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 more often 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 value to fund investors relative to a comparable passively managed fund (see, e.g. 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. 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 attempts to fill this void and 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 subsequently outperform relative to managers who do not. I then interpret the

[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), and Franzoni and Schmalz (2017).

[3] There is of course a vast literature that investigates whether fund managers have skill. Evidence for managerial skill is among other studies provided in Pástor and Stambaugh (2002), Kacperczyk et al. (2005), 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 whether managers have private information about their level of skill ex-ante.

results through the lens of an extended BG model in which managers—in contrast to regular investors—are certain about their ability to earn abnormal returns (henceforth "ability") and invest their personal wealth accordingly.

The data come from a unique data set containing detailed personal, non-public (i.e. private) wealth data of 361 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 the vast amount of capital allocated to mutual funds by regular investors, more than 60% of the managers do not invest their own money in their own funds. The funds at which managers do invest their personal money subsequently outperform relative to the funds with no managerial investment. Controlling for wealth differences, a one million Swedish Krona (≈ $150,000) increase in the amount managers invest in their own funds is associated with a 0.07 larger information ratio (IR) estimated relative to the benchmarks stated in the fund's prospectus.[4] Much of the variation of fund performance to personal investments is driven by cross-sectional differences across funds, but even for a given fund years of larger managerial investment are associated with a better performance in the subsequent year.

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 managers to publicly file personal investments in their own funds.[5] Using U.S. data, the previous literature has investigated the relationship between fund performance and managerial commitment for mutual funds (Khorana et al., 2007; Evans, 2008), private equity funds (Robinson and Sensoy, 2013), and hedge funds

[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] 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.

(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, this paper focuses on the actual amount a manager invests in her own fund.[6] Inferring a positive relationship between managerial ownership and fund performance can be misleading whenever fund size is 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, indicating a positive relationship where there really is none. The reason is simple: In a BG world, in within-fund regressions fund size negatively predicts future performance.[7] 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.

In the regressions of fund performance on the amount a manager invests in her fund, ultimately, we would like to know whether the coefficient estimate on the amount has a causal interpretation or whether it is biased. There is good reason to believe the coefficient estimate is biased. The alternative to a moral-hazard interpretation (the coefficient estimate is causal) is self-selection (the coefficient estimate is not causal): managers who know they are able to earn abnormal returns invest in their funds and then indeed they earn abnormal returns. Unfortunately, in the absence of any quasi-random assignment of the amount invested I cannot provide evidence on the size of the bias. However, I do, first, provide evidence that self-selection matters. Over the sample period, the regulator indicated no requirement or recommendation for fund managers to invest in their own funds, and the positive relationship between fund performance and personal investments exists within a fund family, ruling out

[6] 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.

[7] 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).

the fund family as the sole determinant of the amount managers invest in their funds.[8] Second, the main results are consistent with an asymmetric information BG equilibrium which by construction has no room for any moral hazard.

BG assume that both managers and investors are uncertain about a manager's skill and need to update their beliefs from past returns. The positive relationship between fund performance and managers' personal investments can be rationalized once managers are certain about their level of skill. In a BG world, there exists a one-to-one mapping between a manager's skill and fund size. A manager knowing her skill compares equilibrium fund size with actual fund size and invests in her fund and earns an abnormal return whenever actual fund size is below equilibrium fund size. Thus, the positive relationship between managers' personal investments and fund performance. Note that there is an important distinction between a manager's skill and her ability to earn an abnormal return, the latter being the return ultimately paid out to investors. In fact, a manager can be highly skilled but not be able to earn a positive abnormal return (whenever fund size is above its equilibrium size).[9]

The above reasoning, however, relies on some simplifying assumptions. The most important one 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 sending a signal to investors to attract assets which ultimately increase a manager's compensation but also deteriorate the return on her invested capital. In some sense, the fact that the data is not publicly observed is crucial: in equilibrium there is no room for publicly available information to predict abnormal returns. I do not find

[8]European mutual funds, including the vast majority of Swedish funds, are commonly regulated under the UCITS directives. As of 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.

[9]Suppose the decreasing returns to scale technology is the same for all managers. This is in fact the original Berk and Green (2004) parametrization. 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.

evidence that managers who invest in their funds attract more assets which does not provide conclusive evidence but is at least consistent with the assumption. Second, to justify a linear relationship between the amount invested and fund performance I assume that managers' personal investments in their funds do not count towards equilibrium fund size and thereby deteriorate returns. If a manager's personal investment were to count towards equilibrium size, a manager would face a similar tradeoff as above and the shape of the performance-investment relationship would be unclear. Given that managers' personal investments are trivial in relation to fund size, this assumption appears reasonable for mutual funds. The average investment, conditional on a positive investment, is 33,000 SEK ($40,000) while average fund size is 2,150 million SEK ($320 million). Finally, under these two assumptions managers face an arbitrage opportunity in case they know their level of skill. In principle, they would want to borrow unlimited amounts and invest the proceeds in their funds in case size is below its equilibrium, and short the fund in case size is above its equilibrium. In practice, managers face various constraints. For instance, obviously short selling of mutual funds is not possible. I do not model managers' constraints. Instead, I assume the amount managers invest is a result of their (unmodeled) portfolio choice and in the empirical analysis I focus on a fund's information ratio as the measure of fund performance. The information ratio is a more relevant measure of performance for a constrained, risk-averse investor compared with simple abnormal returns. For instance, a CARA-Normal investor does not allocate unlimited amounts to a positive alpha asset but $Amount = (1/\tau)\alpha/\sigma_\epsilon^2$ where τ is the coefficient of absolute risk aversion and α/σ_ϵ is the information ratio.[10]

In the data there is a more subtle way for a manager to gain exposure to her fund's return. In contrast to the managers who directly invest in their own funds, some managers decide not to earn their entire fund's return on their personal capital by investing in their

[10]There are few papers that theoretically study the portfolio choice problem of fund managers who can invest both personally and professionally. A notable exception are Kaniel et al. (2017).

funds but to buy individual components of their funds in their personal accounts (overlapping holdings, OH). Bodnaruk and Simonov (2015) show that managers do well in picking overlapping holdings.[11] In an appendix, I confirm their results and show that 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). I find no conclusive evidence that the amount invested in overlapping holdings is associated with better fund performance.

Next, I examine persistence in fund performance over time. 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, suggests a larger performance difference between the two groups of managers. Specifically, the aforementioned 0.07 coefficient estimate for the information ratio only implies a 0.1 larger t-statistic of alpha for a one-standard-deviation increase in the amount invested which, given a conventional significance level of 1.96 defining a "good" manager, is too small relative to implied value in the original calibration. 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 small performance difference and a weak flow-performance relationship. The simple equilibrium model with asymmetric information can explain the main facts in the data but it struggles to explain at least one other fact. While the fact that both groups of managers earn negative information ratios relative to the benchmark can be rationalized once the assumption of a benchmark return that is achievable at zero cost is relaxed, there is some persistence in performance when sorting on past performance where there really should be none. The model can only generate this persistence

[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.

once the assumption of rational expectations is dropped.[12]

I make two main contributions to the aforementioned literature on fund manager commitment and performance. First, I highlight that inferring a positive relationship between managerial ownership, defined as absolute investments over fund size, and fund performance may be misleading whenever fund size is correlated with fund performance even when fund size is separately controlled for. In a BG world, fund size naturally predicts future performance to the econometrician's eye because of the decreasing returns to scale technology. Second, I show that the main empirical facts are consistent with an asymmetric information equilibrium model in which managers, in contrast to regular investors, are certain about their ability to earn abnormal returns.

The rest of this paper is organized as follows. Section 2 motivates the main specification. Section 3 describes the data and methodology. 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 compares the data to model implied persistence. Section 6 discusses the possibility of managerial investments being used as a signal and reasons that making the data on managers' personal investments publicly available leads to a pooling equilibrium which ultimately decreases the size of the active fund industry. Section 7 provides robustness tests. Finally, Section 8 concludes.

2 Main Specification and Argument

The previous literature regularly estimates a correlation between managerial ownership, defined as the amount invested over fund size, and fund performance. For instance, Khorana et al. (2007) document a 2.76- to 3.65 percentage point increase in annual (four-factor) alpha

[12]Roussanov et al. (2018) extend the BG model to include marketing expenses and costly investor search to rationalize that many 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.

for every one-percentage-point increase in ownership. In untabulated results, I find a similar and significant coefficient estimate of 2.25 for the Swedish sample.

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 A contains the details. 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 definition entirely driven by fund size. Controlling for fund size (Figure 1 Panel (b)) mitigates the problem but does not eliminate it. BG focus on the evolution of returns and size for a given fund but such mechanical correlations may arise more generally in the cross-section if managers of different ability are matched to different fund sizes.

Because a similar argument can be made against scaling the amount by wealth if wealth is correlated with fund performance (Pool et al. (2017) make a similar argument when studying the impact of managerial housing wealth shocks on fund risk taking), my main specification has the amount invested as the main independent variable while controlling for both net wealth and fund size separately:

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

Where $\widehat{IR}_{i,t}$ is a fund's information ratio and $X_{i,t-1}$ is a vector of controls. In a BG equilibrium, no publicly available variable can predict abnormal performance in real time. If it did, rational 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 equilibrium size.[13] Therefore, to an econometrician looking at the data ex-post any variable that enters significantly in Equation 1 has to be correlated with deviations from equilibrium size.

A positive and significant coefficient δ_1 on the amount a manager invests in her own fund can be rationalized fairly simple once managers—in contrast to regular investors—are certain about their skill, thus equilibrium fund size, and thus deviations from equilibrium fund size. A manager being certain about her fund's equilibrium size invests in her fund whenever her fund runs below equilibrium size and otherwise not. Hence, her investment reveals deviations from equilibrium size and enters significantly in Equation 1. As mentioned in the introduction, the key assumption underlying this argument, however, is that managers' investments in their own funds do not decrease deviations from equilibrium size either directly through the actual investment or indirectly through attracting fund flows. The former assumption is, however, only needed to justify a linear relationship between performance and managers' investments.[14]

Following Kosowski et al. (2006) and Fama and French (2010) the main measure of fund performance in Equation 1 is a fund's information ratio, which scales a fund's alpha in a given year ($\alpha_{i,t}$) by its residual volatility ($\sigma_{\epsilon,i,t}$). BG instead focus on plain alphas by assuming that investors can diversify away idiosyncratic risk.[15] For a fund manager

[13] BG show that 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 devations of the assets a manager actively manages from equilibrium size. Since the time-varying fee contract is counterfactual, the simulations in this paper use the fixed fee contract. This is also one of the reasons 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 equilibrium size. For a zero coefficient estimate on ownership, however, one would need to control for both total assets and the part of the assets that are actively managed.

[14] In the model, fund size maps one-to-one into managerial skill. A manager whose actual skill is above her perceived skill by investors invests in her fund and vice versa. The abnormal return she expects to earn, given that she knows her level of skill α, is $E_t[r_{t+1}|\alpha] = 2f\,(\alpha/\phi_t - 1)$ where f is the management fee and ϕ_t is perceived skill by investors.

[15] Pástor and Stambaugh (2012) relax this assumption by explicitly considering the portfolio choice problem

who invests in her own fund this assumption is less reasonable because after all her labor income is directly tied to the fund's performance. Perhaps the easiest way to think about the manager's problem is to envision an additional entity, a risk-neutral fund family, that maximizes fee revenue and decides on the management fee.[16] After the fee is set by the fund family, a risk-averse manager solves her (unmodeled) personal portfolio choice problem observing deviations from equilibrium size. In that case, the information ratio is a more relevant measure of performance for the constrained, risk-averse managers compared with simple abnormal returns.

3 Data

3.1 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 B.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 belonging to 91 fund companies (identified by Morningstar's

of mean-variance investors.

[16] The fund family would correspond to the "manager" in the original BG terminology.

"BrandingName" variable). 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. Unfortunately, around 180 funds for sale in Sweden or the Nordic region are not domiciled in Sweden and, thus, no holdings data is available.[17]

3.2 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 B.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

[17] 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.

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 cash in bank accounts, real estate ownership, and outstanding debt. Returns and prices for non–mutual fund Nordic personal holdings up to 2009 are retrieved from the FINBAS database. For securities not covered by FINBAS, I use Datastream and Morningstar.

The raw data include 832 managers, but the final sample contains only 361 managers. Many of the manager names are Finnish, Danish, or Norwegian and likely stem from the inclusion of Nordic cross-borders funds. The final sample contains 556 funds. Table B1 shows in detail how I arrive at the final sample.

3.3 Definitions

A fund's monthly gross return is its monthly net return plus the annual TER divided by 12. Returns are net of costs unless otherwise indicated. A manager's personal risky financial wealth (risky portfolio) is 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).

3.4 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:

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

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

$$Wealth_{i,t} = 1/N_{i,t} \sum_{m=1}^{N_{i,t}} Wealth_{m,t} \tag{4}$$

where $Amount\ in\ OH_{m,i,t} = \sum_j (w_{i,j,t} \times Amount\ in\ OH_{m,i,j,t})$ and $w_{i,j,t}$ is the weight of security j in fund i.

To assess yearly fund performance, I estimate a standard factor regression year-by-year:[18]

$$R_{i,s} - R_{f,s} = \alpha_i^{BM} + \beta_i^{BM}(R_{i,s}^{BM} - R_{f,s}) + \epsilon_{i,s}^{BM} \tag{5}$$

where s indicates a month, $R_{i,s}$ is the net fund 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

[18] To estimate the coefficients, a full set of 12 monthly observations is required. This approach is slightly different from the one used in Ibert et al. (2018) to keep the regressions predictive. They estimate betas over the whole sample and then compute abnormal returns within a year.

the ultimate reason why investors pay a fee to the manager.[19] Appendix B.3 provides details about the prospectus benchmarks and describes alternative benchmark/factor models. Unfortunately, I lack data on passive funds tracking the benchmarks to gauge the cost of achieving a particular benchmark return. Finally, a fund's information ratio is estimated as the empirical counterpart of $\alpha_{i,t}/\sigma_{\epsilon,i,t}$.

3.5 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 investment, conditional on a positive investment, is 33,000 SEK ($40,000) while average fund size is 2,150 million SEK ($320 million) (untabulated). Given that managers' personal investments on average account only for a tiny proportion of fund size, the assumption that managers' personal investments do not count towards equilibrium size appears reasonable. Table 2 shows summary statistics for data aggregated to the manager level.

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. Two facts stick out. First, fund managers invest a larger fraction of their financial wealth in risky assets than the average Swede which is consistent with Calvet, Campbell, and Sodini (2007) who find that financially sophisticated investors invest more aggressively. Second, whereas the average Swede's risky portfolio consists mainly of mutual funds, fund managers invest a sizable part of their financial wealth directly in the stock market. Panel (c) decomposes managers' risky assets further into professionally

[19] See Dahlquist, Engström, and Söderlind (2000) and Flam and Vestman (2014) for earlier studies of fund performance in Sweden.

managed funds by the very same manager, funds from the same fund family, unrelated funds, overlapping stocks, and finally 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.[20] 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 investments publicly and I have found no indication that they do so voluntarily in the funds' prospectuses.

4 Fund Performance and Managerial Commitment

4.1 Main results

This section estimates versions of Equation 1. The vector of controls $X_{i,t}$ 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.

Column (1) of Table 3 shows the main specification without controls and with fund and year fixed effects turned off. A one million SEK increase in the amount a manager invests in her fund in a given year is associated with a 0.08 larger information ratio in the following year.[21] Column (2) of Table 3 shows that the positive relationship between personal

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

[21] The results are robust to winsorizing the amount invested and information ratios at the 1 and 99% levels. The results are also robust when standard errors are clustered by fund family.

investments and fund performance survives the inclusion of the control variables.

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 (quasi-) random assignment in the amount invested, I cannot establish the size of a potential bias. Instead I, first, provide evidence that self-selection matters, and, second, provide an interpretation based on a model without any moral hazard.

First, if the cross-sectional dispersion in personal investments was not driven by self-selection according to ability, there would remain few players that could induce the observed cross-sectional dispersion. More specifically, some fund families may require managers to invest in their own funds. For instance, the requirement to invest personal wealth is a common feature of hedge fund firms or private equity firms. Column (3) of Table 3 shows that the results are not driven by such fund family fixed effects. Even if they were, the matching of managers to fund families is unlikely to be exogenous but likely based on managerial skill.

Second, in a BG equilibrium with asymmetric information a manager invests in her fund whenever she expects a positive abnormal return, which generally happens when the fund runs below equilibrium size. The fact that some managers invest in their funds, thus, suggests that they believe their funds run below equilibrium size. The fact that these managers do better suggests that their beliefs are accurate.

Another implication of the equilibrium is that to the econometrician's eye fund returns decline with fund size. Since fund size is unlikely to be randomly paired with managerial skill, the literature on decreasing returns to scale nowadays estimates a fund fixed effects specification and finds evidence of decreasing returns to scale for actively managed mutual funds (see, e.g. Pástor et al., 2015; Zhu, 2018). Column (4) of Table 3 includes fund fixed effects and finds a negative coefficient estimate on fund size for the Swedish sample, too. The coefficient on the amount invested also survives the inclusion of fund fixed effects. The equilibrium interpretation of the fixed effects specification is that managers increase the exposure to their own funds in times when fund size is further away from its equilibrium and vice versa.

Interestingly, while the total capital allocated to a fund by regular investors deteriorates fund performance, the total amount *all* fund managers in the sample allocate to a particular fund, excluding the manager(s) who manage the fund, correlates positively with fund performance (untabulated). Thus, there is some evidence that fund managers as a group are able to identify an outperforming fund even when the fund is not their own. The relevant coefficient estimate in a specification similar to Column (2) of Table 3 is 0.15 with a t-statistic of 2.

4.2 Overlapping holdings

Theoretically, directly investing in one's own fund and entirely replicating one's own fund buy buying all individual components in one's personal account is equivalent in terms of the return on the invested capital. Replicating in one's own account may even avoid paying the fund's management fee.

Empirically, investing in one's own fund directly and replicating it in one's personal account capture two different aspects. First, 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. Second, in contrast to managers who invest in their own funds, throughout Table 3 there is no conclusive evidence that managers who invest in overlapping holdings perform better with their funds. The coefficient estimates are positive but not significant. On the other hand, Appendix D.1 shows that managers perform well in their overlapping holdings relative to holdings that do not overlap, which has been documented in Bodnaruk and Simonov (2015), and that managers tilt both their funds and their personal accounts towards overlapping holdings.[22] I conjecture that regulatory diversification or fund level tracking error constraints prevent some managers from tilting their funds even further towards their overlapping holdings. Investigating why some managers choose one (investing in overlapping holdings) over the other (investing in their funds) is beyond the scope of this paper and remains an interesting avenue for future research.

5 Persistence and Performance Relative to Benchmark

The BG equilibrium has several implications for the persistence of fund performance when sorting on managers' investments and past returns. 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.

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.[23] In the simulations, managers invest in their funds whenever fund size is below equilibrium 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 economically small. More specifically, in Column (2) of Table 3 the standardized coefficient estimate is 0.03, corresponding to a $\sqrt{12} \times 0.03 = 0.1$ larger t-statistic of alpha for a one-standard-

[22] Appendix D.2 examines whether managers front run their funds and the associated performance. Appendix D.3 examines the performance of managers in their entire risky portfolios, which is the focus of Bodnaruk and Simonov (2015).

[23] The confidence bounds in the figures test against the null that the means are equal to zero. The means in Panel (a) of Figure 3 across the two groups are also statistically different from each other (not shown).

deviation increase in the amount invested. Given a conventional significance level of 1.96 defining a "good" manager, a 0.1 increase is too small to match the performance gap in the original calibration.

The Swedish calibration 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 running above (below) equilibrium size is closer to its equilibrium size and the performance gap tightens. A higher precision about managerial skill compared to the original calibration also fits neatly with the weak flow-performance relationship in the data (see next section).[24] The shapes of Panel (c) and Panel (a) look similar which is one of the main points of the paper: the empirical results are consistent with a simple asymmetric information equilibrium model.

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.[25] 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 actually 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.

[24] A higher precision about managerial skill does, however, have implications for fund survival rates which naturally become larger relative to the original calibration. The Swedish calibration addresses this by lowering average managerial skill.

[25] 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.

The BG model is designed to explain the absence of performance persistence. Thus, how are the presented results consistent with the model? In a BG world past performance does not predict future performance. Other variables not observable to fund investors, however, may predict performance if they are correlated with deviations from equilibrium size. 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 again 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, suggesting investors ignore some of the information in past performance. The model could only generate the persistence in performance when sorting on past performance by departing from the assumption of rational expectations. In that case, investors' prior precision about managerial skill would be detached from the actual standard deviation of managerial skill. While investors' prior about managerial skill would be, thus, still right on average, they would be wrong, on average, about the dispersion of managerial skill. Investors with tight priors about managerial skill would then ignore some of the information in past returns and allow for persistence in performance when sorting on past performance.[26]

In sum, a BG equilibrium with asymmetric information matches the general patterns in the data. However, it cannot easily explain the persistence in performance when sorting based on past performance.

[26]Suppose for instance that investors are certain about managerial skill, that is their priors have infinite precision. Whenever not all managers have the same skill, that is there is some dispersion in skill, fund performance will be predictable. The reason is that investors assign the same fund size to all funds and never update, whereas the true equilibrium size is different across managers.

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 in their own funds. 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 credibly signal investments poses a threat to the reasoning in this paper so far because it introduces the possibility that managers invest in their funds for reasons not related to earning an abnormal return. While this possibility may seem natural, it changes the game and the empirical results can no longer be illustrated with the simple asymmetric information equilibrium model. Essentially, if managers can signal their investments they are facing a complicated trade off between attracting flows through signaling, deteriorating the return on their invested capital by attracting new assets, and revealing their type.

If managers can signal their investments, an intuitive prediction is that they attract more inflows and that they have lower flow-performance sensitivities as uncertainty about their type is resolved. Spiegel and Zhang (2013) argue that the typical convex percentage-flow-performance relationship (Chevalier and Ellison, 1997; Sirri and Tufano, 1998) is driven by unobserved heterogeneity across funds and that the true flow-performance relationship is in fact linear. I am primarily interested in the impact of managers' personal investments on fund flows, not on the impact of past returns. To remain consistent with the classic flow-performance literature I consider a fund's percentage flow:[27]

$$\%Flow_{i,t} = (AUM_{i,t} - AUM_{i,t-1} \times (1 + R_{i,t}))/AUM_{i,t-1} \times 100 \tag{6}$$

and I address unobserved heterogeneity by including fund fixed effects in selected specifications. In Equation 6, $AUM_{i,t-1}$ 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 4 shows regressions of fund flows on managers' investments in their own funds but, in short, find no evidence that more committed managers attract larger flows. The point estimates on the amount invested in own funds in Columns (1)–(5) are positive but insignificant. Columns (4) and (5) of Table 4 test 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 and the amount invested is negative but again not statistically different from zero.

The coefficient estimate on alphas in the previous year, $\widehat{\alpha}^{BM}_{i,t-1}$, in Column (2) is positive but not statistically different from zero either. In this case, the test does not reject the null almost certainly due to a lack of power. Both Ferreira et al. (2012) and Ibert et al. (2018) document a significant flow-performance relationship for Sweden using larger samples. Having assumed that flows occur at the end of the year, one may as well consider returns during the year, $\widehat{\alpha}^{BM}_{i,t}$, as the main independent variable. The coefficient estimates on alphas in Columns (5) and (6) become larger and significant, suggesting that flows respond to intrayear returns. In either case, the flow-performance relationship is economically weak. Even in Column (5) of Table 4, a 100% increase in alphas only leads to a 115% increase

[27] Flows are winsorized at the 1 and 99% level. Another 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.

in flows. Eyeballing the estimates of Chevalier and Ellison (1997) Figure 1, already a 20% excess return leads to the same percentage increase in flows.

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. A higher precision about managerial skill implies that flows are less responsive to past performance. Finally, at least part of the weak-flow performance sensitivity may be due to some funds being started before the start of the sample, that is before 1999. For such funds, investors naturally have a higher precision at the start of the sample, and thus flows respond less to performance.

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? In any equilibrium in which investment attracts non-negative flows, a manager who knows that her fund runs below equilibrium size invests in her fund because investing is a dominant strategy: The manager stands to win an abnormal return on her personal investment and to increase compensation by attracting assets. The assumption that managers' investments do not decrease deviations from equilibrium size, however, can no longer be sustained because their investments serve as a signal to attract flows. Thus, in determining the size of her investment the manager trades off increasing compensation versus a deteriorating abnormal return on her personal capital as fund size approaches its equilibrium. A manager who knows that her fund runs above equilibrium size is immediately revealed unless she pools and invests too. Revelation results in outflows as investors update their beliefs to take into account that no-investment funds run above their equilibrium size. Signaling, however, is costly for managers whose funds run above equilibrium size because they earn a negative abnormal return on their personal investment.

In sum, if the data were to made public managers whose funds run above equilibrium size would pool with managers whose funds run below equilibrium size and invest in their funds if the additional compensation through flows outweighs the negative return earned on their investment. If the cost of signaling is too high, a manager does not invest, her type is revealed, and she faces outflows. If the resulting fund size is too small to cover the fixed costs of running a fund, the fund shuts down. Therefore, making the data on managers' personal investments in their funds public would likely lead to a decrease in the number of funds in the economy and to a more efficient allocation of capital.

7 Robustness

7.1 Alphas

Table 5 replicates Table 3 but uses yearly fund alphas as the dependent variable. The results are robust. In Column (2) of Table 5 a one million SEK increase in the amount invested is associated with a 4 percentage points larger future annual fund alpha.

7.2 Alternative benchmarks, tracking error and value added

Table 6, Columns (1)–(5) replicate Column (2) of Table 3 but with information ratios estimated relative to the alternative benchmark models. The results are robust. Table 6, Column (6) predicts a fund's root mean square error (RMSE), more commonly known as tracking error, relative to the prospectus benchmark. Deviating from the benchmark is a necessary but not sufficient condition for outperforming the benchmark. Thus, it is not surprising that funds with larger personal investments deviate more from their benchmarks. Consistently, Cremers and Petajisto (2009) show that funds that deviate more from their benchmarks outperform. In Column (6), a one million SEK increase in the amount invested is associated with a 0.3 percentage points larger annual tracking error.

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. 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.

7.3 Equity funds and other investment categories

Table 7 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 7 constrains the sample to equity funds and shows that the results hold up and are in fact strongest among equity mutual funds.

7.4 Team management and busy managers

Columns (1) and (2) of Table 8 exclude team managed funds from the relevant specifications in Table 3 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 8 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 Columns (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 earn larger abnormal returns. The main results are consistent with a simple model in which fund managers, in contrast to fund investors, are certain about 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, thus, decreases the size of the active fund industry. Whether this effect is desirable, and from which perspective, is an interesting question for future research.[28]

[28] 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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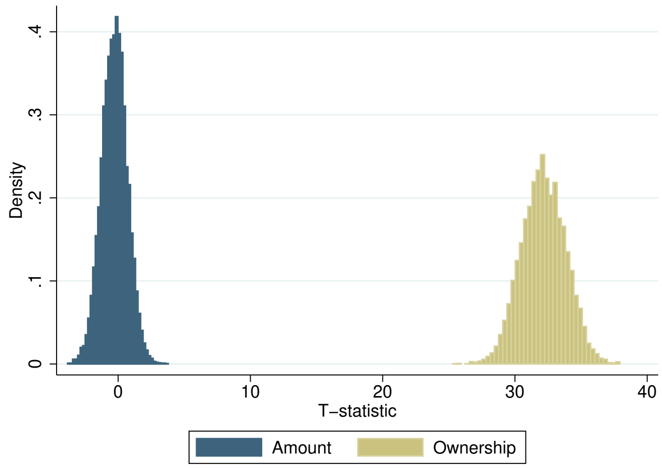
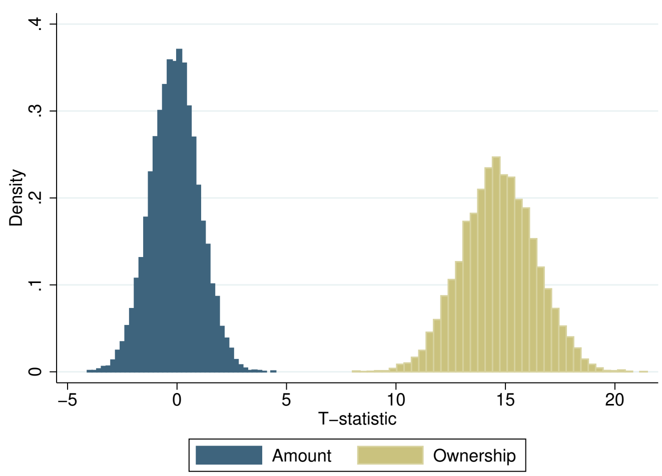
Figure 1: Distribution of simulated t-statistics

(a) No controls, 5000 managers, 20 years



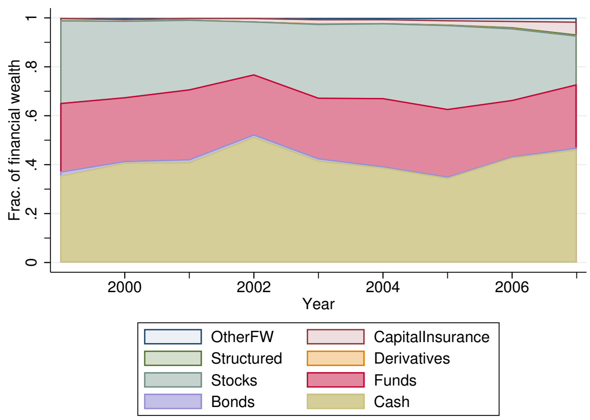
(b) AUM control, 5000 managers, 20 years



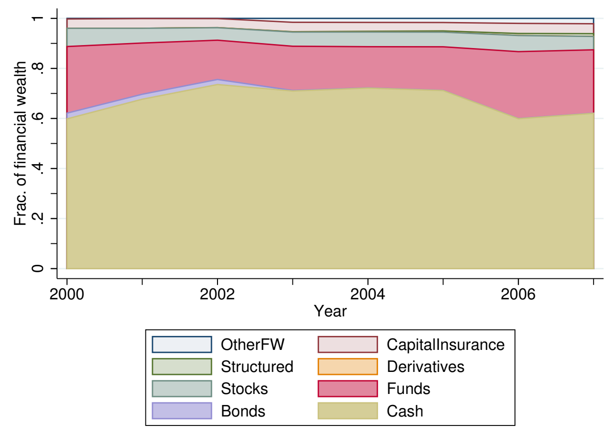
I simulate a Berk and Green world 10,000 times and randomly assign managers an amount that they invest in their own funds as described in Appendix A. The figure shows distributions of t-statistics obtained from regressions of fund abnormal returns on the lagged amount invested and lagged ownership (amount 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

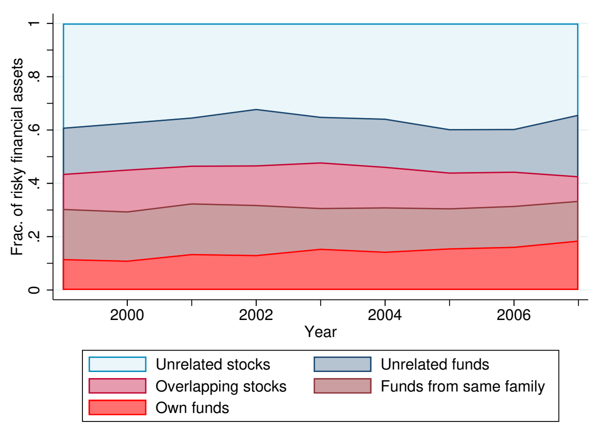
(a) Financial wealth composition



(b) Financial wealth composition (Swedish pop.)



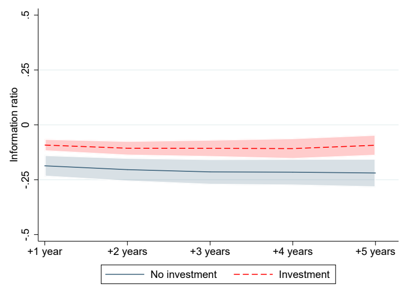
(c) Risky financial assets composition



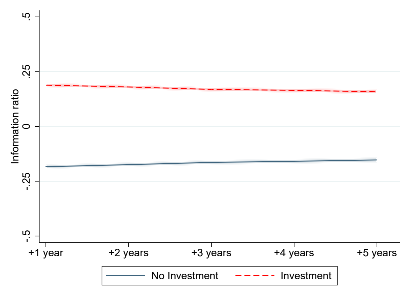
Panel (a) shows the average composition of personal managerial financial wealth over time. Panel (b) is similar to Panel (a) but shows the average composition of financial wealth for the whole Swedish population. Panel (c) shows the average composition of the sum of non money–market mutual funds and 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

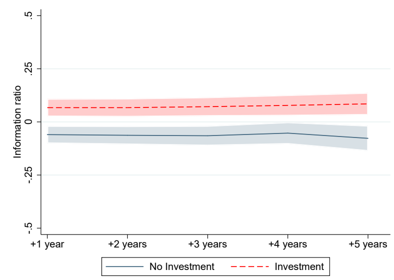
(a) Investment sorts (data)



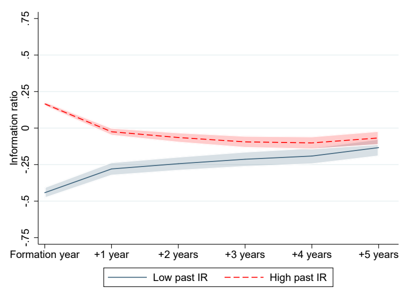
(b) Investment sorts (model baseline)



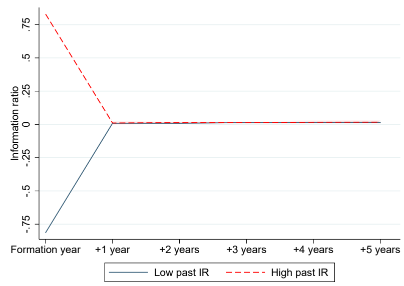
(c) Investment sorts (model Swedish calibr.)



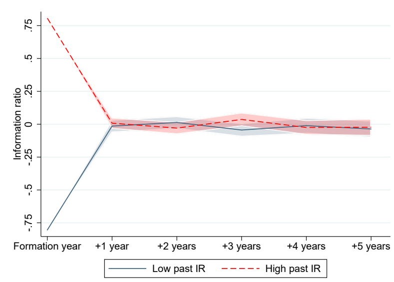
(d) Past performance sorts (data)



(e) Past performance sorts (model baseline)



(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 equilibrium size and otherwise not, see Appendix A. Panel (d) ranks funds based on past information ratios. Panels (e) and (f) do the same as Panel (d) using the simulated data.

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								
$12 \times \widehat{\alpha}_{i,t}^{BM}$ (%)	-9.29	-4.04	-0.97	1.70	7.93	-0.96	9.69	2,449
$\widehat{IR}_{i,t}^{BM}$	-0.59	-0.34	-0.11	0.12	0.35	-0.14	0.45	2,449
$12 \times \widehat{\alpha}_{i,t}^{GF5}$ (%)	-14.14	-5.80	-0.71	2.90	9.15	-1.72	11.30	2,432
$\widehat{IR}_{i,t}^{GF5}$	-0.70	-0.35	-0.07	0.14	0.33	-0.14	0.45	2,432
D. 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

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. Panels B shows performance measures net of costs relative to the prospectus benchmark return in excess of the one-month STIBOR rate and a global five factor model (GF5). Fund alphas are estimated according to Equation 5. IR is a fund's information ratio, that is alpha scaled by residual volatility. *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.

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 the manager-year observations in the final sample. $FinWealth$ 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.

Table 3: Predictive regressions of information ratios on manager and fund characteristics

	(1) $\widehat{IR}_{i,t}^{BM}$	(2) $\widehat{IR}_{i,t}^{BM}$	(3) $\widehat{IR}_{i,t}^{BM}$	(4) $\widehat{IR}_{i,t}^{BM}$
$Amount\ in\ MF_{i,t-1}$	0.0813***	0.0692***	0.0595**	0.0715**
	(0.0147)	(0.0147)	(0.0270)	(0.0346)
$Amount\ in\ OH_{i,t-1}$	0.266	0.172	0.237	0.0239
	(0.194)	(0.164)	(0.159)	(0.0796)
$Wealth_{i,t-1}$		0.00248**	-0.0000964	-0.00307
		(0.00125)	(0.00145)	(0.00217)
$AUM_{i,t-1}$		-0.00527	-0.00554*	-0.0234***
		(0.00354)	(0.00327)	(0.00568)
$TER_{i,t-1}$		0.0358*	0.0647**	-0.0146
		(0.0217)	(0.0258)	(0.0340)
$NumManagers_{i,t-1}$		0.0292**	0.0176	-0.0167
		(0.0138)	(0.0146)	(0.0128)
$Income_{i,t-1}$		-0.000930	-0.000773	-0.0110
		(0.00747)	(0.0110)	(0.0105)
$Age_{i,t-1}$		-0.00316	-0.00456*	0.00243
		(0.00257)	(0.00245)	(0.00268)
$Exper_{i,t-1}$		-0.00356	-0.00163	-0.00540
		(0.00264)	(0.00268)	(0.00369)
$NumCategories_{i,t-1}$		-0.0570	-0.0556*	-0.0249
		(0.0373)	(0.0324)	(0.0408)
$NumFunds_{i,t-1}$		0.00501	0.00700*	-0.000678
		(0.00404)	(0.00378)	(0.00517)
$Female_{i,t-1}$		-0.109**	-0.0785	-0.00524
		(0.0489)	(0.0522)	(0.0487)
Constant	-0.147***			
	(0.0152)			
Year FE	No	Yes	Yes	Yes
Fund FE	No	No	No	Yes
Firm FE	No	No	Yes	No
N	2449	2449	2439	2339
Adjusted R^2	0.007	0.058	0.087	0.345

The table shows predictive regressions of information ratios, that is alphas scaled by residual volatility, on manager and fund characteristics. Information ratios are estimated relative to the fund's prospectus benchmark according to Equation 5. *Amount in MF* is the absolute amount managers invest in their funds in millions of SEK. *Amount in OH* is the absolute amount managers invest in overlapping holdings in millions of SEK. *Wealth* is managerial net wealth in millions of SEK. *AUM* (fund size) is scaled in billions of SEK. Standard errors are clustered by funds.

Table 4: Fund flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\%Flow_{i,t}$	$\%Flow_{i,t}$	$\%Flow_{i,t}$	$\%Flow_{i,t}$	$\%Flow_{i,t}$	$\%Flow_{i,t}$	$\%Flow_{i,t}$
$Amount\ in\ MF_{i,t-1}$	0.0188	0.247	3.159	1.580	4.663	-5.412	-6.341
	(3.164)	(2.817)	(2.718)	(3.171)	(2.951)	(4.414)	(4.820)
$Amount\ in\ OH_{i,t-1}$	31.02	-18.29	2.299	-18.17	2.313	-4.360	9.852
	(47.33)	(11.42)	(12.77)	(11.44)	(12.76)	(29.82)	(35.66)
$12 \times \widehat{\alpha}^{BM}_{i,t-1}$		0.203	-0.0558	0.222	-0.0373		
		(0.191)	(0.249)	(0.198)	(0.254)		
$12 \times \widehat{\alpha}^{BM}_{i,t}$						1.154^{***}	1.153^{***}
						(0.248)	(0.278)
$12 \times \widehat{\alpha}^{BM}_{i,t-1} \times Amount\ in\ MF_{i,t-1}$				-11.58	-12.59		
				(9.223)	(13.64)		
Constant	28.09^{***}						
	(2.212)						
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	No	Yes	No	Yes
N	2447	1843	1752	1843	1752	2447	2336
Adjusted R^2	-0.000	0.017	0.113	0.017	0.112	0.052	0.181

The table shows regression of fund flows on manager and fund characteristics. $\%Flow_{i,t}$ 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 in millions of SEK. *Amount in OH* is the absolute amount managers invest in overlapping holdings in millions of SEK. Standard errors are clustered by funds.

Table 5: Predictive regressions of alphas on manager and fund characteristics

	(1) $\widehat{\alpha}_{i,t}^{BM}$	(2) $\widehat{\alpha}_{i,t}^{BM}$	(3) $\widehat{\alpha}_{i,t}^{BM}$	(4) $\widehat{\alpha}_{i,t}^{BM}$
$Amount\ in\ MF_{i,t-1}$	0.0423**	0.0424**	0.0203*	0.0364**
	(0.0189)	(0.0193)	(0.0122)	(0.0150)
$Amount\ in\ OH_{i,t-1}$	0.0433	0.0319	0.0482	0.0197
	(0.0454)	(0.0459)	(0.0434)	(0.0243)
$Wealth_{i,t-1}$		-0.000103	-0.000480	-0.00169**
		(0.000400)	(0.000400)	(0.000744)
$AUM_{i,t-1}$		-0.000523	-0.000271	-0.00763***
		(0.000432)	(0.000417)	(0.00168)
Constant	-0.0129***			
	(0.00224)			
Year FE	No	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Fund FE	No	No	No	Yes
Firm FE	No	No	Yes	No
N	2449	2449	2439	2339
Adjusted R^2	0.037	0.067	0.162	0.185

The table shows predictive regressions of alphas on manager and fund characteristics. Alphas are estimated relative to the fund's prospectus benchmark according to Equation 5. *Amount in MF* is the absolute amount managers invest in their funds in millions of SEK. *Amount in OH* is the absolute amount managers invest in overlapping holdings in millions of SEK. *Wealth* is managerial net wealth in millions of SEK. *AUM* (fund size) is scaled in billions of SEK. Standard errors are clustered by funds.

Table 6: Alternative benchmarks

	(1) $\widehat{IR}_{i,t}^{GF5}$	(2) $\widehat{IR}_{i,t}^{CAPM}$	(3) $\widehat{IR}_{i,t}^{FF4}$	(4) $\widehat{IR}_{i,t}^{BM,gross}$	(5) $\widehat{IR}_{i,t}^{BM,\beta=1}$	(6) $RMSE_{i,t}^{BM}$
$Amount\ in\ MF_{i,t-1}$	0.0409***	0.0595***	0.0551***	0.0415***	0.0509**	0.00283**
	(0.0123)	(0.0144)	(0.0120)	(0.0120)	(0.0199)	(0.00123)
$Amount\ in\ OH_{i,t-1}$	0.0176	-0.0227	-0.0632	0.0309	0.126	0.0131
	(0.153)	(0.165)	(0.0939)	(0.115)	(0.125)	(0.00871)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	2432	2449	2449	2449	2449	2449
Adjusted R^2	0.150	0.108	0.111	0.034	0.068	0.232

Columns (1)–(5) replicate Column (2) of Table 3 using alternative benchmarks to estimate information ratios. Columns (1) uses returns adjusted relative a global five-factor model (GF5), Column (2) uses gross instead of net benchmark returns, Column (3) uses a Swedish market model (CAPM), Column (4) uses a Swedish four-factor model (FF4), Column (5) restricts the beta w.r.t. to the benchmark to equal one. All models are described in detail in Appendix B.3. Column (6) employs a fund's root mean square error (tracking error) as the dependent variable. *Amount in MF* is the absolute amount managers invest in their funds in millions of SEK. *Amount in OH* is the absolute amount managers invest in overlapping holdings in millions of SEK. $Wealth$ is managerial net wealth in millions of SEK. Standard errors are clustered by funds.

Table 7: Differences across investment categories

	(1) $\widehat{IR}_{i,t}^{BM}$	(2) $\widehat{IR}_{i,t}^{BM}$	(3) $\widehat{IR}_{i,t}^{BM}$	(4) $\widehat{IR}_{i,t}^{BM}$
$Amount\ in\ MF_{i,t-1}$	0.0482***	0.0752	0.0290	0.149
	(0.0140)	(0.0602)	(0.0181)	(0.682)
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	0.084	0.134	0.098	0.214

The table replicates Column (2) of Table 3 and shows predictive regressions of information ratios, that is alphas 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 5. *Amount in MF* is the absolute amount managers invest in their funds in millions of SEK. *Amount in OH* is the absolute amount managers invest in overlapping holdings in millions of SEK. *Wealth* is managerial net wealth in millions of SEK. Standard errors are clustered by funds.

Table 8: Team management and busy managers

	(1) $\widehat{IR}_{i,t}^{BM}$	(2) $\widehat{IR}_{i,t}^{BM}$	(3) $\widehat{IR}_{i,t}^{BM}$
$Amount\ in\ MF_{i,t-1}$	0.0806***	0.0657***	0.0370
	(0.0148)	(0.0173)	(0.0384)
$Amount\ in\ OH_{i,t-1}$	0.190	0.130	-0.149
	(0.162)	(0.145)	(0.141)
Constant	-0.165***		
	(0.0191)		
Year FE	No	Yes	Yes
Controls	No	Yes	Yes
Manager FE	No	No	Yes
N	1780	1780	1726
Adjusted R^2	0.005	0.062	0.227

The table shows predictive regressions of information ratios, that is alphas 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 5. *Amount in MF* is the absolute amount managers invest in their funds in millions of SEK. *Amount in OH* is the absolute amount managers invest in overlapping holdings in millions of SEK. *Wealth* is managerial net wealth in millions of SEK. Standard errors are clustered by funds.

Appendices

A Berk and Green Model Simulations

A.1 Model

In Berk and Green (2004) managers have skill alpha that is unknown to both managers and investors. 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 the flow-performance relationship and the absence of persistence in fund returns.

In the model, managerial ability α is randomly assigned with prior belief ϕ_0, prior standard deviation η, and prior precision $\gamma = \frac{1}{\eta^2}$. That is, $\alpha \sim N(\phi_0, \eta^2)$. The return before costs R_t^{abn} follows $R_t^{abn} = \alpha + \epsilon_t$ 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 actively manages. 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

$$\phi_t = \phi_{t-1} + \frac{r_t}{h(q_{t-1})} \left(\frac{\omega}{\gamma + t\omega} \right) \tag{A7}$$

And equilibrium fund size is implicitly given by

$$\frac{c(q_t)}{h(q_t)} = \frac{c(q_{t-1})}{h(q_{t-1})} + \frac{r_t}{h(q_{t-1})} \left(\frac{\omega}{\gamma + t\omega} \right) \tag{A8}$$

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

$$\frac{q_t - q_{t-1}}{q_{t-1}} = \begin{cases} -1 & \text{if} \quad r_t < 2\left(\frac{\bar{\phi}-\phi_{t-1}}{\phi_{t-1}}\right)\left(\frac{\gamma+t\omega}{\omega}\right) f \\ \frac{r_t}{f}\left(\frac{\omega}{\gamma+t\omega}\right) + \frac{r_t^2}{4f^2}\left(\frac{\omega}{\gamma+t\omega}\right)^2 & \text{otherwise.} \end{cases} \tag{A9}$$

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

Table A1: 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

the threshold that is required to recover the fixed costs of running a fund.

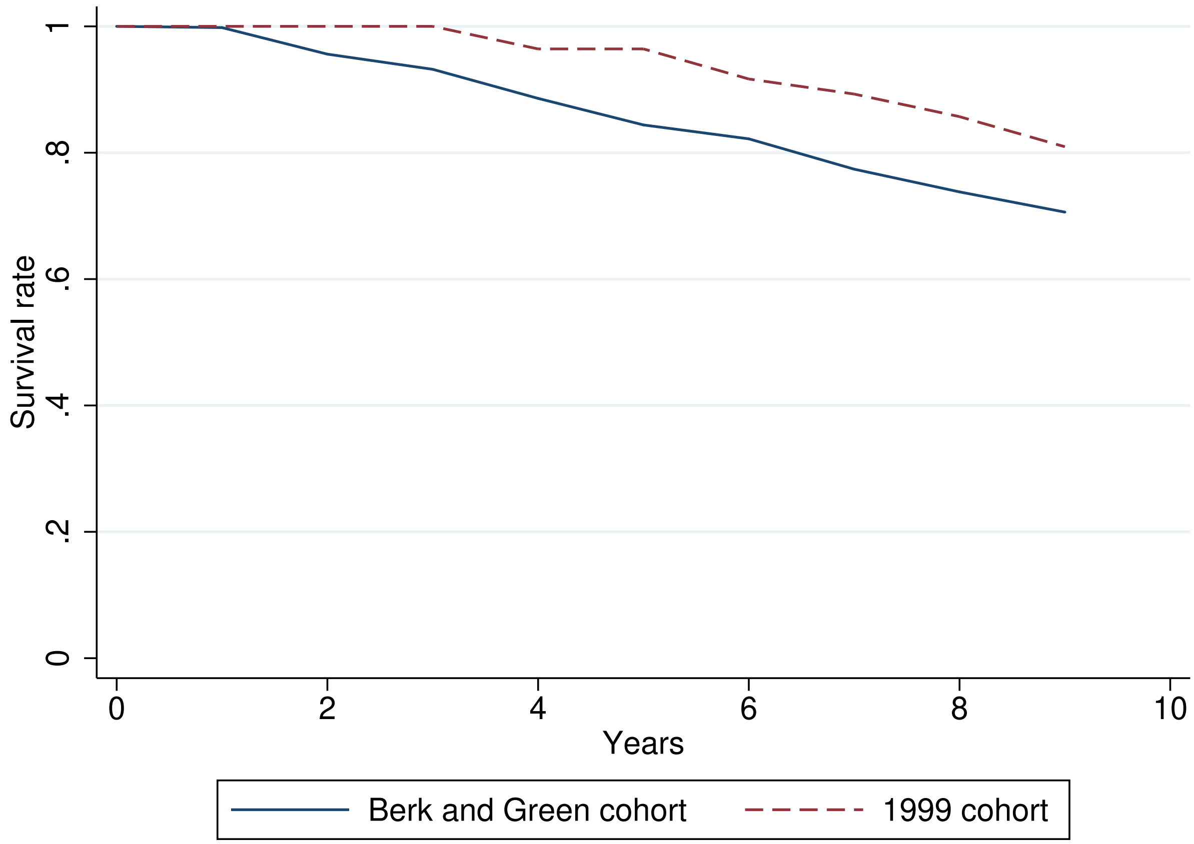
A.2 Calibration and simulation

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 A1. 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. Finally, I repeat the process 10,000 times.

To construct Figure 3, I simulate one cohort of Berk and Green funds using both the baseline 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 equilibrium size and otherwise zero. In Figure 3 Panels (e) and (f) funds are sorted according to past information ratios. 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%.

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 survival probabilities are plotted in Figure A1.

Figure A1: 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 line shows the actual survival rates for the 1999 cohort of funds in the data.

B Data

B.1 AUM and TER imputation algorithms

B.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:

$$AUM_k = F \times AUM_{k-1}(1 + r_k), \quad \text{for } k \in [t+1, t+n-1], \tag{B10}$$

$$F \equiv \left(\frac{1}{\prod_{k=t+1}^{t+n}(1 + r_k)} \frac{AUM_{t+n}}{AUM_t} \right)^{\frac{1}{n}} \tag{B11}$$

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

B.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:

$$imputed\_TER_{ijt} = MNG_{ijt} \left(\frac{1}{N_{jt}} \sum_{h \in \Omega_{jt}^{-i}} \frac{TER_{hjt}}{MNG_{hjt}} \right) \tag{B12}$$

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:

$$imputed\_TER_{ijt} = MNG_{ijt} \left(\frac{1}{T} \sum_{\substack{k \in \Gamma \\ k \neq t}} \frac{1}{N_{jk}} \sum_{h \in \Omega_{jk}^{-i}} \frac{TER_{hjk}}{MNG_{hjk}} \right) \tag{B13}$$

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:

$$imputed\_TER_k = \left(\frac{\overline{TER}_{[t+n,t+n+H_2]}}{\overline{TER}_{[t-H_1,t]}} \right)^{\frac{1}{n}} \times TER_{k-1}, \quad \text{for } k \in [t+1, t+n-1], \tag{B14}$$

where

$$\overline{TER}_{[t-H_1,t]} = \frac{1}{H_1+1} \sum_{k=t-H_1}^{t} TER_k \tag{B15}$$

$$\overline{TER}_{[t+n,t+n+H_2]} = \frac{1}{H_2+1} \sum_{k=t+n}^{t+n+H_2} TER_k \tag{B16}$$

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:

$$\log TER_{ik} = a_i + b_i k + \varepsilon_{ik}, \quad \forall k \in [t_0, T] \tag{B17}$$

The missing TERs are filled as follows:

$$imputed\_TER_{ik} = \exp(\hat{a}_i + \hat{b}_i k), \quad \forall k \in [t_0, t] \cup [t+n, T] \tag{B18}$$

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.

B.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 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 B1 shows how I arrive at the final sample used for the main regressions.

B.3 Benchmark and factor models

B.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

Table B1: 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.

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.[29]

B.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.

B.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).

B.3.4 GF5

The Global five-factor model uses five global indices to risk-adjust returns. For Equity, Alternative, and Allocation funds, these are (i) the Swedish stock market index return (SIXPRX) in excess of the one-month STIBOR rate, (ii) the global equity index (MSCI) in excess of the one-month U.S. Treasury bill rate, (iii) the North American equity index (MSCI) in excess of the one-month U.S. Treasury bill rate, (iv) the European equity index (MSCI) in excess of the one-month EURIBOR rate, and (v) the Asia ex-Japan equity index (MSCI) in excess of the BOJ basic discount rate. For Fixed Income and the rest, the five factors are (i) the Swedish government bond index return (OMRX) in excess of the one-month STIBOR rate, (ii) the global bond aggregate index (Barclays) in excess of the one-month U.S. Treasury bill rate, (iii) the U.S. bond aggregate index (Barclays) in excess of the one-month U.S. Treasury bill rate, (iv) the euro bond aggregate index (Barclays) in excess of the one-month EURIBOR rate, and (v) the Asian Pacific bond aggregate index (Barclays) in excess of the BOJ discount rate.

All returns are converted into Swedish krona.

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,

[29] 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.

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 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 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 investigates personal performance of fund managers in overlapping holdings assuming a buy and hold strategy throughout the year.

D.1 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:[30]

$$R_{m,s}^{p,OH} - R_{m,s}^{p,-} = \alpha_m^{FF4} + \beta_m^{FF4,\prime} FF4_s + \epsilon_{m,s}^{FF4} \tag{D1}$$

where $FF4_s = \begin{bmatrix} MKT_s & SMB_s & HML_s & MOM_s \end{bmatrix}'$, $r_{m,s}^{p,OH}$ is the value-weighted portfolio return of the subportfolio of overlapping holdings in her personal account each month, and $r_{m,s}^{p,-}$ 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).

The alpha in Equation D1 exists for 123 managers and is on average positive at 3.3% (FF4), 3.07% (GF5), 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

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

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:

$$R^{p,OH}_{m,s} - R_{m,s} = \alpha^{BM}_m + \beta^{BM}_m (R^{BM}_{m,s} - R_{f,s}) + \epsilon^{BM}_{m,s} \tag{D3}$$

where $R^{BM}_{m,s}$ 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.

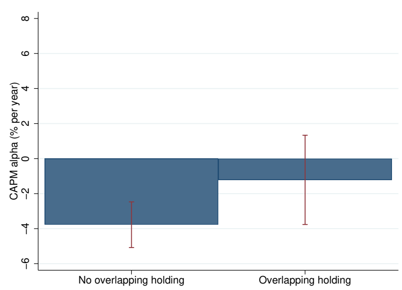
An alternative way to assess performance in overlapping holdings is to evaluate performance on the individual security level before individual security returns are aggregated to form a portfolio return. While such tests have more power, the caveat is of course that a manager may outperform with a subset 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 D1 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, except the estimates for the GF5 alphas.

One concern is that overlapping holdings may arise mechanically because managers manage Swedish funds and have a home bias. Although the vast majority of securities in fund managers' personal portfolios are domiciled in Sweden and many funds (31%) do have Sweden as their main investment area, overlapping holdings appear not to be just a mechanical result of managers investing in their home country and managing funds that invest in securities in the same country. Figure D2 Panel (a) plots the weights of individual positions in funds conditional on whether the manager personally holds the position in her personal account or not. Overlapping holdings do appear to be "best ideas" (Cohen, Polk, and Silli, 2010)—their average portfolio weight in a mutual fund is 1.5 percentage points larger relative to positions that do not overlap. Put differently, managers tilt their funds towards those securities that are also held in their personal accounts. Panel (b) repeats the exercise for personal portfolio weights instead of fund weights. Both the differences in mean in Panels (a) and (b) are statistically different from each other.

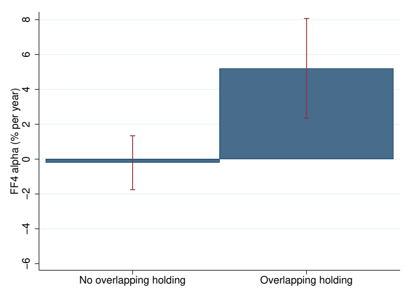
In conclusion, there is evidence that managers have superior information about individual securities when they invest in overlapping holdings and that they tilt both their personal and professional portfolios towards overlapping holdings. Potential reasons for why managers do not tilt their portfolios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

Figure D1: Performance individual security level

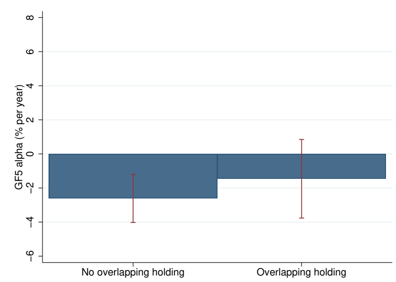
(a) CAPM alpha



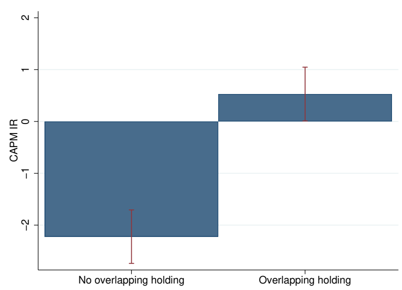
(b) FF4 alpha



(c) GF5 alpha

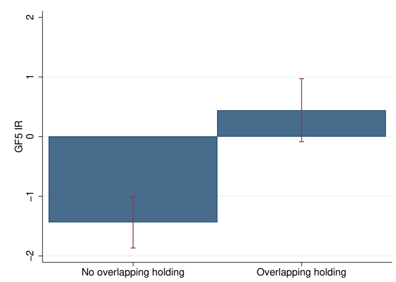


(d) CAPM information ratio



(e) FF4 information ratio

(f) GF5 information ratio



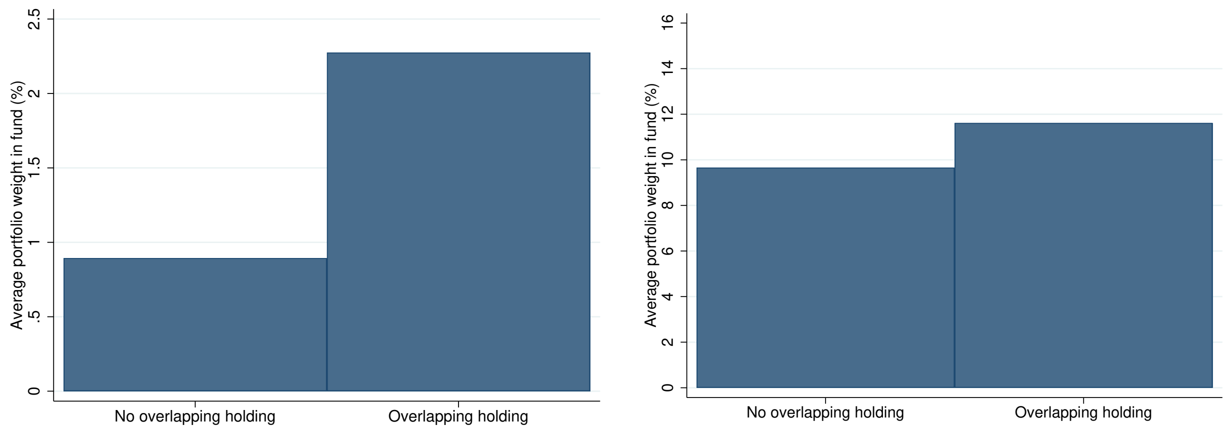
The figure plots alphas and information ratio relative to three different factor models. Alphas and information ratios are estimated over the entire period a manager holds a particular security in her personal account, conditional on whether the security is also held in her professionally managed fund 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.

D.2 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 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

Figure D2: Overlapping holdings weights

(a) Fund weights (b) Personal portfolio weights



The figure plots the portfolio weights of individual securities in active mutual funds and managers' personal portfolios conditional on whether the manager holds the security in both her fund and her personal portfolio or not.

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.3 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 5. 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.