What Do Mutual Fund Managers' Private Portfolios Tell Us About Their Skills?

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Abstract

I collect a registry-based dataset on the personal portfolios of Swedish mutual fund managers. The managers who invest personal money in the very same funds they professionally manage outperform the managers who do not. The main results are consistent with a Berk and Green (2004) equilibrium in which fund managers, in contrast to regular investors, are certain about their ability to generate abnormal returns—or lack thereof—and invest their personal wealth accordingly.

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1 Introduction

Actively managed mutual funds remain the primary investment vehicle of households with an enormous \$40 trillion dollar of assets under management (AUM) worldwide (Investment Company Fact Book 2017). However, the vast majority of studies on the performance of active mutual funds conclude that after costs the average mutual fund delivers no abnormal returns (see, e.g. Kosowski et al., 2006; Fama and French, 2010). Do these two facts imply fund investors would be better off by investing less capital in active funds? Not necessarily. Berk and Green (2004) reason that in equilibrium investors cannot expect to earn any abnormal returns.[1] In their model, both managers and investors are uncertain about a manager's skill and fund returns decrease with fund size. Investors update their beliefs from past returns and allocate capital to the fund such that the fund's expected abnormal return going forward is zero. Numerous studies have tested related theories and focused on the capital allocation decisions of regular fund investors.[2] While it seems reasonable that investors are uncertain about managerial skill, it is much less clear what information the managers possess and how certain they are about their assessment. After all, their job is to collect and process information. This paper studies the information managers possess as revealed by their personal investment decisions.[3]

I use the Berk and Green (BG) model to motivate my main specification and show that managers who invest personal money into the very same funds they professionally manage

[1]Similarly, Pástor and Stambaugh (2012) develop an equilibrium model that rationalizes the size of the active fund industry. In their model investors can earn positive abnormal returns, albeit small in magnitude.

[2]See, for instance, Chevalier and Ellison (1997), Sirri and Tufano (1998), and more recently Spiegel and Zhang (2013), Berk and van Binsbergen (2016), Barber et al. (2016), Franzoni and Schmalz (2017), and Harvey and Liu (2019).

[3]There is a vast literature that investigates whether fund managers have skill. Evidence for managerial skill is among other studies provided in Wermers (2002), Chen et al. (2000), Bollen and Busse (2001), Pástor and Stambaugh (2002), Kacperczyk et al. (2005), Jiang et al. (2007), Kacperczyk et al. (2008), Baker et al. (2010), Kacperczyk et al. (2014), and Berk and van Binsbergen (2015). These studies, however, focus on the measurement of skill ex-post, not on whether managers have private information about their level of skill ex-ante.

subsequently outperform relative to managers who do not. The majority of managers do not invest their own money in their own funds. Controlling for wealth differences, a one-standard-deviation increase in the amount managers invest in their own funds (around 440,000 SEK $\approx$ 66,000 USD) is associated with a 0.08 larger information ratio (IR), which is equivalent to a 0.28 larger t-statistic of alpha, estimated relative to the benchmark stated in the fund's prospectus.[4] I then interpret the results through the lens of an extended BG model in which managers—in contrast to regular investors—are certain about their level of skill, hence their ability to earn abnormal returns (henceforth "ability"), and invest their personal wealth accordingly. The distinction between "skill" and "ability" is important. Both in the original BG world and in my extension, a manager may be highly skilled but not be able to earn an abnormal return (whenever actual fund size is above efficient fund size, i.e. the fund size if all parameters of the model were known) and vice versa.[5]

The data come from a unique data set containing detailed personal, non-public (i.e. private) wealth data of 363 Swedish mutual fund managers from 1999 to 2007. To construct it, I start from Morningstar data on the universe of mutual funds sold in Sweden—a country with a highly developed mutual fund industry—and then link the names and tenure of the individuals managing funds to tax records.

In contrast to Sweden and to the best of my knowledge any other country in the world, in the U.S. the SEC as of 2005 requires mutual fund managers to publicly file personal investments in their own funds.[6] Using this or similar U.S. data, the previous literature has investigated the relationship between fund performance and managerial commitment

[4] All Swedish Krona (SEK) amounts in this paper are expressed in 2005 SEK. The exchange rate between the U.S. dollar and the Swedish krona was 1 to 6.71 at the beginning of 2005.

[5] In Berk and Green (2004) the decreasing returns to scale technology is the same for all managers and the BG measure of managerial skill is then the return on the very first dollar invested. Berk and van Binsbergen (2015) introduce value added as a measure of skill which holds more generally when there may be heterogeneity in the decreasing returns to scale technology across managers.

[6] The SEC requires managers to report whether the dollar ownership in their own funds falls in one of the following ranges: \$0, \$1 – \$10,000, \$10,001 – \$50,000, \$50,001 – \$100,000, \$100,001 – \$500,000, \$500,001 – \$1,000,000, or above \$1,000,000.

for mutual funds (Khorana et al., 2007; Evans, 2008), private equity funds (Robinson and Sensoy, 2013), and hedge funds (Gupta and Sachdeva, 2017). In the literature, the amount a manager invests in her fund is commonly scaled by fund size. I refer to the resulting variable as "ownership." Instead, I focus on the actual amount a manager invests in her own fund.[7] Inferring a positive relationship between managerial ownership and fund performance can be misleading whenever fund size is correlated with performance. I illustrate this argument by simulating a BG world in which fund returns deteriorate with fund size by construction. In the simulations, I randomly assign managers an amount they invest in their funds and regress returns on managerial ownership. The resulting coefficient estimates on ownership are positive and significant even when fund size is separately controlled for, indicating a positive relationship where there really is none. The reason is simple: in within-fund regressions fund size negatively predicts future performance.[8] With decreasing returns to scale—as there are in the Swedish sample—large (small) fund size means both small (large) returns and small (large) ownership. Stepping out of the BG world, there is evidence that fund size is correlated with fund performance in the cross-section as well, both in the Swedish sample and in the U.S. (see, e.g., Chen et al., 2004), which makes scaling by fund size potentially misleading.

Absent any exogenous variation, neither the previous literature nor I can establish causality in the relationship between fund performance and the amount managers invest in their funds.[9] Instead, I make several other contributions to the literature. One way to test the

[7] Chen et al. (2008) and Cremers et al. (2009) analyze the personal investments of mutual fund directors and focus on the amount invested as well. Other studies that focus on fund manager commitment include Kumlin and Puttonen (2009), Fu and Wedge (2011), Martin and Sonnenburg (2015), Dimmock et al. (2015), Hornstein and Hounsell (2016), and Ma and Tang (2019).

[8] To the econometrician's eye, fund returns are, thus, not unpredictable. To the real-time BG investor they are. There is an important difference between the subjective and the objective size-performance relation as explained in Pástor et al. (2015).

[9] Self selection according to ability likely matters: the regulator indicated no requirement or recommendation for fund managers to invest in their own funds. European mutual funds, including the vast majority of Swedish funds, are commonly regulated under the UCITS directives. Only with the introduction of UCITS V in June 2016, remuneration structures need to include rules on variable and fixed compensation, including a requirement that at least 50% of variable remuneration be in the form of units of the fund.

usefulness of theoretical economic models is to confront them with moments in the data that they are not designed to match. I provide such a test for the Berk and Green (2004) model, confront it with data on managers' personal investments, and show that the main empirical results can be rationalized with a simple extension: The main empirical results are consistent with an asymmetric information equilibrium model in which managers, in contrast to regular investors and to the original BG model, are certain about their skill and, thus, certain about their ability to earn abnormal returns. Under my reading of the results, the positive relationship between fund performance and managers' personal investments is merely a correlation. I also offer alternative explanations for the facts in the data that the baseline model cannot explain and discuss the equilibrium implications of making the data publicly available. Specifically, I reason that if investors' and managers' incentives are well aligned, making the data public could decrease the size of the active fund industry. Finally, I contribute to the literature by showing that it may be misleading to infer a positive relationship between managerial ownership, defined as absolute investments over fund size, and fund performance when fund size is correlated with fund performance even when fund size is separately controlled for.

In the original BG model both managers and investors are uncertain about a manager's skill and need to update their beliefs from past returns. In the model, skill maps one-to-one into fund size. That is, true skill maps into efficient fund size, i.e. the fund size if all parameters of the model were known, whereas skill as perceived by investors maps into actual fund size. The positive relationship between fund performance and managers' personal investments can be rationalized once managers are certain about their level of skill. A manager knowing her skill compares efficient fund size with actual fund size and she invests in her fund when actual fund size is below efficient fund size. Because of the decreasing returns to scale technology, which implies that funds which run below efficient size on average earn positive abnormal returns and vice versa, she can then expect to earn an abnormal return.

Thus, her personal investment correlates positively with her fund's abnormal performance. The key assumption underlying this reasoning is that managers cannot credibly signal the investments they make in their own funds to investors. If they could, a manager would face a complicated tradeoff between investing in her fund and changing AUM (which ultimately affect compensation) by revealing her type and deteriorating or increasing the return on her invested capital.[10] In this sense, the fact that the data are not publicly observed is crucial: in equilibrium there is no room for publicly available information to predict abnormal performance. I do not find evidence that managers who invest in their funds attract more assets, which is consistent with the assumption.

In the data there is a more subtle way for a manager to gain exposure to her fund's return. Some managers decide not to earn their entire fund's return on their personal capital by investing in their funds but to buy individual components of their funds in their personal accounts (overlapping holdings, OH). Bodnaruk and Simonov (2015) show that managers perform well in picking overlapping holdings.[11] I find similar results. Moreover, I find that overlapping holdings are mostly Swedish large cap stocks, but their existence does not appear to be mechanical. Even after controlling for various characteristics, managers tilt their funds and personal portfolios towards overlapping holdings, consistent with the notion that managers are betting personal money on their "best ideas" (Cohen et al., 2010). There is some evidence that managers who invest in overlapping holdings achieve better fund performance but it is weaker compared with the evidence on the managers who directly invest in their funds.

[10] Similarly, on the intensive margin, i.e. the manager's decision of how much to invest in the fund, a manager may trade-off the size of her personal investment versus deteriorating the return on that investment. Gupta and Sachdeva (2017) argue that this is the case for hedge funds. Compared to hedge funds, mutual fund managers' investments are trivial both absolutely and in relation to fund size making it likely that investor fund flows are the only source of capital that affects returns.

[11] Bodnaruk and Simonov (2015) study a similar data set of personal wealth data for 84 Swedish fund managers from 2001 to 2007. They find no evidence that managers outperform in their personal portfolios relative to a group of peer investors. While they focus on evaluating the performance of the average manager in her personal portfolio, this paper focuses on the performance of fund managers in their funds.

Next, I examine persistence in fund performance and calibrate the model to the data. Managers who invest in their funds, either directly or through overlapping holdings, consistently achieve a better performance than the ones who invest in neither. The original BG calibration, however, implies a larger performance difference between the two groups of managers. In the calibration to match the Swedish data, investors have a higher precision about managerial skill while still not being certain about it. The higher precision is a direct implication of the observed performance difference and fits nicely with a weak flow-performance relationship in the Swedish data. While it appears that many funds run at or above their efficient sizes and, thus, deliver no abnormal performance to investors, the Swedish calibration implies that almost all managers possess investment skill.[12] The asymmetric information model can match the main empirical results but it fails to explain some persistence in fund performance when sorting on past performance and the time-series behavior of managers' personal investments.[13] Specifically, according to the model managers should update their personal investments as actual fund size fluctuates around efficient fund size. Empirically, the time-series evolution of managers' personal investments is too persistent. I offer a simple explanation for the persistence in fund performance when sorting on past performance and the persistence of managers' personal investments by slightly departing from the frictionless rational framework and by introducing additional persistence in investors' beliefs about managerial skill similar to models with sticky expectations (Mankiw and Reis, 2002; Coibion and Gorodnichenko, 2015). A slight departure from the frictionless rational framework can at least qualitatively explain both features of the data that the frictionless rational model

[12] Evidence that some funds run above their efficient sizes is not unique to the Swedish sample. Roussanov et al. (2018) extend the BG model to include marketing expenses and costly investor search to rationalize that some funds are too large relative to the BG equilibrium. Choi et al. (2016) examine investors' capital allocations to managers with multiple funds and find that investors' learning from past returns only is incomplete.

[13] There is some evidence for performance persistence in the U.S. as well. Carhart (1997) documents persistence for the worst performing funds. Bollen and Busse (2004) find evidence of short-term persistence using daily data.

cannot explain.

The rest of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 motivates the main specification. Section 4 shows that managers who invest in their own funds subsequently outperform relative to managers who do not. Section 5 studies persistence in fund performance and calibrates the model to the data. Section 6 discusses the possibility of managerial investments being used as a signal and equilibrium implications of making managers' investments publicly available. Section 7 provides robustness tests. Finally, Section 8 concludes.

2 Data

2.1 Fund data

From Morningstar Direct, I retrieve a survivorship bias-free dataset of open-ended mutual funds for sale in Sweden or the Nordic region for the period 1990 to 2015. The sample is then restricted to funds that were present at some point during 1999–2007 due to the availability of manager wealth data. The data are on the share class level and include AUM and return series, annual total expense ratio (TER) series, an investment category indicator, and the name of the prospectus benchmark index. The AUM and TER time series from Morningstar Direct are complemented by two additional sources, Bloomberg and some hand-collected data from AMF Fonder. Missing AUM and TER values for a given fund are imputed using the algorithms described in Appendix A.1. Several funds have multiple share classes. The different share classes of a fund are aggregated into a single fund observation by summing up AUM across share classes and taking AUM-weighted averages for all other variables. The raw data include 1,103 funds. From this sample, I eliminate money market mutual funds, index funds (identified by Morningstar as such or by the word "index" in their name), and the four government pension funds that invest public pension money. These funds are fundamentally different from an ordinary actively managed mutual fund. The funds' remaining investment categories are: Equity, Allocation, Alternative, Fixed Income, and a Rest category in which commodity funds, miscellaneous funds, and funds where the category variable is missing are grouped. The funds invest their assets in various international markets, but by far the two most common investment areas are "Sweden" and "Global."

For the funds domiciled in Sweden, I obtain holdings data from the Swedish Financial Supervisory Authority (Finansinspektionen) and hand-match these to the funds in Morningstar based on ISINs. Finansinspektionen requires the funds domiciled in Sweden to file quarterly holdings and makes the data publicly available. Around 180 funds for sale in Sweden or the Nordic region are not domiciled in Sweden and, thus, no holdings data is available.[14]

2.2 Manager data

Morningstar provides a manager history for each fund. The history contains the first and last name of each manager with a start and end date. Using publicly available sources, the manager names are hand-matched to social security numbers, which are then matched with tax records from Statistics Sweden, the government's statistical agency. Appendix A.2 details the matching procedure. The data from Statistics Sweden include demographic information such as age, gender, and education as well as income variables such as labor and capital income. The data set is similar to the one used in Ibert et al. (2018). Unique to this paper is the use of highly disaggregated wealth information available from 1999 until 2007 when Sweden levied a wealth tax. On December 31 of each year, the data show a snapshot of the portfolio holdings at the individual security level (identified by an ISIN) as well as

[14]The most common domiciles besides Sweden are Luxembourg and Finland. In general, the holdings data is quarterly, but there are gaps: The data starts in 09/2000, has a one-year gap between 12/2000 and 12/2001, a half-year gap between 06/2002 and 12/2002, a half-year gap between 12/2003 and 06/2004, and finally a one-year gap between 06/2004 and 09/2005. When working on the monthly frequency, I fill in the holdings for each fund forward from the last quarterly observation, except for the first nine months in 2000, for which I fill in backwards. For funds with missing holdings, overlapping holdings are assumed to be zero.

cash in bank accounts, real estate ownership, and outstanding debt. Monthly returns and characteristics for non–mutual fund securities are from the FINBAS database. For securities not covered by FINBAS, I use CRSP/Compustat, Datastream, and Morningstar.

The raw data include 832 managers, but the final sample contains only 363 managers. Many of the manager names are Finnish, Danish, or Norwegian and stem from the inclusion of Nordic cross-borders funds. The final sample contains 556 funds. Table A1 shows in detail how I arrive at the final sample.

I define a manager's personal risky financial wealth to be the sum of non–money market fund and direct stock investments. Cash is the sum of money market funds and bank account holdings. Financial wealth is the sum of risky financial wealth, cash, bonds, capital insurance, structured products, derivatives, and other financial wealth. (Net) Wealth is the sum of financial wealth, commercial, and noncommercial real estate net of debt. These definitions closely follow Betermier, Calvet, and Sodini (2017).

2.3 Aggregation and performance measurement

The data consist of a panel of fund-month observations for high frequency fund level variables such as returns and fund size and a panel of manager-year observations for the personal wealth data. The distinction between a manager and a fund arises because a manager can manage multiple funds, a fund can have multiple managers at the same time, and a fund can turn over its managers over time. The combined panel is aggregated to the fund level (indexed by i) by taking equal-weighted averages of manager (m) level variables whenever the dependent variable in a regression varies on the fund level. Specifically, in cases of team management the amount the $N_{i,t}$ managers of a given fund i in a given year t directly invest in their fund, the amount they invest in overlapping holdings, and the fund's wealth are defined as follows:

$$Amount\ in\ MF_{i,t} = 1/N_{i,t} \sum_{m=1}^{N_{i,t}} Amount\ in\ MF_{m,i,t} \tag{1}$$

$$Amount\ in\ OH_{i,t} = 1/N_{i,t} \sum_{m=1}^{N_{i,t}} Amount\ in\ OH_{m,i,t} \tag{2}$$

$$Wealth_{i,t} = 1/N_{i,t} \sum_{m=1}^{N_{i,t}} Wealth_{m,t} \tag{3}$$

where $Amount\ in\ OH_{m,i,t} = \sum_j Amount\ in\ OH_{m,i,j,t}$ and j is the subscript for a particular security.

To assess yearly fund performance, as in Ibert et al. (2018) I first estimate a standard factor regression using the entire time-series of returns for each fund:[15]

$$R_{i,s} - R_{f,s} = \alpha_i + \beta_i(R_{i,s}^{BM} - R_{f,s}) + \epsilon_{i,s} \tag{4}$$

where s indicates a month, $R_{i,s}$ is the fund's net return, $R_{f,s}$ is the risk-free rate as approximated by the one-month STIBOR rate, and $R_{i,s}^{BM}$ is the fund's benchmark return as stated in the fund's prospectus. The prospectus benchmark is of particular relevance since an active fund manager promises to deliver an alpha relative to the prospectus benchmark which is the ultimate reason why investors pay a fee to the manager. Appendix A.3 provides details about the prospectus benchmarks and describes alternative benchmark/factor models. Using the estimated coefficients, I then calculate the abnormal return in each month ($R_{i,s,abn} = \widehat{\alpha}_i + \widehat{\epsilon}_{i,s}$) and annualize. The advantage of estimating a constant coefficients model is more precise estimates; the disadvantages are a look-ahead bias in finite samples when predicting performance and a misspecification in case coefficients are time-varying. Alternatively, I estimate the coefficients in Equation (4) in year-by-year regressions with twelve

[15] To estimate the coefficients, at least 12 monthly observations are required. See Dahlquist, Engström, and Söderlind (2000) and Flam and Vestman (2014) for earlier studies of Swedish fund performance.

observations. Finally, a fund's information ratio scales the estimated alpha by the empirical counterpart of σ_ϵ (estimated over the full sample for a given fund or estimated year-by-year).

2.4 Descriptive statistics

Table 1 shows summary statistics for the 2,449 fund-years, corresponding to 556 funds and 9 years, that enter the final sample. The median fund-year is managed by exactly one manager, has 586 million SEK in AUM, and a yearly TER of 1.4%. The average and median investment in one's own fund are 67,000 SEK ($\approx$ \$10,000) and zero, respectively, while average fund size is 2,150 million SEK (\$320 million). Table 2 shows summary statistics for data aggregated to the manager level. Average and median manager wealth are around four million SEK (\$640,000) and 2 million SEK (\$320,000), respectively.

Panel (a) of Figure 2 visualizes the average portfolio composition of fund managers over time. The vast majority of financial wealth is invested either in cash, funds, or directly in stocks. Panel (b) contrasts this with the evolution of the average portfolio composition for the whole Swedish population. The average Swede invests a smaller fraction of her financial wealth in risky assets and invests less in individual stocks. Panel (c) decomposes managers' risky assets further into professionally managed funds by the very same manager, funds from the same fund family, unrelated funds, overlapping stocks, and unrelated stocks. The average manager invests slightly less than 15% of her risky portfolio in her own funds.

Swedish managers only face loose regulatory trading restrictions in their personal accounts mostly related to insider trading laws. In short, managers can invest fairly unrestricted in their personal accounts. Appendix C summarizes the evidence.[16] Although the econometrician can observe managers' personal investments in their own funds ex post, contrary to the U.S. there exists no requirement for Swedish fund managers to file their

[16] Kaniel, Tompaidis, and Zhou (2017) discuss in detail the regulations that apply to U.S. fund managers who trade in their personal accounts.

investments publicly and I have found no indication that they do so voluntarily in the funds' prospectuses.

3 Motivating the Main Specification

The previous literature regularly estimates a correlation between managerial ownership, defined as the amount invested over fund size, and fund performance. In a BG world, however, for a given fund such a correlation arises mechanically because a larger (smaller) fund size implies both lower (larger) future returns and lower (larger) ownership. To show that regressions of fund performance on ownership can pick up a correlation where there really is none, I simulate a BG world and randomly assign dollar amounts invested to managers. Appendix B briefly reviews the BG model and provides details on the simulations. Figure 1 Panel (a) shows the simulated distribution of t-statistics on the ownership coefficient from within regressions of fund (abnormal) returns on ownership using the original BG calibration. The mean t-statistic is 32 and the correlation between ownership and fund returns is by assumption entirely driven by fund size. Controlling for fund size (Figure 1 Panel (b)) mitigates the problem but does not eliminate it.[17] In the BG world, fund performance is only correlated with fund size in specifications with fund fixed effects. However, stepping out of the BG world a correlation between fund size and performance may arise more generally in the cross-section if managers of different ability are matched to different fund sizes.[18] Finally,

[17] In a BG world, there is a revenue equivalence between a contract in which managers choose an optimal fee, and a contract in which managers decide on the assets they actively manage (the remaining assets are indexed) with a fixed fee. Since indexed assets do not diminish returns, in the fixed fee contract technically the variable that predicts returns are deviations of the assets a manager actively manages from efficient size. Since the time-varying fee contract is counterfactual, the simulations in this paper use the fixed fee contract. The distinction between total assets and active assets is one reason why controlling for total fund size does not render the coefficient estimate on ownership insignificant in Figure 1. With skill that is not time-varying, fund fixed effects soak up efficient size. For a zero coefficient estimate on ownership, however, one would need to control for both total assets and active assets in addition to controlling for non-linear effects in fund size.

[18] For instance, Khorana et al. (2007) in fact focus on one particular cross-section. Thus, the BG argument for a given fund in this subsection is less of a concern. The matching of managers with different ability to

these arguments do not necessarily imply that previous research on the positive relationship between fund performance and managers' personal investments is false positive. Of course, there could exist a positive relationship between the amount managers invest in their funds and fund performance even when fund size and, hence, ownership are mechanically correlated with fund performance.

Because a similar argument can be made against scaling the amount by wealth if wealth is correlated with fund performance, my main specification has the amount invested as the main independent variable while controlling for both net wealth and fund size separately:[19]

$$\begin{aligned}\widehat{IR}_{i,t} = \gamma_t + \gamma_c + \delta_1 Amount\ in\ MF_{i,t-1} + \delta_2 Amount\ in\ OH_{i,t-1} + \theta Wealth_{i,t-1} \\ + \psi AUM_{t-1} + \zeta' X_{i,t-1} + \eta_{i,t}\end{aligned} \tag{5}$$

Where γ_t and γ_c are year and investment category fixed effects, respectively, and $X_{i,t-1}$ is a vector of observables. Following Kosowski et al. (2006) and Fama and French (2010) the main measure of fund performance in Equation 5 is a fund's information ratio which accounts for the noise in alpha estimates and can be converted into the t-statistic of alpha.

The distribution of the amounts managers invest in their own funds is positively skewed. The majority of managers invest nothing, lots of managers invest small amounts, and some managers invest a million dollars. In the baseline, I winsorize the amount at the 99th percentile to mitigate the impact of the managers who invest a lot on the average effect.[20] I also estimate an extensive margin specification (i.e. whether a manager invests or not), which i) circumvents the discussion of scaling the amount invested and ii) is less prone to

fund size may, however, still be a problem.

[19]Pool et al. (2017) make a similar argument when studying the impact of managerial housing wealth shocks on fund risk taking. In my case, large wealth presumably correlates positively with performance. Hence, ceteris paribus larger wealth implies both a lower fraction of wealth invested in the fund and better performance, therefore a lower coefficient estimate. Thus, scaling the amount invested by wealth increases the risk of a false negative test result.

[20]To be consistent, I also winsorize information ratios and the amount managers invest in overlapping holdings at the 1st and 99th percentiles.

outliers, and in the robustness section a piecewise linear specification.

4 Fund Performance and Managerial Commitment

4.1 Main specification

This subsection estimates versions of Equation 5. The vector of observables $X_{i,t}$ includes age (Age), experience in years as a fund manager ($Exper$), labor income ($Income$), gender ($Female$), TER, the number of categories a manager manages ($NumCategories$), the number of funds a manager manages ($NumFunds$), and the number of managers on a fund ($NumManagers$). Standard errors are clustered by funds.[21]

Column (1) of Table 3 shows the main specification without controls and with category and year fixed effects turned off. A one-standard-deviation increase in the amount a manager invests in her fund in a given year is associated with a 0.154 larger information ratio in the following year. Column (2) of Table 3 shows that the positive relationship between personal investments and fund performance survives the inclusion of year and category fixed effects and other observables, albeit the coefficient estimate declines to 0.082. Columns (3) and (4) of Table 3 focus on the extensive margin. In Columns (3) and (4), the coefficients on the dummy that equals one in case a manager invests in her fund and otherwise zero are 0.203 and 0.128, respectively. That is, managers who invest in their funds earn t-statistics of alpha that are $\sqrt{12} \times 0.128 \approx 0.44$ to $\sqrt{12} \times 0.203 \approx 0.70$ larger. To gauge the economic magnitude of the estimate, recall that the conventional 95% significance level implies that a manager has superior ability if the t-statistic of alpha is larger than 1.96. In that sense, the coefficient estimates are economically large as they can help distinguish a manager with significant ability from a manager without significant ability. Section 5 provides a more structural interpretation of the coefficient estimates and shows that the

[21] The results are robust when standard errors are clustered by fund family.

asymmetric information equilibrium can match these moments in the data, but also that the original BG calibration implies a larger performance difference between the managers who invest and those who do not.

The positive relationship between fund performance and personal investments may arise because of improved incentives (the coefficient estimate has a causal interpretation) or self-selection according to ability (the coefficient estimate is biased). Without any exogenous variation in the amount invested, it is not possible to estimate the size of a potential bias. Instead, Section 5 provides an interpretation based on a model without any moral hazard which entirely relies on the self-selection channel.

4.2 Overlapping holdings

Throughout Table 3 the evidence that managers who invest in overlapping holdings perform better with their funds is weaker. In Column (2) of Table 3, the standardized coefficient estimate for the amount invested in overlapping holdings is only 0.022 and not statistically different from zero.

Since there is no conclusive evidence for why some managers buy the same securities in their personal accounts and their professionally managed funds, I delegate a discussion of the empirical facts and potential explanations to Appendix D for the interested reader. In short, managers tilt both their funds and their personal portfolios towards the securities that they hold in both, even after controlling for firm characteristics. Overlapping holdings are not related liquidity, but to domicile and market cap: Overlapping holdings are mostly Swedish large cap stocks. Similar to Bodnaruk and Simonov (2015), managers perform well in picking overlapping holdings, but the evidence is statistically weak.

5 Model Calibration, Persistence, and Performance Relative to Benchmark

5.1 Performance persistence when sorting on managers' personal investments and model calibration

This subsection interprets the main empirical result—the positive relationship between fund performance and managers' personal investments—through the lens of a modified BG equilibrium. In a BG equilibrium, no publicly available variable can predict abnormal performance in real time. If it did, rational risk-neutral investors would reallocate their capital until the arbitrage opportunity is eliminated. The only variable that predicts future returns in real time are unobserved deviations from efficient size, i.e. the difference between actual fund size, which is based on investors' perception of skill, and efficient fund size. Therefore, to an econometrician looking at the data ex-post any variable that enters significantly in Equation 5 has to be correlated with deviations from efficient size.[22]

A positive coefficient estimate on the amount a manager invests in her own fund can be rationalized once managers—in contrast to regular investors—are certain about their skill, thus efficient fund size, and thus deviations from efficient fund size.[23] Because of the decreasing returns to scale technology, funds that run below efficient size on average perform abnormally well. A manager being certain about her fund's efficient size then invests in her fund whenever her fund runs below efficient size and otherwise not. Hence, her investment reveals deviations from efficient size and enters positively in Equation 5.[24] The key assump-

[22]In this sense, mutual fund managers are not solely responsible for fund performance. Instead, investors in part determine fund performance by allocating more or less than efficient capital to a fund.

[23]Yin (2016) provides evidence that a hedge fund manager knows the efficient size of her fund.

[24]Theoretically, under these assumptions managers face an arbitrage opportunity. In principle, they would want to borrow money and invest the proceeds in their funds in case size is below efficient size, and short the fund in case size is above efficient size. In practice, managers face various constraints (e.g. short-selling of mutual funds is not possible) which I leave unmodeled. Using information ratios as the main outcome variable acknowledges managers' constraints as information ratios are a more relevant measure of performance for a

tion underlying this argument is that managers cannot signal their personal investments to investors. If they could, investments in their own funds could change deviations from efficient size through investor fund flows as discussed in Section 6.

The asymmetric BG equilibrium implies performance persistence when sorting on managers' investments as long as investors have not fully learned managerial skill. Figure 3 Panel (a) plots annual information ratios over time for managers who either invest in their funds or in overlapping holdings and those who do neither. The two portfolios are re-formed every year and performance is tracked over the next five years as in the persistence analysis in Carhart (1997). Performance across the two groups persists over time.[25] Figure 3 Panels (b) and (c) replicate Panel (a) with simulated data from the Berk and Green model using the original calibration and a calibration to match the Swedish data, respectively. In the simulations, managers invest in their funds whenever fund size is below efficient fund size and otherwise not. In the original calibration in Panel (b), the performance gap between the managers who commit to their funds and those who do not is wider than in the data. In other words, the coefficient estimates in Table 3 are small relative to what is implied by the original calibration. The Swedish calibration (see Table B1) addresses the wider performance gap by bumping up investors' precision about managerial skill which—assuming rational expectations—governs the distribution of actual skill. Then, on average a fund's size is closer to its efficient size and the performance gap tightens. The shapes of Panel (c) and Panel (a) look similar: the main empirical result is consistent with a simple asymmetric information equilibrium model.

Berk and Green (2004) calibrate their model to match a positive flow-performance relationship and fund survival rates. A higher precision about managerial skill compared to

constrained investor compared with simple abnormal returns.

[25] The figure plots the information ratios that are estimated year-by-year to make sure that the performance persistence is not driven by a correlation of estimation errors across horizons. Having said that, the results are the same using the constant-coefficients model to estimate information ratios.

the original calibration implies that flows are less responsive to past performance which fits neatly with the weak flow-performance relationship in the data (see Section 6). A higher precision about managerial skill, however, also implies that fund survival rates become larger relative to the original calibration. The Swedish calibration addresses this by lowering average managerial skill. Specifically, manager skill—the return on the first dollar invested—is 3.25% in the Swedish calibration compared with 6.5% in the original calibration, whereas the standard deviation of managerial skill is 1% in the Swedish calibration and 6% in the original calibration.[26] Thus, according to the model Swedish managers are less skilled compared with their U.S. counterparts, but almost all Swedish managers possess some skill.

5.2 Performance relative to the benchmark

In Panel (a) of Figure 3 on average both groups of managers earn negative information ratios relative to the benchmark which may raise the question why the managers who invest in their funds do so. The negative performance relative to the benchmark in Panel (a) can be rationalized through a simple back-of-the-envelope calculation relaxing the assumption that benchmark returns are achievable at zero cost.[27] Average information ratios for the two groups are -0.09 and -0.19, respectively. Average residual volatility across the two groups is 6% and 4.8%, respectively, implying alphas of -0.54% and -0.9%. Thus, the results are consistent with expense ratios for the benchmark in the range of 0.54% to 0.9%. Having said that, it is unclear whether managers pay the same price as regular investors when investing in their own funds. For instance, managers could get a discount on the management fee or a price discount when they buy the fund.

Stronger evidence that many Swedish funds run at or above efficient sizes is perhaps

[26] The resulting fund survival rates are illustrated in illustrated in Figure B1.

[27] Berk and van Binsbergen (2015) use a combination of Vanguard index funds as benchmarks. Since Vanguard funds are investable, they account for the cost of achieving a particular benchmark return. Unfortunately, the number of passive funds that could be used as investable benchmarks is very limited over the Swedish sample period.

revealed by managers' personal investments: Taken at face value, the model and the fact that the majority of managers do not invest in their funds imply that the majority of Swedish funds run at or above their efficient sizes.

5.3 Time-series evolution of managers' personal investments and performance persistence when sorting on past performance

The asymmetric information equilibrium has further predictions for the time-series evolution of performance, size, and personal investments. Most prominently studied is the relationship between performance and size. In the BG world, due to the decreasing returns to scale technology performance decreases with fund size in regressions with fund fixed effects. This does, however, not imply that performance is predictable to the real-time investor (Pástor, Stambaugh, and Taylor, 2015). Column (1) of Table 4 adds fund fixed effects to the main specification. The negative coefficient estimate on fund size mirrors the recent results in the decreasing returns to scale literature (see e.g. Pástor, Stambaugh, and Taylor, 2015; Zhu, 2018) and is consistent with the model.[28]

Column (1) of Table 4, however, also shows that the estimate on the personal amount invested does not survive the inclusion of fund fixed effects. That is, there is no evidence that a manager allocates more to a given fund in times when actual size is further away from efficient size. In theory, managers' personal investments should decrease with fund size: with constant skill efficient size is constant and soaked up by fund fixed effects and, hence, a larger fund size implies that the fund runs closer to efficient size (in case it runs below efficient size) or that it runs further away from efficient size (in case it runs above

[28]Evidence for decreasing returns to scale is not ubiquitous. Pástor, Stambaugh, and Taylor (2015) note that the fixed effects estimator can be biased in small samples, propose a forward-demeaned estimator, and find a negative but insignificant effect of fund size on fund returns. Zhu (2018) argues that the forward-demeaned estimator suffers from a misspecification which results in a loss of power, and finds evidence of decreasing returns to scale after correcting for the misspecification. Chen et al. (2004), McLemore (2019), Busse et al. (2019), and Pástor et al. (2019) find additional evidence for decreasing returns to scale, whereas Elton et al. (2012) and Reuter and Zitzewitz (2015) find no evidence for decreasing returns to scale.

efficient size). In both cases, absent the ability to short-sell, expected abnormal performance for a manager that knows efficient size decreases and, hence, her personal investment should decrease. Past performance should only affect managers' personal investments to the extent that it determines fund flows and, therefore, fund size. Columns (2) and (3) of Table 4 show that neither variation in fund size nor variation in performance significantly correlate with managers' personal investments in their funds. Instead, Column (4) shows that the percent of risky financial wealth invested in the fund is persistent with an autocorrelation coefficient of 0.703 and that past investments explain most of the variation in managers' personal investments in their funds. Moreover, the BG model is designed to explain the absence of performance persistence when sorting on past performance. Figure 3 Panel (e) and (f) illustrate that sorting based on past performance does not predict future performance in the standard BG world. Figure 3 Panel (d) plots the data. The shapes look similar but in contrast to the model there is performance persistence up to three years in the data when sorting based on past performance. The predictability of future performance by past performance implies that investors ignore some of the information in past returns.

Motivated by empirical evidence that investors' learning from past returns is incomplete (see, e.g., Choi et al., 2016), I now offer a simple explanation for the performance persistence when sorting on past performance and the persistence of managers' personal investments by introducing stickiness in investors' expectations. In the frictionless rational case, investors update their beliefs about managerial skill ϕ according to a Kalman filter:

$$\phi_{t+1}^{BG} = \phi_t^{BG} + K_t r_{t+1} \tag{6}$$

where ϕ denotes perceived managerial skill, K is the Kalman gain, and r_{t+1} is an abnormal return. I instead propose that investors' beliefs about managerial skill evolve as:

$$\phi_{t+1} = (1-\lambda)\phi_{t+1}^{BG} + \lambda\phi_t \tag{7}$$

where $0 \leq \lambda \leq 1$ and λ denotes the degree of expectation stickiness. Learning about managerial skill collapses to rational learning if $\lambda = 0$. In the other extreme, $\lambda = 1$ implies that beliefs are fixed at their prior means and never updated. If $\lambda = 1$ and managerial skill varies in the cross-section, then performance differences will persist indefinitely. For intermediate values of λ performance persistence will wear off over time as actual fund size approaches efficient fund size, albeit slower compared to the fully rational case.[29] At the same time, as long as performance differences persist a manager knowing her fund's efficient size continues to invest in her fund, and, hence, managers' personal investments in their funds persist. Thus, a slight departure from the frictionless rational case can at least qualitatively explain both features in the data that the frictionless benchmark model cannot explain.

6 Signaling, Flow-Performance and Disclosure of Data

6.1 Signaling and Flow-Performance

In contrast to the U.S. the data on managerial commitment are currently not required to be publicly disclosed and I have found no evidence that funds publicly advertise their managers' investments. Commitment may be privately signaled to a subset of investors (e.g. large institutional investors) or publicly through channels that I am not aware of. The ability to signal investments introduces the possibility that managers invest in their funds for reasons not related to earning an abnormal return. While this possibility may seem

[29] If $\lambda \neq 0$ the model does not fulfill the stringent requirements of a rational expectations equilibrium anymore, i.e. in a rational expectations equilibrium the objective and subjective distributions of skill have to be the same.

natural, it changes the game and the empirical results can no longer be illustrated with the simple asymmetric information equilibrium model. If managers can signal their investments they face a complicated trade off between changing assets under management by revealing their type, and deteriorating (increasing) the return on their invested capital by attracting (repelling) assets. It is not obvious that a manager who knows that her fund runs below efficient size would want to signal her assessment to investors. Her ultimate decision depends on her fund size incentives, i.e. the increase in compensation through additional assets, and her return incentives, i.e. the availability of personal capital to invest in her positive alpha fund and the sensitivity of compensation to fund performance. In the extreme, a manager may want to take actions to reduce her fund's assets to earn a larger return on her personal capital.

If size incentives dominate and if managers can signal their investments, an intuitive prediction could be that managers who invest in their funds attract more inflows and that they have lower flow-performance sensitivities as uncertainty about their type is resolved. Consistent with the classic flow-performance literature (Chevalier and Ellison, 1997; Sirri and Tufano, 1998) I define a fund's percentage flow as:[30]

$$Flow_{i,t} = \frac{(AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t}))}{AUM_{i,t-1}} \times 100 \tag{8}$$

where $AUM_{i,t-1}$ and $AUM_{i,t}$ measure AUM at the beginning and end of a year, respectively. $R_{i,t}$ denotes the fund's net return from t to $t-1$. The flow measure, thus, assumes that all flows occur at year's end.

Table 5 shows regressions of fund flows on managers' investments in their own funds but, in short, finds no evidence that more committed managers attract more flows. The point

[30] Flows are winsorized at the 1st and 99th percentiles. An issue with the percentage flow specification is that the percentage flow measure becomes less responsive to very large negative returns, which is (partly) addressed by setting the flow variable to -100% whenever a fund liquidates. The results are similar if fund flows are defined as $Flow_{i,t} = \frac{(AUM_{i,t} - AUM_{i,t-1} \times (1+R_{i,t}))}{AUM_{i,t-1} \times (1+R_{i,t})} \times 100$

estimates on the amount invested in own funds in Columns (1)–(6) are zero in a statistical sense. Overall, there is no evidence that managers who invest in their funds attract larger inflows which is consistent with the asymmetric information equilibrium model in which managers cannot signal their investments to investors.

Column (3) of Table 5 tests whether there is heterogeneity in the flow-performance relation conditional on the amount managers invest in their own funds. The coefficient estimate on the interaction between past performance is not statistically different from zero.[31] The coefficient estimate on alphas in the previous year, $\widehat{\alpha}^{BM}_{i,t-1}$, in Column (2) is positive but only weakly statistically significant. In this case, lack of power may be an issue. Both Ferreira et al. (2012) and Ibert et al. (2018) document a significant flow-performance relationship for Sweden using larger samples. The flow-performance relationship is also economically weak. In Column (2) of Table 5, a 10% increase in alphas only leads to a 4.69% increase in flows. Eyeballing the estimates of Figure 1 in Chevalier and Ellison (1997), the same excess return leads to almost a 60% increase in flows for a sample of U.S. funds.

Columns (5) and (6) of Table 5 follow the recommendation of Spiegel and Zhang (2013) and use changes in market shares as the dependent variable and the results are similar, although there is some evidence that managers who invest in overlapping holdings have a larger market share subsequently.[32]

A weaker flow-performance relationship compared with U.S. data is consistent with the higher precision about managerial skill from the previous section necessary to reduce the performance difference between managers who invest in their funds and those who do not. A higher precision about managerial skill implies that flows are less responsive to past per-

[31] To compare with the previous literature, the table uses alphas as a measure of past performance. The results are similar if information ratios are used.

[32] The results are also similar if a convex-flow performance specification is considered. Recent papers, however, question the convexity results of earlier studies. For instance, Spiegel and Zhang (2013) argue that the convexity arises from misspecification, whereas Kim (2019) argues that convexity in the flow-performance relationship has disappeared after 2000.

formance.[33] The weak flow-performance relationship is in principle also consistent with the performance persistence when sorting on past performance documented in the previous section. The performance persistence when sorting on past performance implies that flow-performance is not only weak, but *too* weak (Berk and Tonks, 2007).

6.2 Disclosure of data

From an equilibrium perspective, what would happen if managers were required to publicly disclose the investments they make in their own funds from one moment to the other? I denote by ϕ_0 investors' prior mean of managerial skill and, for simplicity, I assume that there are two types of managers which occur equally likely, one with $\alpha^L < \phi_0$ and one with $\alpha^H > \phi_0$. To focus on the signaling problem and not the portfolio choice of managers (that is the actual amount managers invest), I assume that managers know their type and can send a signal about being α^H but investors cannot verify the signal. The signal is interpreted as a dummy for whether a manager invests in her fund or not. Moreover, I assume that a manager's payoff depends on investors' posteriors after signals have been observed, ϕ_1, as follows:

$$PRS \times \phi_1 + \mathbb{1}_S W \times (\alpha - \phi_1) \tag{9}$$

where $\alpha \in \{\alpha^L, \alpha^H\}$ and $\mathbb{1}_S$ is an indicator for whether the signal has been sent. $PRS \geq 0$ denotes the pay-revenue-sensitivity, that is the proportion of perceived skill (and equivalently assets) passed on to the manager as income, and represents a manager's size incentives. $W \geq 0$ is the personal capital invested in the fund and represents return incentives. Income compensation based on the fund's return also enters into W.

[33] Some funds are started before 1999 (the start of my sample). For such funds, a weak flow-performance relationship may arise because investors have a higher precision at the start of my sample because they have been able to learn from returns before 1999. The results are, however, similar if these funds are excluded.

While in reduced-form, Equation 9 captures the essence of the manager's tradeoff. A $\phi_1 > \phi_0$ increases the payoff from size incentives, e.g. because a higher posterior skill than prior skill causes an increase in assets. At the same time a high ϕ_1 decreases the return earned on the personal capital, e.g. because of a decreasing returns to scale technology. An equilibrium is a set of strategies with no profitable deviations for both types and under rational expectations the strategies need to be consistent with investors' posterior mean of managerial skill.[34]

If return incentives dominate size incentives, i.e. $W > PRS$, there exists a separating equilibrium in which α^H always sends the signal and α^L never does because the cost of signaling for the low type is too large. If $W > PRS$, the low type does not profitably deviate and rather incurs outflows if:

$$\text{Payoff(“not sending signal”)} \geq \text{Payoff(“sending signal”)} \tag{10}$$

$$PRS\alpha^L \geq PRS\phi_0 + W(\alpha^L - \phi_0) \tag{11}$$

$$\iff \phi_0 \geq \alpha^L \tag{12}$$

which is true by assumption. The high type does not profitably deviate because $PRS\alpha^H + W(\alpha^H - \alpha^H) \geq PRS\phi_0$. There exist only two more pure-strategy equilibria in the special case of $W = PRS$ in which both types of managers either always or never send a signal. In general, there exists no pooling equilibrium in which both types always send a signal: If size incentives dominate the low type wants to mimic the high type and the high type wants to avoid being mimicked.

While the simplified model illustrates a manager's basic tradeoff, in reality there is an additional layer of complexity as a manager can decide on the strength of her signal by varying the actual amount she invests in her fund. In the given framework, compensation

[34]For instance, if a signal is sent investors' posterior mean is $\phi_1^S = (p(s|\alpha^H)p(\alpha^H)\alpha^H + p(s|\alpha^L)p(\alpha^L)\alpha^L)/(p(s|\alpha^H)p(\alpha^H) + p(s|\alpha^L)p(\alpha^L))$.

contracts that are less sensitive to the fund's size result in more efficient outcomes by aligning managers' incentives with investors' incentives. For instance, if return incentives dominate size incentives and $\alpha^L < 0$ the unskilled manager is revealed and shuts down her fund. Even if $\alpha^L \geq 0$ some funds may shut down if the resulting fund size is not sufficient to cover the fixed costs of running a fund. Therefore, making the data on managers' personal investments in their funds public could decrease the number of funds in the economy.

7 Robustness and Extensions

7.1 Intensive and extensive margin, and winsorization

Is it the managers that invest small amounts or the managers that invest a million dollars that drive the positive relationship between fund performance and personal investments? Column (1) of Table 6 estimates a piecewise linear specification and dummies out the managers who do not invest in their funds. If the extensive margin drives the results, the dummy for a zero investment should be negative. The dummy is not statistically different from zero, whereas the linear term is. Hence, it is the intensive margin that drives the results.

Column (2) of Table 6 replicates the main specification but does not winsorize the dependent or independent variables at the 1st and 99th percentiles, whereas Column (3) winsorizes the amount invested in own funds and in overlapping holdings as well as the dependent variable at the 5th and 95th percentiles. The results are robust. Columns (4)–(7) replicate Columns (1)–(3) but use the information ratios estimated year-by-year and again the results are similar.

7.2 Scaling the amount invested

Before scaling the amount invested, I present unconditional relationships between performance, fund size, and wealth. If a variable is correlated with fund performance, scaling the amount invested by that variable can be misleading as discussed in Section 3. Column (1) of Table 7 documents the unconditional relationships between wealth, fund size, and fund performance. Wealthier managers perform better. The point estimate on size is negative, but in contrast to the fund fixed effects specification the estimate is not statistically significant. Column (2) documents the same facts but uses risky financial wealth as a proxy for wealth, which is narrower than net worth and has the benefit of being non-negative.

The literature on fund manager ownership and performance has scaled the amounts managers invest in their own funds by fund size (see, e.g., Khorana, Servaes, and Wedge, 2007). Column (3) of Table 7 scales the amount invested in own funds by fund size and the relationship between managers' personal investments and information ratios is significant. Khorana, Servaes, and Wedge (2007) document a 2.76 to 3.65 percentage point increase in annual alpha for every one-percentage-point increase in ownership. The corresponding estimates for the Swedish sample are 1 to 2.1 percentage points (untabulated).

The baseline specification controls for wealth differences such that a higher amount invested implies a larger portfolio share allocated to one's own fund. Column (4) instead scales the amount invested by risky financial wealth. A 10% increase in risky financial wealth allocated to the fund is associated with a 0.13 larger t-statistic of alpha. Columns (5)–(8) of Table 7 replicate Columns (1)–(4) but use the information ratios estimated year-by-year. The results are similar, albeit the estimate on the amount scaled by risky financial wealth in Column (8) becomes borderline insignificant.

7.3 Alternative benchmarks and value added

Table 8, Columns (1) and (2) replicate the main specification but with information ratios estimated relative to the alternative benchmark models. Columns (3) and (4) use information ratios estimated year-by-year. The results are robust.

Berk and van Binsbergen (2015) propose value added, the product of fund size and abnormal returns before management fees, as a measure of managerial skill. There exists a positive relationship between value added and the personal investments of managers in their own funds (untabulated). In the asymmetric information equilibrium the positive relationship is, however, solely driven by the abnormal return component. A manager does not invest in her fund when she believes she is highly skilled. She invests when she expects to earn an abnormal return.

7.4 Alphas instead of information ratios

Table 9 uses fund alphas as the dependent variable. Column (1) uses the prospectus benchmark to risk-adjust returns, Column (2) uses the Swedish market model, and Column (3) uses the Swedish four-factor model. Columns (4)–(6) use alphas estimated year-by-year. The results confirm a positive relationship between fund alphas and managers' personal investments, albeit the coefficient estimates for the CAPM and the four-factor model in Columns (2) and (3) are not different from zero in a statistical sense. In Column (1) of Table 9 a one-standard-deviation increase in the amount invested in own funds is associated with a 0.5 percentage points larger future annual fund alpha.

7.5 Equity funds and other investment categories

Table 10 shows Column (2) of Table 3 by investment category. Most of the literature on mutual funds focuses on equity mutual funds. Column (1) of Table 10 constrains the sample to equity funds and shows that the results hold up among equity mutual funds.

7.6 Team management and busy managers

Columns (1) and (2) of Table 11 exclude team managed funds from the baseline specification and show that the results are robust.

The managers managing multiple funds allow me to study whether managers invest more in those funds that subsequently perform better. Column (3) of Table 11 adds manager fixed effects and identifies the coefficient estimate from variation across funds for a given manager. The coefficient estimate on the amount invested in Column (3) remains positive but is insignificant. From an equilibrium perspective, managers managing multiple funds invest only in those funds that run below efficient size and, thus, there should be a positive relationship between fund performance and managers' personal investments even for a given manager. However, the set of managers managing multiple funds may be a special subset for identification as there may be an endogenous matching between the number of funds a manager manages, skill, and fund size.

8 Conclusion

I collect a dataset of Swedish fund managers' personal portfolio holdings and find large amounts of cross-sectional dispersion in the composition of these portfolios. While some managers invest in their own funds, the majority of managers do not. The managers who do invest in their own funds subsequently perform better. The main results are consistent with a simple model in which fund managers, in contrast to fund investors, are certain about their skill and, hence, their ability to earn abnormal returns and invest their personal wealth accordingly.

The results are relevant for policy makers in evaluating the benefits and costs of disclosure policies and policies that require managers to invest in their own funds. If Swedish fund managers have to publicly file the investments in their own funds, my results imply that it is costly for the managers who lack ability to feign ability to investors. Ultimately, the cost of signaling drives some of the managers who lack ability out of the market. Making managers' personal investments in their funds publicly available could, thus, decrease the size of the active fund industry. Whether this effect is desirable, and from which perspective, is an interesting question for future research.[35]

[35] Disclosure may not always have the intended consequences, see e.g. Berk and van Binsbergen (2017) and Goldstein and Yang (2019).

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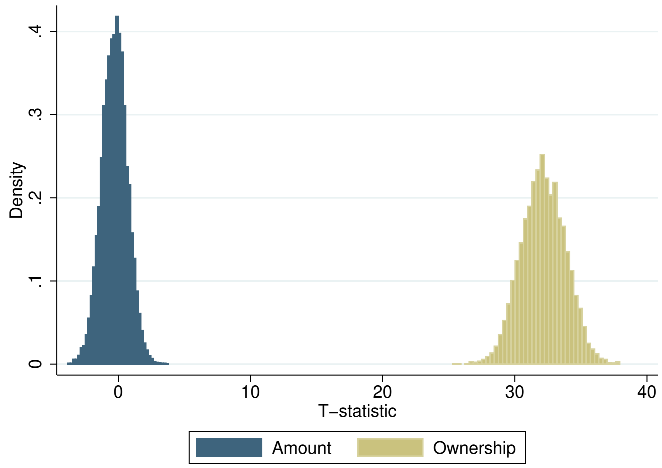
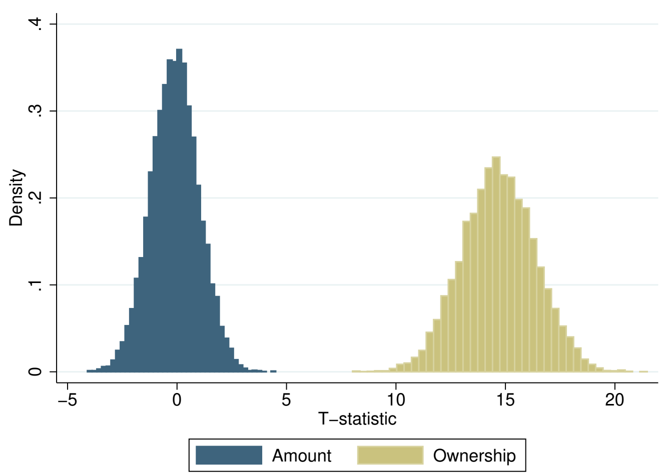
Figure 1: Distribution of simulated t-statistics

(a) No controls, 5000 managers, 20 years



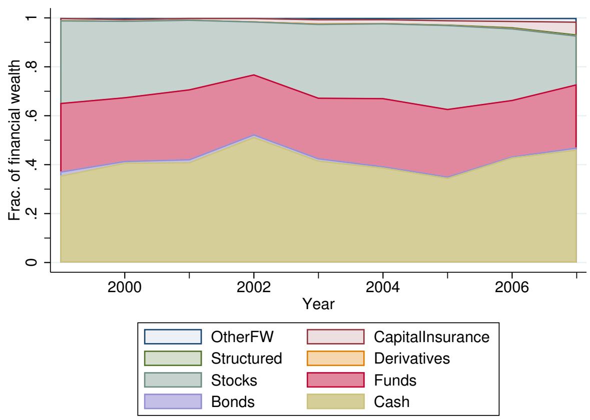
(b) AUM control, 5000 managers, 20 years



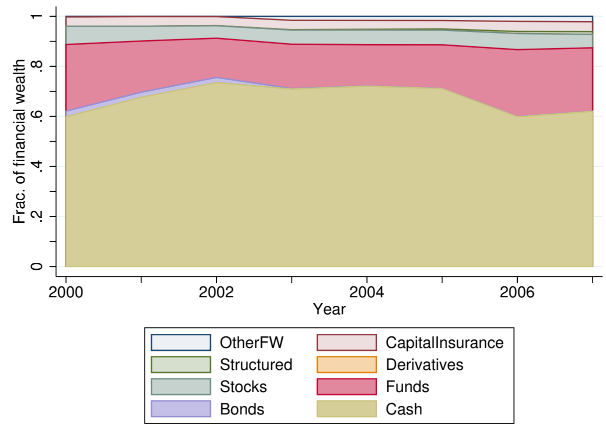
I simulate a Berk and Green world 10,000 times and randomly assign managers an amount that they invest in their own funds as described in Appendix B. The figure shows distributions of t-statistics obtained from regressions of fund abnormal returns on the lagged amount invested and lagged ownership (amount over fund size), respectively. All regressions include fund fixed effects. Panels (a) and (b) simulate 5,000 managers for 20 years. Panel (a) has no additional controls, whereas Panels (b) controls for lagged fund size. That is, for each simulation run Panel (a) estimates $r_{it} = a_i + \beta Ownership_{i,t-1} + \epsilon_{it}$ and $r_{it} = a_i + \beta Amount_{i,t-1} + \epsilon_{it}$, whereas Panels (b) estimates $r_{it} = a_i + \beta Ownership_{i,t-1} + \gamma AUM_{i,t-1} + \epsilon_{it}$ and $r_{it} = a_i + \beta Amount_{i,t-1} + \gamma AUM_{i,t-1} + \epsilon_{it}$.

Figure 2: Evolution of average portfolio compositon

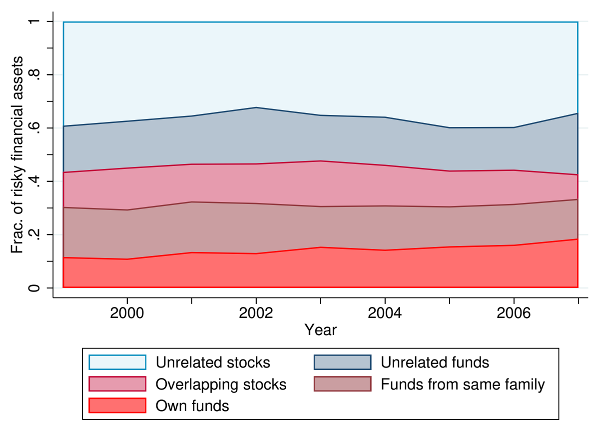
(a) Financial wealth composition



(b) Financial wealth composition (Swedish pop.)



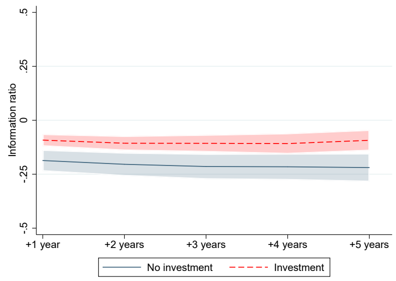
(c) Risky financial assets composition



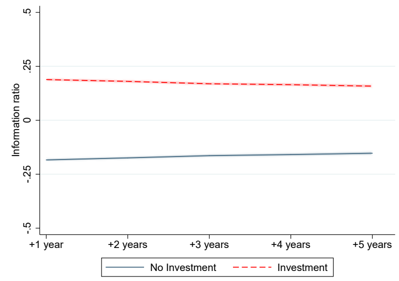
Panel (a) shows the average composition of personal managerial financial wealth over time. Panel (b) is similar to Panel (a) but shows the average composition of financial wealth for the whole Swedish population. Panel (c) shows the average composition of the sum of non money–market mutual funds and direct stock holdings over time. Own funds are professionally managed funds by the manager in question that are in the manager's personal portfolio. Funds from the same family are funds from the manager's fund family (her employer). Unrelated funds are funds in the personal portfolio that are not own funds and not from the same family. Overlapping stocks are direct stock holdings in managers' personal portfolios that are also held in their professionally managed mutual funds. Unrelated stocks are direct stock holdings that are not overlapping.

Figure 3: Persistence in fund performance

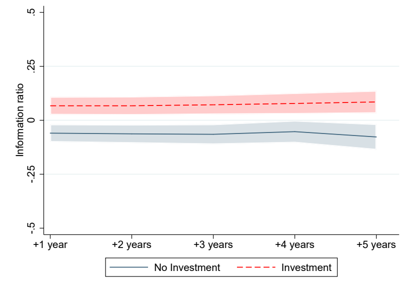
(a) Investment sorts
(data)



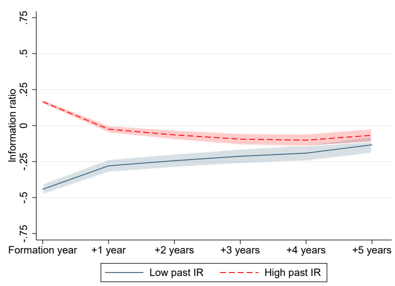
(b) Investment sorts
(model original)



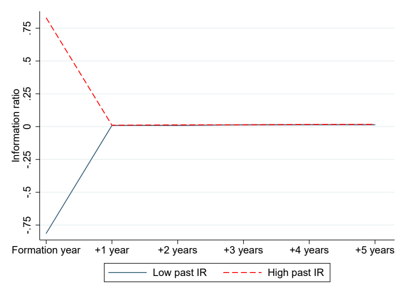
(c) Investment sorts
(model Swedish calibr.)



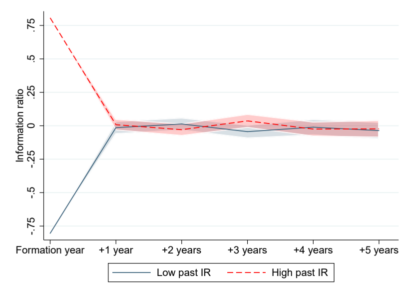
(d) Past performance sorts
(data)



(e) Past performance sorts
(model original)



(f) Past performance sorts
(model Swedish calibr.)



At the beginning of each year, funds are ranked into two bins based on either whether managers at the fund invest in their fund (and/or in overlapping holdings) or not, or based on past performance. The lines in the graphs show the average (equal-weighted) information ratios on the two portfolios in the years subsequent to the initial ranking similar to the analysis in Carhart (1997). The shaded areas represent 95% confidence intervals for the null hypothesis that the means are equal to zero with standard errors clustered by funds. Panel (a) sorts on whether managers invest in their own funds using the actual data. Panels (b) and (c) do the same as Panel (a) but use data from the simulated Berk and Green model assuming a manager invests in her fund whenever it runs below efficient size and otherwise not, see Appendix B. Panel (d) ranks funds based on past information ratios. Panels (e) and (f) do the same as Panel (d) using the simulated data. Information ratios are estimated year-by-year relative to the prospectus benchmark, similar to Equation 4.

Table 1: Summary statistics at the fund level

	10%	25%	50%	75%	90%	Mean	Sd	N
A. AUM, TER and no. of managers								
$AUM_{i,t}$ (mio. SEK)	56.53	177.22	586.25	2,118.87	6,634.30	2,154.79	3,923.75	2,449
$TER_{i,t}$ (%)	0.49	0.74	1.40	1.55	1.80	1.26	0.68	2,449
$NumManagers_{i,t}$	1.00	1.00	1.00	2.00	3.00	1.44	0.86	2,449
B. Net performance								
$12 \times \widehat{\alpha}_{i,t}^{BM}$ (%)	-9.61	-4.11	-0.81	1.87	7.20	-1.06	8.45	2,449
$\widehat{IR}_{i,t}^{BM}$	-1.55	-0.90	-0.27	0.36	1.08	-0.24	1.11	2,449
$12 \times \widehat{\alpha}_{i,t}^{CAPM}$ (%)	-13.87	-6.75	-1.37	2.09	8.77	-1.90	11.52	2,449
$\widehat{IR}_{i,t}^{CAPM}$	-1.65	-1.08	-0.40	0.36	1.12	-0.34	1.14	2,449
$12 \times \widehat{\alpha}_{i,t}^{FF4}$ (%)	-11.91	-6.01	-1.20	2.91	8.81	-1.05	10.73	2,449
$\widehat{IR}_{i,t}^{FF4}$	-1.44	-0.94	-0.27	0.48	1.21	-0.19	1.06	2,449
C. Managerial commitment and controls								
$Amount\ in\ MF_{i,t}$ (TSEK)	0.00	0.00	0.00	0.01	59.36	66.81	440.68	2,449
$Amount\ in\ OH_{i,t}$ (TSEK)	0.00	0.00	0.00	58.77	571.70	345.53	2,183.38	2,449
$Wealth_{i,t}$ (TSEK)	-385.64	518.54	1,943.75	3,990.03	7,938.93	3,711.05	7,758.73	2,449
$Income_{i,t}$ (TSEK)	606.00	916.23	1,317.97	1,849.92	2,588.90	1,563.61	1,285.72	2,449
$Age_{i,t}$	34.00	37.00	41.00	44.00	49.00	41.39	5.94	2,449
$Exper_{i,t}$	1.00	2.33	4.33	7.25	12.17	5.65	4.73	2,449
$NumCategories_{i,t}$	1.00	1.00	1.00	2.00	2.00	1.44	0.63	2,449
$NumFunds_{i,t}$	1.00	2.00	3.00	6.80	11.00	4.87	4.14	2,449

The table shows summary statistics for fund-year observations. In Panel A AUM is fund size, TER is a fund's total expense ratio, and $NumManagers$ is the number of managers working for the fund. Panel B shows performance measures net of costs relative to the prospectus benchmark return in excess of the one-month STIBOR rate, a Swedish market model, and a Swedish Fama and French four-factor model. Fund alphas are estimated according to Equation 4 and the description in the text. IR is a fund's information ratio, that is alpha scaled by residual volatility. Panel C shows the main independent variables and controls. *Amount in MF* is the absolute amount managers invest in their funds in thousands of SEK. *Amount in OH* is the absolute amount managers invest in overlapping holdings, that is securities held both in their personal account and in their funds, in thousands of SEK. $Wealth$ is the average net wealth (worth) of managers at a particular fund in thousands of SEK. $Income$ is labor income, Age is managerial age, $Exper$ is manager experience in years, $NumCategories$ is the number of investment categories managers manage, and $NumFunds$ the number of funds managers manage. No winsorization is applied to any variable in the table.

Table 2: Summary statistics at the manager level

	10%	25%	50%	75%	90%	Mean	Sd	N
A. Characteristics								
$Age_{m,t}$	33.00	37.00	41.00	46.00	50.00	41.66	6.55	1,399
$Exper_{m,t}$	0.83	1.67	3.75	6.67	10.75	4.97	4.65	1,399
$NumCategories_{m,t}$	1.00	1.00	1.00	1.00	2.00	1.22	0.49	1,399
$NumFunds_{m,t}$	1.00	1.00	2.00	3.00	6.00	2.72	2.68	1,399
B. Income & wealth (1000s of SEK)								
$Income_{m,t}$	507.54	775.54	1,189.06	1,737.14	2,621.92	1,476.94	1,379.72	1,399
$FinWealth_{m,t}$	44.83	224.78	691.82	2,059.03	5,532.99	2,837.03	8,477.39	1,399
$RiskyFW_{m,t}$	0.19	39.30	308.79	1,319.62	3,866.41	1,855.44	6,510.60	1,399
$Wealth_{m,t}$	-622.03	395.54	1,932.16	4,280.75	9,843.74	4,273.91	10,071.39	1,399
C. Personal portfolio composition								
$Amount\ in\ MF_{m,t}$ (TSEK)	0.00	0.00	0.00	33.11	316.53	171.83	730.01	1,399
$RiskyFW\ in\ MF_{m,t}$ (%)	0.00	0.00	0.00	13.57	63.44	15.09	29.03	1,267
$FinWealth\ in\ MF_{m,t}$ (%)	0.00	0.00	0.00	4.72	26.95	8.02	18.96	1,380
$Wealth\ in\ MF_{m,t}$ (%)	0.00	0.00	0.00	0.99	9.93	3.91	119.60	1,399
D. Fund-level controls (%)								
$AUM_{m,t}$ (mio. SEK)	92.08	327.18	1,208.01	3,607.04	8,215.34	3,672.67	7,688.82	1,399
$TER_{m,t}$ (%)	0.55	0.96	1.39	1.60	1.90	1.35	0.77	1,399
$NumManagers_{m,t}$	1.00	1.00	1.00	2.00	3.00	1.65	0.93	1,399

The table shows summary statistics for manager-year observations. $FinWealth$ is financial wealth, $RiskyFW$ is risky financial wealth and $Wealth$ is net wealth. $Amount\ in\ MF$ the absolute amount managers invest in their funds in thousands of SEK. No winsorization is applied to any variable in the table.

Table 3: Regressions of information ratios on manager and fund characteristics

	(1)	(2)	(3)	(4)
	$\widehat{IR}^{BM}_{i,t}$	$\widehat{IR}^{BM}_{i,t}$	$\widehat{IR}^{BM}_{i,t}$	$\widehat{IR}^{BM}_{i,t}$
$Amount\ in\ MF_{i,t-1}$	0.154***	0.0821***		
	(0.0373)	(0.0273)		
$Amount\ in\ OH_{i,t-1}$	0.0486**	0.0221		
	(0.0189)	(0.0208)		
$Amount\ in\ MF_{i,t-1} > 0$			0.203***	0.128**
			(0.0644)	(0.0618)
$Amount\ in\ OH_{i,t-1} > 0$			-0.00654	0.0292
			(0.0529)	(0.0501)
$Wealth_{i,t-1}$		0.00531		0.00762**
		(0.00363)		(0.00338)
$AUM_{i,t-1}$		-0.0136**		-0.0143**
		(0.00614)		(0.00616)
$TER_{i,t-1}$		-0.0621		-0.0743*
		(0.0424)		(0.0444)
$NumManagers_{i,t-1}$		0.00500		0.000843
		(0.0279)		(0.0292)
$Income_{i,t-1}$		-0.0443**		-0.0448*
		(0.0224)		(0.0231)
$Age_{i,t-1}$		-0.00198		-0.00229
		(0.00494)		(0.00494)
$Exper_{i,t-1}$		-0.00876		-0.00838
		(0.00566)		(0.00569)
$NumCategories_{i,t-1}$		-0.113**		-0.113**
		(0.0539)		(0.0543)
$NumFunds_{i,t-1}$		0.00746		0.00718
		(0.00696)		(0.00715)
$Female_{i,t-1}$		-0.152**		-0.157**
		(0.0773)		(0.0776)
Constant	-0.244***		-0.292***	
	(0.0267)		(0.0360)	
Year FE	No	Yes	No	Yes
Category FE	No	Yes	No	Yes
N	2449	2449	2449	2449
Adjusted R^2	0.023	0.125	0.006	0.122

The table shows regressions of information ratios, that is alpha scaled by residual volatility, on manager and fund characteristics. Information ratios are estimated relative to the fund's prospectus benchmark according to Equation 4 and the description in the text. $Amount\ in\ MF$ is the absolute amount managers invest in their funds standardized to mean zero and unit standard deviation. $Amount\ in\ OH$ is the standardized absolute amount managers invest in overlapping holdings. $Wealth$ is managerial net wealth in millions of SEK. AUM (fund size) is scaled in billions of SEK. $Amount\ in\ MF > 0$ and $Amount\ in\ OH > 0$ are dummy variables for whether a manager invests in her own fund and in overlapping holdings, respectively. Standard errors are clustered by funds.

Table 4: Within-fund regressions of performance on personal investments, and personal investments on observables

	(1) $\widehat{IR}^{BM}_{i,t}$	(2) $Amount\ in\ MF_{i,t-1}$	(3) $Amount\ in\ MF_{i,t-1}$	(4) $\%RiskyFW\ in\ MF_{i,t-1}$
$Amount\ in\ MF_{i,t-1}$	-0.0243			
	(0.0420)			
$Amount\ in\ OH_{i,t-1}$	-0.0192	-0.0214	-0.0297	
	(0.0340)	(0.0368)	(0.0250)	
$\widehat{IR}^{BM}_{i,t-2}$			0.0338	
			(0.0250)	
$\%RiskyFW\ in\ MF_{i,t-2}$				0.703^{***}
				(0.0543)
$\%RiskyFW\ in\ OH_{i,t-2}$				0.0188
				(0.0131)
$Wealth_{i,t-1}$	-0.00193	0.0190^{*}	0.0179^{**}	-0.0387
	(0.00471)	(0.0102)	(0.00896)	(0.0388)
$AUM_{i,t-1}$	-0.0787^{***}	0.00339	-0.00863	0.0872
	(0.0182)	(0.0122)	(0.0163)	(0.0778)
Year FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	No
Controls	Yes	Yes	Yes	Yes
N	2339	2339	1753	1695
Adjusted R^2	0.272	0.609	0.615	0.533

The table shows fund fixed effects regressions of performance on the amount managers invest in their own funds and the amount managers invest in overlapping holdings, and regressions of personal investments on manager and fund characteristics. Information ratios (IR) are estimated relative to the fund's prospectus benchmark according to Equation 4 and the description in the text. *Amount in MF* is the absolute amount managers invest in their funds standardized to mean zero and unit standard deviation. *Amount in OH* is the standardized absolute amount managers invest in overlapping holdings. $\%RiskyFW\ in\ MF$ is the percentage of risky financial wealth a manager invests in her fund. Standard errors are clustered by funds.

Table 5: Fund flows

	(1) $Flow_{i,t}$	(2) $Flow_{i,t}$	(3) $Flow_{i,t}$	(4) $\Delta MS_{i,t}$	(5) $\Delta MS_{i,t}$
$Amount\ in\ MF_{i,t-1}$	0.00144	0.0144	0.0123	0.00596	0.00320
	(0.0190)	(0.0240)	(0.0204)	(0.00660)	(0.00740)
$Amount\ in\ OH_{i,t-1}$	-0.00859	-0.000833	-0.000713	0.00942**	0.00958**
	(0.0100)	(0.0123)	(0.0123)	(0.00430)	(0.00430)
$12 \times \widehat{\alpha}^{BM}_{i,t-1}$	0.408*	0.469*	0.464*	0.0719	0.0655
	(0.237)	(0.276)	(0.276)	(0.0937)	(0.0944)
$12 \times \widehat{\alpha}^{BM}_{i,t-1} \times Amount\ in\ MF_{i,t-1}$			0.0479		0.0652
			(0.144)		(0.0715)
Constant	0.172***				
	(0.0182)				
Year FE	No	Yes	Yes	Yes	Yes
Category FE	No	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
N	1843	1843	1843	1841	1841
Adjusted R^2	0.000	0.028	0.028	0.286	0.286

The table shows regressions of fund flows on managers' investments and past performance. $\%Flow_{i,t}$ is the percentage change in assets under management, that is $\%Flow_{i,t} = (AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t}))/AUM_{i,t-1} \times 100$. Flows are winsorized at the 1% and 99% level. *Amount in MF* is the absolute amount managers invest in their funds standardized to mean zero and unit standard deviation. *Amount in OH* is the standardized absolute amount managers invest in overlapping holdings. Fund alphas are estimated according to Equation 4 and the description in the text. ΔMS_t is the change in a fund's market share from year $t-1$ to t in percent. Standard errors are clustered by funds.

Table 6: Intensive and extensive margin, and winsorization

	(1) $\widehat{IR}_{i,t}^{BM}$	(2) $\widehat{IR}_{i,t}^{BM,nw}$	(3) $\widehat{IR}_{i,t}^{BM,w95}$	(4) $\widehat{IR}_{i,t}^{BM,yby}$	(5) $\widehat{IR}_{i,t}^{BM,nw,yby}$	(6) $\widehat{IR}_{i,t}^{BM,w95,yby}$
$Amount\ in\ MF_{i,t-1} = 0$	-0.0608			-0.00914		
	(0.0640)			(0.0249)		
$Amount\ in\ OH_{i,t-1} = 0$	-0.0160			-0.0133		
	(0.0504)			(0.0212)		
$Amount\ in\ MF_{i,t-1}$	0.0710**			0.0179**		
	(0.0281)			(0.00892)		
$Amount\ in\ OH_{i,t-1}$	0.0191			0.0107		
	(0.0211)			(0.00964)		
$Amount\ in\ MF_{i,t-1}^{nw}$		0.0799***			0.0197***	
		(0.0259)			(0.00521)	
$Amount\ in\ OH_{i,t-1}^{nw}$		0.00818			0.00890	
		(0.0146)			(0.00977)	
$Amount\ in\ MF_{i,t-1}^{w95}$			0.0654***			0.0204**
			(0.0228)			(0.00796)
$Amount\ in\ OH_{i,t-1}^{w95}$			0.00552			0.0119
			(0.0236)			(0.00938)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2449	2449	2449	2449	2449	2449
Adjusted R^2	0.125	0.112	0.126	0.131	0.137	0.116

The table shows regressions of information ratios, that is alpha scaled by residual volatility, on manager and fund characteristics. *Amount in MF* is the absolute amount managers invest in their funds standardized to mean zero and unit standard deviation. *Amount in OH* is the standardized absolute amount managers invest in overlapping holdings. Column (1) is similar to Column (2) of Table 3 but includes a dummy for zero investment. Information ratios and the amounts managers personally invest are winsorized at the 1st and 99th percentiles in Column (1) (the baseline winsorization), not winsorized in Column (2), and winsorized at the 5th and 95th percentiles in Column (3). Columns (4)–(6) replicate Columns (1)–(3) but estimate information ratios year-by-year (yby) using 12 monthly observations instead of estimating a constant coefficients model as described in the text (the baseline). Standard errors are clustered by funds.

Table 7: Scaling the amount invested

	(1) $\widehat{IR}_{i,t}^{BM}$	(2) $\widehat{IR}_{i,t}^{BM}$	(3) $\widehat{IR}_{i,t}^{BM}$	(4) $\widehat{IR}_{i,t}^{BM}$	(5) $\widehat{IR}_{i,t}^{BM,yby}$	(6) $\widehat{IR}_{i,t}^{BM,yby}$	(7) $\widehat{IR}_{i,t}^{BM,yby}$	(8) $\widehat{IR}_{i,t}^{BM,yby}$
$Wealth_{i,t-1}$	0.0114***		0.00756**	0.00904***	0.00290***		0.00159	0.00196*
	(0.00406)		(0.00358)	(0.00346)	(0.00109)		(0.00118)	(0.00119)
$AUM_{i,t-1}$	-0.00696	-0.00657	-0.0118*	-0.0143**	-0.00197	-0.00189	-0.00500*	-0.00526*
	(0.00665)	(0.00679)	(0.00611)	(0.00656)	(0.00317)	(0.00318)	(0.00296)	(0.00288)
$RiskyFW_{i,t-1}$		0.00513**				0.00278**		
		(0.00220)				(0.00132)		
$\%Ownership\ in\ MF_{i,t-1}$			0.0818***				0.0165***	
			(0.0195)				(0.00566)	
$\%Ownership\ in\ OH_{i,t-1}$			0.0163				0.00411	
			(0.0132)				(0.00490)	
$\%RiskyFW\ in\ MF_{i,t-1}$				0.00366**				0.000651
				(0.00153)				(0.000447)
$\%RiskyFW\ in\ OH_{i,t-1}$				-0.000364				0.000289
				(0.00108)				(0.000429)
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Category FE	No	No	Yes	Yes	No	No	Yes	Yes
Controls	No	No	Yes	Yes	No	No	Yes	Yes
N	2449	2449	2449	2291	2449	2449	2449	2291
Adjusted R^2	0.007	0.001	0.124	0.121	0.003	0.001	0.130	0.128

The table shows regressions of information ratios, that is alpha scaled by residual volatility, on manager and fund characteristics. $Wealth$ is managerial net wealth in millions of SEK. AUM is fund size in billions of SEK. $Amount\ in\ OH$ is the absolute amount managers invest in overlapping holdings in millions of SEK. $\%Ownership\ in\ MF$ and $\%Ownership\ in\ OH$ are the amounts managers invest in their funds and in overlapping holdings, respectively, scaled by fund size times 100. $\%RiskyFW\ in\ MF$ and $\%RiskyFW\ in\ OH$ are the amounts managers invest in their funds and in overlapping holdings, respectively, scaled by managers' risky financial wealth times 100. Columns (5)–(8) replicate Columns (1)–(4) but estimate information ratios year-by-year (yby) using 12 monthly observations instead of estimating a constant coefficients model as described in the text (the baseline). Standard errors are clustered by funds.

Table 8: Alternative benchmarks

	(1) $\widehat{IR}_{i,t}^{CAPM}$	(2) $\widehat{IR}_{i,t}^{FF4}$	(3) $\widehat{IR}_{i,t}^{CAPM,yby}$	(4) $\widehat{IR}_{i,t}^{FF4,yby}$
$Amount\ in\ MF_{i,t-1}$	0.0425*	0.0422**	0.0175**	0.0151**
	(0.0219)	(0.0200)	(0.00684)	(0.00634)
$Amount\ in\ OH_{i,t-1}$	0.0211	0.0292	0.0104	-0.00113
	(0.0230)	(0.0203)	(0.00737)	(0.00652)
Year FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	2449	2449	2449	2449
Adjusted R^2	0.239	0.233	0.175	0.190

Columns (1) and (2) replicate Column (2) of Table 3 using alternative benchmarks to estimate information ratios (alpha scaled by residual volatility). Column (1) uses returns adjusted relative to a Swedish market model (CAPM) and Column (2) uses a Swedish four-factor model (FF4). Columns (3) and Columns (4) replicate Columns (1)–(4) but estimate information ratios year-by-year (yby) using 12 monthly observations instead of estimating a constant coefficients model as described in the text (the baseline). All factor models are described in detail in Appendix A.3. *Amount in MF* is the absolute amount managers invest in their funds standardized to mean zero and unit standard deviation. *Amount in OH* is the standardized absolute amount managers invest in overlapping holdings. Standard errors are clustered by funds.

Table 9: Regressions of alphas on manager and fund characteristics

	(1) $12 \times \widehat{\alpha}_{i,t}^{BM}$	(2) $12 \times \widehat{\alpha}_{i,t}^{CAPM}$	(3) $12 \times \widehat{\alpha}_{i,t}^{FF4}$	(4) $12 \times \widehat{\alpha}_{i,t}^{BM,yby}$	(5) $12 \times \widehat{\alpha}_{i,t}^{CAPM,yby}$	(6) $12 \times \widehat{\alpha}_{i,t}^{FF4,yby}$
Amount in $MF_{i,t-1}$	0.517***	0.277	0.278	0.714***	0.395**	0.415*
	(0.176)	(0.201)	(0.174)	(0.245)	(0.177)	(0.228)
Amount in $OH_{i,t-1}$	0.269	0.393	0.446*	0.382	0.556**	0.0761
	(0.215)	(0.293)	(0.240)	(0.264)	(0.245)	(0.237)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2449	2449	2449	2449	2449	2449
Adjusted R^2	0.113	0.177	0.167	0.065	0.135	0.106

The table shows regressions of alphas on manager and fund characteristics. Alphas are estimated relative to the fund's prospectus benchmark, a Swedish market model (CAPM), and a Swedish four-factor model (FF4). *Amount in MF* is the absolute amount managers invest in their funds standardized to mean zero and unit standard deviation. *Amount in OH* is the standardized absolute amount managers invest in overlapping holdings. Columns (4)–(6) replicate Columns (1)–(3) but estimate information ratios year-by-year (yby) using 12 monthly observations instead of estimating a constant coefficients model as described in the text (the baseline). Standard errors are clustered by funds.

Table 10: Differences across investment categories

	(1)	(2)	(3)	(4)
	$\widehat{IR}_{i,t}^{BM}$	$\widehat{IR}_{i,t}^{BM}$	$\widehat{IR}_{i,t}^{BM}$	$\widehat{IR}_{i,t}^{BM}$
$Amount\ in\ MF_{i,t-1}$	0.0500**	0.0587	0.163***	-0.321
	(0.0238)	(0.0922)	(0.0492)	(0.239)
$Amount\ in\ OH_{i,t-1}$	0.0331	-0.0137	1.537***	0.00461
	(0.0221)	(0.0989)	(0.550)	(0.136)
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Category	Equity	Allocation	Alternative	Fixed Income
N	1576	380	120	326
Adjusted R^2	0.096	0.169	0.197	0.105

The table replicates Column (2) of Table 3 and shows regressions of information ratios, that is alpha scaled by residual volatility, on manager and fund characteristics across different investment categories. Information ratios are estimated relative to the fund's prospectus benchmark according to Equation 4 and the description in the text. *Amount in* MF is the absolute amount managers invest in their funds standardized to mean zero and unit standard deviation. *Amount in* OH is the standardized absolute amount managers invest in overlapping holdings. Standard errors are clustered by funds.

Table 11: Team management and busy managers

	(1) $\widehat{IR}_{i,t}^{BM}$	(2) $\widehat{IR}_{i,t}^{BM}$	(3) $\widehat{IR}_{i,t}^{BM}$
$Amount\ in\ MF_{i,t-1}$	0.109**	0.0982**	0.0563
	(0.0486)	(0.0415)	(0.0503)
$Amount\ in\ OH_{i,t-1}$	0.0653**	0.0371	-0.0119
	(0.0324)	(0.0343)	(0.0439)
Year FE	No	Yes	Yes
Category FE	No	Yes	Yes
Controls	No	Yes	Yes
Manager FE	No	No	Yes
N	1780	1780	1726
Adjusted R^2	0.014	0.108	0.243

The table shows regressions of information ratios, that is alpha scaled by residual volatility, on manager and fund characteristics restricting the sample to funds managed by one manager, that is excluding team managed funds. Information ratios are estimated relative to the fund's prospectus benchmark according to Equation 4 and the description in the text. $Amount\ in\ MF$ is the absolute amount managers invest in their funds standardized to mean zero and unit standard deviation. $Amount\ in\ OH$ is the standardized absolute amount managers invest in overlapping holdings. Standard errors are clustered by funds.

Appendices

A Data

A.1 AUM and TER imputation algorithms

A.1.1 Imputing AUM at the share-class level

Only missing values in the middle of AUM series are imputed by using their past values, fund share class returns, and a factor adjusted for flow rates. Specifically, let $[t_0, t]$ and $[t+n, T]$ be periods when a share class has data on AUM. The missing values are filled as follows:

$$AUM_k = F \times AUM_{k-1}(1 + r_k), \quad \text{for } k \in [t+1, t+n-1], \tag{A13}$$

$$F \equiv \left(\frac{1}{\prod_{k=t+1}^{t+n}(1+r_k)} \frac{AUM_{t+n}}{AUM_t} \right)^{\frac{1}{n}} \tag{A14}$$

where F is the factor adjusted for flow rate, and r_k is share class net return.

A.1.2 Imputing TER at the fund level

Missing TER values are imputed for every period funds have a return, using the following steps. First, for funds whose TER series are almost constant (the ratio of the smallest to the largest TER values larger than 0.95), the missing TER values are filled with the mean of the observed values. However, the number of imputations must be less than or equal to the number of periods when a fund has TER data.

Second, I use a fund's management fee (MNG) information to impute for missing TER as follows. For funds that have missing TER at time t but have data on MNG at this time, as well as other times when TER is available, I replace a missing TER with the product of MNG and the mean of the TER-to-MNG ratio. This step is used only if these ratios are not too volatile, meaning the mean of the TER-to-MNG ratio over the standard deviation of the TER-to-MNG ratio should be larger than 0.13.

For funds that do not have TER at all but have data on MNG, I rely on other funds that belong to the same Morningstar investment category to fill the missing values as follows:

$$imputed\_TER_{ijt} = MNG_{ijt} \left(\frac{1}{N_{jt}} \sum_{h \in \Omega_{jt}^{-i}} \frac{TER_{hjt}}{MNG_{hjt}} \right) \tag{A15}$$

where TER_{hjt} is the TER of fund h in Morningstar category j, Ω_{jt}^{-i} is the set of funds (excluding fund i) belonging to category j in year t, and $N_{jt} = |\Omega_{jt}|$. If Ω_{jt}^{-i} is empty, I use this imputation:

$$imputed\_TER_{ijt} = MNG_{ijt}\left(\frac{1}{T}\sum_{\substack{k\in\Gamma \\ k\neq t}}\frac{1}{N_{jk}}\sum_{h\in\Omega_{jk}^{-i}}\frac{TER_{hjk}}{MNG_{hjk}}\right) \tag{A16}$$

where Γ is the set of periods other funds in category j have data on both TER and MNG, and $T = |\Gamma|$.

These first two steps account for 44% of the total number of imputations.

Third, for funds that have missing values in the middle of the TER series, the missing numbers are imputed by using their lag values and the TER growth rates. Precisely, let $0 \leq H_1, H_2 \leq 2$ such that funds have TER at any periods in $[t-H_1, t]$ and $[t+n, t+n+H_2]$. The missing TERs are imputed for each fund as follows:

$$imputed\_TER_k = \left(\frac{\overline{TER}_{[t+n,t+n+H_2]}}{\overline{TER}_{[t-H_1,t]}}\right)^{\frac{1}{n}} \times TER_{k-1}, \quad \text{for } k \in [t+1, t+n-1], \tag{A17}$$

where

$$\overline{TER}_{[t-H_1,t]} = \frac{1}{H_1+1}\sum_{k=t-H_1}^{t} TER_k \tag{A18}$$

$$\overline{TER}_{[t+n,t+n+H_2]} = \frac{1}{H_2+1}\sum_{k=t+n}^{t+n+H_2} TER_k \tag{A19}$$

Fourth, for funds that have missing TER at the tails of the series, I test whether TER series follow the linear time trend. If they do, I replace the missing TER with the forecast values from the model. To be specific, let $[t_0, t]$ and $[t+n, T]$ be periods when TER are missing, and let TER of fund i have the specification:

$$\log TER_{ik} = a_i + b_i k + \varepsilon_{ik}, \quad \forall k \in [t_0, T] \tag{A20}$$

The missing TERs are filled as follows:

$$imputed\_TER_{ik} = \exp(\hat{a}_i + \hat{b}_i k), \quad \forall k \in [t_0, t] \cup [t+n, T] \tag{A21}$$

only if the p-value of $\hat{b}_i$ is less than or equal to 5% and $n \geq 6$. If these conditions are violated, I replace all of the missing TER at the left (right) tail of the series with the mean values of the first (last) three TER values.

A.2 Finding social security numbers

Whenever possible, I first confirm the spelling of first and last names in the Morningstar data by comparing them with the fund company's annual report or the fund company's website. From the same sources, I try to find the fund manager's age or year of birth. If this is not possible, I narrow down the age range by using information about the person's career from Morningstar. I assume that active fund managers are between 25 and 67 years old. For example, if the fund manager has been active as a fund manager for ten years and is active to this date, I adjust the age range to 35 to 67 years. I search the internet for information on recruitment, fund performance, career history, LinkedIn profiles, pictures, comments in annual reports, and so on. This search may provide additional information about year of graduation and earlier jobs. For example, information about an earlier job can make it possible to further increase the minimum age of the fund manager. I flag managers with inconsistent spelling, for example between the fund report and Morningstar. When there are obvious spelling mistakes or erroneous data entry of manager names, I correct for it. Sometimes there is also confusion regarding which is the last name and which the first name, which I sort out using secondary sources, such as websites.

Based on the first name and last name, and if available the year of birth, I collect social security numbers using the websites www.upplysning.se and www.ratsit.se. In the best-case scenario, I find exactly one social security number that fits the first name, last name, and age bracket. For some first and last name pairs, I cannot find any social security number using our data source. I send these names as well as those with spelling inconsistencies to the Swedish Tax Authority. The tax authority investigates whether a person with that first and last name lives in Sweden at any time between 1995 and 2013 and reports back to us one of four possibilities: (i) tax and income information is present, (ii) the person has a social security number but is not paying taxes, (iii) there are more than 100 matches, or (iv) there is no match. In case (i), I receive the social security number. In cases (ii) and (iv), I am now certain that this manager was not a Swedish taxpayer at any point between 1995 and 2013, and therefore has had no labor income in Sweden. In case (3), I assign the manager as being "unidentified."

For many names and age ranges, I obtain multiple social security numbers. For some common names, I may get more than 50 matches on first name, last name, and age range. In such cases, if the manager is still active and I know her or her fund company's office is located in Stockholm, I refine the search to include only the greater Stockholm area. This may allow me to narrow down the number of socials to just one, in which case I get a perfect match, or it may leave me with multiple but fewer matches. If I still get more than 50 hits after including the area information, I classify the fund manager as "unidentified." Based on this procedure, 84 managers remain unidentified.

For these 84 managers I try to find information about which university they attended. If I find such information, I request the manager's transcript from the university in question. This transcript usually contains the social security number as well as the person's address. This allows me to obtain another 32 matches, reducing the unidentified ones to 52.

For managers with multiple candidate social security numbers, I rate each social security number in terms of how likely it is to belong to the fund manager in question. Any available information from websites or other places is used. The rating scale goes from 0 to 3, where 0 means no match at all and 3 represents the most reliable category. Along with this rating, I ask Statistics Sweden to provide information about occupation and industry of employment for each candidate social. I rank all observed occupations and industries based on their appropriateness on a scale from 1 to 3. I then construct an algorithm that picks the most appropriate social based on our rating, the occupation, and the industry. In most cases, it

Table A1: Sample selection criteria

Panel A: Sample selection	Managers	Funds
Morningstar sample 1990–2015		1,744
Drop "Team Management" and "Not Disclosed"	1,324	1,600
Present at some point during 2000–2008	862	1,103
Drop index, money market and pension funds	832	1,019
Assign social security number candidate	535	838
Uniquely identify social security number	383	664
Final sample		
Require nonmissing controls and fund alphas	363	556

The table shows how I arrive at the final sample. A fund is included in the sample if at least one of its managers is identified. In case of missing fund holding data, a manager is included in the sample if at least one of her funds has holdings data.

is evident which the best match is. In the few cases where there are ties, I ask Statistics Sweden to internally check whether the registered employer name matches with the fund complex registered in Morningstar Direct.

Table A1 shows how I arrive at the final sample used for the main regressions.

A.3 Benchmark and factor models

A.3.1 Morningstar prospectus benchmark

The main performance measure in this paper is the average abnormal return over the benchmark. Morningstar reports a Primary Prospectus Benchmark for 74% of the funds. Some funds have linear combinations of indices as their benchmark. There are more than 300 different benchmark indices present in the sample. I find monthly return information for most of them on Morningstar, Bloomberg, and Datastream. For funds with no assigned benchmark or an irretrievable benchmark, I assign a benchmark by hand.[36]

[36] In those cases, I use the Morningstar variable "Category", assigning the most common benchmark for that category to the remaining funds. When the benchmark is a linear combination of indices, and I lack return information on some of the component indices, I assign an alternative only to that component, keeping the other components and the index weighting.

A.3.2 CAPM

For Equity, Alternative, and Allocation funds, the CAPM model employs a one-factor market model with the Swedish all-share index (SIXPRX) in excess of the one-month STIBOR rate as the market proxy. For Fixed Income and the rest, I use the Swedish government bond index return (OMRX) in excess of the one-month STIBOR as the CAPM market factor.

A.3.3 FF4

The Fama and French four-factor model (Fama and French, 1993; Carhart, 1997) has the stock market factor, the size factor (SMB), the value factor (HML), and the momentum factor (MOM). These are constructed from all Swedish stocks and are the same as in Betermier, Calvet, and Sodini (2017).

All returns are converted into Swedish krona.

B Berk and Green Model Simulations

B.1 Baseline model

In Berk and Green (2004) managers have skill alpha that is unknown to both managers and there exists a decreasing returns to scale technology such that fund returns decline with fund size. Alpha can be interpreted as the return on the first dollar the manager invests. Rational bayesian investors update their beliefs about managerial skill by observing past abnormal returns. They allocate assets according to their beliefs such that in equilibrium the expected excess return on their investment is zero. Since fund returns are a decreasing function of assets under management, large (low) past returns leading to inflows (outflows) do not imply large (low) future returns. Thus, the model can replicate both a positive flow-performance relationship and an absence of persistence in fund returns when sorting on past returns.

Specifically, investors' priors about unobserved managerial skill α follow a normal distribution with prior mean ϕ_0, prior standard deviation η, and hence prior precision $\gamma = \frac{1}{\eta^2}$. That is, $\alpha \sim N(\phi_0, \eta^2)$. The return before costs R_t^{abn} is $R_t^{abn} = \alpha + \epsilon_t$ where the residual return ϵ_t follows a normal distribution, $\epsilon_t \sim N(0, \sigma^2)$ with precision $\omega = \frac{1}{\sigma^2}$. Because of decreasing returns to scale and management fees, however, investors only earn $r_{t+1} = h(q_t)R_{t+1} - c(q_t)$, where q_t is fund size, $c(q_t)$ is the unit cost function including management fees, and $h(q_t)$ is the fraction of assets the fund chooses to actively manage. Note that the management fee is earned on total assets, whereas only the fraction of actively managed assets impacts returns via the decreasing returns to scale technology. In equilibrium, investors flow assets in and out of funds such that their expected excess return going forward is zero, that is $E_t[r_{t+1}] = 0$.

Let $\phi_t = E[R_{t+1} \mid R_t, R_{t-1}, ...]$ denote investors posterior belief about managerial ability given the data. By using a simple Kalman filter argument, beliefs follow the recursion

$$\phi_t = \phi_{t-1} + \frac{r_t}{h(q_{t-1})} \left(\frac{\omega}{\gamma + t\omega} \right) \tag{B1}$$

And equilibrium fund size is implicitly given by

$$\frac{c(q_t)}{h(q_t)} = \frac{c(q_{t-1})}{h(q_{t-1})} + \frac{r_t}{h(q_{t-1})}\left(\frac{\omega}{\gamma + t\omega}\right) \tag{B2}$$

As in the original BG calibration, I assume a quadratic total cost function $C(q) = aq^2$. BG then show that the growth in assets follows:

$$\frac{q_t - q_{t-1}}{q_{t-1}} = \begin{cases} -1 & \text{if } \; r_t < 2\left(\frac{\bar{\phi}-\phi_{t-1}}{\phi_{t-1}}\right)\left(\frac{\gamma+t\omega}{\omega}\right) f \\ \frac{r_t}{f}\left(\frac{\omega}{\gamma+t\omega}\right) + \frac{r_t^2}{4f^2}\left(\frac{\omega}{\gamma+t\omega}\right)^2 & \text{otherwise.} \end{cases} \tag{B3}$$

The first part of this equation implies that funds shut down whenever $\phi_t < \bar{\phi}$, that is when perceived skill is below some threshold. Whenever that happens, fund size is below the threshold that is required to recover the fixed costs of running a fund.

B.2 Managers being certain about their skill

The baseline model assumes that both managers and investors are uncertain about managerial skill. In this appendix, I allow managers to be certain about their skill and discuss the resulting implications in light of the model.

First, Equations (B1)–(B3) follow from the assumption that funds optimally choose the management fee, or equivalently, that fees are fixed and funds optimally choose the fraction of assets they actively manage. For my paper, to be consistent and leave managers' portfolio choice problem largely unmodeled (which includes both decisions on the personal and the fund level), perhaps the easiest way to think about the manager's problem is to envision an additional entity, e.g. a risk-neutral fund family, that maximizes fee revenue and decides on the management fee. Fees are then exogenously given for the manager. After the fee is set by the fund family, a risk-averse manager solves her (unmodeled) personal portfolio choice problem observing deviations from efficient size.

I now show that being certain about managerial skill is equivalent to being certain about efficient size, and that a manager being certain about her skill in general faces a positive alpha opportunity.

Proposition 1. *Knowing true managerial skill α is equivalent to knowing efficient fund size.*

Proof. Follows from the one-to-one relationship of skill and fund size. From the cost parametriziation $C(q) = aq^2$ and the fund's optimal choice of fee resulting in the condition $\phi_t = C'(q_t^*)$, the amount of actively managed assets is given by $q_t^*(\phi) = \frac{\phi_t}{2a}$. Efficient size is fund size if all parameters of the model were known, and managerial skill is the only unknown parameter. Fund size, or more precisely the amount of actively managed assets, if all parameters of the model were known is then $q_t^{eff} = \frac{\alpha}{2a}$. □

Proposition 2. *Knowing true managerial skill α triggers personal investments unless $\phi_t = \alpha$.*

Proof. Abnormal returns are given by $r_{t+1} = h(q_t)R_{t+1} - c(q_t)$. From the parametrization of the cost function and the resulting expressions for $h(q_t)$ and $c(q_t)$, it follows that $E_t(r_{t+1}|\alpha) = 2f(\alpha/\phi_t - 1)$. Hence, expected abnormal returns are positive whenever $\alpha > \phi_t$ and negative whenever $\alpha < \phi_t$. From classic portfolio choice models, it is easy to show that positive expected abnormal returns trigger positive investment, whereas negative expected abnormal returns trigger divestment. $\square$

I leave several aspects of the managers' portfolio choice problem unmodeled. First, theoretically managers face an arbitrage opportunity if they know their level of skill when investors do not. In principle, they would want to borrow money and invest the proceeds in their funds in case size is below efficient size, and short the fund in case size is above efficient size. In practice, managers face various constraints (e.g. short-selling of mutual funds is not possible). I acknowledge these constraints by using information ratios as the main measure of fund performance. BG instead focus on plain alphas by assuming that investors can diversify away idiosyncratic risk. For a fund manager who invests in her own fund this assumption may be less reasonable anyway because after all her labor income is directly tied to the fund's performance. Moreover, the information ratio would be the relevant measure of performance for a risk-averse manager.[37]

Second, I do not model a manager's choice of how much to invest in the fund. In theory, a manager will trade of the size of her investment against deteriorating the return on that investment because of the decreasing returns to scale technology. In practice, managers' personal investments are trivial in relation to fund size and mutual fund managers likely do not face such a trade off.

Third, as mentioned extensively in the main text I rule out that managers can signal their personal investments to fund investors.

B.3 Calibration and simulation

The model is simulated as follows. I simulate one cohort of Berk and Green funds using their calibrated parameters as a baseline, which are shown in Table B1. The survival rate of funds after 20 years is on average 62% which closely matches the survival rate in the original paper. To construct Figure 1, I then randomly assign managers an amount they invest in their funds following a normal distribution with mean zero. I set negative values to zero forever. The standard deviation of the normal is chosen to roughly match the observed ownership mean of 30bps in the data. The amount invested conditional on being positive follows a random walk and is set to 0 forever whenever it becomes negative. The results are robust to how exactly the process for the amount invested is specified. I repeat the process 10,000 times and for each simulation run estimate regressions of fund returns on ownership (amount invested over fund size), fund size, and the amount invested. The distribution of t-statistics for the coefficient estimates are plotted in Figure 1.

To construct Figure 3, I simulate one cohort of Berk and Green funds using both the original and the alternative Swedish parameter specification. In Figure 3 Panels (b) and (c) I assign a dummy that equals one whenever actual fund size is below efficient size, that is

[37] Koijen (2014) develops a structural model and estimates a coefficient of relative risk aversion of 5.8 for fund managers.

Table B1: Parameter values

Variable	Symbol	Original calibr.	Alternative (Swedish) calibr.
Percentage fee	f	1.5%	1.5%
Manager skill prior precision	γ	277	10000
Manager skill std	η	6%	1%
Residual return precision	ω	25	100
Residual return std	σ	20%	10%
Mean of prior manager ability	ϕ_0	6.5%	3.25%
Exit mean	$\bar{\phi}$	3%	3%
Number of managers	N	5,000	500
Number of periods	T	20	10

size if all parameters of the model were known, and otherwise zero (equivalently the dummy equals one whenever perceived skill is below actual skill and vice versa). The economic interpretation is that a manager whose actual skill is above her perceived skill by investors invests in her fund.

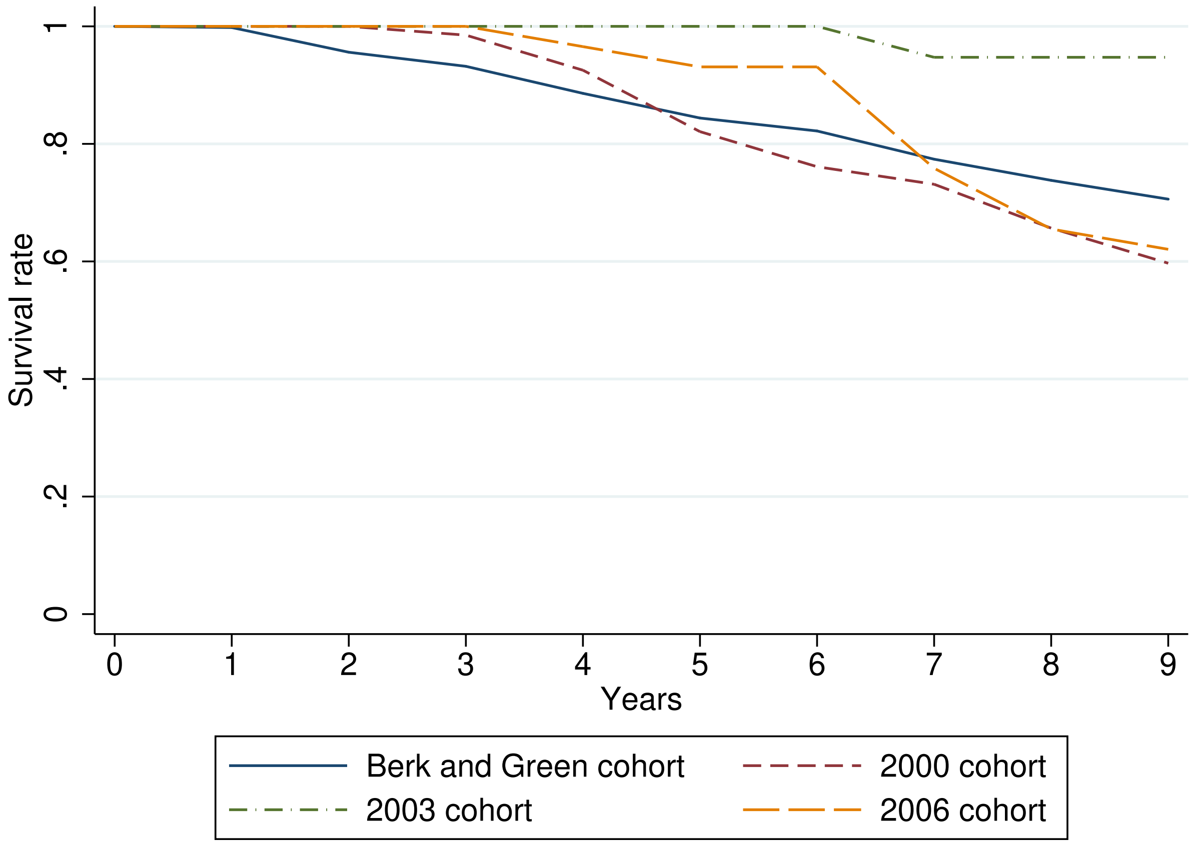
In Figure 3 Panels (e) and (f) funds are sorted according to past information ratios. Information ratios are defined as abnormal return over residual volatility. Residual volatility of a fund depends on the fraction of assets the fund optimally decides to index and is given by $\sigma_{\epsilon,t+1} = h(q_t)\sigma$. In the Swedish calibration, Berk and Green residual volatility σ is set to 10% to match the observed residual volatility in the data σ_ϵ of around 5%.

Berk and Green calibrate their model to match the positive flow-performance relationship and fund survival probabilities. Relative to the original calibration, the Swedish calibration has tighter priors around managerial skill to match a weak flow-performance relation and a weak performance gap between managers who invest in their funds and those who do not. To roughly match the survival probabilities of funds in the data, the mean of prior manager ability is lowered from 6.5% to 3.25%. The resulting model implied survival probabilities together with the actual survival probabilities for selected cohorts of funds are plotted in Figure B1.

C Investment Restrictions

Mutual fund managers may face trading restrictions in their personal accounts either by law or by corporate policies from the fund families that employ them. Not surprisingly, insider trading is prohibited by Swedish law. Moreover, the Swedish Securities Dealers Association, an association representing the common interest of banks and investment services firms active on the securities market, regularly publishes guidelines on employee trading. The historical documents (in English) can be found here: `http://www.fondhandlarna.se/regler-mm/anstalldas-vardepappers-och-valutaaffarer/historik`. Most, if not all, Swedish fund companies are in turn members of the Swedish Mutual Fund Association, and the Swedish Mutual Fund Association references the Dealers Association's guidelines. For the sample period, the guidelines are summarized as follows: (i) All employees shall notify

Figure B1: Survival rates



The solid line plots implied survival rates of funds for a cohort of funds with the Swedish Berk and Green calibration. The dashed lines shows the actual survival rates for selected cohorts of funds.

their employer of their own holdings, and those of closely related persons, of financial instruments and changes in such holdings; (ii) closing a position with a profit until 30 days have passed from when the position was initiated is prohibited (closing with a loss is allowed). There was no legislation or official recommendation requiring a fund manager to be invested in her own fund. Individual corporate policies may, however, deviate from these guidelines.

D Overlapping Holdings and Personal Portfolio Performance

Unfortunately, the personal wealth data is only observed once per year and the true return managers earn in their personal portfolios is, thus, unobserved. This appendix assumes fund managers follow a buy and hold strategy throughout the year in their personal portfolios.

D.1 Overlapping Holdings

Theoretically, directly investing in the fund and entirely replicating it in a personal account earns almost the same return (replicating in the personal account avoids paying the fund's management fee). Empirically, unsurprisingly managers never entirely replicate their funds in their personal accounts. The average fund has around 100 holdings, of which only a handful, if any, are held in a manager's personal account. Moreover, in contrast to managers who invest in their own funds, throughout Table 3 the evidence that managers who invest in overlapping holdings perform better with their funds is weaker. In Column (2) of Table 3, the standardized coefficient estimate for the amount invested in overlapping holdings is only 0.022 and not statistically different from zero.

Why do managers buy the same securities in their personal accounts and their professionally managed funds? Bodnaruk and Simonov (2015) find that managers perform well in overlapping holdings and argue that managers have an information advantage in these securities. Appendix D.2 provides some evidence for outperformance in overlapping holdings but the evidence is statistically weak.[38] Conceptually, an information advantage alone cannot explain the existence of overlapping holdings: in principle a manager with superior information could tilt her fund towards her best ideas, perhaps even with smaller trading costs, instead of buying the securities in her personal account. However, if she cannot tilt her fund further towards her best ideas, e.g. because of tracking error constraints, buying the securities in her personal account may be the optimal response.

Figure D1 and Columns (1)–(3) of Table D1 provide some evidence that managers tilt their funds towards securities that they also hold in their personal accounts consistent with the idea that managers are betting personal money on their high conviction ideas.[39] Panel (a) of Figure D1 plots the weight of a security in a fund conditional on whether the manager holds the security in her personal account or not and shows that overlapping securities feature a higher weight in the fund. Columns (1)–(3) of Table D1 show this formally and also include firm characteristics as controls. The firm characteristics control for liquidity (as measured by the average bid-ask spread in a year), market capitalization, book-to-market ratio, and CAPM beta (estimated relative to the Swedish index). In Column 2) of Table D1 a stock that is held in a manager's personal account has a 1% larger weight in the fund. In terms of characteristics, not surprisingly larger and more liquid stocks have larger fund weights. Moreover, growth stocks and stocks with larger CAPM betas tend to have larger weights. Columns (4)–(6) of Table D1 use the firm characteristics to explain a manager's decision to invest in overlapping stocks and to investigate whether overlapping stocks feature certain common characteristics (e.g. perhaps they are less liquid). In Column (5), overlapping stocks are larger stocks with a larger market beta, but there is no significant relation to the liquidity of a stock or its book-to-market ratio. Moreover, in untabulated results I find that 90% of overlapping stocks are domiciled in Sweden.

In sum, managers tilt their funds towards Swedish large cap stocks that are also held in

[38] Appendix D.3 examines whether managers front run their funds and the associated performance. Appendix D.4 examines the performance of managers in their entire risky portfolios, which is the focus of Bodnaruk and Simonov (2015).

[39] In the table, the sample is restricted to equities. The results in this subsection are similar on the intensive margin and if personal portfolio weights instead of fund weights are used (as in Panel (b) of Figure D1).

Table D1: Fund weights, overlapping holdings, and firm characteristics

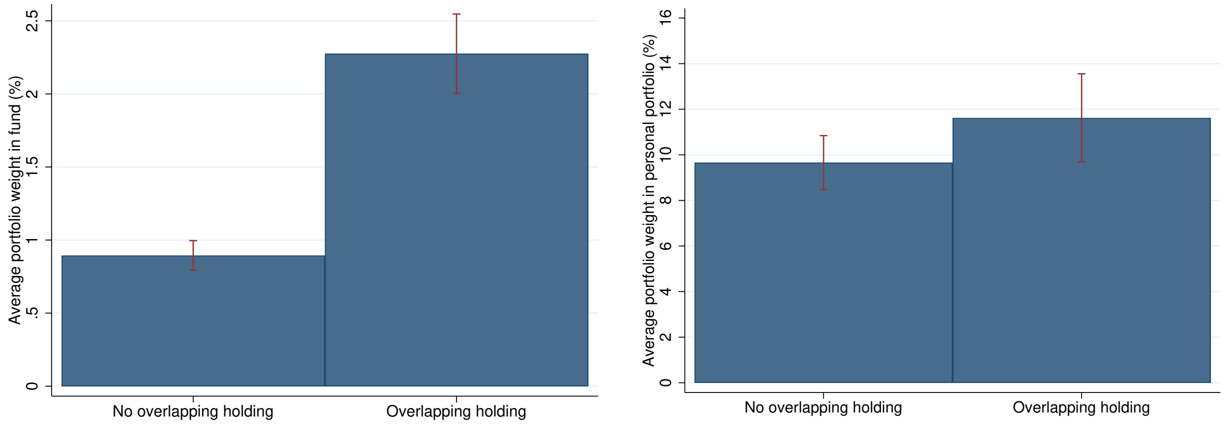
	(1)	(2)	(3)	(4)	(5)	(6)
	$Weight_{i,j,t}$	$Weight_{i,j,t}$	$Weight_{i,j,t}$	$Amount\ in\ OH_{i,j,t} > 0$	$Amount\ in\ OH_{i,j,t} > 0$	$Amount\ in\ OH_{i,j,t} > 0$
$Amount\ in\ OH_{i,j,t} > 0$	1.450***	1.045***	0.213**			
	(0.142)	(0.125)	(0.0995)			
$Bid - Ask\ spread_{j,t}$	-0.240*	-0.954**	-0.153*	0.0317	0.00409	0.00501
	(0.138)	(0.414)	(0.0814)	(0.0220)	(0.0106)	(0.00411)
$Market\ value_{j,t}$	0.000423***	0.000670***	0.000389***	-0.00000410**	0.0000108***	-0.00000392*
	(0.0000469)	(0.0000486)	(0.0000548)	(0.00000159)	(0.00000114)	(0.00000214)
$BM\ ratio_{j,t}$	-0.0167**	-0.0390***	-0.0243***	0.000786	0.000136	0.00140***
	(0.00838)	(0.0125)	(0.00455)	(0.000502)	(0.000377)	(0.000385)
$CAPM\ beta_{j,t}$	0.682***	0.169***	0	0.0512***	0.0261***	0
	(0.0466)	(0.0499)	(.)	(0.00452)	(0.00444)	(.)
Constant	0.196***			-0.0140***		
	(0.0502)			(0.00281)		
Year FE	No	Yes	Yes	No	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Category FE	No	Yes	Yes	No	Yes	Yes
Domicile FE	No	Yes	Yes	No	Yes	Yes
Security FE	No	No	Yes	No	No	Yes
N	84516	81408	81271	84516	81408	81271
Adjusted R^2	0.045	0.150	0.300	0.021	0.057	0.166

$Weight_{i,j,t}$ is the weight of security j (identified by an ISIN) in fund i at the end of year t in percent, that is the amount invested in the security by the fund divided by fund size times 100 (fund weight). $Amount\ in\ OH_{i,j,t} > 0$ is a dummy for overlapping holdings, i.e. whether the manager(s) of fund i invest personal money in security j at the end of year t. $Bid - Ask\ spread_{j,t}$ is the average bid-ask spread of security j in year t, $Market\ value_{j,t}$ its average equity market value in billions of SEK, $BM\ ratio_{j,t}$ its average book-to-market ratio, and $CAPM\ beta_{j,t}$ its capital asset pricing model beta estimated relative to the Swedish index. Controls include the fund-level controls from Table 3. The sample is restricted to equities and funds for which detailed holdings data is available. A stock's domicile is the country corresponding to the first two letters of its ISIN. Standard errors are clustered by funds.

Figure D1: Overlapping holdings weights

(a) Fund weights

(b) Personal portfolio weights



The figure plots the portfolio weights of individual securities in active mutual funds (Panel (a)) and managers' personal portfolios (Panel (b)) conditional on whether the manager holds the security in both her fund and her personal portfolio or not. The red bars indicate 95% confidence intervals.

their personal accounts. While these results are consistent with some managers thinking that they have an information advantage in these stocks coupled with tracking error constraints on the fund level, future research should try to rule out alternative explanations. For instance, absent clearer evidence on performance in overlapping securities the results could also be consistent with a simple home bias.

D.2 Performance in overlapping holdings

To assess performance in overlapping holdings, I first compare a manager's performance in overlapping holdings relative to positions that are not overlapping in her personal portfolio. Specifically, for a given manager I estimate the following factor regression:[40]

$$R^{p,OH}_{m,s} - R^{p,-}_{m,s} = \alpha^{FF4}_{m} + \beta^{FF4,\prime}_{m} FF4_s + \epsilon^{FF4}_{m,s} \tag{D1}$$

where $FF4_s = \begin{bmatrix} MKT_s & SMB_s & HML_s & MOM_s \end{bmatrix}'$, $r^{p,OH}_{m,s}$ is the value-weighted portfolio return of the subportfolio of overlapping holdings in her personal account each month, and $r^{p,-}_{m,s}$ is the value-weighted portfolio return in a manager's personal portfolio excluding overlapping holdings and investments in her own funds in each month. Personal portfolio data is observed at the end of each year, whereas fund holdings (which are used to determine overlapping holdings) are usually observed quarterly. I assume that the composition of personal portfolios is unchanged from one year to the next and that the composition of fund portfolios is unchanged from one quarter to the next (buy and hold assumptions).

[40] I require at least 12 monthly observations to estimate the coefficients.

The alpha in Equation D1 exists for 123 managers and is on average positive at 3.3% (FF4) and 0.7% (CAPM). While these estimates are economically large, none of the alphas is statistically different from zero.

Next, I compare a manager's performance in overlapping holdings relative to her fund's performance. Since a manager can manage multiple funds and funds can be team managed, I define a manager's monthly return in her professionally managed funds as the value-weighted average of the returns in her funds:

$$R_{m,s} = 1/AUM_{m,s-1} \sum_{i=1}^{N_{m,s-1}} \frac{AUM_{i,s-1}}{N_{i,s-1}} R_{i,s} \tag{D2}$$

I then estimate the factor regression:

$$R_{m,s}^{p,OH} - R_{m,s} = \alpha_m^{BM} + \beta_m^{BM}(R_{m,s}^{BM} - R_{f,s}) + \epsilon_{m,s}^{BM} \tag{D3}$$

where $R_{m,s}^{BM}$ is defined similar as in Equation D2. The alpha in this regression measures how much more or less risk-adjusted returns fund investors—all else equal—had earned had the fund's portfolio been exchanged with the subportfolio of overlapping holdings in a manager's personal account. The alpha in Equation D3 exists for 127 managers and is on average positive at 135 basis points, but again not statistically different from zero.

An alternative way to assess performance in overlapping holdings is to evaluate performance on the individual security level before individual security returns are aggregated to form a portfolio return. While such tests have more power, the caveat is of course that a manager may outperform with a subset of individual securities but that the outperformance disappears in her portfolio because the subset of outperforming securities enters with an insufficient portfolio weight. I estimate alphas and information ratios over the entire period an individual security is held in a manager's personal portfolio, conditional on whether the security was also held in a manager's fund or not. The focus is not on whether overlapping holdings do better than a factor model but whether they do better than non-overlapping holdings. Figure D2 plots the alphas and information ratios for the three factor models and shows that overlapping holdings consistently do better than non-overlapping holdings. All differences in means are statistically significant at least at the 10% level.

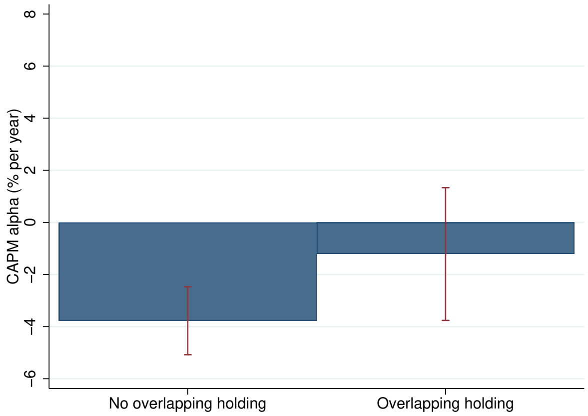
In conclusion, there is evidence that managers have superior information about individual securities when they invest in overlapping holdings and that they tilt both their personal and professional portfolios towards overlapping holdings. Potential reasons for why managers do not tilt their portfolios further towards their best ideas may be regulatory diversification or tracking error constraints.

D.3 Front running

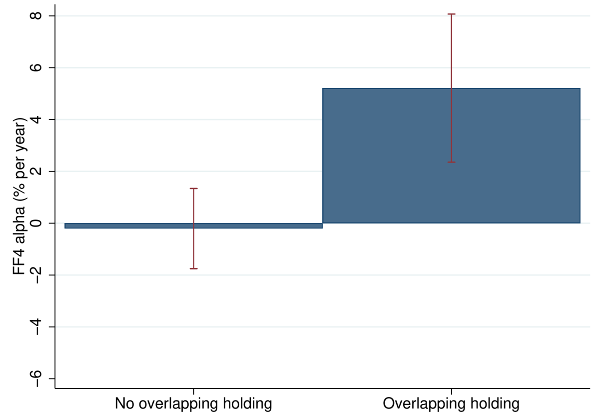
The previous subsection has indicated that managers perform particularly well in the stocks in their personal portfolios that overlap with their professionally managed funds. This suggests that managers are particularly well informed about a subset of stocks, but it also raises concerns of insider trading. This subsection investigates whether managers front run their funds, that is whether they buy individual stocks in their personal portfolios which

Figure D2: Performance individual security level

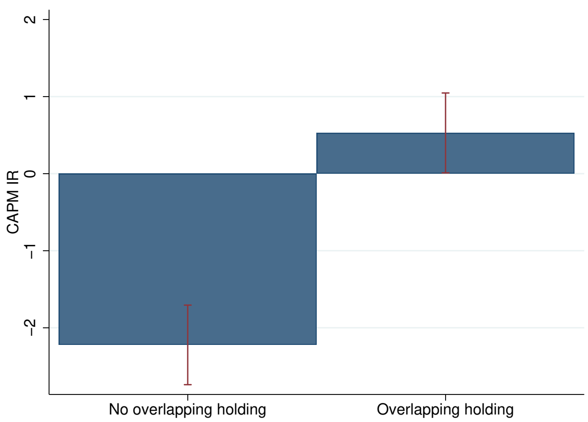
(a) CAPM alpha



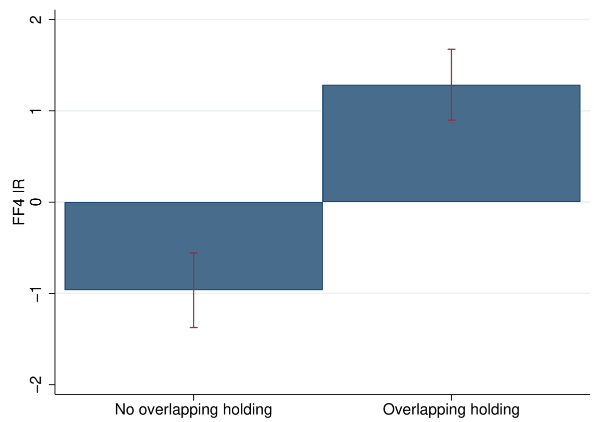
(b) FF4 alpha



(c) CAPM information ratio



(d) FF4 information ratio



The figure plots alphas and information ratio relative to different factor models. Alphas and information ratios are estimated over the entire period a manager holds a particular security in her personal account, conditional on whether the security is also held in her professionally managed fund or not. Because personal portfolios are only observed at the yearly frequency and fund holdings at the quarterly frequency, all missing intermediate monthly data is imputed using a buy and hold assumption. The red bars indicate 90% confidence intervals with standard errors clustered at the manager level for the test that the means are different from zero allowing for different residual variances across the two groups.

are then at some later point in time also bought by their funds. While just investing in stocks that are also held by one's fund may be technically legal, front running one's fund would almost certainly be classified as insider trading in most jurisdictions. The caveat of the analysis in this appendix is the frequency of observations. While fund holdings are observed quarterly, personal portfolio holdings are only observed at the end of every year. I classify a manager as front running her own fund if an individual security appears in her personal portfolio for the first time at the end of year $t-1$ (which means that it could have been bought at any time during $t-1$) and is then bought by at least one of her professionally managed funds over the course of year t. Surprisingly, according to this definition around 50 managers front run their funds at least once over their careers. Managers do extraordinary well if they front run. The average four-factor and CAPM alphas over the course of year t for a security that is held in a manager's personal portfolio at the end of year $t-1$ and then bought by her fund over the course of year t are 9.21% and 7.23%, respectively. Likely due to the very small sample size, these differences are, however, again not significantly different from zero in a statistical sense. Front running potentially comes at the cost of fund investors and these findings, although not part of the main contribution of this paper, should leave more than a bad taste in the mouths of investors and regulators.

D.4 Entire personal portfolio

Personal portfolio returns are a value-weighted average of individual stock and fund positions. Specifically, I estimate a personal portfolio alpha similar to Equation 4. The benchmark model to estimate alphas is the Swedish four-factor model. Across 1,281 manager-year observation and with standard errors clustered by manager, the average four-factor alpha is 1.5% and statistically different from zero at the 5% level, whereas the the average information ratio is on average –0.055 and not statistically different from zero. Personal portfolio performance, however, depends on the benchmark model employed to risk-adjust returns. Alphas relative to a simple Swedish market model are on average negative at –3.34% (information ratio –1.03), both statistically different from zero.