Hedge Fund Manager Education/Certification and Exploiting Anomaly Returns

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September 28, 2018

Abstract

I investigate whether education and/or certification of the hedge fund managers affects hedge funds' tendency to adjust their long positions in-line with the predictions of 13 stock market anomalies. Hedge funds that have managers with PhDs do not change their holdings with respect to the predictions of anomalies. On the other hand, hedge funds that have managers with a CFA charter and/or Master's degree show signs of adjusting their positions to be in-line with the the predictions of anomalies after the papers become available online. These findings suggest that hedge funds having managers with PhDs either do not follow academic papers or prefer to implement their own strategies.

*I thank George Aragon, Luke Stein, Yuri Tserlukevich, Oliver Boguth, and Mark Seasholes for helpful comments and suggestions.

1. Introduction

Getmansky (2012) reported that the number of hedge funds has increased around 25% per year from 1980s to 2007 with total managed assets of $2,2 trillion in 2007. Although there was a slowdown after 2007, according to SEC report, the number of hedge funds is around 9,000 with total net assets of $3.5 trillion at the end of 2016.

Although they have different investment criteria and trading strategies, institutional investors are widely accepted as sophisticated investors. They can access to information easier than retail investors, therefore higher institutional investor levels would cause stock prices to approach fundamental values. Moreover, there is a widely accepted belief that there is a heterogeneity among institutional investors in terms of their sophistication level. Hedge funds are widely known as the most sophisticated institutional investors. However, it is not easy to invest in a hedge fund unless being an accredited investor and having enough money to meet the minimum investment requirement. As the requirements suggested, only a small portion of privileged people can invest in hedge funds. They also have some exceptions in trading strategies such as they can short sell or use leverage etc. These requirements and exceptions by law also support that they are different than other institutional investors. Moreover, it can be claimed that hedge fund managers are the most sophisticated fund managers among all institutional investor managers, therefore rich and accredited investors invest high amounts of money in these managers' funds and allow them to use risky strategies. However, many researchers suspect that hedge fund managers are not more sophisticated than other investment managers even though these reasonable assumptions. For example, some studies show that hedge funds show little signs of superior performance, if any. Griffin and Xu (2009) document that hedge funds stock picking outperforms mutual funds stock picking only by 1.32% annually on value weighted basis. This difference becomes insignificant on equal weighted basis. However, some subgroup of hedge funds might be more successful than others. For instance, Li et al. (2011) document that hedge fund managers from higher SAT undergraduate universities outperform hedge fund managers from lower SAT undergraduate universities. This signals that cross sectional heterogeneity among hedge fund managers might lead differences in performance. Of course, this argument might not be confined to hedge funds. For example, Chaudhuri et al. (2017) reveal that investment funds managed by PhDs outperform otherwise similar funds managed by non-PhDs. Again, we see that education is an important factor in fund performances.

Another way to approach these discussions would be to analyze holdings of institutional investors. If they are really sophisticated as a whole or subgroup, this group of investors must be good at picking underpriced stocks and outperform the counterparts. However, Lewellen (2011) indicates that institutional investors hold market portfolio rather than using sophisticated stock picking strategies. In addition, Edelen et al. (2016) reveal that institutional investors do not exploit anomaly returns. Instead, their portfolio holdings show that they increase their holdings in the short leg of seven well known anomalies. The survey in Richardson et al. (2010) show that only a small fraction of investment professionals read academic papers and follow recent working papers. These findings are surprising since it is expected that institutional investors be knowledgeable and aware of recent developments in the academic papers. Moreover, one would easily expect that institutional investors are good at identifying underpriced securities so that exploit these kinds of anomaly return opportunities.

Going back to effects of heterogeneity among investors, I think that some subgroups of institutional investors might be exploiting these anomay returns although institutional investors as a whole might not have a tendency to do so. Additionally, publication and spread of academic studies might affect anomaly returns. McLean and Pontiff (2016) use a large set of anomalies and document that anomaly returns decline after publication. This suggests that some investors follow these studies and change their strategies to take advantage of these anomaly returns.

I argue that most sophisticated investors quickly notice recent academic papers and use the strategies in these papers if they document profitable trading strategies. Following McLean and Pontiff (2016), Calluzzo et al. (2017) extended this literature and reveal that hedge funds and transient institutions change their holdings with respect to anomaly descriptions after publication. They claim that some subgroups of institutional investors adjust their holdings in-line with the predictions of anomalies. Moreover, Caglayan et al. (2018) analyze hedge funds to see whether they also trade contrary to book-to-market anomaly as other institutional investors do. Their findings reveal that hedge funds tilt their portfolios to exploit this anomaly return after book-to-market data becomes public information. Additionally, they show that hedge funds are also better at picking overpriced growth stocks. Lastly, Chordia et al. (2014) calculate some popular anomaly returns and show that hedge funds play a key role in mitigating anomaly returns in recent increased liquidity and trading activity regime. They state that the decrease in anomaly returns is both economically and statistically significant. These findings suggest that hedge funds are aware of anomalies and have better stock picking ability after the publication. However, is this true for all hedge funds or are these results driven by some more sophisticated subgroups within the hedge funds?

Motivated by these differences among different types of institutional investors, I argue that there might be some cross-sectional differences among hedge fund managers in terms of trading strategies for anomalies. However, it is not easy to argue what kind of characteristics make these hedge fund managers more likely to use these strategies. I connect my idea with the finding that the level and quality of education matters in fund performance. In addition to education, Aggarwal and Jorion (2010) find that hedge fund managers' performance decreases by 0.42% for each additional year. Moreover, Pastor (2015) explains outperformance of young funds by better education and better ability to use technology. Combining these findings, I argue that some hedge fund managers with better education might be more aware of academic papers and use trading strategies in these studies. I construct my hypothesis around the role of education in exploiting anomaly returns.

To the best of my knowledge, there is no study that examines the effects of education on hedge fund managers' trading strategies on anomalies. I analyze whether higher education level and holding CFA make managers more likely to tilt their portfolios in line with the predictions of anomalies. To test this, I use all anomalies in Calluzzo et al. (2016) except for "Distress anomaly" because I am not able to access data used in the original paper. My results show that hedge funds with PhD degrees in fact do not adjust their holdings in-line with the predictions of anomalies. However, managers with CFA and managers with CFA and Master's degree exploit anomaly returns after publication. In addition, managers without PhD, Master's degree, or CFA also exploit anomaly returns after publication. The change in the portfolios of managers with CFA and with CFA and Master's degree together can be explained intuitively. Further academic education and professional training make them more likely to exploit anomaly returns. However, the results for "managers with PhD" and "other managers" are still open to question and requires further analysis for an intuitive explanation.

The remainder of this paper is organized as follows. Section 2 briefly documents anomaly literature and potential explanations for anomalies, section 3 explains the database used in the paper, description of sample, methodology and results. Section 4 discusses the planned improvements and possible extensions. Section 5 concludes.

2. Reasons of Anomaly Returns

The existence of anomalies is attributed to different reasons. Harvey, Liu, and Zhu (2016) claim that their updated hurdle for statistical significance makes many results in financial economics insignificant. For example, of 296 published factors, from 80 to 158 would be considered false discoveries under different adjustments. Similarly, Hou, Xue, and Zhang

(2018) show that when they replicate anomalies by alleviating the effects of micro-cap stocks on results, they find that 64% of the anomalies are statistically insignificant at 5% level. Moreover, when they use Harvey, Liu, and Zhu (2016) hurdle, the number goes up to 85%. They also add that even for significant ones, alpha is often smaller than original paper and using q-factor model also leaves many of the anomalies insignificant. These findings raise question about the accuracy of the anomaly findings. However, the significance of anomaly returns during in-sample period and decline in post-publication period allay these concerns. My analysis is the comparison of different time periods relative to each other. Even if there is a mistake in magnitude and significance of the published papers, it is beyond the scope of this paper.

McLean and Pontiff (2016) point out that there are three main explanations for anomalies. First one is statistical biases which tells that these anomaly returns exist in-sample period and do not exist out-of-sample. Lo and Mackinlay (2002) also state that data snooping might be driving anomaly results. If this explanation is correct for every anomaly, then there is no need to absorb information from anomaly papers and adjusting holdings consistent with these anomalies because this strategy might not offer positive returns in another sample period. Therefore, we can not expect to see positive returns for long-short portfolios out-of-sample. However, we see a decline in returns of my anomaly sample following publication and some of them still remain significant. In addition, raw returns and alphas are still positive even after publication date. Therefore, even though all positive raw returns and alphas do not rule out this explanation, it is a strong evidence against this explanation.

Second, anomaly returns might be related to risk rather than mispricing. If this explanation is correct for some anomalies, then the anomaly returns would not disappear as Cochrane (1999) states because there must be variability in risk taking appetite of different investors both in the in-sample and out-of-sample periods. However, decline in anomaly returns after publication would cast doubt on this explanation.

Third, anomaly returns are caused by mispricing and should start to disappear after these findings be available to investors. In this case, there should be a decline in the post-publication period if some investors follow the literature and exploit anomaly returns. This explanation claims that these anomaly returns exist in the market because investors can not price some securities correctly.

Among these explanations, mispricing is the most consistent with anomaly return patterns in this paper. As Mclean and Pontiff (2016) document, long-short portfolio returns sorted on anomaly variables start to decline after papers become available to investors. One can also ask why mispricing exists in the financial markets? Why market participants are not able to capture these anomalies before academic papers? Investors might be aware of anomalies but can not correct them because of short selling restrictions. However, my analysis shows that stocks in long portfolio tend to be more illiquid. Moreover, there is no huge difference in average prices between long and short portfolios. Therefore, this explanation also can not fully explain anomaly returns both in-sample and out-of-sample periods.

3. Data, Sample Construction, and Descriptive Statistics

In this section, I explain my data sources, sample characteristics and methodology to calculate long-minus short anomaly returns and to measure changes in institutional investors' holding in the short and long leg of the anomaly portfolios between one quarter after and one quarter before the portfolio formation.

3.1 Data and Sample Construction

My main source to obtain hedge fund names and manager characteristics is TASS database. Although TASS is one of the most popular and comprehensive database for hedge funds, it should be noted that it does not cover all hedge fund universe. However, TASS is a large and unbiased sample, making it reliable and good representative of all hedge funds. In my TASS data, there are 20,096 live and defunct hedge funds in total. I include hedge funds if they report manager information and biographies of these managers. After this initial filter, I had 7,919 hedge funds. Since I am interested in equity market, I would expect to see that "Long/Short Equity Hedge" and "Equity Market Neutral" types of hedge funds be main subgroups that benefit from anomaly returns. This additional filter leaves me with 2,767 unique hedge funds. Among these 2,767 hedge funds, I randomly picked 785 of them and implemented my analysis with this sample.

I identify people in hedge funds by using "People.txt" files in TASS. It should be noted that not all people in this data are responsible for creating trading strategies. For example, there are many people in the data who have marketing duties. Therefore, I only include people with "Portfolio Manager" title and use biographies of these portfolio managers. Therefore, although there are some people in a fund have related characteristics to my study with a title other than "Portfolio Manager", I do not use these characteristics as a representative of the fund. In these biographies, TASS provides information about hedge fund managers' backgrounds such as education level, name of university, experience, CFA status etc. I retrieve these biographies from "Notes.txt" file. The only difficulty of pulling out this information is that they are not reported in a standard way. For example, some hedge fund managers disclose all relevant information about themselves whereas some of them only disclose their names and experience and some of them does not disclose anything. To overcome this difficulty, I use some string matching techniques at the beginning to have a rough sample as a starting point. After then, I go over every information set to retrieve additional information and correct what I get at the beginning if there is a mistake. If there is more than one manager and any of them having PhD or Master's degree or CFA charter, I mark that hedge fund as having that characteristics. As a result of this labor-intensive work, I identify hedge fund managers with PhD or Master's degree, and managers who have CFA charter.

After having my final TASS sample with 785 hedge funds, I match them with their fund management companies by using Thomson Reuter's quarterly 13F holdings data. I am able to find a match for 528 of hedge funds. To identify hedge fund management companies, I use multiple resources and techniques. My methodology for this verification depends on portfolio manager's name, the information (usually "Team" or "People" tabs) on management company's website and hedge fund's address. In addition, I also use e-mail addresses and phone numbers as additional inputs for verification. First, I use "Company.txt" file in TASS to get hedge fund management companies. Sometimes, these records do not reflect accurate information and sometimes they are missing. I further search all hedge funds' website if any, Linkedin profiles of managers and Bloomberg website to make sure about the accuracy of management company name. For matched observations, I also retrieve "manager numbers" from 13F data because one "manager number" might belong to multiple manager names that are in fact exactly same. For example, some 13F records end with "LLC" but some other records with same manager number and name end with "L.L.C." etc. I could not match 257 hedge funds with 13F data. The reason for unmatched 257 hedge funds might be related to 13F filing requirements rather than missing data. SEC requires institutions with more than $100 million under management disclose their long positions if the position exceeds 10,000 shares or $200,000 in value. Therefore, some hedge funds might belong to some management companies that do not have to disclose their holdings, therefore these management companies might not exist in the 13F database.

13F holdings disclosure reflects consolidated portfolios of holding company, not fund. Therefore, holdings of management companies might reflect many hedge funds' aggregated holdings. Moreover, one fund management company might have many hedge funds and non-hedge funds at the same time. Therefore, some management companies' main line of business might not be hedge fund management. One last filter for my sample is to identify management companies whose main line of business is hedge fund management. I follow Griffin and Xu (2009) for this identification. I retrieve all Form ADVs, if exist, for each management company. If there is no Form ADV, I mark this company as hedge fund. Among the ones that have Form ADV, if a management company invest at least 50% of its assets in "pooled investment vehicles" or at least 50% of its clients are "high net worth individuals" and their fee structure includes performance-based fees, then I mark this company as hedge fund management company as well. The only problem with this procedure is that some forms are terminated and not available on the website. I search these companies on internet to make sure that their main business is hedge fund management. This additional filter leaves me with 310 unique hedge funds. To find final sample of management companies, I consolidate my results at management company level because one management company might have multiple funds. So, for example, one fund might have managers with PhD and others do not. I assume that there is an interaction within the hedge fund management company. However, for example, some management companies might have high skilled managers for their hedge funds and average skilled managers for their other funds. My filter prevents this to happen. Although it is not 100% true to identify management company as having PhD manager if at least one of its fund managers have PhD, Master's degree or CFA charter, this can be a proxy for my study. My final data has 125 hedge fund management companies.

At final stage, I use CRSP data for returns, shares outstanding, and price information. I retrieve accounting data from Compustat. I use Kenneth French's website for three-factor returns.

[Table 1]

Table 1 shows the number of hedge funds for each category and the ratio of these groups in the sample. I have 310 hedge funds and 125 hedge fund management company in my final sample. Panel A reports density of each group at fund level and Panel B reports at management company level. When we compare numbers of each category, it can be seen that they do not differ a lot. PhD or Master's degree is counted if they are most advanced degree in that company. For example, if a manager holds PhD and other manager holds Master's degree I classify this fund or management company as PhD holder since PhD is a more advanced degree than Master's.

3.2 Anomaly Sample

I analyze holdings of these hedge fund management companies both in short leg and long leg of each anomaly. I use 13 of 14 anomalies in Calluzzo et al. (2017). I do not add "Distress Anomaly" because of data restrictions. Table 2 shows all anomalies used in the analysis, authors and publication years, "In-sample" periods, when paper was published at SSRN, and number of citations per year. If a paper was not published at SSRN before publication year, I take publication year as first available year. Stambaugh et al. (2012) document the details of construction of short and long legs of 10 anomalies. Also, I check original papers to make sure that I do not miss any extra exclusions from the sample. For additional 3 anomalies, I directly follow the original papers. I use "Return on Asset" anomaly in Chen et al. (2010) but this paper is not published yet. Therefore, I take first availability as publication year. I use "publication per year" as a proxy for popularity of the paper. Publication per year is the ratio of total citations shown at Google Scholar to the number of years since publication.

[Table 2]

The oldest published paper in the list is Bernard and Thomas (1989) and the most recent one is Novy-Marx (2013). The oldest five papers were not posted to SSRN before their publication date. That is why "Available" column is equal to these papers' publication years. ITA and NOA were posted to SSRN in their publication year. The paper with highest number of citations per year is Fama and French (1992). Jegadeesh and Titman (1993) comes in second. Among 13 anomalies, Xing (2008) has lowest number of citations per year.

3.3 Descriptive Statistics and Anomaly Returns

I start my analysis by identifying the characteristics in each quintile portfolio sorted on all anomalies when available. Table 3 represents the characteristics of stocks in all quintiles. I use 1962-2016 sample period to construct percentile rankings for each anomaly. I do not take publication year into account to form these portfolios and describe anomaly portfolios accordingly. Similar to Calluzzo et al. (2017), I take the equal weighted average of these percentile rankings to form finalized quintile portfolios. After then, I take the average of each variable within each quintile portfolio every June and then take the time series average of these averages. This table shows that on average, stocks in the long (short) leg tend to have higher (lower) book-to-market ratios, and momentum returns. Although the relation from long to short portfolio is not strictly monotonic, it can be argued that stocks in long portfolio tend to be larger and have higher prices. I use illiquidity measure in Amihud (2002). It is the ratio of absolute return during a month to dollar volume of trading. Therefore, high values indicate more illiquidity for stocks. It is reasonable to expect that stocks in short leg tend to be more illiquid, therefore more difficult to short sell so that overpricing does not go away in anomalies. However, the results are exactly opposite. This finding makes anomaly returns stronger because the relation between anomaly returns and short sale restrictions seems very limited, if any.

[Table 3]

McLean and Pontiff (2016) find that anomaly returns decrease after publication, therefore academic research has a significant effect on anomaly returns. Calluzzo et al. (2017) also confirm their results by comparing in-sample period and post publication periods. I start my analysis by replicating each anomaly to both construct portfolios and make sure that methodologies are quite similar. I calculate in-sample returns as in the original paper with minor modifications. Ex-post returns are anomaly returns starting from publication year of the anomaly until June 2016. Among anomalies, "Gross Profitability" has only a few observations because its publication year is 2013, so the results might not be capturing an accurate trend. "Return" column is quarterly raw returns of long-short strategy and "3-factor Alpha" is the intercept of regressing long-short returns on Fama-French three factors. Table 4 shows that quarterly raw returns decrease for all anomalies after publication. Moreover, 3-factor alphas decrease for 7 out of 13 anomalies. However, alphas are highly statistically significant for in-sample periods and only one of them (CEI) remains statistically significant at 1%. We also have three alphas that are statistically significant at %10. Therefore, we can argue that 3-factor alphas also tend to decline after publication year. In-sample raw returns for OS, PEAD, and ROA require further explanation. Although 3-factor alphas are significant at 1%, 1%, and 5% levels respectively, in-sample raw returns are not statistically significant for these three anomalies. The decreasing trend of returns also exist in these anomalies, however lack of statistical significance is open to question. I use annual Compustat data for all anomaly rankings except for ROA and PEAD. The portfolios for these two anomalies are constructed by using quarterly accounting data. In my paper, following the literature, there is a 6 to 17 month gap between CRSP data date and Compustat end of year date. For quarterly data, I update this time period as 4 to 6 months. Different gap period selection might cause this difference. When I try 6 to 8 months, the results are very similar, however any other scheme might be driving the differences in results. For OS, some data is not available and I calculate this variable by using other variables. The difference for OS results might be caused by this approach. Nevertheless, these results are mainly parallel with the findings in the literature and confirm that I sort long-short portfolios correctly. I report the raw and risk-adjusted returns of each anomaly in Table 4.

[Table 4]

I calculate each anomaly measure to sort portfolios into quintiles in the "In-sample" and "Ex-Post" periods. I create all anomaly portfolios and calculate returns of these portfolios to see the difference between in-sample and ex-post returns. Ex-post period starts with the year that the paper was published. I also calculate 3-Factor alphas for both periods. I convert monthly returns of each factor to quarterly returns as in Calluzzo et al. (2017). So, all anomaly returns and three factor returns are quarterly returns during their in-sample and ex-post period. In addition, the returns in this table are long-short portfolio returns which is the difference between value weighted long leg portfolio returns and value weighted short leg portfolio returns. To form quintile portfolios for each anomaly, I sort stocks with respect to anomaly variable every June and calculate value weighted portfolio returns for next 12 months on a quarterly basis. I exclude stocks for a given year if price is less than $5 or stock does not have a valid price. I also exclude stocks for that year if market equity is negative in June. I check original papers and apply further filters if necessary. I calculate value weighted returns with respect to market capitalizations at the end of June and use these weights throughout the year.

3.4 Changes in Portfolio Holdings

I define two periods very similar to Mclean and Pontiff (2016): "In-sample" period is the sample period in the original paper documented in Table 1. Post-publication period starts with the publication year and ends in June 2016. This is because I assume that the paper is available at the beginning of publication year. I rank stocks by following methodology of Calluzzo et al. (2017). I take equally weighted average of percentile ranks of each anomaly to finalize quintile portfolios. For in-sample period, if a year corresponds to some paper's in-sample period, I take the average of these anomaly rankings if at least half of the anomaly percentile rankings is available for a particular stock. Therefore, I do not have observation after 2009 for in-sample period because most recent end of in-sample year is 2009 in Novy-Marx (2013). Similarly, post-publication period starts in 1989 as oldest paper was published in 1989. Pre-publication period is the period between when a paper is available at SSRN and publication year. Early post-publication period is the first year following the publication year. By analyzing these last two periods, I aim to understand whether a group of investors are quick in absorbing the information from academic research and use this information in their trading strategies.

”All” refers to all institutional investors, ”HF” is for hedge funds and so on. The numbers in this table are time series average of change in holdings in finalized long and short portfolios. I define ”change in holdings” as the percentage change of ownership in a quintile for corresponding institutional investor group between September and March for each year. It means that each element of time series captures the institutional ownership change in a quintile right after ranking and right before ranking since I rank stocks in June. ”Long” stands for time series average of changes in portfolio holdings in long leg of anomaly and ”Short” is same as long. ”Long-Short” is the difference of changes in long and short legs of quintile portfolios. I report the results in Table 5.

[Table 5]

Panel A shows trading behavior of the groups in ”In-Sample” period. For long-short strategy, changes in holdings are never statistically significant except for hedge funds with managers who hold PhD degrees. Hedge funds trade contrary to anomalies before publication and do not trade in-line with these anomaly descriptions. Along with other subgroups’ results, none of these group of investors is aware of the anomalies until publication.

Panel B documents the results for post-publication period. Hedge funds are better able to tilt their portfolios with respect to the predictions of anomalies. Change in trading of hedge funds are highly significant. On the other hand, hedge funds with PhD managers are not able to take advantage of anomaly returns and the sign of long-short is negative. I am aware that hedge funds with PhD constitutes a small subgroup of hedge funds so that my sample selection might affect this result more than it affects any other result. Nevertheless, results require some intuitive explanations in this way. In addition, managers with CFA change their trading strategies and tilt their portfolios toward the stocks in the long leg of anomalies after publication. This result is significant at 5% level. In addition, hedge fund managers with CFA and Master’s degree together also show little signs that they exploit anomaly returns. However, this result is only significant at 10% level. Moreover, last column shows that hedge funds without specified characteristics also exploit anomalies. They change their long-short portfolio by 0.062% between two quarters and this result is statistically significant at 5% level.

Calluzzo et al. (2016) use "Pre-publication Period" as the period between end of sample year and publication date. However, I modify this term and use it as the period between one year after when the paper was first published at SSRN and two years after publciation. I do not take publication year at SSRN because there might not be other ways for managers to be aware of this paper. Moreover, if a study becomes available at SSRN, then this definition makes analysis more standardized because of differences in the posting month. When a study becomes publicly available, I would expect to see that managers with strong education background use the information in that study. To do that, they would be searching papers at least on the internet. Therefore, if a study becomes available, they would try to make profit by using underlying trading strategy. This definition is more appropriate for this study because the main idea is that some hedge fund managers are better at exploiting trading strategies in the academic studies because they are both in a closer relation with academia and quicker in following the recent works. For robustness, I also define "Early Post-Publication Period" defined as the publication year in the journal and the year after. This would also sign to what extent money managers follow academic journals. Most sophisticated and educated ones are expected to pay more attention to recently published papers and use them if there exists a profitable strategy in these papers.

Panel C shows the portfolio changes starting from the following year of one or more anomaly papers posting to SSRN. I only take the years following a posting and analyze portfolio holdings of institutional investor groups between t+1 and t+2. When a study becomes publicly available, "Other Hedge Funds" change their holdings by 0.145% and this result is highly significant at 1% level. In addition, "all hedge funds" and "hedge funds with CFA managers" also tilt their portfolios parallel to anomaly definitions as well. They change their ownership in long-short portfolio by 0.173 % and 0.018% respectively and these results are significant at 5%. All institutions also show some signs of changing their holdings with respect to anomalies. However, this result is significant only at 10% level. The results for hedge funds with Master's degree and CFA are similar to results for all institutions.

Panel D documents the change in portfolios in publication year. I assume that the study is available at the beginning of the year to all managers. Changes in "long-short" portfolio of hedge funds is again positive and statistically significant at 5%. If we look at subgroups of hedge funds, "hedge funds with Master's degree" also has similar tendency. The sign of long-short portfolio for hedge funds with PhD is positive in Panel C. However, in Panel

D, this positive sign reverses to negative. In both cases, the results are not statistically significant though.

In Panel E, I show how popularity of anomalies affect ex-post portfolio holdings of institutional investors. I rank stocks on average number of citations per year since the publication. I then calculate changes in portfolio holdings in top 6 anomalies by following same methodology in Panel A and Panel B. These anomalies are "BM", "MOM", "ACC", "NSI", "GP", and "AG". I take equally weighted average of percentile rankings of these anomalies to identify quintile portfolios and then calculate the change in long-short portfolios similarly. The results reveal that "all hedge funds", "hedge funds with CFA", and "other hedge funds" change their portfolios with respect to most popular anomaly trading strategies at 5% significance level. Again, "hedge funds with PhD" trade contrary to the predictions of anomalies. "All institutional investors" and "hedge funds with Master's degree and CFA" show little signs of changing their holdings with respect to these anomaly descriptions.

4. Planned Improvements

I aim to finalize my paper by doing some additional analysis and improvements to my data. My first goal is to include all hedge funds in TASS database. Although my sample is random and has many hedge funds, adding all hedge funds might convey more reliable results. One other improvement would be to add managers without biography information to my sample. This will require again hand collection of data. I can search Google, Linkedin profiles, and LexisNexis database to retrieve background information about these managers. One might suspect that hedge fund managers who have solid backgrounds report information about themselves. If this is the case, this would create a bias in my analysis. One last improvement would be to identify hedge fund management companies as an owner of some characteristics if half of their funds in TASS has that specific characteristic.

In addition to improvements, I also plan to make some extensions to have a more comprehensive analysis. One of my goals is to look at the effect of location in portfolio holdings. Hong et al. (2005) document that mutual fund managers in the same city tend to take similar positions. It seems that there is an interaction among themselves as a result of living at close locations. This effect might be existent in anomaly portfolios in two ways. First, hedge fund managers in the same city might discuss recent papers among themselves, therefore have a tendency to exploit similar anomaly returns. Second, there might be knowledge spillover between academicians and investment professionals if they live in the same city or state. For instance, fund managers might be aware of publications whose authors live in the same city, therefore exploit these anomaly returns but not others. Moreover, they might be more interested in these strategies because they have a chance to discuss potential problems and further improvements. I believe that it is worth identifying hedge fund managers' locations and authors' locations around publication date. This extension might help us to understand role of location on hedge fund managers' tendency to exploit anomaly returns.

Additionally, the quality of university is at least as important as the level of the degree. For example, a manager with an undergraduate degree from a good research-oriented university might be more interested in academic papers than a manager with PhD degree from an average university. I retrieve all universities that hedge fund managers attended from TASS database. My plan is to rank universities and understand the effects of research rankings of these universities in Finance field on following academic studies and attacking anomalies. My argument would be that for the same degree, hedge fund managers from more research-oriented schools would be more aware of recent academic papers since they have more exposure to research during their studies. The quality of university might also matter even the level of degrees are different. I can also distinguish between recent graduates and older graduates to see how years spent outside the university affect their motivation to read academic papers.

5. Conclusion

I retrieve hedge fund managers' educational background and CFA status from TASS database and use 13 anomalies to test whether education affects exploiting anomaly returns. The results show that CFA and/or Master's degree increase hedge funds' tendency to exploit anomaly returns. However, hedge funds with PhD managers do not adjust their positions according to anomaly trading strategies and sometimes their positions are against these strategies. These findings suggest that hedge funds having managers with PhDs either do not follow academic papers or prefer to implement their own strategies. There might be two other possible explanations driving these results. First, I use a sample of hedge funds and my data does not completely represent TASS database. Second, 13F holdings reflect holdings at the end of each quarter and I look at the differences in holdings between the quarter after and the quarter before sorting stocks. It is possible that hedge funds change their positions according to anomaly trading strategies but change their portfolios before reporting again.

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Figures and Tables

Table 1: Manager Characteristics

This table describes hedge fund and hedge fund management company sample. "HF" stands for hedge fund and "HFMC" stands for hedge fund management company. If at least one manager of a hedge fund has characteristics below, I mark this hedge fund with that characteristics. For hedge fund management companies, at least one manager of a hedge fund under management company has to have that characteristics. For educational classification, PhD shows that most advanced degree is PhD and Master's shows that most advanced degree is Master's. If both degress exist in a fund or management company, I took more advanced one.

Panel A: Hedge Fund Sample

Group	Number	%
All Hedge Funds	310	100.0
- *HF with PhD*	17	5.5
- *HF with Master's Degree*	149	48.1
- *HF with CFA*	48	15.5
- *Other HF*	96	30.9

Panel B: Hedge Fund Management Company Sample

Group	Number	%
All HFMC	125	100.0
- *HFMC with PhD*	9	7.2
- *HFMC with Master's Degree*	54	43.2
- *HFMC with CFA*	26	20.8
- *Other HFMC*	36	28.8

Table 2: Anomalies

This table briefly describes anomalies in the paper give some descriptive information. First four column shows the anomalies used in this paper, author and year of the paper, sample period in the original paper, and abbrevations of variables that is used to sort stocks respectively. The second last column shows when the corresponding paper became available online. I use first posting date on SSRN websites if there is. If not, I use publication year. Oldest five papers were not posted to SSRN but after 1996, all papers are posted. The last column shows approximate number of citations per year.

Anomaly	Paper	Abbrevation	Sample Period	Available	# of citations per year
Post-Earnings Announcement Drift	Bernard and Thomas (1989)	PEAD	1974-1986	1989	75
Book to Market	Fama and French (1992)	BM	1963-1990	1992	718
Momentum	Jegadeesh and Titman (1993)	MOM	1965-1989	1993	403
Net Stock Issues	Loughran and Litter (1995)	NSI	1970-1990	1995	190
Accruals	Sloan (1996)	ACC	1962-1991	1996	219
Ohlson O-Score	Dichev (1998)	OS	1981-1995	1996	50
Capital Investments	Titman et al. (2004)	CI	1973-1996	2001	83
Net Operating Assets	Hirshleifer et al. (2004)	NOA	1964-2002	2004	41
Composite Equity Issues	Daniel and Titman (2006)	CEI	1968-2000	2001	80
Asset Growth	Cooper et al. (2008)	AG	1963-2003	2005	97
Investment to Assets	Xing (2008)	ITA	1964-2003	2008	33
Return on Assets	Chen et al. (2010)	ROA	1963-2003	2010	48
Gross Profitability	Novy-Marx (2013)	GP	1963-2009	2010	174

Table 3: Quintile Characteristics

This table documents some characteristics of each quintile portfolios for all sample. BM is book-to-market, ME is market capitalization, MOM is momentum returns which is cumulative return from t-7 to t-1, ILLIQ is the illqiuidity measure in Amuhid (2012), and PRC is price at the end of June. I used again 1962-2016 sample period and take equally weighted average of each anomaly percentile rankings to form quintile portfolios. I take the average of each variable in each quintile every June and then take the time series average of them. Illiquidity is measured for last month before sorting.

Quintile	BM	ME(10^9)	MOM (%)	ILLIQ (10^9)	PRC
Long	0.84	2.78	28.21	15.6	28.26
2	0.76	3.01	19.48	10.3	29.64
3	0.69	2.41	16.20	9.36	28.71
4	0.64	1.74	11.75	9.15	25.32
Short	0.54	1.09	5.27	9.6	21.45

Table 4: Anomaly Returns

This table shows quarterly raw and risk-adjusted returns for each anomaly. "In-Sample" is the sample period in the original paper. "Ex-Post" is the period starting from publication year until 2016. I constructed every portfolio in June and tracked value weighted 12 month returns of long-short portfolio. The numbers under "Return" columns are time series average of these portfolio returns. To calculate 3-factor alphas, I modified Kenneth French's 3-factor data in his library and make returns quarterly. "3-factor alpha" is the intercept of regression of portfolio returns on three risk factors which are "Small-Big", "High-Low", and "Excess Market Eeturn". *, **, *** are for 10%, 5%, and 1% significance levels respectively.

	In-Sample		Ex-Post	
Anomaly	Return (%)	3-Factor Alpha (%)	Return (%)	3-Factor Alpha (%)
PEAD	1.26	3.27***	0.16	0.31
BM	1.41**	1.26**	0.96	0.82
MOM	1.69*	1.54*	0.51	0.52
NSI	1.40***	0.78**	0.67	0.90
ACC	1.21*	1.66***	0.68	0.75
OS	1.14	2.01***	0.76	1.29*
CI	1.01**	1.13***	0.02	0.15
NOA	1.37***	1.46***	1.04	1.01
CEI	1.69***	1.49***	0.93	1.59***
AG	1.47***	0.74*	1.09	1.16
ITA	1.30***	0.84***	0.78	1.45
ROA	0.83	1.41**	0.52	0.98*
GP	0.85**	1.52***	0.26	2.70*

Table 5: Change in Trading

This table shows the change in holdings of different groups of institutional investors. "In-sample" period is the sample period in the original paper documented in Table 1. Post-publication period starts with publication year and ends in 2016. All sample period is from 1962 to 2016. At the end of June of every year, I assign a percentile rank for each stocks for each anomaly as Calluzzo et al. (2017) did and calculated returns for next 12 months on a quarterly basis. I formed portfolios by taking equally weighted average of percentile ranks for each anomalies to finalize quintile portfolios. "All" refers to all institutional investors, "HF" is for hedge funds and so on. The numbers in this table are time series average of change in holdings in finalized long and short portfolios. Change in holdings are defined as the percentage change of ownership in a quintile for corresponding institutional investor group between September and March for each year. *, **, and *** denote 10%, 5%, and 1% significance levels respectively.

Panel A: In Sample Period

Subgroup	Long	Short	Long-Short
All	1.876**	1.9062***	-0.029
HF	0.003	-0.001	0.003
- HF with PhD	-0.003	0.004	-0.007*
- HF with Master's Degree	-0.002	-0.007	0.005
- HF with CFA	0.000	-0.008	0.008
- HF with PhD + CFA	0.000	0.000	0.000
- HF with Master's + CFA	0.001	-0.010	0.011
- Other HF	0.009	0.001	0.008

Panel B: Post-Publication Period

Subgroup	Long	Short	Long-Short
All	2.205***	1.460***	0.745*
HF	0.024**	-0.061**	0.085***
- HF with PhD	-0.005	-0.002	-0.002
- HF with Master's Degree	0.004	-0.018	0.022*
- HF with CFA	0.005*	-0.011*	0.017**
- HF with PhD + CFA	0.000	0.000	0.001
- HF with Master's + CFA	0.004**	-0.007	0.012*
- Other HF	0.023**	-0.038	0.062**

Table 5 continued

Panel C: Pre-Publication Period

Subgroup	Long	Short	Long-Short
All	2.003**	1.169	0.834*
HF	0.056***	-0.118	0.173**
- *HF with PhD*	0.000	0.000	0.000
- *HF with Master's Degree*	-0.008	-0.035	0.026
- *HF with CFA*	0.005	-0.013	0.018**
- *HF with PhD + CFA*	0.000	0.000	0.000
- *HF with Master's + CFA*	0.005	-0.011	0.016*
- *Other HF*	0.064***	-0.081	0.145***

Panel D: Early Post-Publication Period

Subgroup	Long	Short	Long-Short
All	2.447***	0.993**	1.454*
HF	0.021	-0.075*	0.096**
- *HF with PhD*	-0.008	-0.001	-0.007
- *HF with Master's Degree*	0.022	-0.045	0.067**
- *HF with CFA*	0.008	-0.042	0.050*
- *HF with PhD + CFA*	0.000	-0.001	0.001
- *HF with Master's + CFA*	0.008	-0.038	0.046*
- *Other HF*	0.008	-0.026	0.034

Panel E: Most Popular Anomalies

Subgroup	Long	Short	Long-Short
All	2.331**	0.870	1.462*
HF	0.039	-0.097*	0.136**
- *HF with PhD*	-0.008	0.005	-0.014
- *HF with Master's Degree*	0.016*	-0.025	0.041
- *HF with CFA*	0.008	-0.038**	0.046**
- *HF with PhD + CFA*	0.000	0.000	0.000
- *HF with Master's + CFA*	0.008	-0.033*	0.042*
- *Other HF*	0.031	-0.073*	0.104**