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Abstract

Mutual fund families are increasingly assigning traders to manage corporate bond mutual funds. Using this setting to study the role of traders in investment management, we document that trader managers identify and exploit short-term trading opportunities at lower transaction costs. These skills are particularly valuable during periods of market stress. Moreover, trader managers exhibit sophisticated risk management behavior: They reduce credit risk during periods of market stress and take more maturity risk during periods of large interest rate fluctuations, while holding portfolios with greater convexity. The combination of these skills produces relative outperformance during periods of large interest rate fluctuations.

Keywords: traders; fund managers; transaction costs; corporate bonds

JEL codes: G11, G23, D83, J24

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"Investment management has two components. One component is forecasting or pricing a security, and the second component is structuring the trade," he says. "I'd say at least 95 percent of the emphasis from the media and also practitioners is on that pricing and forecasting element. And that's important, but equally important — and potentially sometimes more important — is the structure of the trade, and the risk management, and those are aspects that almost never get discussed."

Quote of Richard Dewey, portfolio manager at Royal Bridge Capital, speaking in Childs (2022).

1. Introduction

The performance of actively managed mutual funds is the subject of an ever-growing academic literature. This performance is a function of the active decisions of mutual fund managers, who generate investment ideas, but also of the decisions of affiliated traders, who are responsible for executing those investment ideas. While mutual fund managers have received a great deal of attention in the literature, we know little about the role of traders in the investment process.[1]

Traders working for fund families can potentially contribute by helping structure and execute trades in cost-efficient ways. They can also contribute in other ways that go beyond controlling transaction costs. In particular, they can provide additional alpha by identifying and exploiting profitable short-term trading opportunities and providing liquidity. In fact, some fund families have recognized the latter potential contribution of traders and have integrated them in investment teams by giving them portfolio management mandates.[2] These potential contributions notwithstanding, traders are not without their critics, however. In popular culture, traders are portrayed as dubious personas that operate in a testosterone-fueled environment and take outsized risks, sometimes recklessly.[3] Some evidence from academic research suggests that professional

[1] See, for example, Golec (1996); Chevalier and Ellison (1999); Greenwood and Nagel (2009); Kempf, Manconi, and Spalt (2017); Cici et al (2018); Chuprinin and Sosyura (2018); Bai et al. (2019); and Agarwal, Cochardt, and Orlov (2022).

[2] A PIMCO managing director describes the role of traders in portfolio management as follows (Barnes, 2022): "That group of portfolio managers are our eyes and ears in the market, really working with the dealer community and maintaining relationships. Taking it a step further, we really want them to feel like they co-own the risk. In practice that might mean noting when a security starts to look rich, or becomes cheap because there's a block for sale; sharing those technicals and being aware of relative value; understanding where other bonds trade; understanding what issuers need – to the extent they can help work with the research analyst towards a potential reverse inquiry opportunity. That is the value-add."

[3] Examples of this include depictions of traders in movies such as "The Wolf of Wall Street," based on the book of the same name by Belfort (2007) and in the semi-autobiographical book "Liar's Poker" by Michael Lewis, which covers his experience as a bond trader on Wall Street (Lewis 1998).

traders exhibit a propensity to take elevated risks[4] and critics have even suggested that professional traders' risk-taking behavior contributed to the most recent financial crisis (Adams 2011). In this paper, we use a unique feature from the corporate bond mutual fund sector to study the role of traders in investment management.

A challenge in trying to understand this role is that we cannot observe how traders contribute to investment management while they work as traders for a fund family's trading desk because of data limitations. We are able to bypass this limitation by directly looking at bond mutual fund managers and exploiting the fact that their career progression follows two distinct tracks whereby an individual works either as a bond trader or as an analyst before becoming a bond fund manager. Thus, many fund families hire former bond traders as fund managers of their corporate bond funds. By way of illustration, Figure 1 shows that the fraction of funds with at least one former trader in the portfolio management team was 63% as of the end of 2020, up from 34% in 2003. This feature allows us to study the performance, portfolio characteristics, and actions of traders when they work as corporate bond mutual fund managers (hereafter, trader managers). Following this approach and comparing this group of fund managers with the more traditional fund managers that did not follow a trading career path, we can shed light on the role of traders in investment management.

The corporate bond setting is ideal for this analysis because trading is far more complex in the corporate bond market than in the equity market for several reasons. First, the corporate bond market is fragmented, more illiquid than the equity market, and lacks pre-trade transparency. Second, trading is concentrated in the hands of a few dealers and is relationship-driven. Third, there is a lower level of electronification. Finally, recent regulatory changes have led to reduced dealer inventories pushing dealers toward a market matching as opposed to a traditional market

[4] For example, Haigh and List (2005) show in an experimental setting that professional traders exhibit stronger myopic loss aversion than students, which is indicative of these traders becoming more risk-taking when facing short-term losses. In another experimental study, Cipriani et al. (2020) document that professional traders in general exhibit less risk aversion.

making role. This suggests that traders potentially play a bigger role in the investment management of corporate bond funds.

Using the distinction between trader and non-trader fund managers, we study the contribution of traders in the active management of corporate bond funds. We hypothesize that, relative to non-trader managers, trader managers benefit from an ability to process and act quickly on new short-lived information that enables them to take advantage of short-term profitable trading opportunities. We refer to this hypothesized ability as "agile reaction" ability. Such ability could arise because of selection, meaning that individuals with the ability to think and act quickly in fast-changing conditions are more likely to be hired for trading jobs. Such skills could also be acquired by these managers in their previous trading jobs, which required them to operate in fast-moving and rapidly changing market environments. We expect trader managers to have yet another advantage that complements their hypothesized agile reaction ability. We hypothesize that trader managers can trade at lower transaction costs because of their trading experience and trading relationships they developed as former traders. These two advantages, agile reaction and trading cost advantage, are likely to interact in that the ability to generate lower transaction costs would better position trader managers to take advantage of short-term trading opportunities, thus amplifying the gains from their agile reaction ability.[5]

To test these hypotheses, we identify trader managers by manually checking the biographies of all corporate bond fund managers. We classify a fund manager as a trader manager if that individual worked as a trader before becoming a fund manager. The large fraction of funds that are run by teams of managers makes attribution of fund outcomes to actions of individual managers challenging. Therefore, we follow two approaches for our comparisons. One approach focuses on single-managed funds. The second approach utilizes the entire sample to compare the

[5] Another type of skill that trader managers might enjoy is the ability to learn the strategic sophistication of other market participants with whom they interact (Cipriani et al. 2020) and anticipate their direction of trading.

performance of funds whose management team is dominated by trader managers (trader-dominated funds) against other funds.

To measure the combined return contribution of a trader manager's interim trading activities due to the manager's agile reaction ability and the manager's ability to generate lower trading costs, we employ the return gap measure of Kacperczyk, Sialm, and Zhang (2008), which is the difference between the reported fund return and the holdings-based return of the fund's most recently disclosed portfolio. We document that trader-dominated funds generate higher return gaps than other funds. This result holds for both sets of comparisons that employ either only single-managed funds or all funds. However, the return gap difference is almost twice as large for the comparison based on single-managed funds, where the attribution of manager skills to fund outcomes is more precise. Specifically, the monthly return gap difference between trader-dominated funds and other funds is 3.82 bps per month for the comparison based on single-managed funds and 2.34 bps for the comparison based on all funds. These differences are statistically significant. They are also economically significant given that the return gap for the average sample fund is -0.63 bps.

In the next group of tests, we confirm the presence of each hypothesized ability among trader managers. We start with a direct test for the trading cost advantage of trader managers. Detailed data on trades of fund managers needed for trading cost computations are not publicly available. Therefore, we use trades inferred from changes in portfolio holdings for a given fund that we match to actual customer trades in TRACE happening in the same direction and with the same size. We use those trades to compute unit transaction costs for each trade, which we then use to compute a value-weighted transaction cost measure per fund and month. We document that trader-dominated funds generate significantly lower transaction costs than other funds. This trading cost difference between the two groups is economically significant, ranging between 25% to 56% of the trading cost of the average sample fund.

In related tests we show that trader-dominated funds generate even greater return gaps compared to other funds during periods of market stress, when market illiquidity is more pronounced or when there are large interest rate fluctuations. This is consistent with trader managers benefitting even more from processing and acting quickly on short-lived information during periods of market stress, when there are more short-term profitable trading opportunities to exploit. It is also consistent with trader managers enjoying greater trading costs advantages during periods of market stress when trading costs are typically higher. However, the widening of the return gap difference between trader-dominated funds and other funds during illiquid market periods is not accompanied by a similar effect for the transaction cost difference between the two groups. This suggests that during periods of market illiquidity, the agile reaction ability of trader managers plays a more prominent role than the trading cost advantage. Interestingly, both the return gap difference and the trading cost difference of trader-dominated funds vs. other funds become stronger during periods of large interest rate fluctuations. The trading cost advantage of trader managers during such periods is consistent with trader managers paying less for trade immediacy when most bond fund managers must reposition their portfolios in response to large changes in interest rates. This advantage is most likely coming from stronger relationships that trader managers have developed with larger dealers that enjoy central positions in dealer networks and charge their customers less for providing trade immediacy (Dick-Nielsen, Poulsen, and Rehman 2023).

It is unclear whether the advantages we have documented so far for the trader managers translate into superior performance. We document that over the entire sample period funds dominated by trader managers exhibit similar risk-adjusted returns as other funds. This suggests that, overall, these advantages are not large enough to generate a clear performance advantage for the trader managers. Nonetheless, trader managers can generate better performance during periods of larger fluctuations in interest rates. As these results mirror the finding that during such periods trader managers generate higher return gaps and lower trading costs relative to other managers, we can conclude that the agile reaction ability and trading cost advantage of trader managers translate into performance advantages for these managers but only during periods of high interest rate fluctuations.

A natural question is whether the opportunistic trading activities of trader managers correspond to higher risk-taking by these managers. Trader managers might resemble the typical trader stereotype characterized by a high appetite for risk-taking or they could have been selected simply because of their ability to handle risk better given their aptitude to operate in fast-moving markets. Therefore, whether trader managers exhibit more or less risk-taking propensity than other managers is an empirical question. To assess differences in risk-taking between the two groups of managers, we compute the reaching-for-yield (RFY) measure of Choi and Kronlund (2018) and its components, i.e., reaching-for-maturity and reaching-for-rating, and compare them between trader-dominated funds and other funds. Our results show that, on average, trader-dominated funds do not engage in overall RFY that is different from other funds. However, during periods of high illiquidity in the market or sudden extreme changes in interest rates, trader-dominated funds exhibit a significantly lower RFY compared to other funds, primarily due to trader managers reducing their exposure to lower credit quality bonds. Taken together with the evidence of higher return gaps produced by trader managers during such periods, this result suggests an ability by trader managers to benefit from exploiting profitable trading opportunities in periods of market stress while at the same time de-risking their portfolios. Interestingly, we find some evidence that trader-dominated funds tilt their portfolios toward bonds with longer maturities, which is consistent with an intent to capture the maturity risk premium. They do so, however, while managing interest rate risk proficiently because they construct bond portfolios with a higher level of convexity than other funds. Overall, these results portray trader managers as cautious risk takers, who do not shy away from exploiting opportunities in periods of market stress, but they do so in a measured way that keeps their portfolio risk in check.

Our paper is related to a nascent literature that studies the role of trading desks—units of investment management firms responsible for trade execution of investment ideas generated by the firms' portfolio managers—in managing trading costs. These papers study the heterogeneity of trade execution ability across trading desks along with persistence of such ability (Anand et al. 2012), and how trading desk ability affects performance of the firms' investment vehicles (e.g., mutual funds) that rely on those trading desks (Cici, Dahm, and Kempf 2018). Rather than focusing on the trading desk, our paper looks at the role of individual traders that are directly embedded in portfolio management, shedding light on a recent development in the investment management industry that is making traders an integral part of the investment process by giving them skin in the game. In addition, by looking at trader portfolio managers that have sole decision-making responsibilities in managing mutual funds, we can analyze the role of traders in a more holistic way that goes beyond transaction cost management and extends to other dimensions of skill such as the ability to exploit short-term opportunities and risk management.

Our paper also contributes to the literature that studies risk-taking by corporate bond mutual funds, especially to the reaching for yield literature (e.g., Becker and Ivashina 2015, Choi and Kronlund 2018). Choi and Kronlund (2018) provide some evidence of cross-sectional variation in reaching for yield behavior across bond mutual funds driven by investor preferences, reputational concerns, as well as career concerns of fund managers. Focusing on reaching for yield as a key manifestation of risk-taking behavior, we document that trading expertise leads to differences in risk-taking behavior. Contrary to popular beliefs regarding the risk-taking behavior of traders, our results suggest that trader managers act as cautious risk takers. They do not shy away from exploiting opportunities in periods of market stress, but they do so cautiously while reducing their portfolio credit risk. Even when they respond to market conditions by taking more interest rate risk, they do so proficiently as shown by their ability to construct bond portfolios with greater convexity than other managers.

Our paper is also related to a nascent literature studying the abilities of corporate bond mutual funds and how they relate to fund performance. This literature documents cross-sectional differences related to valuation skills (Cici and Zhang 2023), profitable liquidity provision (Anand, Jotikasthira, and Venkataraman 2021), and activeness (Choi, Cremers, and Riley 2021), all of which have predictive power for fund performance. We contribute to this literature by documenting the presence of a different skill related to trading expertise of certain fund managers that come from a trading background. This skill manifests itself in the form of profitable interim short-term trading and lower transaction costs, which become consequential for fund performance during periods of market stress. Mutual fund families seem to have taken note of this particular skill and have been increasingly hiring more traders as portfolio managers.

Finally, we also contribute to the literature that studies how differences in human capital across fund managers resulting from different types of experience affect decision making and performance. These different experiences result from: attending premiere universities (Chevalier and Ellison 1999); going through a marriage or divorce (Lu, Ray, and Teo 2016); having prior professional experience outside the financial sector (Cici et al. 2018); coming from a wealthy family (Chuprinin and Sosyura 2018); being relatively older when beginning kindergarten (Bai et al 2019); experiencing family disruptions (Betzer et al. 2021); and being an older child in a family (Agarwal, Cochardt, Orlov 2022). Our paper is the first to study the human capital that fund managers acquired when they worked as traders prior to becoming fund managers. Furthermore, we document that these skills are indeed valuable for fund managers in that such managers are able to act quickly on short-term information, manage transaction costs better, and exhibit proficient risk-management. These are advantages that lead to considerable performance differences during periods of market stress.

2. Data and Methodology

2.1. Mutual Fund Data

To construct our sample, we start by downloading holdings, assets, and return data on US mutual funds from nine bond fund categories from Morningstar.[6] We require the funds in our sample to hold on average at least 40% of their assets in corporate bonds throughout our sample period from January 2003 until December 2020.[7] The resulting sample includes 710 funds (3,218 unique share classes). As in Pástor, Stambaugh, and Taylor (2015), we weight returns of the individual share classes by their relative assets to calculate returns at the fund-level. We calculate family assets every month as the sum of assets of all share classes with the same firm name ID in Morningstar. We calculate a fund's age as the difference in years between the current date and the inception date of the fund.

For the holdings, we follow Pastor, Stambaugh, and Taylor (2020) and eliminate observations for which the sum of holdings is lower than 50% or is higher than 200% of total assets. We use holding data at the highest frequency available in Morningstar. Some funds report holdings every month, others report every two or three months. If the reporting window is larger than one month, we use the holdings from the last holding report until the next holding report, for a maximum of two months (i.e., if the fund reports holdings in December and March, we use December holdings for December, January, and February). For each fund and month, we calculate the fraction of the fund's holdings invested in corporate bonds as the sum of the market value of all corporate bond holdings divided by total fund assets.

We flag the period when the fund is in incubation to control for incubation bias (Evans 2010). We define incubation as the period until the fund's lifetime exceeds one year and the assets

[6] The Morningstar Categories are US Fund Corporate Bond, US Fund Multisector Bond, US Fund Nontraditional Bond, US Fund Bank Loan, US Fund Short-Term Bond, US Fund Long-Term Bond, US Fund High-Yield Bond, US Fund Intermediate Core Bond, and US Fund Intermediate Core-Plus Bond.

[7] Corporate bond holdings are identified based on the holding type in Morningstar (Bond - Corp Inflation Protected, Bond - Corporate Bond, or Bond – Corporate Passthru FRN).

of the fund exceed 5 million dollars. We define a dummy variable that indicates if the fund is in incubation for every fund-month and include that dummy in our regressions.

Data on fund characteristics, portfolio breakdowns and asset allocations, and expense ratios come from Morningstar. We use the expense ratio from Morningstar that is reported on a fiscal-year basis and assign it backwards for one year. Variables that can vary across share classes (e.g., the net expense ratio) are calculated as an asset-weighted average across the share classes of a fund. To control for different investment styles, we use the historical Morningstar Category and fill in gaps in the data with the latest value that is available. As fund turnover is only reported on a yearly basis in Morningstar, we calculate a more granular fund turnover based on the changes in a fund's holdings. Depending on the frequency of holding reports, we calculate turnover for every reporting window as the minimum of total sales and total purchases divided by the total holdings of the fund. Similar to Cici and Gibson (2012), we do not count matured bonds as sales. We then annualize the turnover measure to make it comparable across different frequencies of holding reports.

Table 1 provides summary statistics for our sample. The average fund has \$1.2 billion in total assets, belongs to a family with an average of \$130.3 billion in assets, and is 14 years old. The funds in our sample invest on average 65.6% of their assets in corporate bonds. The average annualized fund turnover is around 60%. However, the turnover ratio shows a relatively high dispersion with a 25% percentile of around 25% and a 75% percentile of around 77% turnover. The average net expense ratio in our sample is 0.85%. To minimize the effect of outliers, we winsorize fund turnover and fraction of portfolio invested in corporate bonds at the 1% and 99% levels.

Information on individual bond trades comes from Enhanced TRACE, which we clean using the filters in Dick-Nielsen (2014). We use Mergent for bond characteristics like credit rating histories and amount outstanding. We fill in gaps in the data on a bond's amount outstanding with

Refinitiv Eikon. For the calculation of the return gap and the alphas, we use several indices from the ICE and Bloomberg.

2.2. Data on manager biographies

The data on manager biographies and managers' trading experience are hand-collected and come from three sources. We use the manager history of the fund from Morningstar to extract the names of the managers and the time span when they managed the fund. We collected biographical information on these managers from Morningstar, FactSet, and LinkedIn. Our first source of information covers the short biographies and job histories from Morningstar. In a second step, we add biographies and job histories from FactSet based by matching names, which we verify manually. We first match identical names between the two databases. For the managers with no identical name match in the two databases, we use a fuzzy text match based only on their family names and manually verify the matches. We then manually check the manager names for uniqueness (i.e., if two names most likely belong to the same person) and assign a unique manager-id to every manager. Managers for which we still have no or very little information on their job history are manually searched on LinkedIn to complete the data. We end up with 2,095 unique managers that manage one of our sample funds between 2003 and 2020.

We classify all managers as traders or non-traders. We first searched for trading experience in the biographical information of the managers by employing a key-word search which was then manually checked.[8] If there is a trading job mentioned in the job history or the biographies, then a manager is classified as a trader. We are able to classify 76.9% of managers as either trader or analyst. 11.1% of managers are classified as pure traders, 17.2% have been traders and analysts before joining fund management, and 48.5% are classified only as analysts. For the remaining managers, the biographical information does not provide adequate information to classify them as

[8] We used the following key words: trading, trade, sales, dealer, broker.

either traders or analysts. We manually look at all managers that we cannot classify and employ a final LinkedIn search to verify their classification status.

We next aggregate the trader/non-trader classification to the fund level. For single-managed funds, we can make a clear distinction if the fund is trader-managed or not. Here, we use a dummy variable which equals one if the fund manager has trading experience and zero otherwise. In the analyses that employ the full sample, which includes funds managed by teams, the classification is based on the share of traders in the management team. We compute the share of traders in the management team as the ratio of the number of managers with trading experience to the total number of fund managers. The average share of traders is nearly 28% in our sample. However, there is substantial cross-sectional variation. The median fund only has a share of traders of 16.6% and many funds do not have a trader in their management team at all. For team-managed funds, we classify a fund as trader-dominated if the management team is dominated by traders. Specifically, we use a dummy variable (Trader_Dominated) that is one if the share of traders in the management team is larger than the 80th percentile of the share traders across all funds in that month (and 0 otherwise).

2.3. Methodology

2.3.1. Main Specification

To assess the presence of the hypothesized abilities among trader-dominated funds, we employ pooled regressions specified as follows:

$$Var_{i,t} = \alpha \quad + \beta^{T\text{-}D} \times Trader\_Dominated_{i,t-1} + \theta \times Controls_{i,t-1} + \epsilon_{i,t} \qquad (1)$$

where $Var_{i,t}$ is the variable of interest used to measure a certain dimension of ability or other related characteristic for fund *i* at time *t*; $Trader\_Dominated_{i,t-1}$ is a dummy variable that equals 1 if the fund's management team is dominated by traders; $Controls_{i,t-1}$ is a vector of control variables that include a dummy variable for the fund incubation period, the share of corporate bond holdings, the logarithm of fund and family assets, the logarithm of fund age, the net expense ratio, and the fund turnover. We lag right hand side variables by one month. We include time fixed effects to control for common time-varying factors and style fixed effects based on Morningstar categories to control for account for commonalities within investment styles. We cluster standard errors by fund and month. We estimate regressions for our full sample as well as for a subsample that only includes funds that are single-managed. The sample that only uses single-managed funds allows to clearly isolate trader-specific effects, which, however, comes at the cost of a reduced sample size. We therefore also look at the full sample to see if our results are stable to this kind of sample selection.

2.3.2. Variables Capturing Hypothesized Abilities

To measure the net contribution to fund returns from the hypothesized agile reaction ability and the ability to generate lower trading costs of trader managers, we employ the return gap measure of Kacperczyk et al. (2008). The return gap in a given month for a given fund is the difference between the net reported return of the fund and the net holdings return of the most recently disclosed portfolio of fund holdings, computed as follows:

$$RG_{i,t} = RF_{i,t} - (RH_{i,t} - EXP_{i,t}) \qquad (2)$$

where $RF_{i,t}$ is the reported return of fund *i* in month *t*, which is net of the fund's expense ratio; $RH_{i,t}$ is the holdings return in month *t* of the most recently disclosed fund portfolio; and $EXP_{i,t}$ is one twelfth of the fund’s expense ratio. The return gap captures the net effect of value-increasing short-term trading (i.e., interim trading that happens between holdings report dates) and associated value-decreasing trading costs. The intuition is that the value created or destroyed by unobserved interim actions will be reflected in the reported return but not in the holdings return. The holdings return of the most recently disclosed portfolio includes the returns from the corporate bond holdings of the fund and from the funds’ remaining assets, i.e., cash, treasuries, municipal and government bonds. For the corporate bond part of the portfolio, we use the returns of the individual bonds. For the remaining part we use index returns of different asset classes that we weight with portfolio asset class weights from Morningstar, following Moneta (2015). A detailed description of the methodology is in Appendix A.1. We winsorize the return gap every month at the 1% and 99% levels.

A challenge for measuring mutual funds' trading costs is that we cannot observe the exact time and amount of each trade undertaken by a given mutual fund. One common approach is to infer trades based on changes in portfolio holdings over consecutive reporting dates and assume that these trades happen on reporting dates (Chen, Jegadeesh, and Wermers 2000). To most accurately measure trading costs, we attempt to identify each fund's true trades in the transaction data from TRACE. We first infer individual trades that each fund made from changes in each fund's holdings; we use only funds with monthly reporting for this computation. Next, we try to locate in TRACE each trade inferred from holdings changes in the previous step by searching for customer trades in the same direction and with the same trade size, which we mark as possible trades of the corresponding fund. Although this approach cannot identify all fund trades, for the subset of trades that we can match to TRACE, we are able to identify the exact time of execution with a high degree of confidence because trades in the same direction and with the same size are usually not very frequent within one month.

For each matched trade, we compute its trading cost (unit transaction cost) as the percentage difference between the price of the trade and a benchmark (Hendershott and Madhavan 2015 and Yan 2020) as follows:

$$UTC = \frac{Trade\ Price - Benchmark}{Benchmark} \times Trade\ Direction \qquad (3)$$

where $Trade\ Direction$ equals 1 if the trade is a buy and -1 if it is a sale. To identify a benchmark price for each trade, we first look for an offsetting interdealer trade on the same day and classify the trade that happened closest in time to the matched trade as the benchmark trade. If no offsetting interdealer trade on the same day is found, we look for offsetting customer trades on the same day and again choose the trade that was closest in time as benchmark trade.[9] If we cannot find an offsetting trade (interdealer or customer), we then take the nearest interdealer price (which is not on the same day) of that month as benchmark price. If for a holding change, we find multiple matches, we use the average UTC. Finally, we calculate a value-weighted (by trade size) average unit transaction cost of the fund in that month and winsorize the measure at 1% and 99% every month.

3. Results

3.1. Return Gap Comparisons

We hypothesized that trader managers have the ability to identify short-term trading opportunities and exploit them at the lowest possible cost. We thus would expect trader-dominated funds to exhibit higher return gaps than other funds. To test this prediction, we estimate Model (1), where we regress the return gap on our trader variable and controls. Results are reported in Table 2. Column (1) reports results for all funds, while Column (2) reports results only for the single-managed funds.

Results from Table 2 show that trader-dominated funds have higher return gaps than non-other funds. This holds for both samples, respectively, in Columns (1) and (2). The comparison from Column (1), which employs all funds, suggests that funds, the management of which is dominated by traders, have a return gap that is 2.34 basis points higher than other funds. This difference becomes even stronger when looking at single-managed funds, which allows us to more cleanly isolate the net impact of short-term trading skills of trader managers. Specifically, the return gap difference of 3.82 bps documented in Column (2) is nearly double the difference documented in Column (1). These differences are statistically significant at the 5% level. They are also economically significant given that the average return gap among all funds is -0.63 bp per

[9] If the benchmark trade is an interdealer trade, we use the trade price of the interdealer trade as benchmark price. When we use a customer trade as benchmark, we calculate the benchmark price as the average of the trade price of the matched trade and the trade price of the offsetting trade.

month and they constitute an annual return contribution of 28 to 46 bps.[10] Regarding the control variables, we find that funds from larger families and younger funds have higher return gaps. Overall, our evidence from Table 2 suggests that trader-dominated funds can profit from interim trading activities of their fund managers.

3.2. Trading Cost Comparisons

Although the return gap is an intuitive measure of the net impact of interim trading activities on fund returns, it does not allow us to disentangle the agile reaction ability from the trading cost advantage. In this section, we conduct analysis to confirm the presence of each hypothesized ability among trader managers.

The hypothesized transaction cost advantage could come from an ability to assess and manage liquidity and also choose the trade size and the transaction time that best minimize transaction costs. It could also come from relationships with dealers and dealer networks that trader managers built before becoming fund managers that persist after switching to fund management. In this respect, trader managers might have access to larger and more central dealer networks, which can provide lower transaction costs (Dick-Nielsen, Poulsen, and Rehman 2023).

To directly test for the hypothesized transaction advantage of trader-managed funds, we estimate Equation (1) whereby we use the average fund unit transaction cost as the dependent variable. Regression results are reported in Table 3. From Column (1), which uses all funds in our sample, we find significantly lower transaction costs for funds that are predominantly managed by traders. The transaction costs of these funds are, on average, about 5.47 basis points lower than those of other funds, a difference that amounts to about 25% of the average transaction cost for the overall fund sample. For single-managed funds, the transaction cost differential is even starker, with trader-dominated funds generating transaction costs that are 12.28 basis points lower than for

[10] The sample average for the return gap suggests that, on average, the hidden costs of unobserved actions nearly equal the hidden benefits. However, there is a large dispersion in the cross-sectional distribution of the return gap indicating that some funds create value from unobserved actions whereas other funds destroy value with their unobserved interim trading. This becomes evident from the interquartile range of the return gap, which is more than 50 basis points.

other funds. Again, this is an economically strong effect as it corresponds to about 56% of average transaction costs in the sample. For both samples, the effect is statistically significant at the 1% level. Regarding the control variables, we find that funds from smaller families and younger funds have lower transaction costs. Smaller funds, in contrast, have higher transaction costs. An explanation for this result is that trading in smaller funds involves smaller trades, which come with higher transaction costs (see, e.g., Edwards, Harris, and Piwowar 2007).

This section provides clear evidence that trader-managed funds have superior ability to control their transaction costs and the previous section documents that the combined contribution of both types of abilities has a positive net impact on fund returns. Although a direct test for the agile reaction ability of trader managers cannot be implemented, we can use the coefficient estimates from the last two sections to assess the relative importance of the agile reaction ability versus the transaction cost advantage in explaining the return gap difference between trader-run and other-run funds. To do so, we convert the difference in average unit transaction costs estimated in Table 3 to a difference in average annual total transaction costs (using the average portfolio turnover) as a fraction of the annualized return gap differences.[11] This computation reveals that the total transaction cost difference between trader-managed funds and other funds explains only 23 to 31 percent of the annualized return gap difference estimated in Table 2, suggesting that the rest of the return gap difference is likely attributable to the agile reaction ability of the trader-managed funds.

3.3. Optimal Assignment of Trader Managers and Confounding Effect

We expect fund families to be aware of the transaction cost advantage of trader managers and to optimally use the skills of these managers by assigning them to funds where management of transaction costs is most important. This selection process could act as a confounding factor in

[11] The total transaction cost of a given fund is a function of the average transaction cost per trade and the trading activity of the fund. Therefore, for this conversion, we multiply two times the average turnover by the difference in average unit transaction costs estimated in Table 3 and then divide by the annualized return gap difference between the two groups estimated in Table 2. For example for the sample of all funds, this computation is as follows: [(59.163%*2*5.468]/(2.340*12)=23.04%≈23%.

our estimation of the hypothesized effects. Previous research on corporate bonds documents that trading costs are high for small trades, low for medium-sized trades, and increase again for very large trades (see Edwards, Harris, and Piwowar 2007, Feldhütter 2012, Reichenbacher and Schuster 2022). This suggests a u-shaped relation between trading costs and fund size (e.g., Yan 2020), which further suggests that fund families, trying to capitalize on the transaction cost advantages of trader managers, would assign disproportionately more trader managers, in decreasing order, to small funds, large funds, and medium funds.

To analyze this relation, in Table 4 we report the fraction of trader-dominated funds for every fund size quintile. Fund size quintiles are formed every month by ranking all funds by their total assets. First, we see that the highest fraction of trader-dominated funds is in the smallest size quintile, where about 15.6% of funds are trader dominated (for single-managed funds, nearly 33% of funds are trader dominated). In both samples, the smallest share of trader-dominated funds is found in the third fund size quintile, leading to a u-shaped pattern. For the very large funds, we again find a higher share of trader dominated funds (relative to the third size quintile) of 12.8% for all funds and nearly 26% for single-managed funds. Testing for differences in the average fraction of trader-dominated funds across size quintiles using a Newey-West correction, we find that the smallest funds have a significantly higher fraction of trader-dominated funds than the largest funds and medium-sized funds, respectively. Similarly, the largest funds have a higher fraction of trader-dominated funds than the medium-sized funds.

The assignment of trader managers to funds with higher trading costs — which is related to fund size but not in a linear way — might bias against documenting the hypothesized effect that trader managers have on transaction costs and return gaps. We therefore follow Hartzmark and Sussman (2019) and compute an average treatment effect in a balanced sample of trader-dominated funds and other funds that have been selected using nearest-neighbor matching. For every observation, we search for one observation of the other treatment level (i.e., we match every trader observation with a non-trader observation and vice versa) that is closest in terms of fund characteristics. Observations are matched every month within Morningstar Categories on fund assets, family assets, corporate share, fund age, net expense ratio and fund turnover. For every observation pair, we then calculate the difference of the outcome variable (return gap and transaction cost). The average treatment effect is the mean of these differences across all matched pairs. This approach allows us to make a more direct comparison of trader-dominated vs. other funds by choosing a peer fund that is as close as possible in terms of confounding factors.

Table 5 shows the results. For the return gap, we observe, for both samples, average treatment effects of slightly lower, but comparable size to the regression coefficients in Table 2. This provides further robustness for our findings. For transaction costs, we see slightly stronger effects than in Table 3, which mitigate concerns that the u-shaped distribution of fund managers across fund size groups affects our results. The fact that results become even stronger implies that this effect works – if at all – against finding significant results.

Summarizing the results so far, our evidence suggests that trader managers are able to achieve lower transaction costs and generate higher short-term profits from trading.

3.4. When Do the Skills of Trader Managers Matter Most?

When the corporate bond market is comparably illiquid, trading becomes more challenging and transaction costs increase. During these times trading advantages can pay off. For example, Di Maggio, Kermani, and Song (2017) show that trading relationships help especially during periods of market turmoil and dealers charge lower spreads to the traders with whom they are connected. As trading becomes even more important during those times, trader managers might be able to profit from their trading skills even more. As a measure of market illiquidity, we calculate the size-adapted average bid-ask spread at the bond-month level as in Reichenbacher and Schuster (2022) and use the market-wide average. To enable better interpretation of this variable, we standardize market illiquidity to have zero mean and a standard deviation of one. We refer to this variable as Mkt. Illiquidity. We then run regressions, where we interact the trader dummy with the Mkt. Illiquidity variable:

$$
\begin{aligned}
Var_{i,t} = \alpha \quad & + \beta^{T\_D} \times Trader\_Dominated_{i,t-1} \\
& + \beta^{T\_D \times Mkt.Illiquidity} \times Trader\_Dominated_{i,t-1} \times Mkt.Illiquidity_t \\
& + \theta \times Controls_{i,t-1} + \epsilon_{i,t} \qquad (4)
\end{aligned}
$$

Results are reported in Table 6. Looking at columns (1) and (5) in Table 6, we see that traders can achieve an even higher return gap when market illiquidity increases. This result holds for both the full sample and single-managed funds. A one standard deviation increase in market illiquidity (this refers to an increase in the average bid-ask spread of 12.51 bps) is associated with an additional return gap for the trader-dominated funds relative to other funds of around 5.6 bps per month. An effect of similar size is documented for the single-managed fund sample. The coefficients are significant at the 5% level. However, results on transaction costs in columns (3) and (7) show that trader managers cannot improve (reduce) their average transaction costs further as market illiquidity rises. This suggests that during illiquid times the ability to act quickly on new opportunities created by these market conditions dominates the ability to control transaction costs.

Other periods of market stress, in which the skill set of traders might be beneficial, are when interest rates change by a lot. When there are larger interest rate changes, fund managers must reposition their portfolios, which requires timely execution of bond trades. Traders could profit from the relationships they formed before becoming fund managers. For example, they could have access to larger dealer networks that provide them with lower charges for trade immediacy. As a measure of the size of interest rate changes, we employ the squared monthly change in the 10-year treasury rate. To ease interpretation, we again standardize the squared rate change to have zero mean and a standard deviation of one. We refer to this variable as Rate Change. We modify Equation (4) by replacing Mkt. Illiquidity with Rate Change.

Looking at columns (2) and (6) of Table 6, we observe that a one standard deviation increase in the rate change measure comes with a relative increase in return gap of 7.15 bps per month for the full sample and 6.27 bps for the single-managed funds, with both coefficients being statistically significant at the 5% level. Looking at columns (4) and (8), we also see significant effects for transaction costs. A one standard deviation increase in the rate change measure leads to a further relative transaction cost decline of 9.02 bps for the full sample and even 14.35 bps for the single-managed funds.

It is worth noting that a comparison of the coefficients of the interaction terms across the two scenarios that lead to worse market conditions, i.e., higher illiquidity and larger change in interest rates, suggests that the skills of trader managers are more valuable during periods of large interest rate changes than during periods of higher illiquidity. For example, focusing on the all-funds sample, a one standard deviation increase in Mkt. Illiquidity leads to a relative return gap increase of 5.62 bps. However, a one standard deviation increase in Rate Change leads to a return gap increase of 7.15 bps. This pattern is even stronger for transaction costs, whereby the relative transactions cost improvements for a one standard deviation increase in Mkt. Illiquidity and Rate Change are, respectively, 3.14 bps and 9.02 bps. Overall, this evidence suggests that trader managers' abilities place them at a greater comparative advantage during periods of large interest rate changes than during periods of worsening market liquidity.

3.5. Performance Comparisons

So far, we have documented that trader managers benefit from their agile reaction ability as well as a transaction cost advantage. A natural question is: Do these advantages translate into superior performance, i.e., a higher risk-adjusted returns, for trader-managed funds? Our measure of fund performance is an alpha measure computed as the actual gross return of the fund minus its expected return in that month. Similar to Cici and Gibson (2012), the expected return is estimated based on a four factor model. The first factor, a stock market factor (STK), is the excess return of the CRSP value-weighted stock index. The remaining three factors are: a BOND factor, which is the excess return of the Bloomberg Aggregate Bond Index; a default factor (DEF), which measures the difference in returns between the Bloomberg US Corporate High Yield Index and the Bloomberg US Intermediate Government Index; and an option factor (OPTION), which is calculated as the return difference between the Bloomberg US GNMA Bond Index and the Bloomberg US Intermediate Government Index. We use a rolling window regression to estimate the factor betas. Specifically, for every fund and every month we estimate the following time-series regression:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,STK} STK_t + \beta_{i,BOND} BOND_t + \beta_{i,DEF} DEF_t + \beta_{i,OPTION} OPTION_t + \varepsilon_{i,t} \quad (5)$$

where $R_{i,t}$ is the (winsorized) gross return of fund i in month t, $R_{f,t}$ is the one-month treasury bill rate, and STK, $BOND$, DEF, and $OPTION$ are the asset pricing factors described above. The expected return of a fund is then calculated as the sum of the products of factor realizations in month t and the estimated factor betas. Betas are estimated using data from months $t - 36$ to $t - 1$ requiring a minimum of 30 non-missing return observations.

We report regression results from Equation (1), modified with alpha as the dependent variable, in Table 7. Results show no significant difference in alpha between trader-dominated funds and other funds. A potential reason is that the return gap and transaction cost advantages of traders are somehow correlated with the asset pricing factors and, therefore, are (partially) captured by the factor betas but not by the alpha. However, in times when interest rates change, we find a significantly positive effect on fund alpha. This effect holds for both single-managed funds and the full sample of funds. For single-managed funds, we find that when our rate change measure increases by one standard deviation, alpha is 3.19 bps per month (38.28 bps per year) larger for trader-managed funds. In the full sample, we document a 4.59 bps per month (55.08 bps per year) higher alpha. These results suggest that the abilities of trader managers have a positive impact on performance in situations when fund managers must react quickly to changes in market conditions due to large fluctuations in interest rates. We do not find a similar performance effect when market illiquidity increases. This is consistent with the evidence from the previous section documenting that the comparative advantages of trader managers are greater during periods of large interest rate fluctuations than during periods of worsening market liquidity.[12]

4. Risk-taking Comparisons

4.1. Reaching for Yield

In Section 3, we evaluated the effect of trader managers on fund performance and related aspects. We now turn to understanding their risk-taking behavior. On one hand, trader managers might resemble the typical trader stereotype, characterized by a relatively stronger propensity to take risk. On the other hand, since their skills matter the most during times of market stress—riskier times, when risk management is especially important — they might have been selected because of a superior ability to manage risk. Whether trader managers' risk-taking behavior is different from that of other managers is thus an empirical question.

One popular form of risk taking is reaching for yield (RFY), a tendency to position the portfolio in the direction of relatively higher-yielding bonds. Choi and Kronlund (2018) show that this behavior can lead to higher inflows and produces, on average, higher raw fund returns. The higher raw returns, however, come at a cost because funds that exhibit RFY are exposed to greater liquidity, default, and fire sale risks. Therefore, RFY is a form of risk taking for corporate bond mutual funds, with the downsides materializing in times of market stress. We examine differences in RFY between funds managed by traders and other funds, both overall and in times of market stress. We measure RFY following Choi and Kronlund (2018) as

$$RFY_{i,t}^{Total} = \sum_b w_{b,i,t}(y_{b,t} - y_t^{AGG}),$$

[12] Using the Cici and Gibson (2012) approach to isolate the part of the fund return due to bond selection, we find that trader-dominated funds do not have superior bond selection relative to other funds. Results are reported in Section A.2 of the Appendix. This is likely due to the interplay of two opposing plausible effects that cancel each other out. On one hand, the abilities of trader managers revolve around trading and their career progression might have kept them from acquiring skills to conduct fundamental analysis, which are needed for bond selection. On the other hand, traders might be more familiar with complex structures of bonds like embedded options that depend on interest rate risk, which might provide them an advantage in bond selection. In the next section, we present some evidence that trader managers are skilled at managing interest rate risk.

where $w_{b,i,t}$ is the market weight of bond b in fund i's holdings, $y_{b,t}$ is the yield of bond b and y_t^{AGG} is the value-weighted benchmark yield of all bonds (see below). The total RFY measure captures higher yield due to credit risk as well as higher interest rate risk and any other kind of risk. Therefore, Choi and Kronlund (2018) propose a decomposition of the (total) RFY measure into three components:

$$RFY_{i,t}^{Total} = \sum_b w_{b,i,t}(y_{b,t}^R - y_t^{AGG}) + \sum_b w_{b,i,t}(y_{b,t}^{R,M} - y_{b,t}^R) + \sum_b w_{b,i,t}\left(y_{b,t} - y_{b,t}^{R,M}\right)$$
$$= RFR_{i,t} + RFM_{i,t} + RFY_{i,t}^{WRM}.$$

The RFR component is the reaching for rating component, RFM is the reaching for maturity component, and RFY^{WRM} is reaching for yield within a rating and maturity bucket.[13] $y_{b,t}^R$ is the weighted average yield of all bonds with the same rating notch as bond b, $y_{b,t}^{R,M}$ is the weighted average yield of all bonds with the same rating notch and maturity bucket as bond b. Additional detail on the construction of *RFY* and its components is provided in Appendix A.3.[14] Summary statistics for RFY and its components are reported in Panel B of Table 1. On average, the funds in our sample exhibit RFY, especially by holding bonds with lower credit ratings. Also, we document a large variation across funds in RFY, indicating that some funds engage a lot in RFY whereas others are relatively conservative.

We regress the four RFY measures on our trader dummy and control variables in line with Equation (1) and report results in Table 8. Panel A shows results for the full sample, Panel B shows results for single-managed funds. Overall, we do not see more risk-taking via RFY for trader-managed funds. The coefficient in column (1) is insignificant both for the entire sample in Panel A and the single-managed funds in Panel B. Consistent with Choi and Kronlund (2018), we find

[13] *RFR* can be seen as reaching for yield via holding bonds with higher credit risk, i.e., a lower rating. *RFM* can be seen as reaching for yield via holding bonds with a higher interest rate risk, i.e., a longer maturity. The last component, RFY^{WRM}, includes reaching for yield that is not due to higher credit or interest rate risk, but to any other kind of risk. Possible other sources of risk include, for example, embedded optionalities, special structures, or a bond's illiquidity.

[14] As a robustness analysis, we modify the approach of Choi and Kronlund (2018) by including all index eligible bonds in a fund's portfolio (i.e., including treasury and agency bonds) and not just corporate bonds. Results in Appendix A.3 are qualitatively similar and even a bit stronger in terms of economic and statistical significance.

that RFY is positively associated with fund size and the expense ratio and negatively correlated with fund age. Looking at columns (2) and (3), we document a lower RFY measure for trader-dominated funds in times of market stress suggesting that traders de-risk their portfolios in stressful market phases.

The results in columns (8) and (9) show that the lower RFY behavior of traders in illiquid and volatile market periods comes mainly from the reaching for rating component, i.e., holding bonds with lower ratings. Hence, trader managers de-risk their portfolios with regard to credit risk in times of market stress. During turbulent market conditions, reaching for rating is likely the riskiest way of reaching for yield.

Contrary to the reaching for rating results, in columns (4) to (6) of Panel A we see that trader-dominated funds increase their reaching for maturity relative to other funds in stressful periods. This result is statistically significant only for the full fund sample. Interestingly, for the single-managed funds, results suggest that trader-dominated funds exhibit consistent higher reaching for maturity behavior than other funds that does not change across market phases. We will explore this result in more depth in the next section where we look at portfolio duration and convexity in the context of interest rate risk management. Similarly, columns (11) and (12) show an increased RFY behavior of trader managers within a given rating-and-maturity category in times of market stress. This is consistent with traders taking the opposite side of trades in periods of market stress for bonds with higher yields due to their illiquidity, special cash flow structure, or embedded options.

4.2. Duration and Convexity

As trader managers' abilities matter the most during periods of high interest rate volatility, we next dig deeper to understand how traders manage interest rate risk. Especially, we look at the sensitivity of their portfolios to changes in interest rates. To measure the sensitivity of a fund's portfolio to changes in interest rates, we use the average duration and convexity of the bonds in the portfolio. The higher the duration, the more sensitive the portfolio is to changes in interest rates. The convexity is defined as the curvature of the relation between interest rates and bond prices. A higher convexity means that bond prices react more favorably when interest rates change sharply in both directions. A higher convexity therefore helps reduce interest rate risks. Given the results on reaching for maturity, we hypothesize that traders have a higher exposure to interest rate risk by holding bonds with higher durations. If, at the same time, the convexity of their portfolios is higher, this would limit their overall risk-exposure and potentially could lead to an excess return compared to their peers in times of sharp interest rate movements.

We calculate average duration and convexity of a fund in each month as the value-weighted average of the (modified) duration of corporate bonds in the funds' portfolio. Durations come from the bond return file of WRDS and we calculate a bond’s convexity analogous to the duration. We fill in missing data for the duration and convexity with data from Refinitiv Eikon. We winsorize average duration and average convexity at the 1% and 99% levels.

Table 9 shows regression results with duration and convexity as the dependent variables. We find evidence that traders in single-managed funds tilt their portfolios toward bonds with longer maturities and higher duration. We also find evidence that the portfolios of traders have higher bond convexity. Together with our previous results of higher return gaps and higher alphas for trader-dominated funds in times when interest rates change, this result indicates that traders are able to manage interest rate risk proficiently.

5. Conclusion

In this paper, we examine the role of traders in fund management and uncover a number of novel findings. First, we show that trader managers benefit from an ability to exploit short-term trading opportunities that cannot be easily exploited by others and an ability to control transaction costs. These benefits are strongest among single-managed funds, for which attribution of trading abilities to fund outcomes is most precise, producing a relative return contribution of about 55 basis points per year over our sample period. The benefits are even stronger in illiquid periods or in periods of large fluctuations in interest rates. Second, we find direct evidence that trader managers use their trading skills to achieve substantially lower transaction costs. Again, this effect is strongest for single-managed funds, for which we document about 60% lower average transaction costs compared to peers. Finally, we show that trader managers are not excessive risk takers. On the contrary, they take on risks cautiously and even de-risk their portfolios in times of market stress. For example, trader managers decrease their exposure to bonds with high credit risk in turbulent market phases. Finally, we find that trader-dominated funds take on more interest rate risk than other funds in periods of large interest rate fluctuations. The higher alphas these funds produce during such periods together with their higher portfolio convexities indicate, however, that they are able to manage interest rate risk proficiently and to their advantage.

Overall, our results suggest that there are benefits from employing traders as fund managers. These traders bring skills that are valuable and don't fit the cliché of excessive risk taking. Especially during times of market stress, trading experience and the agile reaction ability of traders are of high importance. Fund families can make the best use of those skills by placing traders in funds where their skills produce the greatest benefits. Our analysis suggests that fund families indeed do some of this matching—they place disproportionately more trader managers to manage smaller funds where transactions costs are typically higher. The extent to which fund families place trader managers in funds where risk management or quick reaction to market conditions is more important is worthy of future research.

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Table 1: Descriptive statistics

This table shows summary statistics for the sample. Panel A shows summary statistics for fund characteristics and control variables, Panel B shows summary statistics for our dependent variables.

Panel A

	N	Mean	Std. Dev.	P5	P25	Median	P75	P95
Fund assets [$ million]	85,693	1,217.634	3,079.888	12.026	78.246	322.397	1,009.024	5,210.300
Family assets [$ million]	85,613	130,282.01	293,101.22	199.496	4,535.721	37,205.142	98,542.915	540,020.87
Fund age	85,693	14.208	10.883	1.133	5.591	12.482	20.007	35.573
Corporate share [%]	80,397	65.627	22.479	29.950	46.709	67.707	86.120	95.481
Fund turnover [%]	79,402	59.163	52.394	3.475	25.301	46.635	76.617	157.858
Net expense ratio [%]	83,195	0.851	0.360	0.268	0.639	0.829	1.055	1.411
Share traders [%]	85,693	27.941	32.828	0.000	0.000	16.558	49.692	100.000

Panel B

	N	Mean	Std. Dev.	P5	P25	Median	P75	P95
Return gap [bps]	77,266	-0.633	49.779	-80.872	-27.321	-0.855	26.117	80.124
Value weighted average transaction costs [bps]	29,705	21.736	64.216	-43.591	0.420	14.555	37.880	114.951
Alpha [bps]	71,562	3.683	53.632	-81.224	-23.019	4.476	31.869	85.507
Reaching for yield (total) [bps]	79,704	41.618	110.579	-122.513	-48.315	36.089	132.863	199.229
Reaching for maturity [bps]	79,704	-7.451	24.164	-52.921	-16.972	-3.063	3.941	22.859
Reaching for rating [bps]	79,704	67.067	111.005	-71.905	-33.265	34.234	172.265	231.226
Reaching for yield (within) [bps]	79,704	-17.998	30.391	-65.353	-36.189	-12.996	-0.808	19.227
Average portfolio duration	80,086	4.738	1.825	1.917	3.763	4.608	5.534	7.773
Average portfolio convexity	80,035	43.369	37.818	6.063	22.600	32.526	52.458	112.398
Selection [bps]	72,039	-4.279	57.534	-95.489	-31.013	-3.911	22.488	84.892

Table 2: Return Gap

This table shows regressions of the return gap (in bps) on a dummy variable that indicates if the fund is managed predominately by traders. Control variables include a dummy variable for the fund incubation period, the share of corporate bond holdings on the total fund holdings, the logarithm of fund assets, the logarithm of family assets, the logarithm of fund age, net expense ratio, and fund turnover. Column (1) reports results for the full sample and column (2) reports results for single-managed funds only. All columns include month and Morningstar Category fixed effects. Standard errors are clustered by fund and month and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All funds	Single-managed funds
	(1)	(2)
traderdominated	2.340**	3.822**
	(1.096)	(1.590)
incubation	-2.705	-5.924
	(1.667)	(4.542)
corp. share	-0.037	-0.072
	(0.049)	(0.059)
log(fund assets)	-0.594*	-0.129
	(0.322)	(0.366)
log(family assets)	1.069***	0.981***
	(0.213)	(0.334)
log(fund age)	-0.674*	-1.649*
	(0.391)	(0.875)
net expense ratio	1.838	1.770
	(1.137)	(1.837)
turnover	-0.001	0.030***
	(0.006)	(0.011)
Month FE	Yes	Yes
Morningstar Cat. FE	Yes	Yes
Observations	75,583	17,428
R^2	0.359	0.305
Adjusted R^2	0.357	0.295

Table 3: Transaction costs

This table shows regressions of value weighted fund transaction costs (in bps) on a dummy variable that indicates if the fund is managed predominately by traders. Control variables include a dummy variable for the fund incubation period, the share of corporate bond holdings on the total fund holdings, the logarithm of fund assets, the logarithm of family assets, the logarithm of fund age, net expense ratio, and fund turnover. Column (1) reports results for the full sample and column (2) reports results for single-managed funds only. All columns include month and Morningstar Category fixed effects. Standard errors are clustered by fund and month and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All funds	Single-managed funds
	(1)	(2)
traderdominated	-5.468***	-12.280***
	(1.504)	(4.542)
incubation	10.875***	30.792**
	(3.742)	(12.428)
corp. share	-0.108*	-0.203
	(0.065)	(0.180)
log(fund assets)	-4.509***	-5.459***
	(0.614)	(1.665)
log(family assets)	0.677**	1.657*
	(0.331)	(0.984)
log(fund age)	2.709***	5.182*
	(0.927)	(2.833)
net expense ratio	-0.661	10.740
	(2.781)	(7.169)
turnover	0.001	0.034
	(0.010)	(0.035)
Month FE	Yes	Yes
Morningstar Cat. FE	Yes	Yes
Observations	28,766	4,745
R^2	0.037	0.041
Adjusted R^2	0.029	-0.009

Table 4: Share of trader-dominated funds [%] in different fund size groups

This table reports the average share of funds which are predominantly managed by traders in different size quintiles. Size quintiles are formed every month, with Q1 being the smallest size quintile and Q5 the largest. We report tests of the difference in means between different size quintiles at the bottom of this table. Newey-West adjusted standard errors are in parentheses.

Size quintiles (formed every date)	All funds	Single-managed funds
Q1	15.598	32.833
Q2	14.045	24.819
Q3	9.869	15.745
Q4	10.769	24.696
Q5	12.845	25.946
Q1-Q5	2.752***	6.888***
	(0.970)	(1.777)
Q1-Q3	5.729***	17.088***
	(0.793)	(1.840)
Q5-Q3	2.977***	10.201***
	(0.956)	(2.186)

*p<0.1, **p<0.05, ***p<0.01

Table 5: Return gap and transaction costs results matching on fund characteristics

This table reports the average treatment effect of a fund being trader dominated on return gap and fund transaction costs using nearest neighbor matching. Funds are matched every month within Morningstar Categories on fund assets, family assets, corporate share, fund age, net expense ratio and fund turnover. Matching is adjusted for the bias discussed in Abadie and Imbens (2006, 2011). Abadie-Imbens standard errors are in parentheses. *,** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	return gap [bps]		value weighted average transaction costs [bps]	
	(1)	(2)	(3)	(4)
All funds	2.041***		-7.697***	
	(0.693)		(1.459)	
Single-managed funds		3.051**		-18.687***
		(1.371)		(7.255)
Observations	69,593	12,211	18,852	706

Table 6: Turbulent market phases

This table examines whether the impact of trader dominance on return gaps and value weighted fund transaction costs changes in turbulent market periods. Measures for turbulent market periods are market illiquidity, measured by a market-wide average of monthly corporate bond bid-ask spreads, and ratechange squared, measured as the squared monthly change in the 10-year US Treasury bond rate. Market illiquidity and ratechange squared are standardized to have zero mean and a standard deviation of one. Control variables include a dummy variable for the fund incubation period, the share of corporate bond holdings on the total fund holdings, the logarithm of fund assets, the logarithm of family assets, the logarithm of fund age, net expense ratio and fund turnover. Columns (1) to (4) report results for the full sample, columns (5) to (8) report results for single-managed funds only. All columns include month and Morningstar Category fixed effects. Standard errors are clustered by fund and month and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All funds				Single-managed funds			
	return gap [bps]		transaction costs [bps]		return gap [bps]		transaction costs [bps]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
traderdominated	2.849**	2.618**	-5.718***	-5.963***	3.430**	3.496**	-12.311***	-11.118**
	(1.194)	(1.110)	(1.608)	(1.497)	(1.484)	(1.464)	(4.354)	(4.314)
incubation	-2.898*	-2.845*	10.952***	11.033***	-6.353	-6.143	30.787**	31.669**
	(1.683)	(1.685)	(3.757)	(3.762)	(4.533)	(4.569)	(12.371)	(12.607)
corp. share	-0.036	-0.036	-0.110*	-0.109*	-0.069	-0.067	-0.203	-0.209
	(0.049)	(0.049)	(0.064)	(0.065)	(0.060)	(0.060)	(0.177)	(0.179)
log(fund assets)	-0.592*	-0.590*	-4.503***	-4.499***	-0.127	-0.117	-5.457***	-5.502***
	(0.322)	(0.322)	(0.614)	(0.613)	(0.375)	(0.372)	(1.654)	(1.658)
log(family assets)	1.081***	1.078***	0.663**	0.652*	1.029***	1.009***	1.657*	1.607
	(0.211)	(0.212)	(0.333)	(0.331)	(0.326)	(0.330)	(0.984)	(0.984)
log(fund age)	-0.707*	-0.698*	2.725***	2.741***	-1.710*	-1.692*	5.179*	5.416*
	(0.391)	(0.394)	(0.925)	(0.924)	(0.888)	(0.886)	(2.765)	(2.832)
net expense ratio	1.908*	1.897*	-0.676	-0.711	2.043	1.956	10.733	11.099
	(1.136)	(1.144)	(2.773)	(2.777)	(1.891)	(1.874)	(7.257)	(7.146)
turnover	-0.001	-0.001	0.001	0.002	0.027**	0.029***	0.034	0.040
	(0.006)	(0.006)	(0.010)	(0.010)	(0.011)	(0.011)	(0.034)	(0.036)
traderdominated × market illiquidity	5.617**		-3.137		5.618**		0.138	
	(2.414)		(3.052)		(2.652)		(7.347)	
traderdominated × ratechange		7.154**		-9.018**		6.273**		-14.351**
		(3.391)		(4.403)		(2.595)		(6.765)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,583	75,583	28,766	28,766	17,428	17,428	4,745	4,745
R^2	0.359	0.359	0.037	0.038	0.306	0.307	0.041	0.043
Adjusted R^2	0.357	0.357	0.029	0.030	0.296	0.297	-0.009	-0.007

Table 7: Alpha

This table shows regressions of a funds' alpha on a dummy variable that indicates if the fund is managed predominately by traders. Columns (1) and (4) show baseline regression results. Columns (2), (3), (5), and (6) show results when the traderdominated variable is interacted with measures for turbulent market periods. Measures for turbulent market periods are market illiquidity, measured by a market-wide average of monthly corporate bond bid-ask spreads, and ratechange squared, measured as the squared monthly change in the 10-year US Treasury bond rate. Market illiquidity and ratechange squared are standardized to have zero mean and a standard deviation of one. Control variables include a dummy variable for the fund incubation period, the share of corporate bond holdings on the total fund holdings, the logarithm of fund assets, the logarithm of family assets, the logarithm of fund age, net expense ratio, and fund turnover. Columns (1) to (3) report results for the full sample, columns (4) to (6) report results for single-managed funds only. All columns include month and Morningstar Category fixed effects. Standard errors are clustered by fund and month and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All funds			Single-managed funds		
	(1)	(2)	(3)	(4)	(5)	(6)
traderdominated	0.637	0.695	0.833	0.155	0.091	0.019
	(0.810)	(0.831)	(0.783)	(1.294)	(1.306)	(1.309)
incubation	4.328	4.118	3.583	2.867	2.583	2.512
	(4.386)	(4.518)	(4.692)	(3.167)	(3.446)	(3.335)
corp. share	0.046	0.047	0.047	0.042	0.042	0.044
	(0.052)	(0.052)	(0.052)	(0.075)	(0.076)	(0.076)
log(fund assets)	-0.804*	-0.804*	-0.803*	-0.086	-0.086	-0.077
	(0.427)	(0.427)	(0.428)	(0.535)	(0.535)	(0.536)
log(family assets)	0.360	0.362	0.368	0.137	0.145	0.148
	(0.277)	(0.275)	(0.276)	(0.459)	(0.453)	(0.457)
log(fund age)	-0.888	-0.891	-0.903	-0.803	-0.808	-0.827
	(0.811)	(0.815)	(0.813)	(1.074)	(1.073)	(1.075)
net expense ratio	0.584	0.593	0.622	4.121**	4.173**	4.197**
	(1.756)	(1.760)	(1.759)	(1.826)	(1.819)	(1.824)
turnover	0.030***	0.030***	0.029***	0.051***	0.050***	0.050***
	(0.008)	(0.008)	(0.008)	(0.014)	(0.018)	(0.014)
traderdominated × market illiquidity		0.612			1.120	
		(1.454)			(1.571)	
traderdominated × ratechange			4.586**			3.190*
			(1.820)			(1.718)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,463	67,463	67,463	15,856	15,856	15,856
R^2	0.151	0.151	0.151	0.173	0.173	0.173
Adjusted R^2	0.148	0.148	0.148	0.160	0.160	0.161

Table 8: Reaching for Yield

This table shows regressions of reaching for yield and its components on a dummy variable that indicates if the fund is managed predominately by traders Columns (1), (4), (7), and (10) show baseline regression results. The remaining columns show results when the traderdominated variable is interacted with measures for turbulent market periods. Measures for turbulent market periods are market illiquidity, measured by a market-wide average of monthly corporate bond bid-ask spreads, and ratechange squared, measured as the squared monthly change in the 10-year US Treasury bond rate. Market illiquidity and ratechange squared are standardized to have zero mean and a standard deviation of one. Control variables include a dummy variable for the fund incubation period, the share of corporate bond holdings on the total fund holdings, the logarithm of fund assets, the logarithm of family assets, the logarithm of fund age, net expense ratio, and fund turnover. Panel A reports results for the full sample, Panel B reports results for single-managed funds only. All columns include month and Morningstar Category fixed effects. Standard errors are clustered by fund and month and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full sample

	Reaching for Yield (total) [bps]			Reaching for Maturity [bps]			Reaching for Rating [bps]			Reaching for yield (within) [bps]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
traderdominated	0.753	-0.247	0.524	2.201	2.395	2.240	-4.012	-6.192	-4.431	2.564*	3.550**	2.715*
	(4.133)	(4.293)	(4.170)	(1.632)	(1.614)	(1.629)	(4.054)	(4.428)	(4.121)	(1.466)	(1.669)	(1.496)
incubation	1.174	1.579	1.314	-2.186	-2.265	-2.210	5.186	6.069	5.442	-1.826	-2.225	-1.918
	(6.447)	(6.363)	(6.432)	(1.918)	(1.897)	(1.912)	(6.784)	(6.577)	(6.737)	(2.213)	(2.190)	(2.201)
corp. share	0.021	0.019	0.021	-0.078***	-0.078***	-0.078***	0.285	0.280	0.284	-0.185***	-0.183***	-0.185***
	(0.145)	(0.145)	(0.145)	(0.029)	(0.029)	(0.029)	(0.174)	(0.173)	(0.173)	(0.052)	(0.051)	(0.052)
log(fund assets)	5.698***	5.693***	5.694***	1.305***	1.306***	1.306***	3.820***	3.810***	3.813***	0.572	0.577	0.575
	(1.367)	(1.366)	(1.367)	(0.396)	(0.396)	(0.396)	(1.346)	(1.344)	(1.345)	(0.440)	(0.441)	(0.440)
log(family assets)	0.079	0.055	0.071	0.216	0.221	0.218	0.429	0.375	0.414	-0.566*	-0.542*	-0.561*
	(0.954)	(0.952)	(0.953)	(0.296)	(0.296)	(0.296)	(0.807)	(0.801)	(0.805)	(0.310)	(0.309)	(0.310)
log(fund age)	-6.107***	-6.043***	-6.085***	-1.094*	-1.106*	-1.098*	-4.064*	-3.925*	-4.023*	-0.949	-1.012	-0.964
	(2.190)	(2.179)	(2.187)	(0.658)	(0.656)	(0.657)	(2.138)	(2.118)	(2.132)	(0.802)	(0.806)	(0.802)
net expense ratio	34.408***	34.274***	34.350***	1.465	1.491	1.474	29.210***	28.917***	29.104***	3.734*	3.866*	3.772*
	(6.255)	(6.241)	(6.248)	(1.846)	(1.841)	(1.845)	(5.446)	(5.382)	(5.424)	(2.138)	(2.132)	(2.136)
turnover	0.101***	0.101***	0.101***	0.019**	0.019**	0.019**	0.078***	0.079***	0.079***	0.003	0.003	0.003
	(0.024)	(0.024)	(0.024)	(0.009)	(0.009)	(0.009)	(0.023)	(0.023)	(0.023)	(0.008)	(0.008)	(0.008)
traderdominated x market illiquidity		-11.210**			2.174**			-24.435***			11.051***	
		(4.822)			(0.962)			(7.940)			(3.828)	
traderdominated x ratechange			-6.088**			1.042**			-11.152**			4.022**
			(2.882)			(0.431)			(4.787)			(1.989)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,811	75,811	75,811	75,811	75,811	75,811	75,811	75,811	75,811	75,811	75,811	75,811
R^2	0.591	0.592	0.591	0.367	0.368	0.368	0.543	0.546	0.544	0.453	0.456	0.453
Adjusted R^2	0.589	0.590	0.590	0.365	0.366	0.366	0.542	0.545	0.542	0.451	0.455	0.452

(Continued)

Table 8 – *Continued*

	Panel B: Single-managed funds											
	Reaching for Yield (total) [bps]			Reaching for Maturity [bps]			Reaching for Rating [bps]			Reaching for yield (within) [bps]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
traderdominated	-0.928	0.584	-0.366	8.310***	8.160**	8.252***	-13.198*	-10.068	-12.180	3.960	2.492	3.562
	(7.197)	(7.205)	(7.187)	(3.119)	(3.156)	(3.128)	(7.690)	(7.741)	(7.638)	(2.673)	(2.606)	(2.608)
incubation	-4.733	-2.933	-4.276	0.211	0.033	0.164	-0.193	3.534	0.637	-4.752	-6.500	-5.076
	(11.437)	(11.117)	(11.372)	(3.939)	(3.877)	(3.923)	(13.880)	(12.976)	(13.687)	(4.880)	(4.711)	(4.825)
corp. share	-0.318	-0.333	-0.326	-0.081	-0.080	-0.080	-0.075	-0.105	-0.089	-0.162	-0.148	-0.156
	(0.231)	(0.231)	(0.231)	(0.055)	(0.055)	(0.055)	(0.266)	(0.263)	(0.264)	(0.111)	(0.108)	(0.110)
log(fund assets)	2.913	2.898	2.888	0.350	0.352	0.353	1.444	1.412	1.398	1.119	1.134	1.137
	(2.619)	(2.593)	(2.614)	(0.796)	(0.799)	(0.796)	(2.645)	(2.594)	(2.635)	(0.941)	(0.920)	(0.938)
log(family assets)	1.382	1.198	1.337	1.452**	1.470**	1.456**	1.128	0.746	1.046	-1.198*	-1.018	-1.165
	(2.087)	(2.059)	(2.079)	(0.646)	(0.645)	(0.646)	(1.933)	(1.874)	(1.915)	(0.711)	(0.707)	(0.708)
log(fund age)	-5.496	-5.234	-5.417	-1.737	-1.763	-1.745	-2.313	-1.770	-2.170	-1.446	-1.701	-1.502
	(3.979)	(3.961)	(3.975)	(1.459)	(1.456)	(1.458)	(4.246)	(4.223)	(4.233)	(1.705)	(1.705)	(1.701)
net expense ratio	42.651***	41.570***	42.314***	2.443	2.550	2.478	35.203***	32.965***	34.592***	5.005	6.055	5.244
	(9.547)	(9.515)	(9.532)	(3.010)	(3.012)	(3.011)	(9.373)	(9.383)	(9.331)	(4.003)	(4.099)	(4.006)
turnover	0.138***	0.149***	0.140***	-0.003	-0.004	-0.003	0.110***	0.133***	0.114***	0.031	0.020	0.029
	(0.044)	(0.044)	(0.044)	(0.016)	(0.016)	(0.016)	(0.038)	(0.039)	(0.038)	(0.021)	(0.021)	(0.021)
traderdominated x market illiquidity		-21.329***			2.107			-44.145***			20.709***	
		(7.558)			(1.508)			(12.447)			(6.292)	
traderdominated x ratechange			-10.295**			1.056			-18.650**			7.299**
			(4.940)			(0.822)			(8.538)			(3.511)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462
R^2	0.617	0.623	0.619	0.378	0.379	0.378	0.570	0.586	0.574	0.481	0.501	0.484
Adjusted R^2	0.612	0.617	0.614	0.370	0.371	0.370	0.565	0.581	0.568	0.474	0.494	0.477

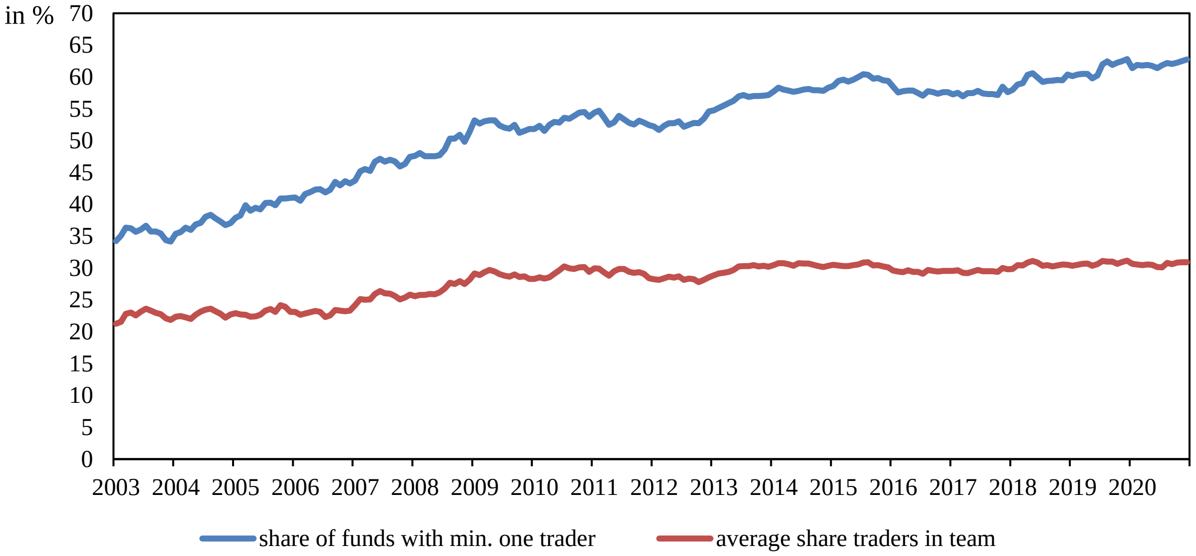
Table 9: Duration and Convexity

This table shows regressions of average portfolio duration and average portfolio convexity on a dummy variable that indicates if the fund is managed predominately by traders. Control variables include a dummy variable for the fund incubation period, the share of corporate bond holdings on the total fund holdings, the logarithm of fund assets, the logarithm of family assets, the logarithm of fund age, net expense ratio, and fund turnover. Columns (1) to (3) report results for the full sample, columns (4) to (6) report results for single-managed funds only. All columns include month and Morningstar Category fixed effects. Standard errors are clustered by fund and month and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All funds			Single-managed funds		
	average portfolio duration	average portfolio convexity		average portfolio duration	average portfolio convexity	
	(1)	(2)	(3)	(4)	(5)	(6)
traderdominated	-0.016	2.121	2.529***	0.414**	9.512**	1.961
	(0.110)	(2.612)	(0.958)	(0.180)	(4.043)	(1.444)
average duration			19.996***			18.458***
			(0.585)			(1.148)
incubation	0.255**	1.199	-3.576***	-0.055	-7.934	-6.958**
	(0.128)	(3.136)	(1.093)	(0.265)	(6.730)	(2.761)
corp. share	0.002	0.017	-0.037**	0.003	0.062	0.010
	(0.003)	(0.051)	(0.017)	(0.004)	(0.081)	(0.035)
log(fund assets)	0.070**	1.689**	0.294	-0.056	-1.053	-0.063
	(0.034)	(0.731)	(0.248)	(0.063)	(1.323)	(0.493)
log(family assets)	0.059**	1.130**	-0.060	0.197***	3.538***	-0.054
	(0.024)	(0.520)	(0.176)	(0.047)	(1.044)	(0.386)
log(fund age)	0.039	-0.227	-1.018**	0.036	-1.350	-1.968**
	(0.052)	(1.169)	(0.443)	(0.094)	(2.091)	(0.904)
net expense ratio	-0.122	-2.338	-0.015	0.169	3.164	0.068
	(0.134)	(2.979)	(1.038)	(0.223)	(4.594)	(1.869)
turnover	0.002***	0.046***	-0.001	0.0004	-0.004	-0.011
	(0.001)	(0.015)	(0.005)	(0.001)	(0.019)	(0.009)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,119	76,071	76,041	17,574	17,581	17,567
R^2	0.558	0.527	0.920	0.558	0.526	0.896
Adjusted R^2	0.557	0.526	0.920	0.552	0.519	0.895

Figure 1: Traders in fund management over time

The figure shows the percentage of funds that have at least one trader in the management team and the average share of traders in the team. The observation period is January 2003 until December 2020.



Appendix

A.1. Details on the Computation of the Holdings Return

The holdings return is constructed following Moneta's (2015) approach, which we modify to use returns of individual bonds for the corporate bond part of the portfolio. We use portfolio breakdowns at the asset allocation level (US bond, equity, convertible bond, preferred stock, and non-US bond) and within the US bond asset class we use a finer breakdown based on fixed income super sectors (corporate bonds, government bonds, securitized bonds, and municipal bonds). Historical portfolio breakdown data comes from Morningstar. With the exception of corporate bonds, we proxy for the returns of holdings categorized by asset class or fixed income super sector with corresponding index returns.

We set missing values in the asset allocation variables equal to zero. We use various ICE BofA indices as benchmark returns for the different asset classes a fund holds as follows: for cash we use the ICE BofA US Treasury Bill Index; for equity we use the S&P 500; for convertible bonds we use the ICE BofA Convertible Index; for preferred stock we use the ICE BofA Fixed Rate Preferred Securities Index; and for foreign bonds we use a weighted average of three indices, which include ICE BofA Emerging Markets Sovereign Bond Index, ICE BofA Global Non-Sovereign Excluding US Dollar Index, and ICE BofA Global Government Excluding the US Index.[15] For fixed income super sector allocations we use indices as follows: for government bonds we use ICE BofA US Treasury Index; for municipal bonds we use ICE BofA US Municipal Securities Index; and for securitized bonds we use ICE BofA US Mortgage Backed Securities Index. The only exception is the corporate bond allocation of the fund portfolio. Here, no index is used to proxy for the return, and instead we use the value-weighted average of the corporate bonds held in the portfolio based on bond returns from the WRDS bond returns database.

[15] We use the market capitalization of the indices from the end of the previous month as weights to calculate the weighted average return.

We take weights from the previous month to multiply them with the index return of month t. When portfolio weights of month $t-1$ are not available, we use weights of up to two months before. The holding return calculation is done as follows:

$$
\begin{aligned}
&Holding\ Return\\
&\quad = asset\ allocation\ US\ Bond \times FI\ supersector\ corporates\\
&\quad \times holding\ based\ corporate\ bond\ return\\
&\quad + asset\ allocation\ US\ Bond\ \times FI\ supersector\ government\\
&\quad \times US\ Treasury\ Index\\
&\quad + asset\ allocation\ US\ Bond\ \times FI\ supersector\ securitized\\
&\quad \times Mortgage\ Backed\ Securities\ Index\\
&\quad + asset\ allocation\ US\ Bond\ \times FI\ supersector\ municipals\\
&\quad \times US\ Municipal\ Index + asset\ allocation\ cash\ \times Treasury\ Bill\ Index\\
&\quad + asset\ allocation\ equity\ \times S\&P500\\
&\quad + asset\ allocation\ convertible\ bond\ \times Convertible\ Index\\
&\quad + asset\ allocation\ preferred\ stock\ \times Preferred\ Securities\ Index\\
&\quad + asset\ allocation\ non\ US\ Bond\ \times value\ weighted\ foreign\ bond\ index
\end{aligned}
$$

We rescale the asset allocation weights of US and non-US bonds, equity, convertible bonds, preferred stock, and cash from Morningstar so that they add up to 100%. We also rescale the portfolio weights within US-bonds asset allocation that are based on fixed-income super sector allocations so that they add up to 100%.

Finally, we use the maturity breakdown from Morningstar and the weights of different maturities in the indices to adjust returns for differences in maturity breakdown between the fund portfolio and the ICE indices. We use the maturity correction for the government and the mortgage part of the portfolio. For the municipal index, there are no maturity weights available. For every maturity bucket, we calculate the difference between the weight of the maturity bucket in the fund's holdings and the weight of the maturity bucket in the index and multiply it with the index return of the respective maturity bucket. Table A1 provides an overview over the three dimensions used to break down the funds' portfolios and the indices that we use.

A.2. Selection

One important task of a fund manager is to select bonds that outperform other bonds with similar characteristics. Selection is one of the key components of fund performance. Bond picking requires fundamental analysis skills regarding the issuers as well as a good sense for the structure and the characteristics of a bond. We expect fund managers that followed the analyst career track to bring skills related to fundamental analysis. We do not expect such an ability from traders. However, traders might be more familiar with special structures of bonds like embedded options, which might provide them an advantage regarding selection. Because these two channels work in different directions, we have no clear hypothesis of the effect direction here. We measure selection ability similar to Cici and Gibson (2012), who use duration and rating buckets to define the set of bonds with similar characteristics. To separate selection effects from the already documented liquidity-related effects, we independently sort bonds into 100 portfolios according to their rating, duration, and liquidity. We use ten credit-quality categories (AAA, AA, A, BBB, BB, B, CCC, CC, C, and D), five duration categories, and two liquidity groups based on the bond's size-adapted average bid-ask spread. We then calculate our selection measure as

$$BS_{i,t} = \sum_b w_{b,i,t-1}(R_{b,t} - R_t^{P_{b,t-1}}),$$

where $w_{b,i,t-1}$ is fund i's portfolio weight of bond b in month $t-1$, $R_{b,t}$ is the buy-and-hold return of bond b during month t and $R_t^{P_{b,t-1}}$ is the buy-and-hold return of the benchmark portfolio that was matched to bond b during month $t-1$. We also winsorize our selection measure at the 1% and 99% levels on a monthly basis.

We run regressions of selection ability on our trader variable and the interactions with measure of market stress. Regression results are reported in Table A2. We do not find evidence that traders have a superior selection ability compared to analysts. If anything, the effect seems to be negative, suggesting that trader fund managers are in no way better in selection than other fund managers, probably tending to be even worse. Also, for the interaction with the periods of market stress, we do not find evidence for differences in selection ability between trader-dominated funds and other funds.

A.3. RFY Calculation Detail and Robustness

In this section we provide more detail on the construction of RFY and some robustness. Following Choi and Kronlund (2018), we use five maturity buckets (<= 3 years, >3 and <= 5 years, >5 and <=7 years, >7 and <= 10 years, and >10 years) and use the bid yields from Refinitiv Eikon to calculate the measures. To minimize the effects of outliers, we winsorize yields at the 1% and the 99% level every month (we then do not winsorize at the measure level again). To calculate benchmark yields, we start with all corporate bonds in Mergent FISD that satisfy inclusion criteria in the two main Bloomberg bond indices for investment-grade bonds and high-yield bonds. Investment-grade bonds must fulfill the inclusion criteria of the Bloomberg US Aggregate Bond Index and high-yield bonds must fulfill the inclusion criteria of the Bloomberg US Corporate High Yield Index. We use the historical inclusion criteria to define the set of bonds in every month.[16]

Whereas the RFY results in the main part of the paper that follow Choi and Kronlund (2018) are restricted to the corporate bond portion of the portfolio, in Table A3 we use a more general RFY measure that includes all index-eligible bonds (i.e., including treasury and agency bonds). The results in Table A3 are qualitatively similar and even a bit stronger compared to the results of Table 8.

[16] (Historical) inclusion criteria can be accessed on the Bloomberg Terminal via the Tickers (LBUSTRUU and LF98TRUU) -> DES-> Reference Documents -> Index Methodology.

Table A1: Portfolio breakdown and matched indices

Panel A: Portfolio breakdown in Morningstar

Asset allocation (as % of TNA)	Fixed income supersector allocation (as % of bonds)	Maturity breakdown
US Bond	Corporates	1-3 years
Non-US Bond	Government	3-5 years
Cash	Securitized	5-7 years
Convertible Bond	Municipals	7-10 years
Equity		10+ years
Preferred stock		

Panel B: Asset classes and matched indices

Cash	ICE BofA US Treasury Bill Index
Equity	S&P 500
Convertible bonds	ICE BofA Convertible Index
Preferred stocks	ICE BofA Fixed Rate Preferred Securities Index
Non-US bonds	(ICE BofA Emerging Markets Sovereign Bond Index, ICE BofA Global Non-Sovereign Excluding US Dollar Index and ICE BofA Global Government Excluding the US Index
US government bonds (US Bond x Government)	ICE BofA US Treasury Index
Municipal bonds (US Bond x Municipals	ICE BofA US Municipal Securities Index
Mortgage (US Bond x Securitized)	ICE BofA US Mortgage Backed Securities Index
Indices for Maturity correction for high yield funds	ICE BofA 1-3 Year BBB US Corporate Index ICE BofA 3-5 Year BBB US Corporate Index ICE BofA 5-7 Year BBB US Corporate Index ICE BofA 7-10 Year BBB US Corporate Index ICE BofA 10+ Year BBB US Corporate Index
Indices for Maturity correction for all other funds	ICE BofA 1-3 Year US Broad Market Index ICE BofA 3-5 Year US Broad Market Index ICE BofA 5-7 Year US Broad Market Index ICE BofA 7-10 Year US Broad Market Index ICE BofA 10+ Year US Broad Market Index

Table A2: Selection

This table shows regressions of selection ability on a dummy variable that indicates if the fund is managed predominately by traders. Columns (1) and (4) show baseline regression results. Columns (2), (3), (5), and (6) show results where the traderdominated variable is interacted with measures for turbulent market periods. Measures for turbulent market periods are market illiquidity, measured by a market-wide average of monthly corporate bond bid-ask spreads, and ratechange squared, measured as the squared monthly change in the 10-year US Treasury bond rate. Market illiquidity and ratechange squared are standardized to have zero mean and a standard deviation of one. Control variables include a dummy variable for the fund incubation period, the share of corporate bond holdings on the total fund holdings, the logarithm of fund assets, the logarithm of family assets, the logarithm of fund age, net expense ratio, and fund turnover. Columns (1) to (3) report results for the full sample, columns (4) to (6) report results for single-managed funds only. All columns include month and Morningstar Category fixed effects. Standard errors are clustered by fund and month and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	All funds			Single-managed funds		
	(1)	(2)	(3)	(4)	(5)	(6)
traderdominated	-0.692	-0.902	-0.688	-0.468	-0.468	-0.466
	(1.095)	(1.513)	(1.334)	(1.697)	(1.700)	(1.691)
incubation	6.649**	6.932**	6.645**	7.480***	7.524**	7.515***
	(3.227)	(3.341)	(3.259)	(2.676)	(3.215)	(2.632)
corp. share	0.00002	-0.0003	0.00002	0.042	0.042	0.041
	(0.043)	(0.042)	(0.043)	(0.086)	(0.122)	(0.088)
log(fund assets)	-0.301	-0.300	-0.301	0.235	0.235	0.233
	(0.258)	(0.257)	(0.258)	(0.726)	(0.727)	(0.730)
log(family assets)	0.407	0.403	0.407	-0.039	-0.041	-0.042
	(0.288)	(0.282)	(0.284)	(0.684)	(0.656)	(0.674)
log(fund age)	-0.300	-0.291	-0.300	-0.667	-0.666	-0.664
	(0.570)	(0.583)	(0.575)	(1.205)	(1.217)	(1.214)
net expense ratio	1.063	1.045	1.063	3.578*	3.568*	3.563*
	(1.279)	(1.301)	(1.289)	(1.952)	(1.992)	(1.964)
turnover	-0.007	-0.007	-0.007	-0.018	-0.018	-0.018
	(0.008)	(0.008)	(0.008)	(0.030)	(0.048)	(0.033)
traderdominated x market illiquidity		-1.577			-0.235	
		(4.235)			(4.699)	
traderdominated x ratechange			0.065			-0.748
			(5.636)			(4.551)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,046	70,046	70,046	15,951	15,951	15,951
R^2	0.105	0.105	0.105	0.093	0.093	0.093
Adjusted R^2	0.102	0.102	0.102	0.080	0.080	0.080

Table A3: Reaching for Yield including all index-eligible bonds

This table shows results for reaching for yield with including all index-eligible bonds instead of only corporate bonds. We regress RFY and its components on a dummy variable that indicates if the fund is managed predominately by traders. Columns (1), (4), (7), and (10) show baseline regression results. he remaining columns show results where the traderdominated variable is interacted with measures for turbulent market periods. Measures for turbulent market periods are market illiquidity, measured by a market-wide average of monthly corporate bond bid-ask spreads, and ratechange squared, measured as the squared monthly change in the 10-year US Treasury bond rate. Market illiquidity and ratechange squared are standardized to have zero mean and a standard deviation of one. Control variables include a dummy variable for the fund incubation period, the share of corporate bond holdings on the total fund holdings, the logarithm of fund assets, the logarithm of family assets, the logarithm of fund age, net expense ratio, and fund turnover. Panel A reports results for the full sample, Panel B reports results for single-managed funds only. All columns include month and Morningstar Category fixed effects. Standard errors are clustered by fund and month and are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full sample

	Reaching for Yield (total) (all bonds) [bps]			Reaching for Maturity (all bonds) [bps]			Reaching for Rating (all bonds) [bps]			Reaching for yield (within) (all bonds) [bps]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
traderdominated	-3.308	-5.217	-3.721	2.095	2.269	2.129	-4.012	-6.192	-4.431	2.421*	3.338**	2.565*
	(4.521)	(4.668)	(4.560)	(1.632)	(1.611)	(1.629)	(4.054)	(4.428)	(4.121)	(1.410)	(1.595)	(1.438)
incubation	6.382	7.156	6.635	-1.998	-2.068	-2.019	5.186	6.069	5.442	-1.925	-2.297	-2.013
	(6.422)	(6.365)	(6.420)	(1.898)	(1.881)	(1.893)	(6.784)	(6.577)	(6.737)	(2.163)	(2.137)	(2.150)
corp. share	0.178	0.174	0.178	-0.068**	-0.068**	-0.068**	0.285	0.280	0.284	-0.191***	-0.188***	-0.190***
	(0.157)	(0.157)	(0.157)	(0.029)	(0.029)	(0.029)	(0.174)	(0.173)	(0.173)	(0.050)	(0.050)	(0.050)
log(fund assets)	4.828***	4.819***	4.822***	1.307***	1.308***	1.307***	3.820***	3.810***	3.813***	0.601	0.605	0.603
	(1.459)	(1.453)	(1.457)	(0.396)	(0.396)	(0.396)	(1.346)	(1.344)	(1.345)	(0.428)	(0.429)	(0.428)
log(family assets)	0.643	0.595	0.628	0.215	0.219	0.216	0.429	0.375	0.414	-0.510*	-0.487	-0.505
	(0.972)	(0.966)	(0.970)	(0.299)	(0.299)	(0.299)	(0.807)	(0.801)	(0.805)	(0.306)	(0.306)	(0.306)
log(fund age)	-5.047**	-4.924**	-5.007**	-1.086	-1.098*	-1.090*	-4.064*	-3.925*	-4.023*	-1.033	-1.092	-1.047
	(2.285)	(2.271)	(2.282)	(0.660)	(0.659)	(0.660)	(2.138)	(2.118)	(2.132)	(0.784)	(0.787)	(0.784)
net expense ratio	27.858***	27.601***	27.753***	1.577	1.601	1.586	29.210***	28.917***	29.104***	3.321	3.444	3.357
	(6.313)	(6.277)	(6.298)	(1.867)	(1.863)	(1.866)	(5.446)	(5.382)	(5.424)	(2.090)	(2.086)	(2.088)
turnover	0.103***	0.104***	0.104***	0.020**	0.020**	0.020**	0.078***	0.079***	0.079***	0.003	0.003	0.003
	(0.025)	(0.025)	(0.025)	(0.008)	(0.008)	(0.008)	(0.023)	(0.023)	(0.023)	(0.008)	(0.008)	(0.008)
traderdominated x market illiquidity		-21.403***			1.943**			-24.435***			10.288***	
		(5.774)			(0.899)			(7.940)			(3.616)	
traderdominated x ratechange			-11.013**			0.907**			-11.152**			3.832**
			(4.544)			(0.359)			(4.787)			(1.892)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,817	75,817	75,817	75,817	75,817	75,817	75,811	75,811	75,811	75,817	75,817	75,817
R^2	0.662	0.664	0.663	0.381	0.382	0.381	0.543	0.546	0.544	0.425	0.428	0.425
Adjusted R^2	0.661	0.663	0.662	0.379	0.380	0.379	0.542	0.545	0.542	0.423	0.426	0.423

(Continued)

Table A3 - *Continued*

	Reaching for Yield (total) (all bonds) [bps]			Reaching for Maturity (all bonds) [bps]			Reaching for Rating (all bonds) [bps]			Reaching for yield (within) (all bonds) [bps]		
Panel B: Single-managed funds												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
traderdominated	-4.400	-1.908	-3.515	7.987**	7.890**	7.945**	-13.198*	-10.068	-12.180	3.775	2.394	3.388
	(8.186)	(8.084)	(8.136)	(3.129)	(3.170)	(3.139)	(7.690)	(7.741)	(7.638)	(2.539)	(2.506)	(2.481)
incubation	-0.937	2.030	-0.216	0.285	0.170	0.251	-0.193	3.534	0.637	-4.109	-5.751	-4.423
	(10.936)	(10.879)	(10.900)	(3.865)	(3.825)	(3.854)	(13.880)	(12.976)	(13.687)	(4.775)	(4.594)	(4.718)
corp. share	-0.212	-0.237	-0.225	-0.078	-0.077	-0.078	-0.075	-0.105	-0.089	-0.171	-0.157	-0.165
	(0.265)	(0.264)	(0.263)	(0.055)	(0.055)	(0.055)	(0.266)	(0.263)	(0.264)	(0.106)	(0.104)	(0.105)
log(fund assets)	1.460	1.434	1.419	0.270	0.271	0.272	1.444	1.412	1.398	1.111	1.125	1.128
	(2.993)	(2.932)	(2.981)	(0.794)	(0.796)	(0.794)	(2.645)	(2.594)	(2.635)	(0.918)	(0.900)	(0.915)
log(family assets)	3.125	2.821	3.054	1.487**	1.499**	1.490**	1.128	0.746	1.046	-1.081	-0.913	-1.050
	(2.110)	(2.045)	(2.092)	(0.651)	(0.649)	(0.651)	(1.933)	(1.874)	(1.915)	(0.715)	(0.713)	(0.713)
log(fund age)	-5.235	-4.803	-5.110	-1.453	-1.470	-1.459	-2.313	-1.770	-2.170	-1.620	-1.859	-1.674
	(4.181)	(4.147)	(4.173)	(1.459)	(1.457)	(1.459)	(4.246)	(4.223)	(4.233)	(1.635)	(1.638)	(1.631)
net expense ratio	39.491***	37.709***	38.960***	2.380	2.450	2.406	35.203***	32.965***	34.592***	5.296	6.282	5.527
	(10.350)	(10.278)	(10.320)	(3.025)	(3.026)	(3.026)	(9.373)	(9.383)	(9.331)	(3.889)	(3.985)	(3.893)
turnover	0.089*	0.107**	0.093*	-0.001	-0.001	-0.001	0.110***	0.133***	0.114***	0.028	0.018	0.027
	(0.053)	(0.051)	(0.053)	(0.016)	(0.016)	(0.016)	(0.038)	(0.039)	(0.038)	(0.020)	(0.021)	(0.020)
traderdominated x market illiquidity		-35.147***			1.364			-44.145***			19.460***	
		(8.543)			(1.409)			(12.447)			(6.032)	
traderdominated x ratechange			-16.220**			0.766			-18.650**			7.071**
			(7.295)			(0.694)			(8.538)			(3.391)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Morningstar Cat. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462	17,462
R^2	0.679	0.689	0.682	0.388	0.389	0.388	0.570	0.586	0.574	0.455	0.474	0.458
Adjusted R^2	0.675	0.685	0.677	0.380	0.380	0.380	0.565	0.581	0.568	0.448	0.467	0.451

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