Passive bond fund management is an oxymoron (or the case for the active management of bond funds)

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Abstract

In sharp contrast to equity funds, passive bond funds underperform the majority of active bond funds. First, bond indexes include numerous illiquid bonds, making passive investing a near-impossible task. Facing a difficult trade-off between tracking their benchmark and maintaining liquidity, passive bond funds become active and hold relatively liquid bonds, while sacrificing performance. Second, the lack of positive skewness in bond returns reduces the advantages of holding a broad-market index. Holding individual bonds frequently outperform the benchmark, making passive investing less attractive. Consistent with these two channels, the average active bond fund outperforms the passive counterpart, while the most active ones—those with high active share in particular—substantially outperform passive funds (0.74% annually, *t*-stat = 2.40).

JEL Classifications: G10, G11, G14, G20, G23

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1. Introduction

The conventional wisdom on active management is that it does not create value for mutual fund investors. That belief has had an enormous impact on the mutual fund industry. In 2011, only 12.3% of mutual fund assets were passively managed. By 2021, that value had grown to 26.2%. That growth, however, has not been equal across all fund styles. At the end of 2021, about 36.0% of domestic equity mutual fund assets were passively managed, but only 17.1% of bond assets were passively managed.[1] That substantial difference raises an obvious question: why have actively managed bond funds remained popular?

The literature from which the conventional wisdom on mutual funds is derived tends to focus on equity funds. A search for "equity mutual fund" on Google Scholar returns 3.7x as many results as "bond mutual fund."[2] The answer to our question could, therefore, be straightforward: bond investing is different from equity investing. First, there are thousands of illiquid bonds that are difficult and costly to trade included in popular bond benchmarks, creating an arduous challenge for passive bond funds that must both track their benchmark closely and maintain high liquidity. That restrictive mandate for passive bond funds can result in higher costs and lower performance. Conversely, active bond funds, not bound by that mandate, can focus on enhancing performance in a less efficient market.

Second, bond returns are significantly less skewed than equity returns. Since individual stock returns display substantial positive skewness, an omission of a "star" stock with an outstanding performance can be highly costly, thus bolstering the case for passive investing in equities. In bond investing, however, constructing a large portfolio mirrors a broad-market

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[1] See Table 42 in the *2023 Investment Company Fact Book* (https://www.icifactbook.org/) published by the Investment Company Institute (ICI).

[2] There are 1,620 results for "bond mutual fund" versus 5,980 results for "equity mutual fund" as of June 26, 2023.

benchmark can lead to underperformance because an inclusion of a "loser" bond with a high default risk can be detrimental to fund performance. Given the lesser skewness in bond returns, Jack Bogle's principle of "buy the entire haystack" may not yield the same level of effectiveness in bond investing, suggesting the performance advantage of passive bond investing is more limited. In this study, we explore these two conceptual channels above.

We begin by considering the performance of those two groups. Passive bond funds underperform relative to the prospective benchmarks that they nominally track. The average passive bond fund has an alpha of −0.21% per year relative to their benchmark. Conversely, active bond funds, relative to sets of equivalent passive bond funds, show some evidence of outperformance and no evidence of underperformance. The average active bond fund has an alpha of 0.35% per year over passive bond funds. Moreover, the typical active bond fund outperforms: about 69% of active bond funds have a positive alpha over passive bond funds. These findings are remarkably robust, as we find similar results across multiple models, fund types, and evaluation techniques. Thus, whether we consider passive bond funds to be capturing the cost of diversification (Berk and van Binsbergen, 2015) or as the alternative investment (Del Guercio and Reuter, 2014), the base expectation about actively managed mutual funds first set by Jensen (1968)—active funds, on average, underperform—does not obtain in our evaluation of active bond funds.[3]

To explain these performance results, we first consider the unique environment of passive bond funds. Relative to passive equity funds, passive bond funds are substantially more active. In particular, Cremers and Petajisto (2009) active share, which measures the overlap between a fund's holdings and its benchmark's holdings, is significantly higher for passive bond funds. Crane and

[3] Elton, Gruber, and de Souza (2019) perform a similar evaluation of active equity funds and do find underperformance.

Crotty (2018) report that the median active share for passive equity funds is 2%—effectively full benchmark replication, as only 2% of the median passive equity fund portfolio can be considered actively managed. Passive bond funds, conversely, have a median active share of 55.3%, suggesting that over half the assets are being actively managed.

Passive bond funds also make a significant number of trades—their average turnover ratio is 71%—which in conjunction with their high active share could suggest an attempt at traditional active management. We, however, contend that passive bond funds' activeness and trading intensity are driven by the characteristics of their benchmarks. The average passive bond fund benchmark contains 7,249 bonds, many of which are highly illiquid. On a given trading day, about half of the assets in the average passive bond fund benchmark do not have a single trade.[4] Consequently, passive bond funds, while intending to track their benchmarks, do not attempt full replications of them, typically excluding thousands of bonds in their benchmarks from their portfolios.

The managers of passive bond funds do not eschew full replication because it is impossible but because they face trade-offs. As embodied by the determinants of net asset flows to passive bond funds, managers of those funds must balance matching their benchmark with maintaining liquidity and controlling costs. A one standard deviation decrease in active share increases net flows in the next month by 1.20%, but one standard deviation increases in expense ratio and illiquidity decrease those flows by 0.90% and 0.97%. Thus, a passive bond fund manager considering matching their benchmark more closely must evaluate whether the benefits of that choice will be more than offset by the accompanying increased fund costs and increased need to

[4] Illiquidity in bond markets is well documented in, e.g., Edwards, Harris, and Piwowar (2007), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhutter, and Lando (2012), Dick-Nielsen and Rossi (2019), and Kargar, Lester, Lindsay, Liu, Weill, and Zuniga (2021).

purchase less liquid assets. Consistent with that trade-off, we find in a multivariate framework that bond liquidity is a key determinant of the holdings of passive bond funds relative to their benchmarks. As the illiquidity of a given bond increases, passive bond funds tend to hold relatively less of that bond.

Passive bond funds face an associated cost-related hurdle compared to passive equity funds. Operating in a high liquidity environment, passive equity funds can replicate the trades of their benchmarks at low cost. Conversely, passive bond funds, operating in a low liquidity environment, cannot, as a practical matter, replicate the trades of their benchmarks at all. As a result, porting to passive bond funds a method of estimating rebalancing-driven transaction costs based on benchmark holdings that is accurate for passive equity funds leads to significant cost underestimation. The estimated annualized cost of quarterly rebalancing a corporate bond benchmark experiencing flows equivalent to that of a matching passive fund is 12.80 basis points (bps), but the matching passive fund itself has estimated costs of 21.09 bps. That gap of 8.29 bps per year arises from the fact that passive bond funds, unlike their benchmarks, must locate any bond they are seeking to trade and contend with a significant inverse relation between trade size and cost (Edwards, Harris, and Piwowar, 2007). Those realities, which are not present for passive equity funds, generate an obstacle for passive bond funds attempting to balance their benchmark match with trading costs.

Next, we investigate the cross-sectional skewness of bond returns. Our results show that, particularly in longer-horizon returns (e.g., 12-months), bond returns are much less skewed than equity returns. Bond returns exhibit much less skewness, with an average cross-sectional skewness of 0.153, compared to a significantly higher average of 1.367 for equity skewness. This lower skewness in bonds results in individual bonds more frequently outperforming their benchmarks than is the case with individual stocks. We also find that the underperformance of benchmarks relative to individual bonds is more pronounced when benchmark returns are value-weighted. This result suggests that the performance of a value-weighted bond index may be adversely affected, as large bonds, often issued by companies with substantial leverage and debt burdens, can carry a greater risk of default. Collectively, these results suggest that diversification is not as effective in bond investing, thereby making passive bond investing a less attractive option.

The difficulty of passive bond fund management creates an opening for active management. Moving beyond results for the average active bond fund, we find readily identifiable subgroups that significantly outperform. In particular, active bond funds with high active share tend to have a large, positive alpha. An equal-weight portfolio of active bond funds in the top quintile of active share has an alpha of 0.54% per year. That result is stronger (i) if, instead of thinking of active share at the bond level, we collapse fund holdings to the firm level before calculating active share and (ii) if we simultaneously consider funds' past performance. An equal-weight portfolio of funds in the top quintile of past performance within the top quintile of firm-level active share has an alpha of 1.86% per year. That result is confirmed in multivariate panel regressions, suggesting that a meaningful set of active bond fund managers create significant value for investors through their skill in selecting firms whose bonds are likely to outperform.

The managers of active bond funds with high active share also appear to have selection skill at the bond level. That particular skill, however, manifests not in alpha but in the management of downside risk. As bond-level active share increases, maximum drawdown, which captures losses from peak to trough, tends to improve. In a multivariate framework, a one standard deviation increase in bond-level active share improves maximum drawdown by an annualized 0.22%. That impact is, furthermore, larger when downside risk management is most important. During the periods when average maximum drawdowns are largest, the same one standard increase improves drawdowns by 0.44%. Thus, active bond fund managers appear to add value through their skill at avoiding particular bond issues with increased downside risk.

To conclude our analysis of active bond funds, we consider their fragility. Goldstein, Jiang, and Ng (2017) suggest that active bond funds have significant run risk as demonstrated by their flow-performance relation, which tends to be linear or concave. We find, however, that active bond funds with high active share tend to a convex flow-performance relation, helping to mitigate that risk. The change in the shape of the flow-performance relation is primarily driven by investors being significantly more responsive to outperformance from active bond funds with high bond-level active share. Given our results with respect to alpha, that response does not appear to be fully rational; however, investors tend not to be fully rational and bond- and firm-level active shares have a high correlation ($\rho = 0.81$).[5] Notwithstanding, an investor in highly active bond funds has less need to be concerned about fragility.

Bringing all of our results together, the answer to our initial question—why have actively managed bond funds remained popular?—is clear. Actively managed bond funds remain popular because they tend to add value relative to passive bond funds. The bond market and bond benchmarks are substantially different from the equity market and equity benchmarks. The 'S&P 500,' the most common equity benchmark, contains five hundred stocks each trading millions of shares a day. Conversely, the 'Bloomberg US Aggregate,' the most common bond benchmark, contains 12,393 bonds as of the end of 2021, many of which do not trade once in a given day. Those differences are emblematic of greater opportunity for active bond funds compared to active

[5] Investors tend to focus on highly salient measures (e.g., Barber, Odean, and Zheng, 2005, and Kaniel and Parham, 2017) and bond-level active share is more salient given that holdings are always reported at the bond level.

equity funds, and that greater opportunity explains why active bond funds add more value and, in turn, remain popular.[6]

2. Related literature

Our results contribute to several areas of the asset management literature—making general and specific contributions to the literature on both passive and active mutual funds. Here, we provide an in-depth discussion of those contributions.

First, the literature has paid limited attention to all aspects of passive bond funds, be it their performance, activeness, or characteristics. Elton, Gruber, and de Souza (2019) include passive bond funds as part of a larger study and find "index funds and passive ETFs do, on average, an excellent job of tracking the indexes they follow (pg. 267)." Our results, to some extent, agree with that finding, but we find little evidence that the average passive bond fund delivers to investors the full performance of their benchmark. Furthermore, we find significant activeness among passive bond funds relative to that observed among passive equity funds. Easley, Michayluk, O'Hara, and Putnins (2021) and Ben-David, Franzoni, Kim, and Moussawi (2023) demonstrate that nominally passive funds can be significantly active in practice, but those studies specifically exclude bond funds and tend to focus on a wide range of novel ETFs. We find large active shares for passive bond funds tracking traditional bond benchmarks such as the 'Bloomberg US Aggregate.' Moreover, we are the first to characterize the portfolios of both passive bond funds and their benchmarks—using that characterization to develop a conceptual framework that explains the activeness of passive bond funds.

[6] The level of opportunity in a market has been previously established as a primary determinant of how mutual funds perform in that market—both cross-sectional opportunity (e.g., Dyck, Lins, and Pomorski, 2013, and Hoberg, Kumar, and Prabhala, 2018) and time-series opportunity (e.g., Pastor, Stambaugh, and Taylor, 2017, and von Reibnitz, 2017). Cremers (2017) labels opportunity, alongside skill and conviction, as one of the three pillars of active management.

Second, we provide new insights into actively managed bond funds. The prior literature tends to find that the active management of bond funds results in average underperformance (see, e.g., Blake, Elton, and Gruber, 1993; Blake, Elton, Gruber, 1995; Chen, Ferson, and Peters, 2010; Cici and Gibson, 2012; and Chen and Qin, 2017). But, we find, relative to passive bond funds, that, at a minimum, active bond funds perform as well as passive bond funds on average. Furthermore, in relatively brief analyses, Amihud and Goyenko (2013), Hunter, Kandel, Kandel, and Wermers (2014), and Jones and Mo (2021) suggest that particular subsets of active bond funds outperform. Using active share to perform a comprehensive analysis, we demonstrate that active bond funds with high active share outperform, especially if they also have strong past performance.

Through our more comprehensive analysis, we are also able to identify the channels, both bond selectivity and firm selectivity, through which the managers of outperforming active bond funds add value. Skill in firm selection increases alpha, while skill in bond selection improves drawdowns. Previous work, such Cici and Gibson (2012) and Choi and Kronlund (2018), tends to not uncover selection skill for bond fund managers. Thus, we also contribute to the general literature on mutual fund manager skill.[7] That literature, in addition to making the activeness of bond funds a secondary consideration, has yet to explicitly incorporate holdings into its measurement. We fill those gaps by adapting the Cremers and Petajisto (2009) active share measure for bond funds.[8] This adaptation accounts for a unique, empirically-important feature of bond investing—a single firm can provide multiple investment choices by offering multiple different bond issues. Through accounting for that feature, we demonstrate that bond-level and

[7] Early studies tend to find evidence against the existence of skilled mutual fund managers (e.g., Jensen, 1968; Fama, 1970; Gruber, 1996; Carhart, 1997; and Zheng, 1999), while later studies have identified many such managers (e.g., Wermers, 2000; Chen, Jegadeesh, and Wermers, 2000; Kacperczyk, Sialm, and Zheng, 2005; Kacperczyk, Sialm, and Zheng, 2008; Cremers and Petajisto, 2009; Amihud and Goyenko, 2013; and Berk and van Binsbergen, 2015).
[8] A potential exception is Qin and Wang (2021), who, while focusing on fund concentration, calculate active share style measures for active bond funds at aggregate levels (particularly firm, industry, and credit rating) using a small set of broad custom benchmarks.

firm-level active shares have, as previously noted, differentially useful information about manager skill.

Third, our results provide a strong demonstration of the general argument in favor of active management in many markets. Dyck, Lins, and Pomorski (2013), Cremers, Ferreira, Matos, and Starks (2016), and Hoberg, Kumar, and Prabhala (2018) show that the payoffs to active management are a decreasing function of interfund competition and asset market efficiency. Comparing the domestic bond and equity markets, among equities (i) there are more active funds—1,411 vs. 592 at the end of our sample, (ii) passive management is less complex and more successful, and (iii) efficiency is higher (e.g., Downing, Underwood, and Xing, 2009, and Hong, Lin, and Wu, 2012). Accordingly, the value of active management for domestic equity funds is relatively low and passive investing is more prominent. For bond funds, conversely, the value of active management is relatively high and passive management is less prominent.

Fourth, our results serve as an out-of-sample test of active share's predictive power. Several studies that followed Cremers and Petajisto (2009) question whether active share actually predicts the alpha of active funds (e.g., Schlanger, Philips, and LaBarge, 2012; Cohen, Leite, Nielson, and Browder, 2014; Frazzini, Friedman, and Pomorski, 2016; Brown and Davies, 2017; and Busse, Jiang, and Tang, 2021). Those studies tend to focus on active equity funds though, whereas we show within an entirely different sample—active bond funds—that active share has significant power to predict alpha. Put another way, this oft-debated measure has significant, recent predictive power within a large segment of the mutual fund industry.[9] Our results complement Cremers, Ferreira, Matos, and Starks (2016) and Cremers, Fulkerson, and Riley (2022a), who find that active

[9] Table 42 in the *2023 Investment Company Fact Book* (https://www.icifactbook.org/) shows that, at the end of 2021, there were $4.6 trillion dollar invested in active bond funds, which is about 21% of all mutual fund assets.

share predicts the performance of active international equity funds and active domestic equity separate accounts, respectively.

Fifth, and finally, we provide novel results on strategic complementarities and financial fragility. Those facets of mutual funds are often contemplated in the context of money market funds (e.g., Kacperczyk and Schnabl, 2013, and Schmidt, Timmermann, and Wermers, 2016), but Jiang, Li, Sun, and Wang (2022) suggest that the illiquidity of the holdings of bond funds can also create fragility. Jiang, Li, and Wang (2021) find that bond funds will fire sales assets to meet investor redemptions in some instances, which produces substantial price pressure; however, Choi, Hoseinzade, Shin, and Tehranian (2020) find little evidence of redemption-driven fire selling by bond funds. Our finding that a significant number of active bond funds have a convex flow-performance relation (i.e., a relatively modest response to poor performance), which contrasts with the base relation documented in Goldstein, Jiang, and Ng (2017), is consistent with Choi, Hoseinzade, Shin, and Tehranian (2020). That is, like liquidity-supplying funds (Anand, Jotikasthira, and Venkataraman, 2021) or the funds using swing pricing (Jin, Kacperczyk, and Suntheim, 2022), highly active bond funds appear to have less fragility. That lessened fragility among a large portion of active bond funds could, moreover, have broader effects, as Hau and Lai (2017), Chernenko and Sunderam (2020), and Falato, Hortacsu, Li, and Shin (2021), among others, all indicate that funds can generate substantial spillover effects through fire sales.[10]

3. Key measures

In this section, we describe the construction of the key measures used in our analysis, with a particular focus on how we measure fund activeness and performance.

[10] The Financial Stability Oversight Council (FSOC) has also expressed the concern that fragility could have spillover effects leading to systemic risk. See, for example, FSOC's *Update on Review of Asset Management Products and Activities* published on April 18, 2016.

3.1. Active share and tracking error

We follow Cremers and Petajisto (2009) and calculate active share as:

$$Active\ Share = \frac{1}{2}\sum_{i=1}^{N}\left|w_{fund,i} - w_{benchmark,i}\right| \tag{1}$$

where $w_{fund,i}$ and $w_{benchmark,i}$ are the portfolio weights on asset i in the fund and its benchmark. The sum is taken over the entire universe of assets. When calculating active share, a benchmark must be specified. We use each fund's primary prospectus benchmark.[11]

Active share measures the overlap between a fund's holdings and its benchmark's holdings. The lower the overlap, the higher the active share. The higher the active share, the more active the fund. An active share of 0% indicates the fund fully replicates the benchmark, and an active share of 100% indicates the fund and benchmark have no common holdings.

Active share was originally designed to evaluate equity funds. Most firms have a single equity share class that is public and economically relevant for funds and their benchmarks. Thus, the level, share class or firm, at which the active share of equity funds is measured has little impact on inferences. In contrast, many firms have multiple public, economically-relevant bond issues. All of a firm's bond issues will tend to share some fundamental characteristics, but the different issues can vary significantly with respect to key dimensions such as rating, maturity, and liquidity. We, therefore, consider active share for bond funds at both the bond and firm levels. The formula remains the same at both levels, but for the firm-level calculation, we first collapse the data using

[11] Since July 1, 1993, Securities and Exchange Commission (SEC) rules have required mutual funds to provide a benchmark (specifically "an appropriate broad-based securities market index") to investors in either their annual report or prospectus. The full text of the rule is available at https://www.sec.gov/files/rules/final/33-6988.pdf.

bonds' six-digit CUSIPs.[12] The difference between bond- and firm-level portfolios is illustrated in Figure 1.

We calculate tracking error conventionally, using the standard deviation of the differences between fund and benchmark returns:

$$Tracking\ Error = \mathrm{SD}(r_{fund} - r_{bench}) \tag{2}$$

where r_{fund} is the monthly net return for the fund and r_{bench} is the return on its benchmark.

3.2. Multi-factor performance measurement

We build two novel multi-factor models for the evaluation of active bond fund performance. The only difference between the models is the number of factors included. Both models have general form:

$$r_t - r_{rf,t} = \alpha + \sum_{i=1}^{N} \beta_i \text{ x } f_{i,t} + \varepsilon_t \tag{3}$$

where r_t is the monthly net return for a given fund in month t, $r_{rf,t}$ is the risk-free return in month t, α is the factor-adjusted performance of the fund across the full time period under consideration, and f_i is the return on factor i in month t. In our eponymous CCR3 model, we include factors related to the stock market, treasury market, and corporate bond market. We further include factors related to the general bond market, the high yield bond market, and the mortgage-backed securities market in our eponymous CCR6 model.

Each of those factors is constructed using the value-weighted net returns on passive funds tracking a benchmark associated with those markets.[13] We use passive funds benchmarked against

[12] US treasuries use multiple different six-digit CUSIPs. When collapsing to the firm level, we create a common identifier for those securities such that, regardless of CUSIP, all US treasuries share a common firm.

[13] Our results on the performance of the average active fund are similar if we use the lowest-cost passive bond fund instead of value weighting. Using value weighting, the alpha of an equal-weight portfolio of active bond funds is 0.29% per year (t-stat = 1.75), whereas using lowest-cost that alpha is 0.27% per year (t-stat = 1.65).

the ‘Bloomberg US Aggregate Bond’ for the general bond market; the ‘S&P 500’ for the stock market; the ‘Bloomberg US Treasury’ for the treasury market; the ‘ICE BofA US Corporate Bond’ for the corporate bond market; the ‘Markit iBoxx Liquid High Yield’ for the high yield bond market; and the ‘Bloomberg US MBS’ for the mortgage-backed securities market.

Our choice of benchmark for a given market is largely determined by the availability of passive funds tracking that market, as, for example, corporate bond passive funds and high yield bond passive funds are still relatively new. Further, because of that newness, we are only able to build these models starting in 2010.[14] As shown in our results, active bond funds have large exposures to later arriving factors, particularly the corporate bond factor and the high yield bond factor. Thus, the inclusion of those factors is important to the models, and those factors cannot be readily excluded to increase the time period of study without significantly decreasing the accuracy of inferences.

3.3. Asset Illiquidity

To measure illiquidity, we use a combination of four measures: zero-trading-days (ZTD), volume, spread, and amount outstanding (AO). These measures operate on different scales and in different directions, so they must be adjusted to work together. First, within a given sample, we z-score each measure. Then, we multiply amount outstanding and volume by negative one. These two steps produce four variables that (i) have matching means and standard deviations and (ii) are

[14] A passive bond fund tracking a corporate bond benchmark does not appear in our sample until 2009 and passive bond funds tracking high yield bond and mortgage-backed-security benchmarks do not appear in our sample until 2010. On occasion, we use this model to estimate two-year past performance starting in 2009, which we accomplish through the combination of backfilled expense ratios and benchmark returns.

aligned such that an increase in value is an increase in illiquidity. Finally, we combine the measures by taking a simple average, meaning that the entire process can be written as:

$$Illiquidity = \frac{(ZTD_z - Volume_z + Spread_z - AO_z)}{4} \tag{4}$$

When we are considering illiquidity at the bond level, we simply begin the process with the values for the bonds; however, when we are considering illiquidity at the fund level, we begin the process with the value-weighted averages of the values for the bonds in each fund's portfolio.

3.4. Maximum drawdown

We use daily net returns to calculate maximum drawdown (MDD) for a given fund in a given period as:

$$MDD = \text{Max}\frac{R_{t_1} - R_{t_2}}{R_{t_1}} \; s.t. \; 0 \leq t_1 \leq t_2 \leq T \tag{5}$$

where R_{t_1} is the cumulative return for the fund from time 0 to t_1. MDD is structured (i) such that it captures fund losses from peak to trough, (ii) such that is non-negative, and (iii) such that an increase indicates a larger drawdown. Riley and Yan (2022), in their analysis of this measure with respect to mutual funds, directly adjust MDD for fund style, while we do not; however, in our analyses using this measure, we use benchmark and time fixed effects that generate a comparable adjustment.

3.5. Net flow

Our measure of monthly net flow for a given fund is constructed using the standard implied method. Specifically, we calculate it as:

$$Net\ Flow_t = \frac{TNA_t - TNA_{t-1} * (1 + r_t)}{TNA_{t-1}} \tag{6}$$

where TNA_t is fund total net assets as of the end of month *t* and r_t is fund monthly net return during month *t*.

4. Data

Here, we first discuss the formation of our samples of active and passive funds, followed by a discussion of our data on fund and benchmark holdings.

4.1. Fund sample

We begin the process of building our samples of passive and active bond mutual funds using Morningstar Direct. From that database, we obtain a complete list of taxable bond funds domiciled in the United States at the share-class level. We also obtain a fund-level identifier (FundId) from Morningstar along with information about (i) the identify of and returns on funds' prospectus benchmarks and (ii) whether a given fund is nominally passive or active. We then merge that information at the share-class level with the CRSP mutual fund database using CUSIPs and tickers, with assets used for verification. From the CRSP database, we obtain a substantial portion of our other fund information including fund returns.

Our attention is on bond funds that primarily invest in the United States with a general, investment grade, or high yield style. We exclude funds with a government, municipal, or mortgage-backed security style. We filter funds on geographic and asset-class focus by (i) algorithmically searching and individually studying fund benchmarks—e.g., we drop funds if their benchmark contains the term 'municipal,' and we drop funds with the benchmark 'Bloomberg Multiverse'—(ii) by algorithmically searching fund names—e.g., we drop funds with 'absolute return' in their name—and (iii) using Lipper objective codes.[15] We exclude actively managed ETFs using an ETF identifier variable available in CRSP, but include passively managed ETFs.

[15] A fund is considered to have an investment grade style if it has Lipper objective code of A, BBB, IID, SID, SII, or USO; a high yield style if it has a Lipper objective code of HY, MSI, or SHY; and a general style if it has a Lipper objective code of GB. Because only a small number of funds have a general style, we collapse that style with investment grade in our analysis.

Our analysis is conducted at the fund level. We collapse our share-class level data to the fund level using FundId. With limited exception, reported information about funds, such as returns, is a value-weighted average of share-class values.[16] Exceptions include assets, which are summed across all share classes, and our dummy variable marking whether a fund is an ETF. A small number of traditional open-end funds have an ETF share class, and in those situations, the ETF dummy is set to 0.5.[17] At the fund level, we account for the incubation bias documented by Evans (2010) by dropping funds from the sample until they are at least two years old and until they first have at least $20 million in assets.

On occasion, we reference an equivalent sample of passive and active equity funds. We follow procedures similar to those described above to build that sample, with the filters adjusted to aim our attention on traditional long-only equity funds that primarily invest in the United States.[18]

In our final bond fund sample, we have 108 unique passive funds with 7,294 fund-month observations and 684 unique active funds with 60,600 fund-month observations. The number of passive bond funds almost quadruples over our time period, increasing from 25 to 96. Active bond funds see a similar growth in the number of funds, 419 to 496, but proportionally their growth is slower. As shown in Figure 2, the proportion of bond fund assets invested passively is growing over our time period, but compared to equity funds, that growth is slower and from a smaller base. About 23% of bond fund assets were passively managed at the end of 2011 compared to 36% at the end of 2021—an annualized growth rate of 4.72%. In comparison, a greater proportion of

[16] To remove clearly erroneous data with extreme values (e.g., 905%) and mishandled splits, share-class level mutual fund monthly returns greater than an absolute value of 49% are dropped. Such returns are rare, with −49% and +49% being about ten times the 1st and 99th percentiles and only 0.004% of returns being filtered.

[17] All of the funds in our sample with an ETF as a share class are offered by Vanguard, which until recently held a patent on that structure.

[18] The Lipper objective codes that qualify a fund in this sample are EIEI, SPSP, SPMC, SCCE, SCGE, SCVE, MLCE, MLGE, MLVE, MCCE, MCGE, MCVE, LCCE, LCGE, and LCVE.

equity fund assets were passively managed at the end of 2011, 31%, and the annualized growth rate was higher, 6.19%, such that about 57% of equity fund assets were passively managed at the end of 2021. At their current rates, passive bond funds would not reach the point passive equity funds are at currently for ten more years, which is indicative of passive management being less popular among bond funds.[19]

ETFs are a substantial part of the passive bond fund sample, with over half of our fund-month observations coming from pure ETFs and over three-fourths of fund-month observations coming from either pure ETFs or funds with an ETF share class. Figure 3 shows the change over our time period in the proportion of funds and assets linked to ETFs (either pure ETFs or funds with an ETF share class) among passive bond funds. The percentage of passive bond fund assets linked to ETFs falls slightly over time—from 75% at the end of 2011 to 70% at the end of 2021—but remains large, while the percentage of passive bond funds linked to ETFs increases meaningfully over time from 60% to 80%.[20]

4.2. Fund and benchmark holdings

We obtain quarterly data on bond fund and bond benchmark holdings from three sources, all of which contain the CUSIP-level holdings and weights necessary to calculate active share. We have fund data provided by Morningstar through the third quarter of 2015. Thereafter, we use fund data from CRSP.[21] Our benchmark data is all downloaded from Bloomberg.

[19] Notably, active bond funds have a positive average net flow, on average, during our time period whereas active equity funds have seen consistent outflows over our time period. The *2023 Investment Company Fact Book* (https://www.icifactbook.org/) notes that "from 2013 through 2022… actively managed domestic equity mutual funds experienced net outflows of $2.3 trillion (pg. 48)."
[20] In untabulated results, we find that the passive bond funds with an ETF as a share class are small in number but large in assets. While only 7% of passive bond funds had that structure at the end of 2021, the passive bond funds with that structure held 45% of passive bond fund assets.
[21] On occasion, we reference results that we calculate based on equity fund holdings. All equity fund holdings are from CRSP.

Bond funds use many different benchmarks (138 in our final sample), and we are not able to obtain holdings for all of them. We have sought to obtain data for the most commonly used benchmarks. In some cases, we are able to build additional benchmarks ourselves using maturity data available in Bloomberg. For example, we can obtain the 'Bloomberg US 1-5 Year Corporate Bond' benchmark by filtering and reweighting the 'Bloomberg US Corporate Bond' benchmark. In the appendix, we provide a detailed accounting of our holdings coverage of the benchmarks of the funds in our sample.

Because of missing holdings, when we require observations in the sample to have an active share measure no more than 12 months old, our sample size is meaningfully reduced—we lose 34% of our fund-months observations. Thus, we only impose that constraint when essential to the analysis. Because of the percentage of observations lost, imposing that constraint also raises the concern of introducing bias, particularly with respect to the performance of highly active bond funds, which we claim outperform. We find, however, that an equal-weight portfolio of active bond funds has nearly the same CCR6 alpha with and without requiring active share (0.29% versus 0.28%), suggesting that the constraint does not introduce bias.

We begin measuring active share in December 2010 and, accordingly, begin evaluating fund performance in January 2011. We have the holdings for few benchmarks before that time, such that studying earlier periods is only possible with small and stylistically skewed samples. This choice of time period is, furthermore, also driven by the prior-discussed issues related to evaluating active bond funds relative to passive bond funds in earlier time periods. We end our study in December 2021 when our data end.

4.3. Bond-level data

While bond funds hold many different types of bonds, we only have bond-level data for corporate bonds. With two exceptions, our data for individual corporate bonds is from CRSP. The first exception is zero-trading-days, which is calculated using TRACE following Choi, Kronlund, and Oh (2022). The second exception is returns, which are primarily from CRSP but supplemented with data from Mergent. Coverage of individual corporate bonds is extensive, but not complete. For example, on average, about 82% of the assets in the 'Bloomberg US Corporate Bond' benchmark have information available on spread in the last month of the quarter.

5. Results

In this section, we present our results on passive and active bond funds. We begin with an analysis of the performance and characteristics of both groups. Then, we separately analyze each group, focusing on different aspects of each. That process starts with passive bond funds and concludes with active bond funds.

5.1. Do active bond funds underperform passive bond funds?

Cremers, Fulkerson, and Riley (2019), after thoroughly reviewing the mutual fund literature, write that "the conventional wisdom is that the average actively managed fund underperforms a passively managed fund that follows the same investment style or mandate (pg. 10)." The vast majority of the evidence supporting that claim though is derived from equity funds. Here, we provide evidence that directly refutes this claim for bond funds.

We begin by considering the performance of our sample of passive bond funds relative to their prospectus benchmarks—a key measure given that those funds' stated goal is to track those benchmarks. However, rather than using the simple difference between the fund's net return and the benchmark's return, here we regress the fund's excess net return on the benchmark's excess return. That method allows us to further evaluate how well the passive bond funds are tracking their benchmark, as, in this test, the ideal passive fund would have a beta of one, an alpha of zero, and an R-squared value of 100%.

We show the distribution of the fund-level betas, alphas, and R-squared values from regressing the full sample of each passive fund's excess net returns on their benchmark's excess net returns in Panel A1 of Table 1. Focusing first on the full sample, the median beta is 0.99, and the 10th and 90th percentiles are 0.95 and 1.02. Further, the median R-squared value is 99.5%, and the 10th and 90th percentiles are 98.1% and 100%. Thus, by these basic metrics, passive bond funds tend to successfully track their benchmarks. They do not, however, successfully match the performance of their benchmarks. The median alpha is only −0.18% per year.

The above results are highly robust. If we focus strictly on investment grade or high yield passive bond funds, the average alpha is −0.22% per year for the investment grade funds and −0.15% per year for the high yield funds. If we focus strictly on a sample of passive bond funds excluding ETFs or only including pure ETFs, those groups have average alphas of −0.27% and −0.19% per year. Moreover, as we show in Panel A2 of Table 1, if we switch approaches and regress excess net returns of equal-weight portfolios of passive bond funds on usage-weighted excess benchmark returns, we find similar results. The average alpha for the full sample portfolio is −0.26% per year (*t*-stat = −6.39).[22] That underperformance, as shown in the internet appendix, cannot be attributed in full to fund fees, as the average gross alpha of the same portfolio is −0.08% per year (*t*-stat = −2.03).[23]

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[22] We also considered simple differencing of the fund's net return and the benchmark's return. Repeating this result using simple differencing, the alpha is −0.31% per year (*t*-stat = −7.75).

[23] As demonstrated later, passive bond funds and their benchmarks do not have meaningfully different levels of liquidity, which suggests that the remaining underperformance is not attributable to passive bond funds having greater liquidity than their benchmarks. Likewise, including the Bai, Bali, and Wen (2019) liquidity risk factor corrected following Dickerson, Mueller, and Robotti (2023) in the model has no meaningful impact on the gross alphas. The corrected factor is available at https://openbondassetpricing.com/.

Those outcomes for passive bond funds indicate two things: first, that obtaining diversified exposure to the bond market is not free and, second, that active bond funds relative to their clear alternative have a, perhaps, lower than expected bar to clear. We first evaluate the performance of active bond funds relative to passive bond funds through matching. In particular, we first attempt to match each active bond fund to a value-weighted portfolio of passive bond funds tracking the same benchmark. Then, within the matched sample, we regress the excess net return of each active bond fund on the excess net return of their passive equivalents. Here, we would not necessarily expect betas to be near one, as active bond funds are under no obligation to maintain such an exposure.

We show the distribution of the fund-level betas, alphas, and R-squared values from this analysis in Panel B1 of Table 1. Looking first at the full sample results, the R-squared values indicate this style of matching leaves a significant portion of active bond fund returns unexplained. The average R-squared value is only 61.6%. With this style of matching though, the active bond fund alphas tend to be positive. The average alpha is 0.77% per year and even the 25th percentile of alpha is positive at 0.16% per year. Accordingly, this test suggests that, relative to their passive equivalents, active bond funds tend to add value for investors. That conclusion is unchanged if we focus strictly on investment grade or high yield funds. If, as in Panel B2, we switch to using portfolios, we find positive alphas, but those alphas are statistically indistinguishable from zero—0.57% per year (*t*-stat = 0.87) in the full sample—which suggests that the active bond funds are no worse than passive bond funds.

This matching method, however, has important flaws that prevent us from using it to draw strong conclusions. First, for many active bond funds, there is not a passive bond fund tracking the same benchmark. Consequently, when we require a match, we lose 37% of the fund-month observations in our active bond fund sample, limiting the generality of our results. Second, that loss of funds is not equal across styles—before requiring a match 27% of the sample is high yield, but after requiring a match that drops to 19%—which makes the sample unrepresentative. Third, consistent with prior research showing that the prospectus benchmarks of actively managed funds are inaccurate (Sensoy, 2009) and biased (Cremers, Fulkerson, and Riley, 2022b), using the matched passive bond funds produces upward biased alphas that lead to incorrect inferences. If we add the CCR6 model factors to our full sample portfolio evaluation in Panel B2, the alpha decreases by 0.42% per year (*t*-stat = 2.63), which suggests that the matching method suffers from omitted factors.

To obtain quality inferences, we accordingly switch in Panels C1 and C2 of Table 1 to using our multi-factor models constructed based on value-weighted portfolios of passive bond funds. Panel C1 reports the full sample performance of individual active bond funds using our basic CCR3 model, and Panel C2 reports performance using our expanded CCR6 model. We also report performance for passive bond funds to help evaluate the quality of the models. If the models are well-specified, they should tend to produce alphas of zero for passive funds, although not all passive bond funds should have a zero alpha since not all passive funds are of equal value.

We begin by considering the full sample. Compared to the matching analysis, the active bond funds have much larger R-squared values using the multi-factor models. Using the CCR3 model, the average R-squared value is 81%, and using the CCR6 model, the average R-squared value is 86%. Therefore, these models leave much less of the returns of active bond funds unexplained. Like the matching analysis, both CCR models agree that the average active bond fund has a positive alpha, albeit one of lesser magnitude. The average CCR3 model alpha is 0.36% per year, and the average CCR6 model alpha is 0.35% per year. A histogram of these alphas, shown in Figure 4, indicates that both full sample distributions tend to cluster above zero and have right tails larger than their left. That is, the distributions provide no evidence that active bond funds tend to underperform passive bond funds. The models also agree that both investment grade active bond fund and high yield active bond funds have, on average, positive alphas. Again though, those alphas are less in magnitude than in the matching analysis.

Considering the passive bond funds, the CCR6 model appears to be of relatively higher quality compared to the CC3 model. The average and median CCR6 model alphas among passive bond funds are 0.09% per year and 0.00% per year, whereas the CCR3 model has equivalent values of 0.21% per year and 0.13% per year. Thus, we tend to use the CCR6 model for the evaluation of active bond funds in subsequent analyses.[24]

In Panels D1 and D2 of Table 1, we perform a similar analysis to that in Panels C1 and C2, but focus on active bond funds and switch to using equal-weight portfolios. We report here both alphas and factor exposures, with the CCR3 model results in Panel D1 and the CCR6 model results in Panel D2. Given its higher quality though, we focus on the CCR6 model results, providing the CCR3 model results primarily for completeness. Using the CCR6 model, the full sample active bond fund portfolio has little exposure to the stock and mortgage-backed securities factors and no statistically significant exposure to the treasury factor. The three factors driving its returns are thus the general bond market, the corporate bond market, and the high yield bond market. The R-squared value of the portfolio is 97.1%, suggesting that the CCR6 model explains nearly all of the variation in the portfolio's returns. Most importantly, there is some evidence here that the

[24] The internet appendix contains additional analysis of the CCR3 and CCR6 models with respect to passive bond funds and reaches the same conclusion. Most notably, we show that (i) the CCR3 model tends to produce a statistically significant positive alpha for a portfolio of investment grade passive bond funds, (ii) the CCR3 model has substantially less explanatory power than the CCR6 model with respect to a portfolio of high yield passive bond funds, and (iii) the cumulative abnormal returns for a portfolio of all passive bond funds are consistently nearer to zero when using the CCR6 model compared to when using the CCR3 model.

average active bond fund has a statistically and economically significant positive alpha. The full sample alpha is 0.29% per year (*t*-stat = 1.75). If, as shown in Figure 5, we consider the CCR6 model cumulative abnormal returns of this portfolio, we can see a final return of 3.27% without any period of substantial drawdown. Both of those results suggest that investors would have benefited from investing in active bond funds instead of passive bond funds.

Consistent with their styles, the high yield active bonds funds relative to the investment grade active bond funds have a lower corporate bond market exposure and a greater high yield bond market exposure. Accounting for those differences, the investment grade active bond funds show less evidence of outperformance than the full sample, with an alpha of 0.18% per year (*t*-stat = 1.28), while the high yield active bond funds show somewhat equivalent evidence of outperformance, with an alpha of 0.50% per year (*t*-stat = 1.70). Put another way, whether an investor was interested in investment grade or high yield bond mutual funds, there is little evidence that they would have been better off choosing passive management.

5.2. Stylized Facts of Passive and Active Bond Investing

Here, we characterize our samples of passive and active bond funds on key dimensions—both contrasting those two groups and developing an understanding of the unique dynamics of passive bond funds.[25] To help accomplish the latter goal, we also provide a characterization of these funds' benchmarks along key dimensions. Panels A1 and A2 of Table 2 show broad characteristics for both passive and active bond funds, and Panels B1 and B2 show characteristics

[25] The samples of passive and active bond funds do not have identical benchmark distributions—creating the possibility that the results discussed in this section are driven primarily by differences in benchmarks. As shown in the internet appendix though, matching on benchmark, which significantly reduces our sample size, does not change our conclusions.

of passive and active bond fund's holdings.[26] The number of observations varies because not all characteristics are available for all funds at all times.

5.2.1. Fund activeness

Passive bond funds are less active than active bond funds, but not nearing full replication of their benchmarks. At the bond level, active bond funds have an average active share of 95.8% and passive bond funds have an average active share of 48.3%. Put another way, about half of the average passive bond fund's portfolio's assets can be thought of as actively managed. At the firm level, the average active share for active bond funds decreases to 77.3%—similar to the level observed for active equity funds in Cremers, Fulkerson, and Riley (2022b)—and the average active share for passive bond funds decreases to 25.4%—still leaving about one-quarter of the average passive bond fund's portfolio's assets as actively managed. For comparison, Crane and Crotty (2018) report an average active share for passive equity funds of 14% and a median active share for passive equity funds of only 2%.[27]

Figure 6 provides a visual representation of the activeness of passive bond funds. As an example, it deconstructs the portfolio of the Vanguard Total Bond Market Fund, the largest passive bond fund by assets, during the last quarter of our sample. The fund is benchmarked against the 'Bloomberg US Aggregate Float Adjusted,' and at the bond level, the active share of the fund relative to that benchmark is 38%. Thus, we can think of 62% of the assets in the portfolio as being passively managed. Of the actively managed 38%, 12% comes from the fund not buying a bond

[26] If we compare the average values for the passive and active bond funds using *t*-statistics calculated from standard errors clustered by fund and year-month, those values tend to be statistically different from each other even when they are not economically different, so we focus on economic differences in this discussion.

[27] The gap in active share between passive equity and passive bond funds is directionally consistent with the language often found in their prospectuses, although such language is not indicative of the magnitude of the difference. For example, the Vanguard Total Bond Market Fund notes in its prospectus that "the Fund invests by sampling the Index (pg. 2)," while the Vanguard 500 Fund notes in its prospectus that "the Fund attempts to replicate the target index (pg. 3)." The full prospectuses are, respectively, available at https://personal1.vanguard.com/pub/Pdf/p584.pdf and https://personal1.vanguard.com/pub/Pdf/p540.pdf.

in the benchmark at all (Out-of-Fund), 7% comes from the fund buying a bund in the benchmark but underweighting it (Underweight), 8% comes from the fund buying a bund in the benchmark but overweighting it, and 11% comes from the fund buying a bond outside the benchmark (Out-of-Benchmark). The last is particularly notable, as it indicates that the fund invests a meaningful portion of its assets in non-benchmark securities.[28]

Average tracking error is likewise less for passive bond funds than active bond funds, but again, the individual values are indicative of substantial activeness from passive bond funds. The average tracking error in our passive bond fund sample, 0.10%, is only slightly less than same value in our passive equity fund sample, 0.12% (untabulated). Based on medians, the passive equity funds have lower tracking error than the passive bond funds, 0.02% (untabulated) versus 0.06%. Those results occur despite equity markets being significantly more volatile than bond markets, which is embodied in the average tracking error in our active equity fund sample, 1.25% (untabulated), being more than double the average tracking error in our active bond fund sample, 0.52%. In this analysis, we are using the tracking error over the twenty-four months prior to the fund-month observations, but our conclusions are the same if we instead use full-sample tracking errors for each fund.

5.2.2. Fund costs and trading intensity

Passive bond funds tend to charge lower fees than active bond funds, with an average expense ratio about one-quarter that of active bond funds, and tend to trade less than active bond funds, with an average turnover about half that of active bond funds. Passive bond funds do, however, still charge meaningfully non-zero fees, with an average expense ratio of 0.19% per year,

[28] The Vanguard Total Bond Market Fund has the flexibility to invest up to 20% of its assets in non-benchmark securities. Specifically, the fund's prospectus states that "at least 80% of the Fund's assets will be invested in bonds held in the Index (pg. 2)." The full prospectus is available at https://personal1.vanguard.com/pub/Pdf/p584.pdf.

and make a substantial number of trades, with an average turnover ratio of 71%. Crane and Crotty (2018) report an average turnover ratio for passive equity funds of 42%, suggesting that passive bond funds, relative to passive equity funds, engage in significantly more trading.

That difference in turnover ratio suggests that the trading intensity required for passive bond funds to track their benchmarks at the level they track them is greater than the equivalent trading intensity required for passive equity funds. Given that passive bond funds are trading more than passive equity funds but do not track their benchmarks as well as passive equity funds, the variables causing trade-required changes in bond benchmarks (e.g., bonds maturing, bonds being called, maturity restrictions, and rating restrictions) are likely generating more changes than the variables causing trade-required changes in equity benchmarks (e.g., mergers, delistings, value restrictions, and size restrictions).[29] The end result is passive bond funds choosing to trade more despite operating in a less liquid market in which uninformed trading should be expected to have a significant negative impact on performance.

5.2.3. Fund and benchmark holdings

Consistent with their need to track their benchmark, passive bond funds hold many more bonds than active bond funds, with, on average, passive bond funds holding 2,435 and active bond funds holding 533. Each of those values is small, however, relative to the number of bonds in the funds' benchmarks. Indicative of their activeness, passive bond funds have only 38.5% as many bonds as their benchmark and only 54.3% as many firms. Thus, even if we incorrectly assume passive bond funds exclusively invest in securities in their benchmark, there are thousands of

[29] As a more concrete demonstration of the different amounts of change, consider that the most commonly used bond benchmark, the 'Bloomberg US Aggregate,' tends to have a higher active share with its past self than does the most commonly used equity benchmark, the 'S&P 500.' For example, the 'Bloomberg US Aggregate' at the end of 2021 has an active share relative to the 'Bloomberg US Aggregate' at the end of 2020 of 30.4%. The same value for the 'S&P 500' is only 9.4%.

benchmark bonds and hundreds of benchmark firms that the average passive bond fund chooses not to hold.

Passive and active bond funds show similarly low levels of asset liquidity, with no suggestion that passive bond funds' holdings are more liquid. On average, both groups have almost half of their assets experiencing zero trades in a given day (% Zero Trading Days), and both groups have similar value-weighted spreads and amounts outstanding. The only indication of a difference in liquidity is that value-weighted volume is greater among active bond funds than passive bond funds. That result, however, if it suggests anything, suggests greater liquidity for active bond funds.

The asset illiquidity of passive bond funds, their limited number of holdings relative to their benchmarks, and their high active shares and tracking errors relative to those of passive equity funds are all explicable given the illiquidity of the assets in passive bond funds' benchmarks. About half of the assets in the benchmark of the average passive bond fund do not trade in a given day, and the average value-weighted spread of the assets in those benchmarks is 0.39%. Those high values, moreover, understate the illiquidity problem faced by a passive bond fund attempting full replication. Consider the distribution of zero-trading-days at the holdings level for the most commonly used passive bond fund benchmark, the 'Bloomberg US Aggregate,' in the last quarter of our sample (untabulated). At the 90^{th} percentile, the bonds in that benchmark trade only one out of every seven trading days, suggesting that ten percent of the bonds in that benchmark are trading less often than that infrequent rate. A passive bond fund attempting full replication of this benchmark would thus face a difficult and costly process, especially given that the relatively high turnover of passive bond funds suggests that they are already trading relatively intensely to reach their presently observed levels of activeness.

5.3. The incentives and choices of passive bond funds

Here, we first consider the incentive structure faced by passive bond fund managers that leads them to hold relatively active portfolios. We then explore how the liquidity of a given bond influences its weight in passive bond fund portfolios.

5.3.1. Why are passive bond funds active?

The incentive structure faced by mutual fund managers is, either directly or indirectly, strongly influenced by the behavior of investors. Given that fund companies want to attract capital, the managers of mutual funds will have incentive to take actions that increase net flows and to avoid actions that decrease net flows. While simple on its face, potential actions are often in conflict, creating trade-offs for fund managers. We contend that such trade-offs are generated for passive bond fund managers because they need to match their benchmark closely while also maintaining liquidity and controlling expenses.

We seek to capture those trade-offs—and increase our understanding of the substantial activeness of passive bond funds—by looking at the determinants of passive bond fund flows. Our general model of flows for passive bond funds is:

$$\begin{aligned} Flow_{i,t+1} = {} & \beta_1 \text{ x } Perf_{i,t} + \beta_2 \text{ x } Expense_{i,t} + \beta_3 \text{ x } Active_{i,t} + \beta_4 \text{ x } Illiquid_{i,t} \\ & + \gamma \text{ x } Controls_{i,t} + FE + \varepsilon_{i,t+1} \end{aligned} \tag{7}$$

where $Flow_{i,t+1}$ is the net flow of fund *i* in month *t* + 1, $Perf_{i,t}$ is the simple difference between the gross return on fund *i* and fund *i*'s benchmark's return over the twenty-four months ending in month *t*, and $Expense_{i,t}$ is the expense ratio of fund *i* during the period of performance measurement. $Active_{i,t}$ is a measure of activeness for fund *i* as of the end of month *t*. We consider the most recently available bond-level and firm-level active shares as of the end of month *t* and the natural log of the fund's tracking error over the twenty-four months ending in month *t*.

$Illiquid_{i,t}$ is the most recently available fund-level asset illiquidity measure for fund i as of the end of month t. $Controls_{i,t}$ is a vector of information about fund i as of the end of month t that includes the natural log of assets, the natural log of age, and the turnover ratio. FE represents both benchmark and year-month fixed effects. All continuous variables in the model are winsorized at the 2.5% and 97.5% levels. To ease interpretation, we z-score the activeness measures and expense, with our illiquidity measure being inherently interpretable like a z-scored variable.

We show results from this model in Table 3. In column (1), we focus on fund performance and find that investors are indifferent to the gross performance of passive bond funds. All of the effect of performance on net flow arises from the impact of expenses on the net return. Changes in gross performance have a statistically insignificant impact on net flows (t-stat = 0.62), while a one standard deviation increase in the expense ratio decreasing net flows by 0.97% per month (t-stat = −3.00). Thus, while fund managers may not directly control their fund's expense ratio, they have incentive to run their fund in such a manner that it can be profitable for their company at a low expense.[30]

In columns (2) through (5), we consider measures of activeness. Neither bond-level active share nor tracking error have a significant relation with net flows, but firm-level active share has a strong negative relation. Considered in isolation, a one standard deviation increase in firm-level active share decreases net flows by 1.87% per month (t-stat = −2.10). The result is similar after controlling for bond-level active share and tracking error. Accordingly, investors appear to have little reaction to (i) how closely a fund's past performance tracked the fund's benchmark's past

[30] We do not intend to imply that gross performance is invariably irrelevant to understanding passive bond fund flows. We expect that if a passive bond fund had a gross benchmark-adjusted return of −10% per year that such performance would impact their flows. Rather, we believe that, within the range of gross benchmark-adjusted returns generated by actual passive bond funds, investors tend to be indifferent. The need to maintain sufficient gross performance could, therefore, also be a constraint on passive bond fund managers.

performance or (ii) how close a fund's bond-level holdings are to the fund's benchmark's bond-level holdings. Investors do, however, react strongly when the composition of firms in the fund differs substantially from those in the fund's benchmark, which, in turn, gives fund managers incentive to keep a close firm-level match.

The lack of a significant relation between tracking error and flows for passive bond funds is surprising given the anecdotal prominence of tracking error in passive fund investors' minds. That there is, at the same time, a significant relation between active share and flows for passive bond funds adds to that surprise. We conjecture that those relations obtain empirically because tracking error and active share measure two distinct aspects of active management and passive bond funds have a differential focus on those two aspects.

As described in Cremers and Petajisto (2009), tracking error measures factor bets and active share measures security selection. Passive bond funds tend to focus on minimizing the former using their discretion with the latter. For example, the Vanguard Total Bond Market Fund states in its prospectus that it "invests by sampling the Index" while seeking "to maintain a dollar-weighted average maturity consistent with that of the Index" and "to maintain an average duration consistent with that of the Index (pg. 2)."[32] In other words, the fund seeks to avoid factor bets by engaging in careful security selection.

We expect that, all else equal, investors would prefer passive bond funds make no factor bets and perform no security selection. In practice, however, passive bond funds place substantially more focus on minimizing factor bets, such that passive bond funds tend to have low tracking errors and low cross-sectional variation in tracking error. The result is that, while tracking error is a constraint on passive bond fund managers, investors tend to be indifferent to tracking error within

[32] The full prospectus is available at https://personal1.vanguard.com/pub/Pdf/p584.pdf.

the range generated by actual passive bond funds. Thus, when considering the empirical relation between passive bond fund flows and measures of activeness, only active share shows a significant relation because only active share tends to be large and variable enough to be a differentiator.[33]

In column (6), we consider illiquidity. A one standard deviation increase in illiquidity decreases net flows by 1.19% per month (t-stat = −2.32). Fund managers, consequently, have incentive not to hold a portfolio of relatively illiquid assets. In isolation, that is straightforward for a passive bond fund manager to accomplish; however, as the full model in column (7) shows, they face a difficult trade-off. If a passive bond fund seeks to minimize its firm-level active share to increase its net flows, it will have to contend with offsetting effects from decreased liquidity and increased costs. That trade-off, which, at minimum, should be significantly weaker among passive equity funds where liquidity is greater and active shares are lower, helps drive the substantial activeness of passive bond funds.

5.3.2. How does bond liquidity impact the construction of passive bond fund portfolios?

The results with respect to fund flows suggest that passive bond funds face a trade-off between activeness and liquidity. Here, we detail that trade-off at the holdings level—demonstrating how bond liquidity drives a systematic wedge between the portfolios of passive bond funds and those of their benchmarks. Our general model of the holdings of passive bond funds is:

$$Diff_{i,j,t} = \beta_1 \text{ x } Illiquid_{j,t} + \gamma \text{ x } Controls_{j,t} + FE + \varepsilon_{i,j,t} \quad (8)$$

[33] It is unclear how to test this range hypothesis, since we cannot test the response of investors to events that did not occur. However, consistent with the hypothesis, if we repeat column (4) while neither taking the natural log of tracking error nor winsorizing tracking error—heightening the impact of more extreme values—tracking error, with a t-statistic of −1.70, does have a negative relation with flows that clears the traditional 10% minimum threshold for statistical significance. We do not draw strong conclusions from that result though, as the statistical significance is marginal, the economic significance is relatively small (0.35% per standard deviation), the statistical and economic significance is subsumed by firm-level active share, and the most extreme values of an unbounded variable tend to be more uncertain.

where $Diff_{i,j,t}$ is the difference between fund i's weight on bond j at the end of month t and the fund's benchmark's weight on the same bond at the same time. Put another way, our model is attempting to explain deviations in portfolio weights between funds and their benchmarks. $Illiquid_{j,t}$ is the bond-level asset illiquidity measure for bond j in month t. We use two versions of the illiquidity measure in this instance: our typical measure with four inputs and a measure that excludes the amount outstanding. Fund's benchmarks tend to be value-weighted, so including the amount outstanding on the right-hand-side of the model could induce a spurious relation. $Controls_{j,t}$ is a vector of information about bond j as of the end of month t. It includes the natural log of the amount of time since the bond was issued, the numeric rating of the bond, the duration of the bond, and the yield of the bond. As represented by FE, we also include CUSIP and fund-year-month fixed effects. All continuous variables in the model are winsorized at the 2.5% and 97.5% levels. Because we observe fund holdings quarterly, only the months of March, June, September, and December are included in our estimations.

We show results from this model in Table 4—providing separate estimations in which we include all bonds held by either a fund or its benchmark (Full) and in which we include only bonds held by both a fund and its benchmark (In Both). Because fund and benchmark weights can be very small, we multiple the difference in weight by one million in our reported results to ease interpretation. As shown in column (1), if we consider all of the holdings of both a fund and its benchmark, there is a negative relation between the illiquidity of a bond and a fund's holdings of that bond relative to its benchmark. A one standard deviation increase in bond illiquidity reduces the relative holdings of a bond by 2.68 (t-stat = −6.08). To give that value context, a decrease in weight of that size is enough to move a bond from the 50th percentile of the difference in weight to around the 45.5th percentile. If, as in column (2), we only consider fund and benchmark holdings that overlap, we obtain a similar coefficient and statistical significance. If, as in columns (3) and (4), we exclude amount outstanding from our illiquidity measure, we find similar, albeit economically weaker, results. Accordingly, we conclude that, when a passive bond fund manager chooses to deviate from the fund's benchmark with respect to a given bond, the liquidity of that bond is an important dimension of that choice.

5.4. The cost of passive bond fund rebalancing

The manager of any passive fund must assess the costs and benefits of rebalancing. On the one hand, each rebalancing incurs transaction costs. On the other hand, each rebalancing lessens the mismatch between the fund and benchmark (lowering active share and expected tracking error). This assessment is more difficult for passive bond funds than passive equity funds because of the large differences in liquidity between the two markets. Each trade for a passive bond fund will incur significantly more transaction costs.

The rebalancing differences between the two markets, however, are not limited to straightforward transaction costs. Bond benchmarks rebalance in a manner that is, for practical purposes, impossible for a passive bond fund to replicate. Because their trades are hypothetical, when bond benchmarks rebalance, they not only pay no transaction costs, but they are also able to locate all bonds and trade any amount of any bond. Passive bond funds, because they must make actual trades, must locate any bond they are seeking to trade and trade a significant amount of the bond, else incur additional transaction costs (Edwards, Harris, and Piwowar, 2007) in excess of the meaningful transaction costs they would incur regardless. As we demonstrate here, the impact of these practical matters is that the transaction costs of tracking of a bond benchmark are substantially higher than analyses sufficient for equity benchmarks would suggest.

Our analysis of the transaction costs associated with tracking a benchmark operates on a quarterly basis. At the start of each quarter, we begin with the current complete benchmark portfolio. The assets in the portfolio then experience their actual quarterly returns. At the end of the quarter, in some instances, the portfolio also experiences a net flow of assets as a percentage of the portfolio's beginning-of-quarter assets. The portfolio is then rebalanced to match the new current complete benchmark portfolio. The cost of this rebalancing is then calculated as a proportion of end-of-quarter assets using the asset-level average spreads during the last month of quarter.[34] To estimate similar costs for passive funds, we perform the same procedure but use the fund portfolio at the beginning and end of each quarter.

We use two approaches for fund flows: simulation and actual. In our simulation approach, we assume that flows are drawn from a normal distribution with mean zero and differing levels of volatility (0%, 10%, 15%, and 20%).[35] When flow volatility is non-zero, we run 10,000 simulations of each quarter and report the average. This approach allows us to observe the expected impact of different levels of flow volatility, but it also has the potential to mislead because the rebalancing choices made by passive bond funds are endogenous to their flows. Thus, we also consider an actual flow approach in which both the benchmark and the passive bond fund experience the actual flow of the passive bond fund during the quarter.

We only have bond-level data for corporate bonds, so we focus our analysis on corporate bond benchmarks and passive bond funds with corporate bond benchmarks. We rescale the portfolio weights of the benchmarks and passive bond funds to unity to account for any

[34] When spread data is missing for a given bond at a given time, we use the average spread of bonds at that time with similar ratings, maturities, and amounts outstanding. In particular, we sort all corporate bonds in our sample into independent quintiles each month by rating, maturity, and amount outstanding. If a bond is missing its spread in a month, then we use the average spread of the bonds in the same monthly quintile grouping.
[35] Flow volatility in our full sample is 16.1% per quarter for passive bond funds and 11.1% per quarter for active bond funds.

non-corporate holdings and for any holdings with missing data. To enable a clean test, we require the benchmarks and funds to match in time (i.e., results are only reported if both a fund's holdings and its benchmark's holdings are observed at the beginning and end of a given quarter). Our time period—the second quarter of 2011 through the third quarter of 2021—generally matches our other analyses but benchmark-fund pairs are not available for all reported benchmarks in all quarters.[36]

The annualized transaction costs associated with the simulated flows are reported in Panel A of Table 5. Across the different benchmarks, there is a consistent, large gap between benchmark rebalancing costs and passive fund rebalancing costs. For example, ignoring flows, the average annualized cost to rebalance the 'Bloomberg Intermediate Corporate Bond' benchmark is 5.31 basis points (bps), while the average annualized cost to rebalance the passive fund tracking the 'Bloomberg Intermediate Corporate Bond' benchmark is 18.77 basis points. Consequently, while this analysis suggests somewhat modest costs to rebalance corporate bond benchmarks, passive funds tracking those benchmarks are not able to match those modest costs in practice, despite also, as shown earlier, not achieving a particularly close holdings-level match to their benchmarks. This gap arises from the benchmark being able to make unrealistic hypothetical trades. The benchmark can trade a single unit of any bond at the average spread, while the fund, even if it could locate all bonds, still must contend with the actual relation between trade size and transaction costs.[37]

Further, as the simulated flows demonstrate, expected transaction costs increase as flow volatility increases—indicating that real rebalancing costs will meaningfully exceed no-flow

[36] In the rare instances in which we have multiple passive bond funds tracking the same benchmark in the same quarter, we treat the observations independently, with the exception of a later presented figure where we use the average. If we limit the analysis to the time period in which benchmark-fund pairs are consistently available for all reported benchmark (2018Q4 through 2021Q3), our conclusions are unchanged.

[37] Assuming that passive bond funds trade at the average spread may also underestimate their transaction costs. Because they do not attempt to fully replicate their benchmark, passive bond funds have some discretion in their trading, but their discretion is less than that of some other traders, such as active bond funds. All else equal, lower trading discretion should result in higher transaction costs.

estimates. The passive fund tracking the 'Bloomberg US Corporate' benchmark, for example, has expected annualized rebalancing costs of 26.89 without flows, but expected costs of 33.77 if flow volatility is 20%. The presence of flows tends to lessen the gap between the benchmarks and the passive funds but still leaves the gap large. For example, the gap between the 'Bloomberg US Long Corporate' benchmark is 36.88 without flows and 28.41 with a flow volatility of 20%. Thus, regardless of assumptions about flows, the benchmarks still appear substantially less expensive to track than they are in practice.

Panel B of Table 5 repeats this analysis using actual flows, while also testing for a statistical difference between the benchmark and fund transaction costs. This test can be thought of as matching on benchmark, time, and actual flow. As shown, our previous conclusions still hold. The 'Bloomberg VLI High Yield' benchmark, for example, after being treated with the actual flows of the passive fund tracking that benchmark, still has average annualized rebalancing transaction costs 5.10 bps less than the passive fund (t-stat = −2.73).

Figure 7 shows the time trend in these actual-flow transactions costs, with the result for each quarter being the across benchmark average. To enable cleaner inferences, we limit the time period to the fourth quarter of 2018 through the third quarter of 2021 because results for each benchmark are available during that window, but our takeaways are similar with other approaches (e.g., studying each benchmark separately). As shown, rebalancing transaction costs are decreasing for the funds over time, falling from an average of 22.14 bps to 10.39 bps over this time period; however, the gap between the funds and their benchmarks does not close, with a gap of 5.37 bps remaining in the final quarter. Furthermore, that gap is notably large at 42.67 bps at the end of the first quarter of 2020 during the market upheaval at onset of the COVID pandemic (e.g., Haddad, Moreira, and Muir, 2021, and Kargar, Lester, Lindsay, Liu, Weill, and Zuniga, 2021), which is indicative of benchmark-based estimates of rebalancing costs being particularly misleading during market turmoil.

We acknowledge that the assumptions we use in this analysis are unrealistic. What is important though is that this analysis is much more unrealistic in the bond market than in the equity market, such that estimating transaction costs associated with rebalancing a passive equity fund using its benchmark would not be deceptive. For example, if we replicate this analysis using the iShares S&P 500 ETF or the iShares Russell 2000 ETF, we obtain average no-flow annualized rebalancing costs of 0.13 bps and 1.75 bps, respectively. We do not have the full actual holdings of the S&P 500 or the Russell 2000 to run the matching benchmark analysis, but as discussed before, like most passive equity funds, these two funds are very similar in holdings to their benchmarks (e.g., on average, the iShares S&P 500 ETF holds 495 stocks and the iShares Russell 2000 ETF holds 1,967). Thus, since benchmark rebalancing costs are, at a minimum, zero, the maximum gap is 0.13 for the iShares S&P 500 ETF and 1.75 for the iShares Russell 2000 ETF, but the actual gap is, in expectation, much smaller. Put another way, when we run this analysis on actual passive equity funds, we observe very low costs, both in general and relative to the benchmark.

The key conclusion is that, because of differences between equity and bond markets, this style of analysis does not port well from passive equity funds to passive bond funds. The result of that conclusion is that passive bond funds are more costly to rebalance than expected based on equity-aligned methods, despite a lack of full benchmark replication. This headwind is another component in explaining why passive bond funds have experienced less growth than passive equity funds.

5.5. Implication of cross-sectional skewness for passive fund performance

Bessembinder (2018) shows that individual stock returns exhibit significant positive skewness, indicating that a small number of star stocks with spectacular performance account for a substantial portion of the aggregate U.S. stock market returns. Such pronounced cross-sectional return skewness is one of the reasons for why diversification, as implemented in essentially all passively managed index funds, is important in equity investing, which also explains the outperformance of passively managed index funds over the majority of actively managed funds in equities. Given the positive skewness in cross-sectional returns, the (equal) average of individual stock return should exceed the median. Passive funds, being highly diversified and encompassing a broad range of stocks, are more likely to include these star stocks, while poorly diversified active funds can exclude them, negatively impacting their performance.

It is a priori not clear whether this diversification-due-to-skewness principle would apply to bond fund investing. Unlike stock returns, bonds returns do not exhibit extreme skewness. Their prices are capped at par upon maturity. While decreases in interest rates can drive up bond prices, the possibility of default can result in substantially negative returns, and when default occurs, bond prices typically do not recover. While most bonds mature without defaulting, the few that do suggest that cross-sectional skewness in bond returns should be less pronounced than in equity returns. Passive bond funds, being diversified, are likely to include these small number of "loser" bonds, which can help explain the relative underperformance of passive funds compared with active bond funds with median performance.

Figure 8 plots the cross-sectional skewness of bond and equity returns over time. For one-month returns, while in some periods bond returns exhibit more positive skewness than equity returns, on average bond returns exhibit less positive skewness (0.237) than equity returns (0.475).

In a longer horizon (the bottom graph), however, we find that much higher skewness in equity returns. The average skewness in 12-months bond returns is 0.153, while that of equity returns is significantly higher at 1.367.

In Figure 9, we plot the time series of the fractions of bonds (or equities) that outperform their benchmarks, using the Bloomberg Agg and Russell 1000 indexes, respectively. The observed patterns largely align with those found in Figure 8: over twelve-months horizons, a substantially higher fraction of bonds in the Bloomberg Agg outperforms the benchmark compared with the fractions of equities outperforming the Russell 1000 index. We find a similar pattern in one-month returns in the top panel, though the difference is less pronounced. These findings indicate that skewness in bond returns are less pronounced than in equities, suggesting that the advantage of diversification seen in equity returns, i.e., the inclusion of star stocks in a portfolio, is smaller in bond investing. Thus, Jack Bogle's principle of "buy the entire haystack" may not be as effective for bonds as it is for equities.

In Table 6, we report the fractions of bonds that beat the value- and equal-weighted benchmarks, further examining the effect of correlation between bond size and performance. This analysis aims to assess the extent to which negative outcomes in large companies (that tend to issue large bonds) affect the performance of passive bond funds. The results in Table 6 show that individual bonds tend to outperform their benchmarks, particularly when benchmark returns are value-weighted. For example, 57.7% of bonds in the Agg index exceed the benchmark returns over a 12-months horizon. By contrast, only 46.9% of stocks in the Russell 1000 index manage to outperform the index. Thus, value-weighted passive funds are more likely to underperform than individual bonds as larger bonds, which can be issued by firms with high leverage and debt burden.

These results are also consistent with the earlier observation that the benefit of diversification in bond returns might be limited, primarily because of their low cross-sectional skewness.

It is important to note that we do not argue diversification is generally detrimental. It plays a crucial role in reducing portfolio risk, potentially leading to a higher Sharpe. However, it is also important to recognize that the majority of diversification benefits can be achieved with a relatively small number of securities. In the case of large bond portfolios, the risk of putting loser bonds may offset (or even outweigh) the benefit of diversification.

5.6. Active share and active bond funds

In this subsection, we consider the impact of active share on multiple characteristics of active bond funds. We first consider the relation between active share and performance. We then consider the relations between (i) active share and downside risk and (ii) active share and fragility.

5.6.1. The impact of active share on active bond fund performance: Portfolio analyses

We first consider the relation between active share and performance among active bond funds using a portfolio approach. Particularly, in Panel A of Table 7, we sort funds into quintiles each month based on their most recently available measure of active share (as of the end of the prior month) and form equal-weight portfolios using the resulting groups. We then report the net CCR6 alphas of those portfolios, repeating the test using both bond- and firm-level active share.[38]

Using bond-level active share, we see a significant difference in performance between low (bottom quintile) and high (top quintile) active share funds. The difference in alphas is 0.39% per year (t-stat = 1.94), which is indicative of a positive relation between active share and performance. We also see an economically and statistically significant positive alpha of 0.54% per year (t-stat =

[38] Our conclusion in this subsection and the next are the same if, instead of using CCR6 alphas, we use CCR3 alphas.

2.01) for just the high active share funds, which is indicative of investors being able to obtain outperformance from investing strictly in high active share bond funds. Furthermore, while Cremers and Petajisto (2009) document substantial underperformance from active equity funds with low active share, active bond funds with low active share have an alpha indistinguishable from zero (0.15%, *t*-stat = 1.14). Thus, even the lowest performing group of active bond funds here performs no worse than a set of equivalent passive funds.

Using firm-level active share, our conclusions are the same, but both the difference in alpha between the low and high active share funds at 0.80% per year (*t*-stat = 3.12) and the alpha of the high active share portfolio at 0.74% per year (*t*-stat = 2.40) are larger using firm-level active share. This suggests that the relation between active share and performance may be stronger at the firm level than at the bond level, which is confirmed in subsequent panel regression analyses.

Before moving to that test though, we first want to consider the interaction between active share and past performance. Building on the Cremers (2017) idea that high active share is a necessary, but not sufficient, condition for a fund to outperform, Cremers, Fulkerson, and Riley (2022a) show that, in recent years, sorting active equity portfolios on active share alone has limited value. Active share must instead be interacted with past performance to identify outperformance. To consider the power of that interaction in the context of active bond funds, we take our active share quintiles used in Panel A and subdivide them into quintiles based on funds' net CCR6 model alphas over the prior twenty-four months in Panel B. For the resulting twenty-five groups, we form equal-weight portfolios for which we report net CCR6 alphas. We use firm-level active share in this test, since prior and subsequent analyses indicate it has a stronger relation with performance.

Past performance, in isolation, has a positive relation with future performance. The funds with poor past performance (bottom quintile) underperform the funds with strong past performance (top quintile) by 1.28% per year (*t*-stat = 3.60), and the funds with strong past performance, considered on their own, have an alpha of 0.98% per year (*t*-stat = 3.86). While this stands in contrast to the canonical result among active equity funds shown in Carhart (1997), the performance persistence we identify for active bond funds is consistent with the findings of Hunter, Kandel, Kandel, and Wermers (2014), Chen and Qin (2017), and Jones and Mo (2021).[39] Most importantly though, the portfolio formed using the high active share funds with the strongest past performance has an alpha of 1.86% per year (*t*-stat = 3.82), which is more than double the alpha from using high active share alone. Thus, as with active equity portfolios, active share has significantly greater value among active bond funds when considered in conjunction with past performance.

Choi, Kronlund, and Oh (2022) show that bond funds have significant stale pricing. If the level of stale pricing is greater among active bond funds than among passive bond funds, then the use of the CCR6 model in this section could result in overstating the performance of active bond funds. One aim of the CCR6 model is to provide an investable alternative to active bond funds; therefore, using lagged factors to account for a potential difference in stale pricing is inconsistent with the model's aims. As a more consistent substitute, we reperformed the above analyses using quarterly portfolio returns, which lessens any impact of stale pricing and still provides sufficient observations. We show in the internet appendix that results using quarterly returns do not change our previous conclusions.

[39] The Berk and Green (2004) equilibrium model contends such persistence should not occur; however, one of that model's key assumptions—diseconomies of scale—is not supported by empirical studies of bond funds (Hearth, Philpot, Rimbey, and Schulman, 1998; Gutierrez, Maxwell, and Xu, 2009; Rohleder, Scholz, and Wilkens, 2018; Jones and Mo, 2021; Reuter and Zitzewitz, 2021; and Yan, 2021). Garleanu and Pedersen (2018) and Roussanov, Ruan, and Wei (2021), moreover, both note that adding frictions to the Berk and Green (2004) model can significantly modify its equilibrium.

5.6.2. The impact of active share on active bond fund performance: Panel regressions

We next consider the questions tested in the prior subsection (and an additional question) using panel regressions. This approach allows us to better isolate our relations by controlling for other variables that may be impacting performance. Our general model is:

$$\begin{aligned} Alpha_{i,t+1} = {} & \beta_1 \text{ x } Active_{i,t} + \beta_2 \text{ x } Top\ Alpha\ Dum_{i,t} \\ & + \beta_3 \text{ x } Active_{i,t} \text{ x } Top\ Alpha\ Dum_{i,t} + \gamma \text{ x } Controls_{i,t} + FE \\ & + \varepsilon_{i,t+1} \end{aligned} \tag{9}$$

where $Alpha_{i,t+1}$ is the annualized net alpha of fund i in month t + 1 calculated by subtracting from fund i's excess net return in month t + 1 the product of the CCR6 factor realizations in month t + 1 and fund i's CCR6 factor exposures measured over the prior twenty-four months. $Active_{i,t}$ is a measure of activeness for fund i as of the end of month t. We consider the most recently available bond-level and firm-level active shares as of the end of month t and the R-squared value between the fund and the CCR6 model over the twenty-four months ending in month t. Each activeness measure is z-scored to ease interpretation. $Top\ Alpha\ Dum_{i,t}$ is a dummy variable equal to one if fund i is in the top quintile of CCR6 model net alpha over the twenty-four months ending in month t. Each of these variables is trimmed at the 1% and 99% levels before any z-scoring or dummy variable conversions. $Controls_{i,t}$ is a vector of information about the fund as of the end of month t that includes the natural log of assets, natural log of age, turnover ratio, and expense ratio. FE represents both benchmark and year-month fixed effects.

We show results from this model in Table 8. In columns (1) and (2), we find, consistent with our portfolio results, that both bond- and firm-level active share, if considered separately, have a positive relation with future performance. A one standard deviation increase in bond-level active share predicts an increase in annualized alpha of 0.12% (t-stat = 2.23), while a one standard deviation increase in firm-level active share predicts an increase of 0.18% (*t*-stat = 3.55). If, however, both measures are considered simultaneously, as in column (3), firm-level active share subsumes the impact of bond-level active share. The impact of a one standard deviation increase in firm-level active share remains about the same, 0.19% (*t*-stat = 3.75), but the impact of a one standard deviation increase in bond-level active share falls to near zero, −0.02% (*t*-stat = −0.38). Thus, as initially suggested by our portfolio results, we conclude that firm-level active share is a stronger predictor of fund performance than bond-level active share.[40]

Amihud and Goyenko (2013) propose an alternative measure of activeness—the R-squared value from regressing a fund's past returns on a factor model. They find that a low R-squared is predictive of outperformance for both active equity and active bond funds. But, as shown in column (4), when considered against firm-level active share (*t*-stat = 3.30), the impact of R-squared is not statistically significant at conventional levels (*t*-stat = −1.48). Furthermore, R-squared has a significantly smaller economic impact, with a one standard decrease in R-squared increasing alpha by about half the amount of a one standard deviation increase in firm-level active share. Therefore, firm-level active share appears to be the stronger predictor of future performance among active bond funds.[41]

We test the interaction between activeness and performance in the final two columns. In column (5), we add the dummy variable related to strong past performance to the model alongside firm-level active share. Consistent with our portfolio results, being in the top 20% of past performance predicts that a fund's subsequent annualized alpha will be 0.57% greater (*t*-stat =

[40] We obtain highly similar results if, instead of using benchmark fixed effects, we use fund fixed effects, which indicates that the relation between firm-level active share and future performance holds within both the cross-section of active bond funds and the time-series of individual active bond funds.

[41] Considered separate from firm-level active share in untabulated analysis, a one standard deviation decrease in R-squared predicts annualized alpha will increase by 0.12% (*t*-stat = −1.91). Accordingly, we do not contend that R-squared is without predictive power, but rather that R-squared is (i) a weaker predictor than firm-level active share and (ii) a predictor whose power is significantly subsumed by firm-level active share.

4.66). We interact that dummy variable with firm-level active share in Column (6) and, again consistent with our portfolio results, find that the relation between active share and future performance is stronger among funds with strong past performance. Among funds not in the top 20% of past performance, a one standard deviation increase in firm-level active share predicts annualized alpha will be 0.11% greater (*t*-stat = 2.21); however, among funds in the top 20% of past performance, the predicted performance increase is 0.28%, which is a difference of 0.17% (*t*-stat = 2.25). There is, consequently, strong evidence that, relative to passive bond funds, investors can benefit substantially from investing in active bond funds with high firm-level active share and strong past performance.

5.6.3. The impact of active share on active bond fund downside risk

Among active equity funds, prior research shows evidence of skilled downside risk management (e.g., Bodnaruk, Chokaev, and Simonov, 2019, and Polkovnichenko, Wei, and Zhao, 2019). Here, we consider whether such downside risk management skill is present among active bond funds. If such skill is present, it suggests another benefit to investing in active bond funds instead of passive bond funds. To measure downside risk, we use maximum drawdown (MDD), a common industry measure which captures fund losses from peak to trough. MDD was shown in Riley and Yan (2022) to be associated with fund manager skill and to be salient to fund investors.

Our general model of a fund's maximum drawdown is:

$$MDD_{i,t+1} = \beta_1 \text{ x } Active_{i,t} + \gamma \text{ x } Controls_{i,t} + FE + \varepsilon_{i,t+1} \tag{10}$$

where $MDD_{i,t+1}$ is the annualized maximum drawdown of fund *i* in calendar year-quarter *t* + 1. $Active_{i,t}$ is the most recently available measure of active share for fund *i* as of the end of calendar year-quarter *t*. We consider both bond- and firm-level active share, and we z-score those values to ease interpretation. Both maximum drawdown and the active share measures before z-scoring are trimmed at the 1% and 99% levels. $Controls_{i,t}$ is a vector of information about fund i as of the end of calendar year-quarter t. It includes the natural log of assets, natural log of age, turnover ratio, and expense ratio. FE represents both benchmark and calendar year-quarter fixed effects.

We show results from this model in Table 9. Column (1) considers bond-level active share in isolation and finds that a one standard deviation increase in bond-level active share decreases (i.e., improves) maximum drawdown by 0.22% (t-stat = −2.35). Switching to firm-level active share, as in column (2), does not produce an equivalent result: a one standard deviation increase in firm-level active share improves maximum drawdown by only a statistically insignificant 0.12% (t-stat = −1.17). These results suggest that, in contrast with our results with respect to alpha, bond-level, not firm-level, active share is associated with better downside risk management. That suggestion is confirmed in column (3), which considers both types of active share simultaneously. In that test, the impact of bond-level active share is nearly identical to before, while firm-level active share has economically and statistically zero impact. Thus, the managers of highly active bond funds do appear to have downside risk management skill that benefits investors. If, however, investors are seeking to capture both benefits associated with active bond funds with high active share—increased alpha and improved downside risk management—they must consider activeness at both the bond and firm levels.

We conclude our analysis of downside risk in Columns (4) and (6), which detail when the benefits of the above-documented downside risk management are largest. In those columns, we repeat the test considering bond-level active share in isolation within three different subsamples: periods with low, medium, and high maximum drawdowns. We define those periods by sorting into terciles the average maximum drawdown across all active bond funds within each calendar year-quarter. Investors, we expect, are most focused on drawdowns during periods when drawdowns tend to be large, and our results indicate that those are the periods when the downside risk management skill of highly active bond funds has the most impact. During low and medium periods, a one standard deviation increase in bond-level active share improves maximum drawdown by 0.08% and 0.16%, respectively, both of which are statistically insignificant (*t*-stats = −1.30 and −1.47). Conversely, during high periods, a one standard deviation increase in bond-level active share improves maximum drawdown by 0.44% (*t*-stat = −2.24). Accordingly, when managing downside risk is most important, the skill of high active share bond funds in that regard has its largest positive impact.

5.6.4. The impact of active share on active bond fund fragility

Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017) demonstrate strategic complementarities among fund investors. The genesis of those complementarities is that investors redeem at a fund's net asset value (NAV) on the day of the redemption request; however, the trades that mutual funds make in response to redemption requests often occur on later days. This timing mismatch creates a first-mover advantage, as the non-redeeming fund investors bear the costs of the redemption-driven trades. The end effect is significant "run risk," since "investors might have a stronger incentive to redeem their shares just because they expect other investors will do so, and so large redemptions become a self-fulfilling phenomenon (Goldstein, Jiang, and Ng, 2017, pg. 597)." This financial fragility is magnified when funds hold illiquid assets, which is the case for bond funds.

Strategic complementarities can be identified empirically by studying the relation between fund flows and performance. In canonical work, Sirri and Tufano (1998) show that active equity funds tend to have a convex flow-performance relation in which the benefits of outperformance exceed the costs of underperformance. But, when fragility is high, there should be an increased response of outflows to poor performance, because investors will attempt to be the first movers. The consequence of that behavior is discernible among active bond funds through a linear or concave flow-performance relation.

Here, we examine how the shape of the flow-performance relation for active bond funds is impacted by active share. Our prior performance results provide a potential channel through which the shape of the flow-performance could be impacted by activeness. Investors should be more sensitive to outperformance from more actively managed funds—moving their flow-performance relations towards convexity—because the outperformance of those funds is, as shown earlier, more likely to persist. Our general model of the flow-performance relation for active bond funds is:

$$\begin{aligned} Flow_{i,t+1} = {} & \beta_1 \text{ x } Low_{i,t} + \beta_2 \text{ x } Mid_{i,t} + \beta_3 \text{ x } High_{i,t} + \beta_4 \text{ x } Active\ Dum_{i,t} \\ & + \beta_5 \text{ x } Low_{i,t} \text{ x } Active\ Dum_{i,t} + \beta_6 \text{ x } Mid_{i,t} \text{ x } Active\ Dum_{i,t} \\ & + \beta_7 \text{ x } High_{i,t} \text{ x } Active\ Dum_{i,t} + \gamma \text{ x } Controls_{i,t} + FE + \varepsilon_{i,t+1} \end{aligned} \tag{11}$$

where $Flow_{i,t+1}$ is the net flow for fund i in month *t*. $Low_{i,t}$, $Mid_{i,t}$, and $High_{i,t}$ are piecewise measures of performance designed to help capture the shape of the flow-performance relation. They are formed following Sirri and Tufano (1998) and calculated over the twenty-four months ending in month *t* using both CCR6 model net alpha and the simple difference between net fund return and benchmark return.[42] $Active\ Dum_{i,t}$ is a variable equal to one if fund *i*'s most recently available measure of active share as of the end of month *t* is within the top quintile. We consider both bond- and firm-level active shares. To determine the impact of activeness on the flow-performance relation, we interact $Active\ Dum_{i,t}$ with our piecewise performance variables. Each of these variables is trimmed at the 1% and 99% levels before any piecewise or dummy

[42] The recent literature suggests that investors use relatively simple measures of performance to evaluate mutual funds (e.g., Berk and van Binsbergen, 2016; Barber, Huang, and Odean, 2016; and Ben-David, Li, Rossi, and Song, 2022).

variable conversions. $Controls_{i,t}$ is a vector of information about fund i as of the end of month t. It includes the natural log of assets, natural log of age, turnover ratio, and expense ratio. FE represents benchmark and year-month fixed effects.

We show results from this model in Table 10. First, using the CCR6 model to measure performance and not accounting for activeness, we find, in column (1), a linear flow-performance relation for active bond funds. Statistically, there is no difference between the response of flows to performance in low range and the response of flows to performance in the high range (p-value = 0.165). If, as in column (2) though, we interact our performance variables with a dummy variable for high bond-level active share, we find (i) a linear relation for active bond funds that do not have high active share and (ii) a convex relation for active bond funds that do have high active share. The response of flows to performance in the low and high performance ranges is statistically the same for the non-high active share funds (p-value = 0.582), but statistically different for high active share funds (p-value = 0.035). The difference is driven by investors being significantly more responsive to outperformance from high active share funds, rather than them being less responsive to those funds' underperformance.

That result suggests some rationality on the part of investors, as our prior results show that outperformance is more persistent for high active share funds; then again, our prior results also indicate that investors should be responding more to firm-level active share and less to bond-level active share. As shown in column (3), however, regardless of firm-level active share, we find a linear relation between flows and performance. If we repeat these tests using simple benchmark-adjusted returns instead of CCR6 model alphas, we reach the same conclusions with respect to the impact of active share on flow-performance convexity.

Consequently, while these results are not indicative of perfect rationality on the part of fund investors, they are indicative of the most actively managed active bond funds having less fragility. In their study of actively managed corporate bond funds, Goldstein, Jiang, and Ng (2017) suggest fragility, across a large number of performance measures, through their finding that the flow-performance relation is "either concave or linear, but never convex (pg. 601)." We show here, though, that such fragility is mitigated among active bond funds with high active share because investor behavior generates for them a convex flow-performance relation.

6. Conclusion

Crane and Crotty (2018) compare passive and active equity funds and conclude that "no risk-averse investor should choose a random active fund over a random index fund (pg. 33)." Investors have embraced that conclusion and others like it. From 2011 through 2021, actively managed mutual funds had a combined net outflow of $1.96 trillion. That trend, however, is not universal. In particular, actively managed bond mutual funds over the same time period had a combined net inflow $920 billion.[43] Seeing that difference, we ask: why have actively managed bond funds remained popular? Our answer is simple—active bond funds tend to add value—but that response masks significant complexity.

We first consider how well active and passive bond funds perform relative to each other. Contrary to typical expectations about passive and active funds, we find no evidence that the average active bond fund underperforms a set of equivalent passive funds. An equal-weight portfolio of active bond funds even shows some evidence of outperforming its equivalent passive fund set.

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[43] See Table 43 in the *2023 Investment Company Fact Book* (https://www.icifactbook.org/) published by the Investment Company Institute (ICI).

Our subsequent analysis of passive bond funds reveals, however, that calling them passive could be a misnomer. Relative to passive equity funds, passive bond funds trade intensely and are very different from their benchmarks. We attribute those characteristics to the unique challenges of tracking bond benchmarks, which contain a fast changing set of thousands of, often highly illiquid, bonds. As indicated by their net flows, the managers of passive bond funds do not attempt full benchmark replication because they must balance replicating their benchmark with maintaining liquidity and controlling costs. Accordingly, we show that the liquidity of a given bond is a key determinant of how much of that bond a passive funds holds relative to how much the fund's benchmark holds.

Turning to active bond funds, we find that those that are most active tend to substantially outperform, particularly if they have strong past performance. The most active bond funds also tend to have improved maximum drawdowns. The impact on alpha is attributable to their firm-level selection skill, whereas the impact on drawdowns is attributable to their bond-level selection skill. Moreover, the most active bond funds tend to exhibit less financial fragility. The flow-performance relation is convex for those funds, while being linear for other active bond funds. Thus, along multiple dimensions, there are strong, rational reasons for investors to consider active bond funds.

Returning to our original question, the answer is clear. The bond market and bond benchmarks are substantially different from the equity market and equity benchmarks. As a result, there is greater opportunity for active bond funds compared to active equity funds. That greater opportunity allows active bond funds to add significant value. That significant value explains why active bond funds have remained popular.

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Appendix: Benchmark Holdings Availability

Benchmark	Holdings	% of Fund Observations
Bloomberg US Agg Bond	Yes	43.9%
Bloomberg US Govt/Credit 1-3 Yr	Yes	7.3%
ICE BofA US HY Constnd	No	4.4%
Bloomberg US Corporate High Yield	Yes	4.0%
Bloomberg US Govt/Credit Interm	Yes	3.9%
ICE BofA US High Yield	No	3.3%
Bloomberg US Credit	Yes	2.9%
ICE BofA 1-3Y US Corp&Govt	No	2.4%
Bloomberg US Govt/Credit	Yes	2.1%
Bloomberg US Corp Bond	Yes	1.5%
Bloomberg US Govt/Credit 1-5 Yr	Yes	1.5%
ICE BofA 1-5Y US Corp&Govt	No	1.0%
Bloomberg Short-term Gov/Corp	No	0.9%
Bloomberg US Agg Interm	No	0.9%
ICE BofA BB-B US HY Constnd	No	0.8%
ICE BofA US Cash Pay HY	No	0.8%
Bloomberg US Aggregate 1-3 Yr	No	0.7%
Bloomberg US Govt/Credit Long	Yes	0.7%
Bloomberg Credit 1-5 Yr	Yes	0.7%
ICE BofA BB-B US CP HY Constnd	No	0.6%
Bloomberg Credit 1-3 Yr	Yes	0.5%
Bloomberg US Interm Credit	Yes	0.5%
Bloomberg US Long Corporate	Yes	0.5%
ICE BofA 1-3Y BB US Cash Pay HY	No	0.5%
Bloomberg US Agg Float Adj	Yes	0.4%
Markit iBoxx Liquid High Yield	No	0.4%
ICE BofA 1-3Y US Corp	No	0.4%
Bloomberg USD Corp Bd 1-5 Yr	Yes	0.4%
ICE BofA US Cash Pay HY Constnd	No	0.4%
Bloomberg US Govt/Credit A+Interm	No	0.4%
ICE BofA US Corporate	No	0.4%
Bloomberg US Long Credit	Yes	0.3%
Bloomberg US Corp 1-3 Yr	Yes	0.3%
Bloomberg US Credit A+ Long	No	0.3%
Bloomberg US Credit 5-10 Yr	No	0.2%
Bloomberg USFRN 5- Yr	Yes	0.2%
Morningstar LSTA US LL	No	0.2%
ICE BofA BB-B US CP NDistre HY	No	0.2%

Benchmark	Holdings	% of Fund Observations
ICE BofA 1-10 AAA-A US Corp&Gvt	No	0.2%
ICE BofA 5-10Y US Corp	No	0.2%
RAFI Bonds US High Yield 1-10	No	0.2%
Bloomberg US Gov/Credit 1-7 ExBaa	No	0.2%
Morningstar US 1-3Y Gov&Corp	No	0.2%
Bloomberg US L Govt/Credit Fl Adj	Yes	0.2%
Bloomberg US Corp IG	No	0.2%
ICE BofA BB US HY Constnd	No	0.2%
Bloomberg US 5-10 GovCredit FlAdj	Yes	0.2%
FTSE US HY Cash Pay Custom	No	0.2%
Bloomberg VLI High Yield	Yes	0.2%
ICE BofA 1-5Y US Corp	No	0.2%
Bloomberg US Credit Baa	No	0.2%
ICE BofA 1-3Y A-BBB US Corp	No	0.2%
Bloomberg US 1-5Y GovCredit FlAdj	Yes	0.2%
Markit iBoxx Liquid IG	No	0.2%
ICE BofA 1-5Y BB-B Cash Pay HY	No	0.2%
BBgBarc US Corporate IG	No	0.2%
Bloomberg Interm Corp	Yes	0.2%
Bloomberg US Universal 10+ Years	No	0.2%
Bloomberg US Credit Corp 5-10 Yr	Yes	0.2%
ICE BofA 10+Y US Corp	No	0.2%
Bloomberg US Corporate 10+ Yr	Yes	0.2%
Other	No	5.0%

Figure 1: Bond- versus firm-level portfolios
This figure shows the portfolio of a hypothetical bond fund at the bond and firm levels.

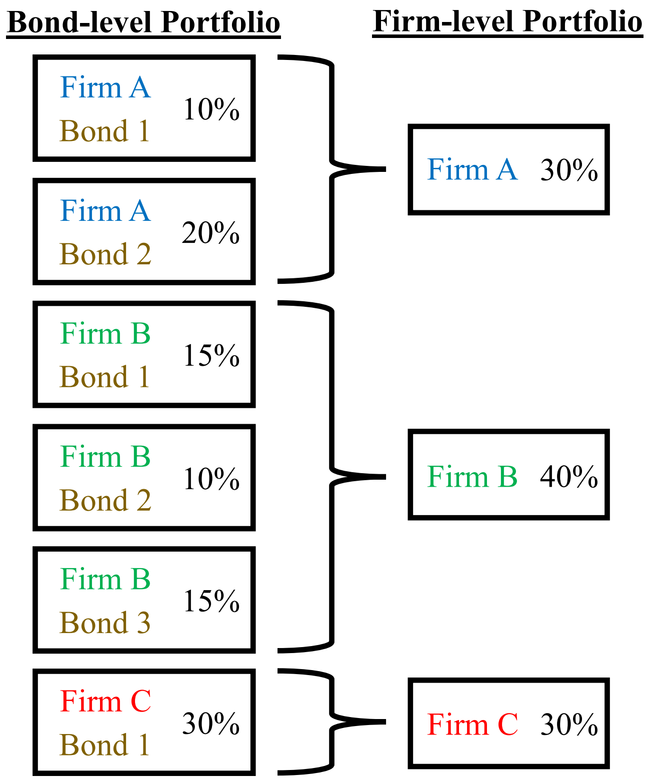


Figure 2: Growth of passive management among bond and equity mutual funds
This figure shows the percentage of mutual fund assets in our sample that are passively managed at the end of each year from 2011 through 2021. We report the percentage separately for bond and equity funds.

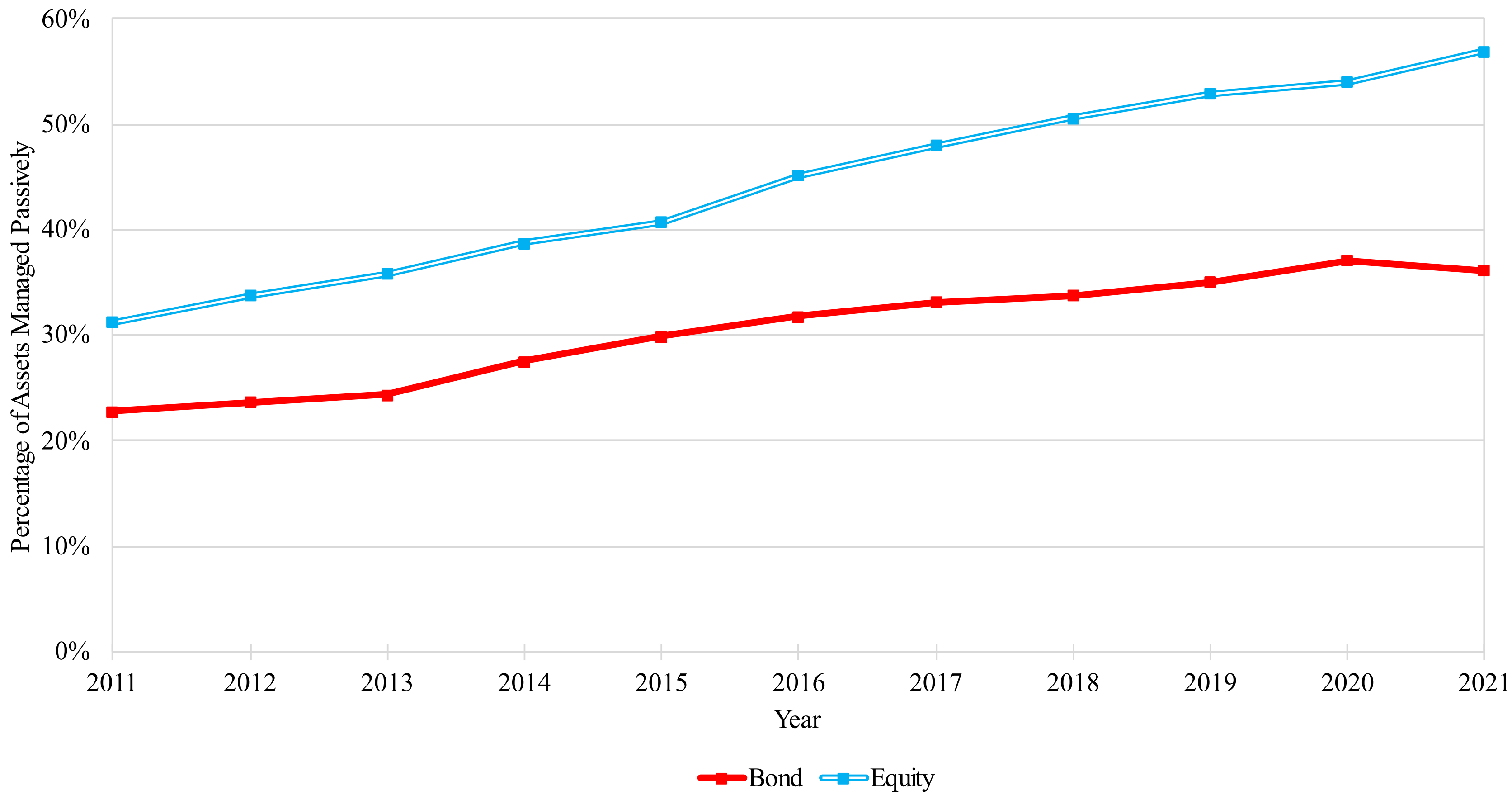


Figure 3: Importance of ETFs among passive bond funds
This figure shows the percentage of passive bond funds and the percentage of passive fund assets in our sample that are linked to ETFs—either a pure ETF or a fund with an ETF share class—at the end of each year from 2011 through 2021.

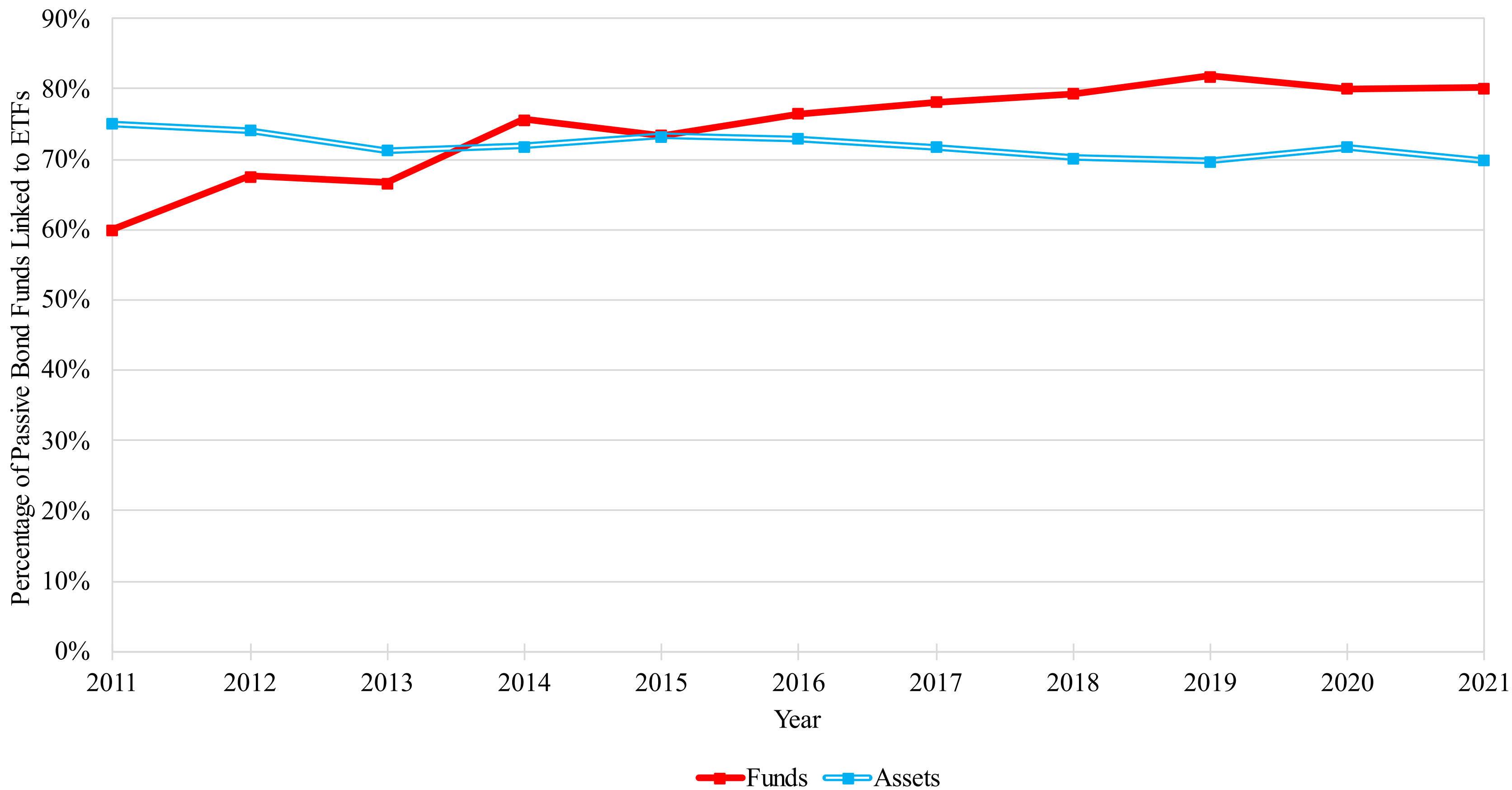


Figure 4: Histogram of active bond fund alphas
This figure shows the distributions of active bond fund alphas calculated using the CCR3 and CCR6 models. The alphas for each fund are measured using all fund returns available from 2011 through 2021.

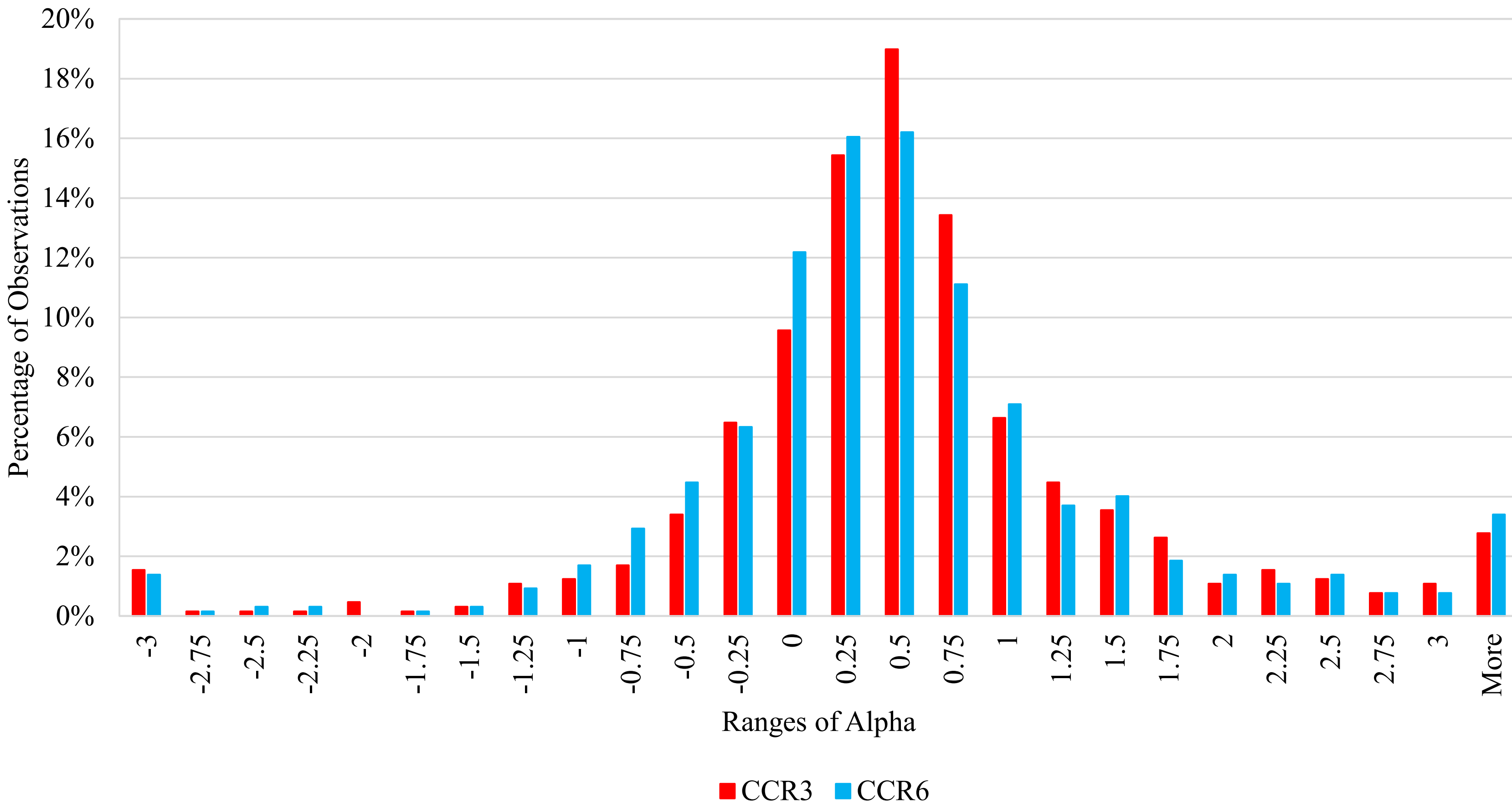


Figure 5: Cumulative abnormal returns of active bond funds

This figure shows the cumulative abnormal returns on an equal-weight portfolio of active bond funds from January 2011 through December 2021. The abnormal returns are calculated using both the CCR3 and CCR6 models.

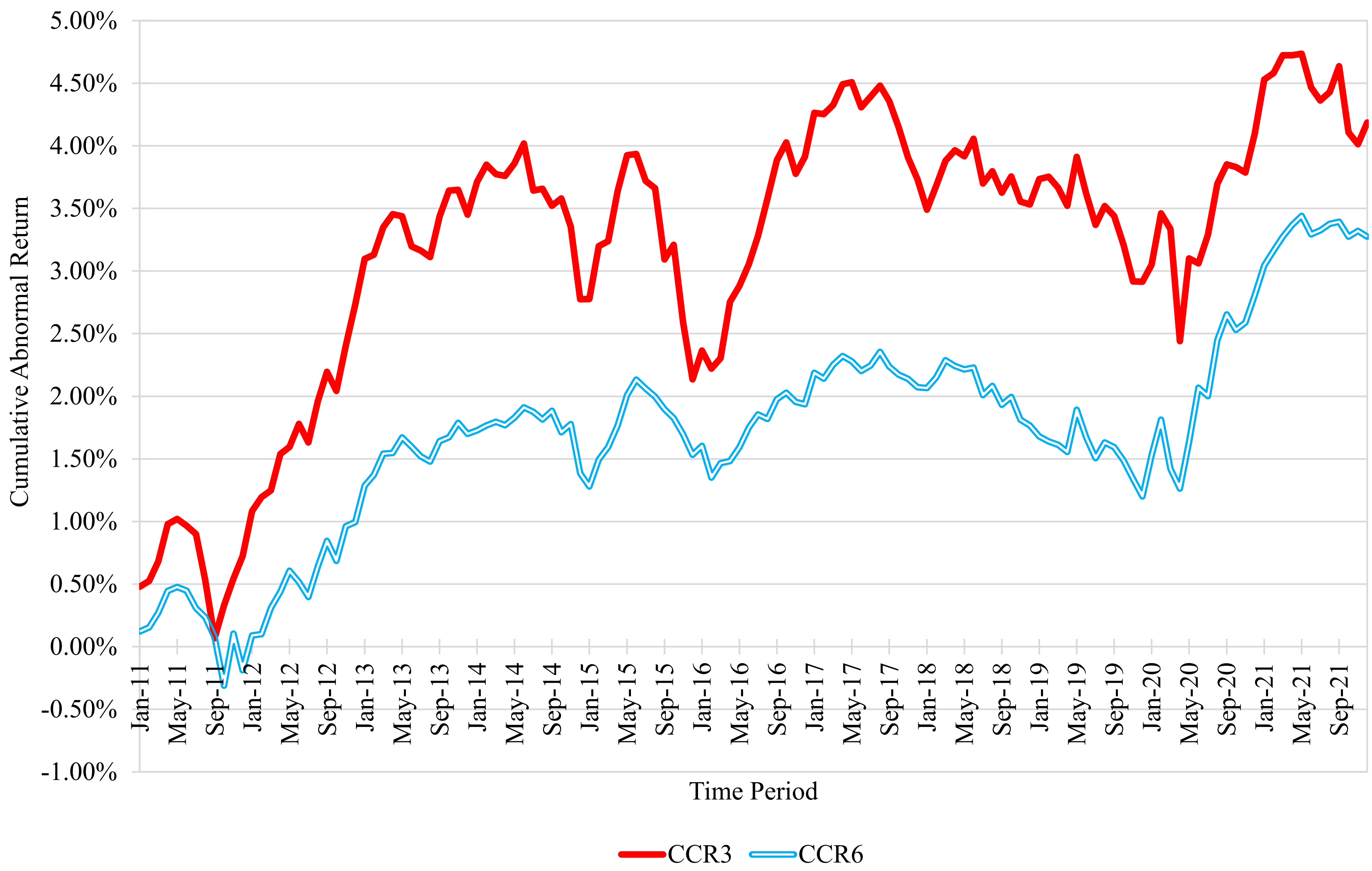


Figure 6: Visualizing the bond-level active share of a passive bond fund

This figure illustrates the bond-level active share of the Vanguard Total Bond Market Fund relative to its benchmark, the 'Bloomberg US Aggregate Float Adjusted,' during the final quarter of our sample (fourth quarter of 2021). Passive indicates the portion of the fund portfolio matching the benchmark, Out-of-Benchmark indicates the portion in the fund but not in the benchmark, Underweight indicates the portion in both but with less weight in the fund, Overweight indicates the portion in both but with more weight in the fund, and Out-of-Fund indicates the portion in the benchmark but not in the fund.

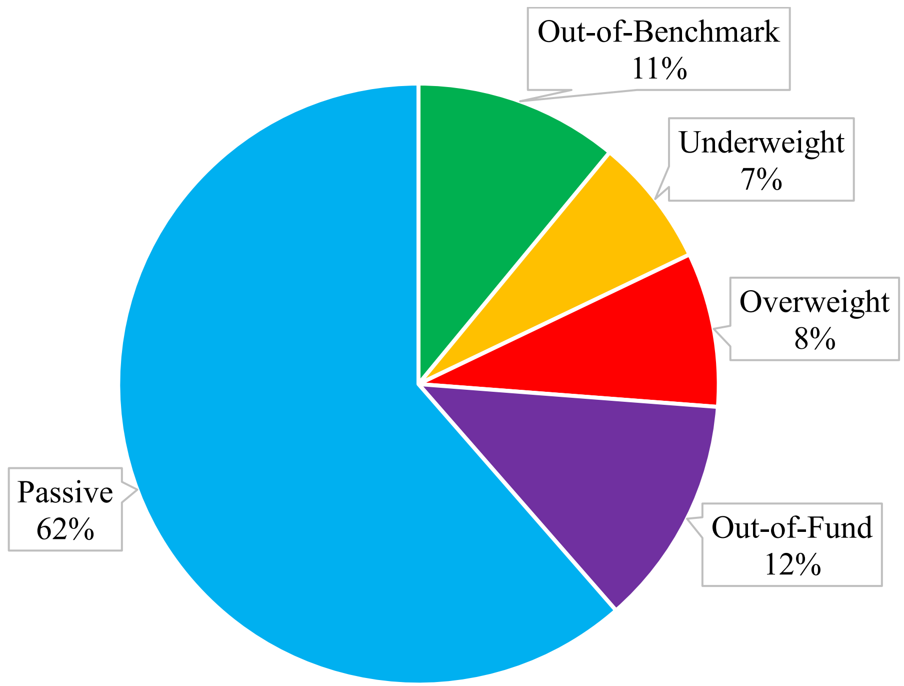


Figure 7: Trend of passive fund and benchmark rebalancing transaction costs

This figure shows annualized estimates of the transaction costs associated with quarterly rebalancing of corporate bond benchmarks and passive funds tracking those benchmarks. Estimates are reported for each quarter from the fourth quarter of 2018 through third quarter of 2021. The reported values for each quarter are across benchmark averages and are calculated using the actual quarterly net flows of the passive funds.

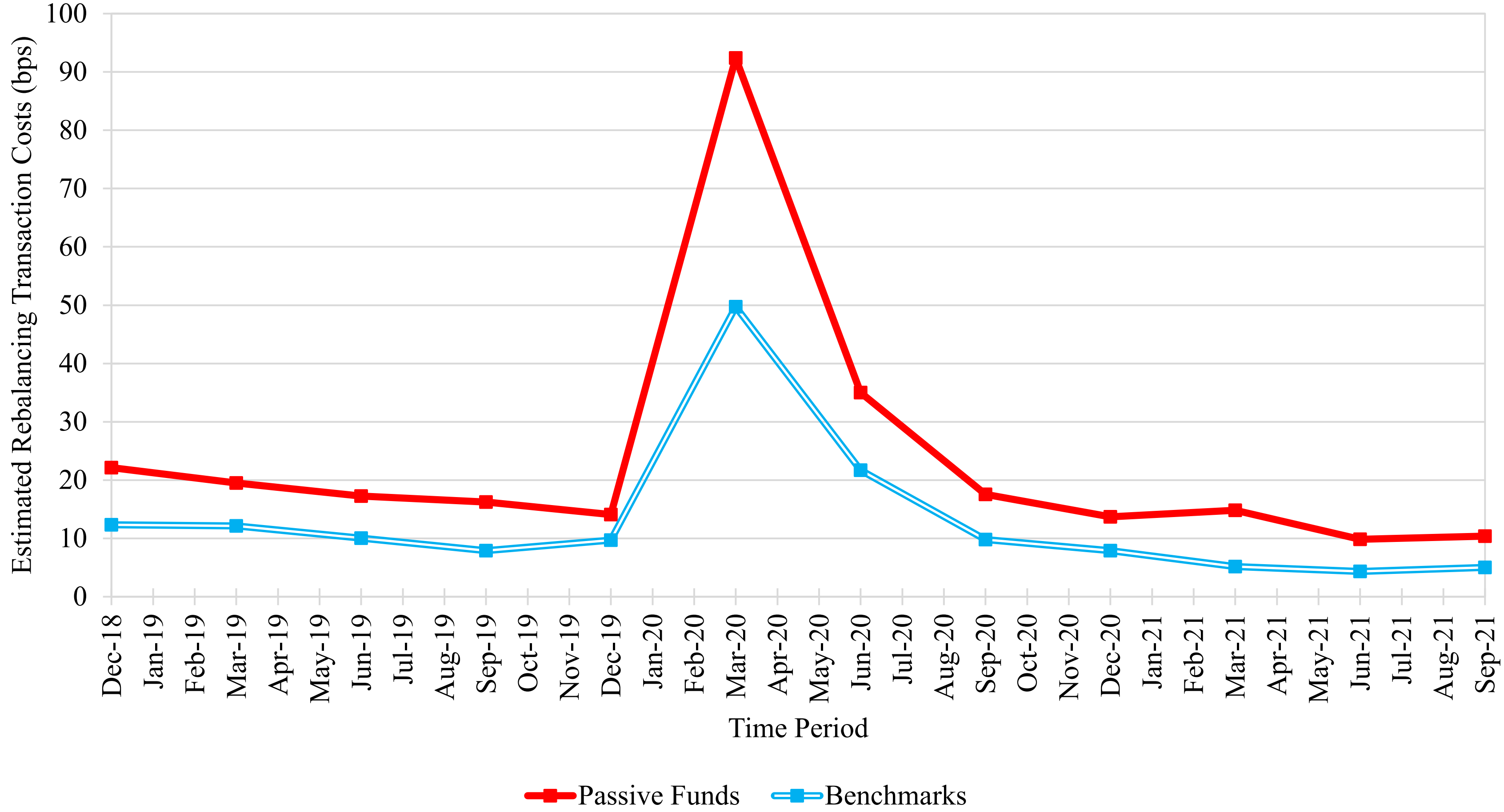
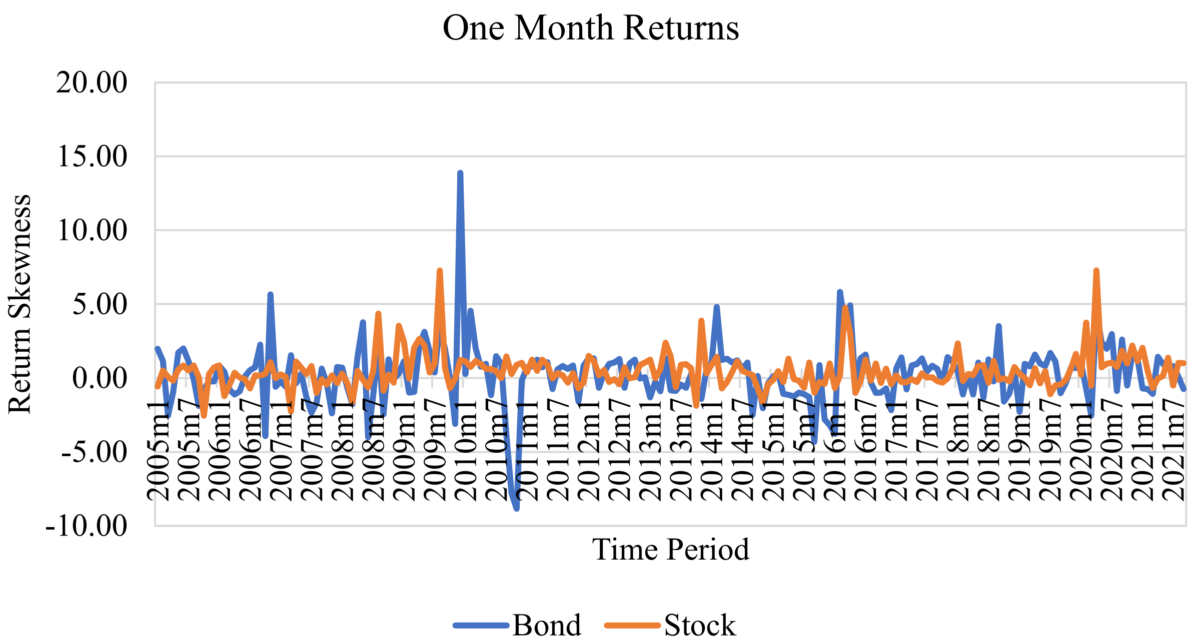


Figure 8: Cross-sectional return skewness: bonds vs. equities
The top (bottom) figure plots times series of the cross-sectional skewness of one-month (12-months) bond and equity returns, using bonds and stocks included in the Bloomberg Agg and Russell 1000 indexes.



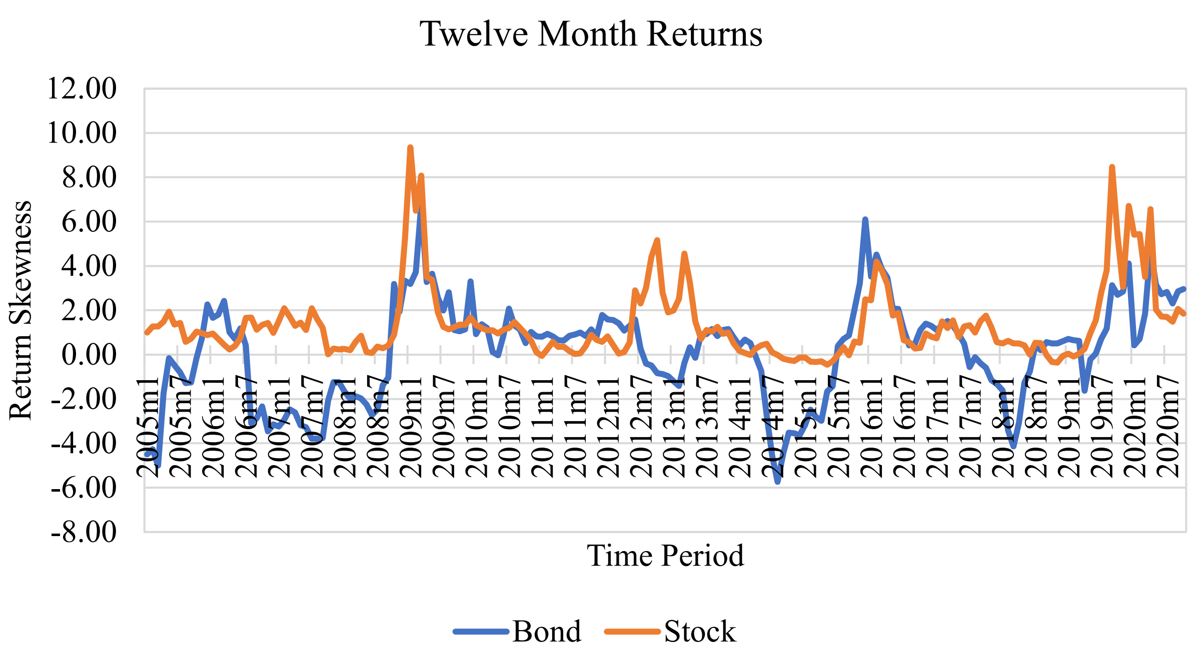
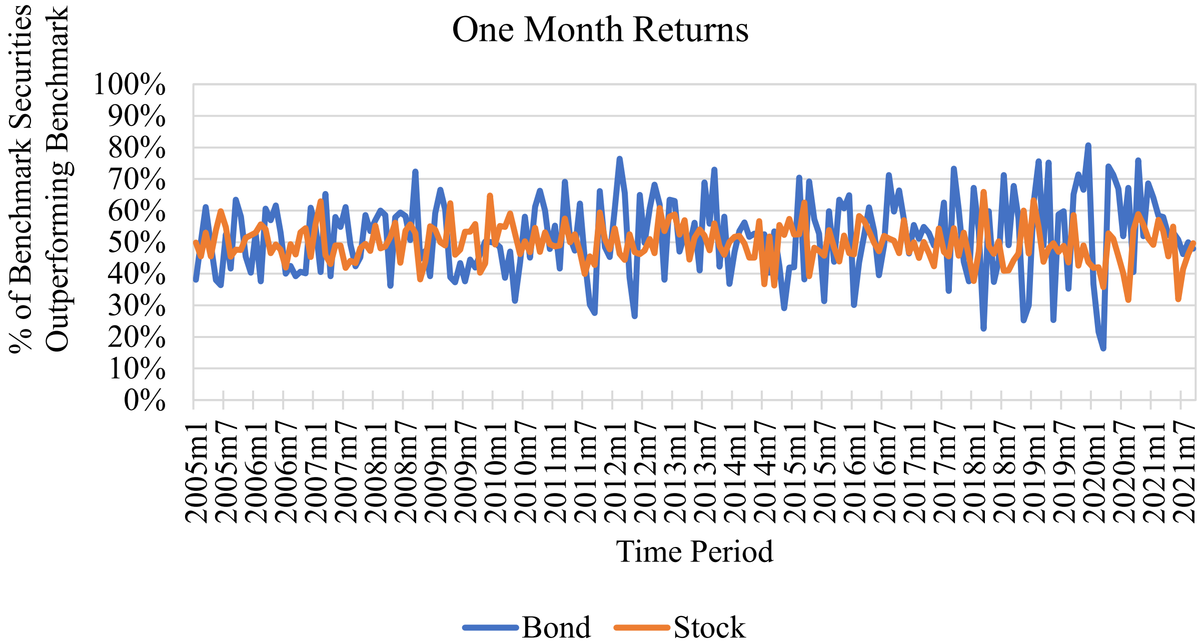


Figure 9: Percentage of securities that beat the benchmark: bonds vs. equities
The top (bottom) figure plots times series of the percentage of bonds and stocks whose one-month (12-months) returns outperform their benchmarks, using bonds and stocks included in the Bloomberg Agg and Russell 1000 indexes.



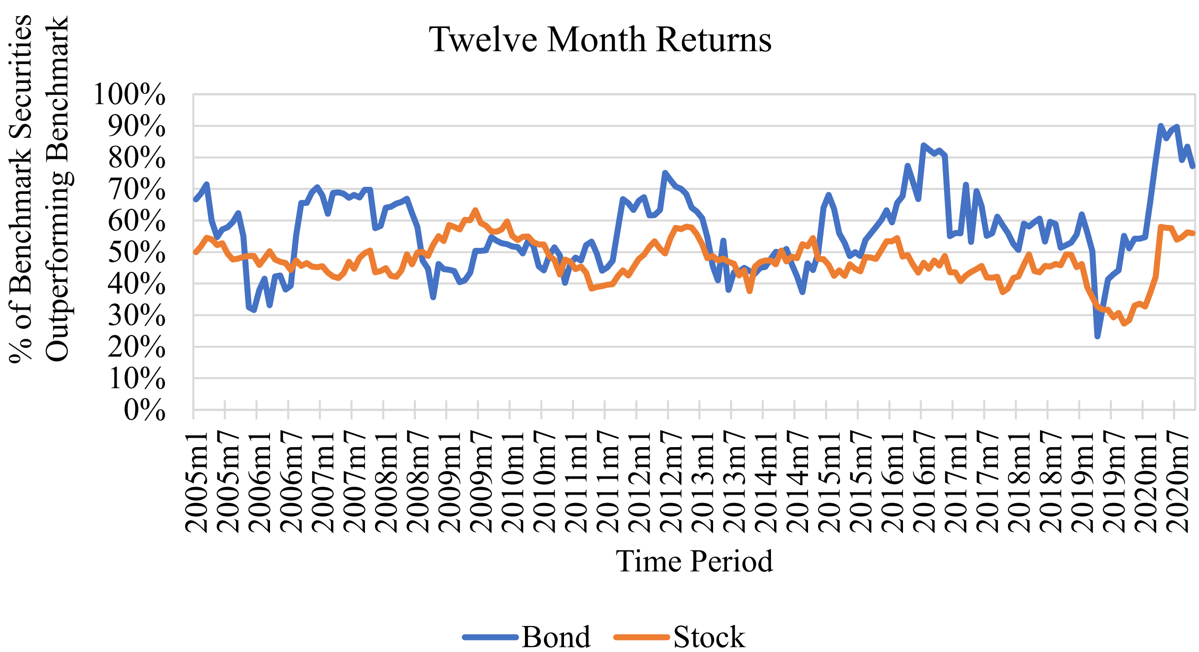


Table 1: The performance of passive and active bond mutual funds

This table shows the performance of our samples of passive and active bond funds using multiple approaches. In Panel A1, we report the distribution of passive bond fund alphas, betas, and R-squared values resulting from regressing each fund's excess returns on their benchmark's excess returns. In addition to the mean value, the standard deviation of the values (SD) and various percentiles in the distribution (e.g., P10 to the 10th percentile) are presented. Separate distributions are reported for the full sample of passive bond funds, investment grade passive bond funds, high yield passive bond funds, passive bond funds not linked to ETFs (i.e., not a pure ETF and without an ETF share class), and passive bond funds that are pure ETFs. In Panel A2, we report passive bond fund alphas, betas, and R-squared values resulting from equal-weight portfolios of the same groups. For the portfolios, *t*-statistics robust to heterogeneity are reported in brackets below their respective coefficients. If Panels B1 and B2, we report similar analyses for active bond funds, regressing their excess returns on those of matched passive bond funds. In Panels C1 and C2, we report similar distributional analyses for active and passive bond funds using the CCR3 and CCR6 models to evaluate performance. In Panels D1 and D2, we report similar portfolio analyses for active bond funds, again using the CCR3 and CCR6 models to evaluate performance. The time period of analysis in all cases is January 2011 through December 2021.

Panel A1: Performance of Individual Passive Bond Funds Relative to Prospectus Benchmarks

		Number	Mean	SD	P10	P25	P50	P75	P90
Full Sample	Beta	78	0.99	0.05	0.95	0.98	1.00	1.01	1.02
	Alpha	78	-0.21	0.25	-0.46	-0.32	-0.18	-0.09	0.01
	R^2	78	99.0%	1.7%	98.1%	98.9%	99.5%	99.9%	100.0%
Investment Grade	Beta	63	0.99	0.05	0.95	0.99	1.00	1.01	1.02
	Alpha	63	-0.22	0.16	-0.40	-0.31	-0.19	-0.11	-0.07
	R^2	63	98.8%	1.9%	97.9%	98.8%	99.4%	99.9%	99.9%
High Yield	Beta	15	0.97	0.03	0.94	0.96	0.98	0.99	1.00
	Alpha	15	-0.15	0.47	-0.90	-0.53	-0.08	0.13	0.29
	R^2	15	99.6%	0.5%	98.7%	99.6%	99.8%	99.9%	100.0%
No ETFs	Beta	22	1.00	0.02	0.98	0.99	1.00	1.01	1.02
	Alpha	22	-0.27	0.20	-0.40	-0.34	-0.23	-0.15	-0.07
	R^2	22	98.8%	1.2%	98.2%	98.5%	99.2%	99.7%	99.7%
Pure ETFs	Beta	49	0.98	0.05	0.88	0.97	0.99	1.00	1.01
	Alpha	49	-0.19	0.28	-0.50	-0.32	-0.16	-0.09	0.13
	R^2	49	99.0%	2.0%	97.9%	99.1%	99.8%	99.9%	100.0%

Panel A2: Performance of Passive Bond Fund Portfolios Relative to Prospectus Benchmarks

	Full Sample	Investment Grade	High Yield	No ETFs	Pure ETFs
Beta	0.99	0.99	0.98	1.01	0.97
	[208.07]	[228.07]	[150.58]	[213.97]	[247.84]
Alpha	-0.26	-0.25	-0.49	-0.28	-0.29
	[-6.39]	[-6.21]	[-5.95]	[-6.87]	[-7.10]
R^2	99.9%	99.8%	99.9%	99.8%	99.9%

Panel B1: Performance of Individual Active Bond Funds Relative to Matched Passive Funds

		Number	Mean	SD	P10	P25	P50	P75	P90
Full Sample	Beta	466	0.88	0.38	0.53	0.81	0.94	1.01	1.11
	Alpha	466	0.77	2.55	-0.32	0.16	0.60	1.21	2.40
	R^2	466	61.6%	32.4%	7.1%	35.5%	71.8%	89.0%	95.8%
Investment Grade	Beta	361	0.91	0.39	0.69	0.87	0.96	1.02	1.11
	Alpha	361	0.51	2.63	-0.26	0.13	0.50	0.91	1.58
	R^2	361	65.5%	28.8%	15.7%	49.5%	73.7%	88.3%	95.4%
High Yield	Beta	105	0.75	0.31	0.28	0.54	0.82	0.99	1.12
	Alpha	105	1.65	2.04	-0.44	0.39	1.37	2.46	3.77
	R^2	105	48.2%	39.8%	1.4%	8.5%	41.6%	90.2%	98.7%

Panel B2: Performance of Active Bond Fund Portfolios Relative to Matched Passive Funds

	Full Sample	Investment Grade	High Yield
Beta	0.97	0.94	1.10
	[9.79]	[18.62]	[5.86]
Alpha	0.57	0.53	0.62
	[0.87]	[1.14]	[0.49]
R^2	73.3%	78.6%	57.7%

Panel C1: Individual Active and Passive Bond Fund Performance - CCR3 Model

			Number	Mean	SD	P10	P25	P50	P75	P90
Full Sample	Active	Alpha	648	0.36	2.15	-0.54	-0.04	0.35	0.76	1.57
		R^2	648	0.81	0.18	0.64	0.77	0.86	0.93	0.96
	Passive	Alpha	78	0.21	0.63	-0.52	-0.23	0.13	0.42	1.06
		R^2	78	0.90	0.11	0.77	0.84	0.94	0.98	0.99
Investment Grade	Active	Alpha	465	0.24	2.12	-0.44	0.00	0.31	0.63	1.09
		R^2	465	0.83	0.18	0.66	0.78	0.89	0.95	0.96
	Passive	Alpha	63	0.13	0.46	-0.43	-0.15	0.12	0.34	0.74
		R^2	63	0.91	0.12	0.77	0.87	0.97	0.99	0.99
High Yield	Active	Alpha	183	0.68	2.20	-1.15	-0.13	0.61	1.56	2.67
		R^2	183	0.76	0.17	0.55	0.74	0.80	0.86	0.90
	Passive	Alpha	15	0.53	1.03	-0.58	-0.52	0.23	1.27	2.02
		R^2	15	0.83	0.07	0.77	0.80	0.84	0.89	0.91

Panel C2: Individual Active and Passive Bond Fund Performance - CCR6 Model

			Number	Mean	SD	P10	P25	P50	P75	P90
Full Sample	Active	Alpha	648	0.35	2.04	-0.69	-0.11	0.28	0.77	1.56
		R^2	648	0.86	0.15	0.70	0.82	0.92	0.96	0.98
	Passive	Alpha	78	0.09	0.55	-0.60	-0.19	0.00	0.46	0.87
		R^2	78	0.95	0.08	0.79	0.93	0.98	1.00	1.00
Investment Grade	Active	Alpha	465	0.19	1.96	-0.57	-0.11	0.23	0.56	1.06
		R^2	465	0.86	0.15	0.70	0.81	0.91	0.96	0.98
	Passive	Alpha	63	0.04	0.46	-0.52	-0.19	-0.02	0.30	0.68
		R^2	63	0.94	0.09	0.79	0.91	0.98	1.00	1.00
High Yield	Active	Alpha	183	0.76	2.18	-0.88	-0.17	0.58	1.54	2.81
		R^2	183	0.87	0.15	0.69	0.85	0.93	0.96	0.97
	Passive	Alpha	15	0.30	0.82	-0.73	-0.43	0.30	0.67	1.57
		R^2	15	0.98	0.02	0.95	0.97	0.98	0.99	1.00

Panel D1: Active Bond Fund Portfolio Performance - CCR3 Model

	Full Sample	Investment Grade	High Yield
Stock	0.04	0.01	0.13
	[5.10]	[1.98]	[6.18]
Treasury	-0.13	0.08	-0.71
	[-5.14]	[4.57]	[-11.27]
Corporate	0.63	0.53	0.89
	[26.27]	[34.79]	[15.01]
Alpha	0.38	0.29	0.57
	[1.38]	[1.76]	[0.84]
R^2	93.3%	96.8%	84.6%

Panel D2: Active Bond Fund Portfolio Performance - CCR6 Model

	Full Sample	Investment Grade	High Yield
Bond	0.50	0.75	0.96
	[1.23]	[2.45]	[1.27]
Stock	0.00	-0.00	0.01
	[0.25]	[-0.47]	[0.64]
Treasury	-0.25	-0.27	-0.68
	[-1.46]	[-2.03]	[-2.10]
Corporate	0.31	0.27	0.07
	[2.60]	[3.13]	[0.35]
High Yield	0.19	0.04	0.61
	[8.73]	[2.90]	[17.02]
Mortgage	-0.05	-0.07	-0.29
	[-0.40]	[-0.73]	[-1.24]
Alpha	0.29	0.18	0.51
	[1.75]	[1.28]	[1.70]
R^2	97.1%	97.7%	97.0%

Table 2: Describing passive and active bond funds

This table shows descriptive statistics for our sample of fund-month observations. Panels A1 and A2 show, respectively, broad fund characteristics for passive and active bond funds. Panels B1 and B2 show, respectively, holdings-level information for passive and active bond funds. In each panel, we report, in addition to the mean value, the standard deviation of the values (SD) and various percentiles in the distribution (e.g., P10 is the 10^{th} percentile). The time period of analysis is January 2011 through December 2021.

Panel A1: Passive Bond Funds - Pooled Statistics - Broad Characteristics

	N	Mean	SD	P10	P25	P50	P75	P90
Net Return	7294	0.32%	1.47%	-0.95%	-0.21%	0.23%	0.89%	1.81%
Assets	7294	11.1	32.0	0.1	0.2	1.2	6.4	26.0
Turnover	7194	71%	85%	12%	22%	46%	81%	156%
Expense	7134	0.19%	0.13%	0.06%	0.10%	0.15%	0.23%	0.41%
Age	7294	9.9	7.3	3.3	4.4	7.4	12.6	22.5
Net Flow	7226	1.73%	9.30%	-4.23%	-0.57%	0.74%	3.21%	8.05%
Flow Volatility	7208	7.39%	6.48%	1.85%	3.13%	5.61%	9.12%	15.08%
Active Share (Bond)	2910	48.3%	24.2%	15.7%	23.1%	55.3%	67.5%	76.2%
Active Share (Firm)	2910	25.4%	15.9%	5.9%	8.5%	27.4%	39.4%	44.1%
Tracking Error	5456	0.10%	0.12%	0.02%	0.03%	0.06%	0.11%	0.21%
High Yield Dummy	7294	0.17	0.37	0.0	0.0	0.0	0.0	1.0
ETF Dummy	7294	0.70	0.42	0.0	0.5	1.0	1.0	1.0

Panel A2: Active Bond Funds - Pooled Statistics - Broad Characteristics

	N	Mean	SD	P10	P25	P50	P75	P90
Net Return	60800	0.32%	1.31%	-0.79%	-0.15%	0.27%	0.85%	1.60%
Assets	60800	3.0	10.8	0.1	0.2	0.5	1.9	5.9
Turnover	59769	138%	171%	27%	44%	75%	158%	347%
Expense	58942	0.70%	0.31%	0.40%	0.50%	0.66%	0.86%	1.08%
Age	60800	18.3	12.3	4.8	9.0	17.0	24.4	31.9
Net Flow	60493	0.32%	6.40%	-3.08%	-1.20%	-0.03%	1.34%	3.81%
Flow Volatility	60373	4.35%	4.76%	1.05%	1.69%	2.94%	5.05%	8.86%
Active Share (Bond)	38771	95.8%	4.6%	90.9%	94.5%	97.1%	98.6%	99.4%
Active Share (Firm)	38771	77.3%	12.8%	59.9%	68.4%	78.2%	87.1%	93.7%
Tracking Error	56863	0.52%	0.51%	0.13%	0.21%	0.35%	0.64%	1.09%
High Yield Dummy	60800	0.28	0.45	0.0	0.0	0.0	1.0	1.0
ETF Dummy	60800	0.00	0.00	0.0	0.0	0.0	0.0	0.0

Panel B1: Passive Bond Funds - Pooled Statistics - Holdings Information

	N	Mean	SD	P10	P25	P50	P75	P90
% Corporate Bonds	7162	63.7%	33.7%	23.4%	26.6%	79.0%	98.1%	99.1%
% Municipal Bonds	7162	0.9%	2.7%	0.0%	0.0%	0.4%	1.1%	1.5%
% Government Bonds	7162	24.2%	24.4%	0.0%	0.1%	15.7%	44.3%	56.2%
% ABS	7162	0.2%	0.5%	0.0%	0.0%	0.0%	0.3%	0.5%
% MBS	7162	9.0%	13.8%	0.0%	0.0%	0.0%	24.7%	30.4%
% Cash	7162	0.0%	4.5%	-3.3%	-0.2%	0.4%	1.3%	2.3%
% Other	7162	2.2%	5.9%	0.0%	0.0%	0.3%	1.3%	4.9%
# of Holdings	5304	2435	3241	282	649	1591	2589	4848
Holdings HHI	5304	0.005	0.005	0.001	0.002	0.003	0.006	0.010
# of Firms	5304	801	672	190	359	650	984	1513
Bmk # of Holdings	3894	6321	3872	1140	2072	7856	9700	10982
Bmk Holdings HHI	3894	0.002	0.001	0.001	0.001	0.002	0.002	0.003
Bmk # of Firms	3894	1475	679	567	808	1958	2094	2148
% Zero Trading Days	5304	46.1%	7.6%	35.4%	42.2%	46.6%	50.7%	54.0%
Spread	5121	0.36%	0.12%	0.22%	0.28%	0.35%	0.43%	0.52%
Volume	5121	150.6	57.3	86.3	111.5	144.3	181.3	220.8
Amount Outstanding	5121	1353	212	1104	1246	1360	1453	1579
Bmk % Zero Trading Days	3894	50.0%	6.0%	43.2%	47.0%	49.7%	53.0%	55.1%
Bmk Spread	3726	0.39%	0.12%	0.23%	0.30%	0.38%	0.46%	0.56%
Bmk Volume	3726	147.4	35.3	99.1	131.2	146.2	168.3	189.2
Bmk Amount Outstanding	3726	1341	96	1212	1277	1355	1422	1460
Average Return	5121	0.15%	1.92%	-1.34%	-0.35%	0.18%	1.01%	2.28%
Yield	5121	3.30%	1.38%	1.78%	2.35%	3.17%	3.86%	5.05%
Time since Issuance	5121	4.2	1.0	2.8	3.5	4.1	4.8	5.6
Time to Maturity	5121	9.7	5.9	2.9	5.1	10.4	11.8	17.1
Duration	5121	6.7	3.2	2.7	4.3	6.8	8.0	11.3
Rating	5121	8.1	2.2	6.8	7.0	7.2	7.6	12.7
Coverage	5121	48.8%	28.8%	20.6%	23.0%	36.8%	80.9%	92.7%

Panel B2: Active Bond Funds - Pooled Statistics - Holdings Information

	N	Mean	SD	P10	P25	P50	P75	P90
% Corporate Bonds	59340	53.8%	25.1%	24.9%	34.1%	49.0%	76.4%	91.6%
% Municipal Bonds	59340	1.7%	5.3%	0.0%	0.0%	0.4%	1.5%	4.4%
% Government Bonds	59340	16.5%	15.5%	0.0%	2.5%	13.3%	26.4%	38.0%
% ABS	59340	9.4%	12.3%	0.0%	0.1%	4.9%	14.6%	24.4%
% MBS	59340	11.9%	13.4%	0.0%	0.0%	6.3%	22.5%	31.8%
% Cash	59340	0.8%	9.3%	-7.3%	0.0%	1.2%	3.3%	6.8%
% Other	59340	5.9%	11.3%	0.0%	0.3%	2.6%	9.2%	19.6%
# of Holdings	50174	533	826	103	182	335	629	1064
Holdings HHI	50174	0.014	0.013	0.004	0.006	0.009	0.016	0.029
# of Firms	50174	346	324	88	150	254	431	682
Bmk # of Holdings	45740	7249	3491	1604	4328	8200	9908	11152
Bmk Holdings HHI	45740	0.002	0.001	0.001	0.002	0.002	0.002	0.005
Bmk # of Firms	45740	1668	567	673	1171	2006	2112	2153
% Zero Trading Days	50174	48.1%	8.3%	38.5%	42.4%	47.3%	52.6%	58.9%
Spread	50093	0.39%	0.15%	0.21%	0.29%	0.37%	0.47%	0.56%
Volume	50093	216.5	162.9	79.1	116.9	174.0	268.6	399.1
Amount Outstanding	50093	1235	398	768	965	1202	1465	1743
Bmk % Zero Trading Days	45740	49.0%	4.5%	42.6%	47.0%	49.4%	52.6%	54.4%
Bmk Spread	45740	0.38%	0.11%	0.22%	0.30%	0.37%	0.45%	0.55%
Bmk Volume	45740	142.3	33.1	93.6	123.6	144.1	161.1	186.5
Bmk Amount Outstanding	45740	1320	131	1205	1264	1349	1415	1457
Average Return	50084	0.13%	1.85%	-1.35%	-0.35%	0.18%	0.88%	2.04%
Yield	50090	3.92%	1.85%	1.90%	2.67%	3.62%	4.78%	6.41%
Time since Issuance	50093	3.5	1.4	2.1	2.7	3.3	4.2	5.3
Time to Maturity	50093	7.7	4.3	2.5	4.5	7.2	10.2	12.5
Duration	50090	5.5	2.4	2.3	3.8	5.4	6.9	8.2
Rating	50057	9.4	2.4	7.1	7.8	8.6	10.1	13.5
Coverage	50093	33.0%	18.2%	13.0%	19.5%	29.1%	43.9%	59.5%

Table 3: Determinants of net flows for passive bond funds

This table reports results from, following Eq. (7), regressing the monthly net flows of passive bond funds on fund characteristics and gross benchmark-adjusted return as of the end of the month preceding the flow. The time period of analysis is January 2011 through December 2021. The coefficients associated with the control variables are, for brevity, suppressed. *t*-statistics, which are calculated using standard errors clustered on fund and year-month, are reported below their respective coefficients in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gross Bench-Adj. Ret.	0.44						0.21
	[0.62]						[0.43]
Expense	-0.97						-0.90
	[-3.00]						[-3.70]
Active Share (Firm)		-1.87			-1.90		-1.20
		[-2.10]			[-1.90]		[-2.08]
Active Share (Bond)			-0.63		0.16		
			[-1.06]		[0.23]		
Tracking Error				-0.20	-0.06		
				[-0.73]	[-0.21]		
Illiquidity						-1.19	-0.97
						[-2.32]	[-3.42]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,603	2,603	2,603	2,603	2,603	2,603	2,603
R-squared	14.9%	14.1%	13.3%	13.3%	14.1%	14.2%	16.1%

Table 4: Impact of bond liquidity on passive bond fund holdings
This table reports, for passive bond funds and following Eq. (8), results from regressing the difference between bond-level fund and benchmark weights on bond characteristics. We consider both (i) all holdings held be either the fund or benchmark (Full) and (ii) only holdings held by both (In Both). We also consider Illiquidity both with and without accounting for the bond's amount outstanding (AO). The time period of analysis is the first quarter of 2011 through the last quarter of 2021. *t*-statistics, which are calculated using standard errors clustered on bond and year-month, are reported below their respective coefficients in brackets.

	(1)	(2)	(3)	(4)
Sample	Full	In Both	Full	In Both
Illiquidity	-2.68	-2.85		
	[-6.08]	[-5.17]		
Illiquidity (No AO)			-1.46	-2.15
			[-4.77]	[-5.43]
Time Since Issuance	5.81	5.06	5.70	5.08
	[10.54]	[6.74]	[10.33]	[6.76]
Rating	-0.35	1.35	-0.39	1.33
	[-0.56]	[1.60]	[-0.62]	[1.58]
Duration	10.46	28.14	10.23	28.12
	[6.55]	[14.78]	[6.42]	[14.77]
Yield	0.53	-1.41	0.51	-1.40
	[1.38]	[-2.80]	[1.32]	[-2.79]
Bond FE	Yes	Yes	Yes	Yes
Fund-Year-Month FE	Yes	Yes	Yes	Yes
Observations	2,702,302	1,289,166	2,702,302	1,289,166
R-squared	7.2%	39.5%	7.2%	39.5%

Table 5: Passive fund and benchmark rebalancing transaction costs

This table shows estimates of the annualized transaction costs associated with quarterly rebalancing of corporate bond benchmarks and passive funds tracking those benchmarks. The costs reported are estimated based on the trades required to rebalance the benchmark or passive fund at the end of the quarter and are reported in basis points relative to end-of-quarter assets. We only report results when both benchmark and fund holdings are available at both the beginning and end of a given quarter. The time period of analysis is the second quarter of 2011 through third quarter of 2021, but not all benchmarks have a matching passive fund in all quarters. Panel A shows average cost estimates using 10,000 simulated flows drawn from a normal distribution with mean zero and a standard deviation of 0%, 10%, 15%, or 20%. Panel B shows average cost estimates using the actual quarterly flows of the passive funds. When testing individual benchmarks, the reported *t*-statistics are estimated using standard errors robust to heterogeneity, and when testing the full set of benchmarks, the reported *t*-statistic is estimated using a standard error clustered by benchmark and year-quarter.

Panel A: Simulated Flows

		Flow Volatility							
		0%		10%		15%		20%	
Benchmark	Obs.	Bench	Fund	Bench	Fund	Bench	Fund	Bench	Fund
Bloomberg Inter Corp	19	5.31	18.77	8.61	19.90	10.83	21.19	13.69	22.98
Bloomberg US Corp 1-3 Yr	19	10.61	13.78	12.54	14.63	13.92	15.59	15.75	16.87
Bloomberg US Corp	23	5.77	26.89	10.08	29.04	13.03	31.07	16.79	33.77
Bloomberg US Long Corp	19	8.85	45.74	14.87	47.66	19.15	49.93	24.70	53.11
Bloomberg US Corp 1-5 Yr	42	8.16	13.27	10.93	14.55	12.85	15.97	15.35	17.82
Bloomberg VLI High Yield	19	15.06	21.76	18.27	23.52	20.90	25.55	24.45	28.27

Panel B: Actual Flows

Benchmark	Obs.	Bench	Fund	Difference	*t*-stat
Bloomberg Inter Corp	19	7.92	17.15	-9.23	-4.77
Bloomberg US Corp 1-3 Yr	19	12.29	13.72	-1.44	-2.82
Bloomberg US Corp	23	14.18	24.44	-10.26	-3.91
Bloomberg US Long Corp	19	15.31	44.94	-29.64	-4.15
Bloomberg US Corp 1-5 Yr	42	10.14	11.81	-1.67	-3.06
Bloomberg VLI High Yield	19	19.88	24.98	-5.10	-2.73
All	141	12.80	21.09	-8.29	-2.03

Table 6: Percentages of bonds and stocks that outperform their benchmarks

This table reports the percentages of bonds in the bond (Bloomberg Agg) and stock index (Russell 1000) whose one-, six-, or 12-months returns that outperform their benchmarks. For each return horizon (one, six, and 12 months), we calculate the percentage of bonds in the indexes that outperform the value-weighted (VW) and equal-weighted (EW) benchmarks. We also report averages and skewnesses of returns for quintiles based on weights in their benchmarks.

		Bond (Bloomberg Agg)				Stock (Russell 1000)			
Time Horizon	Benchmark Weight	Average Return	Skewness	% Beat VW Benchmark	% Beat EW Benchmark	Average Return	Skewness	% Beat VW Benchmark	% Beat EW Benchmark
1 Month	Low	0.54%	2.33	52.4%	47.7%	1.11%	2.43	49.6%	49.2%
	2	0.49%	0.60			1.02%	0.14		
	3	0.46%	-0.26			1.01%	0.47		
	4	0.43%	-1.18			0.95%	0.53		
	High	0.40%	-0.69			0.89%	-0.23		
	All	0.46%	0.58			1.00%	1.34		
6 Months	Low	3.15%	4.22	54.7%	48.9%	7.60%	9.31	48.9%	48.0%
	2	2.88%	1.94			6.79%	1.09		
	3	2.75%	1.32			6.43%	0.68		
	4	2.65%	0.79			6.12%	0.74		
	High	2.48%	0.90			5.86%	0.64		
	All	2.78%	2.30			6.56%	6.01		
12 Months	Low	6.30%	5.35	57.7%	47.3%	14.15%	7.06	47.3%	46.9%
	2	5.87%	2.58			13.13%	1.60		
	3	5.65%	2.17			12.23%	1.22		
	4	5.44%	1.38			11.95%	1.17		
	High	5.08%	1.34			11.61%	3.32		
	All	5.67%	3.18			12.62%	5.02		

Table 7: Active share and active bond fund performance – Portfolio evidence
This table shows the annualized CCR6 alphas associated with equal-weight portfolios of active bond funds formed using active share and past performance. In Panel A, portfolios are created by sorting funds in quintiles at the start of each month based on those funds' most recently available measures of active share as of the end of the prior month. We consider active share at both the bond and firm level. In Panel B, portfolios are created by subdividing each firm-level active share quintile into quintiles based on funds' CCR6 alphas during the preceding twenty-four months. The time period of analysis is January 2011 through December 2021. *t*-statistics robust to heterogeneity are reported below their respective alphas in brackets.

Panel A: Sorting on Active Share

		Active Share					
All		Low	2	3	4	High	High − Low
0.28	Bond	0.15	0.22	0.28	0.22	0.54	0.39
[1.74]		[1.14]	[1.39]	[1.77]	[1.31]	[2.01]	[1.94]
	Firm	-0.05	0.08	0.31	0.34	0.74	0.80
		[-0.46]	[0.63]	[2.08]	[1.62]	[2.40]	[3.12]

Panel B: Sorting on Active Share and Past Alpha

			Active Share (Firm)					
		All	Low	2	3	4	High	High − Low
Past Alpha	All	0.25	-0.06	0.10	0.33	0.21	0.68	0.74
		[1.56]	[-0.51]	[0.74]	[2.18]	[1.04]	[2.24]	[2.97]
	Low	-0.30	-0.47	-0.21	0.02	-0.75	-0.07	0.40
		[-1.20]	[-1.53]	[-0.78]	[0.06]	[-2.43]	[-0.14]	[0.82]
	2	0.19	-0.03	-0.30	0.25	0.41	0.65	0.69
		[0.97]	[-0.18]	[-1.25]	[1.12]	[1.34]	[1.87]	[2.16]
	3	0.19	-0.20	0.20	0.11	0.30	0.58	0.78
		[1.25]	[-1.10]	[0.90]	[0.50]	[1.37]	[2.11]	[2.71]
	4	0.23	0.07	0.23	0.34	0.07	0.43	0.36
		[1.28]	[0.39]	[1.25]	[1.38]	[0.32]	[1.32]	[1.18]
	High	0.98	0.40	0.65	0.94	1.04	1.86	1.46
		[3.86]	[1.32]	[1.86]	[3.82]	[3.02]	[3.82]	[2.96]
	High − Low	1.28	0.86	0.86	0.92	1.79	1.92	1.06
		[3.60]	[1.65]	[1.70]	[2.54]	[4.27]	[3.66]	[1.65]

Table 8: Active share and active bond fund performance – Panel regression evidence

This table reports results from, following Eq. (9), regressing the annualized monthly CCR6 alphas of active bond funds on those funds' active shares, past performances, and other characteristics as of the end of the preceding month. The time period of analysis is January 2011 through December 2021. The coefficients associated with the control variables are, for brevity, suppressed. *t*-statistics, which are calculated using standard errors clustered on fund and year-month, are reported below their respective coefficients in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
Active Share (Bond)	0.12		-0.02			
	[2.23]		[-0.38]			
Active Share (Firm)		0.18	0.19	0.17	0.14	0.11
		[3.55]	[3.75]	[3.30]	[2.87]	[2.21]
R-squared				-0.09		
				[-1.48]		
Top 20% Alpha Dummy					0.57	0.53
					[4.66]	[4.27]
Active Share (firm) x Top 20%						0.17
						[2.25]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,062	34,062	34,062	34,062	34,062	34,062
R-squared	21.1%	21.2%	21.2%	21.2%	21.5%	21.6%

Table 9: Active share and active bond fund downside risk
This table reports results from, following Eq. (10), regressing the annualized calendar year-quarter maximum drawdowns (MDDs) of active bond funds on those funds' prior active shares. The time period of analysis is the first quarter of 2011 through the last quarter of 2021. We report results using both the full time period and subperiods created by dividing the calendar year-quarters into terciles based on average maximum drawdown. The coefficients associated with the control variables are, for brevity, suppressed. *t*-statistics, which are calculated using standard errors clustered on fund and year-month, are reported below their respective coefficients in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All Quarters	All Quarters	All Quarters	Low Avg MDD Quarters	Mid Avg MDD Quarters	High Avg MDD Quarters
Active Share (Bond)	-0.22		-0.22	-0.08	-0.16	-0.44
	[-2.35]		[-2.53]	[-1.30]	[-1.47]	[-2.24]
Active Share (Firm)		-0.12	0.00			
		[-1.17]	[-0.01]			
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,874	12,874	12,874	4,459	4,358	4,057
R-squared	72.9%	72.8%	72.9%	43.0%	41.4%	72.9%

Table 10: Active share and active bond fund net flows

This table reports results from, following Eq. (11), regressing the monthly net flows of active bond funds on fund characteristics and performance as of the end of the month preceding the flow. We consider active share (AS) at both the bond and firm levels, and we evaluate performance using both the CCR6 model and simple benchmark adjustment. The time period of analysis is January 2011 through December 2021. The coefficients associated with the control variables are, for brevity, suppressed. *t*-statistics, which are calculated using standard errors clustered on fund and year-month, are reported below their respective coefficients in brackets. *p*-values associated with differences in key coefficients are also reported.

	(1)	(2)	(3)	(4)	(5)	(6)
Active Share Type	-	Bond	Firm	-	Bond	Firm
Performance Measure	CCR6	CCR6	CCR6	Benchmark	Benchmark	Benchmark
Low Performance	1.75	1.61	1.20	2.68	2.22	1.61
	[2.33]	[2.10]	[1.42]	[3.29]	[2.53]	[1.81]
Mid Performance	1.10	1.13	1.09	1.25	1.42	1.38
	[6.15]	[6.04]	[5.72]	[7.32]	[8.16]	[7.55]
High Performance	3.37	2.24	3.10	3.84	2.34	2.46
	[3.37]	[2.37]	[3.16]	[3.88]	[2.37]	[2.43]
High Active Share Dum		-0.27	-0.47		-0.30	-0.76
		[-1.04]	[-2.11]		[-1.30]	[-2.94]
Low Perf x High AS		-0.38	1.66		1.02	3.87
		[-0.24]	[1.19]		[0.66]	[2.51]
Mid Perf x High AS		0.07	0.20		-0.75	-0.49
		[0.15]	[0.43]		[-1.95]	[-1.28]
High Perf x High AS		4.02	0.67		5.51	4.19
		[1.75]	[0.32]		[2.80]	[2.25]
Low Perf = High Perf	0.165	0.582	0.124	0.328	0.922	0.495
Low P + (Low P x High AS) = High P + (High P x High AS)	-	0.035	0.666	-	0.027	0.569
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Benchmark FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,642	34,642	34,642	34,627	34,627	34,627
R-squared	9.4%	9.6%	9.5%	10.3%	10.4%	10.4%

Internet Appendix for:
"Passive bond fund management is an oxymoron
(or the case for the active management of bond funds)"

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Figure IA.1: Cumulative abnormal returns of passive bond funds

This figure shows the cumulative abnormal returns on an equal-weight portfolio of passive bond funds from January 2011 through December 2021. The abnormal returns are calculated using both the CCR3 and CCR6 models.

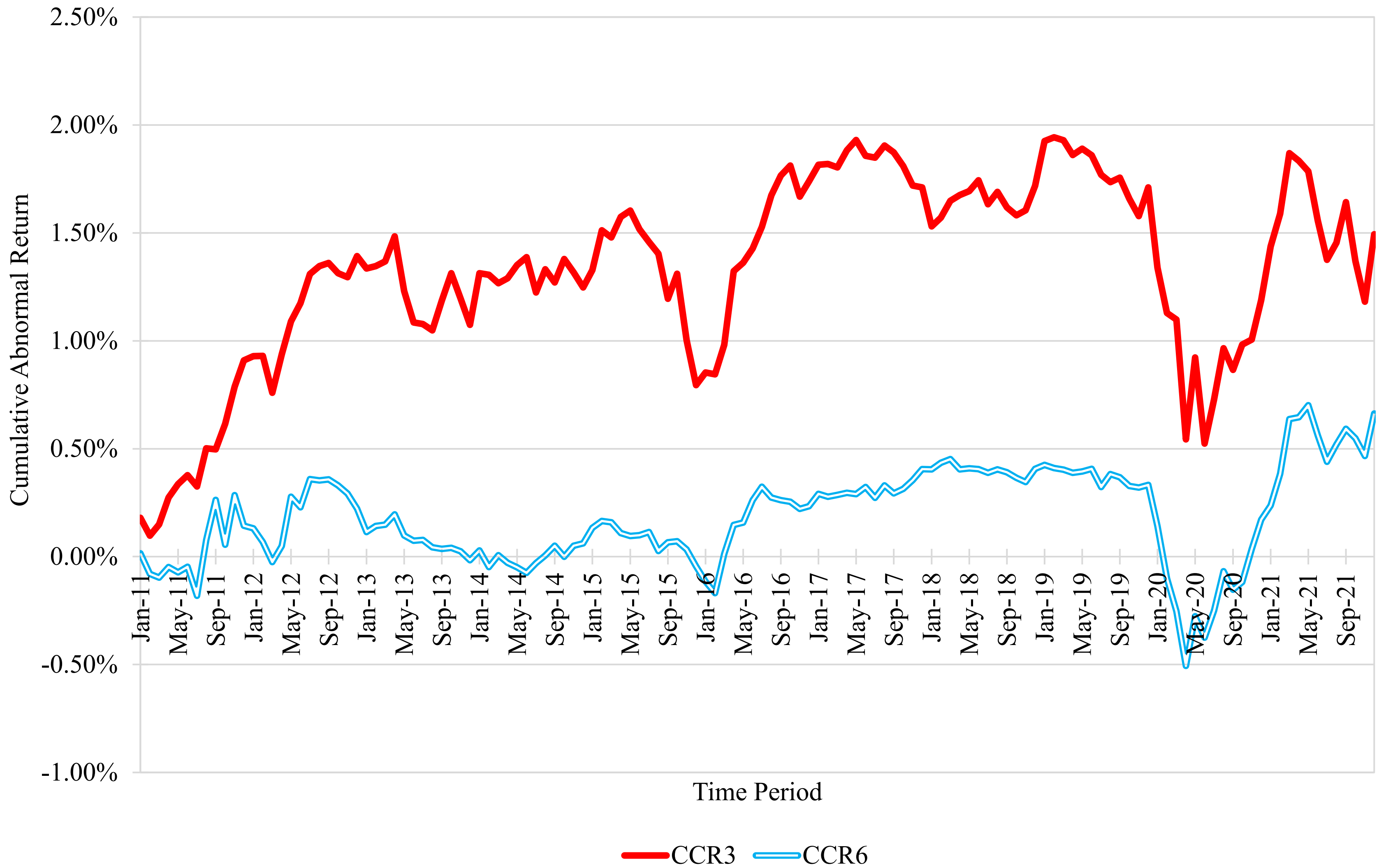

Table IA.1: Gross performance of passive bond fund portfolios relative to prospectus benchmarks

This table shows the gross performance of equal-weight portfolios of passive bond funds. We report the portfolio alphas, betas, and R-squared values that result from regressing the portfolio excess returns on usage-weighted benchmark excess returns. Separate results are reported for the full sample of passive bond funds, investment grade passive bond funds, high yield passive bond funds, passive bond funds not linked to ETFs (i.e., not a pure ETF and without an ETF share class), and passive bond funds that are pure ETFs. *t*-statistics robust to heterogeneity are reported in brackets below their respective coefficients. The time period of analysis in all cases is January 2011 through December 2021.

	Full Sample	Investment Grade	High Yield	No ETFs	Pure ETFs
Beta	0.99	0.99	0.98	1.01	0.97
	[220.11]	[247.04]	[149.89]	[220.62]	[250.21]
Alpha	-0.08	-0.10	-0.08	-0.09	-0.08
	[-2.03]	[-2.64]	[-0.96]	[-2.24]	[-2.09]
R^2	99.9%	99.8%	99.9%	99.8%	99.9%

Table IA.2: Passive bond fund portfolio performance using CCR3 and CCR6 models
This table shows the performance of equal-weight portfolios of passive bond funds. We form the portfolios using the full sample, just investment grade funds, and just high yield funds. Performance is evaluated using the CCR3 model in Panel A and the CCR6 model in Panel B. *t*-statistics robust to heterogeneity are reported in brackets below their respective coefficients. The time period of analysis is January 2011 through December 2021.

Panel A: Passive Bond Fund Portfolio Performance - CCR3 Model

	Full Sample	Investment Grade	High Yield
Stock	0.02	0.00	0.16
	[3.77]	[0.70]	[5.23]
Treasury	0.16	0.32	-0.63
	[9.55]	[26.28]	[-5.50]
Corporate	0.61	0.53	0.87
	[40.02]	[58.69]	[8.51]
Alpha	0.14	0.17	0.23
	[0.89]	[1.85]	[0.26]
R^2	97.9%	99.2%	77.6%

Panel B: Passive Bond Fund Portfolio Performance - CCR6 Model

	Full Sample	Investment Grade	High Yield
Bond	-0.21	-0.03	1.06
	[-0.67]	[-0.13]	[2.02]
Stock	-0.00	0.00	-0.01
	[-0.32]	[0.25]	[-1.22]
Treasury	0.26	0.28	-0.47
	[1.99]	[2.57]	[-1.98]
Corporate	0.56	0.53	-0.19
	[6.24]	[7.94]	[-1.49]
High Yield	0.10	0.00	0.86
	[8.26]	[0.12]	[37.42]
Mortgage	0.20	0.15	-0.30
	[2.10]	[2.14]	[-1.96]
Alpha	0.06	0.09	0.14
	[0.60]	[1.17]	[0.62]
R^2	99.1%	99.5%	98.6%

Table IA.3: Describing passive and active bond funds – Benchmark-matched statistics
This table shows descriptive statistics for a benchmark-matched sample. Panels A considers active share and tracking error. There, we match each fund-month observation for an active bond fund with an observation for a passive bond fund with the same benchmark at the same time. If no match is available, the active fund observation is dropped. If more than one match is available, the average of the passive fund observations is used. 'A – P' reports the difference between the active and passive fund results. Panel B considers holdings-level information. There, in addition to requiring an active-passive match, we further require a match to data on the benchmark. 'A – B' reports the difference between the active fund and benchmark results, and 'P – B' reports the difference between the passive fund and benchmark results. In each panel, we report, in addition to the mean value, the standard deviation of the values (SD) and various percentiles in the distribution (e.g., P10 is the 10th percentile). The time period of analysis is January 2011 through December 2021. The *t*-statistics associated with the differences in means are calculated using standard errors clustered on benchmark and year-month.

Panel A: Broad Characteristics - Matched Sample

		Active	Passive	A − P
Active Share (Bond)	N	27473	27473	-
	Mean	96.7%	67.4%	29.4% [16.04]
	Median	97.6%	68.9%	28.8%
	SD	3.0%	8.8%	-5.8%
	P10	92.8%	62.0%	30.8%
	P90	99.5%	75.1%	24.5%
Active Share (Firm)	N	27473	27473	-
	Mean	77.7%	36.9%	40.8% [10.91]
	Median	78.5%	40.4%	38.1%
	SD	12.5%	10.9%	1.6%
	P10	60.4%	12.3%	48.1%
	P90	94.2%	44.4%	49.9%
Tracking Error	N	34793	34793	-
	Mean	0.58%	0.08%	0.50% [11.96]
	Median	0.40%	0.05%	0.35%
	SD	0.56%	0.12%	0.43%
	P10	0.15%	0.04%	0.11%
	P90	1.24%	0.10%	1.14%

Panel B: Holdings Information - Matched Sample

		Active	Passive	Benchmark	A − P	A − B	P − B
# of Holdings	N	27057	27057	27057	-	-	-
	Mean	689	2698	8818	-2008	-8129	-6120
					[-13.11]	[-9.67]	[-8.72]
	Median	435	2526	9347	-2091	-8912	-6821
	SD	1058	1237	2592	-179	-1534	-1355
	P10	127	1184	5173	-1057	-5046	-3989
	P90	1380	4292	11902	-2912	-10522	-7610
Holdings HHI	N	27057	27057	27057	-	-	-
	Mean	0.015	0.006	0.002	0.009	0.013	0.004
					[10.89]	[43.55]	[6.87]
	Median	0.010	0.005	0.002	0.005	0.009	0.003
	SD	0.014	0.004	0.001	0.010	0.013	0.003
	P10	0.004	0.003	0.002	0.001	0.003	0.001
	P90	0.030	0.009	0.002	0.020	0.027	0.007
% Zero Trading Days	N	27057	27057	27057	-	-	-
	Mean	47.4%	47.2%	49.2%	0.2%	-1.8%	-2.0%
					[0.79]	[-5.41]	[-7.66]
	Median	46.6%	47.7%	49.2%	-1.1%	-2.6%	-1.6%
	SD	7.9%	4.7%	3.8%	3.2%	4.1%	0.9%
	P10	38.6%	40.5%	45.1%	-1.9%	-6.4%	-4.6%
	P90	57.5%	53.3%	54.5%	4.3%	3.0%	-1.3%

		Active	Passive	Benchmark	A − P	A − B	P − B
Volume	N	27000	27000	27000	-	-	-
	Mean	252.4	159.5	145.2	92.9	107.2	14.3
					[10.50]	[11.52]	[7.77]
	Median	211.5	155.4	146.1	56.1	65.4	9.4
	SD	185.9	40.6	32.6	145.3	153.3	7.9
	P10	85.5	115.6	96.1	-30.0	-10.5	19.5
	P90	451.8	208.0	187.1	243.8	264.7	20.9
Spread	N	27000	27000	27000	-	-	-
	Mean	0.39%	0.37%	0.38%	0.01%	0.01%	-0.01%
					[2.73]	[1.47]	[-5.51]
	Median	0.37%	0.37%	0.37%	0.00%	0.00%	0.00%
	SD	0.13%	0.10%	0.11%	0.03%	0.03%	0.00%
	P10	0.23%	0.23%	0.24%	0.00%	-0.01%	-0.01%
	P90	0.55%	0.52%	0.54%	0.03%	0.02%	-0.02%
Amount Outstanding	N	27000	27000	27000	-	-	-
	Mean	1350	1381	1352	-31	-2	28
					[-3.18]	[-0.14]	[1.61]
	Median	1320	1393	1379	-73	-59	13
	SD	400	89	82	312	318	6
	P10	888	1282	1214	-394	-326	68
	P90	1852	1472	1457	379	394	15

Table IA.4: Active share and active bond fund performance – Portfolio evidence using quarterly portfolio returns

This table shows the annualized CCR6 alphas associated with quarterly returns on equal-weight portfolios of active bond funds formed using active share and past performance. In Panel A, portfolios are created by sorting funds in quintiles at the start of each quarter based on those funds' most recently available measures of active share as of the end of the prior quarter. We consider active share at both the bond and firm level. In Panel B, portfolios are created by subdividing each firm-level active share quintile into quintiles based on funds' CCR6 alphas during the preceding two years. The time period of analysis is January 2011 through December 2021. *t*-statistics robust to heterogeneity are reported below their respective alphas in brackets.

Panel A: Sorting on Active Share

		Active Share					
All		Low	2	3	4	High	High − Low
	Bond	-0.00	0.20	0.25	0.13	0.51	0.51
0.21		[-0.01]	[1.23]	[1.65]	[0.73]	[1.56]	[1.99]
[1.22]	Firm	-0.13	-0.07	0.24	0.30	0.74	0.87
		[-0.94]	[-0.52]	[1.51]	[1.20]	[2.25]	[3.50]

Panel B: Sorting on Active Share and Past Alpha

			Active Share (Firm)					
		All	Low	2	3	4	High	High − Low
	All	0.19	-0.15	0.00	0.23	0.10	0.76	0.91
		[1.09]	[-0.92]	[0.02]	[1.76]	[0.40]	[2.27]	[3.62]
	Low	-0.23	-0.35	-0.19	-0.04	-0.99	0.45	0.80
		[-0.81]	[-0.94]	[-0.51]	[-0.13]	[-2.21]	[0.94]	[1.55]
	2	0.10	0.00	-0.35	0.09	0.30	0.44	0.44
		[0.47]	[0.02]	[-1.12]	[0.42]	[0.93]	[1.08]	[1.25]
Past Alpha	3	-0.03	-0.59	0.14	-0.25	0.13	0.42	1.01
		[-0.21]	[-2.28]	[0.65]	[-0.90]	[0.52]	[1.38]	[3.93]
	4	0.20	-0.00	0.18	0.49	-0.07	0.44	0.44
		[0.95]	[-0.01]	[0.96]	[2.30]	[-0.23]	[1.05]	[1.09]
	High	0.94	0.25	0.27	0.91	1.14	2.08	1.83
		[3.64]	[0.64]	[0.65]	[2.76]	[2.58]	[4.30]	[3.06]
	High − Low	1.17	0.59	0.46	0.95	2.13	1.63	1.03
		[2.95]	[0.97]	[0.79]	[1.88]	[4.33]	[3.38]	[1.66]