Returns to Specialization:
Evidence from Health Mutual Fund Managers

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Abstract

We investigate the benefits of specialized knowledge in generating superior performance in the asset management industry. We compare the returns of health sector mutual fund managers with prior health-related education or experience (specialists) to those without such a background (generalists). Specialists outperform generalists by 4.7% per year in annualized net returns, and up to 7.8% per year after adjusting for risk and controlling for observable fund and manager characteristics. We also find evidence of differences in anticipating major medical-related events, as specialists reduce holdings of stocks prior to Food and Drug Administration (FDA) drug rejections. The paper provides new evidence on the competitive advantages that can be used to generate true alpha.

1. Introduction

Investment managers often need specialized knowledge to understand and process firm- and industry-specific information related to modern complex corporations. However, the overwhelming majority of portfolio managers have a very specific "generalist" profile: an undergraduate degree in business, finance, or economics, a post-undergraduate job in the financial industry, sometimes two years in business school for an MBA, followed by work at an asset management firm.[1] Realizing the problem of a knowledge gap in portfolio managers' understanding of the esoteric terminology and workings of various industries, asset management companies sometimes employ in-house analysts with specialized knowledge or contract out to "expert networks" that facilitate consultations between the portfolio manager and an outside industry expert.[2] Whether these efforts to bridge the knowledge gap are successful remains an open question.

The effect of specialization on performance has been studied among CEOs (e.g., Custodio, Ferreira, and Matos, 2013) and venture capitalists (e.g., Gompers, Kovner, and Lerner, 2009), but has yet to receive meaningful attention in the area of asset management. In this paper, we investigate whether a specialized background improves portfolio manager performance by using health sector mutual funds as our laboratory. We find a significant positive return to specialization, with mutual fund managers that have a biology or medical degree, or health industry experience ("specialists") outperforming their peers ("generalists") by 4.7% per year in annualized returns (net of expenses), extending to 7.8% per year after adjusting for risk and controlling for differences in observable fund and manager characteristics. These results are

[1] This observation is based on analyzing biographical manager profiles in Morningstar as well as profiles hand-collected from LinkedIn.
[2] A 2009 report by Integrity Research Associates found that 36% of surveyed investment management firms used expert networks.

economically significant and outstrip the typical annual expense ratios of 1.5% charged by health sector funds.

While health sector funds make up just a tiny fraction of the multi-trillion dollar mutual fund industry, they are a perfect setting for measuring the return to specialization in asset management. First, unlike diversified mutual funds, health funds invest in only one industry, so we know what we mean by industry-specific knowledge when we are classifying managers as specialists or generalists. Moreover, this particular industry-specific knowledge overlaps with a discipline (medicine) and a field of study (biology). Specialization is not as clear for specialty funds that invest in other sectors such as utilities, consumer staples, consumer discretionary, basic materials, industrials, communications, energy, or information technology.

Second, the medical industry uses a technical language that can be difficult to understand for non-experts. As Richard W. Bank, a gynecological oncologist who went on to become a successful hedge fund manager, put it: “Everybody needs an edge. Mine is fluency in ‘doctor speak.’”[3] Third, there is significant cross-sectional variation in specialization among health sector funds, with more than a quarter of health mutual fund managers being specialists. This provides enough statistical power to measure differences in performance between health specialists and generalists. Finally, drug approvals and rejections by the U.S. Food and Drug Administration (FDA) are a health industry-specific sample of events that we use to examine *how* specialists are able to outperform generalists.

In order to give the reader an idea of the typical profile of specialists and generalists, we provide a brief biographical comparison of two managers: Kris Jenner who managed the T. Rowe Price Health Sciences Fund from 2000 to 2013, and Derek Taner who has managed the AIM/Invesco Global Health Care Fund since 2006 and is still managing this fund in 2016. Kris

[3] “The Best Medicine Was a Different Career, ” by Geraldine Fabrikant, New York Times, 1/30/2001.

Jenner earned a bachelor's degree in chemistry from the University of Illinois at Urbana-Champaign, an M.D. from Johns Hopkins, and a Ph.D. in molecular biology from Oxford University. He completed two years of a general surgery residency at Johns Hopkins Hospital and worked at Brigham and Women's Hospital of Harvard Medical School before joining T. Rowe Price in 1996 and becoming a portfolio manager in 2000.

Derek Taner received a bachelor's degree in business administration from the University of California at Berkeley. He worked at Franklin Templeton as an analyst and portfolio manager from 1993 to 2005, and received an MBA from Berkeley in 2000. He then joined Invesco in 2005 and became a portfolio manager in 2006. It is clear that Kris Jenner and Derek Taner had very different career paths to becoming mutual fund managers, and we try to exploit such differences in this study to understand the returns to specialization. We are also mindful of the fact that they differ along other dimensions and control for observable differences in our tests.

Our sample consists of 73 health sector funds, 130 lead managers (30 specialists, 100 generalists), and 7,742 fund-month observations from January 1998 through December 2014.[4] Figure 1 illustrates the cumulative returns from investing $1000 at the start of the sample period and reinvesting each month among funds managed by specialists versus generalists. The $1000 turns into $12,321 (at the end of the sample period) from investing with the specialists, $5,559 from investing with the generalists, and $4,658 from investing in a value-weighted basket of health sector stocks in CRSP. The generalists generate a monthly alpha of about 6 basis points while the specialists generate a monthly alpha of about 46 basis points, for a difference of 39.5 basis points per month (or about 4.7% annualized).[5] In cross-sectional Fama-MacBeth (1973)

[4] The first specialist in our sample is Selena Chaisson of the Dresdner RCM Global Health Care Fund, which first entered the Morningstar sample in December 1997. Thus, we start our analyst in January 1998.
[5] For these alphas, we regress net returns on five factors, where we replace the MKTMRF in the Fama-French + Carhart four factors with a health and non-health basket of CRSP stocks.

regressions, we include controls for fund characteristics, manager characteristics, sub-industry weights, and the average style-adjusted returns of the family's other equity offerings, and find a difference in alpha of 65 basis points (or about 7.8% annualized) between specialists and generalists.

Next, we test several alternative hypotheses for our results that are unrelated to positive benefits of specialized knowledge. One possible explanation is that higher intelligence or work ethic is needed for to get a medical degree, do a residency, and/or work in the medical field. We test this hypothesis by including separate variables for a biology bachelor's degree and an advanced medical degree/industry experience. We find that the advanced degree and industry experience variable is not associated with a statistically significant benefit in generating higher returns. This result suggests that even the less advanced, but comprehensive, familiarity with medicine that is obtained at the undergraduate level is enough to outperform generalist managers.

Another possibility is that graduating with a STEM (science, technology, engineering, and math) major is a proxy variable for intelligence or some other characteristic that is correlated with asset management skills. We test this hypothesis by including a dummy variable for whether a manager holds a STEM degree outside of biology and chemistry, and find no evidence that such managers are able to generate higher alpha. We also examine the dynamics of team-managed funds. We find similar results to our baseline findings when we average specialization across all members of the team instead of just focusing on the lead manager. In addition, we do not find any (additional) positive effect from having both a generalist and a specialist on a managerial team, implying that specialists are likely to already have the financial skills that generalists bring to the table.

In our final set of tests, we investigate *how* specialists are able to beat their peers, by examining mutual fund holdings of health stocks around events with significant price impacts: FDA approvals and rejections of major new drugs, earnings announcements, and merger announcements. Consistent with the role of specialized knowledge in improving timing ability, we find that specialists (relative to generalists) decrease their holdings in stocks before the company has a major drug rejected by the FDA. The estimates run in the other direction (specialists increase portfolio weights) prior to FDA approvals but are not statistically significant, as approvals are significantly more common than rejections and therefore move stock prices less. We find no differential timing ability for merger or earnings announcements, suggesting that the performance differences are not due to specialists having better access to insider information from the firm. Overall, these findings are consistent with a mechanism by which specialized knowledge helps a manager better interpret company signals about probability of FDA approval, but are inconsistent with the alternative hypothesis that being a specialist is correlated with an unobservable variable (such as higher intelligence) that leads to better asset management skills.

Our findings generate several intriguing questions. First, why are the returns of specialist-managed funds not eroded by inflows and decreasing returns to scale as predicted by the model of Berk and Green (2004)? In fact, consistent with Berk and Green (2004), we find that the outperformance by specialist-led funds is significantly lower in the second half of the sample period. However, the erosion process is likely to happen slowly as investors learn from historical data that they can make more money by investing with specialist managers. During this learning process, the return gap between specialists and generalists will persist. Finally, health sector funds are generally pretty small, with 90% of them having less than \$2.5 billion in assets under management, as there is a limited clientele of investors that is interested in such products. Therefore, these funds do not reach the scale that would limit their ability to take advantage of mispricing.

Another puzzling question is why are only a minority of health sector funds managed by specialists? If specialists generate such large alphas, then shouldn't specialized medical knowledge be a prerequisite for getting a job as a health fund manager? Again, the evidence suggests that mutual fund companies are learning and adapting to the need for specialization. The proportion of health sector funds with a specialist manager increased from zero in 1997 to around 40% by the end of the sample period. However, interest and knowledge in both finance and medicine is a fairly rare trait, and hedge funds offer better opportunities to a manager that can generate alpha than mutual funds (Kostovetsky, 2010). In fact, Kris Jenner, the specialist manager who we profiled above, left T. Rowe Price in 2013 to start his own hedge fund, Rock Springs Capital.

This paper contributes to the debate on the value of specialized versus general skills. The CEO literature suggests that general managerial skills are valuable, associated with a higher CEO salary (Custodio, Ferreira, and Matos, 2013) and more innovation in the form of patents at the CEO's firm (Custodio, Ferreira, and Matos, 2015). In addition, Frydman (2009) and Murphy and Zabojnik (2004, 2007) argue that general skills have become more important in the CEO labor market over the last few decades. In contrast, specialization seems to be more valuable in venture capital (VC), with VC firms that specialize in a particular industry outperforming those that diversify across multiple industries (Gompers, Kovner, and Lerner, 2009). This firm-level effect is mitigated if the generalist firms have industry specialization by the individual venture capitalists (the partners), suggesting that it is the manager-level specialization that is more important that firm-level specialization.

In contrast, the question of specialized knowledge in the asset management industry has not received as much attention. One significant exception is a paper by Cici, Gehde-Trapp, Göricke, and Kempf (2014), which examines the effect of non-financial industry work experience of managers prior to their fund tenure on performance at diversified mutual funds. They compare the returns of fund holdings in the (non-financial) industry in which the manager has prior work experience to returns of holdings in non-experience industries, and find a performance difference of approximately three percentage points over the following twelve months.

One issue with looking within diversified mutual funds for the effects of specialized knowledge is that there is the potential for a substitution effect due to familiarity. Managers might spend more time and effort on industries with which they are more familiar and this extra time and effort, and not any specialized knowledge, would lead to outperformance. In addition, in contrast to our study, their returns are buy-and-hold returns calculated from previously reported holdings data. This omits the return gap, which includes profits from intra-quarter transactions and trading costs (Kacperczyk, Sialm, and Zheng, 2008). Furthermore, they do not include specialized knowledge acquired at the manager's educational institution(s). Finally, we also examine industry-specific events (FDA approvals and rejections) to understand the mechanism by which specialized knowledge leads to better performance.

Zambrana and Zapatero (2016) classify mutual fund managers as specialists or generalists based on whether they manage a single style or run funds with different investment styles. They find that families assign managers as specialists if they are better stock pickers and generalists if they are market timers, and that these assignments are optimal in achieving higher returns for the family. Their paper does not look at industry-specific specialization.

Our paper also contributes to a long literature on mutual fund manager characteristics, starting with Golec (1996) and Chevalier and Ellison (1999), who examined the effect of manager education and age. Other papers have highlighted the importance of geographic familiarity (Pool, Stoffman, and Yonker, 2012), social interactions (Pool, Stoffman, and Yonker, 2013), political values (Hong and Kostovetsky, 2012), and learning from experience (Ding and Wermers, 2009; Kepmf, Manconi, and Spalt, 2014). This literature has provided evidence that the named portfolio manager is important for mutual fund portfolio decisions and performance. In this paper, we aim to explain why the portfolio manager matters and what kind of knowledge is used to generate better performance.

The remainder of the paper is organized in the following way. In Section 2, we discuss the data and the construction of variables used in our analysis. Section 3 presents the paper's main results on returns of specialist versus generalist fund managers. Section 4 examines fund portfolio holdings during events that are known to have significant implications for stock prices. Section 5 concludes.

2. Data and methodology

The main data sources for this paper are the CRSP Survivor-Bias-Free US Mutual Fund Database and annual Morningstar Principia CDs. Our initial sample consists of 85 actively managed, open-end, health sector mutual funds operating in the U.S. from 1998 through 2014. We construct this sample by merging CRSP and Morningstar, using CUSIP codes, ticker symbols and (when CUSIP codes and ticker symbols are missing) by manually matching fund names. We eliminate index funds by removing all funds with the words "index", "S&P", "Dow Jones", and "NASDAQ" in the fund name. Exchange-traded funds (ETFs) and variable annuity underlying funds are also excluded based on the ET_FLAG and VAU_FUND variables in CRSP. Health sector funds are identified using three variables that are available during different time periods: Strategic Insight objective code (HLT for health funds), Lipper class name (Health/Biotechnology Funds; Global Health/Biotechnology Funds), and Morningstar category (Health; Specialty-Health).

We aggregate fund variables across fund classes using the Morningstar portfolio identifier (PORTCODE) or MFLinks variable (WFICN), leaving one observation per portfolio-month. We remove incubated funds by excluding funds that were not contemporaneously reported in Morningstar or had a blank fund name in CRSP at the start of the calendar year. This leaves us with 79 portfolios and 7,848 portfolio-month observations.

Figure 2 depicts the trend over time in the number of health sector funds. There were approximately a dozen such funds operating during the mid 1990s, but this category dramatically expanded during the late 1990s and early 2000s. The number of funds increased from 16 in 1997 to 85 in 2002. The growth then leveled off and the number has stayed approximately constant since 2002. However, as has been the case throughout the mutual fund industry, ETFs and index funds have replaced traditional actively managed open-end mutual funds. The latter dropped from a peak of 75 in 2003 to 42 in 2014, as investors opted for lower fees (ETFs and index funds) and the convenience of intraday trading (ETFs).

2.1. Manager characteristics

Mutual funds are required to report biographical information on their manager or management teams, as well as any turnover in management. Morningstar collects this information from SEC filings, and we use the Morningstar manager start and end dates to determine the portfolio manager(s) of each fund at any point in time. Increasingly, team management is the preferred management structure for mutual funds (see Patel and Sarkissian, 2015). Because our sample size is already small, we do not exclude the 40% of the sample consisting of funds with more than one manager. Instead, for each team, we designate the "lead manager" as the individual with the longest tenure at the fund (and use age if there is a tie in length of tenure), and focus on the lead manager's characteristics in the remainder of the paper. In an alternative specification, we also average manager-level variables across all team members, and find that our results continue to hold (see Table 5).

Our sample consists of 266 managers and 141 lead managers. An anonymous team, in which the fund company does not provide manager names, is approximately 3% of portfolio-month observations, and these observations are dropped from our analysis. We hand-collect biographical data on managers from LinkedIn profiles, Morningstar biographies, company websites, and SEC disclosure documents. We are able to find educational institutions and degrees for 97% of observations. The remaining observations are excluded from our analysis.

We define our explanatory variable of interest, *SPECIALIST*, to equal one if a manager holds a bachelor's or advanced degree in health, biology, chemistry, biochemistry, chemical engineering, or related subfields (e.g., genetics, immunology, or microbiology). *SPECIALIST* is also set to one if the manager is a medical doctor or has industry experience in the health or medical industry. The remaining managers have *SPECIALIST* set to zero and are referred to as "generalists". Figure 3 shows the trend over time in the number of health sector funds run by specialists versus generalists. Before the start of our sample period, in 1997, there were no specialist managers, but the proportion of specialists has steadily increased since then, and reached almost 50% near the end of the sample period, before dropping slightly in 2014. This secular increase in the proportion of specialist managers at health sector funds is consistent with the main results of this paper, showing a significant return to specialization.

We define several additional manager-level variables that are used to run additional tests or are used as control variables. *SPECIALIST+EXPERIENCE* is set to one only if a manager has a health-related advanced degree or industry experience. Managers with just a health-related undergraduate degree but no other training or experience are not regarded as specialists for the purposes of this variable. *STEM MAJOR NONBIO* equals one if a manager has an undergraduate degree in math, physics, engineering, or computer science, and zero otherwise. We also define a dummy variable, *MANAGER FEMALE*, for each manager's gender based on pronouns used in the manager's biographical profile, and *MANAGER AGE* for each manager's age based on the year of bachelor's degree (subtracting 22 to get the most likely year of birth).[6] *MANAGER MEDSAT* is the average SAT score (as of 2005) for incoming students at the educational institution where the manager received a bachelor's degree.[7]

2.2. Fund characteristics and holdings data

The CRSP database is our source for monthly net returns, assets under management, expense ratios, and the first offer date of the oldest fund class (used for calculating *FUND AGE*). We add assets of all fund classes of a portfolio to calculate *SIZE*, a portfolio's total assets under

[6] When the year of bachelor's degree is not available, we subtract 27 from year of master's degree or 30 from year of doctoral degree to get the most likely year of birth. When no degree dates is available, we look up the current age on www.ussearch.com.
[7] We set *MANAGER MEDSAT* to 1000 for managers with a degree from non-U.S. educational institutions. The results are robust to dropping these managers.

management. We take value-weighted (using lagged *SIZE*) average of returns and expense ratios across fund classes for the portfolio returns and expenses. The name of the fund advisor in Morningstar at the end of the prior year is used to calculate *FAMILY SIZE*, the sum of assets under management of all funds (not just health funds) managed by that advisor. Finally, for each family-month we calculate *FAMILY CAT-ADJ RETURNS* as the value-weighted category-adjusted returns (using Morningstar categories) of all non-health equity funds managed by the family during that month.

We use two different sources for fund holdings: Thompson Reuters Mutual Fund Holdings (s12) and CRSP Mutual Funds Portfolio Holdings. The advantage of Thompson Reuters is that it has pre-2003 holdings while CRSP data is only available for most funds starting in 2003. The advantage of CRSP is that it has much better coverage after 2009 and reports holdings on a monthly basis (instead of quarterly or semiannually) for most funds. We merge Thompson Reuters to our dataset using the MFLinks database and manually collect FUNDNO identifiers for any remaining unlinked funds, while CRSP is matched using the CRSP_PORTNO identifier. We then match the two databases based on report date, un-adjust for splits[8], and find that more than 99% of observations are the same in both databases. After checking several original filings on EDGAR, we determine that Thompson Reuters is typically correct in case of discrepancies and therefore use its data when the two databases report different holdings.

2.3. Health-related stocks

We collect stock-level returns and price data from the CRSP Monthly and Daily Stock Files. Because health-related stocks belong to multiple Fama-French 48 industries and Standard

[8] The reported shares in the holdings datasets are adjusted for splits that happen between the report date and the file date. We undo these adjustments prior to merging since the two datasets often have different file dates. We then re-adjust when calculating shares held in later months when a split occurs.

Industry Classification (SIC) codes, we use the holdings of health sector funds to come up with a comprehensive list of SIC codes. We also subdivide the health sector into five sub-industries, and present the list of SIC codes for each sub-industry in Panel A of Table 1. Most of the value of the publicly traded health sector (62.1% in the average month from 1998 through 2014) is in pharmaceuticals. This is not necessarily a reflection of their share of GDP since most health-related companies are not publicly traded.[9]

We calculate the market capitalization of each stock by multiplying the absolute value of its price, *PRC*, by its shares outstanding, *SHROUT*, and then calculate the market weight of each stock in the health sector by dividing its market capitalization by the sum of the market capitalizations of all health stocks. We also calculate health sector monthly returns, *HRET*, by taking a value-weighted average of returns for all stocks in the health sector, and perform the same task for all stocks outside the health sector to calculate *NHRET*.

2.4. Event variables

We collect data on FDA approvals of new molecular entities (NMEs) and new biologics form the FDA website.[10] There were 462 such approvals from 1998 through 2014. For each approved drug, the FDA shows the approval date as well as the name of the applicant. We look up parent companies for subsidiaries and merge the applicants to the CRSP stock file. After eliminating international firms unlisted in the United States, privately held firms, and non-health

[9] Most service providers in the United States are either non-profit hospitals or privately held medical practices.

[10] This data is available in annual form starting in 1999 at the following website:
http://www.fda.gov/Drugs/DevelopmentApprovalProcess/HowDrugsareDevelopedandApproved/DrugandBiologicApprovalReports/NDAandBLAApprovalReports/ucm373420.htm
We gather data by hand for 1998 from drug approval reports at:
http://www.accessdata.fda.gov/scripts/cder/drugsatfda/index.cfm?fuseaction=Reports.ReportsMenu

care firms,[11] we are left with 298 approvals by 113 different U.S. publicly listed companies. We merge companies and approval dates with the CRSP Daily Stock File and calculate cumulative abnormal return (CAR) by adding the stock return on the day of approval to the return on the day after approval minus the return of the health sector *HRET* on those two days. The average CAR is 5% but the FDA approval decision is not always good news (or a surprise) as only 58% of CARs are positive.

The data collection for FDA rejections is more difficult as the FDA does not publicly announce when it refuses to approve a drug. As a result, our data on rejections is purely based on voluntary disclosure by the firm. We start with an aggregator website[12] that includes a list of rejected drugs, applicants and rejection dates. We supplement this list with Google searches using the terms "FDA" and different versions of the words "reject" and "non-approval". We only include the first date that a drug was rejected since many drugs were rejected multiple times. After merging with CRSP, we are left with 49 rejections by 39 different U.S. publicly listed companies. Our findings of far fewer rejections than approvals is not surprising since FDA approval rates have averaged around 75% over the last decade and news about rejections is voluntarily disclosed.[13] We calculate CARs in the same way as for approvals. Since FDA rejections are less likely than approvals, it's not surprising that the magnitude of price declines is much larger, -14.8% for the average rejection. More than 83% of CARs are negative.

We collect data on merger announcements in the health industry. We start with all delisted health stocks with a 200s delisting code (indicating mergers). We merge these funds

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[11] Applicants for approval for several of the drugs were large companies DuPont, Dow Chemical, General Electric, and Procter & Gamble. We also dropped eight drugs that were jointly developed by more than one company.
[12] Vaughn's Summaries collects data on new drugs that have been voted down by the FDA: http://www.vaughns-1-pagers.com/medicine/prescription-drugs-rejected.htm
[13] Forbes Magazine cites annual data from BioMedTracker. See "The FDA Is Basically Approving Everything. Here's The Data To Prove It," by Matthew Herper, Forbes.com, 08/20/2015.

with SDC Platinum to obtain announcement dates, and hand-collect all remaining announcement dates for several M&A transaction not covered by SDC. We are left with a sample of 649 acquired health companies. We calculate CARs in the same way as for FDA events. Consistent with the mergers literature, the average CAR is 22.4% and 77.4% of firms have positive CARs around earnings announcement.

We collect data on brokerage estimates for quarterly earnings reports from the Summary History-Summary Statistics file of IBES. Our sample includes a total of 33,251 quarterly earnings announcements. We compare actual earnings to the median analyst estimate to calculate the percentage earnings surprise. We calculate CARs in the same way as for FDA events. We find an average CAR of -2.7% for earnings misses, and 2.02% when earnings exceeds estimates by more than one penny. CARs are almost exactly equal to zero when the earnings exceed estimates by exactly one penny.

2.5. Measuring performance

We measure mutual fund performance using a number of different measures. The simplest measure of performance is *NET RETURNS*, which is directly provided by CRSP. Next, we calculate *GROSS RETURNS* by adding one-twelfth of the annual expense ratio and adding it back to *NET RETURNS*. We calculate *HOLDINGS RETURNS* as the returns to an investor who buys and holds a portfolio using the same weights as the fund at its last report date. *DGTW RETURNS* are holdings-based characteristic-adjusted returns where the returns on each stock holding are adjusted for the return to a basket of stocks with the same size, value, and momentum characteristics. (Daniel, Grinblatt, Titman, and Wermers, 1997)

We use daily data, which starts in September 1998, to calculate loadings on risk factors. For each fund-month, we regress the prior three months of daily fund returns (minus the daily risk-free rate) on daily factor returns, and use the factor loadings to calculate the monthly alpha. We calculate alpha from the Capital Asset Pricing Model (MKTMRF as the single factor), from the usual four-factor model with MKTMRF, SMB, HML, and MOM (see Fama and French, 1992, 1993; Carhart, 1997), and from a five-factor model where MKTMRF is replaced by the excess returns from the health sector, *HRETMRF*, and the non-health sector *NHRETMRF*. *ALPHA-FF4F+H*, the alpha from the five-factor model, is used for our baseline results, because the returns to health sector mutual funds are best explained by the returns to the health sector, *HRET*.

2.6. Summary statistics

Table 2 presents time series averages of summary statistics for the main variables used in this study. The first five rows present the main measures of performance. The average health sector mutual fund earns 1.04% in monthly returns during our sample period. After controlling for the return of the health sector and various risk factors, this declines to an average of 0.38% in five-factor alpha. In Section 3, we will present evidence that most of this alpha is driven by specialist-managed funds. The next six rows provide summary statistics for manager-level variables. On average, 27% of fund managers in our sample are specialists and 15% have an advanced health-related degree and/or industry experience. Interestingly, 13% had a STEM bachelor's degree outside of health-related majors. 11% of managers are women and the average manager age is 42, significantly lower than the high 40s that are the average age for managers of diversified mutual funds. The average team consists of slightly fewer than two managers.

The next six rows of Table 2 display summary statistics for fund level variables. The distribution of fund size has a high positive skewness, with an average size of nearly $1.2 billion, but a median size of only about $300 million. Family size is similarly positively skewed. Therefore, as is common practice, we use the natural logarithm of both fund size and family size as explanatory variables in regression analysis. The average fund is 10 years old and charges 1.53% in annual expenses, slightly higher than the 1.2% average commonly found for diversified mutual funds.

The last six rows of Table 2 show the proportion of portfolio holdings in different sub-industries of the health sector, as defined in Panel A of Table 1, as well as outside the health sector (as we define it). Comparing these sample averages to the average market weights in Panel A, we can see that health mutual funds are not significantly deviating for any sector. They do overweight service providers such as hospitals (holding 11% versus 7.6% for the market), and they also hold 7.2% outside in non-health stocks. We investigate the non-health stocks that are held and find that most are companies that have a non-health SIC code but have large divisions that are related to medicine. Some examples of these "non-health" firms include Thermo-Fisher Scientific (lab equipment), Monsanto (agriculture), VCA (animal hospitals), WebMD (information technology). Clearly, such firms are not fully outside the health sector but belong to industry classifications that contain mostly non-health firms, so this grouping can also be labeled "health-miscellaneous."

3. Main results – specialization and mutual fund returns

In this section, we describe the main results of the paper, pertaining to the performance gap between specialist and generalist managers, as defined in Section 2. We begin, though, by examining the determinants of specialization to better understand whether it is endogenously related with fund or manager characteristics.

3.1. Predictors of manager specialization

In order to study the relationship between the indicator variable, manager specialization, and other fund or manager characteristics, we estimate a Probit regression model, and report the results in Table 2. The coefficients reported in Table 2 are marginal effects at the mean values of the independent variables. In Column 1, fund characteristics are the only explanatory variables. The only significant fund-level predictor of specialization is fund age, with younger funds being more likely to employ specialist managers than older funds. The standard deviation of *LOG FUND AGE* is 6.3 so a one-standard deviation increase in a fund's age (around the mean) is associated with a 1.9% decline (-0.3*6.3) in the probability of having a specialist manager. This result is consistent with Figures 2 and 3, which showed a large number of newly opened health funds in the late 1990s and early 2000s and a concurrent increase in the proportion of specialist managers. This finding might be troubling since Pastor, Stambaugh, and Taylor (2015) find that performance worsens as funds get older, although we do control for fund age in our performance tests.

In Column 2 of Table 2, the explanatory variable is the value-weighted average style-adjusted return of the family's other offerings. We include this control because we are worried that intrinsically better families (for other reasons) are also more likely to attract specialists and/or may have led the industry in understanding the importance of managers. However, although the point estimate on *FAMILY CAT-ADJ RETURNS* is positive, this coefficient is not statistically significant. In Column 3, manager-level characteristics are the only explanatory variables. Surprisingly, even though *SPECIALIST* is a manager-level variable, none of the other manager-level variables are associated with it in a statistically significant way in our sample. However, we should be wary of arguing they are uncorrelated in the population since we have a very small sample of 130 lead managers.

In Column 4 of Table 3, the explanatory variables are sub-industry fund weights, as defined in Panel A of Table 1. Interestingly, all the coefficients are negative and statistically significant, indicating that holding "non-health stocks" (the omitted industry) is actually positively associated with specialist managers. On the surface, this result seems paradoxical, since we wouldn't expect health specialists to be *underweighting* health stocks and *overweighting* non-health stocks. One possible explanation is that specialists are better able to identify opportunities in companies that are not commonly identified with the health sector but that have health divisions or connections to the health sector. Their specialized knowledge essentially increases the universe of stocks (and possibilities for profits) that they can take advantage of to achieve better performance. Given these statistically significant differences, we also control for sub-industry weights in our performance tests.

Finally, in Column 5, we include all the predictive variables from the first four columns. Again, we find that only fund age and sub-industry portfolio weights are predictive of whether a fund's manager is a specialist or a generalist. Overall, these results provide some comfort that our main variable of interest is a proxy for certain observable characteristics.

3.2. Returns on portfolios of specialists' and generalists' funds

We take an equal-weighted average of returns of funds that are managed by specialists to form a long portfolio, and an equal-weighted average of returns of funds that are managed by generalists to form a short portfolio. We then compare the performance of these two portfolios and present the results in Table 3. Panel A displays simple time-series averages of *NET RETURNS*, *GROSS RETURNS*, and *HOLDINGS RETURNS* for the short portfolio (Column 1), the long portfolio (Column 2), and the long minus short portfolio (Column 3). Standard errors are corrected for autocorrelation with up to six lags (Newey and West, 1987).

The short portfolio, consisting of funds managed by generalists, averages 0.966% per month (11.6% annualized) in net returns during our sample period, while the long portfolio, consisting of funds managed by specialists, averages 1.4% (16.8% annualized) in net returns. Interestingly, both groups outperform the health sector, *HRET*, which averages 0.84% (10% annualized), even though the fund returns are measured after subtracting fees and expenses.

This last result contradicts the large body of research that indicates diversified mutual funds underperform their benchmarks in terms of net (of fee) returns. One reason for this apparent contradiction is that the health sector may be an area where fund managers are better able to generate alpha (relative to other industries). Furthermore, we do not include the returns of the entire universe of health sector funds, since we drop funds that are anonymously managed or where we are not able to find any educational information about the manager (as described earlier in Section 2.1). Still, this is a surprising result that may be an interesting subject for further research.

The estimate of interest is displayed in Column 3, which shows the returns from buying the long portfolio and selling the short portfolio. Returns from this strategy average 0.435% (5.2% annualized) and are statistically significant at the 5% level, with a t-statistic of 2.34. There are also positive and significant gross returns (before expenses) and holdings-based returns from buying the long portfolio and selling the short portfolio. The long minus short return based on holdings is 0.314% (3.8% annualized) with a t-statistic of 2.10. *HOLDINGS RETURNS* are calculated using previously reported holdings information, so it is rare and significant to find that the more than two-thirds of the overall effect for reported returns also exists for returns derived from stale holdings.

We next adjust for risk by regressing the time series of portfolio returns on factors and reporting the intercepts. We start with the CAPM, by regressing portfolio returns (minus the risk-free rate) on the excess returns of the market, MKTMRF, and report the results in Panel B. We continue, in Panel C, with the Fama and French (1992, 1993) plus Carhart (1997) four-factor model, regressing portfolio returns (minus the risk free) on the returns of MKTMRF, SMB, HML, and MOM. Finally, in Panel D, in order to control for the returns of the health sector, we use a five-factor model, in which we replace the market excess returns with the excess returns of the health sector the health sector, *HRETMRF*, and the non-health sector, *NHRETMRF*.

The estimates on the long minus short portfolio returns after risk-adjustment are similar to the simple raw returns from the first three rows, suggesting that there is no correlation between risk factors and manager specialization. Therefore, the specialists are not simply generating higher returns by taking on more risk. Interestingly, using the five-factor model, generalists only obtain an alpha of 6.3 basis points per month (0.76% annualized), which is not statistically significant, while specialists obtain an alpha of 46 basis points (5.5% annualized), which has a t-statistic of 1.95. Therefore, health mutual funds' outperformance of the health sector is explained almost entirely by the funds with specialists.

In addition to statistical significance, these results are also economically significant. The average health fund charges an expense ratio of approximately 1.5% per year. Therefore, by investing with specialists (rather than generalists), investors would be able to reap more than three times the fees and expenses that they paid. An obvious question is why specialists do not raise their fees to take this surplus for themselves. The likely answer is that investors would refuse to pay high expenses for manager types (specialists) that have done well in the past without more certainty that the outperformance is based on persistent skill. Given the lack of prior research into the returns from specialization in asset management, their reluctance is unsurprising.

3.2. Cross-sectional regressions

One explanation for the results in Section 3.1 is that manager specialization is correlated with one or more characteristics that predict returns. In that case, when we formed portfolios based on specialization, we were really sorting on those other characteristics. In order to test this explanation, we run cross-sectional multi-variable regressions of returns on lagged explanatory variables for each time period, and then take the time-series average of the estimated coefficients (Fama and MacBeth, 1973). Table 4 reports these estimates, adjusting for serial correlation in the estimates using Newey-West standard errors.

In Panel A of Table 4, the dependent variable is *ALPHA FF4F+H*, the alpha from a five-factor model where we replace excess market returns with the excess returns of the health and non-health sectors. In Column 1, the explanatory variable is *SPECIALIST*, and we find an estimated coefficient of 0.426% (5.1% annualized) with a t-statistic of 2.51. This column is analogous to Column 3 from Table 3, with the main difference being only 193 months of data instead of 204 months. We need three months of prior daily returns to calculate this performance variable and daily returns are only available on CRSP starting in September 1998. We add fund controls to the regression in Column 2; family style-adjusted returns are added in Column 3; manager controls are added in Column 4; sub-industry weights are added in Column 5.

The coefficient on *SPECIALIST* increases for the full set of control, equaling 65 basis points per month (7.8% annualized). Therefore, our main finding is robust to controlling for a large number of observable characteristics. It is possible that we are omitting an unobserved variable that is correlated with specialization and predicts returns. However, the fact that adding controls doesn't reduce but actually increases the estimated effect does provide some comfort that our results are not spurious. Only two control variables have a statistically significant correlation with alphas. There is a negative estimated coefficient on *EXPENSE RATIO*, consistent with past research that shows funds charging higher fees underperform. There is also a positive estimated coefficient on *FAMILY CAT-ADJ RETURNS*, but this is not predictive since the family's returns and the fund returns are measured concurrently. Since funds in the same family often have large overlaps in their holdings, it is not surprising that the returns are correlated. Including this control, however, helps allay the concern that higher-quality families are more likely to hire specialized managers so the positive effect of specialization is actually a proxy for family quality.

We repeat the tests in Panel A of Table 4 using five other performance measures as dependent variables: *NET RETURNS* in Panel B, *GROSS RETURNS* in Panel C, *HOLDINGS RETURNS* in Panel D, *DGTW RETURNS* in Panel E, and *ALPHA FF4F* in Panel F. The magnitudes are similar to those found in Panel A and all the results with the full set of controls are statistically significant, at least at the 10% level. As with Table 3, different forms of risk-adjustment or characteristic-adjustment do not change the main results of the paper.

3.3. Other measures of specialization and team effects

In this section, we examine several alternative hypotheses and investigate how team management interacts with the effect of specialization on fund returns. One question unanswered by the results so far is whether it is the *experience* from becoming a medical doctor and working in the health industry that is necessary or whether the general familiarity with the language of biology and chemistry that is the key ingredient. We therefore add a dummy variable *SPECIALIST+EXPERIENCE* to our baseline regression (with the full set of controls) from Table 4 to disentangle the two mechanisms, and report the results in Column 1 of Table 5. We find that having a health-related undergraduate degree is enough to generate most of the outperformance (47 basis points per month in *ALPHA FF4+H*) while having more than that (advanced degree and/or industry experience) adds a statistically insignificant 15 basis points per month. This result suggests that it is knowledge about the medical field, rather than relationships acquired through experience in this field, that is the more important component for improved performance.

Another hypothesis is that getting a degree in STEM disciplines is more difficult, and thus requires a higher IQ or a stronger work ethic. Therefore, the specialists are generating outperformance due to their superior abilities, which allowed them to become specialists, and not due to any specialized knowledge. We test this hypothesis by including a dummy variable, *STEM MAJOR NONBIO*, to our baseline regression from Table 4, and report the results in Column 2 of Table 5. Contrary to this hypothesis, we find that non-health-related STEM majors outperform generalists by an insignificant 13 basis points, while specialists outperform specialists by 63 basis points. This finding suggests that it is specialized knowledge of medicine rather than superior ability of scientists that is responsible for the difference in performance.

Next, we examine how specialization across different members of a team affects fund performance. First, we create a continuous variable, *SPECIALIST TEAMAVERAGE*, by averaging specialization across all members of the team. In order to check for the robustness of our main results, we then replace *SPECIALIST* (defined by the lead manager's specialization) with *SPECIALIST TEAMAVERAGE* in our baseline regression from Table 4 and report the results in Column 3 of Table 5. We find that our results are robust to this change in definition. The estimate's magnitude is smaller at 35 basis points per month, but statistically significant at the 5% level.

We also test whether teams with a combination of specialist skills and generalist skills have better performance than have only a specialist or only a generalist managing the fund. The underlying hypothesis we are testing is that specialists are missing some of the financial skills that are acquired from an education and/or experience in finance, and a generalist on the team provides those missing skills. We include a dummy variable, *SPECIALIST ON TEAM*, based on whether there is at least one manager with specialized knowledge on the team, and also, *SPECIALIST + GENERALIST TEAM*, which equals one if there is both a specialist and a non-specialist on the team, and report the results in Column 4 of Table 5. We also control for number of managers on the team and the full set of fund controls, manager controls, and sub-industry weights from Table 4. Consistent with our prior results, we find that funds whose teams have specialist managers outperform funds without any specialists. However, we do not find evidence that having a specialist and a generalist on the team provides improved performance. The point estimate on the *SPECIALIST + GENERALIST TEAM* is negative, -0.372% per month, but statistically insignificant. This finding indicates that having *financial* knowledge is not a competitive advantage for managers in generating alpha.

4. Fund holdings around major market-moving events

In this section, we investigate the mechanism which lets specialists generate better performance, by testing whether specialists and generalists have different skills in market timing around events with major price impacts: FDA announcements on whether a drug is approved for sale in the United States, announcements that the company will be acquired, and quarterly earnings announcements.

For each fund-stock-month observation, we calculate the fund's *adjusted* holdings of the stock in that month by taking its portfolio weight as a share of the total portfolio of health sector stocks[14] (using the most recent reported shares held) and subtracting the market weight of that stock as a proportion of the market capitalization of the health sector. We create fund-stock-month observations equal to zero for stocks that the fund is not holding and calculate adjusted holdings for these observations as well. We then look at prior six-month and twelve-month changes in adjusted holdings prior to months of FDA approval or rejection.

In Panel A of Table 6, we restrict the sample to stock-month observations in which the company had a drug rejected by the FDA during that month. All specifications include event fixed effects, in order to compare changes in holdings for the same stock and time horizon. In Column 1 of Panel A, we regress the six-month change in adjusted holdings on *SPECIALIST*, so as to compare how specialists and generalists change their adjusted holdings prior to FDA rejections. We find a negative and statistically significant coefficient of -0.107% (t-statistic of 2.30), indicating that specialists reduce their holdings to a greater degree than specialists before companies receive bad medical-related news from the FDA. This result suggests specialized

[14] We drop all holdings that are not in the health sector, as defined in Panel A of Table 1.

knowledge allows managers to better predict the FDA announcement and make money by under-weighting stocks whose drugs are more likely to be rejected.

The coefficient on *SPECIALIST*, -0.107%, might seem small, but is actually economically significant. Because we are adding observations with zeros for stocks that are not in a fund's portfolio, the average portfolio weight is less than 0.2%. A reduction of about 0.1% is therefore a very large portion of the average fund's holdings of a stock. It is true that since the average CAR around FDA rejections is about -15%, reducing the portfolio weight by 0.1% only nets a fund about 1.5 basis points in higher returns, well short of the 40-60 basis point outperformance by specialists (and rejections don't happen every month, there are only 49 of them in 17 years from 1998 through 2014). However, we would argue that this is just the tip of the iceberg in how specialists use health-related information for timing and/or stock selection.

We repeat this analysis with our battery of controls (excluding sub-industry weights since those weights are a function of holdings) and report the results in Column 2. The estimated coefficient on *SPECIALIST* is of similar magnitude to Column 1 and is statistically significant. Next, we replace prior six-month changes in holdings with prior twelve-month changes in holdings as the dependent variables, and report the results in Columns 3 and 4. The magnitude of coefficients is very similar to those in the first two columns, but there is more noise over a longer horizon, and the results are not statistically significant. This suggests that most of the selling happens in the six months immediately before the announcement and not in the preceding six months.

In Panel B of Table 6, we perform the same analysis as in Panel A, but restrict the sample to stock-month observations in which the company had a drug approved by the FDA during that month. As explained in Section 2, most drugs get FDA approval and average CARs are lower (approximately 5%) around an approval announcement, with only 58% of CARs being above zero, suggesting that few FDA approval announcements are significant positive surprises. We do not find statistically significant differences in holdings changes prior to approval announcements between specialists and generalists. However, the point estimates are generally positive and, for the twelve-month horizon, are about half the magnitude of those in Panel A for FDA rejections. In addition, although the lack of a statistically significant difference does not show evidence of timing prior to FDA approvals, the positive sign on *SPECIALIST* in Panel B helps rule out the theory that funds are selling stocks prior to FDA rejections because they want to avoid event risk.

Another alternative story is that specialists are better able to collect information from the company, perhaps through connections to insiders. This allows them to learn about the success of drug trials and predict FDA decisions. We test this hypothesis by looking at market-moving events that are unrelated to specialized knowledge about medicine: merger and earnings announcement. In Table 7, we repeat the tests from Table 6, but restrict the sample to stock-month observations in which a company announces that it will be the target in a merger or acquisition. The point estimates on *SPECIALIST* are negative in all specifications, indicating that specialists *reduce* their holdings of companies prior to acquisitions relative to generalists, although all the results are statistically insignificant. This is contrary to the information hypothesis, in which we would expect that specialists would be able to also learn about future mergers news.

We also test whether specialists are better at market timing of earnings announcements, and report the results in Table 8. Because earnings announcement happen each quarter, the methodology of using prior six month or twelve month changes in holdings does not work.

Instead, we use manager by fund by stock fixed effects to look at whether time series variation in adjusted holdings is correlated with earnings surprises. Because time-series variation in holdings can be driven by stock characteristics, we also include stock size, book-to-market, age, and prior year returns, as well as calendar quarter dummy variables. We interact our measures of earnings surprise and stock characteristics with *SPECIALIST* to test whether adjusted holdings of specialists are better at timing earnings surprises than generalists. We also drop all stock-month observations where there was no earnings release.

In Columns 1 and 2 of Table 8, our measures of earnings surprise are *EARNINGS BEAT*, a dummy variable that equals one when a firm beats median analyst estimates by at least 10% and 2 cents, and *EARNINGS MISS*, a dummy variable that equals one when a firm misses median analyst estimates. We find very weak evidence of market timing, with positive, but statistically insignificant, point estimates on *EARNINGS BEAT* and negative and insignificant point estimates on *EARNINGS MISS*. The interaction terms with *SPECIALIST* are not significant, indicating that specialists do not have any extra ability to market time earnings. We repeat the tests in Columns 3 and 4 with a continuous measure of earnings surprise, *% EARNINGS SURPRISE*, and again find no evidence of market timing by either specialists or generalists. In conclusion, the (lack of) results in Tables 7 and 8 is contrary to the idea that specialist fund managers are outperforming generalist fund managers because they are better at collecting non-specialized information from inside the firm prior to its announcement.

One possible explanation for the results on FDA rejections that we are not able to rule out is that specialists are more likely than generalists to have contacts inside the FDA that give them information about the prospects of different drugs. This can be considered a form of "returns from specialization" in the sense that the FDA contacts are gained as a part of the process of getting a specialized education or experience. Still, the return gains from the FDA events are small relative to the total outperformance by specialists, suggesting that there are other ways, other than good contacts, by which they are achieving their success.

5. Conclusion

A large literature attempts to identify whether some asset managers have "skill" or "talent" to attain positive true, as opposed to measured, alpha, or whether they are all just throwing darts (e.g., Fama and French, 2010). There is less research on which skills are necessary to generate true alpha and how you acquire those skills. In this paper, we attempt to fill in this gap by examining whether an education or experience in industry-related discipline is a useful ingredient in providing a competitive advantage in asset management. Industry-specific terminology and processes can often be arcane and difficult to understand and process by outsiders. Internal analysts or external experts might be able to mitigate this knowledge gap but not entirely close it.

We focus on a group of mutual funds that invest in just one industry, the health sector, and test whether managers who received a health-related bachelor's or advanced degree or have health industry experience are able to generate better returns at their funds than their generalist peers. We find a positive and significant return to specialization, with specialists beating generalists by an annualized 4.7% in net returns and 7.8% per annum after adjusting for risk and controlling for fund and manager characteristics. We also provide an example of how specialists use their industry-specific knowledge, by selling stocks before FDA drug rejections.

While our paper uses health sector funds as a laboratory, it has important implications for asset management in general. Given the large economic magnitude of the results, it suggests that esoteric industry-specific news or information is not perfectly priced in to stocks, providing investors and asset managers with better processing skills in those areas an opportunity to beat the market. This is an interesting subject for future research.

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Table 1: Classification of health stocks and summary statistics

Table 1 presents information on the Standard Industrial Classification (SIC) codes that are considered to be in the health sector, and the sub-industries to which they are assigned (in Panel A), along with time-series averages of summary statistics for the fund and manager variables used in this study (Panel B). In Panel A, we list the five sub-industries of the health sector, the time-series average percentage of market value of the health sector for each sub-industry, and the SIC codes belonging to each sub-industry. Panel B displays summary statistics on the sample of actively managed open-end health sector funds from January 1998 through December 2014. It includes the total number of non-missing observations for each variable, along with the time-series averages of cross-sectional means, standard deviations, 10^{th} percentiles, medians, and 90^{th} percentiles. *NET RETURNS* are the monthly fund returns net of expenses, while *GROSS RETURNS* are the monthly fund returns before expenses are subtracted. *HOLDINGS RETURNS* are the returns to an investor who buys and holds a portfolio using the same weights as the fund at its last report date. *ALPHA FF4F* is the alpha from the four-factor model with factors for the market, size, value, and momentum. *ALPHA-FF4F+H* is from a five-factor model where the market factor is replaced by a health sector excess return and the excess return of all other (non-health) stocks. *SPECIALIST* is a dummy variable that is set to one if the lead manager holds a bachelor's or advanced degree in health-related disciplines, is a medical doctor, or has industry experience in the health or medical industry, and zero otherwise. *STEM MAJOR NONBIO* is a dummy variable that is set to one if the lead manager holds a bachelor's degree in a science, technology, engineering, or math discipline that is unrelated to health, and zero otherwise. *SPECIALIST+EXPERIENCE* is a dummy variable that equals one if the lead manager holds an advanced health-related degree or has industry experience in the health or medical industry, and is zero otherwise. *MANAGER AGE* is the age in years of the lead manager. *MANAGER MEDSAT* is the average SAT score (as of 2005) for incoming students at the educational institution where the lead manager received a bachelor's degree. *MANAGER AGE* is a dummy variable, which equals one if the lead manager is female and zero if the lead manager is male. *NUMBER OF MANAGERS* is the number of portfolio managers that are identified by name as responsible for the fund. *SIZE* is the total assets under management of the fund portfolio (in millions of dollars), and *LOG SIZE* is the natural logarithm of *SIZE*. *FAMILY SIZE* is the sum of all mutual fund assets managed by the fund's investment advisor (in billions of dollars), and *LOG FAMILY SIZE* is the natural logarithm of *FAMILY SIZE*. *FUND AGE* is the number of years since the oldest class in the portfolio was first offered, and *LOG FUND AGE* is the natural logarithm of *FUND AGE. EXPENSE RATIO* is the fund's annual expense ratio. *INDUSTRYW: MED DEVICES*, along with the next four rows indicate the proportion of fund holdings in each sub-industry's stocks, as defined in Panel A, using the fund's reported shares held from the most recent report date. *INDUSTRYW: NONHEALTH* represents the holdings in all stocks whose SIC codes are not a part of the health sector, as defined in Panel A.

Panel A: Classifying stocks in the health sector

Sub-industry	Average % of health sector market value	SIC codes included
Medical Devices	15.7%	3826; 3840—3851
Health Insurance	7.4%	6320; 6321; 6324
Pharmaceuticals	62.1%	2830—2836
Supplies	7.3%	5047; 5048; 5120; 5122; 5912
Service Providers	7.6%	8000—8099; 8730; 8731

Panel B: Summary statistics	**Obs.** (1)	**Mean** (2)	**SD** (3)	**p10** (4)	**p50** (5)	**p90** (6)
NET RETURNS (%)	7738	1.04%	2.57%	-2.03%	1.02%	4.20%
GROSS RETURNS (%)	7626	1.18%	2.52%	-1.87%	1.16%	4.34%
HOLDINGS RETURNS (%)	7629	1.13%	2.87%	-2.14%	1.02%	4.60%
ALPHA-FF4F (%)	7466	0.92%	2.54%	-2.15%	0.89%	4.10%
ALPHA-FF4F+H (%)	7466	0.38%	2.46%	-2.52%	0.31%	3.39%
SPECIALIST (dummy)	7742	0.27	0.44	0.00	0.00	0.94
STEM MAJOR NONBIO	7742	0.13	0.34	0.00	0.00	0.85
SPECIALIST+EXPERIENCE (dummy)	7742	0.15	0.35	0.00	0.00	0.88
MANAGER AGE (YEARS)	7484	43	10	32	41	57
MANAGER MEDSAT	7730	1279	152	1018	1301	1475
MANAGER FEMALE (dummy)	7742	0.11	0.31	0.00	0.00	0.54
NUMBER OF MANAGERS	7742	1.9	1.5	1.0	1.2	3.8
SIZE ($MIL)	7716	1183	3442	18	312	2437
LOG SIZE	7716	5.3	2.0	2.6	5.4	7.6
FAMILY SIZE ($BIL)	7292	180	287	1	44	729
LOG FAMILY SIZE ($MIL)	7292	10.1	2.6	6.2	10.6	13.3
FUND AGE (YEARS)	7742	10.3	6.3	4.2	8.2	21.0
LOG FUND AGE	7742	2.2	0.6	1.5	2.1	3.1
EXPENSE RATIO (%)	7630	1.53%	0.59%	0.93%	1.51%	2.13%
INDUSTRYW: MED DEVICES	7634	13.5%	11.4%	1.3%	12.7%	23.6%
INDUSTRYW: INSURANCE	7634	5.6%	6.4%	0.0%	4.6%	11.6%
INDUSTRYW: PHARMA	7634	57.8%	20.4%	33.9%	57.8%	86.2%
INDUSTRYW: SUPPLIERS	7634	4.8%	4.8%	0.0%	4.1%	11.7%
INDUSTRYW: SERVICES	7634	11.0%	7.7%	3.5%	9.6%	19.3%
INDUSTRYW: NONHEALTH	7634	7.2%	6.6%	1.1%	5.9%	14.5%

Table 2: Determinants of specialization

Table 2 presents the estimated coefficients from a Probit regression model, where the dependent variable is *SPECIALIST* and the predictive variables are lagged fund and manager level characteristics. In Column 1, the explanatory variables are the four main fund-level variables. In Column 2, the explanatory variable is *FAMILY CAT-ADJ RETURNS*, the value-weighted average of category-adjusted returns of other funds in the fund family. In Column 3, the explanatory variables are manager-level variables. In Column 4, the explanatory variables are sub-industry portfolio holdings, where *INDUSTRYW: NONHEALTH* is the omitted variable. In Column 5, we include all the explanatory variables from the first four columns. The reported coefficients are marginal effects at the mean values of the independent variables. All specifications include year dummy variables. T-statistics are provided in brackets with standard errors clustered by manager. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable: **Predictive Variables**	SPECIALIST (1)	SPECIALIST (2)	SPECIALIST (3)	SPECIALIST (4)	SPECIALIST (5)
LOG SIZE	0.047				0.056
	[1.29]				[1.46]
LOG FAMILY SIZE	-0.004				0.000
	[0.19]				[0.01]
LOG FUND AGE	-0.301***				-0.331***
	[3.12]				[3.35]
EXPENSE RATIO	-6.247				-2.809
	[1.00]				[0.35]
FAMILY CAT-ADJ RETURNS		0.379			-0.115
		[0.77]			[0.26]
MANAGER AGE			-0.004		-0.002
			[1.01]		[0.46]
MANAGER MEDSAT			0.000		0.000
			[0.29]		[0.61]
MANAGER FEMALE			0.104		0.178
			[0.61]		[1.02]
NUMBER OF MANAGERS			0.024		0.014
			[0.73]		[0.52]
INDUSTRYW: MED DEVICES				-1.451***	-1.460***
				[3.16]	[3.25]
INDUSTRYW: INSURANCE				-1.148*	-1.084*
				[1.94]	[1.82]
INDUSTRYW: PHARMA				-1.372***	-1.201***
				[3.45]	[3.11]
INDUSTRYW: SUPPLIERS				-2.785***	-2.546***
				[3.34]	[2.70]
INDUSTRYW: SERVICES				-1.479***	-0.801
				[3.00]	[1.29]
Year Dummies	YES	YES	YES	YES	YES
Observations	7188	6990	7472	7634	6673
Pseudo R2	0.11	0.04	0.04	0.08	0.16

Table 3: Returns on portfolios sorted by manager specialization

Table 3 presents time-series averages of portfolio returns, where portfolios are determined based on the lead manager's *SPECIALIST* variable. Column 1 shows average returns for the portfolio formed by equal-weighting all funds with *SPECIALIST* equal to zero (short portfolio). Column 2 shows average returns for the portfolio formed by equal-weighting all funds with *SPECIALIST* equal to one (long portfolio). Column 3 shows the average returns from buying the long portfolio and selling the short portfolio. In Panel A, we report time-series averages of portfolio returns. In Panel B, we regress portfolio excess returns on the CAPM factor and report the intercept. In Panel C, we regress portfolio excess returns on the factors from the four-factor model and report the intercept. In Panel D, we regress portfolio excess returns on the factors from our FF+H model (health and non-health sectors replacing the market) and report the intercept. The three return variables are defined in Table 1. T-statistics are provided in brackets using Newey-West standard errors with up to six lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	SPECIALIST = 0 (1)	SPECIALIST = 1 (2)	SPEC1-SPEC0 (3)
Panel A: Raw returns			
NET RETURNS (%)	0.966%***	1.400%***	0.435%**
	[2.60]	[2.97]	[2.34]
GROSS RETURNS (%)	1.108%***	1.551%***	0.443%**
	[3.00]	[3.06]	[2.00]
HOLDINGS RETURNS (%)	1.072%***	1.385%***	0.314%**
	[2.78]	[3.02]	[2.10]
Panel B: CAPM			
NET RETURNS (%) [- RF]	0.418%*	0.824%**	0.406%**
	[1.71]	[2.33]	[2.35]
GROSS RETURNS (%) [- RF]	0.564%**	0.972%**	0.409%**
	[2.31]	[2.48]	[1.97]
HOLDINGS RETURNS (%) [-RF]	0.499%**	0.791%**	0.293%**
	[1.97]	[2.43]	[2.13]
Panel C: FF4F			
NET RETURNS (%) [- RF]	0.345%	0.711%**	0.366%**
	[1.54]	[2.47]	[2.54]
GROSS RETURNS (%) [- RF]	0.483%**	0.837%***	0.354%**
	[2.17]	[2.70]	[2.23]
HOLDINGS RETURNS (%) [-RF]	0.433%*	0.666%**	0.233%**
	[1.85]	[2.47]	[2.25]
Panel D: FF4+H			
NET RETURNS (%) [- RF]	0.063%	0.459%*	0.395%**
	[0.52]	[1.95]	[2.51]
GROSS RETURNS (%) [- RF]	0.204%**	0.572%**	0.369%**
	[1.69]	[2.27]	[2.22]
HOLDINGS RETURNS (%) [-RF]	0.119%	0.368%**	0.249%**
	[1.02]	[2.03]	[2.10]
Observations	204	204	204

Table 4: Fama-MacBeth regressions of fund returns on specialization and controls

Table 4 presents estimated coefficients from Fama-MacBeth (1973) regressions of performance measures on *SPECIALIST* and various lagged control variables. In Column 1 of each panel, the only independent variable is *SPECIALIST*. In Column 2, we also include firm-level controls. In Column 3, we add the value-weighted average of category-adjusted returns of other funds in the fund family. In Column 4, we add manager-level controls. In Column 5, we also include sub-industry portfolio holdings. In Panel A, the dependent variable is *ALPHA FF4F+H*, which is the alpha from the five-factor model. The dependent variables are *NET RETURNS* in Panel B, *GROSS RETURNS* in Panel C, *HOLDINGS RETURNS* in Panel D, *DGTW RETURNS* in Panel E, and *ALPHA FF4F* in Panel F. *DGTW RETURNS* are holdings-based characteristic-adjusted returns, and the other performance measures are defined in Table 1. All independent variables are also defined in Table 1. Estimated coefficients for controls are not shown for Panels B through F. T-statistics are provided in brackets using Newey-West standard errors with up to six lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A: ALPHA FF4F+H **Predictive Variables**	**ALPHA FF4F+H (1)**	**ALPHA FF4F+H (2)**	**ALPHA FF4F+H (3)**	**ALPHA FF4F+H (4)**	**ALPHA FF4F+H (5)**
SPECIALIST	0.426%**	0.438%**	0.379%**	0.616%**	0.651%**
	[2.51]	[2.24]	[2.29]	[2.42]	[2.46]
LOG SIZE		-0.043%	-0.074%*	-0.046%	-0.017%
		[1.04]	[1.69]	[0.85]	[0.41]
LOG FAMILY SIZE		-0.003%	0.025%	0.011%	0.015%
		[0.12]	[0.98]	[0.43]	[0.45]
LOG FUND AGE		-0.090%	-0.117%	-0.165%	-0.070%
		[0.88]	[1.05]	[0.98]	[0.67]
EXPENSE RATIO		-0.194**	-0.297**	-0.308*	-0.186**
		[2.43]	[2.50]	[1.88]	[2.06]
FAMILY CAT-ADJ RETURNS			0.276***	0.249***	0.173**
			[4.60]	[3.74]	[2.54]
MANAGER AGE				-0.003%	0.002%
				[0.61]	[0.40]
MANAGER MEDSAT				0.001%	0.000%
				[1.22]	[0.55]
MANAGER FEMALE				0.116%	-0.231%
				[0.98]	[1.33]
NUMBER OF MANAGERS				0.063%	0.079%
				[1.16]	[1.25]
INDUSTRYW: MED DEVICES					-0.040%
					[0.02]
INDUSTRYW: INSURANCE					-1.863%
					[0.68]
INDUSTRYW: PHARMA					1.795%
					[1.32]

INDUSTRYW: SUPPLIERS					1.012%
					[0.21]
INDUSTRYW: SERVICES					1.868%
					[1.18]
Observations	193	193	193	193	193

Panel B: NET RETURNS **Predictive Variables**	**NET RETURNS (1)**	**NET RETURNS (2)**	**NET RETURNS (3)**	**NET RETURNS (4)**	**NET RETURNS (5)**
SPECIALIST	0.435%**	0.495%**	0.422%**	0.499%*	0.931%**
	[2.34]	[2.25]	[2.07]	[1.87]	[2.46]
Fund Controls	NO	YES	YES	YES	YES
Family Returns	NO	NO	YES	YES	YES
Manager Controls	NO	NO	NO	YES	YES
Industry Weights	NO	NO	NO	NO	YES
Observations	204	204	204	204	204

Panel C: GROSS RETURNS **Predictive Variables**	**GROSS RETURNS (1)**	**GROSS RETURNS (2)**	**GROSS RETURNS (3)**	**GROSS RETURNS (4)**	**GROSS RETURNS (5)**
SPECIALIST	0.443%**	0.494%**	0.421%**	0.498%*	0.923%**
	[2.00]	[2.25]	[2.07]	[1.86]	[2.45]
Fund Controls	NO	YES	YES	YES	YES
Family Returns	NO	NO	YES	YES	YES
Manager Controls	NO	NO	NO	YES	YES
Industry Weights	NO	NO	NO	NO	YES
Observations	204	204	204	204	204

Panel D: HOLDINGS RETURNS **Predictive Variables**	**HOLDINGS RETURNS (1)**	**HOLDINGS RETURNS (2)**	**HOLDINGS RETURNS (3)**	**HOLDINGS RETURNS (4)**	**HOLDINGS RETURNS (5)**
SPECIALIST	0.314%**	0.306%	0.304%	0.363%	0.754%**
	[2.10]	[1.61]	[1.48]	[1.38]	[2.02]
Fund Controls	NO	YES	YES	YES	YES
Family Returns	NO	NO	YES	YES	YES
Manager Controls	NO	NO	NO	YES	YES
Industry Weights	NO	NO	NO	NO	YES
Observations	204	204	204	204	204

Panel E: DGTW RETURNS **Predictive Variables**	**DGTW RETURNS (1)**	**DGTW RETURNS (2)**	**DGTW RETURNS (3)**	**DGTW RETURNS (4)**	**DGTW RETURNS (5)**
SPECIALIST	0.362%**	0.260%	0.240%	0.484%	0.604%*
	[2.34]	[1.39]	[1.16]	[1.47]	[1.83]
Fund Controls	NO	YES	YES	YES	YES
Family Returns	NO	NO	YES	YES	YES
Manager Controls	NO	NO	NO	YES	YES
Industry Weights	NO	NO	NO	NO	YES
Observations	180	180	180	180	180

Panel F: ALPHA FF4F **Predictive Variables**	**ALPHA FF4F (1)**	**ALPHA FF4F (2)**	**ALPHA FF4F (3)**	**ALPHA FF4F (4)**	**ALPHA FF4F (5)**
SPECIALIST	0.444%**	0.386%**	0.325%**	0.582%**	0.615%**
	[2.23]	[1.97]	[2.02]	[2.27]	[2.20]
Fund Controls	NO	YES	YES	YES	YES
Family Returns	NO	NO	YES	YES	YES
Manager Controls	NO	NO	NO	YES	YES
Industry Weights	NO	NO	NO	NO	YES
Observations	193	193	193	193	193

Table 5: Regressions of returns on alternative measures of specialization

Table 5 presents estimated coefficients from Fama-MacBeth (1973) regressions of *ALPHA FF4F+H* on different measures of specialization and experience. In Column 1, the explanatory variables are *SPECIALIST* and *SPECIALIST+EXPERIENCE*, the latter variable indicating whether a manager has more than just a bachelor's health-related degree. In Column 2, the explanatory variables are *SPECIALIST* and *STEM MAJOR NONBIO*, the latter variable indicating whether a manager has a STEM degree unrelated to health. In Columns 3 and 4, we examine specialization of the entire team, not just the lead manager. In Column 3, alpha is regressed on *SPECIALIST TEAMAVERAGE*, which is the average value of *SPECIALIST* across all members of a portfolio team. In Column 4, the explanatory variables are *SPECIALIST ON TEAM*, which equals one if there is at least one specialist on the team and zero otherwise, and *SPECIALIST + NONSPECIALIST TEAM*, which equals one if there is both a specialist and a non-specialist (generalist) on the team. All specifications include the full set of controls from Table 4. In Columns 3 and 4, the manager characteristics are averaged across the members of the team (instead of controlling for the lead manager's characteristics). T-statistics are provided in brackets using Newey-West standard errors with up to six lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent Variable: **Predictive Variables**	**ALPHA FF4F+H (1)**	**ALPHA FF4F+H (2)**	**ALPHA FF4F+H (3)**	**ALPHA FF4F+H (4)**
SPECIALIST	0.471%**	0.632%**		
	[2.04]	[2.47]		
SPECIALIST+EXPERIENCE	0.150%			
	[0.63]			
STEM MAJOR NONBIO		0.128%		
		[0.80]		
SPECIALIST TEAMAVERAGE			0.346%**	
			[2.49]	
SPECIALIST ON TEAM				0.541%**
				[2.03]
SPECIALIST + GENERALIST TEAM				-0.372%
				[1.21]
Fund Controls	YES	YES	YES	YES
Family Returns	YES	YES	YES	YES
Manager Controls	YES	YES	TEAM AVG	TEAM AVG
Industry Weights	YES	YES	YES	YES
Observations	193	193	193	193

Table 6: Regressions of changes in holdings on specialization prior to major FDA announcements

Table 6 presents estimated coefficients from OLS panel regressions of changes in the adjusted portfolio holdings of a stock (relative to the same month's weight in the health sector) prior to approval or rejection decisions by the FDA on *SPECIALIST* and lagged control variables. The unit of observation in this table is fund-month-stock: a fund's adjusted holdings of a stock in a particular month. In Panel A, the set of events is FDA rejections, while in Panel B, the set of events is FDA approvals. In Columns 1 and 3, the only independent variable is *SPECIALIST*, while Columns 2 and 4 also include the battery of fund and manager controls, which are defined in Table 1. In Columns 1 and 2, the dependent variable is the change in adjusted holdings in the six months prior to month of FDA action, while, in Columns 3 and 4, the dependent variable is the change in adjusted holdings in the twelve months prior to the month of FDA action. The coefficient on *MANAGER MEDSAT* is multiplied by 100. All specifications include event (stock-month) dummy variables. T-statistics are provided in brackets with standard errors clustered by stock. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A: Changes in (adjusted) portfolio holdings prior to FDA rejections

Dependent Variable:	**ΔHOLDINGS**			
	6MONTHS		**12MONTHS**	
Predictive Variables	**(1)**	**(2)**	**(3)**	**(4)**
SPECIALIST	-0.107%**	-0.133%**	-0.089%	-0.117%
	[2.30]	[2.33]	[1.48]	[1.58]
LOG SIZE		0.001%		-0.016%
		[0.04]		[0.56]
LOG FAMILY SIZE		-0.006%		-0.001%
		[0.33]		[0.04]
LOG FUND AGE		-0.070%		0.061%
		[0.69]		[0.59]
EXPENSE RATIO		-0.084		0.021
		[1.37]		[0.32]
FAMILY CAT-ADJ RETURNS		-0.009		-0.042
		[0.30]		[1.14]
MANAGER AGE		0.004%		0.005%
		[1.15]		[0.85]
MANAGER MEDSAT		-0.015%		0.048%
		[0.95]		[1.40]
MANAGER FEMALE		-0.095%		-0.014%
		[0.94]		[0.08]
NUMBER OF MANAGERS		-0.011%		0.005%
		[1.45]		[0.39]
Fixed effects	Event	Event	Event	Event
Observations	1594	1481	1529	1430

Panel B: Changes in (adjusted) portfolio holdings prior to FDA approvals				
Dependent Variable:	**ΔHOLDINGS**			
	6MONTHS		**12MONTHS**	
Predictive Variables	**(1)**	**(2)**	**(3)**	**(4)**
SPECIALIST	-0.012%	0.013%	0.048%	0.059%
	[0.31]	[0.34]	[1.09]	[1.24]
LOG SIZE		-0.015%		-0.021%
		[0.74]		[1.18]
LOG FAMILY SIZE		0.000%		0.011%
		[0.02]		[0.86]
LOG FUND AGE		0.055%		0.014%
		[1.10]		[0.25]
EXPENSE RATIO		0.001		0.030
		[0.02]		[0.46]
FAMILY CAT-ADJ RETURNS		0.006		-0.020
		[0.64]		[1.26]
MANAGER AGE		0.003%		0.004%**
		[1.18]		[1.97]
MANAGER MEDSAT		-0.028%		-0.022%
		[1.65]		[1.29]
MANAGER FEMALE		-0.086%		-0.055%
		[1.32]		[0.54]
NUMBER OF MANAGERS		-0.018%*		-0.013%
		[1.90]		[1.29]
Fixed effects	Event	Event	Event	Event
Observations	9674	8661	8797	7997

Table 7: Regressions of changes in holdings on specialization prior to announcement firm will be acquired
Table 7 presents estimated coefficients from OLS panel regressions of changes in adjusted portfolio holdings of a stock (relative to the same month's weight in the health sector) prior to the announcement that the stock will be acquired, on *SPECIALIST* and lagged control variables. The unit of observation in this table is fund-month-stock: a fund's adjusted holdings of a stock in a particular month. In Columns 1 and 3, the only independent variable is *SPECIALIST*, while Columns 2 and 4 also include the battery of fund and manager controls, which are defined in Table 1. In Columns 1 and 2, the dependent variable is the change in the adjusted holdings in the six months prior to the month of M&A announcement, while, in Columns 3 and 4, the dependent variable is the change in adjusted holdings in the twelve months prior to the month of M&A announcement. The coefficient on *MANAGER MEDSAT* is multiplied by 100. All specifications include event (stock-month) dummy variables. T-statistics are provided in brackets with standard errors clustered by stock. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Changes in (adjusted) portfolio holdings prior to M&A acquisition announcement				
Dependent Variable:	**ΔHOLDINGS**			
	6MONTHS		**12MONTHS**	
Predictive Variables	**(1)**	**(2)**	**(3)**	**(4)**
SPECIALIST	-0.004%	-0.002%	-0.017%	-0.011%
	[0.35]	[0.22]	[1.47]	[0.97]
LOG SIZE		-0.001%		0.000%
		[0.15]		[0.01]
LOG FAMILY SIZE		0.001%		0.003%
		[0.47]		[0.90]
LOG FUND AGE		-0.008%		0.000%
		[0.77]		[0.01]
EXPENSE RATIO		0.001		0.019
		[0.06]		[1.53]
FAMILY CAT-ADJ RETURNS		0.000		-0.006
		[0.05]		[1.27]
MANAGER AGE		0.001%		0.000%
		[1.50]		[0.71]
MANAGER MEDSAT		0.000%		0.004%
		[0.12]		[1.17]
MANAGER FEMALE		0.022%*		0.029%**
		[1.80]		[2.06]
NUMBER OF MANAGERS		-0.006%**		-0.006%
		[2.12]		[1.60]
Fixed effects	Event	Event	Event	Event
Observations	21694	19412	19768	17976

Table 8: Regressions of fund holdings on direction of earnings announcement surprises

Table 8 presents estimated coefficients from OLS panel regressions of a fund's adjusted holdings of a stock (relative to the same month's weight in the health sector) on earnings surprises and interactions with *SPECIALIST*. All specifications include fixed effects for MANAGER by FUND by STOCK, so we are comparing adjusted holdings of the same stock for the same fund with the same manager at different points in time. *EARNINGS BEAT* is a dummy variable that equals one if the actual quarterly earnings per share beats the median analyst's estimate by at least 10% and a minimum of 2 cents, and zero otherwise. *EARNINGS MISS* is dummy variable that equals one if the actual quarterly earnings per share are less than the median analyst's estimate, and zero otherwise. Column 1 includes these two variables and their interactions with *SPECIALIST*. Column 2 also includes stock characteristics: *LOG MARKETCAP*, the natural logarithm of the stock's market capitalization, *BOOK TO MARKET*, the stock's book value of common equity divided by its market value, *STOCK AGE*, the number of years since its Initial Public Offering (IPO), and *PRIOR 12M RETURNS*, the cumulative returns over the last twelve months. It also includes interaction terms of these stock variables with *SPECIALIST*. The main explanatory variable in Column 3 is *% EARNINGS SURPRISE*, which is the percentage earnings surprise (actual minus expected divided by expected) where the denominator is set to 20 cents if its absolute value is less than 20 cents, and its interaction with *SPECIALIST*. Column 4 adds stock variables and their interactions with *SPECIALIST*. All specifications include calendar quarter time dummies. T-statistics are provided in brackets with standard errors clustered by stock. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Adjusted portfolio holdings at start of month of earnings announcement				
Dependent Variable:	**ADJUSTED PORTFOLIO HOLDINGS**			
Predictive Variables	**(1)**	**(2)**	**(3)**	**(4)**
SPECIALIST × EARNINGS BEAT	-0.002%	0.000%		
	[0.40]	[0.02]		
EARNINGS BEAT	0.002%	0.004%		
	[0.66]	[0.91]		
SPECIALIST × EARNINGS MISS	0.001%	0.003%		
	[0.15]	[0.63]		
EARNINGS MISS	-0.002%	-0.001%		
	[0.54]	[0.22]		
SPECIALIST × % EARNINGS SURPRISE			-0.001%	0.001%
			[0.14]	[0.29]
EARNINGS SURPRISE			0.001%	0.001%
			[0.62]	[0.37]
SPECIALIST × LOG MARKETCAP		0.038%***		0.038%***
		[3.73]		[3.73]
LOG MARKETCAP		0.012%		0.012%
		[1.07]		[1.06]
SPECIALIST × BOOK TO MARKET		0.017%*		0.017%*
		[1.72]		[1.72]
BOOK TO MARKET		-0.009%		-0.009%
		[1.12]		[1.11]
SPECIALIST × STOCK AGE		-0.008%**		-0.008%**
		[2.27]		[2.27]
STOCK AGE		0.005%		0.005%
		[1.40]		[1.41]
SPECIALIST × PRIOR 12M RETURNS		0.001%		0.001%
		[0.15]		[0.15]
PRIOR 12M RETURNS		0.007%**		0.007%**
		[2.44]		[2.45]
Fixed Effects	MGRxFDxSTK	MGRxFDxSTK	MGRxFDxSTK	MGRxFDxSTK
Calendar Quarter Dummies	YES	YES	YES	YES
Observations	1248544	1127089	1248544	1127089

Figure 1: Compounded growth in investment from specialist versus generalist managed health funds

Figure 1 shows the compounded growth of $1000 invested in January 1998 and then reinvested each month. The blue curve (MF SP=1) illustrates re-investment each month in an equal-weighted portfolio of all health sector funds managed by specialists. The red curve (MF SP=0) illustrates re-investment each month in an equal-weighted portfolio of all health sector funds managed by generalists. The green curve (CRSPHEALTH) illustrates re-investment each month in a value-weighted basked of all health-stocks, as defined in Table 1, in the CRSP database.

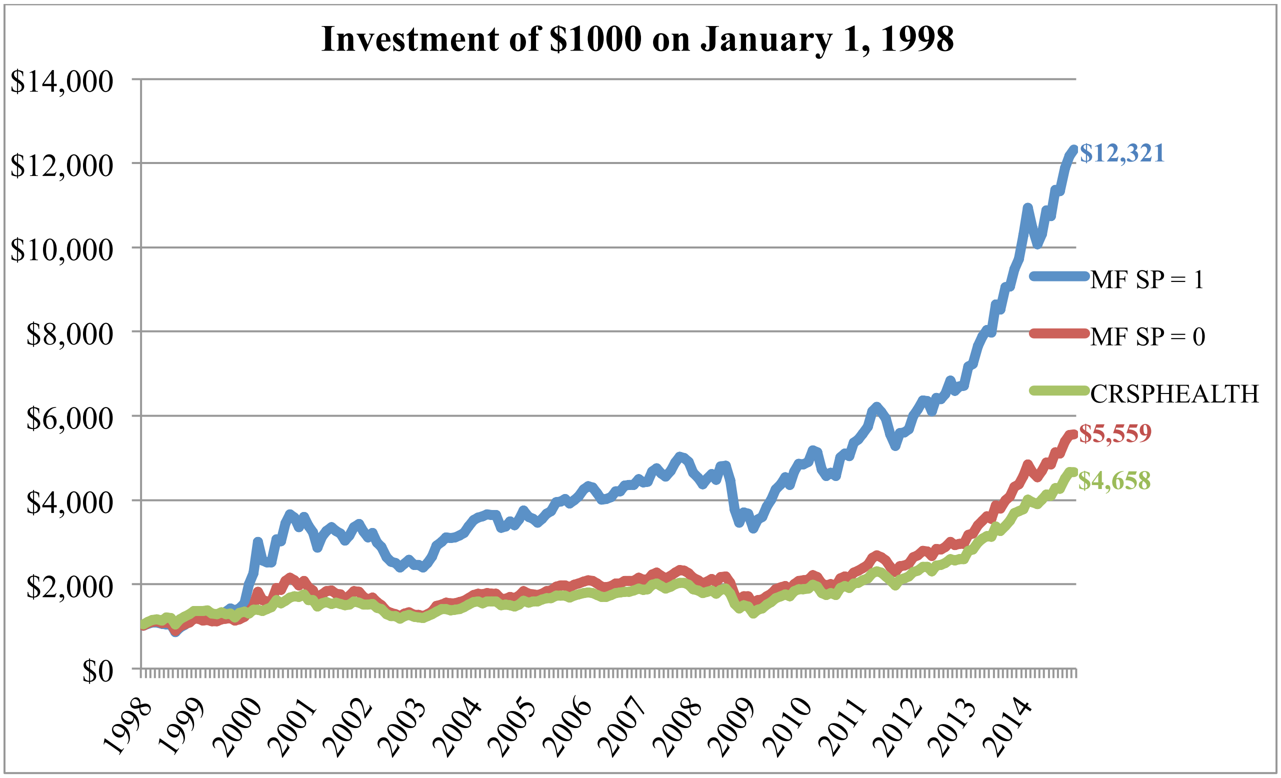

Figure 2: Growth in health/biotech sector mutual funds

Figure 2 shows the number of health sector funds each year from 1993 through 2014. The blue part of the bar consists of open-end actively managed mutual funds, while the red part of the bar are index funds or exchange-traded funds.

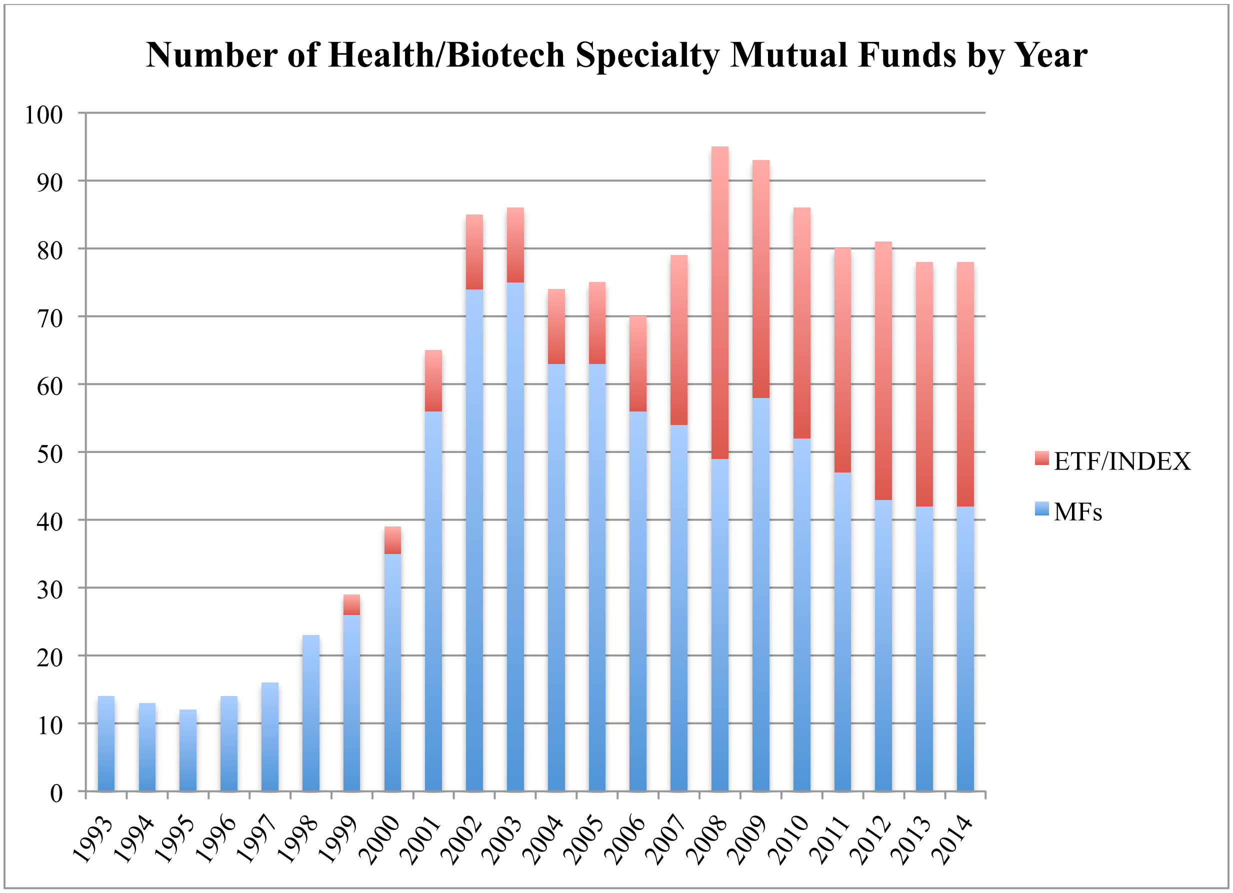

Figure 3: Health sector funds managed by specialist versus generalist managers
Figure 3 shows the number of health sector funds each year and whether specialist or generalist managers manage these funds. The green part of the bar consists of specialists while the red part consists of generalists.