What They Did in their Previous Lives:

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

Gjergji Cici, Monika Gehde-Trapp, Marc-André Göricke, and Alexander Kempf *

This Draft: December 2014

Abstract

We document that prior work experience of mutual fund managers outside the asset management industry has investment value in that it provides managers with a stock picking and industry timing advantage. Fund managers' stock picks from industries where they previously worked outperform those from their non-experience industries by about three percent annually. Moreover, fund managers are better at timing the returns of their experience industries than those of other industries. Finally, the investment value of managers' prior experience is greater when it is gained in hard-to-value industries, and it increases with the extent of experience.

JEL classification: G23, D83, J24

Keywords: Investor Learning, Investor Experience, Mutual funds

---

*Cici (gjergji.cici@mason.wm.edu) is from Mason School of Business, The College of William & Mary. Gehde-Trapp (trapp@bwl.uni-mannheim.de) is from the Department of Finance, University of Mannheim. Göricke (goericke@wiso.uni-koeln.de) and Kempf (kempf@wiso.uni-koeln.de) are from Department of Finance, University of Cologne. All authors are members of the Centre for Financial Research (CFR), Cologne. We thank several individuals who provided helpful comments on an earlier draft of the paper including Vladimir Atanasov, John Boschen, David Chapman, Richard Evans, Michael Gallmeyer, Pedro Matos, John Merrick, and Daniel Metzger and seminar participants at William & Mary and University of Virginia.

1. Introduction

Work experience within an industry can provide an employee with specific human capital in the form of industry-specific knowledge that is otherwise difficult to obtain. For example, because of such experience, professionals working for a mining company are likely to be in a better position to evaluate a new drilling technique than outsiders. Professional investors seem to value such experience. For instance, hedge fund firms are known to often seek the advice of industry professionals belonging to expert networks when they trade outside their own realm of expertise.[1] In addition, some mutual fund companies tout having portfolio managers that trade in an industry in which they have industry experience, while other fund companies structure their investment processes to include individuals with industry work experience in their teams.

In this article, we ask whether industry-specific human capital acquired by fund managers from having worked in an industry outside the asset management industry has investment value. Our identification strategy focuses on managers of diversified mutual funds with prior industry experience. This allows us to compare, for each manager, the performance of stocks she holds in the industry in which she has work experience (experience industry) with stocks from the rest of her portfolio that she holds in industries in which she has no prior work experience (non-experience industries). Thus, we are able to completely isolate the value of prior industry experience from the value of the rest of fund manager's human capital, effectively controlling for both time-invariant manager characteristics and time-variant fund and manager characteristics.

We document that industry experience of U.S. mutual fund managers has investment value. This is illustrated by our findings that U.S. mutual fund managers exhibit both superior

[1] Expert networks are firms that match industry experts with institutional investors who seek unique and professional insights when researching companies and the products that they offer. Expert networks have gained considerable traction in the recent years in the U.S. It is estimated that more than 38 expert networks operated in the U.S. in 2008, with estimated total revenue of $433 million (Integrity Research Associates (2009)). See also the Economist (2011) for a detailed discussion of expert networks.

stock picking and timing ability in industries in which they had prior work experience relative to other industries in which they had no such experience.

Tests of stock picking ability show that portfolios mimicking holdings in the fund managers' experience industries earn significantly higher risk-adjusted returns than portfolios mimicking their holdings in their non-experience industries. The performance difference ranges from three to five percent over the next twelve months and is driven primarily by the strong performance of the experience portfolios. In contrast, portfolios mimicking holdings in their non-experience industries earn risk-adjusted returns that are not consistently different from zero. This evidence shows that portfolio managers are better at picking stocks from their experience industries than from their non-experience industries, clearly supporting the investment value of industry work experience. Furthermore, the performance difference is particularly strong when we condition on positions that reflect larger bets. This is consistent with the view that higher information content is to be found among the big bets of portfolio managers (see, e.g., Jiang, Verbeek and Wang (2013))

We employ an alternative approach of assessing the investment value of industry experience that utilizes the trades of mutual fund managers. In particular, we compare the performance of stock trades from the experience and non-experience portfolios. Results from these new tests are generally consistent with prior industry experience having investment value. Stocks that fund managers buy from their experience industries significantly outperform those they buy from other industries. A similar, although weaker, pattern is observed when comparing the performance of stocks that they sell from their experience and non-experience portfolios.

The observed stock price changes that follow stock picks from the experience portfolios relative to the non-experience portfolios are not short-lived. Instead, they appear to be of a permanent nature, gradually materializing over a subsequent period of three to 36 months. This evidence suggests that stock picks from the experience portfolios reflect new information generated by portfolio managers based on their industry experience, which the markets take time to process and incorporate. The gradual market reaction is likely due to other market participants being at a disadvantage in understanding the soft information embedded in the trades of experienced portfolio managers.[2]

Besides looking for superior stock selection ability within experience industries, we also examine whether portfolio managers are better at timing their experience industries. We find that portfolio managers are more skilled at timing their experience industries than their non-experience industries. Specifically, fund managers increase (decrease) their industry weights prior to those industries experiencing strong (weak) returns in the next 12 months in a significantly stronger fashion in their experience industries relative to their non-experience industries.

In two additional sets of analyses we provide further supporting evidence for the investment value of prior industry experience by showing that experience proves even more valuable when it is expected to provide a greater advantage. First, we find that the investment value of industry experience is greater when managers' experience is earned in industries that comprise hard-to-value stocks. This suggests that experience proves even more valuable when managers face more complex investments. Second, we find that the investment value of industry experience is greater when managers' experience is more extensive. This suggests that not all experiences are created equal, and some prove more valuable than others.

All in all, our results suggest that the investment value of industry experience consists of two parts: (1) the ability to successfully select stocks within one's experience industry, and (2) the ability to successfully make investment timing decisions at the industry level.

[2] See Petersen (2004) for a discussion of differences between soft and hard information. Soft information is more difficult to interpret in a standardized way, while hard information can be collected using quantitative tools and its interpretation is straightforward and uniform across all agents. An example of soft information would be the value of a new drilling technique or the value of a new drug patent, while examples of hard information would be revenue, capital expenditure, or cash flow numbers reported in financial statements.

Our paper contributes to the literature that examines the impact of familiarity on the decisions of professional investors (see, e.g., Coval and Moskowitz (1999) and Pool, Stoffman, and Yonker (2012)).[3] Whether familiarity with certain companies gives rise to an information advantage or to a familiarity bias among professional investors is an open question in this literature.[4] Our contribution consists of showing that our particular source of familiarity, i.e., prior industry work experience, leads to an information advantage rather than a familiarity bias. Specifically, we show that managers with prior work experience do not tend to overweight their experience industries. Instead, they adjust their weights in their experience industries to successfully time their returns and also pick stocks from those industries in a profitable manner. This is consistent with Coval and Moskowitz (1999) whose study of mutual funds' investments in nearby companies shows that mutual funds are not subject to a familiarity bias with respect to local companies, i.e., they do not overweight local companies, but instead invest in them in a profitable manner.

We also make a contribution to a growing literature that examines whether experience that professional investors develop translates into superior performance (see, e.g., Golec (1996); Chevalier and Ellison (1999); Greenwood and Nagel (2009); and Kempf, Manconi, Spalt (2013)).[5] These studies generally focus on experience generated when investors learn by doing, that is, experience gained through actively managing investments. In contrast, our study examines practical experience that fund managers have already acquired in their work within a specific industry by the time they begin fund management. A portfolio manager

[3] Similar questions are asked for individual investors by Grinblatt and Keloharju (2001); Huberman (2001); Ivkovic and Weisbenner (2005); and Seasholes and Zhu (2010).

[4] Coval and Moskowitz (1999) look at the performance of investments made by mutual fund managers in nearby companies, finding evidence of informed local investing, while Pool, Stoffman, and Yonker (2012) look at investments mutual fund managers make in companies from their homes states, finding evidence of a familiarity bias.

[5] There is also another strand of literature that looks at learning by trading among retail investors (Mahani and Bernhardt (2007); Pastor and Veronesi (2009); Seru, Shumway, and Stoffman (2009); Barber, Lee, Liu, and Odean (2010); Linnainmaa (2011); Huang, Wei, and Yan (2012); and Campbell, Ramadorai, and Ranish (2014)).

either has or does not have this kind of experience and cannot acquire it during her investment career in a "learning-by-doing" fashion.

Our findings for mutual fund managers stand in contrast with those of Doskeland and Hvide (2011), who find that Norwegian retail investors are unable to use their practical industry experience to trade profitably but instead succumb to a familiarity bias. By showing that professional investors are in a better position to leverage their industry experience when investing than retails investors, we contribute to furthering understanding of differences between professional and individual investors.[6]

Our finding that the information generating advantage gained through one's industry work experience leads to superior returns supports the key premise of the many theoretical models that purport that the presence of asymmetric information can lead to disparate returns among market participants (see, e.g., Grossman and Stiglitz (1976)). Further, since obtaining this market advantage is costly, as one would have to invest considerable time and effort to gain such experience working in a particular industry, our findings are also consistent with the view of Grossman and Stiglitz (1980, p.393) that "…those who expend resources to obtain information do receive compensation."

The rest of the paper is organized as follows. In Section 2 we discuss our sample selection approach and present descriptive statistics. Section 3 examines the investment value of industry experience. In Section 4 we explore situations where such experience is expected to provide an even greater advantage. Section 5 concludes.

---

[6] The fact that retail investors exhibit a familiarity bias while mutual fund managers do not is perhaps not that surprising since mutual fund managers are professional investors who have received training and gained investment experience. In addition, mutual fund managers are subject to several disciplining mechanisms that do not apply to retail investors. For example, mutual fund managers have to abide by stated objectives, which could imply that they cannot deviate from stated industry weights.

2. Data Collection and Descriptive Results

2.1. Sample selection

To construct our sample, we first identify diversified, domestic U.S. equity funds managed by single managers. Within this sub-universe we then identify funds run by managers that had prior work experience in industries outside the financial sector.

We identify diversified, domestic U.S. equity funds managed by single managers by imposing 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. In other words, we exclude index, balanced, bond, money market, international, and sector funds. For this restriction, we rely on the unified objective codes provided by the CRSP MF database. Second, we drop all funds that are not covered by MFLINKS. The reason for this is that we later use MFLINKS to link fund characteristics from the CRSP MF database with fund holdings from the Thomson Reuters Mutual Fund database, which are crucial for our empirical tests. Finally, we further restrict our sample to include funds that are managed by single portfolio managers. The rationale for this restriction is that our tests for the investment value of industry experience 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 in large part by previous research showing that reported manager information is more accurate in the Morningstar database than in the CRSP MF database (see, 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 1,469 managers who single managed at least one of 1,606 diversified U.S. domestic equity funds between 1996 and 2009.

Focusing on the 1,469 managers identified above, we next proceed to identify managers with prior work experience outside the financial sector. For each fund manager we hand-collect biographical information from various sources including fund company websites, morningstar.com, SEC filings (485APOS), newspaper articles, and websites like zoominfo.com or linkedin.com. We use this information to construct the career path of the manager until she started in the fund management industry by recording the names of her employers, the time periods she worked for them, and her job description.

Since we are interested in fund managers with prior work experience outside the financial sector, we drop all managers who worked only for investment management firms or whose prior jobs were in banking. We also drop managers whose prior work experience was limited to military service or educational institutions because we do not have additional information to assign these particular work experiences to specific industries. Our industry experience categorization is based on the Fama-French industry classification, which consists of 48 industry groupings. However, our main finding that experience adds value also holds when we use alternative industry classifications like the Fama-French 12 industry groupings or the Kacperczyk, Sialm, and Zheng (2005) 10 industry groupings.[7]

We categorize a fund manager as having prior work experience in a particular industry if the company she worked for prior to joining the fund management industry belongs to that particular industry. Using the names of the 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

[7] 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.

listed, we manually search information about their business objective, which we then use to assign them to one of the Fama-French industry groupings.[8]

In addition to information related to the prior work experiences of fund managers, we collect information on a manager's birth year and graduation year, the study major, and all academic and professional degrees she holds. When the birth year is not available, we calculate the age of the manager by assuming (like in Chevalier and Ellison (1999)) that the manager was 21 years old when receiving her first degree.

Our final sample consists of 130 managers (henceforth referred to as sample managers) with experience in 29 industries. These managers are responsible for 199 single-managed funds (henceforth referred to as sample funds).

2.2. Descriptive statistics

Table I provides biographical information for the sample managers and sole managers without industry experience that manage funds with similar investment objectives (hereafter, peer managers and peer funds).

<Insert Table I about here.>

Table I shows that sample managers have an average industry experience of more than five years.[9] Sample managers appear to be slightly older than their peers, which is to be expected given that they worked somewhere else prior to joining the mutual fund industry. The fact that the average manager is almost forty years old when first appearing in our database (i.e., when first recorded to be sole manager of a diversified fund) is consistent with the average manager having worked before in a fund complex perhaps as a sector fund manager, analyst, member of a portfolio management team, or as a staff member providing

[8] 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.

[9] In unreported results we find that the length of experience ranges from one year to a maximum of 23 years.

different types of support (e.g., programming, data management, pricing of positions, etc.) for a few years prior to becoming manager of a diversified fund.

Further comparisons of the two groups show a significantly higher fraction of sample managers holding MBA degrees. Specifically, 70 percent of the sample managers have an MBA degree, compared to 53 percent for the peer group.[10] This is to be expected since individuals with no prior business education usually enroll in an MBA program as part of their strategy to switch to a business career. Again not surprisingly, a significantly higher fraction of sample managers have undergraduate degrees with majors in engineering and natural sciences.

In Table 2 we compare the sample funds with their peer funds. The peer group consists of 1,407 single-managed funds.

<Insert Table II about here.>

The median sample fund is about the same size as the median fund in the peer group.[11] A comparison of expense ratios and turnovers shows that, while they are slightly higher for managers with industry experience, they are of a similar order of magnitude across the two groups. The comparison of fund objectives suggests that our sample is tilted toward growth funds. This is consistent with the view that fund families assign managers with industry experience to funds investing in growth stocks since growth stocks are typically harder to value than value stocks. Therefore, industry experience can provide potentially higher rewards when applied to picking growth rather than value stocks from industries in which the managers have experience.

Table II also compares the fraction of the portfolio that our sample funds hold in their experience industries with the average weights that peer funds hold in those same industries.

---

[10] The fraction of managers with MBA degrees in the peer group is similar in magnitude to evidence from Cohen, Frazzini, and Malloy (2008) who show that about 44 percent of fund managers of U.S. single-managed funds hold an MBA.

[11] The mean fund size is larger in our sample since the Fidelity Magellan fund with a huge fund size of 32 bn USD is part of our sample.

This comparison suggests that our sample funds do not tend to overweight their experience industries relative to their peers, which is inconsistent with the presence of a familiarity bias toward their experience 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 an industry in which the manager has industry experience. We do so for all report dates in the Thomson Reuters Mutual fund database. 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 III shows characteristics of the stocks in the experience and the non-experience portfolios for all funds in our sample.

<Insert Table III about here.>

Table III shows that stocks in the experience and the non-experience portfolios do not differ in size. Consistent with evidence from Table II, stocks in the experience portfolio have a significantly lower loading on the book-to-market factor, suggesting that managers tilt more towards growth stocks in their experience portfolio than in the rest of their portfolios. This is consistent with managers utilizing their experience to identify and exploit stocks with high growth potential within their area of expertise. 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.

3. The Investment Value of Industry Experience

In this section, we examine whether the industry experience of portfolio managers has investment value along two dimensions, stock selection and industry timing. Accordingly, in

Section 3.1 we assess whether managers with industry experience are better at selecting stocks from their experience industries, while in Section 3.2 we examine whether these managers are better at timing their experience industries. In addition, Section 3.3 employs bootstrap analysis as an alternative approach to test for the value of industry experience.

3.1. Stock selection

3.1.1. Performance differences between experience and non-experience portfolios

If industry experience provides portfolio managers with an advantage in processing the information environment surrounding stocks from their experience industries, we expect stocks from their experience portfolio to outperform those from their non-experience portfolio, everything else equal. To compare the investment performance of a manager's experience and non-experience portfolios we use raw returns and risk-adjusted returns. We adjust for risk in two ways. First, we calculate alphas based on linear factor models. In this paper, we present the results based on the most general four-factor model of Carhart (1997), but the results for the three-factor model of Fama and French (1993) and the one-factor model of Jensen (1968) are qualitatively the same. Second, we control for risk by using characteristic benchmarking as in Daniel, Grinblatt, Titman, and Wermers (1997). The advantage of this approach is that it does not rely on a specific model but simply compares a stock with a portfolio of stocks with similar characteristics.

Following the construction of our experience and non-experience portfolios for each fund at the end of each reporting period, we evaluate their subsequent performance. We do so by value-weighting the performance of stocks making up each portfolio by the market value of each position at the beginning of portfolio formation. The performance of each held stock is computed by compounding each of our monthly performance measures over a certain holding period. Recognizing that any proprietary information embedded in the holdings of mutual fund managers might take a while to be incorporated by the markets, we choose holding intervals of different lengths that range from three to 36 months. Monthly raw stock returns come from CRSP stock files.

To obtain Carhart (1997) alphas, 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. We compute monthly stock characteristic-adjusted returns following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW). More specifically, we compute a stock's characteristic-adjusted return in a given month by subtracting from its return the return of the benchmark portfolio to which that particular 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.

Table IV reports average performance measures for the experience and non-experience portfolios and the difference in performance between the two portfolios over different holding periods. To assess statistical significance, we employ t-tests that are based on standard errors clustered by both manager and report date.

<Insert Table IV about here.>

Results from our key test that compares the two portfolios show that the experience portfolio outperforms the non-experience portfolio, no matter what method we use to adjust returns or what holding period is employed. Said differently, stocks that managers select from their experience industries outperform stocks they select from non-experience industries, controlling for differences in risk or stock characteristics. Thus, managers are in a better position to pick stocks from their experience industries than from other industries, which suggests that industry experience has investment value.

Analyzing the sources of the documented performance difference, Table IV shows that the experience portfolio generates significant positive adjusted returns in a consistent manner across the different performance measures and holding periods. In contrast, the non-experience portfolio generates adjusted returns that are not consistently significant across the different performance measures and holding periods. For example, the characteristic-adjusted returns of the non-experience portfolio are never statistically significant. This shows that the performance difference between experience and non-experience is attributable to the strong outperformance of experience portfolios rather than the underperformance of non-experience portfolios.[12]

Another important aspect of the findings presented here is that the observed stock price changes that follow stock picks from the experience portfolio relative to the non-experience portfolio are not short-lived. Instead, they appear to be of a permanent nature, gradually materializing over the next 36 months. This evidence suggests that stock picks from the experience portfolios reflect new information generated by portfolio managers based on their industry experience that the markets take time to process and incorporate. The gradual market reaction is likely due to other market participants being at a disadvantage in understanding the soft information embedded in the trades of experienced portfolio managers.

<Insert Figure 1 about here.>

The statistical evidence from Table IV is visually corroborated by Figure 1, which shows that the performance difference between the experience and the non-experience portfolios grows over time, from about one percentage point over the next three months to more than five percentage points over the next three years.

[12] We also examined whether prior industry experience translates into superior fund performance relative to peer funds. Our sample funds generated significant relative outperformance based on the Carhart (1997) alpha of about 39 basis points per year. The small economic magnitude of this performance result is consistent with the performance of the experience and non-experience portfolios and the fact that experienced managers, on average, hold roughly 9% of their portfolio invested in their experience industries.

3.1.2. Performance differences conditioning on large and small bets

Previous research shows that some fund managers are able to generate superior performance by placing larger bets on stocks that tend to outperform in the future (see, e.g., Cohen, Polk, and Silli (2010) and Jiang, Verbeek, and Wang (2013)). A reasonable interpretation of this evidence is that managers overweight stocks where they have a unique information advantage, suggesting that positions corresponding to large bets have a high information content. Building on this idea, we argue that conditioning on large bets ought to provide more powerful tests of the investment value of industry experience.

We classify positions for each fund and reporting period into large and small bets using two classification approaches. In the first approach, we rank all stock positions of a manager in each reporting period by their portfolio weight and classify positions with above-mean (below-mean) weights as large (small) bets. This measure indicates whether a manager overweights a stock relative to the other stocks she holds. In the second approach, we define a large bet by comparing portfolio weights of each fund with the mean weights of all peer funds with similar investment objectives. To implement the second approach, we first calculate the mean portfolio weight for each stock and reporting date for all funds in the peer group. Next, we classify each position of each sample fund as a large (small) bet if its weight is larger (smaller) than the mean peer weight. Under each classification approach, we split the experience and non-experience portfolios of each manager into two sub-portfolios based on the size of the bets and compute the performance of the four resulting portfolios.

Table V reports performance results for the four portfolios. In the interest of brevity, we only show the results for a 12-month buy-and-hold strategy as the results for other holding periods are qualitatively the same.

<Insert Table V about here.>

When looking at large and small bets within the experience portfolio, the performance of large bets is consistently positive and significant for all performance measures and both classification approaches, while the performance of small bets is not consistently significant. This suggests that portfolio managers tend to overweight their best ideas and benefit significantly from doing so. In contrast, the evidence for large and small bets within the non-experience portfolios is mixed with no clear pattern as both large and small bets are not consistently significant.

Most importantly, experience stocks consistently outperform non-experience stocks only when we condition on large bets but not when we condition on small bets. Thus, conditioning on large bets provides particularly strong evidence in support of the investment value of industry experience. Moreover, another interpretation of these findings is that fund managers are able to not only generate better investment ideas in their experience portfolio but also to know which of those ideas are best and weight them more heavily.

3.1.3. Performance differences conditioning on trades

As an alternative way of assessing the investment value of industry experience, we compare the performance of stock trades from the experience and non-experience portfolios. Conditioning on trades, performance comparisons should also provide supporting evidence for the investment value of industry experience.

We first split trades into stock purchases (buys) and stock sales (sells) by looking at changes in the numbers of shares held between two consecutive report dates. If the number of shares held in a particular stock does not change, we classify this as a “hold”. If the number of shares held goes up (down), we classify this as a buy (sell). Next, we place all buys (sells) within the experience and non-experience portfolios into separate buy (sell) portfolios and calculate the return of these portfolios using the dollar value of bought (sold) shares as weights. We again compute portfolio performance measures for different holding periods ranging from three to 36 months and report separately the performance difference between buys (sells) from the experience portfolio and non-experience portfolio. Results are presented in Table VI. Since the results are qualitatively similar across all holding periods, in the interest of brevity, we again report only the results for the 12-month holding period.

<Insert Table VI about here.>

Evidence from the performance difference between experience buys and non-experience buys shows that the stocks managers buy from their experience industries significantly outperform those they buy from their non-experience industries in the next 12 months, no matter how we measure performance. The outperformance ranges from 4.98 percent for the Carhart alpha to 2.26 percent for DGTW-adjusted returns. This finding confirms the evidence from stock holdings in Table IV, which shows that managers hold stocks in their experience portfolio that subsequently outperform stocks from their non-experience portfolio.

Next we turn to sells. Since mutual fund managers generally face short-selling restrictions, they are able to sell only stocks that are already in their portfolios. This could bias the sell analysis against finding differential ability in stock sales from the experience and non-experience portfolios. For example, if a fund manager is subject to outflows and has to sell stocks across the board, she will have to sell (on average) better performing stocks from the experience than from the non-experience portfolio, given the documented average outperformance of stocks from the experience portfolio (see Table IV). This would misleadingly give the appearance that the manager makes poor stock selling decisions in her experience portfolio. Thus, to account for differences in the opportunity set of stocks that can be sold across the two portfolios, we benchmark the performance of all sells against the performance of all holds in each subset (excluding stocks that were bought). Then we compare the benchmarked performance of sells across the experience and non-experience subsets. A negative difference means that a manager is more skilled at identifying stocks that will underperform in the future in the experience portfolio than in the non-experience portfolio. Results from Table VI provide some evidence of stronger skill among the experience sells than among non-experience sells, however the performance difference is statistically insignificant.[13]

In summary, results from the stock trades of portfolio managers generally support the hypothesis that industry experience has investment value. Managers are more skilled at adding stocks to their experience portfolio that subsequently outperform. They also appear to show a somewhat similar pattern of skill among their stock sales. However, the supporting evidence is stronger among stock purchases than among stock sales.

3.2. Industry timing

The previous section demonstrates that one way in which managers can utilize their prior industry experience is by successfully picking stocks from those industries. In this section, we explore whether, in addition to helping managers gain a stock picking advantage, industry experience helps them gain a timing advantage. The basic hypothesis is that managers can time industry returns better when they have prior work experience in those industries. Thus, the empirical prediction is that the managers' tendency to increase (decrease) their portfolio exposure to an industry prior to strong (weak) industry returns should be more pronounced for their experience industries than for their non-experience industries.

To test for this hypothesized effect, we relate future industry returns to industry portfolio weights of fund managers in a regression framework. The dependent variable is the future return of a given industry, which is computed as the compounded return of a value-weighted portfolio consisting of all stocks from that industry over a 12 month period – starting from the first month after each report date.

[13] Asymmetrical results between buys and sells have also been documented by other papers that study the holdings and trades of portfolio managers (see, e.g., Chen, Jegadeesh, and Wermers (2000) and Alexander, Cici, Gibson (2007)). A possible explanation for these results is that sell decisions are affected by non-information related considerations, such as tax-loss selling (see, e .g., Gibson, Safieddine, and Titman (2000) and Huddart and Narayanan (2002)) or behavioral effects such as the disposition effect, a tendency of investors to sell winners too soon and hold onto past losers too long (see, e.g., Frazzini (2006); O'Connell and Teo (2009); Jin and Scherbina (2011); and Cici (2012)).

The key independent variable is the weight that the manager of a given fund has in a particular industry (from the 48 Fama-French industries) at a given report date. This weight is determined each reporting period by summing the market values of all stock positions that belong to a given industry and dividing the resulting sum by the total portfolio value.

We control for how much a typical fund with a particular style invests in an industry by utilizing the average weight in that industry across all peer funds. Furthermore, we control for possible industry momentum (see, e.g., Grinblatt and Moskowitz (1999)) by adding the previous year's industry return as an additional control variable. Other controls, intended to control for differences in stock characteristics across different industries that managers might try to time, are the factor loadings on the market factor $\hat{\beta}_t^{j,\text{Mkt}}$, HML factor $\hat{\beta}_t^{j,\text{HML}}$, and SMB factor $\hat{\beta}_t^{j,\text{SMB}}$, estimated for industry j and report date t. We obtain these factor loadings by estimating the Fama and French (1993) three-factor model over the last 36 months for each industry's value weighted return. Using these variables, we perform a pooled regression specified as follows:

$$\begin{aligned} r_{t,fut}^{j} &= \alpha_0 + \alpha_1 w_t^{j,f} + \alpha_2 D_{Exp}^{j,f} + \alpha_3 w_t^{j,f} D_{Exp}^{j,f} + \alpha_4 w_t^{j,\text{peer}} + \alpha_5 r_{t,past}^{j} \\ &\quad + \alpha_6 \hat{\beta}_t^{j,\text{Mkt}} + \alpha_7 \hat{\beta}_t^{j,\text{SMB}} + \alpha_8 \hat{\beta}_t^{j,\text{HML}} + \varepsilon_t. \end{aligned} \tag{1}$$

The dependent variable $r_{t,fut}^{j}$ is the 12-month future return of industry j; $w_t^{j,f}$ is the weight of fund f in industry j; and $D_{Exp}^{j,f}$ 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 whether a fund manager has better timing ability in her experience industries than in other industries. The control variables are: the average weight of the funds in the peer group in industry j $\left(w_t^{j,\text{peer}}\right)$, the previous year's industry return $\left(r_{t,past}^{j}\right)$, and the various industry betas. Again, we use standard errors clustered by manager and report date to determine significance of the individual estimates. Regression results are reported in Table VII.[14]

<*Insert Table VII about here*.>

Table VII reports regression results. Results are reported for specifications with and without control variables. The empirical evidence from all specifications clearly shows that higher industry weights predict higher industry returns only if the manager has had prior work experience in that industry. This result supports the hypothesis that managers can time industry returns better when they have prior work experience, suggesting another venue through which industry experience is useful for fund managers.

Regarding the impact of control variables, the lagged return carries a negative coefficient sign, suggesting a certain degree of industry return reversal, and the HML factor carries a positive sign, consistent with the well-documented value effect.

Although our key result that managers are better at timing their experience industries is highly significant in a statistical sense, from this analysis alone it is hard to get a sense for how much timing ability contributes to the overall return of the experience portfolio. Thus, to assess its economic importance, we perform an additional analysis. Since managers appear to have no ability to time their non-experience industries, we focus on the experience portfolio and decompose its gross return into components that measure contribution from selectivity (CS) and timing skills (CT) using the decomposition of Daniel, Grinblatt, Titman, and Wermers (1997). The decomposition of the experience portfolio generates an annual CT measure of 2.90% (t-stat=2.61) and an annual CS measure of 3.96% (t-stat=3.40). This

[14] Our key result is qualitatively similar and still statistically significant when we employ a fund's weight in an industry in excess of its peers or when we use the change in weight over consecutive periods as the dependent variable rather than the level of the weight. However, we decided to use the specification with the level of industry weight since this approach is similar to the one used in Pool, Stoffman, and Yonker (2012).

suggests that timing ability provides roughly 40 percent of the active return component of the experience portfolio and is thus important in an economic sense.[15]

3.3. Bootstrap analysis with random assignment of pseudo experience industries

A possibility is that our results in Section 3.1 and 3.2 are driven by factors that are not related to industry experience. For example, our comparison of a concentrated experience portfolio with a larger, more diversified non-experience portfolio could lead to differences in idiosyncratic risk, which could favor the risk-adjusted performance of the experience portfolio in a way that does not reflect industry-specific skill.

To address these concerns, 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 in effect imposes the null hypothesis of no stock picking and industry timing effect due to industry experience. To replicate our original setup as closely as possible, these 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 a stock holding on one report date. We repeat this random draw 10,000 times for all managers and perform the stock-picking analysis from Table IV and the timing analysis from Table VII (using the full model) for each random draw.

In Figure 2, we display the distribution of the risk-adjusted performance differences for the 12-month holding period between the random pseudo experience portfolios and the managers' remaining non-experience portfolios. In Panels A and B the risk-adjusted performance differences are computed, respectively, based on Carhart alphas and DGTW-adjusted returns.

[15] We also tried a slightly revised version of the decomposition, whereby we modify the DGTW approach by replacing the DGTW 125 stock benchmarks with the 48 FF industry portfolios. The resulting decomposition provided qualitatively similar results, with a CT measure of 3.37% (t-stat=3.01) and a CS measure of 3.68% (t-stat=2.80).

<Insert Figure 2 about here.>

The average values from the bootstrap distributions are 0.011 in Panel A and 0.006 in Panel B, whereas the actual estimates from Table IV are 0.047 and 0.033, respectively. Figure 2 shows that the actual estimates are positioned at the outermost right-hand tail of the bootstrap distribution. More precisely, the actual estimates lie about three standard deviations above the mean bootstrap estimates, with only 0.4% and 0.6% of the bootstrap values, respectively in Panels A and B, lying above the actual estimates. This suggests that our actual estimates are significantly different from the mean of the empirical distribution resulting under the null of no stock-picking effect due to industry experience, strongly rejecting the null in favor of our hypothesis that industry experience provides a stock picking advantage.

We also apply the bootstrap approach to our industry timing analysis of Table VII. Again, our random pseudo experience industry assignment imposes the null of no timing effect from industry experience. Figure 3 shows the distribution of the estimates for the interaction term of the experience dummy and the industry weight we obtain when we re-estimate Equation (1) for each of the 10,000 iterations.[16]

< Insert Figure 3 about here.>

Figure 3 shows that the actual estimate of 0.307 from Table VII lies beyond the right-hand tail of the bootstrapped estimates. Compared to the bootstrap distribution, the actual estimate is four standard deviations above the mean bootstrap estimate of -0.014 resulting under the null of no timing effect due industry experience. Thus, our estimate strongly rejects the null in support of our hypothesis that industry experience provides portfolio managers with a timing advantage.

[16] Since the average weight of managers in their experience industries is higher than the average weight of their non-experience industries, the bootstrapped coefficient estimates for the interaction term are likely to be of a different order of magnitude relative to the actual interaction coefficient in Table VII. Thus, we uniformly scale the weights in each random draw such that the average weight of random experience industries (across all managers and report dates) equals the average true experience industry weight.

4. When is Industry Experience more Valuable?

So far we have shown that portfolio managers with prior work experience in specific industries have a clear stock picking and timing advantage in those industries relative to other industries in which they lack such experience. In this section we examine whether experience in certain industries or certain types of experiences provide a greater advantage. In Section 4.1, we examine whether the investment value of industry experience is greater when managers' experience is earned in industries that comprise hard-to-value stocks. In Section 4.2, we examine whether the investment value of industry experience is greater when managers' experience is more extensive.

4.1. Experience in hard-to-value industries

We hypothesize that industry experience is more valuable when it is earned in industries consisting of stocks that are hard to value. Generally, since hard-to-value assets are expected to deviate temporarily more from their fair values than easy-to-value assets, a manager who has unique insights as a result of her industry experience stands to gain more from applying those insights when trading hard-to-value assets. This is consistent with Fang, Kempf, and Trapp (2014), who show that managerial skill pays off more when skilled managers trade in hard-to-value assets. Since prior industry experience generates industry-specific investment skills, we expect those skills to be even more valuable when they are earned in hard-to-value industries.

We use three ways to classify whether an industry is hard-to-value. Our first measure captures the extent to which an industry is covered by analysts. Intuitively, stocks with lower analyst coverage operate in a more limited information environment, which makes them harder to value. Analyst coverage of industry *j* in period *t* is measured as the average number of analysts covering each firm from that industry. Using the (1/0) indicator variable $D_{\text{cov}}^{f,t}$, we then classify a fund manager as having experience in a hard-to-value industry if the analyst coverage in the industry for which she has experience is below the average value of all industries.

The second measure reflects divergence of analysts' opinions measured by analyst forecast dispersion. Intuitively, we would expect a positive association between a stock being harder to value and the level of divergence in analysts' opinions over its expected earnings. To determine analyst forecast dispersion for industry *j* in period *t*, we first compute the analyst forecast dispersion for each firm belonging to that industry.[17] We then average the firm-specific measures of analyst forecast dispersion across all firms in that industry to come up with a measure at the industry level. Using the (1/0) indicator variable $D_{\text{disp}}^{f,t}$, we then classify a fund manager as having experience in a hard-to-value industry if the analyst forecast dispersion in the industry for which she has experience is above the average value of all industries.

Our last measure reflects whether an industry is predominantly populated by growth or value firms. The intuition is that growth stocks are harder to value than value stocks because the value of growth stocks depends less on a stable cash-flow stream but more on uncertain future growth. For all stocks, we collect their book values and market values of equity at the prior fiscal year end from the merged CRSP/Compustat database and use this information to compute a book-to-market ratio for each firm. We then compute the book-to-market ratio of industry *j* at time *t* by calculating the average book-to-market ratio of all firms belonging to that industry. Using the (1/0) indicator variable $D_{\text{growth}}^{f,t}$, we then classify a fund manager as having experience in a hard-to-value industry if the book-to-market ratio of the industry for which she has experience is below the average value of all industries.

[17] Analyst forecast dispersion for a given firm in a given period is computed as the standard deviation of all earnings forecasts issued by analysts covering that firm, divided by the firm's average stock price over the same period (see, e.g., Garfinkel (2009)).

To examine whether industry experience is more advantageous for stock picking when the experience was gained in hard-to-value industries, we employ a pooled regression, where the dependent variable is the performance difference between the manager's experience and non-experience portfolios. The independent variable is one of the indicator variables used to differentiate between managers having experience in hard-to-value and easy-to-value industries. To examine whether industry experience is more valuable for industry timing when it was gained in hard-to-value industries, we extend the regression (1) by adding a triple interaction term. This term interacts the fund weight with the experience dummy and the hard-to-value dummy. A positive value for this interaction term means that experience helps fund managers time hard-to-value industries in which they have experience more skillfully.

Table VIII shows regression results whereby hard-to-value industries are classified based, respectively, on analyst coverage (Panel A), analyst forecast dispersion (Panel B), and book-to-market value of the industry (Panel C). Results related to the picking analysis are presented in the first three columns, and results related to the timing analysis are reported in the last column. In all regressions, significance is determined using standard errors clustered by both manager and period.

<Insert Table VIII about here.>

Table VIII shows that managers with industry experience exhibit a stronger stock picking and industry timing differential when their experience is in a hard-to-value industry. This holds no matter how we determine hard-to-value industries. In the picking analysis, the impact of the hard-to-value dummy is positive in all cases, and statistically significant in eight out of nine specifications, and in the timing analysis, the triple interaction term is positive and statistically significant at the 1%-level in all cases. Overall, the results clearly support the hypothesis that the investment value of industry experience is greater when the experience was gained in industries that are hard to value.

4.2. Extent of industry experience

In the previous sections, we have shown that prior industry experience is valuable, and even more so in hard-to-value industries. However, not all experiences are created equal in that some of them might be more extensive than some others. Although we cannot observe the extent of experience directly, we believe that certain experience characteristics such as its length, seniority of position held, and its technical nature are likely to be correlated with the extent of experience. In this section, we examine whether the investment value of a manager's industry experience increases with the extent of experience. We use three measures to classify managers by the extent of their experience.

Our first measure is the length of time during which a manager was employed in a particular industry. Intuitively, a manager who happened to work in an industry for many years is likely to have acquired a deeper understanding of that industry than another manager who worked, say, in the same industry for only one year. We take the time between the first date where a manager was employed in a given industry and the date where the manager left the industry as a measure of the length of experience in that industry. For 108 out of our 130 managers, we find both entry and exit dates for their experience industries. Based on this information, we classify whether a manager has long experience using the (1/0) indicator variable $D_{\text{long}}^{f,t}$, which indicates if the manager of fund *f* at date *t* has industry experience with a length of more than five years (the across-manager average).

The second measure captures the seniority of the position a manager held in a particular industry. We argue that managers in more senior positions are likely to have gained deeper insights into their respective industries simply because they would have had to learn a lot more to advance in the career ladder than, say, another manager who simply worked in an entry-level position. To determine whether a manager held a senior position, we screen the job descriptions of all positions a manager held prior to becoming a fund manager for terms indicating seniority (e.g., “senior”, “chief”, “partner”, “associate”, “director”, “president”, “founder”, “supervisor”, “leader”). Overall, 66 of our 130 managers were in a senior position in one of their experience industries. We use the (1/0) indicator variable $D_{\text{sen}}^{f,t}$ to classify whether the manager of fund *f* at date *t* has held a senior position in her experience industry prior to becoming a fund manager.

Our last measure reflects whether a manager gained technical experience. The intuition is that technical experience is likely to be more industry-specific than, e.g., management or sales experience, and thus more likely to give managers a competitive edge. We use two sources of information to capture whether a manager has technical experience. First, we screen the job descriptions of all positions that a manager held prior to becoming a fund manager for terms indicating a technical position (e.g., “engineer”, “manufacturing”, “technical”, “chemist”). Second, for the remaining managers, we check whether they hold a university degree with a technical major (engineering, computer science, mathematics, chemistry, and physics). The intuition is that managers with such technical background most likely had a technical position (even if it is not reported in our database) and gathered technical experience in their respective industries, even if they did not hold technical positions. Overall, we classify 67 out of 130 managers as having technical experience. To indicate whether the manager of fund *f* at date *t* has technical experience in her industry, we use the (1/0) indicator variable $D_{\text{tech}}^{f,t}$.

To examine whether greater depth of industry experience is more advantageous for stock picking, we again employ a pooled regression with the performance difference between the manager’s experience and non-experience portfolios as the dependent variable. The independent variable is an indicator variable used to differentiate between managers with more or less industry experience. To examine whether more industry experience is more valuable for industry timing, we extend the regression (1) by adding a triple interaction term.

This term interacts the fund weight with the experience indicator variable and the indicator variable for more extensive experience. A positive value for the interaction term means that managers with more experience are better at timing their experience industries.

<*Insert Table IX about here.*>

Table IX clearly shows that more extensive experience leads to better picking and timing results in the experience portfolios, no matter how we determine whether a manager has more experience. The indicator variable (in the picking analysis) and the triple interaction term (in the timing analysis) have the expected signs and are statistically significant in nine out of twelve specifications. This suggests that the industry experience is even more valuable when the manager has acquired more extensive experience.

5. Conclusion

In this paper we show that prior industry-specific work experience is valuable from an investment perspective. Identifying industries in which portfolio managers had prior work experience, we split managers' portfolios into two subsets that reflect, respectively, managers' experience and non-experience industries. We find that managers' stock picks from their experience industries generate significant characteristic-adjusted performance of roughly three percent in the following year. In contrast, their stock picks from their non-experience industries generate performance that is indistinguishable from zero. These results are robust to alternative performance measures and holding periods. The superior stock picking ability of portfolio managers within their experience industries is further corroborated by tests that condition on the size of the positions and tests that condition on trades.

The investment value of prior work experience also manifests itself when managers make industry timing decisions, in that they exhibit superior timing ability in their experience industries relative to their non-experience industries. Specifically, managers' tendency to increase (decrease) their portfolio exposure to an industry prior to strong (weak) industry returns is significantly more pronounced for their experience industries than for their non-experience industries.

Additional tests further support the hypothesis that prior industry work experience has investment value. First, we find that managers make better stock picking and industry timing decisions in experience industries that comprise hard-to-value stocks, suggesting that experience proves even more valuable when managers are facing more complex investments. Second, we document that managers with more extensive experience make better picking and timing decisions in their experience industries than their counterparts with less experience, suggesting that more extensive experience is more valuable.

Our findings have implications for how mutual funds should structure their portfolio managers' jobs to extract the most value out of their prior industry experiences. Our findings suggest that when managers make stock picks from their experience industries or when they time the returns of their experience industries, they perform well. However, these portfolio managers are given mandates to run diversified portfolios, which might restrict their ability to utilize their prior experience to the fullest. Thus, fund families should consider either relaxing such investment restrictions for funds managed by portfolio managers with prior industry work experience or give these managers mandates to run sector funds that primarily invest in their experience industries.[18] Following such as strategy would allow these managers to make greater use of their experience in their portfolio decisions.

[18] We were surprised to find out that only 33 funds out of 227 single-managed sector funds were managed by managers with prior experience in the respective industry.

References

Alexander, G., Cici, G., Gibson, S., 2007. Does motivation matter when assessing trade performance? An analysis of mutual funds. Review of Financial Studies 20, 125-150.

Barber, B., Lee, Y., Liu, Y., Odean, T., 2010. Do day traders rationally learn about their ability? Unpublished Working Paper. University of California at Berkeley.

Campbell, J., Ramadorai, T., Ranish, B., 2014. Getting better of feeling better? How equity investors respond to investment experience. Unpublished working paper. National Bureau of Economic Research, Inc.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Chen, H.-L., Jegadeesh, N., Wermers, R., 2000. The value of active mutual fund management: An examination of the stockholdings and trades of mutual fund managers. Journal of Financial and Quantitative Analysis 35, 343-368.

Chevalier, J., Ellison, G., 1999. Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance. Journal of Finance 54, 875-899.

Cici, G., 2012. The prevalence of the disposition effect in mutual funds' trades. Journal of Financial and Quantitative Analysis 47, 795-820.

Cohen, L., Frazzini, A., Malloy, C., 2008. The small world of investing: Board connections and mutual fund returns. Journal of Political Economy 116, 951-979.

Cohen, R., Polk, C., Silli, B., 2010. Best ideas. Unpublished working paper. Harvard Business School.

Coval, J., Moskowitz, T., 1999. Home bias at home: Local equity preference in domestic portfolios. Journal of Finance 54, 2045-2073.

Daniel, K., Grinblatt, M., Titman, S. Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035-1058.

Doskeland, T., Hvide, H., 2011. Do individual investors have asymmetric information based on work experience? Journal of Finance 66, 1011-1041.

Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fang, J., Kempf, A., Trapp, M., 2014. Fund manager allocation. Journal of Financial Economics 111, 661-674.

Frazzini, A., 2006. The disposition effect and underreaction to news. Journal of Finance 61, 2017-2046.

Garfinkel, J., 2009. Measuring investors' opinion divergence. Journal of Accounting Research 47, 1317-1348.

Gibson, S., Safieddine, A., Titman, S., 2000. Tax-motivated trading and price pressure: An analysis of mutual fund holdings. Journal of Financial and Quantitative Analysis 35, 369-386.

Golec, J., 1996. The effects of mutual fund managers' characteristics on their portfolio performance, risk and fees. Financial Services Review 5, 133-148.

Greenwood, R., Nagel, S., 2009. Inexperienced investors and bubbles. Journal of Financial Economics 93, 239-258.

Grinblatt, M., Keloharju, M., 2001. How distance, language, and culture influence stockholdings and trades. Journal of Finance 56, 1053-1073.

Grinblatt, M., Moskowitz, T., 1999. Do industries explain momentum? Journal of Finance 54, 1249-1290.

Grossman, S., Stiglitz, J., 1976. Information and competitive price systems. American Economic Review 66, 246-253.

Grossman, S., Stiglitz, J., 1980. On the impossibility of informationally efficient markets. American Economic Review 70, 393-408.

Huang, J., Wei, K., Yan, H., 2012. Investor learning and mutual fund flows. Unpublished Working Paper. University of Texas.

Huberman, G., 2001. Familiarity breeds investment. Review of Financial Studies 14, 659-680.

Huddart, S., Narayanan, V. G., 2002. An empirical examination of tax factors and mutual funds' stock sales decisions. Review of Accounting Studies 7, 319-341.

Integrity Research Associates. Research focus: Expert networks. December 2009. Available at http://www.integrity-research.com/cms/our-services/researchfocus/expert-networks/.

Ivkovíc, Z., Weisbenner, S., 2005. Local does as local is: Information content of the geography of individual investors' common stock investments. Journal of Finance 60, 267-306.

Jensen, M., 1968. The performance of mutual funds in the period 1945-1964. Journal of Finance 23, 389-416.

Jiang, H., Verbeek, M., Wang, Y., 2013. Information content when mutual funds deviate from benchmarks. Unpublished working paper. Erasmus University.

Jin, L., Scherbina, A., 2011. Inheriting losers. Review of Financial Studies 24, 787-820.

Kacperczyk, M., Sialm, C., Zheng, L., 2005. On the industry concentration of actively managed equity mutual funds. Journal of Finance 60, 1983-2011.

Kempf, E., Manconi, A., Spalt, O., 2013. Learning by doing: The value of experience and the origins of skill for mutual fund managers. Unpublished working paper. Tilburg University.

Linnainmaa, J., 2011. Why do (some) households trade so much? Review of Financial Studies 24, 1630-1666.

Mahani, R., Bernhardt, D., 2007. Financial speculators' underperformance: Learning, self-selection, and endogenous liquidity. Journal of Finance 62, 1313-1340.

O'Connell, P., Teo, M., 2009. Institutional investors, past performance, and dynamic loss aversion. Journal of Financial and Quantitative Analysis 44, 155-188.

Pastor, L., Veronesi, P., 2009. Learning in financial markets. Annual Review of Financial Economics 1, 361-381.

Patel, S., Sarkissian, S., 2013. Deception and managerial structure: A joint study of portfolio pumping and window dressing practices. Unpublished working paper. University of Western Ontario.

Petersen, M., 2004. Information: Hard and soft. Unpublished working paper. Northwestern University.

Pool, V., Stoffman, N., Yonker, S., 2012. No place like home: Familiarity in mutual fund manager portfolio choice. Review of Financial Studies 25, 2563-2599.

Seasholes, M., Zhu, N., 2010. Individual investors and local bias. Journal of Finance 65, 1987-2010.

Seru, A., Shumway, T., Stoffman, N., 2009. Learning by trading. Review of Financial Studies 23, 705-739.

The Economist. Linking expert mouths with eager ears. June 16, 2011. Available at http://www.economist.com/node/18836146.

Table I: Manager characteristics

This table reports characteristics for our sample of fund managers with prior industry work experience and for the peer managers who do not have such experience. Both groups of funds include fund managers who solely managed U.S. domestic equity fund (excluding balanced, bond, money market, index, international, and sector funds) at some point between 1996 and 2009. Our sample consists of 130 managers who worked in at least one of the 48 Fama-French industries outside of financial services prior to their career as fund managers. Manager names were obtained from Morningstar Principia and matched to the CRSP MF database by fund ticker and fund name. Our procedure for hand-collecting biographical information on the managers is described in Section 2. 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 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.

	Sample Managers (with Industry Experience)	Peer Managers (without Industry Experience)	Difference	t-statistic
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	49.86	-2.94	-0.63
PhD [%]	3.07	5.62	-2.55	-1.51
Business/Economics Major [%]	55.34	75.07	-19.73	-3.81
Engineering/ Natural Science Major [%]	43.69	11.52	32.17	6.32
Other Major [%]	11.65	20.87	-9.22	2.71

Table II: Fund characteristics

This table reports characteristics for our sample funds and the peer funds. Our sample consists of 199 diversified, domestic U.S. equity funds single-managed by 130 fund managers with prior industry work experience between 1996 and 2009. The peer group consists of 1,407 funds that have similar investment objectives as our sample but are managed by a single manager with no prior industry experience. The reported funds characteristics include: fund size in million USD; expense ratio measured in percentage points per year; turnover ratio measured in percentage points per year; fraction of funds in the various fund objectives (Micro/Small cap, Mid cap, Growth, Income, and Growth & Income); and portfolio weights of FF48 industries in which our sample managers have experience.

	Sample Funds				**Peer Funds**				**Difference**	
	Mean	Median	1st Percentile	99th Percentile	Mean	Median	1st Percentile	99th Percentile	Difference	t-statistic
Fund size [mn. USD]	1,964	151	1	32,081	1,224	156	1	19,411	739	4.91
Expense ratio [%]	1.38	1.39	0.23	2.64	1.21	1.16	0.04	3.19	0.17	9.45
Turnover ratio [%]	111.34	71.00	1.00	760.00	91.30	61.90	2.22	502.00	20.04	3.54
Micro / small cap [%]	14.44				21.28				-6.84	-9.20
Mid cap [%]	9.78				11.48				-1.70	-2.72
Growth [%]	62.17				38.14				24.03	23.64
Income [%]	5.33				4.69				0.64	1.37
Growth & Income [%]	8.27				24.41				-16.14	-27.11
Weight FF48 Exp. Industry [%]	5.02	2.69	0.00	25.33	4.88	2.83	0.00	16.42	0.14	1.75

Table III: Stock characteristics

This table reports characteristics of stocks held in the experience and non-experience portfolios of our sample 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. 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 S&P 500 index 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**	
	Mean	Median	1st Percentile	99th Percentile	Mean	Median	1st Percentile	99th Percentile	Difference	t-statistic
Market cap (mn. USD)	27,016	11,273	127	172,141	24,601	20,900	292	92,006	2,414	0.89
Market beta	1.15	1.10	0.08	2.94	1.10	1.07	0.76	1.72	0.05	2.15
HML beta	-0.19	-0.21	-2.47	2.29	0.07	0.09	-1.50	0.96	-0.26	-3.86
SMB beta	0.39	0.37	-1.01	2.02	0.35	0.29	-0.26	1.30	0.03	1.26
Momentum beta	0.05	0.01	-1.27	1.80	-0.02	-0.03	-0.44	0.57	0.07	2.01

Table IV: Experience vs. non-experience portfolio performance

This table reports the performance of a manager's experience portfolio, non-experience portfolio, and the performance difference between these two 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. Our performance measures include: the raw return (Return); Carhart alpha (Carhart); and DGTW-adjusted return (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 compound each of our monthly performance measures over holding intervals of different lengths that range from 3 to 36 months to compute the performance of each held stock. Monthly risk-adjusted returns for each stock are computed on a rolling basis from the Carhart (1997) model. We compute monthly stock characteristic-adjusted returns following Daniel, Grinblatt, Titman, and Wermers (1997), where we compute a stock's characteristic-adjusted return in a given month by subtracting from its return the return of the benchmark portfolio to which that particular 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. Estimates are averages across time and portfolios. The performance difference between the experience and the non-experience portfolio is computed as the difference for a given fund and reporting date. If the performance is missing for either portfolio, no difference is computed. The number of observations is denoted by N. All t-statistics are computed using standard errors clustered by manager and date.

	Experience		**Non Experience**		**Difference**	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
			3 months			
Return	0.0239	1.81	0.0168	1.39	0.0042	1.04
Carhart	0.0147	3.00	0.0028	1.33	0.0290	2.30
DGTW	0.0062	1.83	0.0003	0.13	0.0053	1.67
N	2,188		2,767		2,188	
			6 months			
Return	0.0536	2.74	0.0376	2.11	0.0124	1.94
Carhart	0.0296	3.39	0.0066	1.67	0.0240	2.81
DGTW	0.0128	2.30	-0.0011	-0.39	0.0137	2.58
N	2,188		2,767		2,188	
			12 months			
Return	0.1154	4.16	0.0756	3.08	0.0342	3.45
Carhart	0.0596	4.58	0.0155	2.22	0.0469	3.51
DGTW	0.0298	3.16	-0.0030	-0.70	0.0328	3.74
N	2,188		2,767		2,188	
			24 months			
Return	0.2210	5.51	0.1560	4.52	0.0581	3.49
Carhart	0.0826	4.73	0.0250	2.68	0.0632	3.31
DGTW	0.0456	3.21	-0.0029	-0.48	0.0488	3.47
N	2,188		2,767		2,188	
			36 months			
Return	0.2791	6.01	0.2187	5.66	0.0547	2.06
Carhart	0.0935	4.39	0.0395	2.73	0.0639	2.60
DGTW	0.0455	2.23	0.0007	0.10	0.0462	2.19
N	2,188		2,767		2,188	

Table V: Large bets vs. small bets

This table reports performance results for a holding period of 12 months for positions from the experience and non-experience portfolios that are stratified into large and small bets. We distinguish between large and small bets by comparing the portfolio weight of a stock position to two benchmark weights. In Panel A, the benchmark weight is the mean stock weight, measured relative to the all stocks in the fund portfolio at the end of each reporting period. In Panel B, the benchmark weight is the mean portfolio weight of the stock across all peer funds at the same reporting date. We split both the experience and the non-experience portfolio into a large bet and a small bet sub-portfolio and compute sub-portfolio performance measures. 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. Our performance measures include: the raw return (Return); Carhart alpha (Carhart); and DGTW-adjusted return (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 compound each of our monthly performance measures over a holding interval of 12 months to compute the performance of each held stock. Monthly risk-adjusted returns for each stock are computed on a rolling basis from the Carhart (1997) model. We compute monthly stock characteristic-adjusted returns following Daniel, Grinblatt, Titman, and Wermers (1997), where we compute a stock's characteristic-adjusted return in a given month by subtracting from its return the return of the benchmark portfolio to which that particular 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. Estimates are averages across time and portfolios. Estimates are averages across time and portfolios. Estimates are averages across time and portfolios. The performance differences are computed as the difference for a given fund and reporting date. If the performance is missing for any portfolio, no difference is computed. The number of observations is denoted by N. All t-statistics are computed using standard errors clustered by manager and date.

	Experience				**Non-Experience**				**Difference**			
	Large bets		**Small bets**		**Large bets**		**Small bets**		**Large bets**		**Small bets**	
	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Panel A: Benchmark weight is mean fund portfolio weight												
Return	0.1225	4.31	0.0965	3.42	0.0698	2.92	0.0880	3.27	0.0450	3.59	0.0080	0.63
Carhart	0.0652	4.49	0.0491	3.54	0.0109	1.59	0.0243	2.83	0.0582	3.65	0.0277	1.95
DGTW	0.0332	3.14	0.0118	1.15	-0.0053	-1.08	0.0015	0.34	0.0400	3.78	0.0108	1.04
N	1,785		1,949		2,767		2,766		1,785		1,949	
Panel B: Benchmark weight is mean peer fund portfolio weight												
Return	0.1191	4.14	0.0808	2.82	0.0768	3.10	0.0668	2.76	0.0329	3.07	0.0208	1.50
Carhart	0.0653	4.73	0.0485	3.27	0.0158	2.24	0.0091	1.27	0.0516	3.55	0.0457	3.17
DGTW	0.0286	2.87	0.0040	0.37	-0.0033	-0.75	-0.0071	-1.74	0.0304	3.22	0.0166	1.45
N	2,005		1,416		2,767		2,529		2,005		1,389	

Table VI: Buys vs. sells

This table reports the performance differences between stock buys (sells) in the experience and non-experience portfolios. We define a buy as an increase and a sell as a decrease in the number of shares held by a particular fund in a particular stock between two consecutive reporting dates. A hold is defined as a stock position if there is no change in the number of shares held between two consecutive reporting dates. We determine whether a stock belongs to a manager's experience or non-experience portfolios 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. Our performance measures include: the raw return (Return); Carhart alpha (Carhart); and DGTW-adjusted return (DGTW). We value-weight the performance of stocks making up each portfolio by the dollar value the trade (stock price times the number of stock shares a particular firm bought or sold) at the beginning of portfolio formation. We compound each of our monthly performance measures over a holding interval of 12 months to compute the performance of each held stock. Monthly risk-adjusted returns for each stock are computed on a rolling basis from the Carhart (1997) models. We compute monthly stock characteristic-adjusted returns following Daniel, Grinblatt, Titman, and Wermers (1997), where we compute a stock's characteristic-adjusted return in a given month by subtracting from its return the return of the benchmark portfolio to which that particular 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. For buys, the performance difference between the experience and non-experience portfolios are simply computed as the difference in the Return, Carhart, and DGTW measures. For sells, we first benchmark the performance of all sells against the performance of all holds in each subset (excluding stocks that were bought) and then compute the performance difference between the two portfolios. If the performance is missing for either portfolio, no difference is computed. The number of observations is denoted by N. All t-statistics are computed using standard errors clustered by manager and reporting date.

	Experience - Non-Experience		**Experience - Non-Experience**	
	Buys		**Sells**	
	Estimate	t-statistic	Estimate	t-statistic
Return	0.0240	2.01	-0.0168	-1.12
Carhart	0.0498	3.39	-0.0291	-1.47
DGTW	0.0226	2.11	-0.0030	-0.22
N	1,625		860	

Table VII: Fund industry weights and future returns

This table reports results from a regression of future industry returns on funds' industry weights and funds' industry weights interacted with a dummy variable indicating whether a manager has work experience in the industry prior to becoming a fund manager. The dependent variable is the compounded 12-month-ahead industry return from a value-weighted industry portfolio consisting of all stocks belonging to a given Fama-French industry. Control variables include: average industry weight of peer funds; the industry return over the previous year; the industry's market beta; the high minus low (HML) beta; and the small minus big (SMB) beta. The 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 reference industry weight is computed as the average weight of the industry across all CRSP funds at the same reporting date for funds with the same fund objective (Micro Cap, Small Cap, Mid Cap, Growth, Income, Growth & Income). OLS adjusted R^2 are given in percentage points. The number of observations is denoted by N. All t-statistics are computed using standard errors clustered by manager and reporting date.

	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
Constant	0.0998	3.89	0.1191	3.94	0.0802	3.12
Industry weight	-0.3766	-3.35	-0.0327	-0.76	-0.0479	-1.12
Manager w/ experience	-0.0114	-1.41	-0.0005	-0.07	0.0034	0.41
Industry weight * Manager w/ experience	0.2725	3.15	0.2250	2.65	0.3075	3.03
Peer fund weight			-0.6817	-2.87	-0.2698	-1.24
Lagged return			-0.1539	-1.54	-0.1644	-1.68
Market beta					0.0197	1.02
SMB beta					-0.0084	-0.75
HML beta					0.0570	2.89
Adj. R^2 [%]	0.23		2.55		4.01	
N	111,752		111,752		111,752	

Table VIII: Value of experience in hard-to-value versus easy-to-value industries

This table reports incremental stock picking and timing effects of experience in hard-to-value industries relative to easy-to-value industries. We determine whether an industry is hard-to-value using three different measures. The first measure is analyst coverage. Analyst coverage of industry *j* in period *t* is measured as the average number of analysts covering each firm from that industry. We classify a fund manager as having experience in a hard-to-value industry if the analyst coverage in her experience industry is below the average value of all industries. Our second measure is analyst forecast dispersion. To determine analyst forecast dispersion for industry *j* in period *t*, we compute the analyst forecast dispersion for each firm belonging to that industry. We average the firm-specific measures of analyst forecast dispersion across all firms in that industry to come up with a measure at the industry level. We classify a fund manager as having experience in a hard-to-value industry if the analyst forecast dispersion in her experience industry is above the average value of all industries. Our last measure reflects whether an industry is predominantly populated by growth or value firms. For all stocks, we collect their book value and market value of equity at the prior fiscal year end and use this information to compute a book-to-market ratio for each firm. We compute the book-to-market ratio of industry *j* at time *t* by calculating the average book-to-market ratio of all firms belonging to that industry. We classify a fund manager as having experience in a hard-to-value industry if the book-to-market ratio of her experience industry is below the average value of all industries. In the first three columns, we report the results from a regression of the performance difference between the manager's experience and non-experience portfolio on a dummy variable indicating whether the manager has experience in an industry that is hard to value. In the fourth column, we repeat the regression from Table VII, but now add the triple interaction of the industry weight, the dummy variable indicating whether a manager has experience, and the hard-to-value industry dummy. Control variables are as in Table VII and additionally include the hard-to-value industry dummy and various interaction terms. The number of observations is denoted by N. All t-statistics are computed using standard errors clustered by manager and reporting date.

	Stock picking ability difference			**Timing ability difference**
	Gross return	Carhart alpha	DGTW-adjusted return	Industry weight * Manager w/ experience * Hard-to-value
	Panel A: Hard-to-value definition based on analyst coverage			
Estimate	0.0403	0.0248	0.0468	2.0503
t-statistic	1.72	0.92	2.31	7.18
N	2,188	2,188	2,188	111,752
	Panel B: Hard-to-value definition based on analyst forecast dispersion			
Estimate	0.0454	0.0433	0.0289	1.4135
t-statistic	2.25	1.93	1.66	6.83
N	2,188	2,188	2,188	111,708
	Panel C: Hard-to-value definition based on book-to-market ratio			
Estimate	0.0383	0.0578	0.0204	1.4161
t-statistic	2.03	1.78	1.72	4.55
N	2,187	2,187	2,187	111,442

Table IX: Value of experience and extent of experience

This table reports incremental stock picking and timing effects of extensive experience relative to non-extensive experience. We determine whether a manager has extensive experience using three different measures. The first measure is the length of the manager's experience in the industry prior to becoming a fund manager. We obtain this variable for 108 of our 130 managers. We define a dummy variable that equals one if the manager has more than five years of experience, the mean length of experience across the 108 managers. Our second measure is whether the manager held a senior position in the industry. We take this information from the manager's job description by checking whether the job description contains terms that suggest seniority ("senior", "chief", "partner", "associate", "director", "president", "founder", "supervisor", "leader", etc.). Our third measure is whether the manager held a technical position in the industry or obtained a university degree with a technical major. This information is taken from the job description and the university degrees by checking whether the job description or major field of study contain terms that suggest a technical field ("engineer", "manufacturing", "technical", "chemist", etc. for job description, engineering, computer science, mathematics, chemistry, and physics for major). In the first three columns, we report the results from a regression of the performance difference between the manager's experience and non-experience portfolio on a dummy variable indicating whether the manager has extensive experience. In the fourth column, we repeat the regression from Table VII, but now add the triple interaction of the industry weight, the dummy variable indicating whether a manager has experience, and a dummy variable indicating whether a manager has extensive experience. Control variables are as in Table VII and additionally include the more experience dummy and various interaction terms. The number of observations is denoted by N. All t-statistics are computed using standard errors clustered by manager and reporting date.

	Stock picking ability difference			**Timing ability difference**
	Gross return	Carhart alpha	DGTW-adjusted return	Industry weight * Manager w/ experience * more experience
	Panel A: More experience definition based on experience length in years			
Estimate	0.0357	0.0149	0.0428	0.1450
t-statistic	2.40	1.43	2.65	1.61
N	2,000	2,000	2,000	92,648
	Panel B: More experience definition based on job seniority			
Estimate	0.0306	0.0280	0.0276	0.3216
t-statistic	1.80	1.88	2.06	2.29
N	2,188	2,188	2,188	111,752
	Panel C: More experience definition based on technical experience			
Estimate	0.0294	0.0241	0.0225	0.1171
t-statistic	1.87	1.68	1.85	1.83
N	2,188	2,188	2,188	111,752

Figure 1. Experience vs. non-experience portfolio performance

The figure displays performance differences between the experience and the non-experience portfolios for different performance measures and different holding periods. We determine whether a stock belongs to a manager's experience or non-experience portfolios 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. The performance measures include: the gross return (Return), Carhart alpha (Carhart), and DGTW-adjusted return (DGTW). For the Carhart alpha, we estimate risk-factor loadings from the previous 36 months' returns at the stock level, and use these factor loadings to determine alpha as the difference between the realized and expected returns. We use the position of a particular stock held by the fund at the end of a reporting period to determine stock's portfolio weight in the experience and the non-experience portfolio. We then compute the portfolio returns for the next 3, 6, 12, 24, and 36 months. Estimates are averages across time and portfolios.

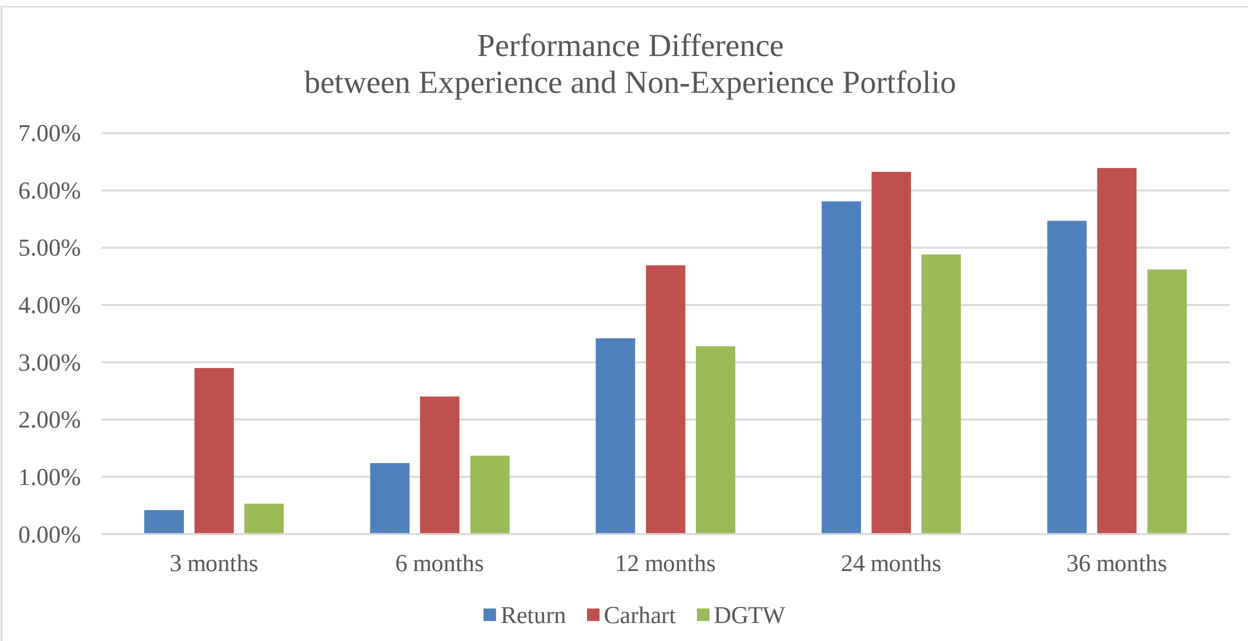
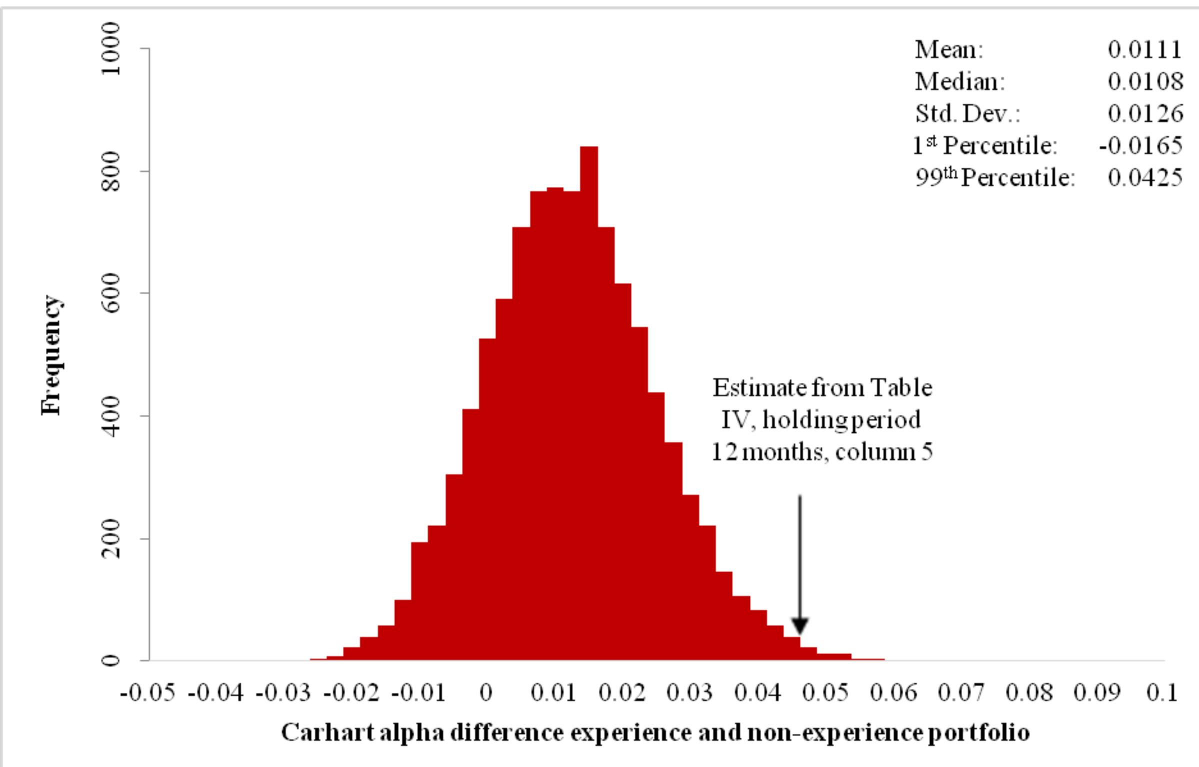


Figure 2. Bootstrap analysis – Picking skill for randomly drawn portfolios

The figure displays the average risk-adjusted performance difference between managers' randomly drawn hypothetical experience portfolio and their remaining non-experience portfolio. We test the null hypothesis of no experience industry picking skill by randomly choosing one industry in which the manager has no experience as her hypothetical experience industry. For managers with experience in multiple industries, we randomly draw the same number of industries. We then compute the 12-month compounded performance of the manager's hypothetical experience portfolio and subtract the 12-month performance of the manager's remaining non-experience portfolio. The performance measures include Carhart alpha (Carhart) and DGTW-adjusted return (DGTW), reported respectively, in Panels A and B. Risk-adjusted returns and portfolio weights are computed as in Table IV. 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 estimates from Table IV.

Panel A. Carhart alpha difference



Panel B. DGTW-adjusted return difference

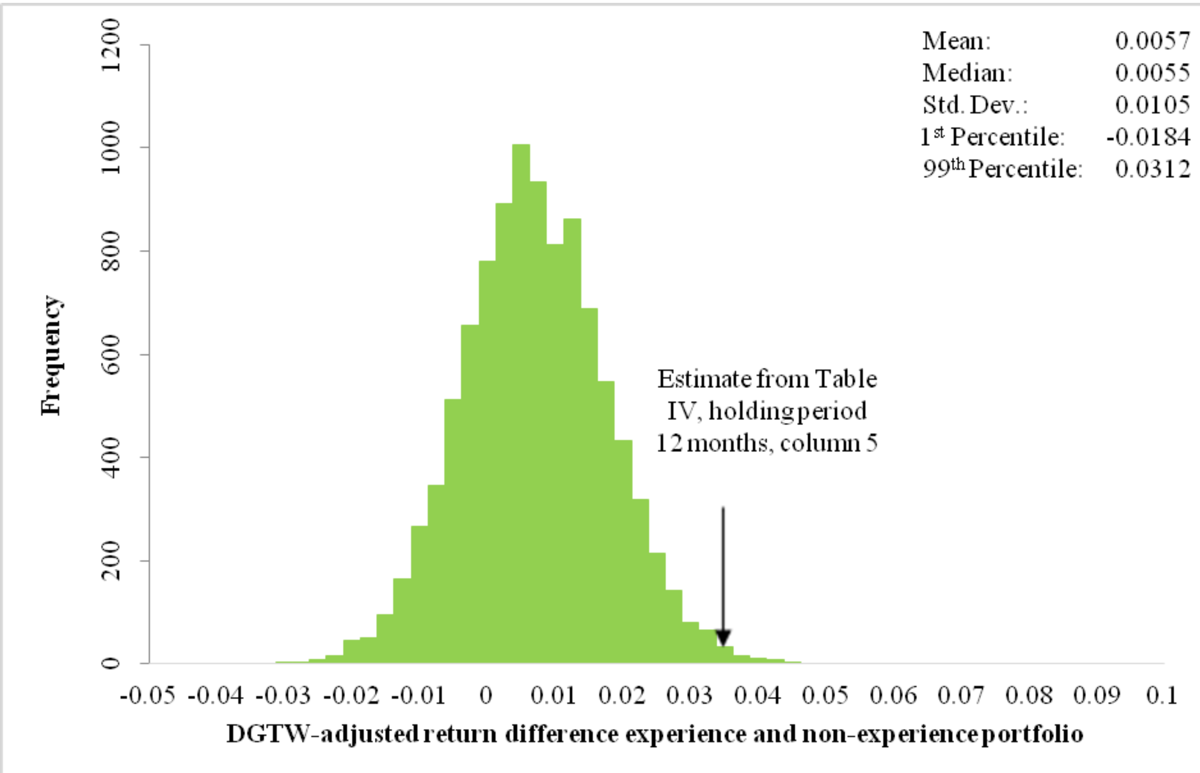


Figure 3. Bootstrap analysis – Timing skill for randomly drawn industries

The figure displays the distribution of *Industry weight measure * Manager w/ experience* coefficient estimates when we use randomly drawn non-experience portfolios as hypothetical experience portfolios. We test the null hypothesis of no experience industry timing skill by randomly choosing one industry in which the manager has no experience as her hypothetical experience industry. For managers with experience in multiple industries, we randomly draw the same number of industries. We do this for each manager, and then re-estimate Equation (1) using the hypothetical experience industries to define the experience dummy as in the last specification of Table VII. We repeat this procedure 10,000 times, and display the distribution of the estimated coefficient estimates below. Since the average weight of managers in their experience industries is higher than the average weight of their non-experience industries, the bootstrapped coefficient estimates for the interaction term are likely to be of a different order of magnitude relative to the actual interaction coefficient in Table VII. Thus, we uniformly scale the weights in each random draw such that the average weight of random experience industries (across all managers and report dates) equals the average true experience industry weight. 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. For comparison, we also indicate the estimate from the last specification of Table VII.