(Not) Everybody's Working for the Weekend: A Study of Mutual Fund Manager Effort

Boone Bowles and Richard B. Evans*

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Abstract

We develop a novel measure of effort based on unique observations of weekend work activity and revisit fundamental questions of asset management: how does effort relate to incentives, and how does effort affect performance? Mutual fund managers facing competitive incentives work more weekends, particularly following outflows and increased tracking error. Also, heightened effort predicts improved future returns – especially among funds with competitive incentives, high active share, and low turnover – and using exogenous variation in local weather we demonstrate a causal link between effort and returns. Finally, we show that the outperformance arises from a mixture of effort, targeted firm-research, and selectively trading the right stocks.

JEL classification: G00, G20, G23

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*Mays Business School, Texas A&M University (boone.bowles@tamu.edu), Darden School of Business, University of Virginia (evansr@darden.virginia.edu). We (the authors) have no conflicts of interest to disclose. The authors thank Jules van Binsbergen, Bruce Carlin, Andrew Chen, Lauren Cohen, Pedro Matos, Adam Reed, Stanislav Sokolinski, Luciano Somoza, Du Nguyen, Mancy Luo, Linlin Ma, Ryan Israelsen, and seminar participants at Baylor University, Darden Business School, McIntire School of Commerce, Texas A&M University, Louisiana State University, Tinbergen Institute/Vrije Universiteit Amsterdam, Universidad Adolfo Ibáñez, Brigham Young University, IE Universidad, Western University, the 15th Annual Hedge Fund Research Conference, the 2024 Eastern Finance Association, the 7th Annual World Symposium on Investment Research, the 2024 European Finance Association, the 7th Quantitative Finance and Risk Analysis Symposium, the 2025 American Finance Association, the 2025 FMA Consortium on Asset Management, and the 2025 Finance Down Under Conference. All errors are our own.

1 Introduction

In their seminal article on the principal-agent problem, Grossman and Hart (1983) propose an optimal incentive scheme between an owner and a manager. The key aspect of the problem is that the principal (e.g., the owner of the firm) cannot observe the agent's (e.g., the manager's) level of effort. While subsequent theoretical work often generalizes these ideas, they remain especially salient in asset management (i.e., Spatt (2020)). In asset management, the principal typically selects an agent (e.g., a fund manager) based on the agent's superior expertise in financial markets and investing, potentially exacerbating the unobservability of effort. Moreover, distinct from other organizational settings, the most important input in the production function for asset management is human capital. This helps explain why so much research has tried to distinguish between luck and skill when measuring managerial ability.[1]

Though fund manager effort may be unobservable to investors – and indeed, the principal-agent literature developed due to the difficulty of observing effort – we develop a novel measure of fund manager effort by capturing the relative amount of work activity occurring on weekends. We use this measure to address two central economic questions in asset management: How does effort relate to incentives, and how does effort affect performance?

In short, we find that managers with stronger incentives exert more effort, and extra effort predicts higher future returns. Specifically, managers in advisory firms with competitive incentives and those who have recently underperformed respond by working harder. Also, while the effort-return relation is both economically and statistically significant on average, it is especially pronounced for managers facing competitive incentives and managing funds characterized by low turnover and high active share funds. Moreover, using exogenous variation in local weather we demonstrate that increased effort is causally linked to higher future returns: rainy weekends induce more effort, and that additional effort translates into better future returns.

[1] For a review of this literature, see Cremers et al. (2019).

In 1993 the SEC introduced the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system which gave interested parties – including mutual fund managers – easier access to corporate filings (i.e., Crane et al. (2023) and Bowles et al. (2024)). In recent years, the SEC released the EDGAR Log Files, data covering EDGAR usage. By enhancing these data with the identification of investment advisors and fund managers, we observe specific investors accessing specific filings. More relevant for this study, we also observe *when* investors access filings and, consequently, we can examine *when* mutual fund managers are working, even if it is on weekends.

While fund management is a highly-paid occupation with an expectation of work outside of routine hours, we still observe considerable variation in the weekend work activity of fund managers. Of the 115 investment advisors in our sample, only eight of them never had employees whom we observed working on the weekend, thus 107 advisory firms had employees working on the weekends at least once across our sample period. Moreover, across the 90 months in our sample, the average advisor had employees working on the weekend 69% of the time, or 62 out of 90 months.

Exploring the determinants of effort, we find that investment advisors with larger funds, higher fees, and stronger competitive incentives (Evans et al. (2020)) exhibit higher weekent work activity – a reflection of heightened effort. Within-advisor analyses reveal that recent outflows, underperformance, and increased tracking error are all associated with relatively more work on the weekends, suggesting that poor recent performance is a powerful trigger for increased effort among fund managers.

We also analyze the outcomes of effort by focusing on changes in portfolio characteristics. These tests reveal that managerial effort is positively associated with portfolio concentration and active share, and is negatively associated with turnover. These relations are particularly strong following increases in effort, not decreases, indicating that effort is associated with deliberate attempts to follow more performance-enhancing strategies.

Given these links between effort, underperformance, and portfolio adjustments, we test whether extra effort predicts better future performance. We test this using future abnormal returns and find that extra effort is associated with long-term outperformance. Indeed, a one-standard-deviation increase in effort predicts a future six-month abnormal return improvement of 20.5 basis points – a sizable effect in active fund management.[2]

While this average return improvement is significant, it understates how effort benefits certain advisors more than others. Specifically, smaller funds with competitive incentives, low turnover, high active share, and concentrated portfolios experience substantially larger effects. In these settings, a one-standard-deviation increase in effort predicts a future benchmark-adjusted return improvement of 60.6 basis points.

Although this strong, intuitive link between effort and future returns is compelling, it is subject to endogeneity concerns. To address this we employ a unique instrument – local weekend rainfall – that exogenously alters the cost of exerting effort while remaining unrelated to subsequent investment opportunities. In particular, rainy weather reduces the appeal of leisure activities, thus raising the likelihood of putting in extra work without meaningfully affecting future market conditions.

These assumptions draw support from both psychology and financial economics research demonstrating that adverse weather boosts productivity (i.e., Lee et al. (2014) and Zhang (2022)). Certainly for an employee weighing the opportunity cost of working on the weekend, such as the cost of forgone leisure, the opportunity cost decreases when bad weather reduces the quality of outdoor leisure. In other words, it is less costly to work on Saturday when it is too rainy to go to the park. At the same time, it is unlikely that local weather conditions would be related to the prevalence of future profitable investment opportunities in public equity markets.

The first stage of our instrumental variables approach shows that weekend rain is associated with increased weekend work, consistent with our proposed instrumental mechanism

[2]One important aspect of our measure is that it is subject to Type II errors, namely some investment advisory employees are working on the weekend, but we do not observe it. However, this will at worst bias our results towards the null hypothesis that there is no relationship between weekend work and performance.

and the prior literature (i.e., Lee et al. (2014) and Zhang (2022)). We then use this instrument and find that exogenous increases in effort are associated with higher abnormal returns; this is especially true for the subset of funds that we expect to benefit most from increased effort. Indeed, for these funds a one-standard-deviation increase in weekend rain predicts that future risk-adjusted returns will increase by between 8 and 15 basis points over a six month period.

Finally, we examine the mechanism through which heightened effort translates into outperformance by focusing on the research activities and trading decisions of fund managers. We find that when managers increase their effort they research fewer firms, review fewer (often older) filings, and seek out more unique information sources. Following this more selective research process, they make correspondingly targeted trades, often selling positions that subsequently underperform. These effects are especially pronounced for managers facing competitive incentives and employing more active investment strategies – reinforcing the notion that heightened effort is not simply a matter of extra hours, but rather is related to a more focused and productive information-gathering process.

Our paper contributes to a small but growing empirical literature on the effort, incentives, and outcomes of financial professionals. The only related paper studying effort empirically is Ben-Rephael et al. (2025), which measures executive effort using Bloomberg activity and finds that harder-working executives earn higher equity returns. In another paper, Ohneberg and Saffi (2023) show that advisory firms with more satisfied employees tend to outperform, while earlier analyses emphasize incentive schemes and tournament structures among fund managers (e.g., Brown et al. (1996); Kempf and Ruenzi (2007)). More recently, Ma et al. (2019) and Ibert et al. (2018) examine how compensation structures influence managerial decisions in the U.S. and Sweden, respectively. Building on this work, we provide the first direct measure of mutual fund manager effort – a critical input – clarify the role of competitive incentives in driving managers to exert more effort, and demonstrate that exogenous effort predicts future returns.

A substantial body of research explores the determinants of mutual fund performance and the role of managerial skill. While Carhart (1997) highlights the difficulty of identifying consistent outperformance, subsequent work has linked fund returns to organizational and manager-specific factors. For instance, Chen et al. (2004) connect large fund size to diseconomies of scale, Pástor et al. (2017) find that trading activity influences performance, and Cremers et al. (2019) show that active managers can add value under certain conditions. More recently, Evans et al. (2020) examine how organizational structure affects fund outcomes, while Ohneberg and Saffi (2023) demonstrate that employee satisfaction at investment firms correlates with better fund performance. At the same time Kacperczyk et al. (2005) and Petajisto (2013) illustrate how concentrated bets and active share can enhance returns. Our paper extends this literature by providing the first direct empirical measure of fund manager effort and showing that increased effort leads to better future performance, particularly for funds where effort is likely to generate the highest returns.

Our work also connects to research on how investment professionals acquire and process information. Recent empirical evidence by Crane et al. (2023) shows that hedge funds' EDGAR usage predicts future performance, building on theoretical insights into limited attention (Hirshleifer and Teoh, 2003) and empirical studies of how managers strategically allocate attention (Kacperczyk et al., 2014, 2016). Chen et al. (2020) further highlight how investors respond differently to salient information, and Zhang (2022) demonstrates the impact of weather on institutional investors' information processing. Our paper contributes to this literature by unveiling how the timing of EDGAR-based research – specifically, weekend work – captures meaningful variation in managerial effort that not only predicts future fund performance but also clarifies the role of incentives in driving managers to seek and use information more effectively.

Beyond establishing that effort leads to improved fund performance, we provide direct evidence on how heightened effort matters in practice. Specifically, we show that managers who invest more weekend hours in research adopt a more selective information-acquisition process. These findings align with earlier work suggesting that deeper analysis of a narrower set of potential investments can generate alpha, as concentrated, well-researched positions often outperform diversified holdings (e.g., Kacperczyk et al. (2005); Pollet and Wilson (2008); Cremers and Petajisto (2009)). By demonstrating how effort amplifies the benefits of meticulous research – especially among funds with competitive incentives and active strategies – our analysis highlights a key mechanism linking managerial behavior to investment outcomes. In doing so, we contribute to the broader literature on selective attention and research intensity among professional investors (e.g., Fang et al. (2014); Crane et al. (2023)), offering novel evidence of the interplay between incentives, effort, and performance.

The remainder of the paper is organized as follows. Section 2 introduces our measure of mutual fund manager effort. Section 3 outlines the data construction. Section 4 examines the determinants of effort, and Section 5 presents results on its portfolio-level outcomes. Section 6 analyzes the link between effort and future performance, while Section 7 presents our instrumental variables strategy. Section 8 investigates the mechanism linking effort to outperformance. Section 9 concludes.

2 Measuring Mutual Fund Manager Effort

In an ideal setting, investors or third-party rating agencies would measure mutual fund effort through direct personal observation. They could position observers inside mutual fund offices, counting the managers and analysts arriving for work each day. Observers could even subjectively assess effort by noting the intensity of employees' work activities or by asking employees directly, "On a scale of 1 to 10, how hard are you working today?"

While this ideal approach would yield detailed data on work activity and managerial effort, the practical limitations – particularly cost and invasiveness – are substantial, especially when scaled across many mutual funds over long periods of time. Consequently, direct empirical measurement of mutual fund manager effort has been elusive.

However, using the ideal setting as a guide, we construct a large-scale panel dataset capturing mutual fund managers' effort indirectly, yet objectively. Our approach uses the EDGAR Log Files, a database tracking online traffic on the SEC's EDGAR filing system. When properly assessed, the observations in the EDGAR Log Files represent employees at a specific investment advisor doing observable work at a specific date and time. With this insight, we measure work activity and effort within investment advisors and across time.[3]

2.1 The EDGAR Log Files

The EDGAR Log Files contain billions of records capturing electronic "requests" to view SEC filings. Each observation specifies the filing requested, the date and time of the request, and the requester.[4] For our analysis, we focus primarily on the requester – identified by the IP address – and the date of each request. Then, after linking IP addresses to a hand-matched sample of investment advisors, we aggregate observations by month and by advisory firm. Specifically, we calculate two monthly measures of work activity for each advisory firm: (i) total requests ($TotalReqs$), defined as the total number of requests made, and (ii) total work-days ($TotalWDs$), defined as the total number of unique IP addresses making requests each day, analogous to the conventional count of employee work-days.[5]

Three considerations are important when interpreting these measures. First, both measures closely parallel the hypothetical ideal measures described earlier: total work-days mimics counting employees coming to work, while total requests approximately measures the total amount of work performed. Second, due to practical matching constraints with masked IP addresses in the EDGAR Log Files, we primarily aggregate these measures at the *investment*

[3]To interpret the observations from the EDGAR Log Files as observations of work activity we assume that the specific activity being recorded – employees within investment advisors reviewing public filings on EDGAR – is positively correlated with other mutual fund manager work activities.

[4]For instance, a typical observation might represent a request for IBM's 2013 annual report (10-K), made at 10:14 AM on March 1, 2014, originating from IP address 123.123.123.*abc*, with the final octet masked. The unmasking procedure for IP addresses is detailed in Appendix A.1.

[5]If five distinct employees worked on both Monday and Tuesday, the conventional count of total employee work-days would be ten. Our measure, $TotalWDs$, analogously counts unique IP addresses as employees, aligning closely with this standard concept.

advisor level. However, for certain tests, we use a subset of data matched at the *individual mutual fund* level.[6] Third, while this section provides essential details regarding our use of EDGAR Log Files, Appendix A.1 contains an extensive discussion of the data and the critical IP-address unmasking procedure.

2.2 Work Activity and Effort

Total work-days and total requests measure work activity within mutual funds, but it is not immediately clear that they accurately proxy for effort. For instance, total work-days might increase simply due to the hiring of additional analysts rather than existing analysts exerting greater effort. Similarly, total requests may increase because newly hired analysts start making requests or because analysts are responding to an increased volume of new filings. In the latter scenario, activity increases without necessarily reflecting greater effort – analysts are merely responding to an increased information supply.

To address these limitations and derive a clearer proxy for managerial effort, we focus on weekend (and market holiday) work activity.[7] We construct two key variables: (i) the ratio of weekend work-days to total work-days ($PctWkWDs$) and (ii) the ratio of weekend requests to total requests ($PctWkReqs$). These ratios measure the relative intensity of work conducted on weekends, more directly proxying for discretionary effort. For example, an observation of 7% for $PctWkReqs$ means that 7% of all requests in a month by an investment advisor occur on weekends; a value of 10% implies relatively higher discretionary effort. In this way, these weekend ratio measures provide a clearer proxy for effort.

With these new measures, two initial questions arise: First, do work activity and effort vary significantly *across* advisory firms, *within* advisory firms, and over time? Second, how strongly correlated are these measures – can they be combined into a single proxy for effort?

[6]Appendix A.1 provides details on advisor-level and fund-level matching procedures. Notably, our core results are robust to fund-level matching (see Appendix A.2), reinforcing our advisor-level findings. The causal analysis presented in Section 7 specifically utilizes fund-level matched data.

[7]Throughout the paper, we use "weekends" to refer collectively to weekends and market holidays. Results remain robust when we limit analysis strictly to weekends and exclude market holidays.

Table 1 provides key descriptive statistics to address these questions.

[Table 1 about here.]

Total work activity shows substantial variation across investment advisors. Panel A of Table 1 reports that advisory firms average 125 work-days and 4,200 requests per month, with large standard deviations of 252 work-days and 10,181 requests. Panel B summarizes the cross-sectional averages and similarly shows considerable dispersion, with average monthly totals of 89 work-days and 2,751 requests and corresponding standard deviations of 196 work-days and 7,492 requests.[8]

The effort proxies also exhibit significant variability. Across our full panel, weekend work-days account for roughly 10% of total work-days (standard deviation 10%), and weekend requests represent approximately 5% of total requests (standard deviation 12%). To place these figures in context, weekends and holidays constitute 31% of the calendar year. Thus, average weekend ratios between 5% and 10% indicate that mutual funds perform the bulk of their work on regular weekdays rather than weekends.[9]

Panel C of Table 1 reveals that while the two total work activity measures are highly correlated ($\rho = 0.86$), the weekend ratios – our proxies for effort – are only moderately correlated ($\rho = 0.58$), suggesting they capture distinct dimensions of activity. Moreover, a principal component analysis (Panel D) shows that the first factor, dominated by overall activity, and the second factor, which loads heavily on the weekend ratios, explain 87% of the variation, thereby justifying our interpretation of the second factor as a measure of effort.

These results inform our empirical analysis in three ways. First, we use the average of the two weekend ratio variables, $PctWk$, as our main ratio variable.[10] Second, we consider this new average weekend ratio variable as a proxy for effort. Third, to enhance our interpretation

[8]Untabulated results show average within-advisor monthly standard deviations of total work-days and total requests to be 27 work-days and 1,081 requests, respectively.

[9]Untabulated results show average within-advisor monthly standard deviations of weekend work-days and weekend requests to be 6% and 5%, respectively.

[10]Summary statistics for $PctWk$ have been included in Panels A and B of Table 1.

of $PctWk$ as a proxy for effort, we control for total work activity using $TotalWDs$ in the tests that follow.

To analyze the time series of effort, we average $PctWk$ across all advisory firms every month. The resulting time series – shown in Figure 1 and detailed in Table 2 – shows considerable temporal variation. Effort also exhibits strong seasonality, with managers exerting more effort from November though February (as indicated by the grey bars). Finally, Table 2 and Figure 2 show that effort is mostly unrelated to other time series of interest, including market returns, market volatility, the number of new filings submitted to EDGAR, and the number of earnings announcements among public firms.

[Table 2 about here.]

[Figure 1 about here.]

[Figure 2 about here.]

3 Data

In addition to the EDGAR Log Files, our study employs two primary data sources – the CRSP Survivorship Bias-Free Mutual Funds Database and the Thomson Reuters mutual fund holdings database. We combine the CRSP Mutual Funds and Thomson Reuters data to obtain mutual fund- and investment advisor-level variables, including: total net assets under management, expenses, turnover, active share, fund flows, fund returns, and other fund and advisor characteristics.

Advisor-level measures of managerial incentives, following Evans et al. (2020), and analyst forecast data from the Institutional Brokers' Estimate System (IBES) allow us to characterize fund portfolios and evaluate the influence of incentive structures on effort. Although our primary use of the EDGAR Log Files is to measure effort, we also analyze them to capture mutual fund managers' information acquisition activities, both in general and with regard to specific stocks.[11]

Our sample spans 90 months (January 2010 – June 2017) and comprises 115 investment advisors, resulting in approximately 40,000 fund-by-month observations with non-missing data.

As described in Section 2.1, we match IP addresses to investment advisors using IP address registration records. However, since many advisory firms did not register large blocks of IP addresses, only 115 out of the 614 advisors in the CRSP database could be matched. Notably, although this sample is biased toward larger advisory firms, these 115 firms account for 48% of total funds and 67% of total net assets managed when compared with the universe. Moreover, the funds in our sample have similar characteristics as the larger universe of funds, both in terms of categories and performance. For detailed summary statistics on our sample and a comparison with the full CRSP universe, see Table 3.

[Table 3 about here.]

4 The Determinants of Effort

We analyze the determinants of mutual fund manager effort to develop a baseline understanding of effort before testing its relation to future performance. Our analysis distinguishes between cross-sectional determinants – reflecting structural differences across investment advisors – and within-advisor dynamics that capture managers' behavioral responses to recent performance changes. For example, do managers with expensive funds exert more effort than those with relatively inexpensive funds? Do managers with more concentrated portfolios work harder than those managing less concentrated portfolios? And, do recent performance and fund flows – signals of underperformance – induce managers to exert extra effort?

[11] The variables and data sources used in this study are detailed in Appendix A.1.2.

To answer these and similar questions we model the determinants of effort as follows:

$$PctWk_{ijt} = \alpha + \beta X_{ijt} + \gamma TotalWDs_{ijt} + \epsilon_{ijt}, \tag{1}$$

where the subscripts represent advisory firm i with mutual fund j in month t. The vector of independent variables, X, includes fund-level covariates such as: $TNAM$, $Expenses$, HHI, $Turnover$, $ActiveShare$, $PctNetFlow$, $Alpha$, and $TrackError$. While many of these fund-level variables (e.g. TNAM, expense ratio, and turnover) are commonly used in the literature, we also include variables that measure manager conviction regarding their portfolio. As indications of manager conviction we measure both the concentration of a manager's portfolio using a Herfindahl-Hirschman Index of holdings weights (HHI) and the uniqueness of a manager's portfolio using $ActiveShare$.

Advisor-level measures of incentives, $Competitive$ and $Incentives$, are also included in the vector of covariates, X. While most of the covariates are measured contemporaneously with $PctWk$, the three variables related to performance – $PctNetFlow$, $Alpha$, and $TrackError$ – are lagged. Specifically, $PctNetFlow$ measures aggregate fund flows over the last year, $Alpha$ measures compound benchmark adjusted returns over the last six months, and $TrackError$ measures the standard deviation of monthly benchmark adjusted returns over the last six months.

We estimate this model over three subsamples. The first includes every observation with non-missing data while the second and third subsamples exclude funds with scant EDGAR activity. As a whole, our sample includes many observations – approximately 15% of the entire sample – where $PctWk = 0$. The prevalence of these "no effort" observations may be accurate, though some may result from mismeasurement because either we erred in unmasking IP addresses for some managers or some managers generally do not use EDGAR. In either case, we account for this by dropping observations where $PctWk = 0$ or by excluding advisory firms if their median total weekend work-days across our sample period is less than one.

[Table 4 about here.]

Table 4 reports the results from estimating Equation 1 on our three subsamples and with two different fixed-effect specifications. The first uses investing style and year-month fixed effects. The coefficient estimates from this model may be interpreted as *across advisory* effects. For instance, Columns 2–4 show that size ($TNAM$) is positive and statistically significant, indicating that advisory firms with bigger mutual funds have managers that exert more effort than advisory firms with smaller mutual funds. As another example, investment advisors with more expensive funds have managers that work harder than investment advisors with less expensive funds. This particular result should comfort mutual fund investors since it shows that managers who charge more for their services are working harder to earn their higher fees.

With regards to portfolio construction, high effort investment advisors hold less concentrated portfolios. In terms of investment and trading behavior, investment advisors with harder working managers have higher turnover and lower active share.

Perhaps the most interesting results from the first specification concerns the relation between effort and incentives and the relation between effort and performance. When it comes to the incentives faced by investment managers – cooperative versus competitive incentives – advisory firms with relatively more competitive incentives have managers that exert more effort. This finding confirms common intuition as having more incentives to boost alpha appears to spur managers to exert more effort. With respect to performance, the results suggest that investment advisors with harder working managers have lower tracking error. Thus, there appears to be payoffs to working harder, though it is not clear that high effort investment advisors generate more alpha or attract more flows.

Columns 5–7 include an advisory firm fixed effect, changing the interpretation of the coefficient estimates to *within advisor* relations. The shift from cross-sectional to within-advisor estimates reveals that once we control for unobserved investment advisor characteristics, performance-related factors become the primary drivers of additional effort.

First, the estimates for $PctNetFlow$ are negative and significant, suggesting that within-advisor outflows are related to increases in effort. This suggests that, within a given advisor, recent outflows – which signal poor performance – prompt managers to work harder, presumably to reverse underperformance. Of course, these negative estimates also suggest that net inflows precede less effort. While both interpretations of the negative coefficients may be true, they tell slightly different stories. To test whether outflows precede more effort or inflows are followed by less effort (or both) we re-estimate Equation 1 but replace the continuous measure of fund flows with indicator variables for high flows and low flows. The coefficient estimates for $HighPctNetFlow$ and $LowPctNetFlow$ – shown graphically in Figure 3 – suggest that the relation between effort and flows is driven by outflows. Thus, the evidence that recent outflows precede (and may inspire) more effort suggests that extra effort may be a response to recent negative performance, as measured by fund flows.

[Figure 3 about here.]

Second, the positive estimates for $TrackError$ suggest that effort increases after periods of high tracking error. Again, the same critique of this interpretation exists as did with fund flows (i.e., the positive coefficient estimate also indicates that effort may decrease after low tracking error). As such, we re-estimate Equation 1 using high and low indicator variables to replace $TrackError$. The results, shown graphically in Figure 3, show that it is high tracking error that is related to higher effort, not low tracking error followed by low effort. This finding reinforces the notion that elevated tracking error, a proxy for volatile or deteriorating performance, similarly triggers an increase in managerial effort.

Third, the estimates for $Alpha$ are negative and significant, suggesting that effort either increases after periods of low returns or decreases after periods of high returns. To test whether this inverse relation is stronger for low returns or high returns, we re-estimate Equation 1 using high and low indicator variables to replace $Alpha$ and show the results in

Figure 3. The results are ambiguous. While Table 4 does show a negative relation between recent returns and effort, it is not clear whether this relation is more driven by high or low returns.

The evidence in Table 4 and Figure 3 yields a clear two-part message. First, structural differences across advisors – such as fund size, expenses, and incentive design – explain much of the cross-sectional dispersion in effort. Second, within a given advisor the dominant trigger for extra effort is poor recent performance, most visibly negative net flows and elevated tracking error. Taken together, these findings – and the intuition that managers would not work harder without expecting a payoff – imply that discretionary effort should translate into economically meaningful outcomes. The next sections tests that implication by examining how heightened effort shapes subsequent portfolio choices and investment performance.

5 The Outcomes of Effort

We test whether effort influences future portfolio and flow outcomes:

$$Y_{ijt} = \alpha + \beta PctWk_{ijt-k} + \gamma TotalWDs_{ijt-k} + \delta Z_{ijt-k} + \epsilon_{ijt}, \tag{2}$$

where $k \in \{3,12\}$ (three-month and one-year lags). Theoutcome vector Y includes portfolio-construction variables – HHI, $Turnover$, and $ActiveShare$ – and performance variables – $PctNetFlow$ and $TrackError$. All regressions contain style, year-month, and advisor fixed effects, and the control vector Z contains the three performance measures that explained within-advisor variation in effort in Section 4 ($PctNetFlow$, $Alpha$, and $TrackError$). Table 5 shows the coefficient estimates for effort, $PctWk$.

[Table 5 about here.]

Table 5 shows that higher weekend effort is followed by statistically significant shifts in portfolio construction: concentration (HHI) rises, active share increases, and turnover falls.

Each of these effects is economically meaningful and consistent with managers moving toward more focused, more aggressive, and higher-conviction strategies after periods of increased work. To illustrate magnitude, consider the effect on *HHI*. A one-standard-deviation increase in effort lifts the average fund's *HHI*, enough to trim approximately two positions from its portfolio – a modest but tangible increase in portfolio concentration.

We also test whether these relations are driven by increases or decreases in effort by replacing the continuous effort proxy with binary indicators for high and low effort. As Figure 4 shows, *only* high-effort months (not low effort) lead to more concentrationg and higher active share. For turnover, both high- and low-effort months contribute to the negative relation.

[Figure 4 about here.]

In terms of future performance, the evidence from Table 5 does not suggest a strong relation between effort and future inflows, though the results in Figure 4 do suggest higher effort leads to higher inflows. There is also a lack of strong evidence that effort is related to future tracking error. However, to further study whether effort is associated with – or even causes – better future performance we must investigate its effect on returns. Following the insights from this section, we move on to consider future risk-adjusted returns as the dependent variable of interest.[12]

6 Effort and Future Performance

The previous evidence suggests that increased effort should translate into better performance. Section 4 shows that advisory firms with harder-working managers perform better on average and that managers appear to increase effort after periods of poor performance. Section 5

[12]In untabulated results we conducted tests of effort and future fund flows similar to the tests in Section 6. Once we control for returns, there is no relation between effort and future flows. This finding supports our assumption that effort is largely unobservable, especially to mutual fund investors.

documents that higher past effort precedes portfolio changes – higher active share and lower turnover – that are commonly associated with superior returns.

Economic intuition likewise predicts a positive link between effort and future performance. Classic principal-agent models treat effort as an input that raises expected output or the probability of a good outcome. Taken together, theory and the prior evidence lead to the hypothesis that manager effort should be positively related to future returns – and may even *cause* those returns.

That said, more observable effort need not improve performance. Our proxy, *PctWk*, might capture "busyness" rather than genuine effort: employees can appear busy without adding value, in which case higher *PctWk* would predict lower returns. Alternatively, extra weekend work could signal over-extended managers; overwork may impair judgment and execution, again depressing performance. Finally, because *PctWk* measures time spent reviewing *public* filings, managers who devote extra hours to public information might crowd out the acquisition of superior *private* information, potentially hurting performance.

To test whether manager effort is related to better or worse performance, we model future benchmark-adjusted returns as follows:

$$Alpha_{ijt+k} = \alpha + \beta PctWk_{ijt} + \gamma TotalWDs_{ijt} + \delta V_{ijt} + \epsilon_{ijt}, \tag{3}$$

where V includes $PctNetFlow$, $TNAM$, $Expenses$, $Turnover$, $ActiveShare$, $Competitive$, and $Incentives$. We estimate two fixed-effect specifications: (i) style and year-month, and (ii) style, year-month, and investment advisor, the latter exploiting only within-advisor variation.

Future returns are measured over six-month windows that begin after a gap of k months to allow effort time to be meaningful. Specifically, we set $k \in \{1,7,13\}$; hence we relate effort in month t to returns earned in months $t+1$ to $t+6$, $t+7$ to $t+12$, and $t+13$ to $t+18$, respectively. In other words, we test whether effort leads to higher returns almost immediately ($k = 1$), after a period of six months ($k = 7$), and after a year ($k = 13$). Table 6 reports the resulting coefficients on $PctWk$.

[Table 6 about here.]

The first specification – with style and year-month fixed effects – shows a positive relation between effort and future returns that strengthens at longer horizons. For $k = 1$ (over the first six months after exerting effort) the point estimate is positive but small and only marginally statistically significant, implying roughly 10 basis points of extra return for a one-standard-deviation increase in effort. For $k = 13$ the effect is three-times larger – about 30 basis points – indicating that the payoff to effort materializes with a delay. This long-horizon relation is robust across all panels and sample definitions in Table 6.

Since these results come from the model that does not include a advisor fixed effect, at best they suggest that funds with harder working managers generally generate higher returns. To more clearly test whether effort leads to future returns, we add an advisor fixed effect and focus on the results in Columns 5–7.

Columns 5 and 6 report the effect of effort in month t on benchmark-adjusted returns over months $t+1$ to $t+6$ and $t+7$ to $t+12$.[13] Across all three panels the estimates are small or negative and generally insignificant, consistent with effort requiring time to translate into measurable performance. Indeed, it is unlikely that more effort on Monday would result in higher returns on Tuesday. Moreover, because effort spikes after poor performance, short-run alphas may still reflect the preceding slump.

Focusing on returns further in the future (Column 7) shows a consistent, positive, and significant return to effort. In Panel A a one-standard-deviation increase in effort is followed by roughly 20 basis points of extra return in the first half of next year; Panels B and C show similar improvement of approximately 17 basis points.

Taken together, the evidence rejects the "busyness" and over-work explanations. Instead, extra effort predicts higher risk-adjusted returns once sufficient time elapses.

[13] For example, if manager effort is measured in December of 2015, $Alpha_{1-6}$ measures benchmark-adjusted returns in January through June of 2016 while $Alpha_{7-12}$ measures benchmark-adjusted returns in July through December of 2016.

6.1 Heterogeneity of the Effort and Performance Relation

The prior tests use either the full sample of non-missing data or the two subsamples that exclude minimally active funds. And though we include a host of control variables (V), our estimates for the relation between manager effort and performance nonetheless identify an average effect that may mask important cross-fund differences. Some funds may reap greater benefits from additional effort than others. Put differently, a positive average effect could conceal subgroups that earn above-average gains and others that see no payoff. In this section, we use subsamples of the data to test whether certain characteristics correspond to a stronger relation between effort and future returns.

We partition the data into high- and low-groups based on monthly medians of key fund attributes. For example, a fund is classified as high size if its $TNAM$ exceeds the cross-section median in that month (and low size otherwise). We then re-estimate Equation 3 – using the advisor fixed effect and $k = 13$ to capture the horizon where effort matters most – within each subgroup and compare coefficients. Besides size, we form splits on $Expenses$, *Competitive*, HHI, $Turnover$, *ActiveShare*, $PctNetFlow$, and *TrackError*. Panel A of Table 7 reports the estimates, and Figure 5 visualizes the differences.

[Table 7 about here.]

[Figure 5 about here.]

Effort pays off very unevenly across funds. Smaller, higher-fee funds in competitively structured advisory firms earn the largest gains: a one-standard-deviation increase in effort is followed by roughly 30 basis points of additional returns (29 – 35 basis points across specifications). Funds already running higher-conviction portfolios – high concentration, low turnover, high active share – see a similar 25 to 34 basis point boost. Effort also delivers positive returns precisely when performance pressure is greatest: funds suffering recent outflows or elevated tracking error benefit disproportionately from additional manager effort.

These patterns dovetail with the broader performance literature – competitive incentives, high active share, low turnover, and concentrated bets are all linked to superior alpha (e.g., Cremers and Petajisto (2009) and Evans et al. (2020)). They also reinforce the findings in Section 4: managers appear to respond to poor recent results with extra weekend work, and that effort subsequently helps reverse the underperformance.

To gauge interaction effects, we re-estimate Equation 3 on subsamples defined by pairs of attributes (*ActiveShare*-by-*Turnover*, *Competitive*-by-*Turnover*, etc.). Figure 6 visualizes the resulting coefficients. Consistent with the single-split results, the large payoffs accrue to funds that simultaneously have high *ActiveShare* AND low *Turnover*: a one-standard-deviation increase in effort lifts alpha next year by about *43* basis points for these funds. Competitive incentives especially amplify the payoff to effort: in highly competitive advisor firms, a one-standard-deviation rise in effort produces over 50 basis poins of extra return – provided the fund also features low turnover, high active share, or recent outflows.

[Figure 6 about here.]

Informed by the subsample results, we construct an Effort-Sensitivity Score (*E-Score*) that counts how many of six characteristics a fund possesses in the "high-payoff" direction: low size, high competitive incentives, high concentration, low turnover, high active share, and high tracking error. A fund satisfying all six earns an *E-Score* of six; a fund with only low size and high competitive incentives scores two.

Panel B of Table 7 shows that the effort premium emerges only once *E-Score* >= 4. For funds scoring five or six, a one-standard-deviation increase in effort is followed by additional returns of up to 60 basis points, confirming that small, concentrated, high-active-share funds with strong competitive incentives reap the greatest benefits from effort. Combined with our previous results, these findings reject the view that weekend work is mere "busyness" or is counterproductive. Instead, extra effort raises future benchmark-adjusted returns – most powerfully in funds where competitive pressure and active portfoliio management make additional research especially valuable.

6.2 Robustness of the Effort and Performance Relation

All preceding tests used six-month benchmark-adjusted returns as the performance metric. To confirm robustness, we re-estimate Equation 3 with alphas from standard risk-adjustment models ($CAPM$, $FF3$, and $FF4$).[14] Table 8 shows that a one-standard-deviation increase in effort continues to deliver economically meaningful gains – almost 20 basis points on average – regardless of the risk-adjustment, and the payoff remains concentrated in high E-Score funds where the return improvement is as much as 45 basis points.[15]

[Table 8 about here.]

7 Causation: Weather and Exogenous Effort

The evidence so far shows that higher effort consistently precedes better risk-adjusted returns – especially in funds whose incentives and portfolio profiles make effort most valuable. Yet effort is endogenous: managers may simply work harder when they expect richer opportunities ahead (Pástor et al. (2017)). To rule out such reverse causation and other omitted factors, we employ an instrumental-variables (IV) strategy that uses local weekend rainfall as an exogenous shock to managerial effort.

The ideal instrument affects effort but is orthogonal to future returns. Because variables tied to the benefits of effort risk violating the exclusion restriction, we focus on the costs of effort. Holding perceived benefits constant, higher costs of effort (e.g., fatigue and foregone leisure) will reduce effort; lower costs of effort will increase it. Weekend weather shifts the opportunity cost of working without altering the investment opportunity set. Rain, in particular, lowers the appeal of outdoor leisure and therefore reduces the cost of staying in the office.

[14] Fama and French (1993) and Carhart (1997).

[15] Appendix A.2 provides further robustness tests by replicating Tables 7 and 8 using the two subsamples from previous tests. That is, excluding advisory firms with very little activity in EDGAR.

Consider a manager in Manhattan: on a sunny Saturday the high value of leisure makes weekend work less likely, whereas steady rain diminishes leisure's value and increases the likelihood of working. Beyond this thought experiment, empirical research supports this intuition. In the psychology literature, Lee et al. (2014) find that bad weather increases productivity by eliminating potential cognitive distractions. A similar finding in financial economics shows that productivity increases among institutional investors after bad weather (Zhang (2022)).

Given this background, weather likely satisfies the relevance condition as an instrument for manager effort. At the same time, weather is plausibly unrelated to the benefits of effort, such as future profitable opportunities. Thus, weather is potentially related to future returns, but only indirectly by influencing the costs and level of effort. As such, as an instrument, weather likely satisfies the exclusion restriction.

We observe monthly weather conditions by city. To use weather as an instrument for manager effort, our measures of effort must also correspond to managers in specific cities. But this is difficult for our advisor-level measure of effort as it does not account for the fact that some advisory firms consist of funds scattered across different cities. To correct this, we obtain fund-level measures of manager effort by matching IP addresses to funds (not fund advisors) using zip codes.[16] We then re-calculate our monthly measures of work activity and effort ($TotalWDs$ and $PctWk$) at the fund level, identify fund locations, and match funds with the weather data according to the city of operations.[17]

The first stage of our IV approach estimates the following model:

$$PctWkF_{ijct} = \alpha + \beta_1 Rain_{ct} + \beta_2 Rain_{ct}^2 + \beta_3 Temp_{ct} + \gamma TotalWDsF_{ijct} + \delta V_{ijct} + \epsilon_{ijct}, \quad (4)$$

where $Rain_{ct}$ and $Temp_{ct}$ denote monthly weekend rainfall and temperature in city c. The control vector V contains $PctNetFlow$, $TNAM$, $Expenses$, $Turnover$, $ActiveShare$, Com-

[16]For full details of this matching process see Appendix A.1.1.

[17]We test whether our main results hold using this new sample of fund-level measures. The results are robust and are found in Table A5 in Appendix A.2.

petitive, and *Incentives*. The model includes year, calendar-month-city, and fund fixed effects. We rename our work activity and effort variables as $TotalWDsF$ and $PctWkF$ to indicate measures are now constructed at the fund level.

The estimates from the first-stage regression – shown in Column 2 of Table 9 – verify that the relevance criteria holds; the Kleibergen-Paap F-statistic is 17.65, above the Stock-Yogo weak-instrument threshold.[18] As an interpretation of the results; more rain increases manager effort ($Rain > 0$), though at a decreasing rate ($Rain^2 < 0$). Figure 7 visualizes this concave relationship: effort rises with rainfall but a very rainy weekend can decrease effort. Going back to the thought experiment, while some rain makes leisure less enjoyable, decreases the cost of effort, and increases the likelihood of weekend work, too much rain also makes it difficult to get to the office. This non-linearity aligns with data from the US Bureau of Labor Statistics showing that work absences increase during extreme weather events, such as hurricanes and snowstorms.[19]

[Table 9 about here.]

[Figure 7 about here.]

In the second stage we regress six-month abnormal returns begining 13 months out on the predicted effort from the first stage:

$$Y_{ijct+13} = \alpha + \beta Pct\hat{W}kF_{ijct} + \gamma TotalWDsF_{ijct} + \delta V_{ijct} + \epsilon_{ijct}, \tag{5}$$

where Y is the benchmark-adjusted return (*Alpha*) or risk-adjusted returns ($FF3$ or $FF4$) and the specification includes year, calendar-month-city, and fund fixed effects. Columns 3–5 of Table 9 present estimates for the full sample of funds while Columns 6–8 limit the sample to managers facing above median competitive incentives and Columns 9–11 limit the sample to mutual funds with *E-Scores* of at least four.

[18]Kleibergen and Paap (2006) and Stock and Yogo (2002).

[19]https://www.bls.gov/opub/ted/2017/work-absences-due-to-bad-weather-from-1994-to-2016.htm.

For the full sample the IV coefficient on predicted effort is small with inconsistent statistical significance (Columns 3–5). This result is unsurprising since roughly half the observations are from funds without a high amount of competitive incentives and with *E-Scores* less than four, a group that earlier tests showed receives little or no payoff from extra effort.

Restricting attention to competitive managers or funds with high *E-Scores* (Columns 6–11) changes the picture. A one-standard-deviation increase in instrumented effort raises future risk-adjusted returns by roughly 30–63 basis points over six months, and the effect is significant at the 1% level for five of the six specifications.[20] These findings confirm that – where incentives and portfolio characteristics make effort valuable – additional weekend work causally improves subsequent performance.

These IV results establish that exogenous increases in effort cause higher risk-adjusted returns. The next question is how additional effort translates into outperformance. Section 8 turns to this mechanism – showing how heightened effort changes managers' information-acquisition patterns and trading decisions, and how those changes drive some of the return improvements documented above.

8 Mechanism: Effort and Information Acquisition

Having shown that weekend effort causally boosts returns, we now ask what managers do differently when they work harder and why those actions translate into outperformance.

Having found that effort both precedes and causes better future performance, two questions linger: (i) what are mutual fund managers doing when they are working harder? and (ii) what is it about effort that leads to higher future returns? To address both questions we use granular measures of manager information acquisition and study whether the nature of a manager's research activities is related to effort. We then examine whether information acquisition and effort combine to enhance future performance.

[20]The standard deviation of $PctWkFPred$ is 0.0618. This is multiplied by the coefficient estimates (4.86 and 10.20) and the products were multiplied by 100 to covert to basis points.

To examine how the nature of information acquisition varies with effort, we regress several monthly information-acquisition metrics on $PctWk$ while controlling for total work-days and including advisor and year-month fixed effects:

$$Y_{it} = \alpha + \beta PctWk_{it} + \gamma TotalWDs_{it} + \epsilon_{it}, \tag{6}$$

where the dependent variables – $Y \in \{$*PctUniqueFirms, PctUniqueFiling, Pct10KQ, MedFilingAge, PctNonHoldings*$\}$ – capture different aspects of information acquisition. Specifically, *PctUniqueFirms* measures the percentage of unique firms managers review filings for, *PctUniqueFilings* captures the number of distinct filings accessed, *Pct10KQ* represents the proportion of 10-K and 10-Q filings accessed, *MedFilingAge* measures the median age of filings reviewed, and *PctNonHoldings* tracks the extent to which managers acquire information about firms they do not currently hold. Using the independent variable $PctWk$ as the proxy for effort and including year-month and advisor fixed effects allows us to interpret the coefficient estimate on $PctWk$ as the effect of effort on the nature of information acquisition. The results are presented in Table 10.

[Table 10 about here.]

The pattern is unambiguous: higher effort coincides with a deeper, more selective research process. Managers view filings for fewer firms and fewer documents overall, devote less attention to routine 10-K/10-Q reports, and, on average, consult slightly older filings – suggesting they revisit historical information. Economically, a one-standard-deviation rise in effort reduces the breadth of firms covered by about 20% (coefficient of 0.32). The tendency to analyze non-holdings grows as well, although that effect is only in one subset of the sample. As with previous results, these effects are particularly pronounced among fund managers with highly competitive incentives and high active share, as illustrated in Figure 8.

[Figure 8 about here.]

Having documented that extra effort coincides with a deeper, more selective research process, we next test whether this targeted information gathering feeds directly into trading and, ultimately, performance. Specifically, we examine whether managers trade the stocks they research more, particularly when they put in more effort. We also ask: when managers put in more effort and trade the stocks they have researched, do those stocks outperform the rest of the fund benchmark? In other words, do effort and information acquisition combine to explain the outperformance we document in Sections 6 and 7

To test whether extra effort shapes how information translates into trades, we estimate a fund-stock-month panel regression:

$$\begin{aligned}\Delta Position_{ijlt+3} = \alpha + \beta_1 MFIA_{ijlt} + \beta_2 PctWk_{ijt} \\ + \beta_3 (MFIA_{ijlt} \times PctWk_{ijt}) + \gamma X_{ijt} + \epsilon_{ijlt},\end{aligned} \tag{7}$$

where $\Delta Position_{ijlt+3}$ equals 1 if fund j initiates a new position in stock l (or fully liquidates a current position) within the next quarter. The independent variable *MFIA* flags months in which the fund accessed filings on stock l while *PctWk* proxies for effort. The interaction of these variables (*PctWk*×*MFIA*) captures whether research and effort jointly trigger trading and is the focus of this test.

Table 11 shows that the interaction term is positive and significant for sales, but largely insignificant for buys: heightened effort coupled with research makes managers more likely to exit existing positions. Notably, this selective selling aligns with earlier evidence that effort leads to greater portfolio concentration, implying that managers exert more effort and do research to refine – rather than expand – their holdings.

[Table 11 about here.]

We next ask whether these research-driven sales are related to better performance using the following model:

$$\begin{aligned} ExcessReturn_{ijlt+13} = \alpha + \beta_1 MFIA_{ijlt} + \beta_2 PctWk_{ijt} \\ + \beta_3 (MFIA_{ijlt} \times PctWk_{ijt}) + \gamma X_{ijlt} + \epsilon_{ijlt}, \end{aligned} \tag{8}$$

where $ExcessReturn_{ijlt+13}$ measures six-month excess returns for stock l relative to fund j's benchmark.

As before, we estimate the model separately for buys and sells and, given the trading results, we expect a significant effort-research premium for sells only. Table 12 confirms this pattern: stocks sold after high effort and research underperform the benchmark, whereas no consistent effect emerges for purchases.

[Table 12 about here.]

In the full sample (Columns 2 and 5) the interactin between effort and research is insignificant for both buys and sells. But the picture changes in the subsamples where effort has been most valuable – funds with strong competitive incentives or high *E-Scores* – especially for sales. Within these groups, the interaction of effort and research reliably precedes the liquidation of positions that subsequently underperform, while no comparable effect appears on the buy side. Thus, when managers are exerting more effort and engaged in research, they tend to sell off the right stocks, improving overall portfolio performance.

These findings illuminate the mechanism: extra effort shifts attention from breadth of research to depth. Managers narrow their research list, deepen their analysis on a subset of stocks, and act primarily by trimming losers – thereby increasing portfolio concentration and boosting risk-adjusted performance. Taken together with earlier sections, the evidence confirms that managerial effort is an important – but heterogeneous – ingredient for fund success, delivering the greatest benefits in competitively incentivized, high-conviction funds.

9 Conclusion

We introduce a novel, activity-based measure of fund manager effort – *weekend* EDGAR usage relative to *weekday* usage – and document its substantial variation across funds and over time. Effort is higher among managers facing strong competitive incentives and managing large, high-fee funds, and effort rises in response to poor recent performance, measured by outflows and elevated tracking error. We also show that higher effort reshapes portfolios in economically meaningful ways: portfolios become more concentrated, active share rises, and turnover falls. Moreover, increased manager effort is followed by superior benchmark- and risk-adjusted returns, indicating that effort translates into higher alpha.

Using local weekend rainfall as an instrument, we show that exogenous variation in effort causally enhances future returns. This confirms that there is not only a positive *relation* between effort and future performance, but there is a causal link: more effort *causes* higher future returns.

Mechanism tests reveal that extra effort channels managers toward deeper but narrower research: they analyze fewer firms and older, more unique filings, and use this information chiefly to prune existing positions. In highly incentivized funds, these selectively sold stocks go on to underperform, confirming that effort combines with focused research to drive the return improvements.

By quantifying managerial effort, our study deepens the practitioner's toolkit for manager selection and incentive design, and enriches the academic understanding of principal-agent dynamics in asset management. Our study also opens several promising avenues for future research: (i) examining how technological changes affect the effort-performance relationship, (ii) investigating whether effort measures can predict fund manager skill, and (iii) integrating effort metrics into screening models for fund evaluation.

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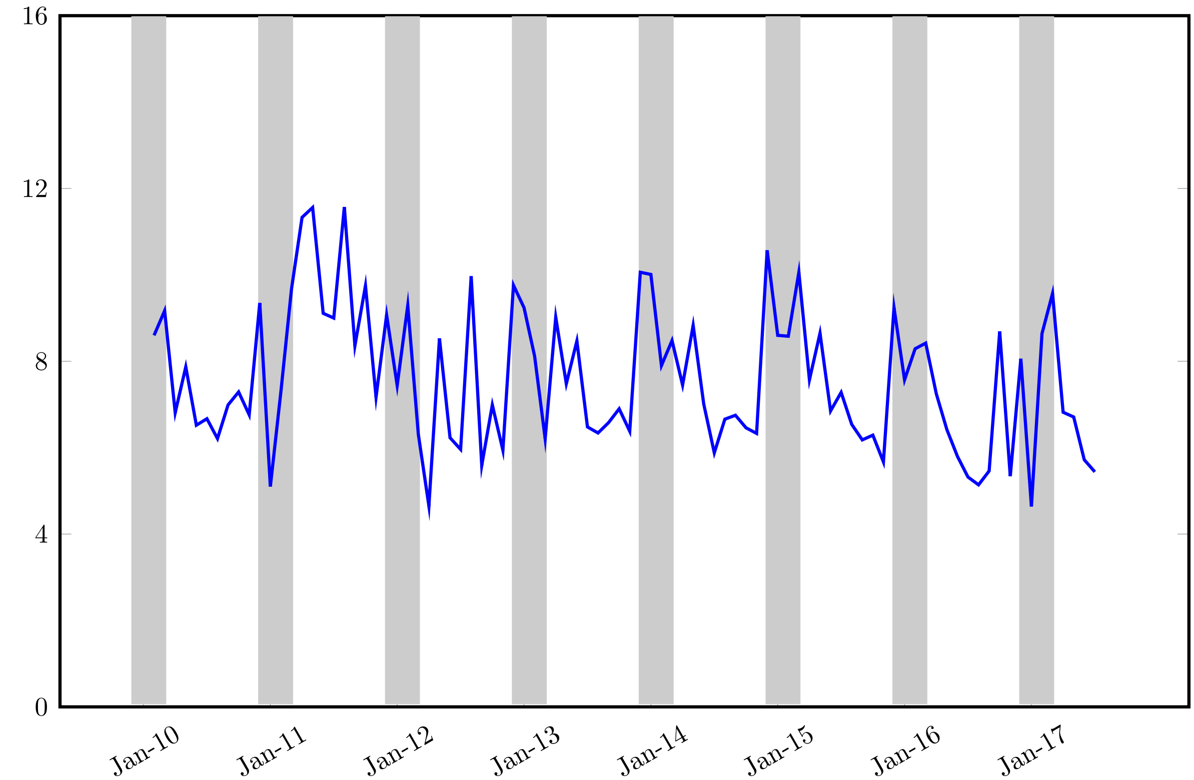
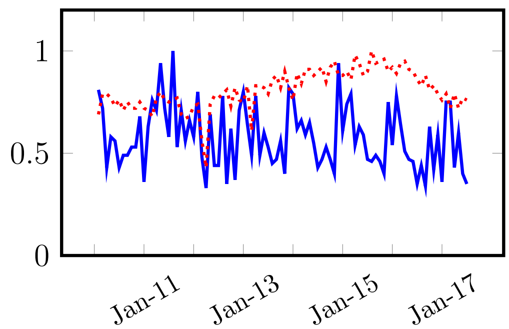
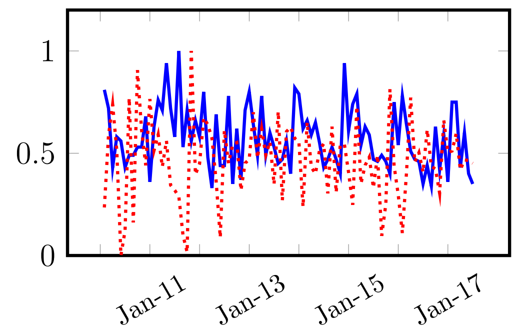


Figure 1: Time Series of Effort

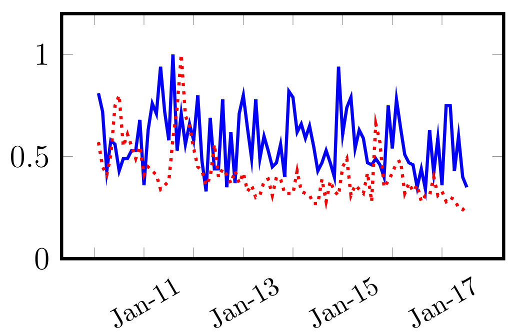
The figure shows the time series of effort, as proxied by $PctWk$. In this time series, $PctWk$ is measured as the mean $PctWk$ across all mutual fund families every month. The vertical axis is in percent. The weekend measures have been scaled to account for different months having different numbers of weekends and holidays.



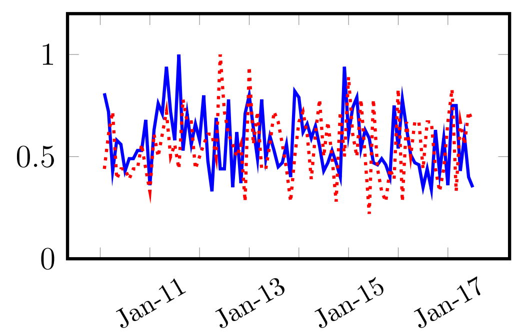
(a) *pctWk* and *totalWDs*



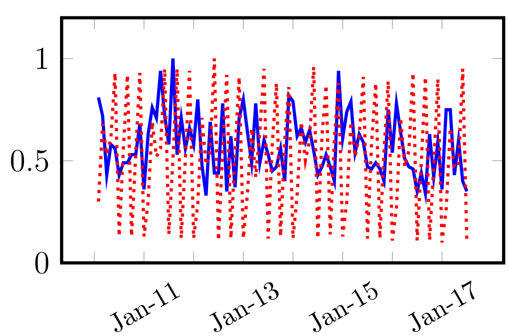
(b) *pctWk* and *MktRet*



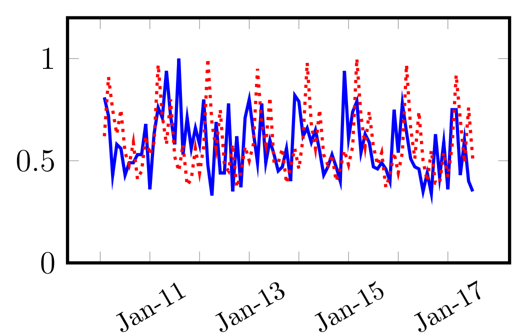
(c) *pctWk* and *VIX*



(d) *pctWk* and *nRain*



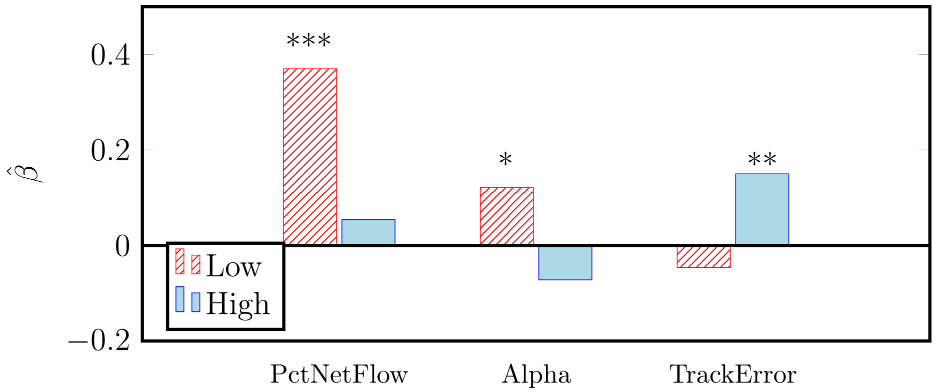
(e) *pctWk* and *eadates*



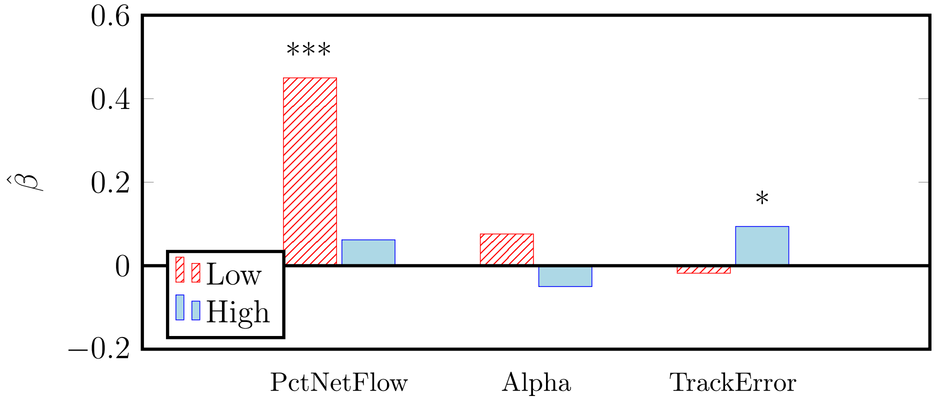
(f) *pctWk* and *filings*

Figure 2: Time Series of Effort, Activity, and Other Variables

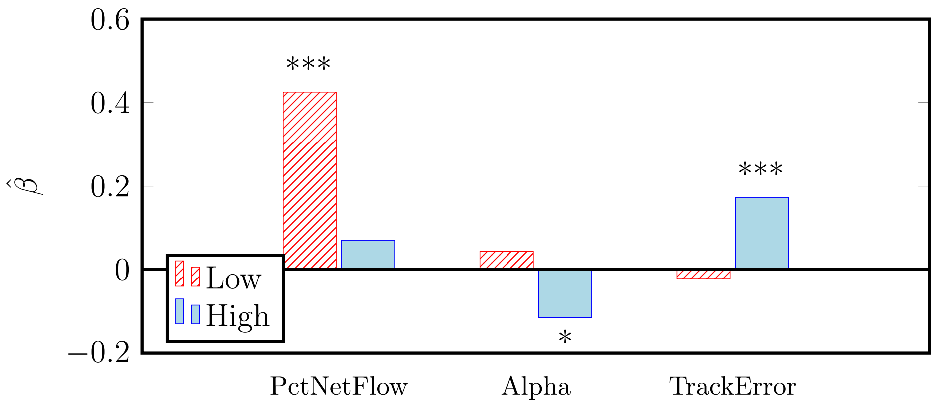
The figure shows the monthly time series of effort (*PctWk*) with other measures, including: activity (*TotalWDs*), market returns (*MktRet*), the market volatility index (*VIX*), the number of rainy days in New York City (*nRain*), the number of earnings announcements (*EaDates*), and the number of filings registered with EDGAR (*Filings*). Each time series has been scaled as the monthly value divided by its maximum over the 90 months of the series. The series for *MktRet* has been shifted up each month by the absolute value of the most negative return.



(a) All Observations



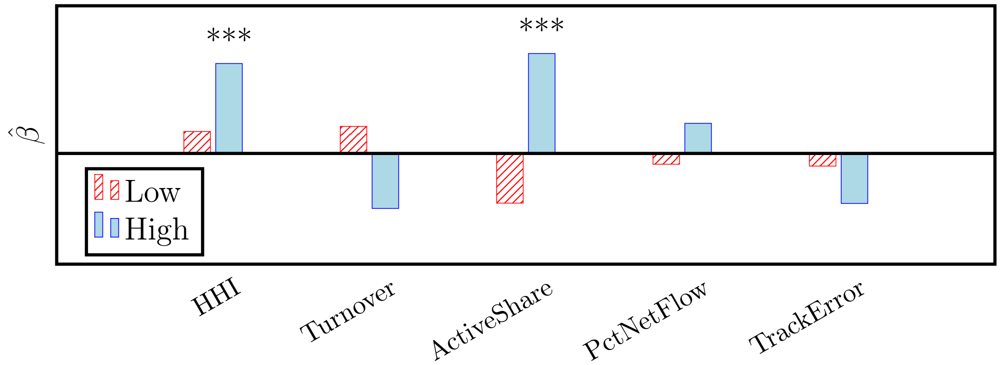
(b) $PctWk > 0$



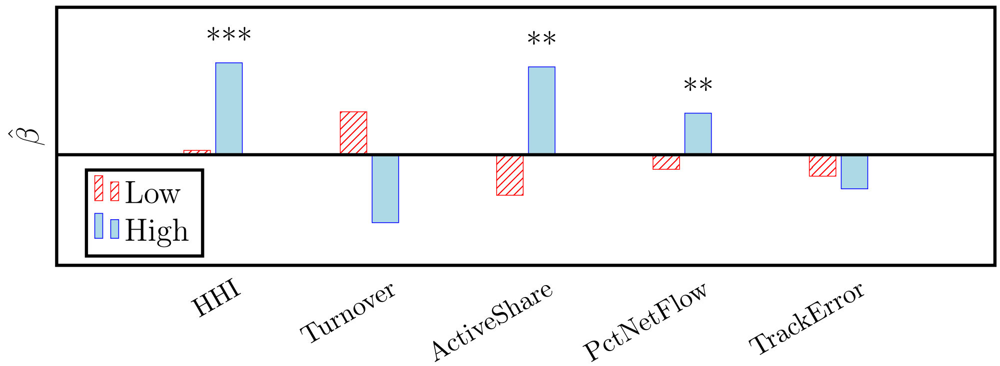
(c) $MedWk > 1$

Figure 3: Low versus High Performance and the Determinants of Effort

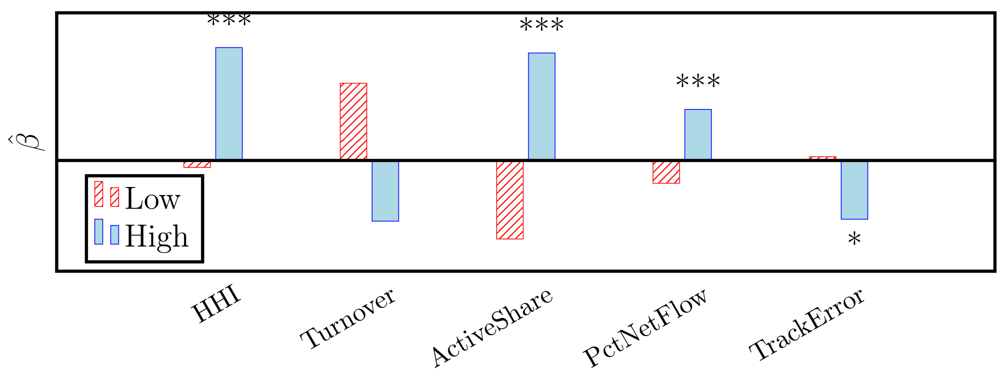
The figure plots coefficient estimates from estimating Equation 1 using high and low indicators in place of the noted continuous variables. For example, the coefficient estimates for *HighPctNetFlow* and *LowPctNetFlow* replace the continuous variable *PctNetFlow*. Panel (a) uses the entire sample while Panels (b) and (c) limit the sample as indicated. Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.



(a) All Observations



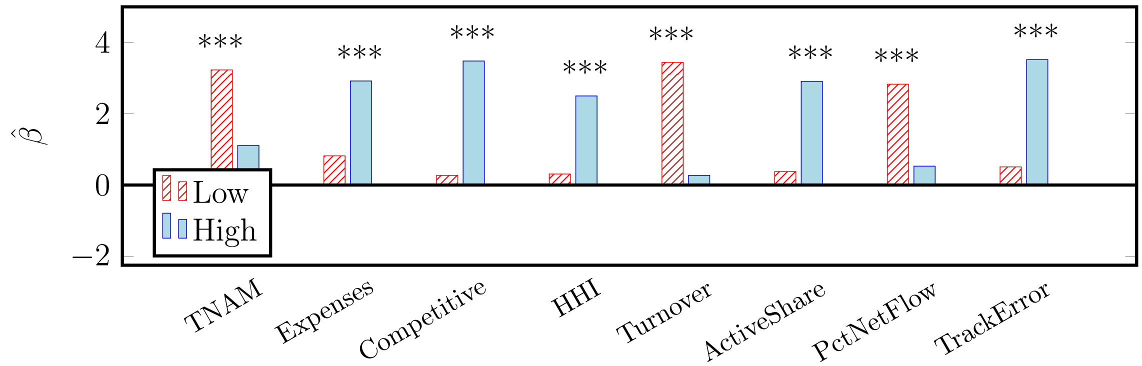
(b) $PctWk > 0$



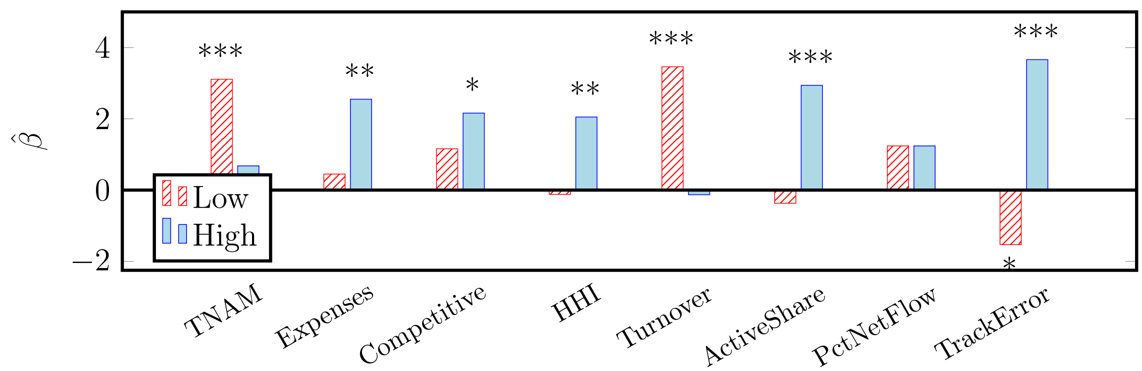
(c) $MedWk > 1$

Figure 4: Low versus High Effort and Outcomes

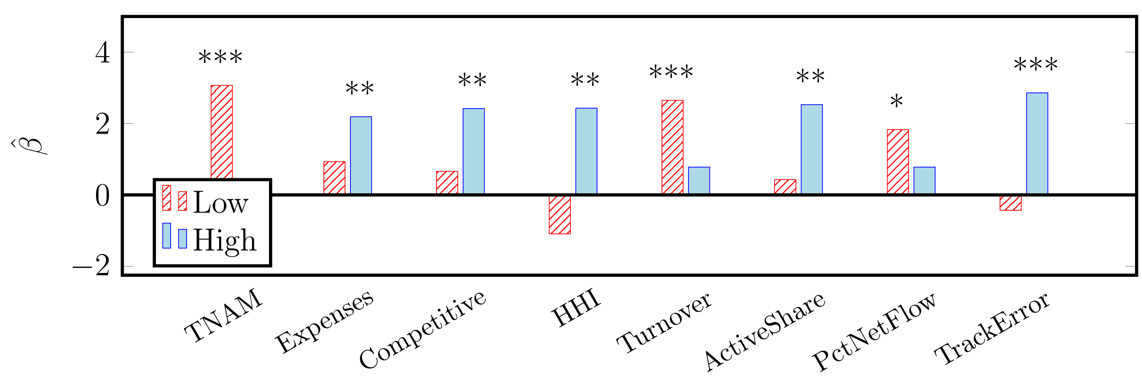
The figure plots coefficient estimates from estimating Equation 2 using high and low indicators in place of the continuous effort variable ($PctWk$). Panel (a) uses the entire sample while Panels (b) and (c) limit the sample as indicated. Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.



(a) All Observations



(b) $PctWk > 0$



(c) $MedWk > 1$

Figure 5: Low versus High Characteristics and the Effort-Return Relation

The figure plots coefficient estimates from estimating Equation 3 using high and low indicators in place of the noted continuous variables. For example, the coefficient estimates for $HighTNAM$ and $LowTNAM$ replace the continuous variable $TNAM$. Panel (a) uses the entire sample while Panels (b) and (c) limit the sample as indicated. Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Turnover \ ActiveShare	Low	High
Low	1.50	4.32***
High	-0.62	0.37

ActiveShare \ Competitive	Low	High
Low	0.32	0.49
High	0.04	5.06***

Turnover \ Competitive	Low	High
Low	0.61	5.56***
High	-0.04	0.68

PctNetFlow \ Competitive	Low	High
Low	0.15	4.91***
High	0.22	0.99

Figure 6: Sensitivity of Future Alpha to $PctWk$: Based on High v. Low

The figure shows the coefficient estimates from Equation 3 after sub-sampling the data in two dimensions. For example, we compare the estimates from Equation 3 from mutual funds with low $Turnover$ and low $ActiveShare$ with the estimates from funds with high $Turnover$ and high $ActiveShare$. Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

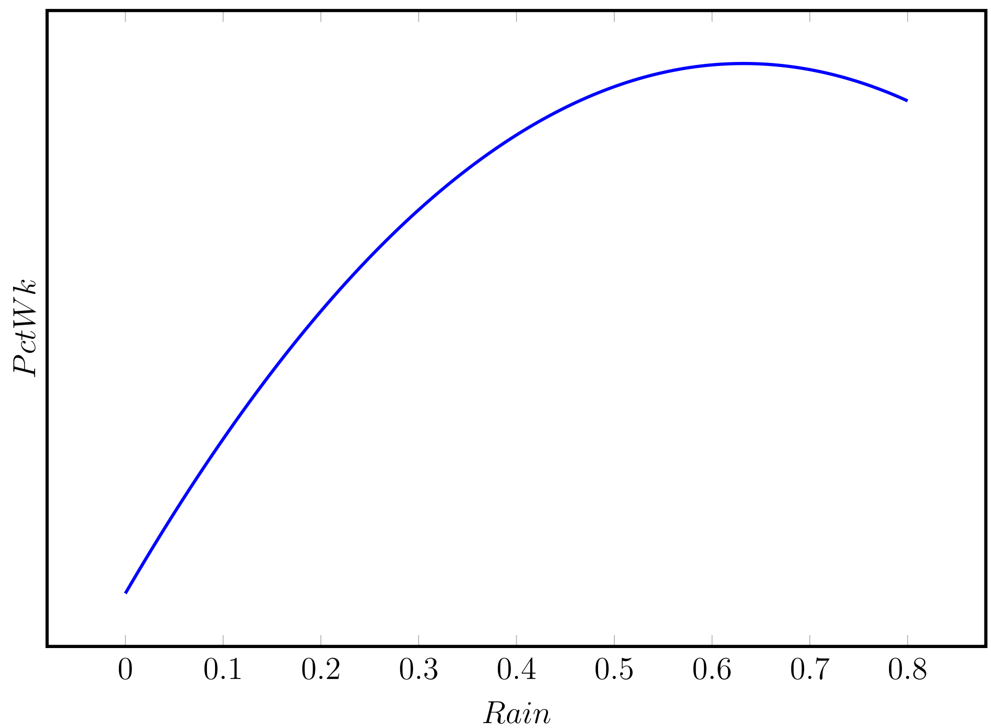


Figure 7: Effort and Rain - 1st Stage

The figure shows relation between $PctWk$ and $Rain$ implied from the first-stage regression estimating Equation 4.

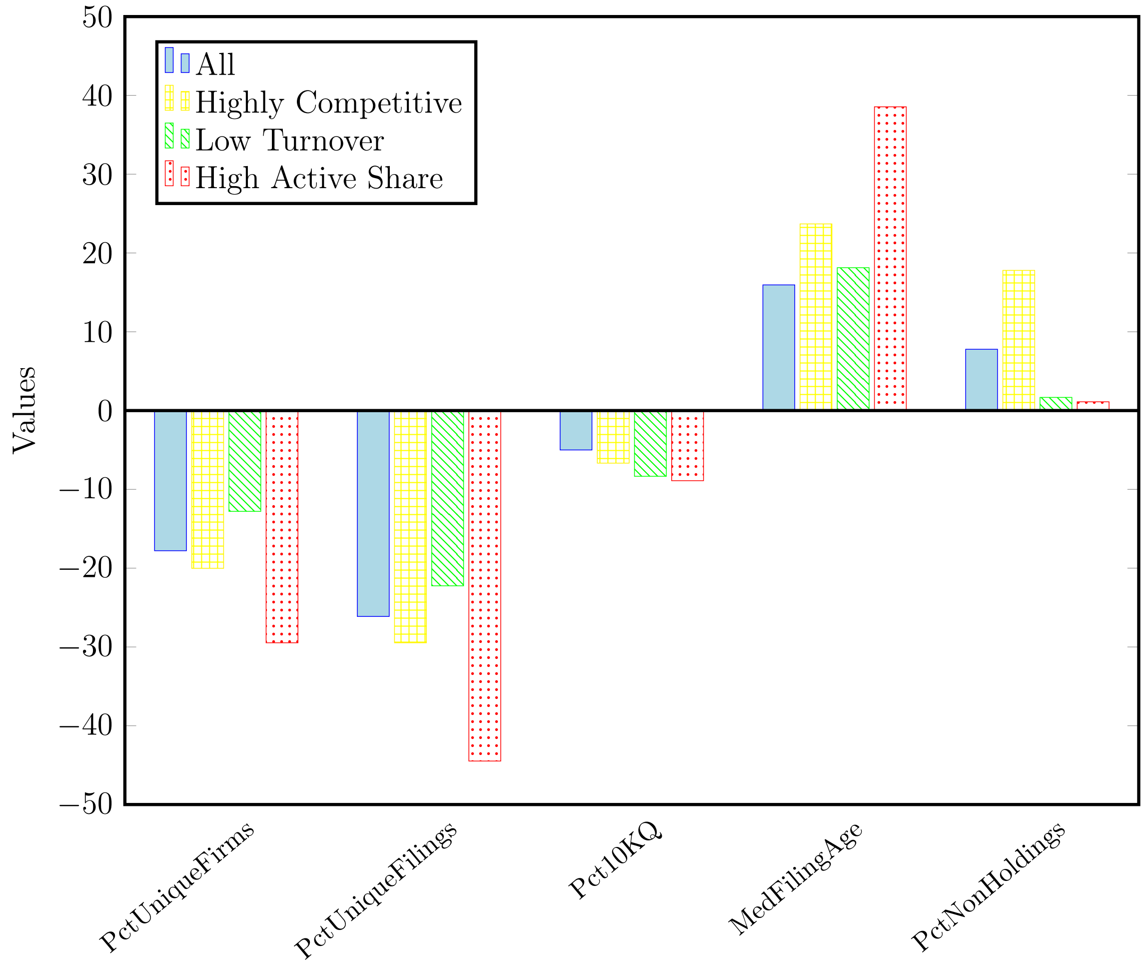


Figure 8: Information Acquisition Activities and Effort

The figure plots scaled coefficient estimates from estimating Equation 6 using subsamples of mutual funds: All funds, funds facing high competitive incentives, funds with low turnover, and funds with high active share. The coefficient estimates are scaled to show the percentage change in the noted dependent variable from a one-standard-deviation increase in effort ($PctWk$). For example, the value of negative 30% for high active share with respect to $PctUniqueFirms$ means that a one-standard-deviation increase in effort is associated with a 30% reduction in the number of unique firms viewed in EDGAR.

Table 1: Summary Statistics: Activity and Effort

The table provides a summary of the activity and effort measures. The sample consists of 115 advisory firms across 90 months (from January 2010 through June of 2017). Panel A and Panel B provide summary statistics across the entire panel and in the cross-section, respectively. A correlation matrix among the four activity and effort variables is in Panel C. Panel D shows the factor loadings, eigenvalues, and proportion of explained variation from a principal components analysis.

(1)	(2)	(3)	(4)	(5)	(6)	(7)

Panel A. Summary of the Panel (Advisor-by-Month Observations)

				Percentile		
Variable	Mean	Std. Dev.	Skewness	25^{th}	50^{th}	75^{th}
TotalWDs	125	252	4.61	21	39	131
PctWkWDs	0.10	0.10	1.43	0.01	0.08	0.16
TotalReqs	4,200	10,181	4.38	205	923	3,546
PctWkReqs	0.05	0.12	4.84	0.00	0.02	0.05
PctWk	0.08	0.10	2.95	0.01	0.05	0.11

Panel B. Summary of the Cross-Section (Advisor-level Observations)

				Percentile		
Variable	Mean	Std. Dev.	Skewness	25^{th}	50^{th}	75^{th}
TotalWDs	89	196	5.11	18	28	64
PctWkWDs	0.08	0.08	1.40	0.03	0.05	0.11
TotalReqs	2,751	7,492	5.11	134	543	1,782
PctWkReqs	0.04	0.08	5.47	0.01	0.02	0.03
PctWk	0.06	0.07	2.87	0.02	0.04	0.08

Panel C. Correlation Matrix in the Panel

	TotalWDs	TotalReqs	PctWkWDs	PctWkReqs
TotalWDs	1.00	0.86	0.24	0.07
TotalReqs	0.86	1.00	0.34	0.07
PctWkWDs	0.24	0.34	1.00	0.58
PctWkReqs	0.07	0.07	0.58	1.00

Panel D. Principal Component Analysis in the Panel

Variable	Factor 1	Factor 2
TotalWDs	0.84	-0.46
TotalReqs	0.87	-0.42
PctWkWDs	0.67	0.59
PctWkReqs	0.45	0.79
Eigenvalues	2.12	1.36
Proportion of Variation	0.53	0.34

Table 2: Time Series Analysis of Activity and Effort

The table provides a time series analysis of the mean of $TotalWDs$ and $PctWk$ across 90 months (from January 2010 through June of 2017). The table includes correlations of other time series variables in the panel. The other time series variables include: market returns ($MktRet$), the market volatility index (VIX), the number of filings registered with EDGAR ($Filings$), and the number of earnings announcements ($EaDates$).

(1)	(2)	(3)
Panel A. Time Series Analysis		
	ΔTotalWDs$_{t,t-1}$	PctWk$_t$
μ	3.01	0.04
	(5.84)	(0.03)
AR(1)	-0.37***	-0.01
	(0.10)	(0.11)
AR(12)	0.23**	0.45***
	(0.10)	(0.11)
MktRet	-55.27*	-0.04
	(31.16)	(0.06)
VIX	-0.17	0.00
	(0.17)	(0.00)
Filings	0.00	0.00
	(0.00)	(0.00)
EaDates	0.00	0.00
	(0.00)	(0.00)
TotalWDs		0.00
		(0.00)
N	90	90
Panel B. Correlation Matrix in the Panel		
	TotalWDs	PctWk
TotalWDs	1.00	0.19***
PctWk	0.19***	1.00
MktRet	-0.01	-0.01
VIX	-0.01	0.03**
Filings	-0.01	0.03**
EaDates	0.00	0.01

Table 3: Summary Statistics: Mutual Funds and Advisory Firms

The table shows summary statistics for the mutual funds their advisory firms in our sample. Panel A summarizes across the fund-by-month panel. Panel B summarizes across the advisor-by-month panel after aggregating funds within advisory firms. Panel C compares our sample with the universe of mutual funds.

(1)	(2)	(3)	(4)	(5)
Panel A. Summary of Fund-by-Month Observations				
Variable	Mean	Std. Dev.	Median	N
TNAM (*millions*)	3,310	10,300	759	46,573
HHI	1.55	0.73	1.44	39,841
Expenses	1.19	0.33	1.22	46,561
Turnover	71	55	58	46,561
ActiveShare	77	13	79	46,576
PctNetFlow	-0.51	2.39	-0.64	46,570
Alpha	-0.59	2.68	-0.56	41,657
TrackError	0.91	0.45	0.82	41,657
Panel B. Summary of Advisor-by-Month Observations				
Variable	Mean	Std. Dev.	Median	N
Funds	56	57	40	5,631
TNAM (*millions*)	130,000	319,000	41,000	5,631
HHI	1.75	0.64	1.66	4,927
Expenses	1.13	0.32	1.17	5,632
Turnover	52	31	46	5,632
ActiveShare	77	10	77	5,631
PctNetFlow	0.01	1.11	0.06	5,631
Alpha	-0.78	1.92	-0.71	4,957
TrackError	0.92	0.34	0.87	4,957

Panel C. Comparison of Sample versus Universe of Mutual Funds

Variable	Sample	Universe
No. of Advisory Firms	115	614
No. of Funds	1,408	2,922
Total Net AUM (*millions*)	$10,818,135	$16,134,532
Mean Advisor Net AUM (*millions*)	$99,249	$26,891
Pct. Of Large Cap Categories	57%	55%
Mean Alpha	-0.10%	-0.11%
Mean Morningstar Stars	3.41	3.30

Table 4: Determinants of Effort

The table shows the results from estimating Equation 1 to test the relation between effort ($PctWk$) and various mutual fund characteristics. Columns 2–4 include style and year-month fixed effects while Columns 5–7 add an advisory firm fixed effect. The table shows estimates across the entire sample as well as when limiting the sample to observations where $PctWk > 0$ or for advisors with median total weekend work-days greater than one ($MedWk > 1$). Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All Obs.	PctWk > 0	MedWk > 1	All Obs.	PctWk > 0	MedWk > 1
	PctWk	PctWk	PctWk	PctWk	PctWk	PctWk
TotalWDs	2.64***	2.04***	2.32***	1.47***	-0.62*	0.85**
	(0.09)	(0.11)	(0.10)	(0.30)	(0.32)	(0.35)
TNAM	0.17***	0.16***	0.14***	0.01	0.01	0.02**
	(0.03)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
Expenses	2.41***	2.91***	3.34***	-0.05	0.03	-0.03
	(0.25)	(0.26)	(0.27)	(0.08)	(0.08)	(0.08)
Competitive	10.33***	11.90***	13.76***	0.42	0.97	0.91
	(0.65)	(0.74)	(0.73)	(1.50)	(1.60)	(1.64)
Incentives	3.85***	4.81***	4.93***	0.10	-1.64	-2.00*
	(0.35)	(0.37)	(0.40)	(1.13)	(1.08)	(1.10)
HHI	0.01	-0.05	-0.21**	0.12***	0.15***	0.15***
	(0.09)	(0.09)	(0.10)	(0.05)	(0.04)	(0.04)
Turnover	0.16***	0.16***	0.17***	-0.01	-0.02	0.01
	(0.06)	(0.06)	(0.07)	(0.03)	(0.03)	(0.03)
ActiveShare	-0.05***	-0.04***	-0.05***	-0.01**	-0.01***	-0.01**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
PctNetFlow	1.91	2.94	3.25	-2.15*	-2.36**	-2.04*
	(1.93)	(2.05)	(2.00)	(1.11)	(1.13)	(1.08)
Alpha	0.02	0.02	-0.01	-0.03**	-0.01	-0.02**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
TrackError	-0.39***	-0.52***	-0.63***	0.14**	0.11*	0.11*
	(0.11)	(0.11)	(0.11)	(0.06)	(0.06)	(0.06)
N	23,937	20,367	18,634	23,937	20,367	18,634
R^2	0.39	0.34	0.40	0.71	0.72	0.74

Table 5: Outcomes of Effort

The table shows the results from estimating Equation 2 to test the relation between effort ($PctWk$) and future mutual fund characteristics and outcomes. The independent variables are lagged three months and twelve months, as indicated below. All three fixed effects – style, year-month, and advisor – are included. Panel A shows estimates when using the entire sample. Panel B limits the sample to observations where $PctWk > 0$. Panel C limits the sample to advisors with median total weekend work-days greater than one ($MedWk > 1$). Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: All Observations.										
	HHI		Turnover		ActiveShare		PctNetFlow		TrackError	
PctWk$_{t-3}$	0.16**		-0.29***		0.53		0.00		0.14*	
	(0.07)		(0.10)		(0.88)		(0.00)		(0.08)	
PctWk$_{t-12}$		0.18**		-0.28**		3.76***		0.00		-0.13
		(0.07)		(0.11)		(0.95)		(0.01)		(0.09)
N	23,713	20,865	25,492	20,990	25,564	21,059	25,564	21,059	24,807	20,478
R^2	0.53	0.53	0.27	0.27	0.66	0.65	0.83	0.33	0.37	0.37
Panel B: Observations where $PctWk > 0$.										
	HHI		Turnover		ActiveShare		PctNetFlow		TrackError	
PctWk$_{t-3}$	0.21***		-0.40***		-0.45		0.00		0.14	
	(0.08)		(0.12)		(1.01)		(0.00)		(0.09)	
PctWk$_{t-12}$		0.25***		-0.37***		3.77***		0.01		-0.07
		(0.08)		(0.13)		(1.07)		(0.01)		(0.09)
N	20,276	18,045	21,671	18,135	21,737	18,198	21,737	18,198	21,208	17,793
R^2	0.53	0.53	0.25	0.25	0.64	0.63	0.83	0.32	0.37	0.37
Panel C: Observations where $MedWk > 1$.										
	HHI		Turnover		ActiveShare		PctNetFlow		TrackError	
PctWk$_{t-3}$	0.30***		-0.30**		1.30		0.00		0.07	
	(0.08)		(0.13)		(1.11)		(0.00)		(0.09)	
PctWk$_{t-12}$		0.32***		-0.38***		4.77***		0.01***		-0.23**
		(0.08)		(0.14)		(1.24)		(0.01)		(0.09)
N	18,603	16,495	20,047	16,534	20,119	16,603	20,119	16,603	19,576	16,165
R^2	0.56	0.56	0.23	0.23	0.64	0.63	0.82	0.32	0.37	0.37

Table 6: Effort and Future Performance

The table shows results from estimating Equation 3 to test the relation between effort (*PctWk*) and future performance (*Alpha*) measured as the compound benchmark adjusted return over six months beginning at month $t+k$ for $k \in \{1,7,13\}$. Control variables include: *PctNetFlow*, *TNAM*, *Expenses*, *Turnover*, *ActiveShare*, *Competitive*, and *Incentives*. The model always includes style and year-month fixed effects while an advisor fixed effect is only included in Columns 5–7. Panel A shows estimates when using the entire sample. Panel B and Panel C limit the sample to observations where $PctWk > 0$ and to advisors with median total weekend work-days greater than one ($MedWk > 1$). Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. All Observations.						
	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$
PctWk	0.90*	1.54***	3.03***	-1.25*	-0.78	2.05***
	(0.47)	(0.46)	(0.47)	(0.68)	(0.61)	(0.69)
TotalWDs	0.14***	0.08***	0.04*	0.16***	-0.04	-0.00
	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)
PctNetFlow	1.63*	-1.13	-1.15	-0.55	-3.29***	-3.22***
	(0.88)	(0.85)	(0.84)	(0.94)	(0.87)	(0.86)
TNAM	-0.06***	-0.05***	-0.02	-0.08***	-0.07***	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Expenses	-0.65***	-0.78***	-0.69***	-0.43***	-0.48***	-0.29***
	(0.06)	(0.06)	(0.06)	(0.08)	(0.08)	(0.08)
Turnover	-0.09***	-0.05*	-0.05*	-0.13***	-0.10***	-0.13***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
ActiveShare	-0.01***	-0.01***	-0.02***	-0.00	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Competitive	0.00	-0.28*	-0.43***	0.52	0.13	0.19
	(0.16)	(0.16)	(0.15)	(0.44)	(0.44)	(0.45)
Incentives	-0.21**	-0.22**	-0.24**	0.32	-0.03	0.12
	(0.09)	(0.09)	(0.10)	(0.36)	(0.37)	(0.39)
N	25,259	25,359	25,515	25,257	25,357	25,513
R^2	0.10	0.10	0.10	0.13	0.12	0.12
Panel B. Observations where $PctWk > 0$.						
	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$
PctWk	0.02	0.80	1.92***	-1.00	-1.52**	1.69**
	(0.48)	(0.50)	(0.48)	(0.78)	(0.73)	(0.79)
N	21,139	21,127	21,187	21,137	21,125	21,185
R^2	0.11	0.11	0.11	0.13	0.13	0.13
Panel C. Observations where $MedWk > 1$.						
	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$
PctWk	-0.42	0.74	2.09***	-1.74**	-1.01	1.70**
	(0.49)	(0.49)	(0.48)	(0.77)	(0.77)	(0.73)
N	19,563	19,616	19,677	19,561	19,614	19,675
R^2	0.11	0.11	0.11	0.13	0.12	0.13

Table 7: Effort and Future Performance: Heterogeneous Effects

The table shows results from estimating Equation 3 to test the relation between effort ($PctWk$) and future performance ($Alpha_{13-18}$). In Panel A, the sample is split between high and low groups, subject to the specified criteria. For example, Columns 2 and 3 estimate the model after splitting the sample between low $TNAM$ mutual funds and high $TNAM$ mutual funds. In Panel B, six characteristics are combined into a variable called *E-Score* which counts the number of highs and lows corresponding to better returns to effort. Control variables include: $PctNetFlow$, $TNAM$, *Expenses*, $Turnover$, *ActiveShare*, *Competitive*, and $Incentives$. The model always includes style, year-month, and advisor fixed effects and standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Low v. High Based on Mutual Fund Characteristics

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TNAM		Expenses		Competitive		TrackError	
	Low	High	Low	High	Low	High	Low	High
	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
PctWk	3.23***	1.11	0.82	2.92***	0.27	3.48***	-0.51	3.52***
	(0.98)	(0.82)	(0.79)	(0.92)	(0.84)	(1.09)	(0.73)	(0.95)
N	11,306	14,207	11,369	14,142	12,262	13,250	10,320	14,932
R^2	0.13	0.14	0.14	0.13	0.14	0.12	0.15	0.14

	HHI		Turnover		ActiveShare		PctNetFlow	
	Low	High	Low	High	Low	High	Low	High
	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
PctWk	0.31	2.50***	3.44***	0.27	0.38	2.91***	2.83***	0.53
	(1.14)	(0.85)	(0.98)	(0.85)	(0.73)	(0.95)	(0.93)	(0.78)
N	8,819	12,518	13,319	12,216	11,290	14,222	13,512	12,001
R^2	0.12	0.18	0.13	0.16	0.20	0.11	0.14	0.15

Panel B: Sample Split by E-Score.

	E-Score ≤ 2	E-Score $= 3$	E-Score $= 4$	E-Score ≥ 5
	Alpha	Alpha	Alpha	Alpha
PctWk	-1.19	-0.44	3.51***	6.06***
	(0.91)	(0.97)	(1.35)	(1.23)
N	6,337	6,203	5,182	7,785
R^2	0.20	0.17	0.13	0.12

Table 8: Effort and Future Performance – Factor Model Alphas

The table shows results from estimating Equation 3 to test the relation between effort ($PctWk$) and future performance measured using factor-model alphas over six months from $(t+13)$ to $(t+18)$. The table includes alphas from the one-factor ($CAPM$), three-factor ($FF3$), and four-factor ($FF4$) models. Control variables include: $PctNetFlow$, $TNAM$, $Expenses$, $Turnover$, *ActiveShare*, *Competitive*, and *Incentives*. Panel A shows estimates when using the entire sample. Panel B uses *E-Score*, which counts the number of highs and lows corresponding to better returns to effort. The model always includes style and year-month fixed effects while an advisor fixed effect is only included in Columns 5 through 7. Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. All Observations.						
	CAPM	FF3	FF4	CAPM	FF3	FF4
PctWk	3.24***	3.83***	3.71***	1.08	1.90***	1.95***
	(0.55)	(0.48)	(0.48)	(0.83)	(0.67)	(0.64)
TotalWDs	0.03	0.01	0.00	-0.02	-0.09	-0.11*
	(0.03)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)
PctNetFlow	2.19**	3.01***	1.93*	-0.12	1.02	0.24
	(1.11)	(0.99)	(1.01)	(1.18)	(1.05)	(1.07)
TNAM	-0.03**	-0.06***	-0.05***	-0.01	-0.04**	-0.03**
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Expenses	-0.79***	-0.75***	-0.68***	-0.75***	-0.60***	-0.51***
	(0.08)	(0.07)	(0.07)	(0.12)	(0.10)	(0.10)
Turnover	-0.28***	-0.25***	-0.28***	-0.35***	-0.31***	-0.32***
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
ActiveShare	-0.03***	-0.02***	-0.01***	-0.02***	-0.01***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Competitive	-0.57***	-0.50***	-0.26	0.36	0.33	0.09
	(0.19)	(0.17)	(0.17)	(0.54)	(0.49)	(0.50)
Incentives	-0.48***	-0.42***	-0.30***	-0.37	-0.40	-0.44
	(0.11)	(0.10)	(0.09)	(0.43)	(0.41)	(0.42)
N	21,557	21,557	21,557	21,555	21,555	21,555
R^2	0.20	0.09	0.09	0.22	0.12	0.12

Panel B: Sample Split by E-Score.

	CAPM		FF3		FF4	
	E-Score <4	E-Score ≥ 4	E-Score <4	E-Score ≥ 4	E-Score <4	E-Score ≥ 4
PctWk	-1.43	3.18***	-0.88	4.33***	-0.89	4.53***
	(0.95)	(1.21)	(0.75)	(0.98)	(0.79)	(0.91)
N	10,065	11,489	10,065	11,489	10,065	11,489
R^2	0.22	0.24	0.13	0.14	0.13	0.13

Table 9: Effort and Future Performance: Instrumental Variable

The table uses an instrumental variables approach to test whether effort affects future performance. Three future performance variables are used: $Alpha_{13-18}$, $FF3_{13-18}$, and $FF4_{13-18}$. Column 2 reports the results from the first-stage regression, estimating Equation 4. Columns 3–11 report the second-stage results, estimating Equation 5. In Columns 6–8, the sample is limited to advisors with above median competitive incentives and in Columns 9–11 the sample is limited to advisors with *E-Score* ≥ 4. Fixed effects include year, fund, and city-month and standard errors are clustered by yearmonth-fund and city. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	First Stage	Second Stage								
	All Funds	All Funds			High Competitive			E-Score ≥ 4		
	PctWkF	Alpha	FF3	FF4	Alpha	FF3	FF4	Alpha	FF3	FF4
$\text{Pct}\hat{\text{W}}\text{kF}$		1.02	2.03	4.66**	10.20**	4.86**	6.90***	13.79	6.61***	8.23***
		(3.51)	(1.73)	(2.02)	(3.82)	(1.97)	(1.84)	(12.82)	(2.32)	(2.06)
Rain	0.04***									
	(0.01)									
Rain^2	-0.03***									
	(0.01)									
TotalWDsF	0.01	-0.10	-0.03	-0.07*	-0.29*	-0.05	-0.10***	-0.26	-0.09*	-0.12**
	(0.01)	(0.12)	(0.02)	(0.03)	(0.14)	(0.03)	(0.03)	(0.32)	(0.05)	(0.05)
PctNetFlow	0.05	-8.27***	-1.28***	-2.56***	-6.82	-1.41**	-2.65**	-11.77***	-1.85**	-3.18**
	(0.04)	(2.75)	(0.40)	(0.51)	(4.79)	(0.67)	(1.00)	(3.95)	(0.78)	(1.25)
TNAM	0.00	-0.54***	-0.12***	-0.12***	-0.56**	-0.11**	-0.12**	-0.81**	-0.16***	-0.17***
	0.00	(0.18)	(0.03)	(0.04)	(0.24)	(0.05)	(0.05)	(0.31)	(0.03)	(0.02)
Expenses	-0.01	0.02	0.06	0.04	-0.39	0.04	0.06	-0.21	0.10	0.04
	(0.01)	(0.32)	(0.10)	(0.08)	(0.27)	(0.11)	(0.09)	(0.42)	(0.15)	(0.06)
Turnover	-0.00	0.13	0.07**	0.08	0.17	0.08*	0.09	0.47	0.08	0.12
	(0.00)	(0.12)	(0.03)	(0.05)	(0.14)	(0.04)	(0.06)	(0.34)	(0.06)	(0.07)
ActiveShare	0.00	0.01	-0.00	-0.01	-0.01	-0.01	-0.00	0.01	-0.00	0.00
	(0.00)	(0.01)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.03)	(0.01)	(0.01)
Competitive	-0.09***	-0.50	0.06	0.35	3.19	0.83**	1.03***	3.69	0.92**	1.02**
	(0.03)	(1.94)	(0.36)	(0.34)	(2.67)	(0.39)	(0.27)	(3.16)	(0.43)	(0.37)
Incentives	0.04	-0.86	-0.21	-0.50	0.07	-0.30	-0.58*	-0.33	-0.13	-0.44
	(0.04)	(1.37)	(0.22)	(0.33)	(2.15)	(0.31)	(0.29)	(1.68)	(0.31)	(0.45)
N	12,347	11,955	11,852	11,852	9,684	5,758	5,664	5,664	4,836	
R^2	0.75	0.15	0.18	0.18	0.14	0.18	0.18	0.19	0.24	0.24
KP F-Stat	17.65									

Table 10: Effort and Information Acquisition Activities

The table shows the results from estimating Equation 6 to test the relation between effort ($PctWk$) and the information acquisition activities of mutual fund managers. The independent and dependent variables are measured contemporaneously. Five measures of information acquisition are used to measure the proportion of EDGAR requests for unique firms ($PctUniqueFirms$), the proportion of requests for unique filings ($PctUniqueFilings$), the proportion of requests for 10-K or 10-Q filings ($Pct10KQ$), the age (in days) of the median filing viewed ($MedFilingAge$), and the proportion of requests for firms not currently held by the advisory firm ($PctNonHoldings$). Both year-month and advisor fixed effects are included. Panel A shows estimates when using the entire sample. Panel B limits the sample to observations where $PctWk > 0$. Panel C limits the sample to advisors with median total weekend work-days greater than one ($MedWk > 1$). Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Observations.					
	PctUniqueFirms	PctUniqueFilings	Pct10KQ	MedFilingAge	PctNonHoldings
PctWk	-0.32***	-0.47***	-0.09	1.32***	0.14
	(0.08)	(0.09)	(0.06)	(0.46)	(0.09)
TotalWDs	-0.04***	0.02*	0.04***	-0.31***	0.05***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.01)
N	4,563	4,563	4,563	4,563	4,563
R^2	0.44	0.30	0.45	0.29	0.55
Panel B: Observations where PctWk > 0.					
	PctUniqueFirms	PctUniqueFilings	Pct10KQ	MedFilingAge	PctNonHoldings
PctWk	-0.40***	-0.58***	-0.16***	1.90***	0.09
	(0.06)	(0.07)	(0.05)	(0.42)	(0.08)
TotalWDs	-0.07***	-0.04***	0.03***	-0.02	0.01
	(0.01)	(0.01)	(0.01)	(0.06)	(0.01)
N	3,649	3,649	3,649	3,649	3,649
R^2	0.61	0.50	0.54	0.36	0.68
Panel C: Observations where MedWk > 1.					
	PctUniqueFirms	PctUniqueFilings	Pct10KQ	MedFilingAge	PctNonHoldings
PctWk	-0.51***	-0.70***	-0.08	1.22***	0.22**
	(0.07)	(0.09)	(0.06)	(0.44)	(0.09)
TotalWDs	-0.05***	-0.01	0.04***	-0.14**	0.02*
	(0.01)	(0.01)	(0.01)	(0.06)	(0.01)
N	3,186	3,186	3,186	3,186	3,186
R^2	0.51	0.39	0.53	0.39	0.67

Table 11: Effort, Information Acquisition Activities, and Trading

The table shows the results from estimating Equation 7 to test the relations between effort ($PctWk$) and information acquisition activity ($MFIA$) with the likelihood of buying new positions or selling current positions in a mutual fund's portfolio. The independent variables are measured contemporaneously while the dependent variables are indicators for changes in holdings next quarter. For example, $BuyNewPosition$ is an indicator equal to 1 if a stock that was not in a given mutual fund's portfolio during month t, but was in the portfolio during the next quarter, at month $t+3$. Similarly, $SellEntirePosition$ indicates an entire position is sold. The model includes fund, stock, and year-month fixed effects. Panel A shows estimates when using the entire sample. Panel B and Panel C limit the sample to observations where $PctWk > 0$ and to advisors with median total weekend work-days greater than one ($MedWk > 1$). Standard errors are clustered by fund and stock-month. Control variables in the vector X are $TotalWDs$ and $PctNetFlow$. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: All Observations.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Buy New Position			Sold Entire Position		
PctWk	-0.034***	-0.032*	0.014	0.005	-0.043	0.064
	(0.013)	(0.016)	(0.024)	(0.030)	(0.043)	(0.064)
MFIA	0.009***	0.007***	0.011***	-0.010***	-0.006*	-0.011**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
MFIAXPctWk	0.007	0.034**	0.012	0.094***	0.060*	0.098**
	(0.015)	(0.017)	(0.031)	(0.029)	(0.033)	(0.041)
N	9,380,095	5,603,908	1,037,289	3,851,872	2,318,627	527,322
R^2	0.02	0.02	0.04	0.09	0.09	0.11
Sample	All Funds	Competitive	E-Score >= 4	All Funds	Competitive	E-Score >= 4

Panel B: Observations where $PctWk > 0$

	(2)	(3)	(4)	(5)	(6)	(7)
	Buy New Position			Sold Entire Position		
PctWk	-0.048***	-0.036*	-0.011	0.020	-0.048	0.078
	(0.014)	(0.019)	(0.032)	(0.036)	(0.050)	(0.085)
MFIA	0.007***	0.006***	0.006*	-0.010***	-0.005	-0.010*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
MFIAXPctWk	0.021	0.049***	0.046	0.094***	0.061*	0.102**
	(0.015)	(0.017)	(0.031)	(0.030)	(0.035)	(0.049)
N	8,389,541	5,023,476	866,959	3,394,293	2,027,089	432,808
R^2	0.02	0.02	0.04	0.08	0.09	0.11
Sample	All Funds	Competitive	E-Score >= 4	All Funds	Competitive	E-Score >= 4

Panel C: Observations where $MedWk > 1$

	(2)	(3)	(4)	(5)	(6)	(7)
	Buy New Position			Sold Entire Position		
PctWk	-0.039**	-0.039*	0.011	0.035	-0.011	0.076
	(0.017)	(0.021)	(0.031)	(0.039)	(0.049)	(0.081)
MFIA	0.007***	0.005**	0.007*	-0.009***	-0.006*	-0.010*
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.005)
MFIAXPctWk	0.018	0.052***	0.036	0.087***	0.069*	0.089*
	(0.016)	(0.018)	(0.031)	(0.031)	(0.036)	(0.047)
N	7,975,720	4,699,168	828,157	3,173,469	1,853,299	399,182
R^2	0.02	0.02	0.05	0.08	0.08	0.11
Sample	All Funds	Competitive	E-Score >= 4	All Funds	Competitive	E-Score >= 4

Table 12: Effort, Information Acquisition, Trading, and Returns

The table shows the results from estimating Equation 8 to test whether effort ($PctWk$) and information acquisition activity ($MFIA$) are associated with the excess returns to buys and sells. The model is estimated on stocks that were not held by fund j at month t but were subsequently purchased (New Positions), and on stocks that were held by fund j at month t but were subsequently sold entirely (Sold Positions). The dependent variables in both panels represent the excess returns to a given stock over the six-month period indicated beginning one year after the independet variables are measured ($k = 13$). Excess returns are measured as the stock's return minus the fund benchmark's return. The model has been estimated over the entire sample as well as subsamples of funds with highly competitive incentives (Columns 3 and 6) or funds with *E-Scores* ≥ 4 (Columns 4 and 7). The model includes fund, stock, and year-month fixed effects. Panel A shows estimates when using the entire sample. Panel B and Panel C limit the sample to observations where $PctWk > 0$ and to advisors with median total weekend work-days greater than one ($MedWk > 1$). Standard errors are clustered by stock and year-month. Control variables in the vector X are $TotalWDs$, $PctNetFlow$, and lagged excess returns. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: All Observations.						
	Return to New Position			Return to Sold Position		
PctWk	2.09*	1.64	-1.99	-0.61	1.89	2.70
	(1.19)	(2.09)	(2.96)	(1.13)	(2.50)	(3.32)
MFIA	-0.19	-0.14	0.01	-0.11	-0.01	1.02*
	(0.24)	(0.30)	(0.52)	(0.20)	(0.30)	(0.53)
MFIAXPctWk	-2.47	-4.57	0.31	-1.26	-5.38**	-9.11**
	(2.13)	(2.78)	(4.48)	(1.61)	(2.55)	(4.44)
N	831,817	401,891	81,250	858,203	422,072	82,285
R^2	0.20	0.21	0.26	0.21	0.22	0.27
Sample	All Funds	Competitive	E-Score >= 4	All Funds	Competitive	E-Score >= 4
Panel B: Observations where $PctWk > 0$						
	Return to New Position			Return to Sold Position		
PctWk	2.28	1.82	-2.00	-0.92	3.10	0.71
	(1.41)	(2.39)	(3.80)	(1.43)	(2.83)	(3.93)
MFIA	-0.14	-0.06	0.35	-0.13	0.00	0.90
	(0.25)	(0.31)	(0.56)	(0.20)	(0.33)	(0.57)
MFIAXPctWk	-2.73	-5.17*	-2.59	-1.05	-5.52**	-8.74*
	(2.18)	(2.80)	(4.79)	(1.60)	(2.72)	(4.65)
N	736,915	353,327	65,803	755,916	366,797	66,100
R^2	0.20	0.21	0.27	0.21	0.22	0.28
Sample	All Funds	Competitive	E-Score >= 4	All Funds	Competitive	E-Score >= 4
Panel C: Observations where $MedWk > 1$						
	Return to New Position			Return to Sold Position		
PctWk	1.93	1.94	-0.34	-1.67	2.51	-1.14
	(1.60)	(2.52)	(4.20)	(1.58)	(2.76)	(4.56)
MFIA	-0.18	-0.02	0.07	-0.19	-0.09	0.64
	(0.24)	(0.30)	(0.55)	(0.20)	(0.34)	(0.62)
MFIAXPctWk	-2.77	-5.68**	-0.86	-1.06	-4.81*	-7.80
	(2.15)	(2.75)	(4.68)	(1.63)	(2.80)	(4.97)
N	704,297	334,792	64,094	719,943	343,652	63,658
R^2	0.20	0.22	0.27	0.22	0.23	0.28
Sample	All Funds	Competitive	E-Score >= 4	All Funds	Competitive	E-Score >= 4

Appendix

This appendix provides additional details and empirical evidence to supplement the main text. There are two primary sections of this appendix. Appendix A.1 contains details about the EDGAR Log Files and the process of unmasking mutual fund IP addresses (see Appendix A.1.1) as well as a table detailing the variables used in the paper (see Appendix A.1.2). Appendix A.2 contains various tables that extend the main results from the body of the paper.

A.1 Data Appendix

A.1.1 Unmasking IP Addresses in the EDGAR Log Files

The EDGAR Log Files contain billions of observations of "requests" or "requests to view a filing." Each observation details the filing requested (accession number), the date and time of the request, and the requester (the IP address making the electronic request). A snapshot of the raw EDGAR Log Files is shown below:

IP Address	Date	Time	CIK	Accession Number
38.97.91.ecg	20170531	09:47:33	051143	000104746917001061
38.65.241.fhf	20170531	11:07:28	274191	000002741917000008
67.199.249.igg	20170924	12:27:02	320193	000032019317000009
216.223.41.aah	20170924	16:12:55	831259	000083125917000016

Given our focus in this paper on the requester, linking the masked IP addresses to identifiable investors (e.g., invesment advisory firms) is pivotal to our study. To unmask the IP addresses, we first notice the fourth octet in the examples above.[1] In place of the actual digits of the requesting IP address, the fourth octet is reported as a set of three letters. However, organizations typically register blocks of IP addresses, with the most common

[1]For IP addresses, an *octet* is a group of eight bits, or the one to three digit numbers (from 0 to 255) separated by periods in the examples above.

block fixing the first three octets and containing all 256 versions of the fourth octet.[2] In other words, only the first three octets are necessary to identify the organization that has registered that block of IP addresses.

Using this insight, we searched historical IP address registration records from 2010–2017 to identify the blocks of IP addresses registered to investment firms.[3] Then, using this hand-collected mapping between investment firms and IP addresses, we unmask the requesters in the EDGAR Log Files. As a result, the snapshot of raw data from above has been transformed into the following.

Investment Firm	Date	Time	Ticker	Filing
Abrams Capital	20170531	09:47:33	IBM	10-K for 2016
Harbor Capital	20170531	11:07:28	TGT	10-K for 2016
Crabel Capital	20170924	12:27:02	AAPL	10-Q for Q2 2017
Ronin Capital	20170924	16:12:55	FCX	Earnings for Q2 2017

Furthermore, the three letters used to mask the fourth octet is static, not dynamic. This means, for example, that def replaces the digits 146 for every instance of 146. This allows us to identify unique IP addresses. In other words, though an unmasked mutual fund may make 50 requests one day, we can observe how many different IP addresses made those requests. This insight is particularly important as it allows us to calculate $TotalWDs$.

Finally, we have adjusted the data to remove likely bots. As mentioned, the raw EDGAR Log Files contain billions of requests with many thousands of requests per day coming from single IP addresses. It is unlikely that these thousands of requests per day represent a human actually clicking on documents in EDGAR. It is much more likely that they represent computer programs (bots) downloading large quantities of data at a time. Given these IP addresses do not fit with the spirit of our research, we remove them from the data. The

[2]For example, all 256 IP addresses beginning with 38.97.91 will be registered to the same organization.
[3]IP registration records were acquired from MaxMind, https://www.maxmind.com/en/home.

removal process is as follows: we remove IP addresses that either (i) make over 1,000 requests in a day or (ii) make requests for over 100 different CIKs (i.e., firms).

A.1.2 Variable Details

Variable	**Description**
Activity and Effort Variables	Measured at advisor-month level, except for MedWk, which is at the advisor level.
TotalWD	The sum of unique, daily IP addresses making requests for a given invesment advisor over a month. This variable is similar to the idea of employee work-days, which counts how many working days were accomplished by employees over a span of time. TotalWD is winsorized at the 95^{th} percentile and is scaled by the natural log of TotalWD plus one.
TotalReq	The total number of requests made by the IP addresses of a given investment advisor over a month. TotalReq is winsorized at the 95^{th} percentile and is scaled by the natural log of TotalReq plus one.
PctWkWD	The ratio of TotalWD from only weekends and market holidays to TotalWD from all days of the month.
PctWkReq	The ratio of TotalReq from only weekends and market holidays to TotalReq from all days of the month.
PctWk	The average of PctWkWD and PctWkReq.
MedWk	The median number of TotalWD from weekends and market holidays for a given advisor across all months of the sample.
Fund Variables	Measured at the fund-month level.
TNAM	Total net assets under management. Scaled by taking the natural log.
HHI	Herfindahl-Hirschman Index to measure portfolio concentration. Calculated as the sum of the squared portfolio share of each holding within a portfolio. Winsorized at the 99^{th} percentile and divided by 100 for interpretability.
Expenses	Total annual expenses and fees divided by year-end TNA. Winsorized at the 99^{th} percentile.
Turnover	Minimum of aggregate purchases and sales of securities divided by average TNA over the calendar year. Winsorized at the 99^{th} percentile and scaled using the natural logarithm.
ActiveShare	The percentage difference between the holdings of a fund and the holdings an assigned benchmark. The passive benchmark is assigned by choosing the index that produces the lowest Active Share.
PctNetFlow	The net growth in fund assets beyond reinvested dividends (Sirri and Tufano (1998)) over the past one year. Winsorized at the 1^{st} and 99^{th} percentiles.
Alpha	Measures the benchmark-adjusted return for a given fund compounded over a six-month period.
TrackError	Measures the standard deviation of month benchmark-adjusted returns over a six-month period.
E-Score	Count of the number of high indicators and low indicators corresponding to better returns to effort. For example, if a fund has low $TNAM$, high $Competitive$, high HHI, low $Turnover$, high $ActiveShare$, and high $TrackError$, the E-Score is 6. In contrast, if among these six characteristics a fund has only low $TNAM$ and high $Competitive$, E-Score equals 2.
CAPM	Measures the risk-adjusted return for a given fund over a six-month period. The CAPM is used for the risk adjustment using the market return as the only factor.
FF3	Measures the risk-adjusted return for a given fund over a six-month period. The Fama-French three factor model (Fama and French (1993)) is used for the risk adjustment.
FF4	Measures the risk-adjusted return for a given fund over a six-month period. The Fama-French three factor model (Fama and French (1993)) plus the momentum factor (Carhart (1997)) is used for the risk adjustment.
Investment Advisor Variables	

Competitive	Measures the degree to which an advisor has competitive versus cooperative incentives. The measure is the difference between the a standardized index that measures the advisor competitive incentives and a standardized index that measures the advisor cooperative incentives. See Evans et al. (2020) for details on the standardized index.
Incentives	Measures the incentives faced by managers in an advisor. The measure is the sum of a standardized index that measures the advisor competitive incentives and a standardized index that measures the advisor cooperative incentives. See Evans et al. (2020) for details on the standardized index.
Macro Variables	
MkRet	The monthly return on the market, from Kenneth French's database.
VIX	The end-of-month level of the volatility index, VIX.
Filings	The total number of new filings filed with the SEC via EDGAR in a given month.
EaDates	The total number of public firms releasing quarterly or annual earnings in a given month.
City Variables	
Rain	Measured as the ratio of the number of rainy days on weekends or market holidays in a month for a given city and the number of total rainy days in that month. A rainy day is defined as a day where there was some rain.
Information Acquisition and Trading Variables	
MFIA	A monthly indicator variable equal to one if an advisory firm accessed at least one filing of stock l.
PctUniqueFirms	Measured monthly at the advisor level as number of unique firms requested in EDGAR as a percentage of total requests in EDGAR.
PctUniqueFilings	Measured monthly at the advisor level as the number of distinct filings requested in EDGAR as a percentage of total requests in EDGAR.
Pct10KQ	Measured monthly at the advisor level as the number of 10-K or 10-Q filings accessed in EDGAR as a percentage of total requests in EDGAR.
MedFilingAge	Measured monthly at the advisor level as the median age (in days) of filings reviwed.
PctNonHoldings	Measured monthly at the advisor level as the number of requests in EDGAR for non-holdings as a percentage of total requests in EDGAR.
$\Delta Position$	Indicator variable equal to one if fund j initiates a new position in stock l (or fully liquidates a current position) within the next quarter.
ExcessReturn	Monthly variable measuring the six-month excess returns for stock l relative to fund j's benchmark.

A.2 Additional Tables

In this appendix, we replicate several tables from the main analysis on different subsamples of the data. Specifically, we replicate Table 7 on the subsamples where $PctWk > 0$ and $MedWk \geq 1$ (Table A1 and Table A2), and we replicate Table 8 using the same subsample criteria (Table A3 and Table A4). Also, we repliate Table 6 using fund-month levels of information acquistion (Table A5).

[Table A1 about here.]

[Table A2 about here.]

[Table A3 about here.]

[Table A4 about here.]

[Table A5 about here.]

Table A1: Effort and Future Performance: Heterogenous Effects, PctWk > 0

The table shows results from estimating Equation 3 to test the relation between effort ($PctWk$) and future performance ($Alpha_{13-18}$) while excluding observations unless $PctWk > 0$. In Panel A, the sample is split between high and low groups, subject to the specified criteria. For example, Columns 2 and 3 estimate the the model after splitting the sample between low $TNAM$ mutual funds and high $TNAM$ mutual funds. In Panel B, six characteristics are combined into a variable called *E-Score* which counts the number of highs and lows corresponding to better returns to effort. Control variables include: $PctNetFlow$, $TNAM$, *Expenses*, *Turnover*, *ActiveShare*, *Competitive*, and $Incentives$. The model always includes style, year-month, and advisor fixed effects and standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Low v. High Based on Mutual Fund Characteristics								
	TNAM		Expenses		Competitive		TrackError	
	Low	High	Low	High	Low	High	Low	High
	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
PctWk	3.11***	0.68	0.45	2.55**	1.16	2.16*	-1.53*	3.66***
	(1.20)	(0.95)	(0.94)	(1.06)	(0.95)	(1.26)	(0.85)	(1.09)
N	9,304	11,879	9,491	11,690	10,696	10,488	8,922	12,213
R^2	0.13	0.14	0.15	0.13	0.14	0.13	0.15	0.14
	HHI		Turnover		ActiveShare		PctNetFlow	
	Low	High	Low	High	Low	High	Low	High
	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
PctWk	-0.12	2.05**	3.46***	-0.13	-0.37	2.94***	1.24	1.24
	(1.18)	(1.04)	(1.14)	(1.01)	(0.86)	(1.11)	(1.07)	(0.95)
N	7,405	10,473	10,824	10,377	9,816	11,367	11,221	9,963
R^2	0.12	0.18	0.13	0.16	0.21	0.11	0.14	0.14

Panel B: Sample Split by E-Score.

	E-Score ≤ 2	E-Score = 3	E-Score = 4	E-Score ≥ 5
	Alpha	Alpha	Alpha	Alpha
PctWk	-0.92	-1.31	3.01*	5.18***
	(1.06)	(1.12)	(1.55)	(1.56)
N	5,568	5,396	4,252	5,962
R^2	0.20	0.18	0.13	0.12

Table A2: Effort and Future Performance: Heterogenous Effects, MedWk > 1

The table shows results from estimating Equation 3 to test the relation between effort ($PctWk$) and future performance ($Alpha_{13-18}$) while excluding observations unless $MedWk > 1$. In Panel A, the sample is split between high and low groups, subject to the specified criteria. For example, Columns 2 and 3 estimate the the model after splitting the sample between low $TNAM$ mutual funds and high $TNAM$ mutual funds. In Panel B, six characteristics are combined into a variable called *E-Score* which counts the number of highs and lows corresponding to better returns to effort. Control variables include: *PctNetFlow*, $TNAM$, *Expenses*, *Turnover*, *ActiveShare*, *Competitive*, and *Incentives*. The model always includes style, year-month, and advisor fixed effects and standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Low v. High Based on Mutual Fund Characteristics

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TNAM		Expenses		Competitive		TrackError	
	Low	High	Low	High	Low	High	Low	High
	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
PctWk	3.07***	0.38	0.93	2.19**	0.66	2.42**	-0.43	2.86***
	(1.12)	(0.94)	(0.91)	(1.04)	(0.98)	(1.10)	(0.89)	(0.99)
N	8,819	10,856	9,287	10,388	10,420	9,254	8,363	11,196
R^2	0.12	0.15	0.15	0.13	0.14	0.13 0.15	0.14	
	HHI		Turnover		ActiveShare		PctNetFlow	
	Low	High	Low	High	Low	High	Low	High
	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha	Alpha
PctWk	-1.09	2.43**	2.65***	0.78	0.43	2.53**	1.83*	0.78
	(1.06)	(1.02)	(0.98)	(1.02)	(0.86)	(1.01)	(0.94)	(0.96)
N	6,634	9,544	9,975	9,722	9,198	10,477	10,328	9,347
R^2	0.12	0.18	0.12	0.16	0.20	0.11	0.15	0.14

Panel B: Sample Split by E-Score.

	E-Score ≤ 2	E-Score = 3	E-Score = 4	E-Score ≥ 5
	Alpha	Alpha	Alpha	Alpha
PctWk	-0.10	-1.43	1.22	5.19***
	(1.09)	(1.25)	(1.60)	(1.28)
N	5,311	4,793	3,685	5,882
R^2	0.19	0.18	0.14	0.13

Table A3: Effort and Future Performance – Factor Model Alphas, PctWk > 0

The table shows results from estimating Equation 3 to test the relation between effort ($PctWk$) and future performance measured using factor-model alphas over six months from $(t+13)$ to $(t+18)$. The sample is limited to observations where $PctWk > 0$. The table includes alphas from the one-factor ($CAPM$), three-factor ($FF3$), and four-factor ($FF4$) models. Control variables include: $PctNetFlow$, $TNAM$, *Expenses*, *Turnover*, *ActiveShare*, *Competitive*, and *Incentives*. Panel A shows estimates when using the entire sample. Panel B uses *E-Score*, which counts the number of highs and lows corresponding to better returns to effort. The model always includes style and year-month fixed effects while an advisor fixed effect is only included in Columns 5–7. Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. All Observations.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CAPM	FF3	FF4	CAPM	FF3	FF4
PctWk	2.41***	2.84***	2.88***	1.22	1.48*	1.68**
	(0.58)	(0.51)	(0.52)	(1.02)	(0.80)	(0.79)
TotalWDs	0.03	0.01	-0.00	-0.00	-0.13	-0.17**
	(0.03)	(0.02)	(0.02)	(0.09)	(0.08)	(0.09)
PctNetFlow	-0.01	0.75	-0.25	-2.18*	-1.23	-2.00*
	(1.21)	(1.09)	(1.13)	(1.28)	(1.15)	(1.21)
TNAM	-0.01	-0.04**	-0.04**	0.01	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Expenses	-0.76***	-0.74***	-0.70***	-0.66***	-0.53***	-0.47***
	(0.09)	(0.08)	(0.08)	(0.13)	(0.11)	(0.11)
Turnover	-0.29***	-0.26***	-0.29***	-0.34***	-0.31***	-0.32***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
ActiveShare	-0.03***	-0.01***	-0.01**	-0.02***	-0.01*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Competitive	-0.20	-0.11	0.09	0.33	0.07	-0.07
	(0.23)	(0.20)	(0.20)	(0.62)	(0.55)	(0.57)
Incentives	-0.24*	-0.21*	-0.14	-0.33	-0.62	-0.65
	(0.13)	(0.11)	(0.11)	(0.46)	(0.44)	(0.46)
N	17,431	17,431	17,431	17,428	17,428	17,428
R^2	0.19	0.09	0.09	0.21	0.11	0.11

Panel B: Sample Split by E-Score.

	CAPM		FF3		FF4	
	E-Score < 4	E-Score ≥ 4	E-Score < 4	E-Score ≥ 4	E-Score < 4	E-Score ≥ 4
PctWk	-1.67	3.81**	-1.12	3.48***	-1.00	3.72***
	(1.10)	(1.60)	(0.91)	(1.24)	(0.97)	(1.18)
N	8,649	8,779	8,649	8,779	8,649	8,779
R^2	0.22	0.23	0.14	0.12	0.13	0.12

Table A4: Effort and Future Performance – Factor Model Alphas, MedWk > 1

The table shows results from estimating Equation 3 to test the relation between effort ($PctWk$) and future performance measured using factor-model alphas over six months from $(t + 13)$ to $(t + 18)$. The sample is limited to observations where $MedWk > 1$. The table includes alphas from the one-factor ($CAPM$), three-factor ($FF3$), and four-factor ($FF4$) models. Control variables include: $PctNetFlow$, $TNAM$, *Expenses*, $Turnover$, *ActiveShare*, *Competitive*, and $Incentives$. Panel A shows estimates when using the entire sample. Panel B uses *E-Score*, which counts the number of highs and lows corresponding to better returns to effort. The model always includes style and year-month fixed effects while an advisor fixed effect is only included in Columns 5–7. Standard errors are clustered by advisor-month. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. All Observations.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CAPM	FF3	FF4	CAPM	FF3	FF4
PctWk	2.02***	2.97***	3.10***	0.57	1.38*	1.77**
	(0.58)	(0.52)	(0.52)	(0.86)	(0.76)	(0.76)
TotalWDs	-0.01	-0.03	-0.04*	0.04	-0.06	-0.08
	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)	(0.07)
PctNetFlow	0.15	0.39	-0.54	-2.00	-1.45	-2.05
	(1.27)	(1.15)	(1.17)	(1.34)	(1.22)	(1.25)
TNAM	0.00	-0.02	-0.02	0.00	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Expenses	-0.78***	-0.74***	-0.69***	-0.78***	-0.58***	-0.54***
	(0.09)	(0.08)	(0.08)	(0.14)	(0.11)	(0.11)
Turnover	-0.32***	-0.30***	-0.32***	-0.40***	-0.36***	-0.37***
	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
ActiveShare	-0.03***	-0.02***	-0.01***	-0.02***	-0.01**	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Competitive	0.10	-0.00	0.16	0.24	0.23	-0.01
	(0.23)	(0.20)	(0.20)	(0.62)	(0.56)	(0.57)
Incentives	-0.03	-0.05	0.02	-0.22	-0.41	-0.36
	(0.12)	(0.11)	(0.11)	(0.45)	(0.44)	(0.45)
N	16,580	16,580	16,580	16,578	16,578	16,578
R^2	0.18	0.09	0.09	0.20	0.11	0.11

Panel B: Sample Split by E-Score.

	CAPM		FF3		FF4	
	E-Score < 4	E-Score ≥ 4	E-Score < 4	E-Score ≥ 4	E-Score < 4	E-Score ≥ 4
PctWk	-0.81	1.72	-0.60	3.06***	-0.43	3.62***
	(1.07)	(1.26)	(0.96)	(1.09)	(1.02)	(1.06)
N	8,081	8,497	8,081	8,497	8,081	8,497
R^2	0.22	0.21	0.14	0.12	0.13	0.12

Table A5: Effort and Future Performance: Weather Sample

The table shows results from estimating Equation 3 to test the relation between effort ($PctWk$) and future performance ($Alpha$), measured as the compound benchmark adjusted return over six months beginning at month $t+k$ for $k \in \{1,7,13\}$. The sample is limited to those mutual funds for which we can clearly measure location and weather. Control variables include: $PctNetFlow$, $TNAM$, $Expenses$, $Turnover$, $ActiveShare$, $Competitive$, and $Incentives$. Panel A shows estimates using our advisor-by-month setting and including style and year-month fixed effects in Columns 2–4 and including an advisor fixed effect in Columns 5–7. Panel B shows estimates using the fund-by-month setting and including year-month fixed effects in Columns 2–4 and including a fund fixed effect in Columns 5–7. Standard errors are clustered by advisor-month in Panel A and by fund-month in Panel B. Indicators ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Family-Level Effort – PctWk						
	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$
PctWk	0.77	1.32**	2.76***	-1.29	-1.35	1.76*
	(0.69)	(0.64)	(0.68)	(1.03)	(0.89)	(1.04)
TotalWDs	0.21***	0.16***	0.11***	0.16*	0.01	0.06
	(0.04)	(0.04)	(0.04)	(0.09)	(0.09)	(0.10)
PctNetFlow	0.37	-3.03**	-3.62***	-3.32**	-6.42***	-7.25***
	(1.41)	(1.29)	(1.36)	(1.55)	(1.38)	(1.33)
TNAM	-0.04**	-0.05***	-0.00	-0.14***	-0.14***	-0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Expenses	-0.65***	-0.92***	-0.84***	-0.58***	-0.76***	-0.51***
	(0.10)	(0.10)	(0.10)	(0.12)	(0.13)	(0.13)
Turnover	-0.07*	-0.06	0.00	-0.19***	-0.22***	-0.12**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
ActiveShare	-0.02***	-0.02***	-0.02***	-0.01*	-0.01**	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Competitive	0.25	-0.31	-0.64***	1.58**	0.34	0.90
	(0.21)	(0.21)	(0.21)	(0.73)	(0.75)	(0.78)
Incentives	0.02	-0.32***	-0.31**	1.99***	-0.93	-0.56
	(0.12)	(0.12)	(0.13)	(0.72)	(0.78)	(0.73)
N	12,292	12,005	11,983	12,291	12,005	11,982
R^2	0.09	0.09	0.10	0.14	0.14	0.14
Panel B. Fund-Level Effort – PctWkF						
	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$	$Alpha_{1-6}$	$Alpha_{7-12}$	$Alpha_{13-18}$
PctWkF	0.80*	1.90***	3.44***	-1.11*	-1.02	2.35***
	(0.44)	(0.46)	(0.45)	(0.66)	(0.69)	(0.68)
TotalWDsF	0.29***	0.12***	0.02	0.21***	-0.11*	-0.09
	(0.03)	(0.03)	(0.03)	(0.05)	(0.06)	(0.05)
PctNetFlow	0.64	-2.26*	-2.67**	-8.46***	-9.90***	-9.02***
	(1.26)	(1.24)	(1.27)	(1.76)	(1.71)	(1.63)
TNAM	-0.05***	-0.05***	0.00	-0.82***	-0.73***	-0.52***
	(0.02)	(0.02)	(0.02)	(0.08)	(0.08)	(0.08)
Expenses	-0.63***	-0.87***	-0.79***	0.55*	-0.54*	0.03
	(0.09)	(0.09)	(0.09)	(0.30)	(0.32)	(0.36)
Turnover	-0.09**	-0.05	0.02	0.07	-0.03	0.09
	(0.04)	(0.04)	(0.04)	(0.07)	(0.08)	(0.08)
ActiveShare	0.00	0.00	0.00	0.01	0.01	0.02***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Competitive	0.02	-0.67***	-1.04***	1.32**	-0.08	0.53
	(0.17)	(0.18)	(0.17)	(0.59)	(0.60)	(0.62)
Incentives	-0.06	-0.39***	-0.40***	1.69***	-1.09*	-0.89
	(0.10)	(0.10)	(0.10)	(0.55)	(0.61)	(0.60)
N	12,292	12,005	11,963	12,289	12,002	11,975
R^2	0.08	0.08	0.09	0.22	0.20	0.21