

Why Have Actively Managed Bond Funds Remained Popular?

Jaewon Choi*
University of Illinois at Urbana-Champaign
jaewchoi@illinois.edu

K. J. Martijn Cremers
University of Notre Dame
mcremers@nd.edu

Timothy B. Riley
University of Arkansas
tbriley@uark.edu

This Draft: February 2021

* Corresponding author. Disclosure: Martijn Cremers serves as an independent director at Ariel Investments and as an academic advisor to State Street Associates and Touchstone Investments.

Why Have Actively Managed Bond Funds Remained Popular?

Abstract

In sharp contrast to equity funds, actively managed bond funds have remained popular. This paper explores why by examining how active share affects the performance, risk management, and flows of bond funds. We find that bond funds tend to be highly active and often invest outside of their primary asset classes. Bond funds with higher active share persistently earn higher alphas, demonstrate lower downside risk, and exhibit less flow sensitivity to poor performance (consistent with alleviating run risk). In conclusion, our results show that investors tend to benefit from active management in bond funds.

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

Keywords: Bond, Mutual Funds, Active Management, Active Share, Alpha

1. Introduction

The percentage of domestic equity mutual fund assets that are passively managed grew from about 4% in 1993 to about 33% as of 2019. This trend is consistent with what Cremers, Fulkerson, and Riley (2019) call the “conventional wisdom” on active management—the notion that active management does not generally create value for mutual fund investors. Bond mutual fund flows, however, have followed a substantially different trend. Unlike actively managed equity funds, which experienced total net outflows every year from 2006 through 2019, actively managed bond funds saw a total net inflow of \$1.36 trillion over the same period. Put differently, passive management of bond funds has grown much more slowly than passive management of equity mutual funds. In 2019, only about 13% of bond fund assets were passively managed.¹ Considering these contrasting trends, our paper asks the natural question: why have actively managed bond funds remained popular?

Our results suggest a straightforward explanation: actively managed bond funds remain popular because bond markets provide good opportunities for active management, particularly involving security selection and risk management. We examine the active management of bond funds by focusing on their active share (Cremers and Petajisto, 2009). This measure assesses the extent to which the holdings of a fund’s portfolio differ from the holdings of the fund’s benchmark’s portfolio. As we explain below, we find that bond funds are highly active, and more importantly, bond funds with high active share, compared to those with low active share, tend to outperform, provide better downside risk management, and exhibit lower investor run risk.

Because active share was designed for equity funds, we adapt it for use with bond funds to reflect the unique features of bond investing. Since most companies generally have only one share

¹ These statistics are from the 2020 Investment Company Fact Book, which is available at https://www.ici.org/pdf/2020_factbook.pdf.

class, the active shares of equity funds are computed at the company level (i.e., using company-level weights). In contrast, many bond issuers have multiple issues outstanding. Different bond issues from the same issuer, while sharing common issuer-level fundamentals, can differ with respect to their risk and return characteristics, including rating, maturity, and liquidity. We thus separately compute active shares for bond funds at both the issue and issuer levels. Specifically, *issue*-level active share is calculated using the portfolios weights of individual bond issues, while *issuer*-level active share is calculated by aggregating portfolio weights across all issues from the same issuer.

In addition to issue- and issuer-level active shares, we consider other dimensions of activeness in bond investing. Unlike the equity market, the fixed income market offers several asset classes with meaningfully different risk and return characteristics. For example, the primary concern for Treasury bonds is interest rate risk, whereas for high-yield corporate bonds, default and liquidity risks are also significant concerns. Likewise, agency bonds carry little default risk, but their liquidity tends to be lower than that of Treasuries. Bond funds can be active across asset classes—e.g., when a corporate bond funds buys agency bonds—which we find is indeed common for many bond funds. To the extent that funds have expertise and a relative advantage when investing in their primary asset classes, active investment inside versus outside of funds' primary asset classes can have performance and risk implications. We thus consider the extent to which bond funds deviate from their prospectus-benchmark-defined asset classes by separating active share into the “internal active share” (a fund's activeness with respect to holdings inside its primary asset classes) and the “external active share” (the amount of a fund's holdings outside its primary asset classes). Our results show that these differential active share measures unmask information

of significant value to investors and reveal novel details about the abilities of skilled bond fund managers.

We first document the extent to which bond funds are actively managed. Looking at the comprehensive holdings of 541 active taxable bond funds collected from Morningstar over the period 2002–2015, we find that bond funds are highly active at the issue level, with an average issue-level active share of 93%. This result is striking, as it implies that the average bond fund's holdings have only a 7% overlap with the fund's benchmark's holdings. For comparison, Cremers and Petajisto (2009) find that only 21% of equity funds have an active share greater than 90%. Conversely, at the issuer level, average bond fund active share is about 60%, which is similar to the post-2000 average equity fund active share. Thus, a substantial portion of active investing in bond funds is driven by within-issuer bond selection. Bond funds also invest a substantial portion of their assets outside of their primary asset classes. This tendency is most pronounced for investment-grade bond funds, which, on average, invest fewer assets in investment-grade corporate bonds (30%) than in government bonds (45%).

We next use these different dimensions of active share to provide a series of results showing that more active investing predicts higher performance. We find that, while both issue- and issuer-level active share positively predict future fund alphas, the predictive power of issuer-level active share tends to be stronger—indicating that the outperformance of more active bond funds arises mainly from the ability of those funds' managers to identify issuers that offer promising investment opportunities. The economic magnitude of the effect of issuer-level active share is sizable: a one standard deviation increase in issuer-level active share is associated with an increase in annualized alpha of 0.30%, with strong statistical significance. Further, we find that internal active share is more predictive of future performance than external active share, which is

suggestive of a relative advantage when investing in primary asset classes. In combination, these results suggest that bond fund managers outperform when they are active in selecting bond issuers within their primary asset classes.

The abnormal performance of high active share funds is also persistent, which we measure as the performance predictability of lagged fund alpha. A one standard deviation increase in issuer-level active share is associated with a 55% increase in the persistence of alpha. We further find that this persistence in performance is driven largely by past outperformers, suggesting that outperformance in active bond funds is associated with managerial skill. More specifically, when we separate performance persistence into its positive and negative components, we find that high active share is particularly related to positive performance persistence (i.e., funds that previously outperformed continuing to outperform). Moreover, this persistence in performance is stronger when internal active share is high. The results here are both consistent with the performance persistence results for highly active equity funds in Cremers and Petajisto (2009) and indicative of significant skill among highly active bond fund managers.

Next, we consider the following related question: Are more active bond funds also better at risk management? Recent evidence in the literature suggests that how the managers of active bond funds control their downside risk is an important risk management criterion, as negative performance can be particularly costly for bond funds and can even increase financial fragility concerns.² We first focus on downside risk as quantified by the funds' maximum drawdown (MDD), which is a risk measure widely utilized in industry. We find that highly active bond funds have relatively strong risk management, driven mainly by issue-level active share: a one standard

² For example, Bai, Bali, and Wen (2019) show that downside risk is particularly a concern among defaultable bonds; Goldstein, Jiang, and Ng (2017) show that fund flows respond more strongly to negative performance; and Choi, Hoseinzade, Shin, and Tehranian (2020) and Falato, Hortacsu, Li, and Shin (2020) show that low cash funds experiencing outflows can lead to fire sales in the bond market.

deviation increase in issue-level active share increases the next quarter's MDD by 0.20%.³ Thus, while funds with high issue-level active share might forego the higher alpha of funds with high issuer-level active share, they perform better with respect to downside risk management. This could be achieved through, for example, investing in the bonds from an issuer that have relatively lower duration, higher credit rating, or higher liquidity.

In addition to downside risk, we also examine the return volatilities of bond funds. We find that better performance by bond funds with high issuer-level active share comes at the cost of higher idiosyncratic volatility. The prior literature suggests that this trade-off should be expected—to be more active, funds will likely have to take more idiosyncratic risk, which was modeled in general by Treynor and Black (1973) and was demonstrated for mutual funds by Christoffersen and Simutin (2017). Then again, conditional on *issuer*-level active share, a high *issue*-level active share does not represent such a trade-off, because it reduces idiosyncratic volatility without a decrease in alpha. That high issue-level active share is associated with lower idiosyncratic volatility and lower downside risk is indicative of skilled bond fund managers having substantial ability to select bond issues that will improve diversification.

The predictive power of active share varies with market conditions. In “good times,” which we define as periods when VIX and TED spread are relatively low, active share positively predicts performance more strongly. In “bad times,” active share predicts downside risk more strongly. These results are consistent with the ideas of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), who show that skilled fund managers focus on stock picking during booms and market timing during recessions. Our results suggest a similar division of focus. That is, active bond managers focus on different tasks depending on market conditions. They focus on bond picking

³ Bodnaruk, Chokaev, and Simonov (2019) find that active equity fund managers, on average, are able to lower downside risk.

during good times and risk management during bad times. Our results are also consistent with Petajisto (2013), Pastor, Stambaugh, and Taylor (2017), and von Reibnitz (2017), all of whom show that the payoffs to active management are time-varying.

We conclude our analysis by considering bond fund investor behavior. Goldstein, Jiang, and Ng (2017) document strategic complementarities in bond funds. These complementarities manifest when “the expectation that other investors will withdraw their money reduces the expected return from staying in the fund and increases the incentive for each individual investor to withdraw” (Chen, Goldstein, and Jiang, 2010, pg. 240). Such an incentive exists because non-redeeming investors tend to bear the costs associated with other investors’ redemptions. Consequently, there is a first-mover advantage in the redemption process, which can make funds subject to significant run risk. This run risk is heightened when a fund holds relatively illiquid assets (as bond funds do), as the cost of redemptions is higher in those cases. Empirically, Goldstein, Jiang, and Ng (2017) document this risk through their observation of the average bond fund having a concave flow-performance relation.

Our hypothesis related to the results above is that run risk is mitigated when a bond fund is highly active. Because highly active bond funds tend to have positive performance persistence, investor flows should be more sensitive to those funds’ outperformance. Because those same funds tend to have less downside risk, investor flows should also be less sensitive to those funds’ underperformance. The combined result should be that highly active bond funds have a less concave flow-performance relation.

Confirming this hypothesis, we find that, when active share increases, investor flows are less sensitive to underperformance and more sensitive to outperformance. Relative to a typical bond fund, high active share bond funds (i.e., those in the top quartile) have half the flow sensitivity

to underperformance and nearly double the flow sensitivity to outperformance, resulting in a strongly convex flow-performance relation. This shift is driven by increases in issue-level active share, consistent with liquidity management being more about individual issues than issuers. As a whole, our results suggest that a high level of active management helps to mitigate run risk, which should benefit investors in highly active bond funds. Our results also suggest to regulators where strategic complementarities are most powerful.⁴

Finally, we highlight that there are increasing concerns about replicability in science generally (Ioannidis, 2005) and in economics specifically (Harvey, 2017). Because our primary data ends in 2015, we are able to address this concern by replicating our key results using additional data from 2016 to 2019. This replication exercise is a *true* out-of-sample test—the results based on the primary data were obtained before most of the additional data even existed. Relative to the primary data, the additional data has a comparable number of unique funds, but a shorter time horizon. In our out-of-sample test, we find that our key results hold. Increases in active share are associated with increases in alpha, decreases in downside risk, and a less concave flow-performance relation. This successful replication suggests that our results are robust.

2. Related literature

Our results contribute to several areas of the asset management literature. They first contribute to the literature on active mutual fund manager skill. While early studies tend to find evidence against the presence of skilled managers,⁵ the subsequent literature has identified many such managers. Wermers (2000) and Chen, Jegadeesh, and Wermers (2000) both show evidence

⁴ The Financial Stability Oversight Council (FSOC) has expressed the concern that these fund-level strategic complementarities could have spillover effects leading to systemic risk. See, for example, FSOC's April 18, 2016 *Update on Review of Asset Management Products and Activities*.

⁵ These early studies include, among many others, Jensen (1968), Fama (1970), Gruber (1996), Carhart (1997), and Zheng (1999).

of managers' stock selection abilities, and Kacperczyk, Sialm, and Zheng (2005, 2008), using industry concentration and return gap measures, identify particular groups of active funds that consistently outperform. Cremers and Petajisto (2009) utilize their holdings-based active share measure to demonstrate that funds that are more active tend to perform better, while Amihud and Goyenko (2013) use their return-based selectivity measure in a similar demonstration.⁶ Using their value added measure, Berk and van Binsbergen (2015) contend that the average active mutual fund manager has significant skill.⁷

This deep literature has further analyzed the impacts of, for example, geography (Coval and Moskowitz, 2001), social connections (Cohen, Frazzini, and Malloy, 2008), and time variation (Kacperczyk, van Nieuwerburgh, and Veldkamp, 2014).⁸ Despite that depth, however, this literature is still missing a thorough examination of bond fund activeness. We fill that gap by adapting the Cremers and Petajisto (2009) active share measure for bond funds. This adaption accounts for a unique, empirically-important feature of bond investing—a single issuer can provide multiple investment choices by offering many different issues. We find that issue-level and issuer-level active shares have differentially useful information about manager skill. In previous work, bond fund activeness, when considered, has tended to be a secondary consideration (e.g., Amihud and Goyenko, 2013), and its measurement has not yet explicitly incorporated holdings.

Second, our results serve as an out-of-sample test of active share's predictive power. A number of studies that followed Cremers and Petajisto (2009) question whether active share helps

⁶ Titman and Tiu (2011) perform an analysis similar to Amihud and Goyenko (2013), but using hedge funds, and find similar results.

⁷ See Berk and van Binsbergen (2017) for a thorough summary of the basis for their measure.

⁸ More examples, among many possibilities, include decision similarity (Cohen, Coval, and Pastor, 2005), public information (Kacperczyk and Seru, 2007), trade motivation (Alexander, Cici, and Gibson, 2007), self-declared benchmarks (Sensoy, 2009), short selling (Chen, Desai, and Krishnamurthy, 2013), volatility (Jordan and Riley, 2015), patience (Cremers and Pareek, 2016), portfolio turnover (Pastor, Stambaugh, and Taylor, 2017), portfolio liquidity (Pastor, Stambaugh, and Taylor, 2020), and pairwise comparisons (Gronborg, Lunde, Timmermann, and Wermers, 2021).

predict equity fund alpha (e.g., Schlanger, Philips, and LaBarge, 2012; Cohen, Leite, Nielson, and Browder, 2014; Frazzini, Friedman, and Pomorski, 2016; and Brown and Davies, 2017). We show in an entirely different sample of bond funds that active share has significant power to predict future fund alphas. Our result complements the Cremers, Ferreira, Matos, and Starks (2016) finding that active share predicts the performance of a large sample of international equity mutual funds.

Third, we provide new insights specifically into bond fund performance. Much of the prior literature finds that the active management of bond funds results in underperformance (see, e.g., Blake, Elton, and Gruber, 1993; Chen, Ferson, and Peters, 2010; and Cici and Gibson, 2012), but Amihud and Goyenko (2013), Hunter, Kandel, Kandel, and Wermers (2014), and Jones and Mo (2021) note that particular subsets of actively managed bond funds can outperform. Using our novel application of active share, we find results that support the subset argument. Moreover, active share helps to identify the particular bond fund manager skills that drive that subset's performance. Previous work has questioned the overall selection skill of bond fund managers (e.g., Cici and Gibson, 2012) and shown that deviations to "reach for yield" negatively impact performance (Choi and Kronlund, 2018). We show that issuer-level selectivity drives performance improvement.

Fourth, we consider how activeness affects fund risk. Treynor and Black (1973) put forth a model in which managers must trade-off alpha and idiosyncratic volatility. Sialm, Starks, and Zhang (2015) show that the investor flows of mutual funds increase with alpha but decrease with idiosyncratic risk, so there is evidence that the trade-off holds for mutual fund managers (albeit, not unanimous evidence, see, e.g., Clifford, Fulkerson, Jame, and Jordan, 2021). The trade-off can be linked to activeness because, while increased activeness could be expected to increase alpha, it

could likewise be expected to increase idiosyncratic volatility. We find, however, that the trade-off only occurs with respect to issuer-level active share. High issue-level active share is not associated with lower alpha but is associated with lower idiosyncratic volatility (and, in addition, lower downside risk). While notable for investors, this result also indicates that skilled bond fund managers have significant ability to select bond issues that will improve diversification.

Fifth, as detailed previously, we provide novel results on strategic complementarities—i.e., the expectation that some investors will withdraw increasing the incentive for other investors to withdraw, creating run risk. These complementarities have been hypothesized to lead to systemic risk (e.g., Chen, Goldstein, and Jiang, 2010; Kacperczyk and Schnabl, 2013; Schmidt, Timmerman, and Wermers, 2016; Goldstein, Jiang, and Ng, 2017; and Jin, Kacperczyk, Kahraman, and Suntheim, 2020), but our results indicate that highly active bond funds are of relatively limited systemic concern. Accordingly, bond funds with high active share can lessen financial fragility. We thus also contribute to the growing literature that examines fragility in open-end mutual funds in general and illiquid bond funds specifically (e.g., Chernenko and Sunderam, 2016; Di Maggio and Kacperczyk, 2017; Zeng, 2017; Chernenko and Sunderam, 2020; and Choi, Hoseinzade, Shin, and Tehranian, 2020). In particular, our results help explain the findings of Choi, Hoseinzade, Shin, and Tehranian (2020), which show little evidence of redemption-driven fire selling by bond funds.

More generally, our results explain the continued popularity of the actively managed bond fund industry. 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. Competition and efficiency are commonly regarded as being very high for domestic equity funds. Thus, the relative value of active management for domestic equity funds is low, and passive investing is more prominent.

Conversely, for bond funds, competition and efficiency are commonly regarded as being substantially lower, which increases the relative value of active management and decreases the attraction and (thus) prominence of passive investing.

3. Data and variable construction

In this section, we describe how we construct our main sample and calculate our measures of active share. We further provide summary statistics on our active share measures and analyze their determinants.

3.1. Data description

Our sample starts with data on taxable bond funds from Morningstar Direct. The time period spans 2002–2015. We start in 2002 because, prior to that year, Morningstar does not provide the comprehensive holdings information our analysis requires. The holdings data also provides information on security types, maturity, rating, and cash holdings. In addition to holdings, we use Morningstar to obtain information on each fund’s primary prospectus benchmark.⁹ The data from Morningstar includes both surviving and dead funds and thus is free from survivorship bias.

We merge the Morningstar data with the CRSP Survivor-Bias-Free Mutual Fund Database to obtain monthly fund returns and total net assets (TNA). We also use CRSP to obtain quarterly data on turnover, expense ratio, fund age, and other fund characteristics. Based on the Lipper style in CRSP, we divide bond funds into four categories: government, investment-grade, high-yield, and other.¹⁰ We only consider actively managed bond funds and exclude all passive bond funds from the sample.

⁹ Since July 1, 1993, Securities and Exchange Commission (SEC) rules have required mutual funds to provide a benchmark to investors in either the fund prospectus or annual report.

¹⁰ Specifically, funds with the Lipper codes “GUS,” “USM,” “GNM,” “IUG,” “GUT,” “SUS,” “SIU,” “TM,” “USS,” and “SUT” are government bond funds; “A,” “BBB,” “IID,” “MM,” “SID,” “SII,” and “USO” are investment-grade bond funds; and “HY,” “MSI,” and “ACF” are high-yield bond funds. The remainder are other bond funds.

Our analysis is conducted at the fund level, generally at a quarterly frequency (because Morningstar reports quarterly or monthly holdings). If a fund has multiple share classes, all characteristics that can vary across them (e.g., fees) are collapsed into a single asset-weighted average. The only exception is a fund's TNA, for which we use the sum across all share classes.

3.2. Measuring the activeness of bond funds

We propose a number of measures of bond fund activeness. In particular, we show how we calculate active share at different levels of holdings aggregation (issue, issuer, rating, and maturity) and how we separate internal and external active share.

3.2.1. Active share

To measure the extent to which bond funds are actively managed, we focus on a comparison between fund holdings and benchmark index holdings. We make that comparison using active share, which was first introduced in Cremers and Petajisto (2009). Active share, as we will detail, 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.

When calculating active share, a benchmark must be specified. We use each fund's primary prospectus benchmark. The compositions of bond benchmarks are not readily available, so we proxy for them using the holdings of index funds. In our sample, there are 26 benchmarks for which we have index fund holdings. When we have the holdings of multiple index funds for a single benchmark, we value-weight the holdings across the funds. In the Appendix, we provide a list of benchmarks and the number of funds using a given benchmark as their primary prospectus benchmark. The majority of funds use the Barclays Aggregate Bond Index (the "Agg").

Our first measure of active share considers the portfolio weights of each distinct security (i.e., bond issue). This issue-level active share, denoted by AS_{issue} , is calculated as

$$\text{Issue-Level Active Share} = AS_{\text{issue}} = \frac{1}{2} \sum_{i=1}^N |w_{\text{fund},i} - w_{\text{benchmark},i}|, \quad (1)$$

where $w_{\text{fund},i}$ and $w_{\text{benchmark},i}$ are the portfolio weights of bond issue i in the fund and its benchmark. The sum is taken over the entire universe of bond issues. AS_{issue} captures the overlap between a fund and its benchmark at the most granular level—the overlap with respect to individual bond issues.

Our second measure of active share considers the portfolio weights of each distinct bond issuer (e.g., the U.S. federal government or Microsoft). While issue-level active share treats different bond issues from the same issuer as independent securities, all of the issues from a given issuer tend to have similar fundamentals (e.g., default probability) even if the issues have different base characteristics (e.g., maturity). Issuer-level active share, denoted by AS_{issuer} , is calculated as

$$\text{Issuer-Level Active Share} = AS_{\text{issuer}} = \frac{1}{2} \sum_{i=1}^N |x_{\text{fund},i} - x_{\text{benchmark},i}|, \quad (2)$$

where $x_{\text{fund},i}$ and $x_{\text{benchmark},i}$ are the portfolio weights of issuer i in the fund and its benchmark. The sum is now taken over the universe of issuers. AS_{issuer} captures the overlap between a fund and its benchmark if all bond issues from a given issuer are treated as equivalent.

These first two measures of active share are designed to quantify related, but distinct, dimensions of active bond market investing. Because different bond issues from the same issuer have similar default probabilities, the active bond selection identified by issue-level active share primarily involves maturity and liquidity bets. In comparison, the active bond selection identified by issuer-level active share primarily involves detecting bonds that are underpriced given issuer fundamentals.

The next two active share measures allow us to quantify fund activeness with respect to credit rating and maturity. Active bond market investing can involve speculation on both general default probabilities and the term premium. For example, a fund could invest more in

high-maturity bonds than its benchmark, while limiting issuer selection. That choice would result in a relatively high maturity-level active share but relatively low issuer-level active share.

To calculate rating-level active share, denoted by AS_{rating} , we first aggregate each fund's portfolio weights by rating category. We then compare each fund's rating category weights to its benchmark's rating category weights:

$$\text{Rating-Level Active Share} = AS_{rating} = \frac{1}{2} \sum_{i=1}^N |y_{fund,i} - y_{benchmark,i}|, \quad (3)$$

where $y_{fund,i}$ and $y_{benchmark,i}$ are the portfolio weights of rating category i in the fund and its benchmark. The rating categories are based on firm-level credit ratings from S&P. We treat each ratings "notch" as a separate rating category.

We follow a matching procedure to calculate maturity-level active share, denoted by $AS_{maturity}$:

$$\text{Maturity-Level Active Share} = AS_{maturity} = \frac{1}{2} \sum_{i=1}^N |z_{fund,i} - z_{benchmark,i}|, \quad (4)$$

where $z_{fund,i}$ and $z_{benchmark,i}$ are the portfolio weights of maturity category i in the fund and its benchmark. The maturity categories are constructed by rounding each issue's current remaining maturity to the nearest integer in years. We treat each yearly maturity as a separate maturity category.

3.2.2. Internal and external active share

Bond funds have a variety of asset classes available to them. Although they often have a nominal investment focus, bond funds are rarely limited to a single class. Investment-grade corporate bond funds typically invest in treasury, agency, asset-backed, and high-yield corporate bonds, even when their primary prospectus benchmarks focus on investment-grade corporate

bonds. Therefore, we extend our previous active share measures by deconstructing them into their internal and external components.

Internal active share, denoted by $IntAS_{issue}$, measures the activeness of funds with respect to the securities inside their benchmark's asset classes. Conversely, external active share, denoted by $ExtAS_{issue}$, measures the funds' activeness with respect to securities outside those asset classes. Specifically, $IntAS_{issue}$ at the issue level is defined as

$$Issue\text{-Level Internal Active Share} = IntAS_{issue} = \frac{1}{2} \sum_{i \in A} |w_{fund,i} - w_{benchmark,i}|. \quad (5)$$

The sum is taken over the set of securities A , which corresponds to the asset classes of the fund's benchmark. We use five mutually exclusive asset classes: treasury, agency, investment-grade corporate, high-yield corporate, and other securities. Each benchmark in our sample is categorized into a combination of these asset classes based on the rules of the underlying index. $ExtAS_{issue}$ is the remaining active share. It is defined as

$$Issue\text{-Level External Active Share} = ExtAS_{issue} = AS_{issue} - IntAS_{issue}. \quad (6)$$

Internal and external active share for the other levels of active share (issuer, rating, and maturity) are calculated analogously. Note that, by construction, issue-level and issuer-level external active share are identical.

3.2.3. Tracking error and idiosyncratic volatility

In addition to our holdings-based activeness measures, we also consider tracking error, a traditional return-based measure of activeness. We calculate tracking error conventionally: the standard deviation of the differences between the fund and benchmark returns. As discussed by Cremers and Petajisto (2009), active share and tracking error capture different aspects of active management. Tracking error tends to capture whether a fund is engaged in factor timing, while active share tends to capture whether a fund is engaged in security selection. If a fund holds

different bonds than its benchmark, but has a highly diversified portfolio, then active share should be high and tracking error should be low.

We also use returns to calculate idiosyncratic volatility. As with tracking error, we measure idiosyncratic volatility conventionally: the standard deviation of the residuals from our factor model (described in the next subsection).

3.3. Measuring performance, flows, and maximum drawdown

We measure fund performance by estimating quarterly alphas using regressions of daily fund excess returns. Unlike with equity funds, there is little consensus on the correct factor model to measure bond fund performance. We use one stock market factor—the CRSP value-weighted market—and four bond factors. Each of the four bond factors is a Barclays index: Aggregate Bond, Treasury Bond, Corporate Bond, and High-Yield Bond. When estimating the alphas, we use the sum beta approach of Dimson (1979) to address the potential stale pricing issue.¹¹ As a robustness check, we considered alphas estimated from monthly returns and 24- and 36-month rolling windows and found qualitatively similar results.

Our measure of monthly flow for a given fund is constructed as

$$Flow_t = \frac{TNA_t - TNA_{t-1} * (1 + r_t)}{TNA_{t-1}}, \quad (7)$$

where TNA_t is total net assets at the end of month t and r_t is monthly return during month t . Following Coval and Stafford (2007), we define a fund's quarterly flow as the sum of the monthly flows during the quarter.

The maximum drawdown (MDD) in a given month for a given fund is calculated as

$$MDD = \frac{(P_{min} - P_{max})}{P_{max}}, \quad (8)$$

¹¹ Specifically, for each factor f we include its contemporaneous return $r_{f,t}$, its one-day lagged return $r_{f,t-1}$, and the average of its returns on day $t-2$ through $t-4$: $(r_{f,t-2} + r_{f,t-3} + r_{f,t-4})/3$.

where P_{min} and P_{max} are the minimum and maximum fund prices during the month. We define a fund's quarterly MDD as the average of the fund's monthly MDDs during the quarter.

3.4. Summary statistics: Active investing in bond funds

Table 1 provides summary statistics for our primary variables. The sample consists of 541 unique funds with 17,060 quarterly observations. Starting with Panel A, we find that bond funds exhibit high levels of activeness. The average issue-level active share for bond funds is 93.2%, which is much higher than the average active share for equity funds. Cremers and Petajisto (2009) report that, in the post-2000 period, the average active share for an equity fund is only about 60%. This difference is driven by the fact that the bond universe provides more investment options, even within the same set of issuers. If we make the option sets similar in size by aggregating bond holdings at the issuer level, we find that bond and equity funds are similarly active. The average issuer-level active share for bond funds is 60.2%. Notably, the average internal active share is almost 84%, indicating that the majority of issue-level activeness comes from investing within their primary asset classes. The average fund has a tracking error of 2.11% per year, much lower than the tracking error shown for equity funds in Cremers and Petajisto (2009). Given the difference in volatility between equities and bonds, however, this difference is expected.

Moving onto other fund characteristics, we find that the average bond fund has a positive flow. That result is consistent with the overall growth of bond funds during our sample period. The average net alpha is negative at -1.61% per year, which is consistent with the prior bond fund literature (e.g., Blake, Elton, and Gruber, 1993; Chen, Ferson, and Peters, 2010; and Chen and Qin, 2017). The average fund manages \$1.4 billion in total net assets (TNA), charges an expense ratio of 0.80%, and has a turnover ratio of 179%. The high turnover level suggests that bond funds are not typically buy-and-hold investors. We also report the illiquidity of bond funds by calculating

the fraction of zero trading days (ZTDs) in their holdings.¹² The average ZTD is 16.9%, but the standard deviation is 15.2%, which suggests significant variation in liquidity.

Panel B shows separate summary statistics for each of our four styles: government (GB), investment-grade (IG), high-yield (HY), and other (OTHER). The styles have similar average issue-level active share. The lone exception is other, which is substantially lower. The variation in active share across the styles is larger at the issuer, rating, and maturity levels. Illiquidity, as proxied by ZTD, is highest within the high-yield style, consistent with high-yield bonds being relatively illiquid. All of the styles tend to invest outside of their primary asset classes. Most notably, though, funds with an investment-grade style hold an average of 45.8% of their assets in government bonds and only 30.1% of their assets in investment-grade bonds.

3.5. Explaining the active share of bond funds

In Table 2, we examine what explains issue- and issuer-level active share using quarterly panel regressions. In columns (1) through (5), we regress issue-level active share on a set of lagged explanatory variables. The set includes issuer-, rating-, and maturity-level active share; dummy variables indicating fund style; and many other fund-level characteristics. In columns (6) through (8), we regress issuer-level active share on the same set of explanatory variables. All specifications also include quarterly time fixed effects. The reported *t*-statistics are derived from standard errors two-way clustered at the fund and quarter levels. This two-way clustering accounts for both time-series and cross-sectional correlations and results in considerably more conservative *t*-statistics than one-way clustering.

¹² Following Choi, Kronlund, and Oh (2020), ZTDs are first calculated for each security and then averaged (value-weighted) for each fund-quarter, using the transactions reported in the TRACE database. With the exception of corporate bonds, trading data for bonds is generally not available, but other types of bonds tend to be much more liquid than corporate bonds (e.g., Treasury and agency bonds). We assume, therefore, 100% ZTDs for non-corporate bonds.

The results in Table 2 show that dispersion in issue-level active share is largely explained by variation in issuer-, rating-, and maturity-level active share, indicating that funds take active bets with respect to these dimensions. As shown in column (2), for example, a one standard deviation increase in issuer-level active share (21.5%) is associated with an increase in issue-level active share of 6.8% ($=0.215*0.316$). That increase is 47.9% of the standard deviation of issue-level active share. In the multiple regression shown in column (5), however, we find that rating-level active share is no longer statistically significant, suggesting that funds in our sample focus on issuer and maturity bets. The impact of fund style varies, but in the full model in column (5), funds with an investment-grade style have higher issue-level active share than funds with a government style (which is the base level). Conversely, funds with a high-yield or other style have lower issue-level active share than funds with a government style.

Looking at the other fund characteristics, we find that funds with higher turnover or lower TNA have higher issue-level active share. These results suggest that funds that trade more often tend to be more active and that, as funds increase in size, their holdings increasingly resemble their benchmark's holdings. The fraction of a fund's portfolio invested in cash, other funds (e.g., ETFs and index funds), or other securities is positively related to issue-level active share. Accordingly, we include these variables as controls in later regression analyses.

In columns (6) through (8), we find that, as with issue-level active share, a significant portion of the dispersion in issuer-level active share is captured by more aggregated levels of active share (i.e., rating- and maturity-level active share). For example, as shown in column (6), a one standard deviation increase in rating-level active share (21.6%) is associated with an increase in issuer-level active share of 13.4% ($=0.620*0.216$). That increase is 62.3% of the standard deviation of issuer-level active share. For funds with high turnover, issuer-level active share—unlike

issue-level active share—is lower. This could be because funds that are highly active at the issuer level buy bonds with relatively low liquidity, which would discourage them from frequent trading. While there is limited evidence of a positive relation between issue-level active share and expense ratio, the relation is stronger at the issuer level, as shown in column (8). Hence, more active management, on average, leads to higher costs for fund investors. Inflows are associated with lower issuer-level active share, but weakly higher issue-level active share. This result suggests that bond funds tend to invest new capital in the same issuers as their benchmarks, but not necessarily the same issues, which could indicate an attempt at minimizing transaction costs.

4. Main empirical results

In this section, we provide evidence showing that active investing in bond funds is associated with superior performance, persistence in outperformance, better downside risk management, and lower run risk. After establishing these results using our Morningstar sample covering 2002 through 2015, we demonstrate their robustness by providing out-of-sample replications using a CRSP sample covering 2016 through 2019.

4.1. Active share and future fund performance

In Table 3, we consider the extent to which active share can predict fund performance by regressing quarterly fund alphas on issue- and issuer-level active share and a number of control variables (all of which are lagged by one quarter). Different specifications also include style, fund, and time fixed effects. As before, the reported t -statistics are derived from standard errors two-way clustered at the fund level and quarter level.

Table 3, Panel A shows that active share positively predicts fund performance in the next quarter. Starting with column (1), we find that the coefficient associated with issue-level active share is positive, but statistically insignificant. Nevertheless, column (2) shows that, after including

fund fixed effects, the coefficient substantially increases in magnitude and becomes statistically significant at the 5% level. A one standard deviation increase in issue-level active share (14.2%) is associated with an increase in annualized alpha of 0.91% ($=6.438 \cdot 14.2$). Thus, when a fund increases its activeness at the issue level, its alpha tends to subsequently improve.

Panel A further shows that issuer-level active share predicts fund performance in both the cross section and time series. In columns (3) and (4), the coefficients on issuer-level active share are statistically significant at the 1% level. The economic magnitude is also sizable. In the cross section, a one standard deviation increase in issuer-level active share (21.5%) is associated with an increase in annualized alpha of 0.30% ($=1.384 \cdot 21.5$). Columns (5) and (6), which include both issue- and issuer-level active share, show that only issuer-level active share remains statistically significant. The outcome of this test suggests that bond funds outperform when they are active in choosing across issuers, while within-issuer active investing does not lead to outperformance.

In Panel B, we test the predictive power of active share after separating it into its internal and external components. The results from this test are informative of managerial skill because internal and external active share should separate active investing within funds' primary asset classes—where we expect fund managers to have greater expertise—from active investing outside funds' primary asset classes. In these regression analyses, we include external active share at the issue level only, as it is identical to issuer-level external active share. The results in Panel B show that internal active share has stronger predictive power for future performance than external active share, which is consistent with our expertise framework. While the coefficients on external active share are statistically significant in columns (2) and (6), we find a more reliable positive relationship associated with internal issuer-level active share, as shown in columns (3) through (6). These results suggest that an investor choosing between funds should, therefore, focus on internal

active share. Put another way, the investor should focus on a fund's benchmark deviations within the fund's primary asset classes.

The coefficients associated with tracking error in both Panel A and Panel B also merit discussion. We consistently find a statistically significant, negative relation between tracking error and fund performance. In column (6) of Panel B, a one standard deviation increase in tracking error (1.53%) is associated with a decrease in annualized alpha of 0.52% ($=-0.339*1.53$). Thus, of the two proxies for active investing we consider—active share and tracking error—only active share has positive predictive power. This result implies that high levels of bond selectivity, but not factor timing, drive the increase in bond fund alpha.

4.2. Performance persistence

If a fund manager possesses investment skill, their performance should be persistent, particularly for positive performance.¹³ In this subsection, we investigate whether more active bond funds exhibit higher persistence in alpha. To make our evaluation, we take an approach similar to the one in the previous subsection, but add interactions between lagged alpha and different measures of active share.

Panel A of Table 4 shows that fund performance is more persistent when active share is high. The coefficients associated with interactions between lagged alpha and active share are consistently positive and statistically significant. In columns (2) and (3), for example, the interaction coefficients for issue- and issuer-level active share are 0.463 and 0.328 with t -statistics of 6.35 and 4.40, respectively. A one standard deviation increase in issue-level active share

¹³ The Berk and Green (2004) equilibrium model contends otherwise. 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; Reuter and Zitzewitz, 2015; Rohleder, Scholz, and Wilkens, 2018; Yan, 2020; and Jones and Mo, 2021).

(14.2%) is associated with an increase in the coefficient on lagged alpha of 0.07 ($=0.463*0.142$). That increase is 55% of the average persistence of alpha (0.128) reported in column (1).

We also find, in Panel A, that performance persistence tends to be stronger when internal active share is high, suggesting that managers who exhibit activeness within the asset classes of their expertise tend to be skilled. Both the base coefficient associated with external active share and its interaction with lagged alpha are statistically insignificant after we account for internal active share at the issuer level. Consequently, investment skill that leads to persistent performance appears to manifest itself the most in a fund manager's ability to choose the right issuers within the fund's primary asset classes.

In Panel B of Table 4, we examine whether this stronger performance persistence is a “hot hand” or “cold hand” phenomenon. To investigate this question, we first separate lagged alpha into two variables—positive alpha and negative alpha—then interact each with active share. The stronger performance persistence is shown to be a “hot hand” phenomenon. The coefficients associated with the interaction between active share and positive alpha are positive and highly statistically significant. Using issue-level active share in column (3), for example, the coefficient is 1.016, which is more than double the magnitude of the matching coefficient in Panel A (0.463). In comparison, the coefficients associated with the interaction between active share and negative alpha are much smaller in economic magnitude and statistically insignificant. These results suggest that the managers of highly active bond funds are skilled. That inference contrasts with the equity fund results of Carhart (1997).

4.3. Impact of active share on flow-performance sensitivity

In recent studies, 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 a redemption request often occur on later days. This timing mismatch creates a first-mover advantage, as the non-redeeming fund investors bear the costs from 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). The run risk is magnified when funds hold illiquid assets, which is typically the case for bond funds.

These strategic complementarities can be seen empirically in the relation between fund flows and performance. When run risk is high, there should be more outflows in response to poor performance, because investors will attempt to be the first-movers. Here, we examine how fund activeness is related to this flow-performance relation. There are multiple ways in which activeness could affect investors' reactions to performance. Investors could be more sensitive to positive performance from more active funds, since the performance of those funds is more likely to represent skill (see Table 4, Panel B). Investors could also be less sensitive to negative performance from those funds. More active funds could have less run risk—and experience fewer outflows following poor performance—if increased activeness is associated with better downside risk management (see Section 4.4.1) or if more active managers are more skilled at managing liquidation costs.

We test how activeness affects the flow-performance relation using active share. Table 5 reports the results of a regression in which fund flow in the next quarter is regressed on current-quarter fund alpha interacted with an indicator for high active share (top 25% in the cross section). We find that the flows to funds with high active share are less sensitive to

underperformance and more sensitive to outperformance. In column (1), which uses issue-level active share, the sensitivity to underperformance for high active share funds ($0.110=0.218-0.108$) is about half that of other funds (0.218). Likewise, the sensitivity to outperformance almost doubles for high active share funds (0.181 versus $0.352=0.181+0.171$). The end result is that, for bond funds without high active share, the flow-performance relation is linear to concave (0.218 for negative alphas and 0.181 for positive alphas), which is consistent with Goldstein, Jiang, and Ng (2017). For bond funds with high active share, however, the relation is strongly convex (0.110 for negative alphas and 0.352 for positive alphas). This difference suggests that a high level of active management reduces strategic complementarities and lessens run risk.

When we repeat the analysis using issuer-level active share, the results are similar, but weaker statistically. This diminished effect should be expected. The management of a fund's liquidity is, in general, an issue-level matter.

4.4. Relation between active share and fund risk

We now consider how the extent of active management impacts fund risk. In particular, we analyze the relation between a fund's active share and its MDD, total volatility, and idiosyncratic volatility.

4.4.1. Maximum drawdown

We first examine whether activeness reduces downside risk, as measured by MDD. Table 6, Panel A shows results from regressions of next-quarter MDD on active share. We find that as active share increases, MDD also increases, which is analogous with downside risk decreasing. In column (1), for example, the coefficient associated with issue-level active share is 1.407 with a *t*-statistic of 3.47. That coefficient implies that a one standard deviation increase in issue-level active share (14.2%) will increase MDD by 0.20% ($=1.407*0.142$). An increase of that size is

large: it is equivalent to 16.9% ($=0.20/1.18$) of MDD's standard deviation (1.18%). Importantly, higher issue-level active share does not predict lower performance (see Table 3), so this improved downside risk protection is not at the expense of a reduction in alpha.

When we include both issue- and issuer-level active share in columns (5) and (6), only issue-level active share is positive and statistically significant. Hence, the mitigation of downside risk by highly active funds appears to be driven by their avoidance of particular issues, not issuers. Thus, while the managers of funds with high issue-level active share might not generate the same alphas as the managers of funds with high issuer-level active share, they are more effective at managing risk. Such management could be achieved through, for example, opportunistic investing in low duration bonds in anticipation of increasing interest rates. This result also highlights the importance of considering both issue- and issuer-level active share when measuring the degree of active bond investing. Both provide different, but useful, information on fund performance and risk. Higher issuer-level active share predicts higher alpha, and higher issue-level active share predicts lower downside risk. In combination, they suggest that more active bond fund managers have greater skill with respect to both risk and return.

Table 6 contains three other notable results. First, higher tracking error tends to increase downside risk. As shown in column (1) of Panel A, a one standard deviation increase in tracking error (1.53%) is associated with a decrease in MDD of 0.42% ($=1.53* -0.276$). That result, in combination with the results from Table 3, suggests that high tracking error both decreases alpha and increases risk. Second, in Panel B, we find that both internal and external active share are positively related to MDD. This relation implies that active investing both inside and outside of a fund's primary asset classes can reduce downside risk. Third, the issue-level internal active share

has a larger effect than its issuer-level equivalent. This outcome again indicates that downside risk management tends to be about the avoidance of particular issues, not issuers.

4.4.2. Volatility

We next examine whether activeness reduces volatility—both total and idiosyncratic. It is important to consider each form of volatility, as each affects investors' portfolios differently. Total volatility can add undiversifiable systematic risk, whereas idiosyncratic volatility can be diversified away through investors' other holdings.

Table 7, Panel A shows results from regressions of next-quarter idiosyncratic volatility on active share.¹⁴ We find that the impact of active share is mixed. Issuer-level active share is consistently associated with higher idiosyncratic volatility. In column (3), for example, a one standard deviation increase in issuer-level active share (21.5%) is associated with an increase in annualized idiosyncratic volatility of 0.137% ($=0.635 \times 0.215$). However, depending on the model, issue-level active share has either no relation, a positive relation, or a negative relation with idiosyncratic volatility. Controlling for issuer-level active share in columns (5) and (6), we find that increasing issue-level active share decreases idiosyncratic volatility in the cross section but has no statistically significant effect in the time series. Thus, when comparing two funds with the same issuer-level active share, an investor can expect the fund with greater issue-level active share to have lower idiosyncratic volatility.

In Panel B, we repeat the previous test using internal and external active share. As external active share increases, so does idiosyncratic volatility. The coefficients associated with external active share in columns (2) through (6) are all positive and statistically significant at conventional

¹⁴ In this instance, we do not include tracking error as a control variable, because, by construction, it is highly correlated with idiosyncratic volatility.

levels, which suggests that active investing outside of a fund's primary asset classes increases idiosyncratic volatility. The results for internal active share are consistent with Panel A. Specifically, (i) increases in issuer-level internal active share are associated with increases in idiosyncratic volatility and (ii) when we control for issuer-level internal active share, increases in issue-level internal active share are associated with decreases in idiosyncratic volatility in the cross section.

The increase in idiosyncratic volatility associated with some forms of active share is not necessarily a significant problem for investors. A fund's idiosyncratic volatility can be diversified away by an investor who also holds other imperfectly correlated assets. Therefore, in Panel C, we repeat Panel B using total volatility, which is largely undiversifiable. As with idiosyncratic volatility, increasing issuer-level internal active share increases total volatility. However, increasing external active share has no statistically significant effect on total volatility. Issue-level internal active share has the same nuanced relation with total volatility as it does with idiosyncratic volatility.

Considered as a whole, our results with respect to volatility should be interpreted carefully. On the one hand, funds that are highly selective at the issuer level have greater volatility. This result is consistent with the trade-off between activeness and volatility—superior performance achieved through active issuer-level investing often comes at the cost of more portfolio concentration and less diversification. On the other hand, funds that are also highly selective at the issue level can, at least in part, offset that greater volatility.

4.5. Time-series variation in the impact of active share

The prior literature has shown that the payoff to active management is time-varying (von Reibnitz, 2017) and that skilled active managers create value through different means in different

market conditions (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2014). In this subsection, we focus on how market conditions affect the impact of active share. Specifically, in Table 8, we repeat our previous tests on fund alpha, MDD, and idiosyncratic volatility, but interact active share with two measures—the VIX and the TED spread—that have been used previously to capture market conditions (Frazzini and Pedersen, 2014; and Boguth and Simutin, 2018). Both of these measures have significant variation during our sample period, which includes the financial crisis.

Panel A shows results for fund alpha. We find that the benefit of high active share is concentrated during “good times” (i.e., when the VIX and TED spread are low). Across all specifications, the coefficients associated with the interaction terms are negative and statistically significant. In column (3), for example, the interaction between issuer-level active share and the VIX has a coefficient of -5.192 with a t -statistic of -7.42 . Because we standardize our market condition variables, that coefficient is equivalent to a one standard deviation increase in the VIX decreasing the impact of issuer-level active share on alpha by 5.192. The average effect for the equivalent test in Table 3 was just 1.384, so the influence of market conditions is large. These results suggest that, although bond funds with high active share outperform on average, their outperformance dissipates when markets are distressed.

In Panel B, we consider the effect of market conditions on MDD. Consistent with our previous results, funds with high issue-level active share tend to have better downside risk management. During average market conditions, an increase in issue-level active share increases MDD. During “bad times,” the increase in MDD is magnified. In column (5), for example, a one standard deviation increase in the TED spread increases the coefficient associated with issue-level active share by 0.501, a 31.8% increase ($=0.501/1.575$).

Conversely, high issuer-level active share raises downside risk. As shown in column (7), a one standard deviation increase in the TED spread decreases the coefficient associated with issuer-level active share by 0.257. That coefficient is only 0.161 during average market conditions, so after the TED spread passes 0.63 ($=0.161/0.257$) standard deviations above average, increasing issuer-level active share decreases MDD. These results, in Panel B, reiterate the importance of accounting for multiple levels of active share. While higher issuer-level active share is associated with higher alpha, an investor concerned with managing downside risk, particularly during “bad times,” would want to focus on higher issue-level active share.

We further consider risk in Panel C by turning to idiosyncratic volatility. As before, high issue-level active share is associated with lower risk, especially in “bad times.” In column (1), for example, a one standard deviation increase in the VIX decreases the coefficient associated with issue-level active share by 0.596. The average effect in the equivalent test in Table 7 was a statistically insignificant -0.322 , suggesting that the influence of market conditions is large. In contrast, high issuer-level active share is weakly associated with higher idiosyncratic volatility during “bad times.” The coefficients on the interaction terms are positive, but generally not statistically significant at conventional levels. These relations echo our previous assessment that both issue- and issuer-level active share contain important information for investors.

As a whole, these results indicate that highly active bond funds tend to outperform during “good times” and display better risk management during “bad times.” However, an investor who wants to capture both of these facets of skilled active management must consider different levels (issue and issuer) of active share.

4.6. *Out-of-sample results*

Our Morningstar-supplied data on bond fund holdings ends in 2015. Updating the data through 2019 using Morningstar is extremely labor-intensive, as Morningstar no longer provides a batch download for academic purposes. Therefore, instead of performing a full Morningstar update, we use the fund holdings available in CRSP to update our key data—issue- and issuer-level active share—over the 2016–2019 period. We then employ this later period to perform an out-of-sample test of whether our key results are robust. Unlike *pseudo* out-of-sample tests in which researchers have access to both the primary and additional data and can tweak the model to improve the out-of-sample fit, this data extension exercise serves as a *true* out-of-sample test. Our results from the primary Morningstar data were obtained in mid-2017 and were in public circulation before we accessed the additional CRSP data (most of which had not occurred or had not been tabulated in mid-2017).

As a rule, we prefer the Morningstar holdings data because it is more detailed than the CRSP holdings data. Unlike Morningstar, CRSP neither categorizes individual fund holdings (e.g., corporate bond, treasury bond, agency bond, derivative) nor provides the information necessary for an efficient manual individual categorization. This lack of categorization prevents us from calculating internal and external active share. Furthermore, the CRSP data has significant inaccuracies prior to 2008 (Schwarz and Potter, 2016). In light of these constraints, we focus on the out-of-sample replication of our key results for which these constraints are not binding.

The 2016–2019 sample has 470 unique funds and 4,755 fund-quarter observations. The new sample has about 87% as many unique funds as the original sample, which indicates good cross-sectional coverage. Due to the shorter time period, however, the new sample has only 29% as many fund-quarter observations. Given this smaller sample, we focus our replication on certain

estimation methods. First, we estimate the models using fund-style fixed effects rather than fund fixed effects. Active share is highly correlated from quarter to quarter, so identifying the impact of within-fund changes in active share is difficult over a short time period. Second, we do not try to differentiate the effects of issue- and issuer-level active share. The two measures are highly correlated, so their effects are difficult to differentiate in a small sample. We instead focus each replication on the measure that was the most powerful in the original sample.

Table 9 replicates the results for the three key findings mentioned in our paper’s abstract: alpha (Table 3), flow sensitivity (Table 5), and downside risk (Table 6). To ease comparison, we show both the previously reported results from the 2002–2015 period and the new results from the 2016–2019 period. With respect to alpha, we find similar results in the two samples. An increase in issuer-level active share predicts an increase in alpha in both samples, with similar economic magnitude and statistical significance. With respect to flow sensitivity, the conclusion is also similar: unlike other bond funds, high active share bond funds have a convex flow-performance relation. Finally, with respect to downside risk, as issue-level active share increases, downside risk decreases to statistically and economically similar degrees in both samples. The fact that each of our key findings obtains in our out-of-sample replication is a meaningful indication of their robustness.

5. Conclusion

Passive investing is experiencing rapid growth. Assets invested in passively managed mutual funds grew from \$835 billion in 2009 to \$4.28 trillion in 2019—a geometric growth rate of 17.7% per year. This growth has generally come at the expense of actively managed funds. Over the same 2009–2019 time period, actively managed equity funds had a total net outflow of \$2.10 trillion. In contrast to the equity trend, actively managed bond funds during that period had a total

net inflow of \$1.16 trillion.¹⁵ Our study addresses the natural question arising from these statistics: why are actively managed bond funds still popular with investors?

On the surface, the answer is simple: our results show that highly active bond funds tend to create value for investors. That summary, however, masks significant complexity.

Using a novel adaptation of the active share measure of Cremers and Petajisto (2009), we show the importance of measuring bond fund activeness at multiple levels. Bond funds resemble equity funds in average activeness at the issuer level, but are more active, on average, at the issue level. High active share at the issuer level predicts greater alpha and greater positive performance persistence, while high active share at the issue level is associated with better risk management, particularly with respect to downside risk. The performance effect is strongest in relatively calm markets (e.g., low VIX), and the risk effect is strongest in relatively volatile markets. These results suggest that highly active bond fund managers have skill in knowing which issuers to select and which issues from those issuers to avoid.

Highly active bond funds also appear to be less subject to strategic complementarities. Goldstein, Jiang, and Ng (2017) discuss a first-mover advantage for mutual fund investors that arises because non-redeeming investors tend to bear the cost of fund trades made in response to other investors' redemptions. In the average bond fund, this first-mover advantage can be seen empirically through a concave flow-performance relation—i.e., following poor performance, investors redeem en masse in an attempt to be the first-mover. Among high active share bond funds though, the flow-performance relation is convex, suggesting that those funds have relatively low run risk. Our observation that strategic complementarities are lessened when a bond fund is highly active is important for both investors and securities regulators.

¹⁵ These statistics are from the 2020 Investment Company Fact Book, which is available at https://www.ici.org/pdf/2020_factbook.pdf.

References

- Alexander, Gordon, Gjergji Cici, and Scott Gibson. Does motivation matter when assessing trade performance? An analysis of mutual funds. *Review of Financial Studies* 20, 125-250.
- Amihud, Yakov, and Ruslan Goyenko. 2013. Mutual fund's R^2 as predictor of performance. *Review of Financial Studies* 26, 667-694.
- Bai, Jennie, Turan Bali, and Quan Wen. 2019. Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics* 131, 619-642.
- Berk, Jonathan, and Jules van Binsbergen. 2015. Measuring skill in the mutual fund industry. *Journal of Financial Economics* 118, 1-20.
- Berk, Jonathan, and Jules van Binsbergen. 2017. Mutual funds in equilibrium. *Annual Review of Financial Economics* 9, 147-167.
- Berk, Jonathan, and Richard Green. 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy* 112, 1269-1295.
- Blake, Christopher, Edwin Elton, and Martin Gruber. 1993. The performance of bond mutual funds. *Journal of Business* 66, 371-403.
- Bodnaruk, Andriy, Bekhan Chokaev, and Andrei Simonov. 2019. Downside risk timing by mutual funds. *Review of Asset Pricing Studies* 9, 171-196.
- Brown, David, and Shaun William Davies. 2017. Moral hazard in active asset management. *Journal of Financial Economics* 125, 311-325.
- Carhart, Mark. 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.
- Chen, Honghui, Hemang Desai, and Srinivasan Krishnamurthy. 2013. A first look at mutual funds that use short sales. *Journal of Financial and Quantitative Analysis* 48, 761-787.
- Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers. 2000. The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. *Journal of Financial and Quantitative Analysis* 35, 343-368.
- Chen, Qi, Itay Goldstein, and Wei Jiang. 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics* 97, 239-262.
- Chen, Yong, Wayne Ferson, and Helen Peters. 2010. Measuring the timing ability and performance of bond mutual funds. *Journal of Financial Economics* 98, 72-89.
- Chernenko, Sergey, and Adi Sunderam. 2016. Liquidity transformation in asset management: Evidence from the cash holdings of mutual funds. Working paper.
- Chernenko, Sergey, and Adi Sunderam. 2020. Do fire sales create externalities?. *Journal of Financial Economics* 135, 602-628.
- Choi, Jaewon, and Mathias Kronlund. 2018. Reaching for yield in corporate bond mutual funds. *Review of Financial Studies* 31, 1930-1965.
- Choi, Jaewon, Mathias Kronlund, and Ji Yeol Jimmy Oh. 2020. Sitting bucks: Zero returns in fixed income funds. Working paper.

- Choi, Jaewon, Saeid Hoseinzade, Sean Seunghun Shin, and Hassan Tehranian. 2020. Corporate bond mutual funds and asset fire sales. *Journal of Financial Economics* 138, 432-457.
- Christoffersen, Susan, and Mikhail Simutin. 2017. On the demand for high-beta stocks: Evidence from mutual funds. *Review of Financial Studies* 30, 2596-2620.
- Cici, Gjergji, and Scott Gibson. 2012. The performance of corporate bond mutual funds: Evidence based on security-level holdings. *Journal of Financial and Quantitative Analysis* 47, 159-178.
- Clifford, Christopher, Jon Fulkerson, Russell Jame, and Bradford Jordan. 2021. Saliency and mutual fund investor demand for idiosyncratic volatility. *Management Science*, forthcoming.
- Cohen, Lauren, Andrea Frazzini, and Christopher Malloy. 2008. The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy* 116, 951-979.
- Cohen, Randolph, Joshua Coval, and Lubos Pastor. 2005. Judging fund managers by the company they keep. *Journal of Finance* 60, 1057-1096.
- Cohen, Tim, Brian Leite, Darby Nielson, and Andy Browder. 2014. Active share: A misunderstood measure in manager selection. Fidelity research.
- Coval, Joshua, and Erik Stafford. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics* 86, 479-512.
- Coval, Joshua, and Tobias Moskowitz. 2001. The geography of investment: Informed trading and asset prices. *Journal of Political Economy* 109, 811-841.
- Cremers, Martijn, and Ankur Pareek. 2016. Patient capital outperformance: The investment skill of high active share managers who trade infrequently. *Journal of Financial Economics* 122, 288-306.
- Cremers, Martijn, and Antti Petajisto. 2009. How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies* 22, 3329-3365.
- Cremers, Martijn, Jon Fulkerson, and Timothy Riley. 2019. Challenging the conventional wisdom on active management: A review of the past 20 years of academic literature on actively managed mutual funds. *Financial Analysts Journal* 75, 8-35.
- Cremers, Martijn, Miguel Ferreira, Pedro Matos, and Laura Starks. 2016. Indexing and active fund management: International evidence. *Journal of Financial Economics* 120, 539-560.
- Di Maggio, Marco, and Marcin Kacperczyk. 2017. The unintended consequences of the zero lower bound policy. *Journal of Financial Economics* 123, 59-80.
- Dimson, Elroy. 1979. Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics* 7, 197-226.
- Dyck, Alexander, Karl Lins, and Lukasz Pomorski. 2013. Does active management pay? New international evidence. *Review of Asset Pricing Studies* 3, 200-228.
- Falato, Antonio, Ali Hortacsu, Dan Li, and Chaehee Shin. 2020. Fire-sale spillovers in debt markets. *Journal of Finance*, forthcoming.
- Fama, Eugene. 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance* 25, 383-417.

- Frazzini, Andrea, Jacques Friedman, and Lukasz Pomorski. 2016. Deactivating active share. *Financial Analysts Journal* 72, 14-21.
- Goldstein, Itay, Hao Jiang, and David Ng. 2017. Investor flows and fragility in corporate bond funds. *Journal of Financial Economics* 126, 592-613.
- Gronborg, Niels, Asger Lunde, Allan Timmermann, and Russ Wermers. 2021. Picking funds with confidence. *Journal of Financial Economics* 139, 1-28.
- Gruber, Martin. 1996. Another puzzle: The growth in actively managed mutual funds. *Journal of Finance* 51, 783-810.
- Gutierrez, Roberto, William Maxell, and Danielle Xu. 2009. On economies of scale and persistent performance in corporate-bond mutual funds. Working paper.
- Harvey, Campbell. 2017. Presidential address: The scientific outlook in financial economics. *Journal of Finance* 72, 1399-1440.
- Hearth, Douglas, James Philpot, James Rimbey, and Craig Schulman. 1998. Active management, fund size, and bond mutual fund returns. *Financial Review* 33, 115-126.
- Hoberg, Gerard, Nitin Kumar, and Nagpurnanand Prabhala. 2018. Mutual fund competition, managerial skill, and alpha persistence. *Review of Financial Studies* 5, 1896-1929.
- Hunter, David, Eugene Kandel, Shmuel Kandel, and Russ Wermers. 2014. Mutual fund performance evaluation with active peer benchmarks. *Journal of Financial Economics* 112, 1-29.
- Ioannidis, John. 2005. Why most published research findings are false. *PLoS Med* 2, e124.
- Jensen, Michael. 1968. The performance of mutual funds in the period 1945–1964. *Journal of Finance* 23, 389-416.
- Jin, Dunhong, Marcin Kacperczyk, Bige Kahraman, and Felix Suntheim. 2020. Swing pricing and fragility in open-end mutual funds. Working paper.
- Jones, Christopher, and Haitao Mo. 2021. Out-of-sample performance of mutual fund predictors. *Review of Financial Studies* 34, 149-193.
- Jordan, Bradford, and Timothy Riley. 2015. Volatility and mutual fund manager skill. *Journal of Financial Economics* 118, 289-298.
- Kacperczyk, Marcin, and Amit Seru. 2007. Fund manager use of public information: New evidence on managerial skills. *Journal of Finance* 62, 485–528.
- Kacperczyk, Marcin, and Phillip Schnabl. 2013. How safe are money market funds?. *Quarterly Journal of Economics* 128, 1073-1122.
- Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng. 2005. On the industry concentration of actively managed equity mutual funds. *Journal of Finance* 60, 1983-2011.
- Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng. 2008. Unobserved actions of mutual funds. *Review of Financial Studies* 21, 2379-2416.
- Kacperczyk, Marcin, Stijn van Nieuwerburgh, and Laura Veldkamp. 2014. Time-varying fund manager skill. *Journal of Finance* 69, 1455-1484.

- Pastor, Lubos, Robert Stambaugh, and Lucian Taylor. 2017. Do funds make more when they trade more? *Journal of Finance* 72, 1483-1528.
- Pastor, Lubos, Robert Stambaugh, and Lucian Taylor. 2020. Fund tradeoffs. *Journal of Financial Economics* 138, 614-634.
- Petajisto, Antti. 2013. Active share and mutual fund performance. *Financial Analysts Journal* 69, 73-93.
- Reuter, Jonathan, and Eric Zitzewitz. 2015. How much does size erode mutual fund performance? A regression discontinuity approach. Working paper.
- Rohleder, Martin, Hendrik Scholz, and Marco Wilkens. 2018. Success and failure on the corporate bond fund market. *Journal of Asset Management* 19, 429-443.
- Schlanger, Todd, Christopher Phillips, and Karin Peterson LaBarge. 2012. The search for outperformance: Evaluating 'active share'. Vanguard white paper.
- Schmidt, Lawrence, Allan Timmermann, and Russ Wermers. 2016. Runs on money market mutual funds. *American Economic Review* 106, 2625-2657.
- Schwarz, Christopher, and Mark Potter. 2016. Revisiting mutual fund portfolio disclosure. *Review of Financial Studies* 29, 3519-3544.
- Sensoy, Berk. 2009. Performance evaluation and self-designated benchmark indexes in the mutual fund industry. *Journal of Financial Economics* 92, 25-39.
- Sialm, Clemens, Laura Starks, and Hanjiang Zhang. 2015. Defined contribution pension plans: Sticky or discerning money? *Journal of Finance* 70, 805-838.
- Titman, Sheridan, and Cristian Tiu. 2011. Do the best hedge funds hedge?. *Review of Financial Studies* 24, 123-168.
- Treynor, Jack, and Fischer Black. 1973. How to use security analysis to improve portfolio selection. *Journal of Business* 46, 66-86.
- von Reibnitz, Anna. 2017. When opportunity knocks: Cross-sectional return dispersion and active fund performance. *Critical Finance Review* 6, 303-356.
- Wermers, Russ. 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *Journal of Finance* 55, 1655-1703.
- Yan, Zhen. 2020. Returns to scale among corporate bond mutual funds. Working paper.
- Zeng, Yao. 2017. A dynamic theory of mutual fund runs and liquidity management. Working paper.
- Zheng, Lu. 1999. Is money smart? A study of mutual fund investors' fund selection ability. *Journal of Finance* 54, 901-933.

Appendix: Bond Fund Benchmarks

Primary Benchmark	Morningstar ID	Number of Funds
Barclays US Agg Bond	XIUSA000MC	369
Barclays US Govt/Credit Interm	XIUSA000BL	66
Barclays US Treasury US TIPS	XIUSA04G7X	33
Barclays US Corporate High Yield	XIUSA000C3	31
Barclays US Govt Intermediate	XIUSA000MI	24
Barclays US Govt/Credit 1-5 Yr	XIUSA000CT	9
Barclays US Treasury	FOUSA05QDG	2
Barclays US Corp 1-5 Yr	FOUSA09JZL	2
Barclays US Treasury Long	XIUSA000MM	2
Barclays US Treasury 5-10 Yr	FOUSA06EWO	1
Barclays Treasury 1-5 Yr	FOUSA06VGX	1
Barclays US Treasury inflation Note 1-10Y	XIUSA04DXS	1

Table 1. Summary statistics

This table provides summary statistics from July 2002 to June 2015 for our sample of bond funds. The observations for the 541 unique funds are at the fund-quarter level. Panel A provides the average, standard deviation, 25th percentile, median, 75th percentile, and number of observations for the full sample of funds. Panel B provides summary statistics for different substyles: government bond (GB), investment-grade bond (IG), high-yield bond, and other bond (OTHER). Variables are winsorized at the bottom and top 1%.

Panel A: Summary Statistics of Full Sample (# of Funds = 541)						
	Mean	Stdev	P25	Median	P75	N
Active share (Issue)	.932	.142	.944	.971	.989	17060
Active share (Issuer)	.602	.215	.491	.606	.735	17060
Active share (Rating)	.292	.216	.142	.237	.381	17060
Active share (Maturity)	.434	.159	.33	.405	.508	17060
Internal active share (Issue)	.84	.211	.813	.924	.962	17060
Annualized tracking error %	2.11	1.53	1.20	1.62	2.43	17048
Annualized alpha %	-1.61	3.50	-3.56	-1.34	.184	16867
Annualized fund return %	2.61	17.10	-4.80	2.31	9.74	17044
Monthly maximum drawdown (MDD) %	-1.88	1.18	-2.16	-1.61	-1.21	17060
Annualized idiosyncratic vol %	1.70	1.09	1.04	1.40	1.98	17060
Annualized total vol %	3.73	1.92	2.57	3.31	4.37	17060
TNA (\$million)	1394	3566	86	283	1014	17060
Annualized monthly flows %	8.35	70.2	-16.4	-.911	18.3	16981
Exp ratio %	.797	.347	.561	.739	.988	16536
Turnover %	179	189	48	105	251	16481
ZTD of fund (Fraction)	.169	.152	.0705	.131	.222	17060
% in Government bonds	46.6	27.8	29.1	47.2	63.4	17060
% in Investment-grade bonds	21.9	17.8	5.83	20.7	31.9	17060
% in High-yield bonds	12.5	23.7	.403	3.25	10.3	17060
% in Other bonds	14.0	14.1	3.3	10.9	20.2	17060

Panel B: Summary Statistics by Fund Style

	GB		IG		HY		OTHER	
	(# of Funds = 60)		(# of Funds = 346)		(# of Funds = 92)		(# of Funds = 158)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Active share (Issue)	.943	.984	.964	.971	.957	.978	.736	.939
Active share (Issuer)	.515	.542	.600	.590	.802	.810	.456	.499
Active share (Rating)	.156	.116	.267	.23	.472	.388	.316	.202
Active share (Maturity)	.584	.576	.407	.394	.433	.401	.459	.406
Internal active share	.865	.922	.899	.936	.824	.889	.546	.537
Annualized tracking error %	1.97	1.53	1.72	1.47	3.54	3.11	2.54	1.84
Annualized alpha %	-1.45	-1.46	-1.52	-1.25	-1.63	-1.4	-2.16	-2.02
Annualized fund return %	2.2	1.76	2.33	2.09	5.34	6.79	1.27	1.63
Maximum drawdown %	-1.7	-1.38	-1.69	-1.52	-2.48	-2.04	-2.3	-1.99
Annualized idio vol %	1.56	1.28	1.45	1.29	2.27	2.11	2.44	2.06
Annualized total vol %	3.8	3.05	3.52	3.25	3.76	3.26	4.67	4.13
TNA (\$million)	1586	240	1350	314	1546	249	1311	215
Annualized flows %	-1.43	-7.83	5.32	-1.13	16.5	.0201	21.5	4.77
Exp ratio %	.783	.772	.731	.684	1.13	1.13	.784	.72
Turnover %	123	62	207	137	98.9	73	164	83.5
ZTD of fund (Fraction)	.0155	0	.157	.136	.395	.414	.0852	.0286
% in Gov bonds	86.4	91.5	45.8	47.2	14.5	1.81	57.7	63.6
% in IG bonds	3.29	0	30.1	26.7	7.7	3.66	10.5	2.5
% in HY bonds	.325	0	5.22	3.32	58.3	62.5	7.1	.704
% in Other bonds	6.66	1.39	15.8	13.8	13.1	6.44	11.3	3.27

Table 2. Regression of active share on fund characteristics

This table provides the regression results for issue-level and issuer-level active share. The observations are at the fund-quarter level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The numbers in parentheses are *t*-statistics based on standard errors two-way clustered by fund and quarter.

	Active Share (Issue)					Active Share (Issuer)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active share (Issuer)		0.316*** (11.46)			0.224*** (7.30)			
Active share (Rating)			0.233*** (9.47)		0.033 (1.43)	0.620*** (20.61)		0.538*** (16.37)
Active share (Maturity)				0.329*** (9.14)	0.197*** (6.61)		0.513*** (10.18)	0.289*** (5.19)
IG fund (Indicator)	2.323 (1.50)	-0.287 (-0.25)	-0.072 (-0.05)	8.155*** (4.61)	3.626** (2.50)	1.930 (0.66)	17.400*** (6.45)	7.898*** (3.63)
HY fund (Indicator)	-4.483** (-2.43)	-9.638*** (-6.75)	-8.298*** (-4.72)	2.896 (1.36)	-4.262** (-2.42)	6.240* (1.66)	27.903*** (8.37)	14.067*** (4.43)
Other fund (Indicator)	-11.608*** (-4.65)	-9.984*** (-5.15)	-13.057*** (-5.88)	-6.074** (-2.37)	-7.342*** (-3.47)	-8.558*** (-2.80)	3.930 (1.14)	-3.186 (-1.21)
Active share (Internal)	0.313*** (10.45)	0.256*** (11.19)	0.315*** (12.22)	0.304*** (12.04)	0.268*** (12.04)	0.196*** (8.85)	0.176*** (5.80)	0.187*** (8.74)
Track err	1.523*** (4.76)	0.457 (1.55)	0.393 (1.22)	0.528* (1.65)	0.008 (0.03)	0.204 (0.65)	1.662*** (3.39)	-0.271 (-0.84)
Alpha	0.010 (0.47)	-0.024 (-1.36)	-0.020 (-1.10)	-0.008 (-0.45)	-0.029* (-1.81)	0.035 (1.32)	0.087*** (2.74)	0.030 (1.16)
Turnover	0.267** (2.27)	0.714*** (6.69)	0.616*** (5.47)	0.187* (1.88)	0.586*** (6.00)	-0.498*** (-2.79)	-1.555*** (-6.91)	-0.692*** (-3.92)
Exp ratio	4.426*** (3.39)	0.858 (1.00)	1.803 (1.63)	3.290*** (3.23)	0.837 (1.01)	4.493*** (2.59)	9.706*** (5.17)	4.422*** (2.88)
log(TNA)	-1.079*** (-5.19)	-0.437*** (-2.70)	-0.862*** (-4.72)	-0.677*** (-3.95)	-0.351** (-2.23)	-1.401*** (-3.89)	-1.351*** (-3.97)	-1.125*** (-3.38)
log(Age)	0.034 (0.96)	0.030 (1.03)	0.037 (1.10)	0.027 (0.92)	0.027 (1.01)	0.010 (0.16)	-0.008 (-0.12)	0.003 (0.06)
Flow($t-1,t$)	1.806 (0.97)	2.807** (2.02)	0.359 (0.24)	2.148 (1.44)	2.516** (2.00)	-7.367*** (-2.86)	-2.981 (-0.95)	-6.555** (-2.55)
Flow($t-3,t-1$)	0.417 (0.53)	0.463 (0.80)	0.127 (0.19)	-0.376 (-0.54)	-0.067 (-0.12)	-0.831 (-0.82)	-1.296 (-0.99)	-1.425 (-1.37)
% in Cash	0.519*** (6.16)	0.272*** (4.31)	0.294*** (4.09)	0.298*** (4.73)	0.179*** (3.21)	0.084 (0.85)	0.338*** (2.81)	-0.031 (-0.33)
% in Funds	2.649*** (5.24)	1.569*** (5.06)	1.716*** (4.86)	1.563*** (5.09)	1.098*** (4.35)	1.029*** (3.09)	1.818*** (4.01)	0.404 (1.45)
% in Other	0.370*** (9.04)	0.219*** (7.03)	0.288*** (7.91)	0.349*** (8.74)	0.239*** (6.98)	0.253*** (6.37)	0.438*** (8.12)	0.263*** (6.18)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.646	0.764	0.710	0.733	0.791	0.670	0.564	0.696
N	14492	14492	14492	14492	14492	14492	14492	14492

Table 3. Regression of future fund performance on active share

This table provides the results from regressions of annualized fund alphas on active share and controls. All explanatory variables are lagged by one quarter, and the observations are at the fund-quarter level. In Panel A, the main explanatory variables are issue- and issuer-level active share. In Panel B, the main explanatory variables are internal issue- and issuer-level active share and external active share. We suppress the coefficient estimates for the control variables in Panel B to save space. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The numbers in parentheses are *t*-statistics based on standard errors two-way clustered by fund and quarter.

Panel A: Baseline Performance Regression

	Dependent Variable: Annualized Alpha					
	(1)	(2)	(3)	(4)	(5)	(6)
Active share (Issue)	1.585 (1.13)	6.438** (2.00)			0.758 (0.54)	5.018 (1.49)
Active share (Issuer)			1.384*** (2.81)	2.745*** (3.50)	1.267** (2.49)	2.146** (2.46)
Annualized tracking error	-0.102 (-1.52)	-0.303*** (-3.13)	-0.130* (-1.92)	-0.332*** (-3.41)	-0.135* (-1.96)	-0.335*** (-3.43)
Turnover	-0.001 (-0.02)	0.085 (1.12)	0.021 (0.54)	0.101 (1.30)	0.018 (0.48)	0.091 (1.21)
Exp ratio	-0.337** (-2.09)	0.181 (0.35)	-0.406** (-2.57)	0.136 (0.27)	-0.410*** (-2.60)	0.148 (0.29)
log(TNA)	0.123*** (3.63)	-0.375*** (-3.24)	0.131*** (4.11)	-0.402*** (-3.56)	0.136*** (3.98)	-0.380*** (-3.30)
Log(Age)	0.001 (0.11)	-0.008 (-0.20)	0.002 (0.24)	-0.002 (-0.04)	0.001 (0.19)	-0.004 (-0.09)
Flow ($t-1$ to t)	4.321*** (4.29)	3.446*** (3.31)	4.382*** (4.34)	3.562*** (3.42)	4.382*** (4.34)	3.570*** (3.43)
Flow ($t-3$ to $t-1$)	0.556 (1.27)	0.303 (0.68)	0.550 (1.26)	0.316 (0.70)	0.550 (1.26)	0.319 (0.71)
Portion in cash	3.358** (2.46)	3.032* (1.75)	2.879** (2.16)	2.443 (1.45)	2.887** (2.17)	2.305 (1.35)
Portion in fund	-11.743** (-2.28)	-6.197 (-0.79)	-13.505*** (-2.61)	-7.049 (-0.94)	-13.470** (-2.56)	-7.941 (-1.03)
Portion in other	-0.271 (-0.46)	-2.346*** (-2.64)	-0.549 (-0.93)	-3.226*** (-3.55)	-0.544 (-0.93)	-3.167*** (-3.48)
Fund Style FE	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.265	0.299	0.265	0.299	0.265	0.300
N	16375	16369	16375	16369	16375	16369

Panel B: Internal vs. External Active Share

	Dependent Variable: Annualized Alpha					
	(1)	(2)	(3)	(4)	(5)	(6)
Internal active share (Issue)	1.680 (1.18)	6.470** (1.98)			0.749 (0.53)	5.287 (1.55)
Internal active share (Issuer)			1.671*** (3.49)	2.683*** (3.60)	1.556*** (3.14)	2.121** (2.55)
External active share	0.842 (0.56)	6.329* (1.89)	0.737 (0.95)	2.191 (1.29)	1.380 (0.91)	6.646** (2.02)
Annualized tracking error	-0.101 (-1.50)	-0.302*** (-3.12)	-0.145** (-2.13)	-0.337*** (-3.37)	-0.149** (-2.16)	-0.339*** (-3.39)
Fund Style FE	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.265	0.299	0.268	0.301	0.268	0.302
N	16375	16369	16206	16200	16206	16200

Table 4. Performance persistence and active share

This table provides the results from regressions of annualized fund alphas on lagged alphas interacted with active share and controls. All explanatory variables are lagged by one quarter, and the observations are at the fund-quarter level. In Panel A, the main explanatory variables are issue- and issuer-level active share, internal and external active share, and their interactions with lagged alpha. We also include the control variables shown in Table 3, but to save space, we do not report their coefficient estimates. In Panel B, we split lagged alpha into positive and negative components. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The numbers in parentheses are *t*-statistics based on standard errors two-way clustered by fund and quarter.

Panel A: Baseline Persistence Regression					
	Dependent Var: Annualized Alpha				
	(1)	(2)	(3)	(4)	(5)
Lag alpha	0.128*** (4.57)	-0.279*** (-4.69)	-0.079 (-1.64)	-0.281*** (-4.70)	-0.072 (-1.47)
Active share (Issue)		1.278*** (3.10)			
Active share (Issue) * Lag alpha		0.463*** (6.35)			
Active share (Issuer)			1.069*** (3.43)		
Active share (Issuer) * Lag alpha			0.328*** (4.40)		
Internal active share (Issue)				1.279*** (3.11)	
Internal active share (Issue) * Lag alpha				0.462*** (6.29)	
Internal active share (Issuer)					1.085*** (3.39)
Internal active share (Issuer) * Lag alpha					0.339*** (4.36)
External active share				1.186* (1.80)	0.900 (1.37)
External active share * Lag alpha				0.484*** (3.77)	0.193 (1.27)
Time FE	Yes	Yes	Yes	Yes	Yes
R ²	0.221	0.231	0.231	0.231	0.232
N	11957	11957	11957	11957	11841

Panel B: Hot Hand vs. Cold Hand

	Dependent Var: Annualized Alpha			
	(1)	(2)	(3)	(4)
Lag alpha	0.128*** (4.57)			
Lag alpha (Pos)		0.067** (2.10)	-0.844*** (-7.89)	-0.375*** (-6.62)
Lag alpha (Neg)		0.222*** (4.15)	0.407** (2.28)	0.290*** (3.46)
Active share (Issue)			-1.440* (-1.86)	
Active share (Issue) * Lag alpha (Pos)			1.016*** (8.22)	
Active share (Issue) * Lag alpha (Neg)			-0.195 (-0.98)	
Active share (Issuer)				-0.185 (-0.53)
Active share (Issuer) * Lag alpha (Pos)				0.689*** (7.45)
Active share (Issuer) * Lag alpha (Neg)				-0.123 (-0.84)
Time FE	Yes	Yes	Yes	Yes
R ²	0.221	0.223	0.235	0.237
N	11957	11957	11957	11957

Table 5. Flow-performance sensitivity and active share

This table provides the results from regressions of quarterly fund flows on lagged alphas interacted with active share. All explanatory variables are lagged by one quarter, and the observations are at the fund-quarter level. The “High active share” variables are indicators equal to one if a given observation is in the top 25% of the specified level of active share, else zero. The control variables are included, but to save space, their coefficient estimates are not reported. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The numbers in parentheses are *t*-statistics based on standard errors two-way clustered by fund and quarter.

	Dependent Var: Fund Flows in the Next Quarter			
	(1)	(2)	(3)	(4)
High active share (Issue)	-0.145 (-0.46)	-0.606 (-1.46)		
High active share (Issuer)			-0.135 (-0.37)	-0.458 (-0.90)
Lag alpha (Neg)	0.218*** (3.22)	0.237*** (4.09)	0.200*** (3.28)	0.212*** (3.94)
Lag alpha (Pos)	0.181** (2.50)	0.116 (1.63)	0.171** (2.38)	0.125* (1.81)
Lag alpha (Neg) * High active share (Issue)	-0.108* (-1.72)	-0.156** (-2.48)		
Lag alpha (Pos) * High active share (Issue)	0.171** (2.04)	0.158** (2.21)		
Lag alpha (Neg) * High active share (Issuer)			-0.032 (-0.47)	-0.053 (-0.81)
Lag alpha (Pos) * High active share (Issuer)			0.172** (2.20)	0.112 (1.56)
Fund Style FE	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
R ²	0.186	0.267	0.186	0.267
N	16227	16222	16227	16222

Table 6. Downside risk and active share

This table provides the results from regressions of maximum drawdown (MDD) on active share, tracking error, and other control variables. All explanatory variables are lagged by one quarter; the observations are at the fund-quarter level; and the coefficients associated with the controls are suppressed to save space. In Panel A, the main explanatory variables are issue- and issuer-level active share. In Panel B, the main explanatory variables are issue- and issuer-level internal active share and external active share. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The numbers in parentheses are *t*-statistics based on standard errors two-way clustered by fund and quarter.

Panel A: Maximum Drawdown on Issue- and Issuer-Level Active Share						
	(1)	(2)	(3)	(4)	(5)	(6)
Active share (Issue)	1.407*** (3.47)	0.503** (2.36)			1.416*** (3.23)	0.582*** (2.62)
Active share (Issuer)			0.205* (1.86)	-0.051 (-0.51)	-0.013 (-0.11)	-0.120 (-1.16)
Tracking error	-0.276*** (-9.96)	-0.287*** (-16.41)	-0.267*** (-9.01)	-0.285*** (-16.11)	-0.276*** (-9.98)	-0.285*** (-16.10)
Fund Style FE	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.697	0.769	0.693	0.769	0.697	0.769
N	16375	16369	16375	16369	16375	16369
Panel B: Maximum Drawdown on Internal and External Active Share						
	(1)	(2)	(3)	(4)	(5)	(6)
Internal active share (Issue)	1.372*** (3.30)	0.429* (1.91)			1.426*** (3.24)	0.506** (2.18)
Internal active share (Issuer)			0.128 (0.99)	-0.087 (-0.83)	-0.090 (-0.65)	-0.140 (-1.32)
External active share	1.681*** (4.06)	0.755*** (2.62)	0.373** (2.05)	0.323 (1.24)	1.596*** (3.84)	0.749** (2.58)
Tracking error	-0.277*** (-10.01)	-0.288*** (-16.44)	-0.266*** (-8.84)	-0.284*** (-15.76)	-0.275*** (-9.83)	-0.285*** (-15.74)
Fund Style FE	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.698	0.769	0.695	0.770	0.699	0.771
N	16375	16369	16206	16200	16206	16200

Table 7. Volatility and active share

This table provides the results from regressions of idiosyncratic and total volatility on active share and control variables. All explanatory variables are lagged by one quarter, and the observations are at the fund-quarter level. Panel A reports the regression of idiosyncratic volatility on issue- and issuer-level active share. Panel B reports the regression of idiosyncratic volatility on issue- and issuer-level internal active share and external active share. Panel C reports the regression results of total volatility on issue- and issuer-level internal active share and external active share. In Panels B and C, to save space, we do not report the coefficient estimates for the control variables. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The numbers in parentheses are *t*-statistics based on standard errors two-way clustered by fund and quarter.

Panel A: Idiosyncratic Volatility on Issue- and Issuer-Level Active Share						
	(1)	(2)	(3)	(4)	(5)	(6)
Active share (Issue)	-0.278 (-0.55)	0.818*** (2.99)			-0.853* (-1.73)	0.273 (1.05)
Active share (Issuer)			0.635*** (4.28)	0.833*** (7.19)	0.778*** (4.91)	0.800*** (6.77)
Turnover	0.016* (1.79)	0.006 (0.68)	0.025*** (2.79)	0.009 (1.10)	0.028*** (3.07)	0.008 (1.05)
Exp ratio	0.194*** (2.89)	-0.105 (-0.84)	0.136** (1.98)	-0.117 (-0.94)	0.142** (2.09)	-0.116 (-0.93)
log(TNA)	0.023* (1.86)	-0.100*** (-4.24)	0.034*** (2.91)	-0.101*** (-4.39)	0.029** (2.44)	-0.100*** (-4.31)
Age	0.002 (0.52)	0.016* (1.69)	0.001 (0.47)	0.017* (1.90)	0.002 (0.61)	0.017* (1.89)
Flow ($t-1$ to t)	-0.558*** (-3.16)	-0.413*** (-3.02)	-0.514*** (-2.92)	-0.364*** (-2.68)	-0.515*** (-2.93)	-0.364*** (-2.67)
Flow ($t-3$ to $t-1$)	-0.081 (-1.42)	-0.088** (-2.06)	-0.081 (-1.44)	-0.080* (-1.89)	-0.082 (-1.45)	-0.080* (-1.88)
% in Cash	0.015 (0.03)	0.298 (0.98)	-0.280 (-0.57)	0.029 (0.10)	-0.289 (-0.58)	0.022 (0.07)
% in Fund	2.254 (0.91)	1.495 (1.23)	1.043 (0.41)	0.838 (0.71)	1.030 (0.42)	0.789 (0.66)
% in Other	0.879*** (4.55)	1.120*** (6.10)	0.694*** (3.53)	0.790*** (4.45)	0.691*** (3.49)	0.793*** (4.48)
Fund Style FE	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.548	0.722	0.554	0.726	0.556	0.726
N	16375	16369	16375	16369	16375	16369

Panel B: Idiosyncratic Volatility on Internal and External Active Share

	(1)	(2)	(3)	(4)	(5)	(6)
Internal active share (Issue)	-0.264 (-0.51)	0.780*** (2.87)			-0.870* (-1.76)	0.326 (1.23)
External active share	-0.388 (-0.76)	0.943*** (2.59)	0.719*** (4.62)	0.819*** (6.87)	0.864*** (5.43)	0.784*** (6.43)
Internal active share (Issuer)			0.694*** (3.77)	0.775*** (2.77)	-0.041 (-0.09)	1.049*** (2.99)
Fund Style FE	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.549	0.723	0.561	0.727	0.563	0.727
N	16375	16369	16206	16200	16206	16200

Panel C: Total Volatility on Internal and External Active Share

	(1)	(2)	(3)	(4)	(5)	(6)
Internal active share (Issue)	-1.245 (-1.15)	0.796* (1.96)			-1.841* (-1.77)	0.391 (0.94)
External active share	-1.671 (-1.63)	0.446 (0.81)	0.141 (0.41)	0.202 (0.41)	-1.414 (-1.45)	0.531 (0.98)
Internal active share (Issuer)			0.545 (1.34)	0.752*** (4.25)	0.853** (2.16)	0.710*** (3.85)
Fund Style FE	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.651	0.780	0.654	0.784	0.656	0.784
N	16375	16369	16206	16200	16206	16200

Table 8. Fund performance and active share: Interaction with the VIX and the TED spread

This table provides the results from regressions of annualized fund alpha (Panel A), maximum drawdown (Panel B), and idiosyncratic volatility (Panel C) on the interactions of active share with the VIX and the TED spread. All explanatory variables are lagged by one quarter; the observations are at the fund-quarter level; and the coefficients associated with the controls are suppressed to save space. We use quarterly averages of the VIX and the TED spread and exclude the standalone VIX and TED spread because of the time fixed effects. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The numbers in parentheses are *t*-statistics based on standard errors two-way clustered by fund and quarter.

Panel A: Alphas on Interactions between Active Share and VIX/TED								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active share (Issue)	0.396 (0.36)	1.884 (0.83)						
Active share (Issue) * VIX	-11.984*** (-21.25)	-11.883*** (-20.99)						
Active share (Issuer)			0.277 (0.58)	1.421* (1.92)				
Active share (Issuer) * VIX			-5.192*** (-7.42)	-5.303*** (-7.40)				
Active share (Issue)					-0.176 (-0.14)	1.037 (0.37)		
Active share (Issue) * TED					-5.248*** (-9.17)	-4.873*** (-8.05)		
Active share (Issuer)							0.848* (1.79)	2.148*** (2.81)
Active share (Issuer) * TED							-3.172*** (-7.49)	-3.017*** (-6.99)
Fund Style FE	Yes	No	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.336	0.367	0.295	0.328	0.280	0.311	0.277	0.309
N	16375	16369	16375	16369	16375	16369	16375	16369

Panel B: Maximum Drawdown on Interactions between Active Share and VIX/TED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active share (Issue)	1.417*** (3.50)	0.535** (2.39)						
Active share (Issue) * VIX	0.100 (1.47)	0.085 (1.28)						
Active share (Issuer)			0.081 (0.73)	-0.188* (-1.93)				
Active share (Issuer) * VIX			-0.578*** (-6.58)	-0.551*** (-6.84)				
Active share (Issue)					1.575*** (4.04)	1.041*** (3.99)		
Active share (Issue) * TED					0.501*** (9.25)	0.485*** (8.54)		
Active share (Issuer)							0.161 (1.44)	-0.101 (-0.99)
Active share (Issuer) * TED							-0.257*** (-3.02)	-0.253*** (-3.15)
Fund Style FE	Yes	No	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.697	0.769	0.702	0.777	0.700	0.772	0.694	0.771
N	16375	16369	16375	16369	16375	16369	16375	16369

Panel C: Idiosyncratic Volatility on Interactions between Active Share and VIX/TED

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Active share (Issue)	-0.322 (-0.64)	0.606** (2.34)						
Active share (Issue) * VIX	-0.596*** (-9.79)	-0.576*** (-10.80)						
Active share (Issuer)			0.655*** (4.33)	0.847*** (7.17)				
Active share (Issuer) * VIX			0.187** (2.31)	0.094 (1.30)				
Active share (Issue)					-0.463 (-0.93)	0.232 (0.88)		
Active share (Issue) * TED					-0.606*** (-7.91)	-0.538*** (-7.96)		
Active share (Issuer)							0.649*** (4.30)	0.844*** (7.14)
Active share (Issuer) * TED							0.150 (1.55)	0.089 (1.05)
Fund Style FE	Yes	No	Yes	No	Yes	No	Yes	No
Fund FE	No	Yes	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.554	0.727	0.555	0.726	0.555	0.727	0.554	0.726
N	16375	16369	16375	16369	16375	16369	16375	16369

Table 9. Out-of-sample replication of key results (2016–2019)

This table provides the results from our out-of-sample replication of our original results (2016–2019). The original results are also presented to ease comparison (2002–2015). The first two columns consider the results with respect to alpha, the next two flow sensitivity, and the final two maximum drawdown. Column (1) repeats Table 3, Panel A, column (3); column (2) presents the out-of-sample replication of that test. Column (3) repeats Table 5, column (1); column (4) present the out-of-sample replication of that test. Column (5) repeats Table 6, Panel A, column (1); column (6) presents the out-of-sample replication of that test. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The numbers in parentheses are *t*-statistics based on standard errors two-way clustered by fund and quarter.

Dependent Variable: Sample	Alpha		Flow		Maximum Drawdown	
	2002-2015 (1)	2016-2019 (2)	2002-2015 (3)	2016-2019 (4)	2002-2015 (5)	2016-2019 (6)
Active share (Issue)					1.407*** (3.47)	1.062*** (4.14)
Active share (Issuer)	1.384*** (2.81)	1.719*** (2.61)				
High active share (Issue)			-0.145 (-0.46)	0.174 (0.37)		
Lag alpha (Neg)			0.218*** (3.22)	0.225** (2.55)		
Lag alpha (Pos)			0.181** (2.50)	0.208 (1.49)		
Lag alpha (Neg)			-0.108*	0.001		
* High active share (Issue)			(-1.72)	(0.01)		
Lag alpha (Pos)			0.171** (2.04)	0.341** (2.25)		
* High active share (Issue)						
Fund Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.265	0.202	0.186	0.245	0.697	0.252
N	16375	4755	16227	4755	16375	4755