding, rating, time to maturity, percentage amount held by bond active (ACT) and index funds (INDF), order imbalance, past month return and monthly number of bonds in each portfolio. Asset Pricing reports α estimates of regressing excess returns on the stock (MKT, SMB, HML, UMD) and bond factors (TERM, DEF, LIQ, BMOM). Values in parentheses are t-statistics based on heteroscedasticity- and autocorrelation-consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
			Sorting Variable: Index Weight Changes in bp/100			
Δw	−14.237	−2.865	−0.506	1.539	12.037	
			Excess Bond Returns			
R^e_t	−8.069	−4.445	0.025	11.560	31.801	39.870
	(−1.107)	(−0.643)	(0.003)	(1.507)	(2.981)	(2.800)
R^e_{t+1}	−1.032	−1.338	1.823	4.540	8.201	9.233
	(−0.129)	(−0.158)	(0.211)	(0.682)	(1.209)	(0.881)
			Portfolios Characteristics			
Bond Size	1047.802	634.910	517.704	543.913	935.717	
Rating	9.081	9.047	9.067	9.451	9.890	
Time to Maturity	5.653	5.444	5.456	5.911	6.416	
Illiquidity	50.550	49.783	50.405	54.624	59.974	
ACT	0.096	0.089	0.085	0.091	0.103	
INDF	0.025	0.023	0.021	0.019	0.022	
R^e_{t-1}	−0.005	0.000	0.003	0.009	0.024	
OIB_t	−7.820	−5.631	−1.708	6.832	21.667	
OIB_{t+1}	−1.601	−3.428	−1.337	3.643	8.492	
N	456.214	545.814	551.029	482.371	358.393	
			Asset Pricing			
α_t	−0.977	7.780	13.825	23.669	38.535	39.511
	(−0.109)	(0.870)	(1.547)	(2.648)	(4.311)	(4.42)
α_{t+1}	3.856	8.978	12.781	17.560	16.948	13.092
	(0.579)	(1.347)	(1.918)	(2.635)	(2.543)	(1.964)
MKT	0.015	−0.023	−0.046	−0.064	−0.074	−0.089
	(0.513)	(−0.781)	(−1.534)	(−2.154)	(−2.481)	(−2.994)
SMB	0.037	0.039	0.042	0.029	0.023	−0.015
	(0.990)	(1.021)	(1.113)	(0.765)	(0.607)	(−0.383)
HML	−0.004	−0.024	−0.020	−0.012	−0.040	−0.036
	(−0.072)	(−0.458)	(−0.374)	(−0.226)	(−0.761)	(−0.689)
UMD	0.035	−0.001	−0.014	−0.015	−0.050	−0.085
	(1.160)	(−0.021)	(−0.471)	(−0.510)	(−1.682)	(−2.842)
TERM	0.071	0.122	0.187	0.173	0.001	−0.071
	(0.793)	(1.357)	(2.077)	(1.922)	(0.006)	(−0.787)
DEF	0.087	0.100	0.136	0.147	0.056	−0.031
	(1.686)	(1.932)	(2.639)	(2.849)	(1.091)	(−0.595)
LIQ	−0.068	−0.101	−0.082	0.005	0.101	0.168
	(−1.060)	(−1.584)	(−1.278)	(0.074)	(1.576)	(2.637)
BMOM	−0.079	−0.028	−0.006	0.027	0.080	0.159
	(−1.378)	(−0.496)	(−0.104)	(0.470)	(1.406)	(2.784)

Table 3: Portfolios Sorted by Index Weight Changes: HY/IG. I sort corporate bonds based on index weight changes into quintile portfolios and calculate equally-weighted excess returns. P1 contains bonds with the most negative index weight changes, P5 the most positive. P5−P1 presents results for going long P5 and short P1. Panel A and B display results for high yield and investment grade bonds, respectively. In each panel, Sort Variable presents means of the variable used in the sorts. Excess Bond Returns reports monthly means of excess returns in basis points. Portfolios Characteristics summarizes portfolio means of amount outstanding, rating, time to maturity, percentage amount held by bond active (ACT) and index funds (INDF), order imbalance, past month return and monthly number of bonds in each portfolio. Asset Pricing reports α estimates of regressing excess returns on the stock (MKT, SMB, HML, UMD) and bond factors (TERM, DEF, LIQ, BMOM). Values in parentheses are t-statistics based on heteroscedasticity- and autocorrelation-consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
			Panel A: High Yield Bonds			
Sort Variable						
Δw	−38.71	−7.989	−1.341	4.373	27.857	
Excess Bond Returns						
R_t^e	−21.105	−7.293	3.465	29.062	67.870	88.975
	(−1.523)	(−1.084)	(0.380)	(2.639)	(3.051)	(2.734)
Portfolios Characteristics						
Bond Size	747.885	454.684	367.613	394.222	691.655	
Rating	14.026	13.726	13.752	13.886	14.187	
Time to Maturity	7.021	6.871	6.447	6.847	7.620	
Illiquidity	45.180	44.518	46.407	50.204	52.604	
ACT	0.171	0.160	0.157	0.161	0.164	
INDF	0.016	0.011	0.008	0.008	0.014	
R_{t-1}^e	−0.013	−0.003	0.005	0.014	0.039	
OIB_t	−13.804	−7.376	−2.269	9.563	22.877	
N	150.393	170.043	158.350	159.664	145.071	
Asset Pricing						
α_t	−17.137	5.748	19.005	42.390	70.964	88.101
	(−0.770)	(0.258)	(0.854)	(1.904)	(3.188)	(3.957)
			Panel B: Investment Grade Bonds			
Sort Variable						
Δw	−2.202	−0.546	−0.169	0.137	1.279	
Excess Bond Returns						
R_t^e	0.825	−3.111	−0.046	4.913	15.600	14.775
	(0.107)	(−0.421)	(−0.006)	(0.696)	(2.226)	(2.632)
Portfolios Characteristics						
Bond Size	1195.292	716.465	578.229	617.974	1101.695	
Rating	6.652	6.929	7.178	7.257	6.969	
Time to Maturity	4.981	4.799	5.057	5.448	5.598	
Illiquidity	61.804	61.698	60.692	63.815	71.372	
ACT	0.059	0.056	0.057	0.057	0.062	
INDF	0.030	0.028	0.026	0.025	0.028	
R_{t-1}^e	0.000	0.001	0.003	0.007	0.013	
OIB_t	−4.879	−4.842	−1.481	5.481	20.844	
N	308.022	375.771	392.679	322.707	213.321	
Asset Pricing						
α_t	9.286	6.674	10.788	14.490	22.721	13.435
	(2.041)	(1.467)	(2.371)	(3.184)	(4.993)	(2.953)

Table 4: Regression-Based Tests. I present results of regressions exploring the link among corporate bond monthly excess returns and benchmark index weight changes. R^e_{it} (in bps) is the dependent variable in all models. The control variables comprise a set of bond characteristics, lagged returns and fund flows. P1 and P5 are dummies that equal 1 if the bond belongs to the respective quintile, according to a sort based on index weight changes. The reference dummy includes bonds belonging to P2, P3 and P4. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index. All t-statistics (given in parentheses) are based on standard errors clustered at the issuer level.

	All Bonds	**IG**	**HY**
Bond Size	-0.001	-0.002^{***}	0.001
	(-0.800)	(-2.805)	(0.308)
Time to Maturity	2.322^{***}	4.842^{***}	0.985^{***}
	(8.581)	(37.290)	(3.390)
Rating	6.749^{***}	5.318^{***}	14.804^{***}
	(7.567)	(6.662)	(5.652)
P1	-1.960	2.592^{**}	-13.850^{***}
	(-1.425)	(2.528)	(-3.279)
P5	20.079^{***}	14.281^{***}	32.375^{***}
	(10.991)	(10.030)	(6.996)
Coupon	0.598^{**}	0.839^{***}	-0.606
	(2.089)	(4.605)	(-0.533)
R^e_{t-2}	-0.006	-0.028^{***}	0.016
	(-0.963)	(-4.617)	(1.474)
R^e_{t-3}	0.016^{**}	-0.006	0.028^{**}
	(2.290)	(-0.959)	(2.116)
Illiquidity	0.050^{**}	0.048^{***}	0.052^{*}
	(2.401)	(6.403)	(1.701)
$Flow^{ACT}_{t-1}$	-27.997^{**}	-12.316	-86.234
	(-2.440)	(-1.490)	(-1.635)
$Flow^{INDF}_{t-1}$	-56.356^{***}	-22.287	-142.423^{***}
	(-3.592)	(-1.583)	(-5.026)
Intercept	-25.397^{**}	-23.768^{***}	-138.431^{***}
	(-2.571)	(-4.469)	(-3.000)
Observations	282,826	193,970	88,856
Adjusted R^2	0.073	0.193	0.040
Time FE (monthly)	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes

Table 5: Fund Flows and Index Weight Changes: Regressions and Sorts I present results of portfolio sorts and regressions exploring the link among corporate bond monthly excess returns, benchmark index weight changes and bond fund flows. I sort corporate bonds based on index weight changes into quintile portfolios. P1 contains bonds with the most negative index weight changes, P5 the most positive. P5−P1 presents results for going long P5 and short P1. R^e_{it} (in bps) is the dependent variable in all regressions. The control variables comprise a set of bond characteristics, lagged returns and fund flows. P1 and P5 are dummies that equal 1 if the bond belongs to the respective quintile, according to a sort based on index weight changes. The reference dummy includes bonds belonging to P2, P3 and P4. I present results for three different samples: bonds exposed to large outflows, low flows and large inflows in the previous month. In each of them, I consider separately flows from active bond funds (ACT) and bond index funds (INDF). Panels A and B display results for HY and IG bonds, respectively. In each panel, I show the size of the subsample, the equally-weighted excess returns of the sorted portfolios together with the average order imbalance and the regression coefficients on P1 and P5. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index. All t-statistics are given in parenthesis. The ones on the sorts are based on heteroscedasticity- and autocorrelation-consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991) Those in the regressions are based on standard errors clustered at the issuer level.

	Large Outflows		**Low Flows**		**Large Inflows**	
	ACT	*INDF*	*ACT*	*INDF*	*ACT*	*INDF*
Panel A: High Yield						
Sample-Splits						
N (in ’000)	15.436	10.322	57.670	58.274	15.751	20.261
Portfolio Sorts						
P1	−57.577**	15.745	−17.369	−20.555	−30.900	−21.385
	(−2.555)	(1.632)	(−1.362)	(−1.225)	(−1.168)	(−1.230)
P5	39.634**	37.689**	79.478***	84.199***	83.638***	59.103*
	(2.413)	(2.166)	(2.882)	(3.271)	(3.137)	(1.890)
P5-P1	97.212***	21.944	96.847***	104.754***	114.538**	80.488**
	(2.667)	(1.054)	(2.881)	(2.825)	(2.425)	(2.182)
$OIB_t/P1$	−21.107	−21.040	−13.093	−13.356	−9.415	−10.984
$OIB_t/P5$	17.105	20.370	25.153	23.021	19.805	23.818
Regressions						
P1	−40.630***	1.745	−1.723	−22.047***	−7.030	1.901
	(−3.524)	(0.193)	(−0.382)	(−4.007)	(−0.616)	0.244
P5	20.954**	−1.961	28.694***	39.472***	23.556*	12.632
	(2.341)	(−0.240)	(5.117)	(6.566)	(1.782)	(1.472)
Adjusted R^2	0.102	0.106	0.036	0.045	0.098	0.125
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Investment Grade						
Sample-Splits						
N (in ’000)	22.470	10.861	134.760	113.195	36.740	69.914
Portfolio Sorts						
P1	9.933	−4.030	3.208	0.816	−3.637	3.972
	(0.657)	(−0.188)	(0.426)	(0.110)	(−0.490)	(0.351)
P5	15.492*	3.751	16.934**	10.813*	13.298**	25.064**
	(1.852)	(0.251)	(2.374)	(1.727)	(2.363)	(2.059)
P5-P1	5.559	7.782	13.725**	9.997**	16.934***	21.092**
	(0.432)	(0.418)	(2.544)	(2.224)	(2.811)	(2.491)
$OIB_t/P1$	−9.427	−17.327	−4.868	−5.371	−2.277	−2.433
$OIB_t/P5$	24.738	14.480	20.956	21.038	17.351	21.679
Regressions						
P1	−3.389	−9.059*	3.931***	1.310	2.530	5.440***
	(−0.971)	(−1.761)	(3.551)	(1.018)	(1.200)	(3.594)
P5	2.281	−0.676	14.390***	11.933***	16.655***	14.802***
	(0.591)	(−0.101)	(10.173)	(8.145)	(5.398)	(6.135)
Adjusted R^2	0.162	0.128	0.203	0.192	0.207	0.273
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Cash Levels and Index Weight Changes: Regressions and Sorts I present results of portfolio sorts and regressions exploring the link between corporate bond monthly excess returns, benchmark index weight changes and bond funds' cash holdings. I sort corporate bonds based on index weight changes into quintile portfolios. P1 contains bonds with the most negative index weight changes, P5 the most positive. P5−P1 presents results for going long P5 and short P1. R^e_{it} (in bps) is the dependent variable in all regressions. The control variables comprise a set of bond characteristics, lagged returns and fund flows. P1 and P5 are dummies that equal 1 if the bond belongs to the respective quintile, according to a sort based on index weight changes. The reference dummy includes bonds belonging to P2, P3 and P4. I present results for two different samples: bonds held by funds with high and low cash holdings in the previous quarter. In each of them, I consider separately cash holdings of active bond funds (ACT) and bond index funds (INDF). Panels A and B display results for HY and IG bonds, respectively. In each panel, I show the size of the subsample, the equally-weighted excess returns of the sorted portfolios together with the average order imbalance and the regression coefficients on P1 and P5. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index. All t-statistics are given in parenthesis. The ones on the sorts are based on heteroskedasticity and autocorrelation consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991) Those in the regressions are based on standard errors clustered at the issuer level.

	ACT		**INDF**	
	Low Cash	High Cash	Low Cash	High Cash
Panel A: High Yield				
Sample-Splits				
N (in '000)	8.944	7.723	2.520	2.531
Portfolio Sorts				
P1	−46.578*	−15.887	−149.06	−73.762**
	(−1.827)	(−0.573)	(−1.493)	(−2.076)
P5	35.950*	81.393***	14.282**	29.069
	(1.816)	(3.641)	(2.319)	(1.426)
P5-P1	82.527***	97.28**	163.342	102.8324**
	(2.655)	(2.559)	(1.607)	(2.392)
$OIB_t/P1$	−28.783	−17.666	−19.875	−24.07
$OIB_t/P5$	8.98	10.805	16.272	22.51
Regressions				
P1	−27.213**	1.997	1.448	2.137
	(−2.078)	(0.128)	(0.076)	(0.075)
P5	11.640	43.520***	−3.469	−45.408**
	(1.026)	(2.921)	(−0.236)	(−2.26)
Adjusted R^2	0.055	0.137	0.231	0.285
Month FE	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes
Panel B: Investment Grade				
Sample-Splits				
N (in '000)	14.204	15.980	8.658	5.945
Portfolio Sorts				
P1	12.807	−2.681	47.248	−0.248
	(0.664)	(−0.396)	(1.597)	(−0.019)
P5	23.021*	6.492	46.342**	20.078**
	(1.93)	(0.794)	(2.371)	(2.564)
P5-P1	10.214	9.173	−0.906	20.325
	(0.867)	(0.976)	(−0.045)	(1.490)
$OIB_t/P1$	−5.507	0.749	−8.826	−17.676
$OIB_t/P5$	23.13	21.008	17.068	26.522
Regressions				
P1	6.904	6.140**	0.230	−4.450
	(1.531)	(2.399)	(0.022)	(−0.780)
P5	9.156*	9.695***	7.830	17.079***
	(1.835)	(−0.240)	(0.964)	(2.790)
Adjusted R^2	0.181	0.201	0.130	0.285
Month FE	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes

Table 7: Regression-Based Test - Holding Dynamics. I present results of regressions exploring the link between corporate bonds' quarterly variation of portfolio holdings and cumulative quarterly benchmark index weight changes. The dependent variables are quarterly variations of portfolio holdings in the cross-section of institutional investors, and are listed at the top of the table. I consider active bond funds (ACT), bond index funds (INDF) and bond ETFs (ETF) as benchmarked investors, while insurance companies (INS) and pension funds (PENS) are considered non-benchmarked institutions. In the first group of regressions (the first set of rows in each panel), P1 and P5 are dummies that equal 1 if the bond belongs to the respective quintile, according to a sort based on cumulative quarterly index weight changes. The reference dummy includes bonds belonging to P2, P3 and P4. In the second group of regressions (second set of rows in each panel), according to a sort based on cumulative quarterly index weight changes, I include one dummy for each of the quintile portfolios except for P1, which is the reference dummy. The control variables comprise a set of bond characteristics, lagged returns and fund flows. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index. All t-statistics (given in parentheses) are based on standard errors clustered at the issuer level.

	Benchmarked Inv.			**Non-Benchmarked Inv.**	
	ΔACT	$\Delta INDF$	ΔETF	ΔINS	$\Delta PENS$
			Panel A: High Yield		
P1	−15.980***	−2.860***	0.009	−8.671***	−0.231
	(−2.690)	(−2.748)	(0.566)	(−3.028)	(−0.262)
P5	12.120**	1.905**	−0.006	−0.714	1.284
	(1.976)	(2.334)	(−0.403)	(−0.273)	(1.543)
P2-P1	15.741**	3.061***	0.008	6.707**	−0.131
	(2.386)	(2.664)	(0.454)	(2.094)	(−0.136)
P3-P1	14.880**	3.098***	−0.014	9.719***	0.088
	(2.158)	(2.673)	(−0.832)	(2.961)	(0.079)
P4-P1	17.515**	2.309**	−0.027	10.421***	0.916
	(2.455)	(2.010)	(−1.495)	(2.849)	(0.821)
P5-P1	28.169***	4.733***	−0.016	8.135**	1.561
	(4.047)	(4.030)	(−0.969)	(2.365)	(1.561)
N (in '000)	32.677	32.677	32.677	32.677	32.677
Adjusted R^2	0.182	0.088	0.183	0.105	0.207
Quarter FE	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes
			Panel B: Investment Grade		
P1	−1.381	−2.020***	−0.003*	−7.442***	−0.192
	(−0.898)	(−3.217)	(−1.804)	(−2.754)	(−0.385)
P5	−0.061	1.099*	−0.002	−0.738	−1.646***
	(−0.035)	(1.790)	(−1.376)	(−0.236)	(−2.686)
P2-P1	1.426	1.550**	0.004**	6.521**	−0.083
	(0.798)	(2.275)	(2.051)	(2.228)	(−0.145)
P3-P1	1.982	1.843**	0.002	9.647***	0.832
	(1.068)	(2.491)	(0.969)	(2.945)	(1.346)
P4-P1	−0.146	2.943***	0.003	6.260*	−0.141
	(−0.075)	(3.808)	(1.632)	(1.881)	(−0.237)
P5-P1	1.406	3.217***	0.001	6.711*	−1.451**
	(0.655)	(3.866)	(0.404)	(1.878)	(−2.202)
N (in '000)	73.143	73.143	73.143	73.143	73.143
Adjusted R^2	0.148	0.135	0.042	0.167	0.139
Quarter FE	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes

Table 8: Portfolios Sorted by Index Weight Changes: Time Dynamics. I sort corporate bonds based on index weight changes into quintile portfolios and calculate equally-weighted excess returns. P1 contains bonds with the most negative index weight changes, P5 the most positive. I present results for three different time periods: November 2004-December 2007, January 2008-December 2011 and January 2012-June 2016. Results for all bonds, HY bonds and IG bonds are displayed in panel A, B and C, respectively. P5−P1 presents results for going long P5 and short P1. Sort Variable presents means of the variable used in the sorts. Excess Bond Returns reports monthly means of excess returns in basis points. Portfolios Characteristics summarizes portfolio means of amount outstanding, rating, time to maturity, percentage amount held by bond active (ACT) and index funds (INDF), order imbalance, past month return and monthly number of bonds in each portfolio. Asset Pricing reports α estimates of regressing excess returns on the stock (MKT, SMB, HML, UMD) and bond factors (TERM, DEF, LIQ, BMOM). Values in parentheses are t-statistics based on heteroscedasticity- and autocorrelation-consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

	Nov 2004 - Dec 2007			**Jan 2008 - Dec 2011**			**Jan 2012 - Jun 2016**		
	P1	P5	P5-P1	P1	P5	P5-P1	P1	P5	P5-P1
Panel A: All Bonds									
Sort Variable									
Δw in bp/100	−15.204	12.103		−19.581	15.154		−10.177	9.882	
Excess Bond Ret.									
R_t^e	−2.584	15.187	17.770	−1.770	52.060	53.830	−14.666	25.297	39.963
	(−1.294)	(3.258)	(3.057)	(−0.096)	(2.201)	(1.698)	(−1.904)	(2.855)	(2.994)
Portfolio Chars.									
ACT	0.064	0.070		0.109	0.113		0.101	0.114	
INDF	0.003	0.003		0.023	0.019		0.036	0.034	
Asset Pricing									
α_t	−6.553	17.545	24.097	15.788	45.287	29.499	−11.119	29.698	40.817
	(−0.672)	(1.800)	(2.472)	(0.772)	(2.214)	(1.442)	(−0.699)	(1.868)	(2.567)

Table 8 continued on next page.

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	Nov 2004 - Dec 2007			Jan 2008 - Dec 2011			Jan 2012 - Jun 2016		
	P1	P5	P5-P1	P1	P5	P5-P1	P1	P5	P5-P1
Panel B: High Yield Bonds									
Sort Variable									
Δw in bp/100	−33.428	24.287		−55.990	37.063		−29.879	23.881	
Excess Bond Ret.									
R_t^e	−13.633	30.163	43.797	−23.641	110.983	134.624	−21.215	57.610	78.825
	(−3.439)	(4.569)	(10.432)	(−0.705)	(2.454)	(1.977)	(−1.098)	(2.104)	(2.438)
Portfolio Chars.									
ACT	0.126	0.124		0.194	0.182		0.181	0.177	
INDF	0.000	0.000		0.012	0.010		0.028	0.025	
Asset Pricing									
α_t	−24.789	27.893	52.682	10.370	103.517	93.147	−35.179	56.930	92.109
	(−2.141)	(2.409)	(4.549)	(0.208)	(2.074)	(1.867)	(−0.905)	(1.465)	(2.370)
Panel C: Investment Grade Bonds									
Sort Variable									
Δw in bp/100	−2.615	1.365		−3.117	1.709		−1.428	0.945	
Excess Bond Ret.									
R_t^e	5.349	10.435	5.086	13.295	28.534	15.238	−10.142	7.804	17.945
	(1.102)	(2.775)	(1.147)	(0.639)	(1.713)	(1.048)	(−1.388)	(1.347)	(2.184)
Portfolio Chars.									
ACT	0.021	0.022		0.070	0.071		0.065	0.073	
INDF	0.006	0.005		0.028	0.024		0.040	0.040	
Asset Pricing									
α_t	7.721	15.952	8.231	20.925	24.462	3.536	−0.885	17.738	18.623
	(1.173)	(2.424)	(1.250)	(1.545)	(1.806)	(0.261)	(−0.086)	(1.733)	(1.819)

Table 8 continued from previous page.

Table 9: Double Sorts with Past Month Returns and Index Weight Changes. I double-sort corporate bonds first into five past month return (R^e_{t-1}) portfolios, and then into quintile portfolios based on index weight changes, and calculate equally weighted excess returns for all bonds, HY bonds and IG bonds are in panels A, B and C, respectively. In all panels, P1.* contains bonds with the most negative past month returns, P5.* the ones with the most positive. P*.1 contains for the respective past month return portfolio the bonds with the most negative index weight changes, P*.5 the most positive. P*.5P*.1 presents results for going long P*.5 and short P*.1. Sort Variables summarizes the means of the two sort variables in each of the P*.1 and P*.5 portfolios. Excess Returns reports monthly means in basis points. Asset pricing reports α estimates of regressing excess returns on the stock (MKT, SMB, HML, UMD) and bond factors (TERM, DEF, LIQ, BMOM). Values in parentheses are t-statistics based on heteroscedasticity- and autocorrelation-consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

	$P1.5 - P1.1$	$P2.5 - P2.1$	$P3.5 - P3.1$	$P4.5 - P4.1$	$P5.5 - P5.1$
			Panel A: All Bonds		
Sort Variables					
R^e_{t-1}/P*.1	−0.026	−0.004	0.004	0.013	0.034
R^e_{t-1}/P*.5	−0.020	−0.004	0.004	0.013	0.049
Δw/P*.1	−26.095	−13.193	−10.600	−8.156	−8.416
Δw/P*.5	2.772	3.533	5.686	8.856	24.243
Excess Bond Ret.					
R^e_t	101.895	46.129	37.380	30.437	61.317
	(5.067)	(4.152)	(4.099)	(5.812)	(4.611)
R^e_{t+1}	7.474	9.075	6.013	−3.627	3.077
	(0.497)	(2.099)	(1.567)	(−0.666)	(0.320)
Asset Pricing					
α_t	112.079	42.743	32.258	26.346	50.878
	(6.590)	(7.696)	(6.609)	(7.098)	(4.642)
α_{t+1}	17.912	9.626	6.076	−4.047	0.436
	(1.208)	(2.403)	(1.484)	(−0.915)	(0.050)

Table 1 continued on next page.

Table 9 continued from previous page.

	$P1.5 - P1.1$	$P2.5 - P2.1$	$P3.5 - P3.1$	$P4.5 - P4.1$	$P5.5 - P5.1$
			Panel B: High Yield		
Sort Variables					
R^e_{t-1}/P*.1	−0.046	−0.007	0.005	0.017	0.047
R^e_{t-1}/P*.5	−0.027	−0.005	0.005	0.018	0.075
Δw/P*.1	−63.557	−38.263	−31.046	−22.846	−20.055
Δw/P*.5	6.183	9.376	15.425	22.631	50.201
Excess Bond Ret.					
R^e_t	135.636	87.422	64.623	55.878	89.256
	(4.513)	(3.155)	(3.390)	(3.639)	(3.872)
R^e_{t+1}	47.124	22.716	22.749	−6.448	−8.380
	(2.085)	(2.193)	(2.005)	(−0.810)	(−0.520)
Asset Pricing					
α_t	165.191	89.538	61.011	39.269	80.118
	(6.793)	(4.864)	(5.368)	(5.034)	(3.317)
α_{t+1}	72.296	19.845	27.709	−6.440	−13.396
	(2.316)	(1.650)	(2.102)	(−1.064)	(−1.313)
			Panel C: Investment Grade		
Sort Variables					
R^e_{t-1}/P*.1	−0.014	−0.002	0.004	0.011	0.025
R^e_{t-1}/P*.5	−0.015	−0.003	0.003	0.010	0.028
Δw/P*.1	−3.057	−2.377	−2.044	−1.571	−1.400
Δw/P*.5	0.352	0.462	0.701	1.173	2.195
Excess Bond Ret.					
R^e_t	80.547	29.823	25.062	22.986	37.949
	(4.722)	(4.691)	(4.981)	(8.644)	(3.842)
R^e_{t+1}	−19.482	0.854	0.208	−1.770	−0.191
	(−1.393)	(0.156)	(0.041)	(−0.276)	(−0.019)
Asset Pricing					
α_t	73.992	24.544	19.097	21.444	29.544
	(6.452)	(5.565)	(8.598)	(6.531)	(4.213)
α_{t+1}	−13.258	3.754	1.775	−1.094	−0.535
	(−1.345)	(1.055)	(0.520)	(−0.258)	(−0.061)

A Model

A.1 Asset Market

There are two periods, $t = 0, 1$. The financial market consists of a risk-free asset and two risky illiquid assets ($i \in \{x, y\}$). The risk-free asset pays a gross interest rate $R_f = 1$, is in perfectly elastic supply and serves as the numeraire, with its price normalized to 1. Both risky assets have an uncertain fundamental value of $D_i \sim N(\mu_i, \sigma_i^2)$ units. D_x and D_y are uncorrelated and in net supply of $\bar{\theta_i}$ shares. The uncertainty about the fundamental value is resolved in $t = 1$. The prices $S_{0,i}$ of the risky assets are endogenously determined in equilibrium. Both risky assets belong to an exogenous benchmark index with weights $b = (b_x, b_y)$ and $b_x + b_y = 1$.

A.2 Agents

The economy is populated by a continuum of investors with mass one with risk aversion γ, each endowed with the same amount of wealth W_0. All investors maximize their expected utility over terminal compensation with CARA preferences, by choosing the investment in the risky assets $\theta_0^j = (\theta_{0,x}^j, \theta_{0,y}^j)$.

$$\max_{\theta_{0,x}^j, \theta_{0,y}^j} E(U_1^j) = -exp(-\gamma C_1^j) \tag{7}$$

There are two types of investors.

A.2.1 Non-Benchmarked Institutions

A fraction $1 - q$ are non-benchmarked institutions (NI), whose compensation is given by the portfolio value at $t = 1$.

$$C_1^{NI} = \theta_0^{NI'} D + (W_0 - \theta_0^{NI'} S_0) \tag{8}$$

One can think of NI institutions as buy-and-hold investors, whose objective is to maximize portfolio value, but are not explicitly tied to the performance of an index. Moreover, they are not exposed to frequent inflows-outflows by retail investors. In the bond market, important non-benchmarked institutions are insurance companies and pension funds.

A.2.2 Benchmarked Institutions

The remaining fraction q are benchmarked fund managers (BI). They manage the portfolio of un-modeled retail investors, and their terminal wealth/compensation is tied to that of the benchmark index. Moreover, BI face uncertainty about liquidation costs in response to redemptions at $t = 1$ from the retail investors. With probability π, retail investors will withdraw an amount F from the fund at $t = 1$. I assume that the redemption shock is non-fundamental, but corresponds to idiosyncratic liquidity needs of the investors. With probability $1 - \pi$, there will be no redemptions. My results would not change if I assumed that, with probability $1 - \pi$, the fund would experience inflows.

If the redemptions are larger than a fund's cash balances, the manager needs to sell part of the risky assets to a deep-pocketed un-modeled dealer, at a fixed discount of $(1 - \lambda)$, which is due to assets' illiquidity. Cash balances are given by $Cash = (W_0 - \theta_0^{BI'} S_0)$ The idea is that, if redemptions exceeding cash balances are $F - Cash$, the manager needs to sell $(1 - \lambda)(F - Cash)$ of her remaining portfolio value $\theta_{0,x}^{BI} D_x + \theta_{0,y}^{BI} D_y$.[51] The fund manager compensation will be lowered by the decrease in portfolio value obtained from meeting retail investor's redemption. I assume that the amount is larger than the maximum cash buffer a manager would rationally hold.[52]

One can think of this setup as a fund manager that maximizes her compensation in the

[51] As the discount is fixed, the manager is indifferent as to which assets to sell. In the extreme (but unlikely) case that the portfolio value is lower than the redemptions exceeding cash, the manager will get 0 and the fund closes.

[52] This corresponds to assuming that the outflow level is larger than the amount of cash a manager would hold if $\pi = 1$. This corresponds to assuming $F > W_0 - \sum_{i \in \{x,y\}} \theta_{0,i}^{BI} S_{0,i}$, which corresponds to $F > W_0 - \sum_{i \in \{x,y\}} \frac{\bar{\theta}_i \left(1+\gamma\sigma_i^2\hat{\lambda}\right) - \mu_i(1-q)\hat{\lambda} + b_i(1-q)}{\left[1+q\gamma\sigma_i^2\hat{\lambda}\right]} \cdot \frac{\left(\mu_i - \bar{\theta}_i\gamma\sigma_i^2 + q\gamma\sigma_i^2 b_i\right)}{\left[1+q\gamma\sigma_i^2\hat{\lambda}\right]}$

next period and then passes the fund to someone else, after meeting redemptions. The fund manager's compensation is given by

$$C_1^{BI} = \theta_0^{BI'} D + (W_0 - \theta_0^{BI'} S_0) - b'(D - \theta_0^{BI'} S_0) - G \tag{9}$$

where G is the loss in wealth determined by meeting redemptions.

A.3 Optimization Problems

The NI institutions solve the following problem

$$\max_{\theta_0^{NI}} \theta_0^{NI'} \mu + (W_0 - \theta_0^{NI'} S_0) - \frac{\gamma}{2} \theta_0^{NI'} \Sigma \theta_0^{NI} \tag{10}$$

Taking the FOC with respect to $\theta_{0,i}^{NI}$ leads to the mean-variance portfolio weights

$$\theta_{0,i}^{NI} = \frac{\mu_i - S_{0,i}}{\gamma \sigma_i^2} \tag{11}$$

The BI institutions instead solve the following problem

$$\max_{\theta_0^{BI}} (1-\pi) \left[(\theta_0^{BI} - b)'\mu + (W_0 - \theta_0^{BI'} S_0) - \frac{\gamma}{2} (\theta_0^{BI} - b)' \Sigma (\theta_0^{BI} - b) \right] \tag{12}$$

$$\pi \left[(\theta_0^{BI} - b)'\mu - \left(\frac{F - (W_0 - \theta_0^{BI'} S_0)}{(1-\lambda)} \right) - \frac{\gamma}{2} (\theta_0^{BI} - b)' \Sigma (\theta_0^{BI} - b) \right] \tag{13}$$

Taking the FOC with respect to $\theta_{0,i}^{BI}$ leads to the optimal portfolio weights

$$\theta_{0,i}^{BI} = \underbrace{\frac{\mu_i - S_{0,i}}{\gamma \sigma_i^2}}_{\text{mean variance}} \quad \underbrace{- S_{0,i} \pi \hat{\lambda}}_{\text{liquidity management}} \quad \underbrace{+ b_i}_{\text{benchmark hedging demand}} \tag{14}$$

here $\hat{\lambda} := \left(\frac{\lambda}{1-\lambda} \right)$. The optimal portfolio demand of the benchmarked institution has three components. First the mean variance portfolio, as for NI institutions. Second a "liquidity management" component, which decreases the investment in the risky asset (hence increasing cash), and depends on π and λ. The higher the liquidity discounts and/or the likelihood of extreme outflows, the higher (lower) the demand for cash (risky asset) of the fund manager. Interestingly, both π and λ need to be $\neq 0$ for the liquidity management component to appear.

A.4 Market Clearing and Equilibrium Prices

The market clearing condition for asset i is:

$$q\left[\frac{\mu_i - S_{0,i}}{\gamma\sigma_i^2} + b_i - S_{0,i}\pi\hat{\lambda}\right] + (1-q)\left[\frac{\mu_i - S_{0,i}}{\gamma\sigma_i^2}\right] = \bar{\theta}_i \tag{15}$$

This leads to the equilibrium price:

$$S_{0,i} = \frac{\left(\mu_i - \bar{\theta}_i\gamma\sigma_i^2 + q\gamma\sigma_i^2 b_i\right)}{\left[1 + \pi q\gamma\sigma_i^2\hat{\lambda}\right]} \tag{16}$$

The equilibrium price is increasing in the benchmark index weight, and the effect is larger if more BI institutions are present in the market. The price is discounted by a factor that is increasing in both π and λ. If either π or λ is zero, the price is the same as in a standard benchmarking model without costly redemptions due to illiquidity. Substituting the equilibrium price into the portfolio weights I obtain:

$$\theta_{0,i}^{BI} = \frac{\bar{\theta}_i\left(1 + \pi\gamma\sigma_i^2\hat{\lambda}\right) - \mu_i(1-q)\pi\hat{\lambda} + b_i(1-q)}{\left[1 + \pi q\gamma\sigma_i^2\hat{\lambda}\right]} \tag{17}$$

$$\theta_{0,i}^{NI} = \frac{\bar{\theta}_i + \mu_i q\pi\hat{\lambda} - b_i q}{\left[1 + \pi q\gamma\sigma_i^2\hat{\lambda}\right]} \tag{18}$$

A.5 Comparative Statics

I am interested in how the equilibrium quantities move, when there is a simultaneous change in the benchmark index weight b_i and the probability of extreme outflows π. The change in b_i corresponds to the variation in fixed income benchmarks' index weights that I observe on a monthly basis in the data. The change in π is a parsimonious way to capture whether the fund was subjected to net inflows (from investors or coupon/ payments) or outflows (through investors' redemptions) in the past. In practice, when money is coming in, the fund manager needs to invest the additional cash she has at her disposal. This is parsimoniously captured by a drop in the probability of "distress" π, which lower the funds' demand for cash. On the other hand, when a fund is hit by redemptions, cash reserves are reduced and the manager needs to re-build her cash buffer. A similar mechanism is analyzed in a dynamic model by Zeng (2017). I capture the cash re-building mechanism through and increase in π.

In order to highlight the different forces at play, I first perform a comparative statics analysis with respect to b_i and π separately.

$$\frac{\partial S_{0,i}}{\partial b_i} = \frac{q\gamma\sigma_i^2}{1+\pi q\gamma\sigma_i^2\hat{\lambda}} > 0 \tag{19}$$

$$\frac{\partial \theta_{0,i}^{BI}}{\partial b_i} = \frac{(1-q)}{\left[1+\pi q\gamma\sigma_i^2\hat{\lambda}\right]} > 0 \tag{20}$$

$\frac{\partial S_{0,i}}{\partial b_i} > 0$ and $\frac{\partial \theta_{0,i}^{BI}}{\partial b_i} > 0$ hold in any case, since both numerators and denominators are always positive. Intuitively, when the index weight increases, BI institutions have a higher hedging demand for security i and the prices increase accordingly.

$$\frac{\partial S_{0,i}}{\partial \pi} = \frac{\gamma(\hat{\lambda}-1)\hat{\lambda}q\sigma_i^2(\gamma\sigma_i^2(b_iq-\bar{\theta}_i)+\mu_i)}{(\hat{\lambda}(\gamma\sigma_i^2q\pi-1)+1)^2} < 0 \tag{21}$$

$$\frac{\partial \theta_{0,i}^{BI}}{\partial \pi} = \frac{\hat{\lambda}(q-1)(\gamma\sigma_i^2(b_iq-\bar{\theta}_i)+\mu_i)}{(\gamma\hat{\lambda}\sigma_i^2\pi+1)^2} < 0 \tag{22}$$

$\frac{\partial S_{0,i}}{\partial \pi} < 0$ and $\frac{\partial \theta_{0,i}^{BI}}{\partial \pi} < 0$ if $\mu_i > \gamma\sigma_i^2\bar{\theta}_i$, which needs to hold for the price $S_{0,i}$ to be positive. Intuitively, when the likelihood of distress increases, benchmarked institutions decrease their holdings in the risky assets proportionally, which translates into a drop in prices.

Assume that a fund manager experiences a variation in the index weights of the two risky assets, with asset x increasing and asset y decreasing their weights by the same amount. In any case, the demand for asset x (asset y) will increase (decrease) due to the variation in the hedging component of the optimal portfolio. However, the manager's total reaction will depend on whether the fund has been subjected to net inflows (from investors or coupon/principal payments) or outflows (from investor's redemptions). In the first case, the fund manager will have a lower cash demand and increase her investment into the risky assets. This results in an increase in $S_{0,x}$ and $\theta_{0,x}^{BI}$ that is stronger than the drop in $S_{0,y}$ and $\theta_{0,y}^{BI}$. Conversely, if the fund has been subjected to outflows, the fund manager will have an increase in cash demand. This results in an increase in $S_{0,x}$ and $\theta_{0,x}^{BI}$ that is weaker than the drop in $S_{0,y}$ and $\theta_{0,y}^{BI}$.

The model allows for analysis of how the effects on prices would change when more benchmarked institutions are in the economy.

$$\frac{\partial S_{0,i}}{\partial b_i \partial q} = \frac{\gamma\sigma_i^2}{(1+\pi q\gamma\sigma_i^2\hat{\lambda})^2} > 0 \tag{23}$$

$$\frac{\partial S_{0,i}}{\partial \pi \partial q} = \frac{\gamma(\hat{\lambda}-1)\hat{\lambda}\sigma_i^2\{(\mu_i - \gamma\sigma_i^2\bar{\theta}_i)(1-\hat{\lambda}-\hat{\lambda}\pi\sigma_i^2 q) + 2b_i(1-\hat{\lambda})q\}}{(\lambda(\gamma\sigma_i^2 q\pi - 1)+1)^3} < 0 \tag{24}$$

$\frac{\partial S_{0,i}}{\partial b_i \partial q}$ is always positive. When a larger fraction of investors is benchmarked, the impact on prices following index weight changes is stronger. $\frac{\partial S_{0,i}}{\partial \pi \partial q}$ is negative if $\mu_i > \gamma\sigma_i^2\bar{\theta}_i$, which needs to hold for the price $S_{0,i}$ to be positive. When a larger fraction of investors is benchmarked, the impact on prices following shocks to π (interpreted as inflows/outflows) is stronger.

A.6 Testable Hypotheses

Based on the comparatives statics analysis, I formulate the following hypotheses:

H1: Re-Investment Channel: When in a portfolio of funds that experienced net inflows, bonds with index weight increases have positive excess returns that are larger (in absolute terms) than the negative returns on the bonds with index weight decreases. This is the result of bond funds re-investing the additional cash and buying bonds with index weight increases more than selling those with index weight decreases.

H2: Cash Re-building Channel: When in a portfolio of funds that experienced net outflows, bonds with index weight decreases have negative excess returns that are larger (in absolute terms) than the positive returns on the bonds with index weight increases. This is the result of bond funds rebuilding their cash reserves through selling bonds with index weight decreases more than buying those with index weight increases.

H3: Impact of More Benchmarked Investors. When a larger fraction of the investors in the economy is benchmarked, the impact on prices in response to index weight changes and/or fund flows is larger.

The effects highlighted in the hypotheses are represented graphically in Figures A1 and A2 with a calibrated version of the model.

Figure A1: Benchmark Index Weight Changes and Inflows I plot the impact of index weight changes on equilibrium quantities, when benchmarked institutions have experienced inflows. As a starting point, $b_x = b_y = 0.5$ and $\pi = 0.25$. At each point, I shock index weights by 0.1 for asset x and -0.1 for asset y. At the same time, I decrease each time π by 0.05, in order to capture inflows. Therefore, the sequence of index weights and *pi* levels is given by: $b_x = (0.5, 0.6, 0.7, 0.8, 0.9)$, $b_y = (0.5, 0.4, 0.3, 0.2, 0.1)$, $pi = (0.25, 0.2, 0.15, 0.10, 0.05)$. The top panels show the effect on corporate bond prices (left) and BI investors cash demand (right). The bottom panel displays the impact on BI (left) and NI (right) investors' demand for corporate bonds. The black (red) lines refers to an economy where the fraction q of BI investors is 25% (50%). The other parameters are: $\mu_i = 3$, $\sigma_i = 0.1$, $\lambda = 0.2$, $\gamma = 5$

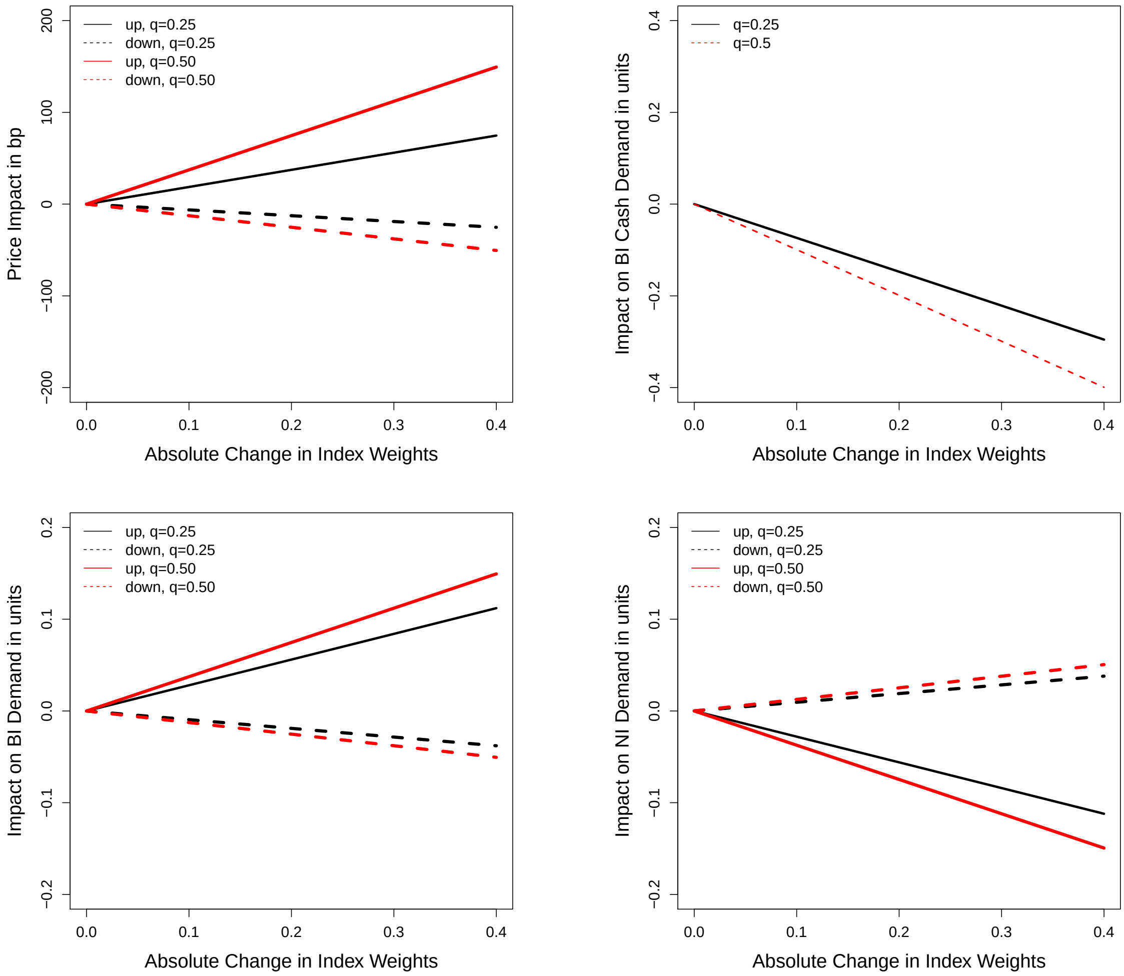
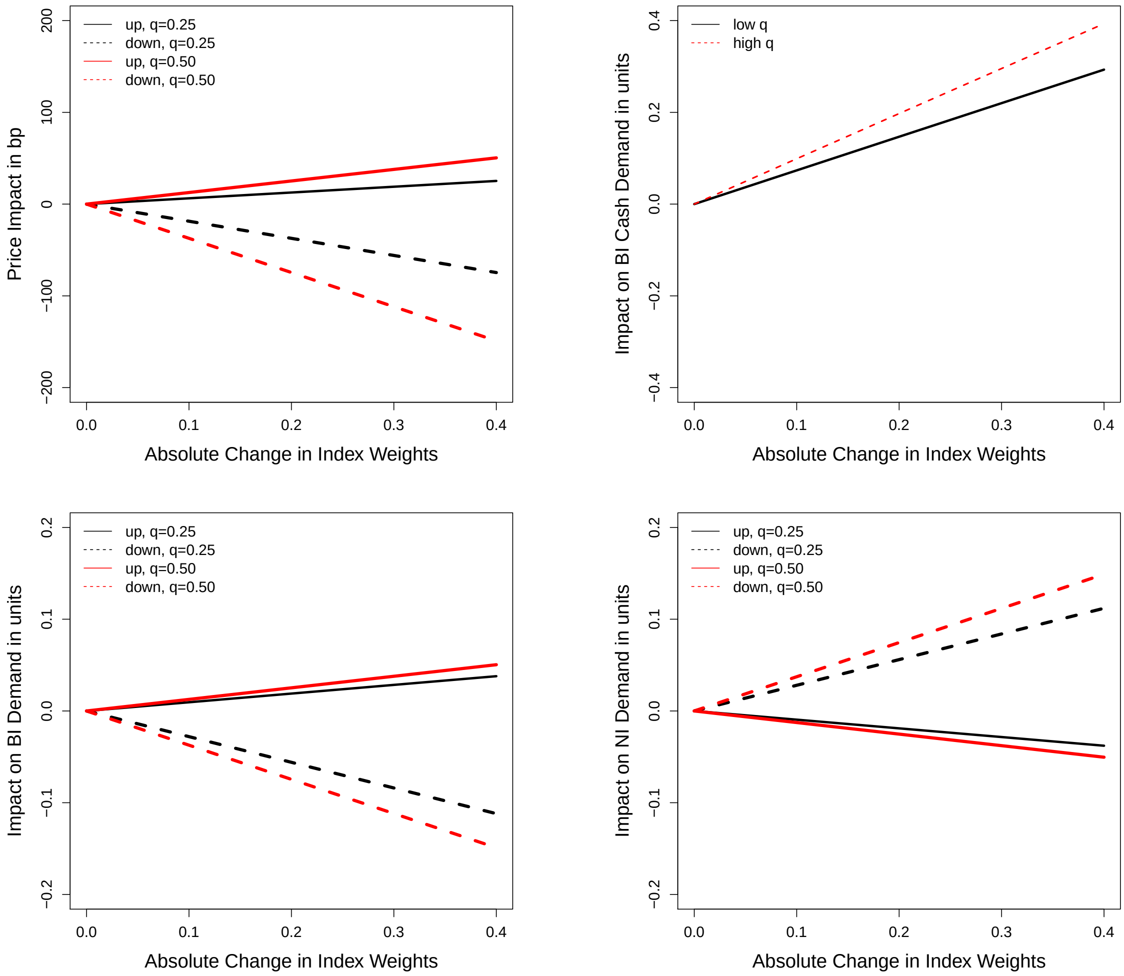


Figure A2: Benchmark Index Weight Changes and Outflows I plot the impact of index weight changes on equilibrium quantities, when benchmarked institutions have experienced outflows. As a starting point, $b_x = b_y = 0.5$ and $\pi = 0.25$. At each point, I shock index weights by 0.1 for asset x and -0.1 for asset y. At the same time, I decrease each time π by 0.05, in order to capture outflows. Therefore, the sequence of index weights and pi levels is given by: $b_x = (0.5, 0.6, 0.7, 0.8, 0.9)$, $b_y = (0.5, 0.4, 0.3, 0.2, 0.1)$, $pi = (0.25, 0.3, 0.35, 0.40, 0.45)$. The top panels show the effect on corporate bond prices (left) and BI investors cash demand (right). The bottom panel displays the impact on BI (left) and NI (right) investors' demand for corporate bonds. The black (red) lines refers to an economy where the fraction q of BI investors is 25% (50%). The other parameters are: $\mu = 5$, $\sigma^2 = 0.01$, $\lambda = 0.2$, $\gamma = 5$



B Variables Description

Table A1: Variables Description. In this table, I describe how the main variables used in the paper are constructed.

Variable Label	Description
panel A: Bond Returns, Index Weight Changes and Asset Pricing Factors	
R_t^e	Monthly return of a bond in month t (with accrued interest) in excess of the risk-free rate
Δw	The variation in index weights of a specific bond from month t-1 to month t. This information is already available at the end of month t. The indexes I use to construct this variable are BofA/ML US High Yield Index and the BofA/ML US Corporate Index.
MKT	Excess return on the market. It is calculated as the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates).
SMB	Average return on the three small portfolios minus the average return on the three big portfolios, SMB = 1/3 (Small Value + Small Neutral + Small Growth) − 1/3 (Big Value + Big Neutral + Big Growth). SMB for July of year t to June of $t+1$ include all NYSE, AMEX, and NASDAQ stocks for which market equity data for December of $t-1$ and June of t, as well as (positive) book equity data for $t-1$, exists.

(Continued)

Variable Label	Description
HML	Average return on the two value portfolios minus the average return on the two growth portfolios, HML =1/2 (Small Value + Big Value)- 1/2 (Small Growth + Big Growth). HML for July of year t to June of $t+1$ include all NYSE, AMEX, and NASDAQ stocks for which market equity data for December of $t-1$ and June of t, as well as (positive) book equity data for $t-1$, exist.
UMD	Six value-weight portfolios formed on size and prior (2-12) returns are used to construct UMD. The portfolios, which are formed monthly, are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on prior (2-12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles. UMD is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios, Mom = 1/2 (Small High + Big High) - 1/2(Small Low + Big Low).
$TERM$	Difference between the monthly returns of the long-term government bond and the one-month Treasury bill.
DEF	Difference between the monthly returns of long-term IG bonds and long-term government bonds.
LIQ	Equally-weighted monthly return differential of going long the bond quintile having the highest Bao, Pan, and Wang (2011) illiquidity measure and short the quintile with the lowest.

(Continued)

Variable Label	Description
$BMOM$	Equally-weighted return differential of going long the bond quintile having the highest cumulative six months return and short the quintile with the lowest.
	panel B: Bond Characteristics
Bond Size	Outstanding amount of a bond in millions of US dollars
Rating	Average bond rating (mapped to natural numbers, i.e. $AAA = 1$, $AA+ = 2$, ..., $D = 21$) of the outstanding bonds of the issuer across the three major rating agencies (*Fitch*, *Moody's*, *Standard and Poor's*)
Time to Maturity	Bond time to maturity in years
Coupon	Coupon of bond i in percent of notional
Illiquidity	The illiquidity of bond i is obtained as follows. On each day t with at least one trade, I compute, following Bao, Pan, and Wang (2011), the auto-covariance between the returns generated from consecutive transaction prices over time window including day t and the previous 20 working days. $\gamma_t = -Cov(\Delta p_{s+1}, \Delta p_s)$, where p_s is the log transaction price of the bond. I then average, in each month, the illiquidity measure of a bond, and obtain a monthly estimate of illiquidity for bond i. Finally, I average the monthly measure across months $t-1$, $t-2$, $t-3$.
$OIB_{i,t}$	Order imbalance of bond i in month t, obtained as the difference between buy volume and sell volume, scaled by the amount outstanding of the bond.
	panel C: Institutional Holdings
$ACT_{i,q}$	Percentage of a bonds' offering amount held by active open end bond funds at the end of quarter q

(Continued)

Variable Label	Description
$INDF_{i,q}$	Percentage of a bonds' offering amount held by open end index bond funds at the end of quarter q
$INS_{i,q}$	Percentage of a bonds' offering amount held by insurance funds at the end of quarter q
$ETF_{i,q}$	Percentage of a bonds' offering amount held by pension funds at the end of quarter q
$PENS_{i,q}$	Percentage of a bonds' offering amount held by pension funds at the end of quarter q
ΔH_{ixq}	variation in par-amount portfolio holdings of bond i, by investor group x, between quarter-end $q-1$ and quarter-end q
panel D: Bond Fund Flows and Cash Holdings	
$Flow_{i,t}$	Ownership-weighted average of the net flows in month t of bond mutual fund holding bond i. The weights are based on the ownership at the end of the previous quarter.
$Cash_{i,q}$	Ownership-weighted average of the cash level in quarter q of bond mutual funds holding bond i. The weights are based on the ownership at the end of the previous quarter.

Internet Appendix

Internet Appendix to

The Impact of Benchmarking in Fixed Income Funds

Table IA1: Regression-Based Tests - Alternative Specification. I present results of regressions exploring the link between corporate bond monthly excess returns and benchmark index weight changes. R^e_{it} (in bps) is the dependent variable in all models. The control variables comprise a set of bond characteristics, lagged returns and fund flows. I include one dummy for each of the quintile portfolios sorted on index weight changes, except for P1, which is the reference dummy. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index. All t-statistics (given in parentheses) are based on standard errors clustered at the issuer level.

	All Bonds	**IG**	**HY**
Bond Size	−0.001	−0.002***	0.001
	(−0.724)	(−2.742)	(0.426)
Time to Maturity	2.284***	4.805***	0.970***
	(8.540)	(36.686)	(3.384)
Rating	6.708***	5.282***	14.694***
	(7.532)	(6.628)	(5.623)
P2-P1	−1.761	−4.181***	4.236
	(−1.259)	(−4.017)	(0.986)
P3-P1	0.350	−2.884**	9.970**
	(0.226)	(−2.446)	(2.040)
P4-P1	8.755***	0.072	29.596***
	(5.248)	(0.057)	(5.976)
P5-P1	22.257***	11.854***	46.621***
	(9.344)	(6.335)	(7.369)
Coupon	0.554*	0.822***	−0.669
	(1.942)	(4.520)	(−0.592)
R^e_{t-2}	−0.006	−0.028***	0.016
	(−1.033)	(−4.663)	(1.422)
R^e_{t-3}	0.016**	−0.006	0.027**
	(2.282)	(−0.964)	(2.105)
Illiquidity	0.050**	0.048***	0.052*
	(2.399)	(6.325)	(1.700)
$Flow^{ACT}_{t-1}$	−28.000**	−12.224	−90.929*
	(−2.436	(−1.477	(−1.722
$Flow^{INDF}_{t-1}$	−56.356***	−22.287	−142.423***
	(−3.592	(−1.583	(−5.026
Intercept	−25.397**	−23.768***	−138.431***
	(−2.571)	(−4.469)	(−3.000)
Observations	282,826	193,970	88,856
Adjusted R^2	0.073	0.193	0.040
Time FE (monthly)	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes

Table IA2: Portfolios Sorted by Past Month Returns. I sort corporate bonds based on past month return into quintile portfolios and calculate equal-weighted excess returns. P1 contains bonds with the most negative past month return, P5 the most positive. P5−P1 presents results for going long P5 and short P1. Panel A, B and C display results for all bonds, high yield bonds and investment grade bonds, respectively. In each panel, Sort Variable presents means of the variable used in the sorts. Excess Bond Returns reports monthly means of excess returns in basis points. Portfolios Characteristics summarizes portfolio means of benchmark index weight change (Δw) and monthly number of bonds in each portfolio. Asset Pricing reports α estimates of regressing excess returns on the stock (MKT, SMB, HML, UMD) and bond factors (TERM, DEF, LIQ, BMOM). Values in parentheses are t-statistics based on heteroscedasticity- and autocorrelation-consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
			Panel A: All Bonds			
Sort Variable						
R^e_{t-1}	−0.02	−0.004	0.004	0.012	0.036	
Excess Bond Returns						
R^e_t	48.46	5.597	−2.644	−5.14	−9.48	−57.941
	(4.582)	(0.596)	(−0.284)	(−0.688)	(−1.13)	(−4.444)
Portfolios Characteristics						
Δw	−0.878	−0.666	−0.42	−0.099	0.217	
N	389.521	545.686	559.271	521.2	369.914	
Asset Pricing						
α_t	54.781	22.902	14.264	15.831	22.449	−32.332
	(2.35)	(0.982)	(0.612)	(0.679)	(0.963)	(−1.387)
			Panel B: High Yield Bonds			
Sort Variable						
R^e_{t-1}	−0.033	−0.006	0.005	0.017	0.054	
Excess Bond Returns						
R^e_t	52.743	6.989	1.255	1.879	18.841	−33.902
	(3.481)	(0.747)	(0.097)	(0.184)	(0.901)	(−1.561)
Portfolios Characteristics						
Δw	−18.492	−9.271	−3.841	1.962	12.067	
N	144.157	160.579	162.921	161.607	150.786	
Asset Pricing						
α_t	54.781	22.902	14.264	15.831	22.449	−32.332
	(2.35)	(0.982)	(0.612)	(0.679)	(0.963)	(−1.387)
			Panel C: Investment Grade Bonds			
Sort Variable						
R^e_{t-1}	−0.012	−0.002	0.003	0.01	0.024	
Excess Bond Returns						
R^e_t	54.658	6.729	−4.259	−8.074	−25.228	−79.886
	(3.672)	(0.747)	(−0.52)	(−1.267)	(−5.13)	(−5.927)
Portfolios Characteristics						
Δw	−0.878	−0.666	−0.42	−0.099	0.217	
N	245.364	385.107	396.35	359.593	219.129	
Asset Pricing						
α_t	51.805	18.969	11.554	6.849	−3.308	−55.113
	(4.468)	(1.636)	(0.996)	(0.591)	(−0.285)	(−4.753)

Table IA3: Regression-Based Tests - Including Past Month Returns. I present results of regressions exploring the link between corporate bond monthly excess returns and benchmark index weight changes. R^e_{it} (in bps) is the dependent variable in all models. The control variables comprise a set of bond characteristics, lagged returns and fund flows. P1 and P5 are dummies that equal 1 if the bond belongs to the respective quintile, according to a sort based on index weight changes. The reference dummy includes bonds belonging to P2, P3 and P4. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index. All t-statistics (given in parentheses) are based on standard errors clustered at the issuer level.

	All Bonds	**IG**	**HY**
Bond Size	−0.001	−0.002***	0.001
	(−1.024)	(−2.834)	(0.239)
Time to Maturity	2.580***	5.637***	1.109***
	(8.940)	(38.228)	(3.993)
Rating	7.402***	6.157***	15.358***
	(7.944	(6.830)	(6.124)
P1	−8.560***	−4.760***	−15.594***
	(−6.303)	(−4.601)	(−3.890)
P5	34.197***	31.969***	35.723***
	(18.665)	(20.376)	(8.058)
Coupon	0.701**	1.169***	−0.948
	(2.394)	(5.647)	(−0.901)
R^e_{t-1}	−0.081***	−0.163***	−0.018
	(−10.139)	(−19.844)	(−1.388)
R^e_{t-2}	−0.010	−0.052***	0.018
	(−1.585)	(−8.175)	(1.632)
R^e_{t-3}	0.013*	−0.016***	0.025**
	(1.822)	(−2.600)	(1.990)
Illiquidity	0.057**	0.060***	0.055
	(2.292)	(6.776)	(1.555)
$Flow^{ACT}_{t-1}$	−26.982**	−16.897**	−67.891
	(−2.358)	(−2.037)	(−1.289)
$Flow^{INDF}_{t-1}$	−49.741***	−11.897	−142.399***
	(−3.087)	(−0.815)	(−4.998)
Intercept	−38.067***	−44.882***	−147.655***
	(−3.759)	(−7.999)	(−3.549)
Observations	274,939	188,206	86,733
Adjusted R^2	0.079	0.211	0.042
Time FE (monthly)	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes

Table IA4: Regression-Based Tests - Including Past Month Returns and Alternative Specifications. I present results of regressions exploring the link between corporate bond monthly excess returns and benchmark index weight changes. R^e_{it} (in bps) is the dependent variable in all models. The control variables comprise a set of bond characteristics, lagged returns and fund flows. I include one dummy for each of the quintile portfolios sorted on index weight changes, except for P1, which is the reference dummy. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index. All t-statistics (given in parentheses) are based on standard errors clustered at the issuer level.

	All Bonds	**IG**	**HY**
Bond Size	−0.0004	−0.002**	0.002
	(−0.514)	(−2.399)	(0.470)
Time to Maturity	2.413***	5.497***	0.979***
	(8.478)	(37.315)	(3.375)
Rating	7.274***	6.093***	14.977***
	(7.652)	(6.849)	(5.683)
P2-P1	2.046	−1.288	6.767
	(1.471)	(−1.234)	(1.606)
P3-P1	7.798***	4.871***	14.121***
	(5.079)	(4.118)	(2.980)
P4-P1	21.674***	16.259***	35.950***
	(12.219)	(11.956)	(7.234)
P5-P1	45.738***	39.062***	58.124***
	(18.471)	(18.785)	(9.468)
Coupon	0.682**	1.145***	−0.653
	(2.250)	(5.548)	(−0.570)
R^e_{t-1}	−0.087***	−0.175***	−0.023*
	(−10.572)	(−20.629)	(−1.814)
R^e_{t-2}	−0.013**	−0.057***	0.015
	(−2.050)	(−8.757)	(1.364)
R^e_{t-3}	0.013*	−0.018***	0.027**
	(1.778)	(−2.841)	(2.068)
Illiquidity	0.055**	0.060***	0.053*
	(2.372)	(6.620)	(1.691)
$Flow^{ACT}_{t-1}$	−28.974**	−16.938**	−91.735*
	(−2.521)	(−2.048)	(−1.737)
$Flow^{INDF}_{t-1}$	−49.768***	−12.521	−141.677***
	(−3.083)	(−0.894)	(−4.963)
Constant	−39.913***	−48.955***	−146.472***
	(−3.827)	(−8.761)	(−3.113)
Observations	282,826	193,970	88,856
Adjusted R^2	0.079	0.214	0.040
Time FE (monthly)	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes

Table IA5: Value-Weighted Portfolios Sorted by Index Weight Changes: All Bonds. I sort corporate bonds based on index weight changes into quintile portfolios and calculate value-weighted excess returns. P1 contains bonds with the most negative index weight changes, P5 the most positive. P5−P1 presents results for going long P5 and short P1. Sort Variable presents means of the variable used in the sorts. Excess Bond Returns reports monthly means of excess returns in basis points. Portfolios Characteristics summarizes portfolio means of amount outstanding, rating, time to maturity, percentage amount held by bond active (ACT) and index funds (INDF), order imbalance, past month return and monthly number of bonds in each portfolio. Asset Pricing reports α estimates of regressing excess returns on the stock (MKT, SMB, HML, UMD) and bond factors (TERM, DEF, LIQ, BMOM). Values in parentheses are t-statistics based on heteroscedasticity- and autocorrelation-consistent standard errorsusing Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
Sorting Variable: Index Weight Changes in bp/100						
Δw	−14.237	−2.865	−0.506	1.539	12.037	
Excess Bond Returns						
R^e_t	−3.766	−3.626	2.202	9.101	25.890	29.657
	(−0.619)	(−0.561)	(0.272)	(1.219)	(2.622)	(2.631)
R^e_{t+1}	6.313	−1.863	1.746	3.195	7.874	1.560
	(0.597)	(−0.226)	(0.236)	(0.511)	(1.197)	(0.123)
Portfolios Characteristics						
Bond Size	1047.802	634.91	517.704	543.913	935.717	
Rating	9.081	9.047	9.067	9.451	9.890	
Time to Maturity	5.653	5.444	5.456	5.911	6.416	
ACT	0.096	0.089	0.085	0.091	0.103	
INDF	0.025	0.023	0.021	0.019	0.022	
R^e_{t-1}	−0.005	0.000	0.003	0.009	0.024	
OIB_t	−7.82	−5.631	−1.708	6.832	21.667	
OIB_{t+1}	−1.601	−3.428	−1.337	3.643	8.492	
N	456.214	545.814	551.029	482.371	358.393	
Asset Pricing						
α_t	1.387	6.979	14.19	19.933	29.85	28.464
	(0.165)	(0.828)	(1.684)	(2.365)	(3.542)	(3.378)
α_{t+1}	7.717	7.599	10.278	14.864	12.922	5.205
	(1.148)	(1.131)	(1.529)	(2.212)	(1.923)	(0.774)
MKT	0.014	−0.02	−0.046	−0.055	−0.055	−0.069
	(0.438)	(−0.646)	(−1.468)	(−1.737)	(−1.763)	(−2.201)
SMB	0.011	0.028	0.047	0.028	0.026	0.015
	(0.377)	(0.981)	(1.632)	(0.976)	(0.914)	(0.537)
HML	0.009	−0.031	−0.019	−0.021	−0.023	−0.031
	(0.174)	(−0.607)	(−0.38)	(−0.411)	(−0.448)	(−0.621)
UMD	0.042	−0.003	−0.023	−0.017	−0.059	−0.102
	(1.028)	(−0.061)	(−0.551)	(−0.412)	(−1.452)	(−2.479)
TERM	0.138	0.138	0.19	0.169	0.075	−0.063
	(1.859)	(1.857)	(2.552)	(2.278)	(1.014)	(−0.845)
DEF	0.148	0.129	0.15	0.152	0.098	−0.05
	(3.981)	(3.473)	(4.038)	(4.091)	(2.645)	(−1.337)
LIQ	0.014	−0.042	−0.035	0.025	0.135	0.121
	(0.304)	(−0.892)	(−0.748)	(0.521)	(2.855)	(2.551)
BMOM	−0.081	−0.029	−0.012	0.025	0.072	0.153
	(−1.5)	(−0.544)	(−0.232)	(0.472)	(1.33)	(2.83)

Table IA6: Value-Weighted Portfolios Sorted by Index Weight Changes: HY/IG. I sort corporate bonds based on index weight changes into quintile portfolios and calculate value-weighted excess returns. P1 contains bonds with the most negative index weight changes, P5 the most positive. P5−P1 presents results for going long P5 and short P1. Panel A and B display results for HY and IG bonds, respectively. In each panel, Sort Variable presents means of the variable used in the sorts. Excess Bond Returns reports monthly means of excess returns in basis points. Portfolios Characteristics summarizes portfolio means of amount outstanding, rating, time to maturity, percentage amount held by bond active (ACT) and index funds (INDF), order imbalance, past month return and monthly number of bonds in each portfolio. Asset Pricing reports α estimates of regressing excess returns on the stock (MKT, SMB, HML, UMD) and bond factors (TERM, DEF, LIQ, BMOM). Values in parentheses are t-statistics based on heteroscedasticity- and autocorrelation-consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
Panel A: High Yield Bonds						
Sort Variable						
Δw	−38.71	−7.989	−1.341	4.373	27.857	
Excess Bond Returns						
R_t^e	−9.016	−1.172	14.886	32.658	56.783	65.800
	(−0.727)	(−0.590)	(1.466)	(2.546)	(2.399)	(2.332)
Portfolios Characteristics						
Bond Size	747.885	454.684	367.613	394.222	691.655	
Rating	14.026	13.726	13.752	13.886	14.187	
Time to Maturity	7.021	6.871	6.447	6.847	7.620	
ACT	0.171	0.16	0.157	0.161	0.164	
INDF	0.016	0.011	0.008	0.008	0.014	
R_{t-1}^e	−0.013	−0.003	0.005	0.014	0.039	
OIB_t	−13.804	−7.376	−2.269	9.563	22.877	
N	150.393	170.043	158.35	159.664	145.071	
Asset Pricing						
α_t	−7.726	10.423	28.349	42.584	53.58	61.306
	(−0.313)	(0.422)	(1.147)	(1.723)	(2.168)	(2.481)
Panel B: Investment Grade Bonds						
Sort Variable						
Δw	−2.202	−0.546	−0.169	0.137	1.279	
Excess Bond Returns						
R_t^e	0.971	−4.334	0.239	3.775	13.708	12.737
	(0.128)	(−0.596)	(0.028)	(0.512)	(2.078)	(2.559)
Portfolios Characteristics						
Bond Size	1195.292	716.465	578.229	617.974	1101.695	
Rating	6.652	6.929	7.178	7.257	6.969	
Time to Maturity	4.981	4.799	5.057	5.448	5.598	
ACT	0.059	0.056	0.057	0.057	0.062	
INDF	0.03	0.028	0.026	0.025	0.028	
R_{t-1}^e	0	0.001	0.003	0.007	0.013	
OIB_t	−4.879	−4.842	−1.481	5.481	20.844	
N	308.022	375.771	392.679	322.707	213.321	
Asset Pricing						
α_t	8.295	3.567	9.869	12.896	19.047	10.752
	(1.809)	(0.778)	(2.152)	(2.812)	(4.154)	(2.345)

Table IA7: Portfolios Sorted by Index Weight Changes: Including Assets Exiting-Entering the Index. I sort corporate bonds based on index weight changes into quintile portfolios and calculate equally-weighted excess returns. P1 contains bonds with the most negative index weight changes, P5 the most positive. P5−P1 presents results for going long P5 and short P1. Panel A, B and C display results for all bonds, HY bonds and IG bonds, respectively. In each panel, Sort Variable presents means of the variable used in the sorts. Excess Bond Returns reports monthly means of excess returns in basis points. Asset Pricing reports α estimates of regressing excess returns on the stock (MKT, SMB, HML, UMD) and bond factors (TERM, DEF, LIQ, BMOM). Values in parentheses are t-statistics based on heteroscedasticity- and autocorrelation-consistent standard errors using Newey and West (1987) with optimal truncation lag chosen as suggested by Andrews (1991). The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index.

	P1	**P2**	**P3**	**P4**	**P5**	**P5-P1**
			Panel A: All Bonds			
Sort Variable						
Δw	−19.33	−2.877	−0.506	1.539	28.827	
Excess Bond Returns						
R^e_t	−8.221	−4.427	0.023	11.565	31.036	39.257
	(−1.109)	(−0.639)	(0.003)	(1.507)	(2.983)	(2.888)
R^e_{t+1}	−1.273	−1.357	1.835	4.528	7.518	8.791
	(−0.16)	(−0.161)	(0.212)	(0.68)	(1.158)	(0.883)
Asset Pricing						
α_t	0.151	7.755	13.823	23.674	37.559	37.408
	(0.017)	(0.873)	(1.556)	(2.665)	(4.229)	(4.212)
α_{t+1}	4.837	8.93	12.793	17.548	16.095	11.258
	(0.763)	(1.409)	(2.018)	(2.768)	(2.539)	(1.776)
			Panel B: High Yield Bonds			
Sort Variable						
Δw	−49.243	−7.989	−1.343	4.372	65.579	
Excess Bond Returns						
R^e_t	−20.528	−7.084	3.462	29.077	64.629	85.157
	(−1.522)	(−1.063)	(0.38)	(2.641)	(3.098)	(2.771)
R^e_{t+1}	−11.615	−1.192	6.337	11.809	18.216	29.831
	(−1.316)	(−0.159)	(0.708)	(1.289)	(1.653)	(1.75)
Asset Pricing						
α_t	−15.579	5.571	19.002	42.407	68.094	83.673
	(−0.728)	(0.26)	(0.888)	(1.982)	(3.182)	(3.91)
α_{t+1}	1.821	14.865	18.854	21.5	16.494	14.673
	(0.13)	(1.06)	(1.345)	(1.533)	(1.176)	(1.046)
			Panel C: Investment Grade Bonds			
Sort Variable						
Δw	−5.235	−0.566	−0.169	0.137	2.787	
Excess Bond Returns						
R^e_t	−0.366	−3.479	−0.456	4.896	14.867	15.232
	(−0.045)	(−0.474)	(−0.059)	(0.699)	(2.161)	(2.734)
R^e_{t+1}	2.94	−0.536	−0.257	1.389	2.012	−0.928
	(0.294)	(−0.057)	(−0.031)	(0.225)	(0.41)	(−0.097)
Asset Pricing						
α_t	9.73	6.595	10.636	14.656	21.983	12.253
	(2.31)	(1.566)	(2.525)	(3.479)	(5.219)	(2.909)
α_{t+1}	8.431	6.918	8.574	14.258	12.209	3.778
	(1.384)	(1.136)	(1.408)	(2.341)	(2.005)	(0.62)

Table IA8: Regression-Based Tests - Time Variation. I present results of regressions exploring the link between corporate bond monthly excess returns and benchmark index weight changes. R^e_{it} (in bps) is the dependent variable in all models. The control variables comprise a set of bond characteristics, lagged returns and fund flows. I include one dummy for each of the quintile portfolios sorted on index weight changes, except for P1, which is the reference dummy. I furthermore include a dummy for the time periods January 2008 - December 2011 and January 2012 - June 2016. The sample comprises joint observations of benchmark index weights (from Bloomberg), corporate bond prices (from TRACE), bond characteristics (from MERGENT FISD), bond holdings (from Lipper eMAXX) and bond funds flows and characteristics (CRSP mutual funds) for the period November 2004 - June 2016. The benchmark indexes I use are the BofA/ML US High Yield Index and the BofA/ML US Corporate Index. All t-statistics (given in parentheses) are based on standard errors clustered at the issuer level.

	All Bonds	**IG**	**HY**
P2-P1	-2.257	-5.209^{***}	4.494
	(-1.575)	(-4.534)	(1.058)
P3-P1	-0.676	-6.053^{***}	10.580^{**}
	(-0.430)	(-4.708)	(2.199)
P4-P1	9.096^{***}	-1.501	31.154^{***}
	(5.340)	(-1.108)	(6.533)
P5-P1	12.673^{***}	2.096	34.144^{***}
	(4.142)	(1.234)	(4.318)
$\mathbb{1}_{2012-2016}$	-5.139^{***}	-5.359^{***}	8.271^{*}
	(-3.401)	(-4.018)	(1.686)
$\mathbb{1}_{2008-2011}$	3.041^{*}	2.051	14.840^{**}
	(1.666)	(1.357)	(2.513)
(P5-P1) $\times \mathbb{1}_{2012-2016}$	11.244^{***}	13.050^{***}	11.115
	(3.219)	(5.975)	(1.193)
(P5-P1) $\times \mathbb{1}_{2008-2011}$	19.815^{***}	11.884^{**}	33.703^{***}
	(3.698)	(2.466)	(2.766)
Observations	274,935	188,204	86,731
Adjusted R^2	0.015	0.015	0.020
Intercept	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes