The Investment Value of Fund Managers' Experience outside the Financial Sector

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Abstract

Human capital acquired while working in other industries before joining fund management provides fund managers with an information advantage. Fund managers exploit this advantage by overweighting their experience industries and by picking outperforming stocks from these industries. These managers' superior information gets impounded into stock prices slowly, suggesting that their information is unique and takes a while to be discovered by the markets. Families exploit their manager's industry-specific human capital by employing their investment ideas broadly in other funds. The investment value of industry experience is unaffected by whether the manager with such experience is in a team or not.

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1. Introduction

Work experience and its impact on productivity has featured prominently in economic theories of human capital (e.g., Becker (1964) and Mincer (1974)). Building on these earlier studies, a growing body of work (e.g., Golec (1996); Chevalier and Ellison (1999); Greenwood and Nagel (2009); and Kempf, Manconi, and Spalt (2014)) examines how experience of investment managers relates to investment performance. The focus of these studies has been on-the-job experience, experience acquired by fund managers in a learning-by-doing fashion during their careers in the mutual fund industry. While this type of experience is an important component of investment managers' human capital, some investment managers have had the opportunity to work in other industries in their prior careers, which provides them with experience in those other industries and industry-specific human capital. The economics literature suggests that industry-specific human capital might be transferrable, as evidenced by the finding that workers receive compensation for industry-specific human capital even after switching industry (e.g., Neal 1995). In this study, we examine whether industry-specific human capital shaped by fund managers' work experience outside the investment industry helps them make better investment decisions.

Being the first to study this question, we hypothesize that industry-specific human capital previously acquired by fund managers outside the investment industry puts them at an information advantage in that specific industry (hereafter, experience industry). Applied to our setting, the equilibrium model of van Nieuwerburgh and Veldkamp (2009) suggests that it is optimal for a manager with such an initial information advantage to not only overweight her experience industry but to also continue investing in gathering information in her experience industry in order to maintain and exploit her initial information advantage. Other fund managers, being aware of their initial information disadvantage relative to the aforementioned manager, decide in equilibrium to not invest in information gathering activities in the same industry but instead specialize in other industries where they are not at an initial information disadvantage. Therefore, the information advantage of the manager in her experience industry persists in the long run, allowing her to generate better performance in the experience industry than in other industries.

We test the information advantage hypothesis using information on portfolio holdings of fund managers with prior industry experience who run diversified U.S. mutual funds. Diversified funds provide an identification advantage in that they allow us to isolate the impact of industry-specific human capital on performance. The performance that a fund manager generates in the part of portfolio invested in her non-experience industries (hereafter, non-experience portfolio) reflects general human capital shaped by education; talent; wisdom; as well as more investment-specific human capital acquired while working in fund management. However, the performance that this same manager generates in the part of the portfolio invested in her experience industry (hereafter, experience portfolio) additionally reflects her human capital specific to that particular industry. Thus, the difference between the performance of a manager's experience and non-experience portfolios gives us an estimate of the investment value of the manager's industry experience.

Our first set of results suggests that fund managers have a clear information advantage in their experience industry. The average performance of a fund manager in her experience portfolio is up to five percentage points per year higher than that in her non-experience portfolio. This difference comes from outperformance of their experience portfolios, not from underperformance of their non-experience portfolios, which perform not differently from passive benchmarks or funds run by non-OIE managers. This suggests that for fund managers with industry experience, the human capital that is not industry-specific is average and comparable to that of managers without any industry experience.

The information that the managers generate about stocks they pick from their experience industries materializes over long horizons. Specifically, extending the holding period of the experience and non-experience portfolios shows that the outperformance of the experience portfolio relative to the non-experience portfolio reaches its peak in about two years. This is compatible with the van Nieuwerburgh and Veldkamp (2009) framework. Simply put, many investors without industry experience, being aware of their information disadvantage, choose to stay on the sidelines, and this contributes to a slow price discovery for the aforementioned stocks.

We find that OIE managers generally tend to overweight their experience industries relative to non-OIE managers, which is consistent with rational behavior as predicted by the equilibrium model of van Nieuwerburgh and Veldkamp (2009). However, we find no evidence that OIE managers are able to increase (decrease) their overweighting prior to periods of experience industry outperformance (underperformance) relative to other industries in a way that would be indicative of timing ability.

Besides looking at the value of experience from the point of view of fund managers, we also look at its value from the perspective of investors and fund families, i.e., the managers' possible clients and employers. The first question we ask is: How can investors benefit from the industry experience of fund managers? Simply buying funds run by managers with industry experience might not be the best option because our OIE managers run diversified funds, with the overall fund performance mainly determined by their non-experience portfolios. Instead, investors might be better off mimicking the stock holdings of fund managers in their respective experience portfolios. We find some evidence suggesting that even though investors receive holdings information with a delay of up to 60 days—based on filing rules enforced by the SEC—they might benefit by replicating the experience portfolios of managers with industry experience. This is consistent with our earlier finding that the information advantage of managers with experience materializes gradually over a relatively long period of time and suggests that mimicking the portfolio holdings of managers with industry experience might be a valuable strategy for investors.

The second question is whether fund families extend the benefits of industry experience of certain managers to other funds in the family. A sensible strategy from the perspective of a fund family would be for the other fund managers in the family (hereafter, affiliated managers) who do not have industry experience to exploit the expertise of managers with industry experience. Consistent with this prediction, we find that affiliated managers tend to follow the ideas that their colleagues generate in their experience industries more than the ideas these same colleagues generate in their non-experience industries. This suggests that fund families and affiliated fund managers are aware of the investment value of industry experience and employ the industry-specific human capital of their managers with industry experience in a sensible way by applying this knowledge to a larger asset base. More broadly, this is consistent with fund families striving to optimally deploy their managers' human capital within their organizations.[1]

In our final investigation, we extend our sample to include also funds that our OIE managers managed as part of a team. Given the growing prevalence of teams in mutual fund management, we want to know whether teams amplify the value of industry experience. Two competing hypotheses guide our analysis. The investment literacy hypothesis suggests that a manager with industry experience benefits from the investment experience of other team members, causing her to make better investment decisions in her experience industry. In contrast, the diversification of opinion hypothesis suggests that because teams make decisions that reflect the average opinion of the team members (e.g., Sah and Stiglitz, 1986 and 1988), teams could dilute the impact of industry experience on the investment decisions in the respective industry. Results do not support the financial literacy hypothesis, as performance of the experience portfolio in our extended sample is not better than in our original sample

[1] Other evidence supporting optimal deployment of managers' human capital by fund families comes from Fang, Kempf, and Trapp (2014), who show that fund families optimally assign more skilled managers to the least efficient market segments.

consisting of single-managed funds only. Rather, we find that the performance of the experience portfolio seems to decline with team size. This suggests that the impact of the manager with industry experience on the experience portfolio becomes weaker when the team becomes bigger providing support for the diversification of opinion theory.

Our paper is related to the literature that examines whether experience that professional investors develop on the job translates into superior performance (e.g., Golec (1996); Chevalier and Ellison (1999); Greenwood and Nagel (2009); and Kempf, Manconi, and Spalt (2014)). These studies generally focus on experience gained through actively managing investments, i.e., on the part of managers' human capital shaped by on-the-job experience acquired while working in fund management. In contrast, our study examines experience that fund managers acquired while working within a specific non-investment industry before their fund management career. More broadly, our paper supports earlier findings from the economics literature that part of industry-specific human capital is transferrable to other industries (e.g., Neal (1995)) by showing that employees can benefit from their industry-specific human capital when switching to the fund industry.[2]

Our paper is also related to Doskeland and Hvide (2011) who analyze whether industry-specific human capital has investment value for retail investors. Doskeland and Hvide (2011) show that retail investors tend to overweight stocks from industries where they work and make strikingly poor investment choices in those industries. They attribute these findings to behavioral biases. Similarly, we also find an overweighting of the experience industry by fund managers with industry experience. However, the overweighting we document is smaller than the one documented in Doskeland and Hvide (2011) for retail investors, and the stocks that fund managers picked from their experience industries exhibit superior performance. This suggests

[2] One can easily find other settings where prior work experience is useful after switching industry. For example, Bradley, Gokkaya, and Liu (2017) document that sell-side analysts with prior industry experience generate more accurate earnings forecasts for companies from their experience industries.

that the net impact of the two competing effects—information advantage and familiarity bias—is more favorable for professional investors than for retail investors. A plausible explanation is that professional investors are better equipped to evaluate investment opportunities and keep behavioral biases in check. [3]

Our findings also support the key premise of theoretical models that asymmetric information can lead to disparate returns among market participants (e.g., Grossman and Stiglitz (1976)) and persist over longer periods (e.g., van Nieuwerburgh and Veldkamp (2009)). Information asymmetries that place institutional investors at an information advantage have been examined in several studies. They appear to arise when institutional investors: engage in local investing (e.g., Coval and Moskowitz (1999, 2001)); are connected via shared education networks with board members of companies (e.g., Cohen, Frazzini, and Malloy (2008)); exploit information related to FDA approvals obtained under the Freedom of Information Act (e.g., Gargano, Rossi, and Wermers (2017); Klein and Li (2015)); and receive SEC filings prior to them becoming public (e.g., Rogers, Skinner, Zechman (2017)). Our contribution is that we document a new venue through which fund managers can obtain an information advantage. This information advantage is costly, however, since considerable time and effort are needed to acquire the industry-specific human capital that we analyze.

Finally, our paper is related to a growing literature that examines various decisions undertaken by fund families. Among others, these papers look at product policies (e.g., Mamaysky and Spiegel (2002); Siggelkow (2003)); centralization of decision making (e.g., Kacperczyk and Seru (2012)); advertising (e.g., Gallaher, Kaniel, and Starks (2006)); introduction of new funds (e.g., Khorana and Serveas (1999)) and closure of existing funds (e.g., Zhao (2004)); performance transfers across family funds (e.g., Gaspar, Massa, and Matos

[3] This is consistent with Alevy, Haigh, and List (2007) who find that a particular behavioral bias, loss aversion, affects the decisions of individual investors but not those of professional investors, who are also more sophisticated in discerning the quality of public information. Similar differences between individual and institutional investors are reported in other studies, e.g., Grinblatt and Keloharju (2000 and 2001)

(2006)); outsourcing versus in-sourcing portfolio management (e.g., Chen, Hong, Jiang, and Kubik (2013)); choosing single versus teams of portfolio managers (e.g., Huang, Qiu, Tang, and Xu (2016)); choosing the type of distribution channel (e.g., Del Guercio and Reuter (2014)); and optimally allocating fund managers to mutual funds (e.g., Fang, Kempf, and Trapp (2014)). Our paper complements this literature by showing that fund families tend to exploit the industry-specific information advantages of their managers with industry experience across a large number of family funds.

2. Data Collection and Descriptive Results

2.1. Sample selection

To construct our sample, we identify diversified, domestic U.S. equity mutual funds managed by single managers. We impose three restrictions introduced sequentially to the mutual fund universe in the CRSP Mutual Fund (CRSP MF) database. First, we limit the universe to include only diversified, domestic U.S. equity funds, thus excluding index, balanced, bond, money market, international, and sector funds. Second, we drop all funds that are not covered by MFLINKS because we later use MFLINKS to link fund characteristics from the CRSP MF database with fund holdings from the Thomson Reuters Mutual Fund database. Finally, we further restrict our sample to include funds that are managed by single portfolio managers. The rationale for this restriction is that our subsequent tests would be less precise for funds managed by multiple managers, especially if some managers have industry experience while some others do not.

To identify the names of fund managers and the time periods during which they managed individual funds, we use Morningstar Principia. Our choice of Morningstar Principia over the CRSP MF database to obtain this information was motivated by previous research showing that reported manager information is more accurate in the Morningstar database than in the CRSP MF database (e.g., Patel and Sarkissian (2013)). We match the manager information obtained from Morningstar to CRSP fund data. We also manually screen manager names for different spellings and/or abbreviations and assign a distinct identification number to each manager. Overall, we identify 1,495 managers who single-managed at least one of 1,619 diversified U.S. domestic equity funds between 1996 and 2009.

To construct career profiles for fund managers, we hand-collect biographical information for each fund manager from various sources including fund company websites, morningstar.com, SEC filings (485APOS), newspaper articles, and websites like zoominfo.com or linkedin.com. We were able to collect biographical information for 1,295 out of the 1,495 aforementioned managers. We use the collected biographical information to construct the career path of the managers until they started in the fund management industry by recording the names of employers, the time periods of employment under each employer, and job descriptions.

Our industry categorization is based on the Fama-French 48 industry groupings.[4] We categorize a fund manager as having prior work experience in a particular industry if a company she worked for prior to joining the fund management industry belongs to that particular industry. Using the names of companies a fund manager worked for, we first determine whether those companies are publicly listed or privately held. When the company is publicly listed, we use the Standard Industrial Classification Code from the CRSP stock database to determine the industry to which it belongs. For companies that are not publicly listed, we manually search information about their business objective, which we then use to assign them to one of the Fama-French industry groupings.[5]

Since we are interested in fund managers with prior work experience outside the financial sector, we exclude all managers who worked only for investment management firms or whose prior jobs were in banking. We also exclude managers whose prior work experience

[4] The Fama-French industry classifications were obtained from Ken French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#HistBenchmarks.

[5] Fund managers who worked as medical doctors are categorized as having experience in the Fama-French industries 11, 12, and 13, the main industries followed by health care sector funds.

was limited to military service or educational institutions because of lack of additional information needed to assign these particular work experiences to specific industries. Our final sample consists of 130 OIE managers. Thus, out of all 1,295 managers that single manage equity funds for whom we could collect biographical information, about ten percent of them have outside industry experience. These managers are responsible for 199 single-managed funds. They have industry experience in 29 of the Fama-French 48 industry groupings.

2.2. Descriptive statistics

Panel A of Table I provides biographical information for the OIE managers and sole managers without industry experience that manage funds with the same investment objectives (hereafter, non-OIE peer managers).

<Insert Table I about here.>

OIE managers have an average industry experience of more than five years and appear to be slightly older than their non-OIE peers, which is to be expected given that they worked somewhere else prior to joining the mutual fund industry.

A further comparison of the two groups shows that the OIE managers have disproportionately more undergraduate degrees with majors in engineering and natural sciences but less in business management and economics. This suggests that the OIE managers tailored their undergraduate education to gain the skills needed in the industries they were planning to join after graduation. In addition, the majority of them has invested time and effort to earn an MBA degree. This is a highly sensible strategy for industry workers who plan to switch into the fund management business for two reasons. First, by doing so, they compensate for their lack of educational and practical exposure to general business, finance, and investing. Second, an MBA degree can reliably signal quality—along with a passion for investments and a life-long commitment to an investment career—to potential employers in the fund management industry (e.g., Spence (1973)). The signal is costly because acquiring an MBA degree entails substantial costs, both direct (e.g., monetary costs in the form of tuition fees) and indirect (e.g., mental energy and lost time and income). Therefore, as industry workers consider these costs against the expected benefits, only the high-quality and highly committed workers find the cost-benefit tradeoff advantageous to pursue an MBA degree in preparation for a career switch.

Panel B of Table I compares the funds managed by OIE managers with the group of funds managed by non-OIE managers, which consists of 1,420 single-managed funds. The average fund managed by an OIE manager is larger than the average fund run by non-OIE managers. However, the median fund (not reported in the table) is about the same size. A comparison of expense ratios and turnovers shows that they are of a similar order of magnitude across the two groups. However, the funds run by OIE managers clearly put more weight on their experience industries than the funds run by non-OIE managers, a finding that is consistent with having an information advantage in or a familiarity bias towards those industries.

We next compare the experience portfolio of a manager with her non-experience portfolio. To determine the experience portfolio, we classify all stocks held by a fund based on whether the stocks belong to the manager's experience industry. The remaining stocks belong to the non-experience portfolio. This provides us with an experience portfolio and a non-experience portfolio for each manager and each report date. We match the stocks in the experience and non-experience portfolio with the CRSP Monthly Stock database to get information on the characteristics of the stocks held. Table II shows characteristics of the stocks in the experience and the non-experience portfolios for all funds in our sample.

<Insert Table II about here.>

Table II shows that stocks in the experience and the non-experience portfolios do not differ in market capitalization. Consistent with this, the loadings on the size factor for the two portfolios are not significantly different. However, stocks in the experience portfolio have a significantly lower loading on the book-to-market factor HML, suggesting that managers tilt more towards growth stocks in their experience portfolio than in the rest of their portfolios. Since growth stocks are less efficiently priced than value stocks (Schultz, 2010), this is consistent with the view that OIE managers use their industry experience to potentially reap higher rewards by focusing their efforts towards picking growth rather than value stocks from industries in which they have experience.[6] We also see that stocks in the experience portfolio have a significantly larger exposure to market risk and momentum, but these differences are small in economic terms. Our performance comparisons in Section 3 will account for these differences in stock characteristics between the two portfolios.

3. The Investment Value of Industry Experience

3.1. Performance differences between experience and non-experience portfolios

To compare the performance of each manager's stocks from the experience and non-experience industries, we use that manager's holdings to construct a value-weighted experience portfolio and non-experience portfolio. Thus, for a fund manager to be included in the analysis in a given period, she must have at least one stock holding in both her experience and non-experience portfolios. We compute buy-and-hold returns for each portfolio until the next holdings report date, at which the portfolios are then updated to reflect any changes in holdings. We do so for each manager each period and treat the performance of the experience portfolio and the non-experience portfolio over the corresponding holding period as distinct observations.

We employ five performance measures: raw returns; risk-adjusted returns; and three versions of characteristic-adjusted returns. Our risk-adjusted returns are based on the four-factor

[6] The economic rationale is that growth stocks are more costly and difficult to analyze and more difficult to short (see Schultz, 2010). Baker and Wurgler (2006) argue that extreme growth stocks have relative subjective valuations and are hard to arbitrage, so they are more likely to be affected by shifts in investor sentiment. Therefore, growth stocks are usually perceived as being more difficult to value (see Kumar, 2009).

model of Carhart (1997).[7] Given that OIE managers exhibit different portfolio choice preferences for certain stocks in their experience and non-experience portfolios and as shown by their stronger tilt towards growth stocks in their experience portfolios, this risk adjustment approach can help us control for such differences in preferences when we compare performance of the two sub-portfolios. We compute monthly Carhart alphas for each stock held in the experience and non-experience portfolios of each manager and use them to estimate risk-adjusted portfolio returns. Specifically, we compute the risk-adjusted return of a stock in a given month as its actual excess return for that month minus its expected excess return based on the Carhart (1997) model. A stock's expected excess return in a given month is computed by summing the products of the realized common factor values and the respective factor loadings estimated using the stock's returns from the previous 36 months.

Although commonly used, there are two potential concerns with the Carhart alpha. First, it assumes a linear risk factor model, which, restrictive as it may be, has not been found to explain the cross sectional variation of stock returns as well as the nonlinear characteristic-based model of Daniel and Titman (1997) and Daniel, Grinblatt, Titman, and Wermers (1997). Second, it tends to produce biased alphas. The bias concern stems from recent research, which has documented both economically and statistically significant non-zero alphas for passive benchmark indices estimated with the Fama-French and Carhart models (e,g., Cremers, Petajisto, and Zitzewitz (2012)).

To ensure that our inferences do not depend on these issues, we also employ characteristic-adjusted returns to measure performance. The three versions of characteristic-adjusted returns follow the idea of Daniel, Grinblatt, Titman, and Wermers (1997). We compute

[7] Results are qualitatively similar for the five-factor model of Fama and French (2015), the three-factor model of Fama and French (1993), and the one-factor model of Jensen (1968). Results are also qualitatively similar when we use the GT performance measure of Grinblatt and Titman (1993), which does not rely on specific risk factors or a specific factor model, or when we use the returns of funds matched on similar characteristics (such as fund size, managerial educational back ground, and loading on the HML factor) to benchmark the performance differences between the experience and nonexperience portfolios of OIE fund managers.

a stock's DGTW-adjusted return in a given month by subtracting from its return the return of the benchmark portfolio to which that stock belongs. Each stock's benchmark portfolio is a value-weighted portfolio that includes all stocks that are part of the same size, book-to-market, and one-year past return quintile. Our fourth measure, intended to adjust for industry-related effects, is constructed by benchmarking the DGTW-adjusted performance of each held stock against that of a portfolio of stocks from the same industry not held in the portfolio (hereafter referred to as industry-adjusted DGTW return). Our last performance measure is constructed by benchmarking the DGTW-adjusted performance of each held stock against that of a portfolio of stocks from the same industry held by non-OIE managers (matched by style) but not held in the portfolio (hereafter referred to as peer-adjusted DGTW return). This measure accounts for the possibility that managers that follow certain styles are more skilled at picking stocks from certain industries. For example, growth managers might be better at picking tech stocks, regardless of whether they have industry experience.

Table III analyzes the value of experience gained outside the investment industry for fund managers. It reports the average annualized performance for the experience and non-experience portfolio along with their performance differences. To assess statistical significance, standard errors are clustered by both manager and report date.

<Insert Table III about here.>

Table III shows that the difference in raw returns between the experience and non-experience portfolios is positive, albeit not significantly different at conventional levels of significance. Since raw returns reflect both, managerial skill and systematic risk taking, and systematic risk taking differs between experience and non-experience portfolio (see Table II), one has to adjust for risk to get a clear picture of whether a fund manager is better in selecting stocks from her experience industry than from other industries. Comparisons based on Carhart alphas and DGTW-adjusted returns suggest that this is indeed the case: The stocks that managers select from their experience industries outperform stocks they select from their non-experience industries, controlling for differences in risk or stock characteristics. This is consistent with OIE managers enjoying an information advantage in their experience industries. In other words, human capital acquired outside the investment industry helps managers pick superior stocks in their respective experience industries. More broadly speaking, our results imply that such industry-specific human capital is valuable after switching to the fund industry.

A possible concern is that our main result does not reflect the value of industry-specific human capital acquired by fund managers in their previous careers but rather the characteristics of the corresponding industries. For example, some industries might perform better than others during certain periods. However, the fourth row rules this possibility out since our key result holds even after we control for industry effects.

The results from the fifth row suggest that the average manager with industry experience picks stocks in her experience industry that outperform stocks that managers without such experience picked in the same industry. This further supports the presence of an information advantage that managers with industry experience enjoy in their experience industries, which results in better performance for the corresponding stock picks from those industries relative to fund managers who do not enjoy such an advantage

All in all, the evidence from this analysis suggests that industry experience has investment value.[8] This investment value is economically significant as documented by the performance difference between the experience and non-experience portfolios, which ranges from 1.89 to 4.96 percentage points annually across the performance measures.[9] In terms of

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[8] We find even stronger results when we classify industries using 3-digit SIC codes instead of Fama-Frend 48 industry groupings. In a second robustness test, we ran a cross-sectional analysis within a sample of 158 sector fund managers, from which 35 had industry experience that matched the sector orientation of the fund. The value of industry experience is again supported by the finding that sector fund managers with matching industry experience outperform their sector fund managers without such experience by up to 3 percent per year.

[9] To check whether outperformance of the experience portfolio is coming from managers having ties with industry insiders in their experience industry, we looked at whether investments in their previous employers' stocks outperform investments in other stocks from their experience industry. This is not the case, suggesting that the outperformance of the experience portfolio comes from the ability of OIE managers to analyze firms from their experience industry, not from personal ties to company insiders.

magnitude, the effect is even stronger than the value of the information advantage in local investments documented by Coval and Moskowitz (2001), who show that mutual fund managers' investments in local companies generate 1.18 percentage points per year more than their non-local holdings on a risk-adjusted basis.

When focusing on the performance of the two portfolios separately, we observe that the experience portfolio generates significant positive adjusted returns in a consistent manner across the performance measures. In contrast, the non-experience portfolio generates adjusted returns that are never statistically significant. Thus, portfolio managers are able to beat the market when they pick stocks from industries where they have the advantage associated with prior work experience, but are unable to do so when they pick stocks from other industries, where this advantage is missing. This suggests that while the general investment expertise that managers with industry experience acquired on-the-job during their careers in fund management is average, their industry-specific human capital acquired outside the investment industry can create a performance advantage.

After having documented in Table III that industry-specific human capital acquired outside the investment industry puts a fund manager at an information advantage in her experience industry, we next examine how long this information advantage lasts. To do so, we extend the holding periods of the experience and non-experience portfolios to 12, 24, and 36 months.

<Insert Table IV about here.>

The reported returns over these longer horizons in Table IV suggest that the information that the managers generate about stocks they pick from their experience industries appears to gradually materialize in the underlying stock returns over a longer period, leading to an outperformance peak of the experience portfolio relative to the non-experience portfolio roughly after 24 months. A plausible explanation, which would be in line with van Nieuwerburgh and Veldkamp (2009), is that many investors without industry experience, being aware of their information disadvantage, choose to stay on the sidelines, which contributes to a slow price discovery for the aforementioned stocks.

Interestingly, a comparison of Table IV with Table III implies that a 12-month buy-and-hold strategy based on the information of the experienced manager performs slightly better than her actual trading strategy for most performance measures. The most likely explanation for this pattern is that fund managers are not immune to behavioral biases such as the disposition effect—the tendency to sell winners too soon and hold on to losers for too long—which can undermine the optimal holding periods of mutual fund managers (e.g., Frazzini (2006), Jin and Scherbina (2011), Cici (2012), and Hartzmark (2015)).

3.2. Validation Exercises

In this section we conduct two tests intended to validate our identification strategy. Our first test examines whether the investment value of industry experience increases with the extent of experience, which is to be expected if our approach is indeed capturing the effect of industry-specific human capital acquired outside the investment industry. Our second test conducts a bootstrap analysis with random assignment of pseudo experience industries to rule out the possibility that our methodology gives rise to a spurious performance difference between the experience and non-experience portfolios.

3.2.1. Extent of experience and investment value of industry experience

More extensive experience is intuitively expected to be more valuable because it provides a manager with a deeper understanding of the industry and thus with a greater information advantage. If our identification strategy is not capturing the effect of industry experience, then more extensive industry experience in a particular industry ought to be unrelated with the performance differences between the two sub-portfolios. We use two measures to classify managers by the extent of their experience.

Our first measure is length of employment in a particular industry. A manager who worked in an industry for a longer period of time is likely to have gained a deeper understanding of that industry than another manager who worked in an industry for a shorter period. We take the time between the first date when a manager was employed in a given industry and the date when the manager left the industry as a measure of the length of experience in that industry. Based on this information, we classify a manager as having long experience if that manager has industry experience with a length of more than five years, which is the cross-manager average; the rest of managers are classified as having short industry experience.

Our second measure is the seniority of the position that a manager held in a particular industry. We argue that a manager who held a more senior position gained a deeper understanding of the industry than somebody who held a junior position. To classify managers as having held senior positions in their experience industries we searched the description of their industry position for the following keywords: "CEO", "CCO" "CFO", "CIO", "COO", "CTO", "director", "president", or "principal". Managers with job descriptions containing at least one of these keywords are classified as having held senior industry positions; the rest of managers are classified as having held junior industry positions.

In Table V, we replicate the analysis of Table III (more precisely, Column 3 of Table III), but now for the two subsets of managers categorized by length of experience (Panel A) and seniority of position (Panel B).

<Insert Table V about here.>

We report performance differences between the experience and non-experience portfolios for the subset of managers with greater extent of experience, for the subset of managers with smaller extent of experience, and most importantly, compare the performance differences between the two. Results show that both types of managers categorized by extent of experience generate higher performance in their experience portfolio than in their non-experience portfolio. However, the extent of experience matters for how much the experience portfolio outperforms the non-experience portfolios. Fund managers with a greater extent of experience generate performance differentials that are significantly larger than those generated by managers with smaller extent of experience, with the difference being up to seven percentage points.

Taken together, the evidence that the investment value of industry experience increases with the extent of experience rejects the null hypothesis that our identification approach does not capture the effect of industry work experience.

3.2.2 Bootstrap analysis with random assignment of pseudo experience industries

There is also the possibility that our methodology might give rise to a spurious performance difference between the experience and non-experience portfolios. For example, in unreported tests we find that the experience portfolio has about twice as much idiosyncratic risk as the larger, more diversified non-experience portfolio. This difference could favor the risk-adjusted performance of the experience portfolio in a way that does not reflect industry-specific skill.

To address this concern, we perform a bootstrap procedure where each manager is assigned random pseudo experience industries, i.e., industries in which the manager has in fact no experience. This sampling approach imposes the null hypothesis of no stock picking effect due to industry experience. To replicate our original setup as closely as possible, the random experience industries must fulfill two conditions. First, the number of random pseudo experience industries assigned to a manager has to equal the number of her actual experience industries in our original sample. Second, these industries are represented in the manager's portfolio by at least one stock holding on one report date. We repeat this random draw 10,000 times for all managers and implement the measurement approach of Table III.

In Figure 1, we display the distribution of Carhart alpha differences between the managers' random pseudo experience portfolios and remaining non-experience portfolios.

<Insert Figure 1 about here.>

We observe that the actual performance difference of Table III is positioned at the right-hand tail of the bootstrap distribution, such that it is significantly greater than the mean of the empirical distribution resulting under the null of no stock-picking effect due to industry experience (p-value=0.0004). This result rejects the null in favor of our hypothesis that industry experience provides a stock picking advantage. Bootstrap results from the other risk- and characteristics-adjusted performance lead to the same basic conclusion.

In sum, the evidence so far suggests that industry experience leads to an information advantage enabling fund managers with industry experience to pick stocks skillfully from their experience industries.

4. Do OIE Managers Overweight Their Experience Industries?

So far we have shown that OIE managers have an information advantage in the stocks that they pick from their experience portfolios. Applied to our setting, the equilibrium model of van Nieuwerburgh and Veldkamp (2009) would suggest that it is optimal for the OIE managers with such information advantage to overweight their experience industries and continue investing in gathering information in those industries in order to maintain and exploit their initial information advantage. If OIE managers are also able to time their experience industries, we would expect the extent of overweighting to depend on the future relative performance of those industries.

We first examine whether fund managers overweight their experience industries. To do so, we use a similar approach as in Pool et al. (2012) and estimate the following regression equation

$$w_t^{j,f} = a_0 + a_1 expindustry^{j,f} + a_2 w_t^{j,\,Peer} + Controls + \varepsilon_t^{j,f} \qquad (1)$$

Where $w_t^{j,f}$ is the weight of fund *f* in industry *j* at time *t*. $expindustry^{j,f}$ is a dummy variable that equals one if the manager of fund *f* has experience in industry *j*. $w_t^{j,\,Peer}$ is the average weight in industry *j* across all funds run by non-OIE managers at time *t* and controls for industry-specific investment patterns related to particular fund styles. The key insights come from the estimate of a_1, which captures the average experience-industry bias per manager, i.e., the percentage of the fund's portfolio abnormally allotted to the manager's experience industry.

We control for possible industry momentum (e.g., Grinblatt and Moskowitz (1999)) using the previous year's industry return as an additional control variable. Other controls are the factor loadings on the market, HML, and SMB factors, computed for industry j and report date *t* by estimating the Fama and French (1993) three-factor model over the last 36 months. We perform a pooled regression and cluster standard errors by manager and report date to determine significance of the individual estimates.

<Insert Table VI about here.>

Table VI reports results. Column 1 presents coefficients for Model 1. The average OIE manager overweights her experience industry by 149 basis points relative to the average non-OIE manager. This result is consistent with the predictions of the van Nieuwerburgh and Veldkamp (2009) model.

Next, we analyze whether OIE managers adjust their overweighting depending on whether the experience industry outperforms (underperforms) other industries. In Column 2 and 3, we estimate regression (1) for two regimes defined by whether industry compounded returns that are market-adjusted are positive or negative in the next 12 month, respectively. The market-adjusted return of industry *j*, denoted by ($r_{t,fut}^{j} - r_{t,fut}^{M}$), is computed by subtracting the value-weighted market return—that excludes industry *j* return—from the value-weighted return of industry *j*. The coefficient on the experience industry dummy is about 1.5% in both regimes and the difference is not statistically significant. Finding that managers overweight their experience industries even prior to periods of industry underperformance suggests that OIE managers have no superior industry timing ability.

To formally test the industry timing ability of the OIE managers, we relate the future market-adjusted return of a given industry *j* to industry portfolio weights of fund managers in excess of peer industry weights. The dependent variable, the market-adjusted future return of industry *j* compounded over the next 12 months, is computed as described above. Using excess industry weights of fund managers as an independent variable allows us to control for investment patterns in an industry that are typical for funds that follow a particular style. Timing ability of a fund manager would suggest that she overweights (underweights) an industry relative to her peers prior to an outperformance (underperformace) of the industry relative to other industries.

$$r_{t,fut}^{j} - r_{t,fut}^{M} = a_0 + a_1 exw_t^{j,f} + a_2 expindustry^{j,f} + a_3 exw_t^{j,f} expindustry^{j,f} + Controls + \varepsilon_t^j \qquad (2)$$

The independent variable $exw_t^{j,f}$ is the weight that the manager of a given fund *f* has in a particular industry *j* at *t* in excess of the average weight of peer funds in that industry. Thus, in this setup we have 48 Fama-French industry returns and 48 industry excess weights for each manager each year. $expindustry^{j,f}$ is a dummy variable that equals one if the manager of fund f has experience in industry j. Our key test is based on the interaction term, which tests for the manager's ability to forecast whether her experience industries outperform or underperform other industries. We employ the same control variables as in Model (1) and perform a similar estimation procedure.

<*Insert Table VII about here*.>

The first column of Table VII reports the regression results of Model (2). The interaction term is positive but not statistically significant. Given the persistent overweighting of experience industries documented in Table VI, using changes in the industry excess weight rather than levels might provide a more powerful test. In Column 2, we report results whereby we replace the excess weight with the change in excess weight. The coefficient of the interaction term remains positive, but again is not statistically significant.[10]

Overall, this section shows that OIE managers generally tend to overweight their experience industries relative to non-OIE managers, which is consistent with rational behavior as predicted by the equilibrium model of van Nieuwerburgh and Veldkamp (2009). However, we find no evidence that OIE managers are able to increase (decrease) their overweighting prior to periods of experience industry outperformance (underperformance) relative to other industries.

5. Can Investors Profitably Exploit the Industry Experience of Fund Managers?

Having established that industry experience has investment value, we now employ an investors' perspective to determine whether investors might be able to benefit from the industry experience of fund managers. An obvious way for investors to do so would be to buy funds run by managers with industry experience. However, the OIE managers run diversified funds and hold, on average, only about 6.42% of the portfolio in their experience industries (see Table I). This means that overall fund performance is mainly determined by the part of the fund portfolio invested in non-experience industries, suggesting that investors might be better off mimicking only the part of the fund portfolio invested in managers' experience industries.

Table IV showed that the stocks picked in the managers' experience portfolios generate returns materializing over a period of time that extends beyond the 60-day grace period after the report date, during which funds are mandated to file their holdings with the SEC. This could suggest that investors can profitably replicate the positions of fund managers' experience portfolios even though holdings information is available to them with a delay.

[10] In two unreported tests we checked the robustness of our timing results. First, we excluded observations from 2008 to rule out the possibility that our results were driven by the financial crisis. The results remain qualitatively unchanged. Second, we extended our sample to include all the 180 managers whose prior work experience was in Fama-French industry grouping 44 (Banks—Banking). Results are robust to both modifications. For this extended sample, we find some timing ability but the results are only borderline significant.

To test whether investors can profitably mimic the experience portfolios of fund managers, we evaluate a simple replication strategy. We assume that, after observing the stock positions of a given manager's portfolio, an investor mimics the experience portfolio of the manager by replicating its weights. The investor then changes the weights when new portfolio holdings are disclosed. Based on this procedure, a series of monthly returns is constructed from replicating the experience portfolio of each manager. Finally, we assume that the investor invests equally across the experience portfolios of all managers. The time series of monthly returns from investing in this aggregate experience portfolio are evaluated using the same performance measures as in Table III.

<*Insert Table VIII about here*.>

Table VIII presents annualized performance numbers for the replicating strategy described above separately for scenarios assuming that the holdings information is available to investors immediately on the report date (time *t*), or with a delay of one, two, and three months. Since mutual funds are required to make their holdings publicly available by filing no later than 60 days after the report date, only the replicating strategy from the third and fourth scenarios would be feasible. Returns from the first two scenarios are hypothetical, however, as investors have access to holdings data for all funds only at the end of the 60-days grace period. Nevertheless, we include the first two scenarios for comparison.

Results from Table VIII show that uninformed investors can benefit from the industry experience of managers by mimicking their experience portfolios. Even when investors get to know the portfolio positions with a delay of two months, they are able to generate significant risk-, and characteristic-adjusted returns from the mimicking strategy. Both the Carhart alpha and DGTW-adjusted return deliver a significant outperformance of 4.98% and 3.04%, respectively. However, there is some evidence to suggest that the earlier the investors learn about the portfolio composition, the more valuable this information is. Raw, risk- and characteristic-adjusted returns decline as the delay with which holdings data are made available for portfolio construction increases. Specifically, annualized Carhart alphas drop from 5.33% (t-stat=2.67) in the first replicating scenario with no information delay to 4.20% (t-stat=2.22) in the last scenario with a three-month information delay. Similarly, DGTW-adjusted returns drop from 3.55% (t-stat=2.10) to 2.36% (t-stat=1.44).

At first blush, this result seems to suggest the presence of a valuable trading strategy based on publicly available information, which would constitute a violation of semi-strong market efficiency. That might well be the case, however, it is also possible that the needed information to implement the strategy is burdensome for investors to collect from SEC filing reports and other sources and/or the trading strategy is hard to implement due to transactions costs or investment restrictions. Thus, the performance of the mimicking strategy would just compensate for these efforts without necessarily indicating a violation of market efficiency.

6. Do Fund Families Scale up the Industry Experience of Fund Managers?

The fact that industry experience enables fund managers to identify superior investments in their experience industries suggests that a rational strategy for fund families would be to extend the benefits of this advantage to a larger asset base encompassing other funds in the family (hereafter, affiliated funds). If fund families are acting in such a fashion, we would expect affiliated funds to utilize the investment ideas from a colleague's experience industry while paying little or no attention to their colleague's ideas in other industries where no clear advantage is evident.

To test this prediction, we employ a linear probability model, which models the likelihood that a trade conducted by a fund manager with industry experience is followed by affiliated funds. The unit of observation is a trade of a given stock conducted by a manager with industry experience in quarter *t*.

$$trade\_follow_t^{j,f} = \alpha_0 + a_1 expindustry^{i,f} + Controls + \varepsilon_t^{i,f} \tag{3}$$

The dependent variable $trade\_follow_t^{i,f}$ is an indicator variable, which equals one if a trade conducted in stock *i* by manager of fund *f* with industry experience is followed by a trade in the same direction by at least one affiliated fund subsequently in quarter *t+1* or *t+2*, and zero otherwise. The key independent variable is $expindustry^{i,f}$, an indicator variable that equals one when stock *i* is from the manager's experience industry. If affiliated managers are more likely to follow the ideas that come from their colleague's experience industry than those that come from their non-experience industries, then we expect the coefficient on this variable to be positive.

We control for firm size, the natural logarithm of market capitalization (stocks outstanding multiplied with stock price at the end of the report date), past 12-month compounded stock return, past 12-month stock return volatility, and book-to-market ratio. We also control for the natural logarithm of the total net assets managed by the fund family. Since the analysis is at the family level and we want to use within-family variation in order to control for family differences, we employ family-by-report date fixed effects. Standard errors are clustered by fund family.

<Insert Table IX about here.>

Results are reported in Table IX. In the first column, we condition on trades that initiate a position in the portfolio of managers with industry experience in stocks that are not concurrently held by any of the affiliated managers. We argue that new ideas that appear for the first time in the portfolio of a manager with industry experience but not in the portfolios of affiliated managers are most likely to have been produced by the former manager.

The coefficient on the experience industry dummy in the first column is positive and statistically significant at the five percent level.[11] Its value suggests that the probability that the

[11] Most likely, this underestimates the size of the economic effect because this test only considers fund managers following their experienced colleagues with a time lag of one or two quarters. Many fund managers will be able to observe the trades of their experience colleagues within the same quarter and thus adopt the ideas of their

new ideas of managers with industry experience are subsequently utilized by the family's other funds is more than 5 percentage points higher when the new ideas are from the experience industry than when they are from other industries. This is economically significant because it constitutes more than a 50 percent increase in probability relative to the baseline probability (not reported in the table) that the family's other funds follow the ideas of their colleagues from their non-experience industries. This evidence is consistent with family's other managers paying greater attention to the investment ideas coming from the experience industries of their colleagues with industry experience and being more likely to act on those ideas.

For completeness, in Column 2, we show results when we condition on the rest of stock purchases conducted by managers with industry experience. The coefficient on the experience industry dummy, although somewhat smaller, continues to be significant. In Column 3 and 4, we replicate the analysis of Column 1 and 2 but restrict it to the sub-sample of affiliated funds that hold at least one stock in the experience industry. The reason for this restriction is to ensure that affiliated managers are not precluded from investing in the experience industries due to possible investment restrictions. The coefficients on the experience industry dummy and its significance continue to be in the same ballpark.

Finally, in the last two columns, we condition on the stock sales of managers with industry experience. Mutual fund managers typically face short-selling constraints. This would prevent affiliated funds from acting on negative information on a specific stock that was generated by their colleagues with industry experience unless they currently own that stock. For this reason, we apply a filter to the stock sales of a manager with industry experience by keeping only those that correspond to stocks that were held by at least one affiliated fund at the beginning of *t*.

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experience colleagues within the same quarter. Cici, Jaspersen, and Kempf (2017) document that the performance effect is the stronger, the earlier information is shared across managers of a fund family.

In Column 5, the observations comprise all sales of managers with industry experience that terminate a position and in Column 6 they comprise the rest of the sales. The coefficient on the experience industry dummy continues to be positive and statistically significant, suggesting that the affiliated managers pay closer attention to the selling decisions of their colleagues when those decisions cover stocks from their colleagues' experience industries.

All in all, results from this section suggest that fund families utilize the industry-specific human capital of their managers with prior industry work experience by applying it to a larger asset base, which goes beyond funds managed by the managers with industry experience themselves.

7. The Value of Industry Experience in a Team Setting

So far, we have specialized our analysis to single-managed funds because such a setting allows for a precise measurement of the value of industry experience. The reason is that in a fund managed by a single decision maker, the performance difference between the manager's experience portfolio and non-experience portfolios cleanly isolates the value of that manager's industry experience. The same cannot be said for a team-managed fund where a clean attribution of stock picks to each of the managers managing the fund is impossible.

However, team managed funds have been gaining importance in the industry and the question arises whether a team setting allows a fund manager with industry experience to better exploit her industry experience. There are two competing hypotheses. The investment literacy hypothesis suggests that the manager with industry experience benefits from the investment experience of the other team members. The complementary nature of industry experience and financial experience would suggest that the experience portfolio delivers better performance in a team-managed fund than in a single-managed fund. In contrast, the diversification of opinion hypothesis predicts the opposite. It posits that teams make decisions that reflect a consensus shaped by the average opinion of the team members (e.g., Sah and Stiglitz, 1986 and 1988).

Supporting evidence for this hypothesis was documented in Bär, Kempf, and Ruenzi (2011). Thus, in a team managed-fund that houses a manager with industry experience, the experience portfolio reflects not only the view of the manager with industry experience but also the views of the other team members that do not have such industry experience. This would keep a team-managed fund from benefiting fully from the industry expertise of a given manager, leading to lower performance of the experience portfolio.

To test these hypotheses, we extend our sample of funds managed by single managers with industry experience to include also funds that these managers managed as part of a team. This allows us to keep the manager with industry experience constant and compare the performance of the experience portfolio under a single manager regime versus a team regime.

We use the following procedure to extend our sample. For each manager with industry experience in our sample, we identify all the funds that she managed as part of a team. We identify 164 such funds. From this set, we exclude 49 funds that are managed by large teams ($\geq$ 5 team members) because that might indicate that the fund is either managed by a combination of portfolio managers and analysts or the fund's management is outsourced to multiple sub-advisers that in turn use teams of portfolio managers (some teams included as many as 30 managers). Finally, we exclude 9 funds where any of the managers that are not in our original sample had prior industry experience. This ensures that the experience portfolio of the single-managed fund and the team-managed fund that share the same manager with industry experience reflect the same extent of industry experience. To identify such managers, we manually checked the various sources used for our original sample construction to obtain biographical information. Our final extended sample includes 305 funds and 333 fund managers.

<*Insert Table X about here*.>

To assess whether industry experience becomes more valuable in a team setting, in Table X we compare the performance differentials between experience and non-experience portfolios for funds managed by single managers against funds managed by teams. Specifically, we regress the performance difference between the experience and non-experience portfolios from the extended sample on an indicator variable, *Team*, which equals one if the fund is managed by a team of fund managers and zero if it is managed by a single manager. Since we want to keep the manager with industry experience constant, we employ variations of fixed effect structures centered on manager fixed effects. The first specification includes manager fixed effects only, the second includes manager and date fixed effects, and the third includes manager by date fixed effects. Standard errors are again clustered by manager and date.

Results from Table X provide no support for the investment literacy hypotheses. The experience vs. non-experience performance differential is not better when the manager with industry experience manages a fund as part of a team than when she manages it solo. In fact, the performance difference is lower for team-managed funds, but not statistically significant.

Given our evidence from Table X that a team management structure does not affect the value of industry experience of a given manager, we now turn our attention to cross-sectional comparisons to assess whether team size matters.[12]

<Insert Table XI about here.>

Table XI replicates the analysis of Table III for subsets from our extended sample that differ by team size. In Panels A, B, and C we include funds managed by teams of up to two, three, and four managers, respectively. Results from this table again provide no support for the investment literacy hypothesis. The performance of the experience portfolio in our extended sample is not better than in our original sample consisting of single-managed funds only (see Table III). If anything, the performance of the experience portfolio seems to decline when we move from small to large teams. This evidence is more in line with the diversification of

[12] Ideally, we would have used within-manager variation, but the number of observations where the same manager with industry experience is in team-managed funds of different sizes is very small.

opinion theory and suggests that the impact of the manager with industry experience on the experience portfolio becomes weaker when the team becomes bigger.

Given that the average manager with industry experience enjoys an information advantage in her experience industry, the findings above beg the question: Why don’t other team managers give the manager with industry experience the ultimate authority to pick stocks from her experience industry. We argue that initially when a manager with industry experience joins a team-managed fund, the other team members might have an imprecise knowledge of the information advantage that the manager enjoys in her experience industry. However, with the passing of time, as other team members learn more about the value of the information advantage enjoyed by the aforementioned manager, they give that manager more freedom to pick stocks from her experience industry. For this reason, we expect to see a positive relation between the performance of the experience portfolio and the tenure that the manager with industry experience has with the fund. However, we would expect no such relation between the performance of the non-experience portfolio and fund tenure because the non-experience portfolio captures the decision-making of all the team members and as such should be unaffected by the tenure of the manager with industry experience.

To test this hypothesis, we use all team-managed funds that we included in the extended sample described above. We employ a regression specification where we regress the performance of the experience portfolio, the performance of the non-experience portfolio, and the performance difference of the two portfolios on the natural log of fund tenure of the manager with industry experience. We employ manager fixed effects to exploit within-manager variation and also include time fixed effects to control for market-wide shocks. Standard errors are clustered by manager and date.

<*Insert Table XII about here*.>

Results from these regressions reported in Table XII show that manager tenure is positively related with the performance of the experience portfolio. This evidence is consistent with the view that as a manager with industry experience becomes more tenured in a fund, his ideas for stock picks from the experience industry become less challenged and the fund ends up better capturing the value of his expertise in that industry.[13] Looking at the non-experience portfolio, we find no such relation. This is consistent with the view that the non-experience portfolio reflects the decisions of all team members. As a consequence of these results, we also find a positive relation between manager tenure and the performance difference of the experience and the non-experience portfolio, again suggesting that the value of industry experience increases with the tenure of the experienced manager in a team setting.

8. Conclusion

In this paper we show that industry-specific human capital acquired outside the investment industry is transferrable to this industry and provides fund managers with an information advantage. Identifying industries in which portfolio managers had prior work experience, we split managers' portfolios into two subsets that reflect, respectively, investments in managers' experience and non-experience industries. We find that managers exploit their industry-specific information advantage by overweighting their experience industries and picking stocks from those industries that generate significant risk- and characteristic-adjusted performance of up to five percent per year. In contrast, their stock picks from their non-experience industries generate performance that is indistinguishable from zero. Extending our analysis to teams of fund managers, we find that overall, the investment value of industry experience is unaffected by whether the manager is part of a team or not.

Besides documenting the value of prior industry experience from the prism of fund managers, our analysis approaches this subject also from the perspective of investors and fund

[13] To support that view, we ran a similar test using our sample of single-managed funds where one expects to find no such effect because a sole manager faces no constraints when making stock picks from her experience industry. Indeed, we find no relation between the performance of the experience portfolio and the tenure of the manager in the sample of single-managed funds.

families. First, our results suggest that investors might benefit from the prior industry experience of fund managers by mimicking the stocks holdings of these managers in their experience industries. Second, we show that fund families utilize the industry experience of their managers with prior industry work experience by applying it to a larger asset base, which is consistent with families striving to optimally deploy the human capital of their employees.

Although industry experience provides fund managers with a clear investment advantage, only about one tenth of diversified funds are run by managers with industry experience. This begs the question: Why don't fund families hire more managers with such experience? One possible explanation is that fund families hire more managers with such experience but allocate a higher fraction of them to sector funds rather than diversified funds. The rationale would be that managers of diversified funds have to diversify across industries and, thus, are constrained from utilizing their industry experience to their fullest. We checked this hypotheses by using biographical information that we hand-collected for 158 sector fund managers that single-managed a sector fund during our sample period. Out of these 158 sector fund managers, 35 managers had a matching industry experience. Thus, almost one quarter of the sector fund managers have prior industry experience whereas only one tenth of the managers of diversified funds have such experience. Another possible explanation is that the considerable costs of acquiring financial skills by investment in post-graduate education in order to provide a reliable signal to the job market might make it attractive only for a subset of industry workers to change industry. Thus, the low percentage of managers with industry experience in fund management might be an equilibrium outcome in the fund labor market – an interesting avenue of future research.

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Table I: Manager and fund characteristics

This table reports manager and fund characteristics. Panel A reports characteristics for our sample of fund managers with prior outside industry experience (OIE managers) and for the managers who do not have such experience (non-OIE managers). Both groups of funds include fund managers who solely managed U.S. domestic diversified equity fund (excluding balanced, bond, money market, index, international, and sector funds) at some point between 1996 and 2009. The first row reports the average length of prior industry experience. In the second row, we report the average age of a manager when she first appears as single manager of a U.S. domestic diversified equity fund in the Morningstar Principia database. The table also reports the fraction of managers that hold an MBA, CFA, or PhD, followed by information on the fraction of managers with a major in a certain discipline. The cumulative fraction for the majors sums up to more than 100% because some managers have more than one declared major. Panel B reports characteristics for funds run by OIE managers and for fund run by non-OIE managers. Our sample consists of 199 diversified, domestic U.S. equity funds single-managed during 1996-2009 by 130 fund managers with prior industry work experience. The group of funds run by non-OIE managers consists of 1,420 funds that have the same investment objectives as our sample but are managed by single managers with no prior industry experience. The reported fund characteristics include: fund size in $ millions; expense ratio measured in percentage points per year; turnover ratio measured in percentage points per year; and portfolio weights of FF48 industries in which our OIE managers have experience. Variables are measured for each report date, we than calculate the average per fund and year.

Panel A: Manager characteristics

Manager characteristic	OIE Managers	Non-OIE Managers	Difference	t-stat
Length of industry experience [years]	5.26	-		
Age of manager when managing first single fund [years]	39.37	37.67	1.70	1.41
MBA [%]	70.00	53.30	16.70	3.86
CFA [%]	46.92	49.85	-2.93	-0.63
PhD [%]	3.07	5.62	-2.55	-1.51
Business/Economics Major [%]	54.81	75.07	-20.26	-3.93
Engineering/ Natural Science Major [%]	43.27	11.52	31.75	6.32
Other Major [%]	11.54	21.00	-9.46	-2.71

Panel B: Fund characteristics

Fund characteristic	Funds run by OIE Managers	Funds run by Non-OIE Managers	Difference	t-stat
Fund size [in $ millions]	1,705.19	890.90	814.29	6.87
Expense ratio [%]	1.34	1.37	0.03	1.67
Turnover ratio [%]	109.62	99.85	9.77	1.28
Weight FF48 Exp. Industry [%]	6.42	3.27	3.16	30.81

Table II: Stock characteristics

This table reports characteristics of stocks held in the experience and non-experience portfolios of the OIE managers. We determine whether a stock belongs to a manager's experience or non-experience portfolio by comparing the issuing company's FF48 industry to the industries in which the manager worked prior to the beginning of her career as a fund manager. We measure market capitalization as number of outstanding shares multiplied by the share price and report it in millions of USD. The market beta, high minus low (HML) beta, small minus big (SMB) beta, and the momentum beta are measured as average factor loadings from a rolling regression of a stock's excess return on the market return, the HML factor, the SMB factor, and the momentum factor. We use 36 monthly returns to determine the factor loadings, and roll the observation window forward by one month in each step. Standard errors for the t-test reported in the last column are computed using standard errors clustered by manager and date.

	Experience Portfolio	**Non-Experience Portfolio**	**Difference**	**t-stat**
Market capitalization	27,026	24,599	2,427	0.93
Market beta	1.15	1.10	0.05	1.91
HML beta	-0.18	0.08	-0.26	-3.66
SMB beta	0.39	0.35	0.04	1.50
Momentum beta	0.06	-0.02	0.07	1.93

Table III: Performance of experience portfolio vs. non-experience portfolio

This table reports performance results for the managers' experience portfolios and non-experience portfolios. We determine whether a stock belongs to a manager's experience or non-experience portfolio by comparing the issuing company's FF48 industry to the industries in which the manager has worked prior to the beginning of her career as a fund manager. Following stock assignments into experience and non-experience sub-portfolios, we keep the stocks in the sub-portfolios until the next report date, when the composition of the sub-portfolios is updated again, to reflect changes in holdings. Our performance measures include: The raw return (Return), Carhart alpha (Carhart), DGTW-adjusted return (DGTW), industry-adjusted DGTW return (Ind.-adj. DGTW), and peer-adjusted DGTW return (Peer-adj. DGTW). Carhart alpha is computed for a given stock each month as the difference between the actual return minus the expected return, estimated using factor loadings computed from a regression of the preceding 36 monthly excess returns on the four risk factors. DGTW-adjusted returns are estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. Industry-adjusted DGTW returns are computed by comparing DGTW-adjusted returns of each portfolio stock with the DGTW-adjusted returns of a portfolio of stocks from the same industry but not held in the portfolio. Peer-adjusted DGTW returns are computed by comparing DGTW-adjusted returns of each portfolio stock with the DGTW-adjusted returns of a portfolio of stocks from the same industry held by funds run by non-OIE managers (matched by style), but not held in the portfolio. We compute buy-and-hold returns for each fund and each sub-portfolio, with the holding period determined by the distance between report dates. The buy-and-hold returns are computed by value-weighting the buy-and-hold returns of the underlying portfolio stocks, with weights based on the market value of the positions at the beginning of the holding period. Estimates are averages across time and portfolios, and t-statistics are computed using standard errors clustered by manager and date. All performance measures are annualized. The number of observations is N = 2,188.

	Experience		**Non-Experience**		**Difference**	
Performance Measures	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Return	0.1005	2.00	0.0776	1.65	0.0229	1.51
Carhart	0.0598	2.99	0.0102	1.12	0.0496	2.39
DGTW	0.0271	2.25	0.0009	0.10	0.0262	2.38
Ind.-adj. DGTW	0.0215	2.02	0.0026	0.41	0.0189	2.06
Peer-adj. DGTW	0.0268	2.85	0.0024	0.43	0.0244	2.60

Table IV: Performance over longer holding periods

This table reports performance results for the managers' experience portfolios and non-experience portfolios over longer holding periods. The experience and non-experience portfolios are constructed as described in Table III. Our performance measures, described in more detail in Table III, include: the raw return (Return), Carhart alpha (Carhart), DGTW-adjusted return (DGTW), industry-adjusted DGTW return (Ind.-adj. DGTW), and peer-adjusted DGTW return (Peer-adj. DGTW). We value-weight the performance of stocks making up each portfolio by the market value of each position at the beginning of portfolio formation. We compute buy-and-hold returns for each fund and each sub-portfolio over holding intervals of different lengths that range from 12 to 36 months. Estimates are averages across time and portfolios, and t-statistics are computed using standard errors clustered by manager and date. All performance measures are annualized. The number of observations is N = 2,188.

	Experience		**Non-Experience**		**Difference**	
Performance Measures	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
			12 months			
Return	0.1154	4.16	0.0812	3.20	0.0342	3.45
Carhart	0.0596	4.58	0.0127	1.90	0.0469	3.51
DGTW	0.0298	3.16	-0.0029	-0.63	0.0328	3.74
Ind.- adj. DGTW	0.0217	2.68	-0.0051	-1.65	0.0268	3.34
Peer-adj. DGTW	0.0300	3.59	-0.0017	-0.55	0.0317	3.83
			24 months			
Return	0.2210	5.51	0.1629	4.50	0.0581	3.49
Carhart	0.0826	4.73	0.0194	2.14	0.0632	3.31
DGTW	0.0456	3.21	-0.0032	-0.47	0.0488	3.47
Ind.- adj. DGTW	0.0327	2.52	-0.0084	-1.61	0.0411	3.12
Peer-adj. DGTW	0.0447	3.32	-0.0041	-0.77	0.0488	3.71
			36 months			
Return	0.2791	6.01	0.2244	5.56	0.0547	2.06
Carhart	0.0935	4.39	0.0296	2.39	0.0639	2.60
DGTW	0.0455	2.23	-0.0006	-0.08	0.0462	2.19
Ind.- adj. DGTW	0.0233	1.21	-0.0079	-1.25	0.0312	1.57
Peer-adj. DGTW	0.0367	1.90	-0.0037	-0.60	0.0404	2.04

Table V: Performance differences and extent of experience

This table reports performance differences between experience and non-experience portfolios for two groups of managers categorized by extent of experience. The performance differences between experience portfolio and non-experience portfolio are calculated as in Table III. We measure extent of experience via length of experience in Panel A and seniority of prior industry position in Panel B. We determine whether a manager has long or short experience using the length of the manager's experience in the industry prior to becoming a fund manager. We categorize managers as having long experience if they have more than five years of experience, the mean length of experience in our sample. The remaining managers are categorized as managers with short experience. We categorize managers as having held a senior position in their experience industry when the manager's job description contains at least one of the keywords "CEO", "CCO" "CFO", "CIO", "COO", "CTO", "director", "president", or "principal". The remaining managers are categorized as having held junior positions. All t-statistics are computed using standard errors clustered by manager and date. All performance measures are annualized. The number of observations is denoted by N.

Panel A: Length of industry experience

Performance Measures	**Managers with long experience**		**Managers with short experience**		**Difference**	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-stat
Return	0.0734	2.69	0.0143	0.92	0.0590	2.14
Carhart	0.1105	3.62	0.0393	1.86	0.0712	2.55
DGTW	0.0757	3.42	0.0178	1.61	0.0579	2.62
Ind.-adj. DGTW	0.0636	3.29	0.0114	1.35	0.0522	3.14
Peer-adj. DGTW	0.0728	4.63	0.0161	1.75	0.0566	4.05
N	318		1,870		2,188	

Panel B: Seniority of industry position

Performance Measures	**Managers with senior industry positions**		**Managers with junior industry positions**		**Difference**	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-stat
Return	0.0690	4.06	0.0212	1.36	0.0477	2.21
Carhart	0.0953	6.06	0.0480	2.24	0.0473	1.91
DGTW	0.0645	4.06	0.0245	2.18	0.0396	2.11
Ind.-adj. DGTW	0.0594	15.48	0.0175	1.84	0.0420	3.44
Peer-adj. DGTW	0.0861	6.11	0.0221	2.26	0.0640	3.43
N	176		2,012		2,188	

Table VI: Overweighting of experience industries

This table reports results from a regression of funds' industry weights on Experience industry, a dummy variable indicating whether a manager has work experience in the industry prior to becoming a fund manager. The dependent variable is the value of a funds' assets in all stocks belonging to a given Fama-French 48 industry relative to the funds' overall stock portfolio at the end of a quarter. Control variables include: the peer fund industry weight; the industry return over the previous year; the industry's market beta; the small minus big (SMB) beta; and the high minus low (HML) beta. Betas are measured as factor loadings from a rolling regression of an industry's excess return on the CRSP market index return, the HML factor, and the SMB factor. The average industry weight of peer funds is computed as the average portfolio weight in a given industry at the end of the same quarter for funds with the same investment objective (Micro Cap, Small Cap, Mid Cap, Growth, Income, Growth & Income). In Column 2 and 3 we estimate the regression for two regimes defined by whether experience industry compounded returns are larger or smaller than the compounded returns of the other industries in the next 12 month, respectively. The return of other industries is defined as the value-weighted market return excluding the experience industry return. R^2 are given in percentages. All t-statistics are computed using standard errors clustered by manager and date. The number of observations is denoted by N.

	All		**Market-adj. Return > 0**		**Market-adj. Return < 0**	
	(1)		**(2)**		**(3)**	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Constant	-0.0025	-1.63	-0.0036	-2.12	-0.0012	-0.51
Experience industry	0.0149	3.14	0.0146	2.93	0.0153	3.08
Peer fund weight	0.8119	27.40	0.7943	24.38	0.8211	18.84
Lagged return	-0.0018	-1.33	0.0003	0.20	-0.0044	-1.93
Market beta	-0.0013	-1.12	-0.0006	-0.46	-0.0020	-1.25
SMB beta	-0.0017	-1.25	-0.0013	-0.93	-0.0021	-1.31
HML beta	-0.0038	-3.26	-0.0027	-2.21	-0.0054	-3.59
R^2 [%]	30.57		27.87		32.63	
N	128,064		66,867		61,197	

Table VII: Industry timing

This table reports results from regressions of future market-adjusted return of a given industry on funds' industry weight variables, a dummy variable indicating whether a manager has work experience in the industry prior to becoming a fund manager and the interaction of this dummy variable with the weight variables. -weighted industry portfolio consisting of all stocks belonging to a given Fama-French industrythe dependent variable is the compounded 12-month ahead market-adjusted return of a given industry. We calculate the market-adjusted future return of industry j by subtracting the value-weighted market return—that excludes industry j return—from the value-weighted return of industry j. The value weighted industry *j* portfolio consists of all stocks belonging to the Fama-French industry *j* and the value weighted market portfolio consist of all stocks of the market excluding stocks of industry *j*. A fund's excess weight in an industry is computed by subtracting the average industry weight of peer funds from the fund's weight in that industry. The average industry weight of peer funds is computed as the average portfolio weight in a given industry at the same reporting date for funds with the same investment objective (Micro Cap, Small Cap, Mid Cap, Growth, Income, Growth & Income). In Column 1 we use the level of excess weights and in Column 2 the change in excess weights. The control variables include: the industry return over the previous year, the industry's market beta, the small minus big (SMB) beta, and the high minus low (HML) beta. Betas are measured as factor loadings from a rolling regression of an industry's excess return on the market index return, the HML factor, and the SMB factor. R^2 are given in percentages. All t-statistics are computed using standard errors clustered by manager and date. The number of observations is denoted by N.

	Level of Excess Industry Weight		**Change in Excess Industry Weight**	
	Estimate	t-stat	Estimate	t-stat
Constant	-0.0259	-1.21	-0.0261	-1.21
(Excess) Industry weight (change)	-0.0600	-0.86	0.0793	1.22
Manager with experience	0.1878	2.14	0.0175	2.12
(Excess) Industry weight change* Manager with experience	0.0905	0.89	0.0889	0.60
Lagged return	-0.0587	-1.35	-0.0610	-1.46
Market Beta	0.0437	2.04	0.0456	2.11
SMB beta	-0.0069	-0.37	-0.0055	-0.30
HML beta	0.0654	3.12	0.0653	3.28
R^2 [%]	4.46		4.72	
N	128,064		123,024	

Table VIII: Performance of investment strategies that mimic experience portfolios

This table reports performance results for investment strategies that mimic the experience portfolios of the OIE managers. Using the most recently reported holdings, we construct the experience portfolio at the end of the report date (No lag) or up to three months after the report date (3-month lag). Our performance measures include: the raw return (Return), Carhart alpha (Carhart), DGTW-adjusted return (DGTW), industry-adjusted DGTW return (Ind.-adj. DGTW), and peer-adjusted DGTW return (Peer-adj. DGTW). With the exception of Carhart alpha, for each fund and experience portfolio, we compute a monthly series of value-weighted performance measures, with weights determined by the market value of each position at the date of the portfolio formation. The performance measures of these portfolios are equally-weighted across all funds each month to construct an aggregate monthly return. This generates a series of monthly performance measures for the aggregate experience portfolio. Carhart alpha is estimated as the intercept from a regression of the monthly excess returns of the aggregate experience portfolio on the four Carhart risk-factors. DGTW-adjusted returns are estimated as in Daniel, Grinblatt, Titman, and Wermers (1997), where a stock's characteristic-adjusted return in a given month is computed by subtracting from its return the return of the benchmark portfolio to which that particular stock belongs. Industry-adjusted DGTW returns are computed by comparing DGTW-adjusted returns of each portfolio stock with the DGTW-adjusted returns of a portfolio of stocks from the same industry but not held in the portfolio. Peer-adjusted DGTW returns are computed by comparing DGTW-adjusted returns of each portfolio stock with the DGTW-adjusted returns of a portfolio of stocks from the same industry held by non-OIE managers (matched by style), but not held in the portfolio. The characteristic-adjusted performance measures are valued-weighted each month at the portfolio level across all portfolio stocks. From left to right, we shift the date of portfolio constructions by one month. Estimates are from the time series of aggregate returns and t-statistics are computed using Newey-West standard errors. All performance measures are annualized. The number of observations is N = 168.

	No lag		**1-month lag**		**2-month lag**		**3-month lag**	
Performance Measures	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Return	0.1288	2.00	0.1273	2.00	0.1238	1.95	0.1160	1.83
Carhart	0.0533	2.67	0.0529	2.69	0.0498	2.68	0.0420	2.22
DGTW	0.0355	2.10	0.0334	2.06	0.0304	1.93	0.0236	1.44
Ind.-adj. DGTW	0.0287	2.08	0.0255	1.77	0.0190	1.33	0.0121	0.80
Peer-adj. DGTW	0.0353	2.76	0.0309	2.35	0.0265	2.14	0.0124	0.93

Table IX: Utilization of ideas and industry experience

This table reports results from a linear regression modeling the probability that a trade by a manager with industry experience is followed subsequently by affiliated managers without industry experience. The observations include the purchases and sales of managers with industry experience at t. The dependent variable is an indicator variable that equals one if a trade of a manager with industry experience is followed by at least one other fund within the same family at t+1 or t+2 and zero otherwise. The observations for the initiating buys are identified as stocks that are held for the first time by such a manager and not held concurrently by an affiliated fund at t. Remaining buys are identified as increases in shares held and exclude initiating buys. For terminating sales the dependent variable equals one if there is at least one other fund within the same family at t+1 or t+2 selling the stock off. Remaining sales are identified as reductions in shares held and exclude terminating sales. The key independent variable, Experience industry, is an indicator variable that equals one when a stock is from an industry where a manager from the family has gained work experience. We control for: firm size, measured as the natural logarithm of market capitalization at the end of the report date; past 12 month compounded stock return; past 12 month stock return volatility; and book-to-market ratio. We also control for the natural logarithm of the total net assets managed by the fund family. In Column 3 and 4, we replicate the analysis of Column 1 and 2 after applying a style similarity condition, whereby we consider only affiliated funds that hold at least one stock from the experience industry at t+1 or t+2. In Column 5 and 6, the observations include stock sales of a manager with industry experience that correspond to stocks that were held by at least one affiliated fund at the beginning of t. R^2 are given in percentages. All t-statistics are computed using standard errors clustered by fund family. The number of observations is denoted by N.

	All Purchases				**Purchases Filtered by Style Similarity Condition**				**Sales**			
	Initiating Buys (1)		**Remaining Buys (2)**		**Initiating Buys (3)**		**Remaining Buys (4)**		**Terminating Sales (5)**		**Remaining Sales (6)**	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Experience industry	0.0500	2.29	0.0446	3.84	0.0502	2.23	0.0421	3.49	0.1056	6.95	0.0576	4.05
Firm size	0.0428	4.01	0.0659	4.05	0.0447	4.06	0.0673	4.12	0.0405	3.01	0.0365	8.03
Past return	-0.0008	-0.51	0.0075	0.69	-0.0010	-0.56	0.0074	0.68	-0.0181	-1.53	0.0178	2.46
Past Volatility	0.0199	0.37	0.1463	2.75	0.0185	0.34	0.1367	2.65	0.7522	6.15	0.4065	6.79
Book to market ratio	-0.0030	-0.44	-0.0058	-1.47	-0.0032	-0.45	-0.0062	-1.54	-0.0008	-0.07	-0.0118	-1.48
Family Size	0.3007	3.31	0.0461	0.82	0.3030	3.33	0.0460	0.76	-0.1083	-9.34	0.1349	1.39
R^2 [%]	27.67		47.47		27.49		46.35		19.86		18.95	
N	9,205		32,477		8,794		31,190		9,504		23,689	

Table X: Performance differences and management structure

This table reports results from regressions that relate performance differences between experience and non-experience portfolios with the management structure of the fund. The analysis is for the extended sample, which includes single-managed and team-managed funds. The independent variable, Team, equals one when the manager manages a fund as part of a team and zero when the manager is the sole fund manager. The dependent variable is the performance difference between the experience portfolio and non-experience portfolio and is calculated as in Table III. We run three specifications with different fixed effect structures. The first specification is run with manager fixed effects, the second with manager and date fixed effects, and the third with manager by date fixed effects. All t-statistics are computed using standard errors clustered by manager and date. The number of observations is denoted by N.

	Manager fixed effects		**Manager and date fixed effects**		**Manager-by-date fixed effects**	
Performance Measures	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Return	-0.0092	-0.45	0.0002	0.01	-0.0016	-0.07
Carhart	-0.0213	-0.94	-0.0136	-0.64	-0.0202	-0.99
DGTW	-0.0290	-1.55	-0.0174	-1.23	-0.0182	-0.93
Ind.-adj. DGTW	-0.0072	-0.61	-0.0015	-0.14	-0.0188	-1.32
Peer-adj. DGTW	-0.0149	-0.71	-0.0062	-0.29	-0.0188	-1.13
N	3,210		3,193		1,483	

Table XI: Experience vs. non-experience portfolios for extended sample

This table reports performance results for the extended sample that includes single-managed and team-managed funds. Results are reported for teams of up to 2, 3, 4 portfolios managers, respectively, in Panels A, B, and C. The construction of the experience and non-experience portfolios and performance measurement is done as in Table III. Estimates are averages across time and portfolios, and t-statistics are computed using standard errors clustered by manager and date. All performance measures are annualized. The number of observations is N=2,580 for Panel A, N=3,043 for Panel B, N=3,215 for Panel C.

Panel A: Up to 2 Managers

	Experience		**Non-Experience**		**Difference**	
Performance Measures	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Return	0.1044	2.10	0.0807	1.79	0.0237	1.65
Carhart	0.0581	3.15	0.0081	0.95	0.0500	2.75
DGTW	0.0262	2.34	0.0006	0.07	0.0256	2.46
Ind.-adj. DGTW	0.0186	1.97	0.0009	0.17	0.0177	2.08
Peer-adj. DGTW	0.0258	2.97	0.0021	0.42	0.0236	2.65

Panel B: Up to 3 Managers

	Experience		**Non-Experience**		**Difference**	
Performance Measures	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Return	0.1028	1.99	0.0798	1.76	0.0230	1.45
Carhart	0.0497	2.76	0.0063	0.77	0.0434	2.45
DGTW	0.0200	1.65	-0.0009	-0.11	0.0209	1.84
Ind.-adj. DGTW	0.0126	1.36	-0.0013	-0.24	0.0139	1.63
Peer-adj. DGTW	0.0190	2.17	0.0007	0.13	0.0183	2.05

Panel C: Up to 4 Managers

	Experience		**Non-Experience**		**Difference**	
Performance Measures	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Return	0.1037	2.02	0.0806	1.79	0.0231	1.47
Carhart	0.0506	2.95	0.0060	0.74	0.0446	2.61
DGTW	0.0189	1.56	-0.0015	-0.20	0.0204	1.79
Ind.-adj. DGTW	0.0116	1.28	-0.0016	-0.30	0.0131	1.59
Peer-adj. DGTW	0.0185	2.12	0.0003	0.05	0.0182	2.04

Table XII: Team dynamics

This table reports coefficient estimates from regressions of performance measures on the fund tenure of the portfolio manager with industry experience. The sample observations include all team-managed funds that were included in the extended sample used in Table X. We employ three regression specifications where the dependent variables are, respectively, the performance of the experience portfolio, the performance of the non-experience portfolio, and the performance difference of the experience and non-experience portfolios. The performance of experience portfolio and non-experience portfolio are calculated as in Table III. The independent variable is the natural log of the tenure of the manager with industry experience with a given fund. All t-statistics are computed using standard errors clustered by manager and date. We use manager and date fixed effects. All performance measures are annualized. The number of observations is N=1,027.

	Experience		**Non-Experience**		**Difference**	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Return	0.0644	1.00	-0.0054	-0.12	0.0698	2.23
Carhart	0.0778	2.65	-0.003	-0.05	0.0782	2.91
DGTW	0.0577	2.37	-0.0015	-0.21	0.0592	2.52
Ind.-adj. DGTW	0.0528	2.49	0.00378	0.58	0.0490	2.64
Peer-adj. DGTW	0.0549	2.63	0.0001	0.02	0.0548	2.70

Fig 1. Bootstrap analysis

The figure displays the average Carhart alpha difference between managers' randomly drawn pseudo experience portfolio and their remaining non-experience portfolio. We test the null hypothesis of no stock picking effect due to experience by randomly choosing one industry in which the manager has no experience as her pseudo experience industry. For managers with experience in multiple industries, we randomly draw the same number of industries. We then compute the Carhart alpha difference as described in table III. We do this for each manager and report date, and estimate the performance difference as the average across all managers and report dates. We repeat this procedure 10,000 times, and display the distribution of the estimates. The x-axis displays the upper interval limit, the y-axis the number of estimates which fall into a given interval. The interval width equals 0.025 in all panels. For comparison, we also indicate the estimate from Table III.