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ACTIVE AND PASSIVE OWNERSHIP'S IMPACT ON POST EARNINGS ANNOUNCEMENT DRIFT

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ABSTRACT

The solution as to why Post Earnings Announcement Drift (PEAD) occurs has eluded academic experts in the field for almost fifty years. Furthermore, because it conflicts with the widely accepted Efficient Market Hypothesis (EMH), it has drawn a great deal of attention. Due to the longevity of its mystery as well as the controversy it causes as a counterargument to EMH, PEAD has become one of the most interesting and researched financial topics of all time. Previous research has narrowed down the list of possibilities for the potential cause of this phenomenon and this work will add to the literature by examining a logical possibility, ownership style. This study will compare Post Earnings Announcement Drift in firms that are owned mostly by active investors against those who are more largely owned by passive investors. This would imply a lack of attention, trading, and liquidity as the root cause of PEAD.

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Chapter 1

The Efficient Market Hypothesis

Efficiency is a largely a relative concept but it is still something that individuals and businesses alike strive for. The idea that if everyone or everything within a system is working optimally makes sense, however, in practicality, exactly what this looks like is tough to pinpoint. What is even harder to comprehend is what this concept looks like when applied to the market. The idea of an efficient market has been around for nearly seventy years (Findlay and Williams 2000) and over the course of this time, the extent of the market's efficiency has been widely researched and debated. This concept has been since formalized and named the Efficient Market Hypothesis (EMH).

The idea of an efficient market, the basis of the EMH, has many implications. One of these implications is that whenever an event occurs with a predictable pattern, the market would find a way to trade on it profitably and it would therefore disappear quickly. This, of course, requires that the cause of the event be determined and that it is possible to turn it into a profitable trading strategy; common sense would lead one to believe that these very logical results of an "efficient market". If an investor can identify a predictable, reoccurring event, there is great profit potential. For this reason, an explanation and a strategy around it often does not take a considerable time to surface. Over the history of the stock market, there has certainly been many instances where an arbitrage opportunity has been found, studied, and quickly traded away. This aligns with the Efficient Market Hypothesis and is used a main argument in support of EMH.

Chapter 2

Intro to PEAD

With money to be made, inexplicable, long lasting stock market phenomena with undetermined profitability are far fewer than those that become exploited. Post earnings announcement drift (PEAD) is the perfect example of this type of irregularity. PEAD is a long-lasting phenomenon without definite answers as to the cause of its occurrence and, subsequently, the profitability of possible trading strategies. Post earnings announcement drift can be defined as "the continuance of abnormal returns after earnings announcement in the direction of quarterly earnings surprises" (Ke and Ramalingegowda 2005).

The first analyzation of its occurrence dates back almost 50 years ago to the studies of Ball and Brown (1968). This makes PEAD the longest occurring market irregularity (Bird, Choi, and Yeung 2014). Given this, one can imagine the attention that it has drawn and the confusion it has caused over the years. Twenty-five years after its discovery, leaving investors plenty of time to exploit the phenomena, PEAD was extensively reexamined and found to be persistent and economically significant before transaction costs (Bernard 1993). Fama (1998) referred to PEAD as being the "granddaddy of all under reaction events", revealing its continued prevalence as well as his opinion that it was an event due to under reaction by investors (an idea that will be touched on later).

As aforementioned, the continued uncertainty behind PEAD's existence has lead authors to submit that post earnings announcement drift is one of the most prominent challenges to the (widely accepted) efficient market hypothesis (e.g., Fama 1998; Kothari 2001; Bird et al. 2014).

Since its origination, EMH has been subdivided into weak form, semi-strong form, and strong form. Weak form efficiency says that past information on share prices is the only factor affecting the current price of a stock. Semi-strong form says that all publicly available information is immediately factored into the price of a share. Lastly, strong form says that both the aforementioned factors as well as private information are all included in a stock's price. It is clear to see then how PEAD presents itself as an issue to this largely accepted theory. If markets were efficient (even by the semi-strong form definition), they would price a stock at its true value immediately after an earnings announcement. This would not result in the observed delay in price adjustment that is so prominently exhibited by PEAD.

Chapter 3

The History of PEAD Analysis

Since the initial discovery, there have been countless attempts to explain what the reason for this phenomena that opposes the EMH so clearly may be. In one of the first attempts to explain PEAD's existence, Jones and Litzenberger (1970) hypothesize that the opinions of professionals (who were assumed to be best able to efficiently price shares) take time to find their way into the market price. Bernard and Thomas (1990) provide evidence backing this idea and show that PEAD persists because naïve investors fail to recognize that current earnings announcements have implications for future earnings. Bartov et al. (2000) again proposes the explanation of unsophisticated investors being a primary cause of post earnings announcement drift. However, all of these potential explanations were eventually refuted by Hirshleifer et al. (2002) who showed there is no statistically significant evidence that nonprofessional investors drive PEAD. Mendenhall (2004) points out that this stands to reason even at the conceptual level since these views would contrast even a semi-strong form efficient market.

Both during and after this period of time, there were studies being conducted which examined if PEAD was the result of some form of costs. Bernard and Thomas (1989) were among the first to suggest a cost-related explanation; specifically, they suggested that risk associated costs may be the reason for the drift. They concluded that risk could, at best, explain only a portion of earnings announcement drift though (1989). Mendenhall (2004) proposed arbitrage risk as being a root cause of PEAD concluding, "The results show that the magnitude of post-earnings-announcement drift is significantly positively correlated to arbitrage risk". Cost-oriented explanations did not end there, however.

Sadka (2006) proposes liquidity risk as being the cause of the perplexing phenomena. Sedka's study found that both momentum (a phenomenon closely related to PEAD in that well performing shares beat poorly performing shares over time) and PEAD portfolios have the largest abnormal returns in the early stages of their construction (when the phenomena are most prevalent). This, in turn, has the implication that these portfolios also have extremely high turnover in order to maintain abnormal returns (Sadka 2006). The results indicate that Sadka's liquidity risk factor (which includes turnover factors) can explain between 40% and 80% of the cross-sectional variation of expected momentum and PEAD portfolio returns. That being said, Barinov (2014) contends that Sadka's (2006) liquidity factor does not accurately incorporate prevalent turnover aspects though. This is because Barinov (2014) finds not only that turnover is unrelated to liquidity, but that the two are mostly negatively correlated, in fact. Sadka (2006) on the other hand, views these two as being very much related.

Two newer, and related, explanations of post earnings announcement drift are information uncertainty (Francis et al. 2007) and investor sentiment (Livnat and Petrovitis 2009). In regards to the work on information uncertainty explanation by Francis (2007) as well as the investor sentiment rational provided by Livnat and Petrovitis (2009), R. Bird et al. (2014) writes, "The underlying proposition in both cases is that the uncertainty or sentiment at the time of the information release impacts the market reaction at that time with the PEAD representing the subsequent market correction to the initial mispricing". Bird and Yeung (2012) find that, using ideas from both theories, investors are more affected by the combination of uncertainty and sentiment than they are by "good" or "bad" news; in fact, they tend to ignore the implication of the news (at first) and instead focus on prevailing market conditions regardless of news. That is to say, even if good news is released and there is high uncertainty with low sentiment, investors will still react negatively and then adjust to prices. R. Bird et al. (2014) best summarize the final results of the study with the following statement:

> We find significant evidence that during the post-announcement period: (i) the strongest downward drift after a bad earnings announcement occurs when uncertainty is high and sentiment is low, and (ii) the strongest upward drift following good news announcements occurs during periods when uncertainty is low and sentiment high. The best example of the combined impact of prevailing uncertainty and sentiment on the PEAD is our finding that there is a strong downward drift after the release of good news during periods when uncertainty is high and sentiment is low.

This implies that there is typically an under reaction to both “good” and “bad” earnings announcements. Furthermore, R. Bird et al. (2014) shows that the bad news reaction generally requires an even greater adjustment than does a positive reaction. It is important to note that a larger adjustment to bad news reaction could be attributed to a variety of things. One explanation that PEAD is more prominently exhibited in downward drifts because of limits to short selling and the subsequent difficulty for sophisticated investors to trade on their opinion of the security’s worth as Lamont and Thaler (2003) showed. Another is that when uncertainty is high, investors take a pessimistic view and underreact to good news but overreact to bad news, causing asymmetry (Williams 2015). Similar studies (while not as robust) by Mian and Sankaraguruswamy (2008) as well as Jiang (2011) also have examined the idea of market sentiment as a factor. They conclude that investors, as a whole, act more significantly towards good news when sentiment is high and also report that the same holds true for negative news when sentiment is low.

While Bird et al. (2014) began to come to conclusions, their study was large scale, market focused. The uncertainty and sentiment that that they were measuring was at the market level instead of at the firm level and it was very unique in this sense. As Bird et al (2014) wrote, “Previous studies have considered uncertainty at the firm level, basing their measure of uncertainty on factors such as the company’s use of accruals, its size, its return volatility and the dispersion of analysts’ earnings forecasts.” Their new approach to this question resulted in a successful determination of why PEAD is more pervasive in some instances than it is in others. They concluded that PEAD exists investors see news through a lens conditioned by the level of market uncertainty and sentiment both at the time of, as well as after, the earnings announcement and this is what causes pricing drifts to exist. However, I contend that because this study factors in sentiment and uncertainty (determined by news) on a continual basis, it is no longer examining PEAD in its traditional sense but is instead focused too much on a behavioral analysis of stock price movement in general. I do not disagree with the idea that these factors certainly affect the size of observed under/over reactions, but no evidence is provided for a base line level of uncertainty and sentiment in which no PEAD is observed. Because of this, I believe it is important to look for the root cause of the phenomena in the first place opposed to factors that magnify its prevalence.

Givoly et al. (2015) begins to move in this direction by again examining uncertainty at the firm level. They shift emphasis and the work instead examines differences between small and large firms in attempts to reach a definitive conclusion. Firstly, they touch on the pervasiveness of small firm bias in existing literature that has come with the increase in data availability throughout the years. They do so by pointing to alarming facts such as sample sizes of over 3500 firms being used by the 1990s compared to a few hundred that were once examined in the 1950s (Givoly et al. 2015). This is alarming, as well as pertinent, because Givoly et al. (2015) points out that large firms account for roughly 90% or more of stock market value. This means that since large firms are significantly fewer in number, value weights need to be taken into consideration in order to examine how truly prevalent PEAD is in a market that is dominated by large firms. This work then breaks up firms by their size (in deciles) and examines the occurrence of PEAD in each decile based on the return of a constructed hedge portfolio. The result is that post earnings announcement drift is insignificant not just for the top decile, but also for almost the entire quartile (Givoly et al. 2015). They narrow down the change from insignificant PEAD to significant PEAD as being somewhere between the largest 20% and largest 25% of firms and make the additional point that this means around 91% of the equity market's value is insignificantly affected by PEAD. This signifies that somewhere along the line, post earnings announcement drift was found to be profitably exploitable in large firms and was therefore traded away, or that it may never have prominently existed in large firms (and therefore the market) at all. It is possible that a persistent small firm bias had only made PEAD seem to be an all-encompassing phenomenon since its initial discovery when this was simply never the case.

There are even more implications to be found upon closer examination of small firms. Givoly et al. (2015) hypothesize that the number of small firms affected by this anomaly may be even less than implied by the aforementioned results because of informational environment. The findings of Bartov et al. (2000) suggest a similar idea in that they show how the level of institutional ownership, a factor of the informational environment, is negatively correlated with abnormal returns resulting from PEAD. In testing this hypothesis, Givoly et al. (2015) identify number of analysts following the firm, percentage of institutional ownership, number of news reports, and the bid-ask spread as being factors determining the extent of a firm's informational environment. The result of the test is that PEAD is found to be insignificant even for the smallest firms if they operate in a rich information environment. At first, it would seem as though the answer to this long-questioned anomaly has been found. However, it cannot simply be that only this information environment level determines the significance of PEAD. This is because it was found that large firms in a poor information environment also do not exhibit significant PEAD (Givoly et al. 2015). This suggests that the information environment may include significant factors beyond the information variables considered in this analysis or that determining the effects of the information environment only provides insight as to exactly what the root cause of PEAD may be.

The question can now be asked, what characteristics do large firms in poor information environments, large firms in rich information environments, and small firms in rich information environments (types of firms that do not exhibit significant PEAD) all have in common. It is likely that they all exhibit higher levels of trade volume due to some combination of sheer firm size and information environment. Trade volume is in fact related to, but not included in, the information environment study of Givoly et al. (2015), leaving a gap in the literature. Unquestionably, trade volume is relative to the size of the firm and is, in and of itself, a measure that may very well be correlated to many things. However, a factor that could logically result in relatively lower than normal trade volume is a high level of passive investors as shareowners in a firm. *Therefore, I question whether the extent of passive ownership in a firm limits trading of the security to the extent that passive investing becomes the root cause of post earnings announcement drift.*

Chapter 4

Methodology

Getting PEAD for the entire data set

The data analysis used in this paper originates from three primary data sets, all of which Jeremiah Green had accessible. First is the data set which will be referred to as Earn and includes surprise unexpected earnings for individual firms. Earn was originally comprised of 810,238 points of data and contained factors (columns) of “permno” (a firm identifier), “gvkey” (another identifier),”datadate”, “rdq”(announcement date), “niq” (net income), and “sue” (surprise unexpected earnings). In order to make the data more manageable, unnecessary columns were eliminated. Earn dates back to January 1, 1960 and up until January 19, 2017. This entire period was kept and analyzed in order to minimize the effect of market events and intermittent trends in the market. Calendar quarters were then added as an additional column so that the drifts could be more easily categorized. Next, surprise unexpected earnings were ranked into deciles and only the top and bottom deciles were kept. The bottom decile for SUE was anything below -3.871% and the top decile was anything above 2.972%. If PEAD is indeed most prevalent in the highest and lowest deciles of sue in passively owned firms, then you can enter the appropriate stock position upon earnings announcements for passively owned firms who are above and below the average thresholds.

Table 1 – SUE by Firm With Percentiles - "Subearn2" in Code

	permno	gvkey	rdq	sue	cqtr	pctl
1	91392	174729	2009-02-13	-1.25762391	2009 Q1	1
2	91392	174729	2010-02-10	0.39667085	2010 Q1	10
3	91660	174743	2008-03-13	-0.05826054	2008 Q1	1
4	91660	174743	2008-05-12	-0.26387867	2008 Q2	1
5	91660	174743	2008-08-11	-0.23887227	2008 Q3	1
6	91660	174743	2008-11-10	-0.47639550	2008 Q4	1
7	91413	174744	2007-11-01	-0.04549055	2007 Q4	1
8	91413	174744	2008-07-24	0.42259753	2008 Q3	10
9	85208	174876	2007-12-07	0.02728891	2007 Q4	10
10	91618	175004	2010-05-10	0.09179280	2010 Q2	10

Next, this data had to be combined with the daily returns for each company for the average drift period after earnings announcement. The data set Return was used for this. Return was originally comprised of 71,106,126 points of data and contained factors (columns) of "Permno" (a firm identifier), Date, and Return. The entire date range was also kept and the two sets were merged. The result was a new data set that had daily returns aligned with the appropriate earnings announcement date. An additional column was added that shows the event date (the number of days after the announcement that the return was).

Table 2 – Returns for Each Firm by Date - "Tempdata" in Code

	permno	rdq	pctl	DATE	dt	RET	dif
1	91392	2009-02-13	1	2009-02-17	14292	6.698570e-02	4
2	91392	2009-02-13	1	2009-02-18	14293	-1.165919e-01	5
3	91392	2009-02-13	1	2009-02-19	14294	-2.030461e-02	6
4	91392	2009-02-13	1	2009-02-20	14295	-6.994818e-02	7
5	91392	2009-02-13	1	2009-02-23	14298	-6.406686e-02	10
6	91392	2009-02-13	1	2009-02-24	14299	5.654765e-02	11
7	91392	2009-02-13	1	2009-02-25	14300	-2.564100e-02	12
8	91392	2009-02-13	1	2009-02-26	14301	4.385960e-02	13
9	91392	2009-02-13	1	2009-02-27	14302	3.361348e-02	14
10	91392	2009-02-13	1	2009-03-02	14305	-1.327913e-01	17

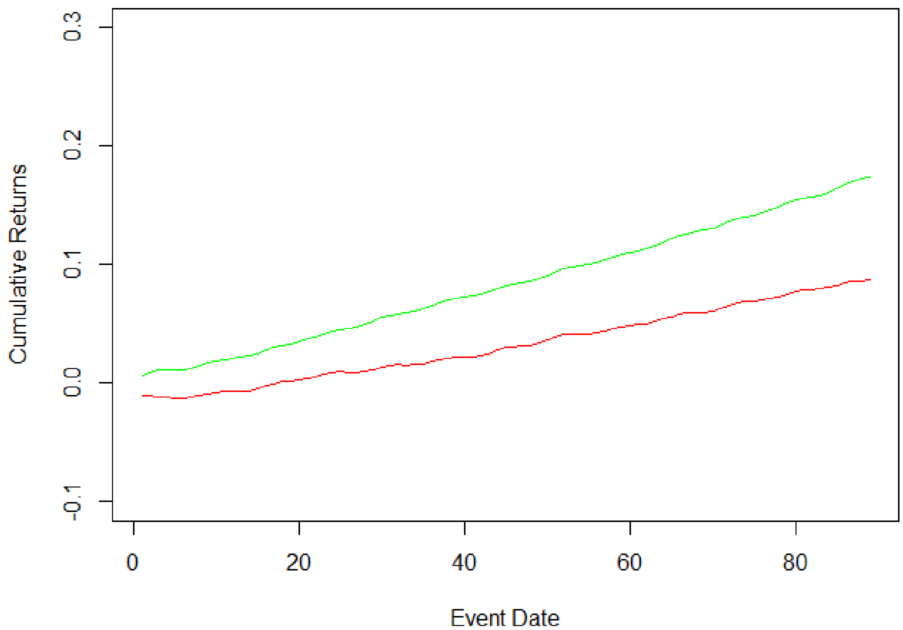
A separate data set called Aggregate was created which shows mean returns by event date and decile.

Table 3 – Mean Returns by Event Date and Decile - "Agg" in Code

	dif	pctl	mret
1	1	1	-1.079214e-02
2	1	10	7.023848e-03
3	2	1	6.900581e-04
4	2	10	1.872357e-03
5	3	1	-1.383138e-03
6	3	10	1.760458e-03
7	4	1	-2.291266e-04
8	4	10	7.897723e-04
9	5	1	-1.374900e-03
10	5	10	-3.223433e-04

From here, cumulative returns could be easily calculated and plotted. Below is a graph of post earnings announcement drift of all firms within the data set. What is shown is expected for firms that experienced high positive and negative SUE. As shown below, there is an upward drift for cumulative returns both in the extreme positive and negative SUE categories. If average returns were to be factored in, you would see get the chart for abnormal cumulative returns and positive SUE would drift up while negative SUE would drift downward below zero. This is because, on average, the stock market has positive returns throughout time.

Figure 1 - PEAD on all firms, 1960 to 2015



Getting PEAD for Actively and Passively owned firms

The last set of data is a breakdown of firm ownership structure utilizing fund characteristics. It contained dates, firm identification number, and then 12 columns regarding the ownership breakdown on a permutation of 3 fund variables. The three variables are the size of the fund (small, medium or high), the amount of stocks that the fund holds (few or many), and the turnover of the fund (low or high). Under each of these columns was the percent of the company that was owned by funds of those characteristics.

From here, a proxy for passively and actively owned companies was constructed on characteristics of the fund management style. Passively owned funds were deemed to be funds that had many holdings and low turnover; this mirrors the characteristics of an index fund.

Actively owned funds were characterized by any fund that had high turnover. After these two new data sets were created, the percent ownership across the columns were added together. Then, similarly to before, they were ranked by deciles and only the 1st and 10th deciles were kept. This resulted in two data sets, one containing the highest actively and lowest actively owned firms and one with the highest and lowest passively owned firms. From this point, the active and passive proxies were each merged with Earn separately and any rows with null values were deleted. This resulted two data sets that included earnings for passive and actively owned firms as well (see Table 4). From here, the same steps were taken as before with the original data sets (Earn and Return) and four separate graphs of PEAD were constructed.

Table 4 - Active Factors added to Earn – "tempdatawactive" in Code

	permno	gvkey	rdq	sue	cqtr	qend	activesum	activepctl
43	91413	174744	2008-02-12	-1.446371e-03	2008 Q1	2007-12-31	0.526749	10
44	91413	174744	2008-05-12	-2.505040e-02	2008 Q2	2008-03-31	0.562626	10
45	91413	174744	2008-07-24	4.225975e-01	2008 Q3	2008-06-30	0.587874	10
46	91413	174744	2008-10-30	-1.315304e-02	2008 Q4	2008-09-30	0.584863	10
47	91413	174744	2009-02-05	-5.628995e-02	2009 Q1	2008-12-31	0.517938	10
48	91413	174744	2009-04-30	6.105925e-03	2009 Q2	2009-03-31	0.542515	10
49	91413	174744	2009-07-29	-3.343653e-02	2009 Q3	2009-06-30	0.557681	10
50	91413	174744	2009-10-28	6.517591e-03	2009 Q4	2009-09-30	0.578519	10
51	91413	174744	2010-02-02	1.405577e-02	2010 Q1	2009-12-31	0.559227	10
52	91413	174744	2010-04-20	3.568850e-03	2010 Q2	2010-03-31	0.652318	10
53	91413	174744	2010-08-03	1.574618e-02	2010 Q3	2010-06-30	0.538901	10
54	91413	174744	2010-10-28	1.652576e-03	2010 Q4	2010-09-30	0.632686	10

Chapter 5

Results

As shown in Figure 2, firms that had high active ownership did not exhibit abnormal cumulative returns. This was anticipated and aligned with my original hypothesis. High active ownership would, according to my reasoning, result in a quicker response to earnings announcements and an efficient pricing of information. Figure 3 also would appear to agree with my hypothesis. Roughly a 2.5% cumulative return for positive SUE over the ninety-day period is significant and by itself agrees with the idea that firms which are not owned largely by active investors would lead to a greater PEAD. However, figures 4 and 5 present a contradictory finding. I anticipated that high passive ownership would result in a graph similar to low active ownership. However, what came to light was the exact opposite. This results agree with the findings of Bartov et al. (2000) in that institutional ownership itself is what is driving away PEAD. Furthermore, given these results alone, it appears as if the type of institutional ownership is entirely irrelevant.

Figure 2 - Most Active Ownership from 1960 to 2015

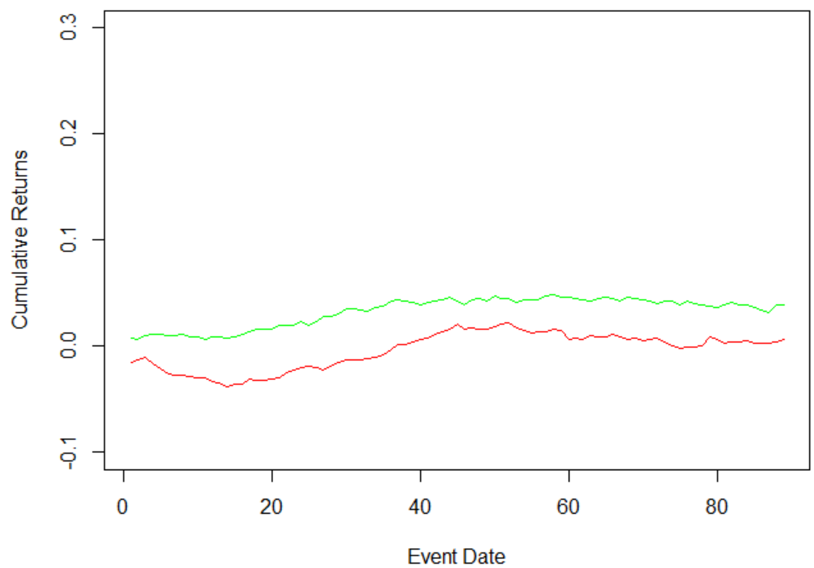


Figure 3 - Least Active Ownership from 1960 to 2015

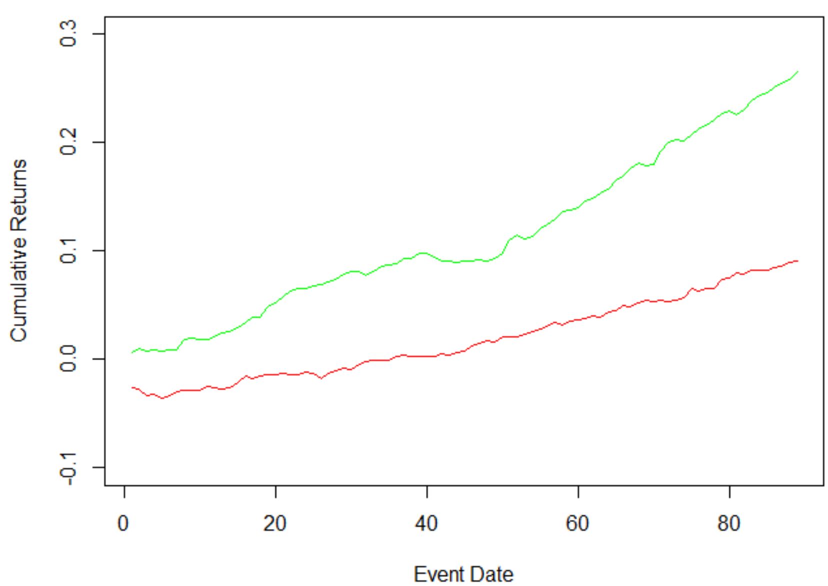


Figure 4 - Most Passive Ownership from 1960 to 2015

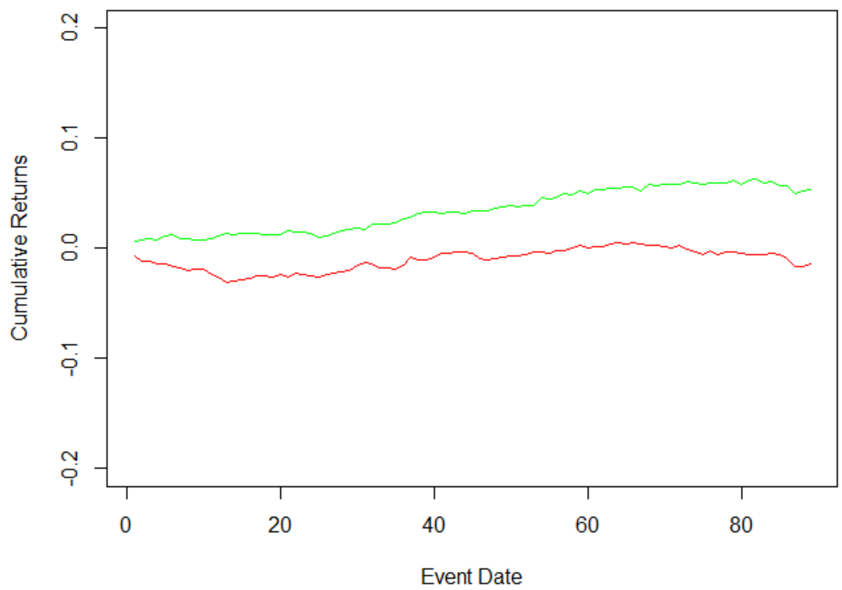
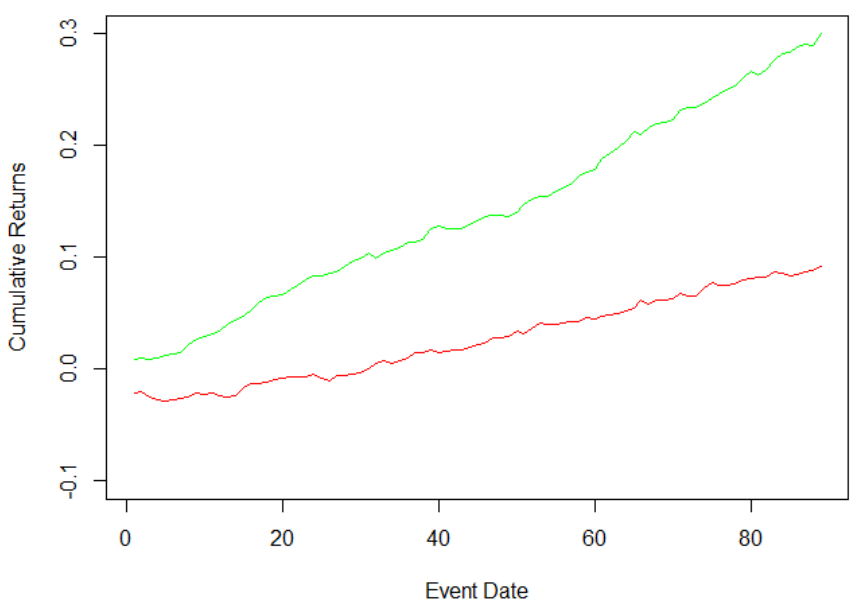


Figure 5 - Least Passive Ownership from 1960 to 2015



In order to confirm this, additional testing had to be done. To do this, the passive and active ownership proxies were merged together, ranked into quintiles (used in order to keep a significant amount of results), and were examined as pairs rather than individually. This reason for this was a more thorough analyzation of factors by ensuring that each factor was being looked at in isolation. Four more tests were then run on this data set. The first examined only the least actively managed and passively managed firms. The second looked only at the most actively and passively managed firms. The third was run only on the least active and most passively owned firms. The fourth and final test grouped the most active and the least passively owned firms together. The results are shown below.

Figure 6 - Least Actively & Passively Owned

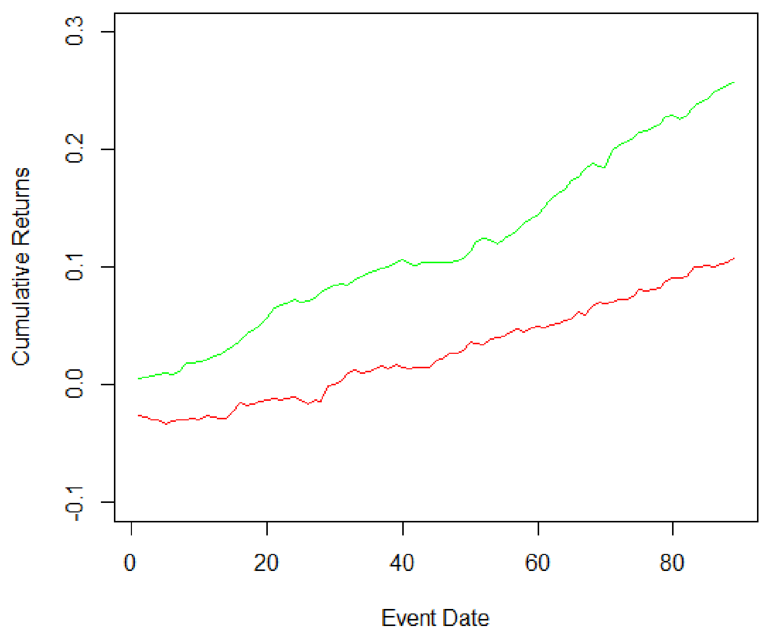


Figure 7 - Most Actively and Passively Owned

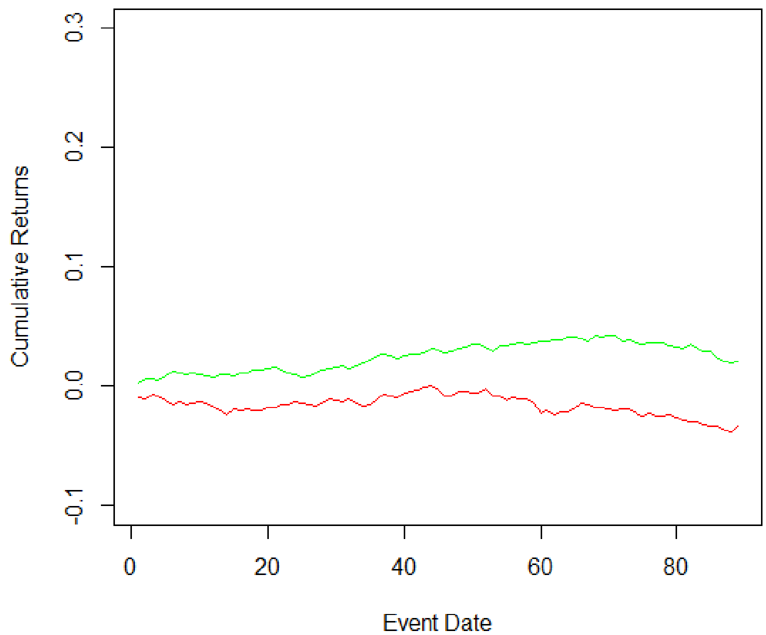


Figure 8 - Least Actively and Most Passively Owned

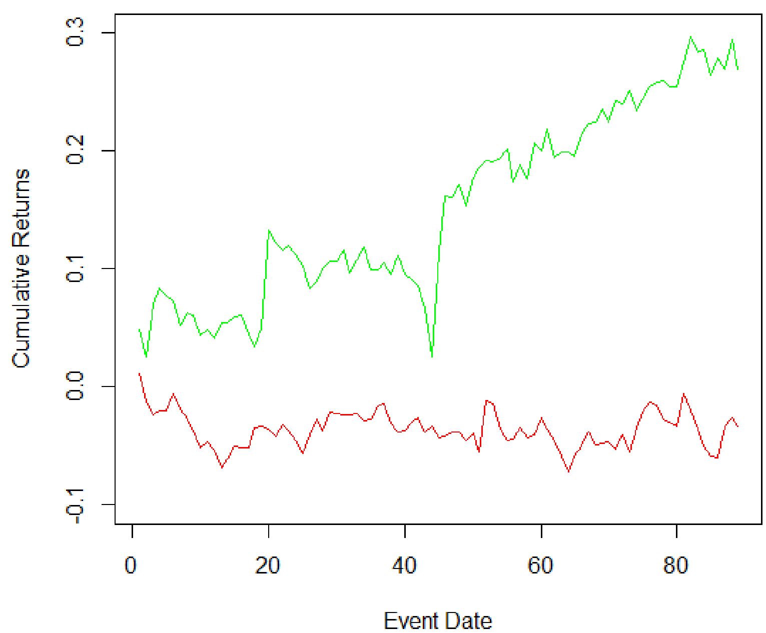
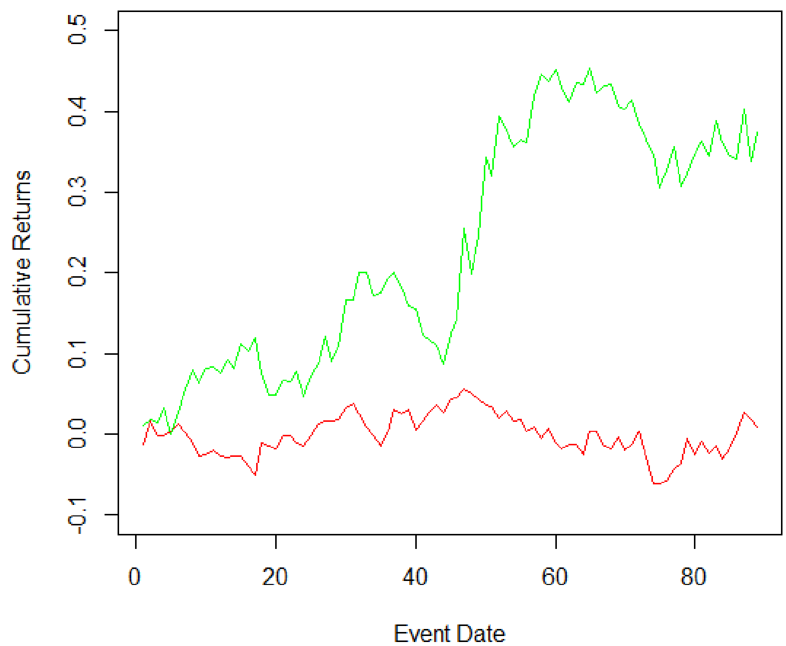


Figure 9 - Most Actively and Least Passively Owned



What resulted from these additional test was a confirmation that institutional ownership, regardless of type, has a significant impact on PEAD. As shown in Figure 7, when there is high institutional ownership, the result is almost no drift. Contrast that with Figure 6, when there is only low institutional ownership, the result is a traditional looking PEAD graph. That being said, Figures 8 and 9, which examine firms on opposite extremes of the spectrum as pairs, yield an interesting result. The data shows that when this is the case, the drift associated with extreme positive SUEs is well above not only PEAD for the entire data set, but also above PEAD for the low active and passive groups when examined alone or together. These were previously the groups that exhibited the largest drift and now are beat by an unexpected pairing of characteristics.

Chapter 6

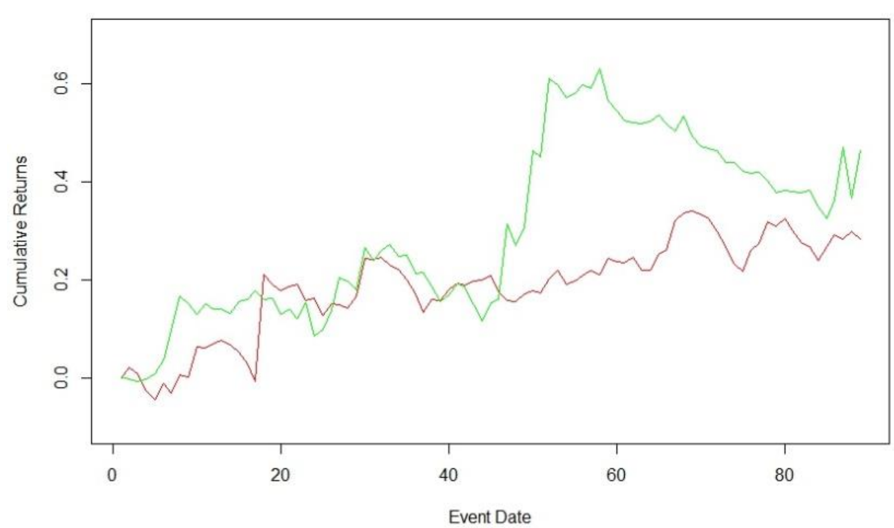
Conclusions, Errors, Advancements

The logical question that results from this finding is clear; what is the reason that combining the inverse quintiles of the groups increase cumulative returns? It is possible that ownership style matters very little or not at all and the reason for this result is mainly firm size. If the firm does not have a large number of shares on the market and very few institutions own them as a result, even one institution's management style could lead to a firm being in the top quintile for one type of ownership and the bottom in the other category (given a large enough position). Therefore, many of the firms in the largest and smallest percentiles of active and passive ownership may be there solely because they are small firms. The implication of this would be that firm size is either a missing factor in this study that would prove ownership style unimportant, or that ownership style determines the difference between high PEAD and the highest PEAD in small firms. Further research could determine which of these two possibilities holds true. Advancements to this work should include firm size as a variable and run the same four final tests used in this paper with only small firms. While there would likely be larger overall PEAD, if there is little difference between the four new graphs, then ownership style could be essentially ruled out as a factor affecting PEAD. However, if PEAD was different among small firms given the ownership factors, conclusions could be drawn about ownership style's influence on an already exhibited PEAD in small firms. The potential difference between the inverse quintile proxies may be as a result of ownership type.

Another possibility is that the institutional data set as a proxy for passively and actively owned firms is simply skewing the results too much to draw any definitive conclusions. This is possible as it has been shown in this study and by Bartov et al. (2000) that while solely examining level of institutional ownership, high institutional ownership of a firm drives away PEAD. A possible way to circumvent this possibility is by using a factor model to determine ownership style instead of the data set used. Factors could include data such as number analysts following companies, number of analyst reports, relative trade volume increase around earning announcements, number of index funds the company is included in, and even google searches/website hits to name a few. Statistical software could then be used to show which factors most significantly affect PEAD and factors could be weighted or eliminated accordingly.

While manipulating the proxies in search of other explanations, there was one interesting discovery that stood out as another possible explanation. At first, I removed the defining characteristic of “many holdings” from the active proxy. My reasoning for that was that if an institution was owned largely by funds who had few holdings, then they would be more closely monitored and actively managed. However, when testing this it could be seen that PEAD was far less prevalent when there were only few holdings for the active proxy. That being said, I ran a test on the inverse scenario and replaced few holdings with many holdings only. The result of this was a significantly higher drift for one scenario than observed before. When firms had the highest level of “active ownership” (fund size irrelative, many holdings and high turnover) combined with the lowest level of “passive ownership” (fund size irrelevant, many holdings, low turnover), cumulative returns of over 6% on average are observed around the 60-day mark for the positive SUE group.

Figure 10 - Highest High Turnover & Lowest Low Turnover



The logical conclusion of this is that it may not be institutional ownership type but instead noise trading that generates PEAD. This stands to reason because market movements caused by turnover would then insight more trades being placed by under informed investors, eventually driving the company's value above where fundamental analysis would price it. This also aligns closely with the various different recent studies showing that market sentiment and uncertainty are the driving factors of PEAD. Certainly high turnover funds will trade more when uncertainty is low. The managers are confident that the market will move in an expected direction allowing for quick trades to be place and at least a small gain realized. As previously mentioned, R. Bird et al. (2014) found that when uncertainty is low and sentiment is high, the strongest upward drift is observed and this data supports the uncertainty aspect of their conclusion.

While no definitive factor has been found for this elusive, persistent phenomenon, this work did not prove to be a fruitless endeavor. First, the study done by Bartov et al. seventeen years ago showing that institutional ownership drives away PEAD has been confirmed as a continuing truth. Second, it has not been ruled out that passive and active ownership types may indeed affect PEAD. It is my wish that this research will be furthered and ownership size will be added as a factor initially. If that yields no definitive results, the research can still be advanced by removing the prevalence of institutional ownership included in this study. This study has not counted out ownership type as a factor, but has instead shown that it is not a leading cause in a world full of investing variables. I believe it is very possible that the information environment (largely firm size related) analyzed by Givoly et al. (2015) is, as a whole, the leading cause of PEAD and that ownership style may be a magnifying factor not considered in their work. Lastly, this work has found evidence that noise trading itself generates abnormal PEAD. This expands recent literature arguing for market sentiment and uncertainty as major causes of PEAD. In any case, it is clear that the door is closing on this phenomenon after nearly seventy years of analyzation. I hope the veil of this mystery is soon lifted so I may see what the root cause to the post earnings announcement drift really is.

Appendix A

Coding Used in R Studio to Obtain Results

```
#install package that will read sas data
.libPaths("D:/")
library(haven)
library(dplyr)
#library(data.table)
library(zoo)
library(sqldf)
#read in earnings data
earn <- (read_sas("D:/Thesis/earn.sas7bdat"))
#read in returns data
ret <- (read_sas("D:/Thesis/dsf data.sas7bdat"))
#adjust from sas dates
earn$datadate<-as.Date( c(earn$datadate), origin="1960-01-01")
earn$rdq<-as.Date( c(earn$rdq), origin="1960-01-01")
#subset data to make small to look at
subearn <- subset(earn, rdq > "1960-01-01" & datadate > "1960-01-
01",select=c(permno,gvkey,rdq,sue))
rm(earn)
gc()
#same thing with return data
ret$DATE<-as.Date( c(ret$DATE), origin="1960-01-01")
subret <- subset(ret, DATE > "1960-01-01")
rm(ret)
gc()
# create calendar quarter
subearn$cqtr<-as.yearqtr(subearn$rdq, format="%Y-%m-%d")
# rank into deciles
subearn2<-
  subearn %>%
  group_by(cqtr) %>%
  mutate(pctl = ntile(sue, 10))
#keep only those in the top and bottom deciles
subearn2 <- subset(subearn2, pctl ==1 | pctl == 10)
gc()
#create matched up data this is to get the data between these dates
subearn2$fordt <- (subearn2$rdq+90)
# needs to be raw vectors for sqldf...
#clean up a little
subearn3 <- subearn2[,c("permno","rdq","fordt","pctl")]
subearn3<-na.omit(subearn3)
subret<-na.omit(subret)
```

```
subret$dt<-as.numeric(subret$DATE)
tempdata <- sqldf("select
subearn3.permno,subearn3.rdq,subearn3.pctl,subret.date,subret.dt,subret.ret
        from subearn3 left outer join subret
         on subearn3.permno = subret.permno
         and subearn3.rdq < subret.dt and subret.dt<subearn3.fordt")
#rough date count
tempdata<-na.omit(tempdata)
tempdata$dif<-as.numeric(tempdata$DATE-tempdata$rdq)
#max(tempdata$dif)
#create mean returns by event date and decile
agg<-sqldf("select dif,pctl,avg(ret) as mret from tempdata group by dif,pctl")
# cumulative returns
subport_l<-subset(agg,agg$pctl==1)
subport_h<-subset(agg,agg$pctl==10)
subport_l$pl1<-1+subport_l$mret
subport_h$pl1<-1+subport_h$mret
subport_l$cumretpl1<-cumprod(subport_l$pl1)
subport_l$cumret_l<-subport_l$cumretpl1-1
subport_h$cumretpl1<-cumprod(subport_h$pl1)
subport_h$cumret_h<-subport_h$cumretpl1-1
togo <- cbind(subport_l[,c("dif","cumret_l")],subport_h[,c("cumret_h")])
colnames(togo)<-c("EventDate","Low","High")
 #plot PEAD
plot(togo$EventDate,togo$Low,type="l",col="red",ylim=c(-0.1,0.3),xlab="Event
Date",ylab="Cumulative Returns")
lines(togo$EventDate,togo$High,type="l",col="green")
own <- (read_sas("D:/Thesis/own.sas7bdat"))

#create a proxy for Index/PassiveOwned companies
#size of fund determined to be irrelevant, many holdings chosen as it is a common passive
strategy, low turnover
PassiveProxy <- subset(own, select = c(permno,qend,smmalo,memalo,himalo))
# Create a proxy for actively owned firms.
# High turnover deemed to be most important in active management
ActiveProxy <- subset(own, select =
c(permno,qend,smfehi,smmahi,mefehi,memahi,hifehi,himahi))
rm(own)
#sum active attributes
ActiveProxy$sum <- as.numeric(ActiveProxy$smfehi + ActiveProxy$smmahi +
ActiveProxy$mefehi + ActiveProxy$memahi + ActiveProxy$hifehi + ActiveProxy$himahi)
#sort into deciles
ActiveProxy2<-
   ActiveProxy %>%
   mutate(sumpctl = ntile(sum, 10))
#cleaning up and renaming
```

```
rm(ActiveProxy)
ActiveProxy <- subset(ActiveProxy2)
rm(ActiveProxy2)
#keep only the bottom and the top deciles
smlactiveproxy <- subset(ActiveProxy, sumpctl ==1 | sumpctl == 10)
#repeat for passiveowned
#get sum
PassiveProxy$sum <- as.numeric(PassiveProxy$smmalo + PassiveProxy$memalo +
PassiveProxy$himalo)
#get deciles
passiveproxy2<-
	PassiveProxy %>%
	mutate(sumpctl = ntile(sum, 10))
#keep 1st and 10th
smlpassiveproxy <- subset(passiveproxy2, sumpctl ==1 | sumpctl == 10)
#cleanup
rm(PassiveProxy)
#cleanup
smlpassiveproxy2 <- smlpassiveproxy[,c("permno","qend","sum","sumpctl")]
smlactiveproxy2 <- smlactiveproxy[,c("permno","qend","sum","sumpctl")]
#specify column names for merging
names(smlactiveproxy2)[names(smlactiveproxy2)=="sum"] <- "activesum"
names(smlactiveproxy2)[names(smlactiveproxy2)=="sumpctl"] <- "activepctl"
names(smlpassiveproxy2)[names(smlpassiveproxy2)=="sum"] <- "passivesum"
names(smlpassiveproxy2)[names(smlpassiveproxy2)=="sumpctl"] <- "passivepctl"
# merge subearn and active/passive proxies
tempdatawpassive <- sqldf("select subearn.*,smlpassiveproxy2.qend,
smlpassiveproxy2.passivesum, smlpassiveproxy2.passivepctl
from subearn left outer join smlpassiveproxy2
on subearn.permno = smlpassiveproxy2.permno
and subearn.rdq > smlpassiveproxy2.qend and subearn.rdq-60<smlpassiveproxy2.qend")
tempdatawactive <- sqldf("select subearn.*,smlactiveproxy2.qend, smlactiveproxy2.activesum,
smlactiveproxy2.activepctl
from subearn left outer join smlactiveproxy2
on subearn.permno = smlactiveproxy2.permno
and subearn.rdq > smlactiveproxy2.qend and subearn.rdq-60<smlactiveproxy2.qend")
#now begins all active work. Repeat from here down when constructing passive
#create calendar quarters
tempdatawactive$cqtr<-as.yearqtr(tempdatawactive$rdq, format="%Y-%m-%d")
#sort into deciles
tempdatawactive2<-
tempdatawactive %>%
group_by(cqtr) %>%
mutate(pctl = ntile(sue, 10))
tempdatawactive2 <- subset(tempdatawactive2, pctl ==1 | pctl == 10)
tempdatawactive2$fordt <- (tempdatawactive2$rdq+90)
```

```
#cleanup
tempdatawactive3 <-
tempdatawactive2[,c("permno","rdq","qend","activesum","activepctl","pctl","fordt")]
#merge this with subreturns
Activeandsubretmerge <- sqldf("select
tempdatawactive3.permno,tempdatawactive3.rdq,tempdatawactive3.pctl,tempdatawactive3.qend,
tempdatawactive3.activesum,tempdatawactive3.activepctl,subret.date,subret.dt,subret.ret
from tempdatawactive3 left outer join subret
on tempdatawactive3.permno = subret.permno
and tempdatawactive3.rdq < subret.dt and subret.dt<tempdatawactive3.fordt")
#get rid of nul values in DATE, dt, RET columns
activeandsubretmerge2 <- Activeandsubretmerge[complete.cases(Activeandsubretmerge[,9]),]
activeandsubretmerge2$dif<-as.numeric(activeandsubretmerge2$DATE-
activeandsubretmerge2$rdq)
#remove all null value cells, gets rid of anything not matching activesumactivepctl and qend
#could have done this earlier
activeandsubretmerge3 <- na.omit(activeandsubretmerge2)
#create data with just high active ownership
highactive <- subset(activeandsubretmerge3, activepctl ==10)
#repeat for low active ownership
lowactive <- subset(activeandsubretmerge3, activepctl ==1)
#aggregatehighthen low, create mean returns by event date and decile
agghighactive<-sqldf("select dif,pctl, activepctl , avg(ret) as mret from highactive group by
dif,pctl")
agglowactive<-sqldf("select dif,pctl, activepctl , avg(ret) as mret from lowactive group by
dif,pctl")
# cumulative returns high active
subport_L_highactive<-subset(agghighactive,agghighactive$pctl==1)
subport_H_highactive<-subset(agghighactive,agghighactive$pctl==10)
subport_L_highactive$pl1<-1+subport_L_highactive$mret
subport_H_highactive$pl1<-1+subport_H_highactive$mret
subport_L_highactive$cumretpl1<-cumprod(subport_L_highactive$pl1)
subport_L_highactive$cumret_l<-subport_L_highactive$cumretpl1-1
subport_H_highactive$cumretpl1<-cumprod(subport_H_highactive$pl1)
subport_H_highactive$cumret_h <-subport_H_highactive$cumretpl1-1
togohighactive <- cbind(subport_L_highactive[,c("dif","cumret_l")], subport_H_highactive
[,c("cumret_h")])
colnames(togohighactive)<-c("EventDate","Low","High")
 #graph high active
plot(togohighactive $EventDate,togohighactive$Low,type="l",col="red",ylim=c(-
0.1,0.3),xlab="Event Date",ylab="Cumulative Returns")
lines(togohighactive $EventDate,togohighactive$High,type="l",col="green")
# cumulative returns low active
subport_L_lowactive<-subset(agglowactive,agglowactive$pctl==1)
subport_H_lowactive<-subset(agglowactive,agglowactive$pctl==10)
subport_L_lowactive$pl1<-1+subport_L_lowactive$mret
```

```
subport_H_lowactive$pl1<-1+subport_H_lowactive$mret
subport_L_lowactive$cumretpl1<-cumprod(subport_L_lowactive$pl1)
subport_L_lowactive$cumret_l<-subport_L_lowactive$cumretpl1-1
subport_H_lowactive$cumretpl1<-cumprod(subport_H_lowactive$pl1)
subport_H_lowactive$cumret_h <-subport_H_lowactive$cumretpl1-1
togolowactive <- cbind(subport_L_lowactive[,c("dif","cumret_l")], subport_H_lowactive
[,c("cumret_h")])
colnames(togolowactive)<-c("EventDate","Low","High")
 #graph low active
plot(togolowactive $EventDate,togolowactive$Low,type="l",col="red",ylim=c(-
0.1,0.9),xlab="Event Date",ylab="Cumulative Returns")
lines(togolowactive $EventDate,togolowactive$High,type="l",col="green")
#now begins the repetition FOR PASSIVE
#create calendar quarters
tempdatawpassive$cqtr<-as.yearqtr(tempdatawpassive$rdq, format="%Y-%m-%d")
#sort into deciles
tempdatawpassive2<-
tempdatawpassive %>%
group_by(cqtr) %>%
mutate(pctl = ntile(sue, 10))
tempdatawpassive2 <- subset(tempdatawpassive2, pctl ==1 | pctl == 10)
tempdatawpassive2$fordt <- (tempdatawpassive2$rdq+90)
#cleanup
tempdatawpassive3 <-
tempdatawpassive2[,c("permno","rdq","qend","passivesum","passivepctl","pctl","fordt")]
#merge this with subreturns
Passiveandsubretmerge <- sqldf("select
tempdatawpassive3.permno,tempdatawpassive3.rdq,tempdatawpassive3.pctl,tempdatawpassive3.
qend,tempdatawpassive3.passivesum,tempdatawpassive3.passivepctl,subret.date,subret.dt,subret.
ret
from tempdatawpassive3 left outer join subret
on tempdatawpassive3.permno = subret.permno
and tempdatawpassive3.rdq < subret.dt and subret.dt<tempdatawpassive3.fordt")
#get rid of nul values in DATE, dt, RET columns
passiveandsubretmerge2 <-
Passiveandsubretmerge[complete.cases(Passiveandsubretmerge[,9]),]
passiveandsubretmerge2$dif<-as.numeric(passiveandsubretmerge2$DATE-
passiveandsubretmerge2$rdq)
#remove all null value cells, gets rid of anything not matching passivesumpassivepctl and qend
#could have done this earlier
passiveandsubretmerge3 <- na.omit(passiveandsubretmerge2)
#create data with just high passive ownership
highpassive <- subset(passiveandsubretmerge3, passivepctl ==10)
#repeat for low passive ownership
lowpassive <- subset(passiveandsubretmerge3, passivepctl ==1)
#aggregatehighthen low, create mean returns by event date and decile
```

```
agghighpassive<-sqldf("select dif,pctl, passivepctl , avg(ret) as mret from highpassive group by
dif,pctl")

agglowpassive<-sqldf("select dif,pctl, passivepctl , avg(ret) as mret from lowpassive group by
dif,pctl")
# cumulative returns high passive
subport_L_highpassive<-subset(agghighpassive,agghighpassive$pctl==1)
subport_H_highpassive<-subset(agghighpassive,agghighpassive$pctl==10)
subport_L_highpassive$pl1<-1+subport_L_highpassive$mret
subport_H_highpassive$pl1<-1+subport_H_highpassive$mret
subport_L_highpassive$cumretpl1<-cumprod(subport_L_highpassive$pl1)
subport_L_highpassive$cumret_l<-subport_L_highpassive$cumretpl1-1
subport_H_highpassive$cumretpl1<-cumprod(subport_H_highpassive$pl1)
subport_H_highpassive$cumret_h <-subport_H_highpassive$cumretpl1-1
togohighpassive <- cbind(subport_L_highpassive[,c("dif","cumret_l")], subport_H_highpassive
[,c("cumret_h")])
colnames(togohighpassive)<-c("EventDate","Low","High")
 #graph high passive
plot(togohighpassive $EventDate,togohighpassive$Low,type="l",col="red",ylim=c(-
0.5,0.2),xlab="Event Date",ylab="Cumulative Returns")
lines(togohighpassive $EventDate,togohighpassive$High,type="l",col="green")
# cumulative returns low passive
subport_L_lowpassive<-subset(agglowpassive,agglowpassive$pctl==1)
subport_H_lowpassive<-subset(agglowpassive,agglowpassive$pctl==10)
subport_L_lowpassive$pl1<-1+subport_L_lowpassive$mret
subport_H_lowpassive$pl1<-1+subport_H_lowpassive$mret
subport_L_lowpassive$cumretpl1<-cumprod(subport_L_lowpassive$pl1)
subport_L_lowpassive$cumret_l<-subport_L_lowpassive$cumretpl1-1
subport_H_lowpassive$cumretpl1<-cumprod(subport_H_lowpassive$pl1)
subport_H_lowpassive$cumret_h <-subport_H_lowpassive$cumretpl1-1
togolowpassive <- cbind(subport_L_lowpassive[,c("dif","cumret_l")], subport_H_lowpassive
[,c("cumret_h")])
colnames(togolowpassive)<-c("EventDate","Low","High")
 #graph low passive
plot(togolowpassive $EventDate,togolowpassive$Low,type="l",col="red",ylim=c(-
0.1,0.3),xlab="Event Date",ylab="Cumulative Returns")
lines(togolowpassive $EventDate,togolowpassive$High,type="l",col="green")
own <- (read_sas("D:/Thesis/own.sas7bdat"))
#create a single proxy for Index/PassiveOwned companies
#size of fund determined to be irrelevant, many holdings chosen as it is a common passive
strategy, low turnover
QuintPassiveProxy <- subset(own, select = c(permno,qend,smmalo,memalo,himalo))
# Create a proxy for actively owned firms.
QuintActiveProxy <- subset(own, select = c(permno,qend,smfehi,smmahi,mefehi,memahi,hifehi,
himahi))
rm(own)
```

```
#sum active attributes
QuintActiveProxy$sum <- as.numeric(QuintActiveProxy$smfehi + QuintActiveProxy$smmahi
+ QuintActiveProxy$mefehi + QuintActiveProxy$memahi + QuintActiveProxy$hifehi +
QuintActiveProxy$himahi)
#sort into quintiles
QuintActiveProxy2<-
   ActiveProxy %>%
   mutate(sumpctl = ntile(sum, 5))
#cleaning up and renaming
rm(QuintActiveProxy)
QuintActiveProxy <- subset(QuintActiveProxy2)
rm(QuintActiveProxy2)
#keep only the bottom and the top quintiles
quintsmlactiveproxy <- subset(QuintActiveProxy, sumpctl ==1 | sumpctl == 5)
#repeat for passiveowned
#get sum
QuintPassiveProxy$sum <- as.numeric(QuintPassiveProxy$smmalo +
QuintPassiveProxy$memalo + QuintPassiveProxy$himalo)
#get quintiles
quintpassiveproxy2<-
      QuintPassiveProxy %>%
      mutate(sumpctl = ntile(sum, 5))
#keep 1st and 5th
quintsmlpassiveproxy <- subset(quintpassiveproxy2, sumpctl ==1 | sumpctl == 5)
#cleanup
rm(QuintPassiveProxy)
#cleanup
quintsmlpassiveproxy2 <- quintsmlpassiveproxy[,c("permno","qend","sum","sumpctl")]
quintsmlactiveproxy2 <- quintsmlactiveproxy[,c("permno","qend","sum","sumpctl")]
#specify column names for merging
names(quintsmlactiveproxy2)[names(quintsmlactiveproxy2)=="sum"] <- "activesum"
names(quintsmlactiveproxy2)[names(quintsmlactiveproxy2)=="sumpctl"] <- "activepctl"
names(quintsmlpassiveproxy2)[names(quintsmlpassiveproxy2)=="sum"] <- "passivesum"
names(quintsmlpassiveproxy2)[names(quintsmlpassiveproxy2)=="sumpctl"] <- "passivepctl"
quinttempdatawpassive <- sqldf("select subearn.*,quintsmlpassiveproxy2.qend,
quintsmlpassiveproxy2.passivesum, quintsmlpassiveproxy2.passivepctl
from subearn left outer join quintsmlpassiveproxy2
on subearn.permno = quintsmlpassiveproxy2.permno
and subearn.rdq > quintsmlpassiveproxy2.qend and subearn.rdq-
60<quintsmlpassiveproxy2.qend")
quinttempdatawpassiveandactive <- sqldf("select
quinttempdatawpassive.*,quintsmlactiveproxy2.qend, quintsmlactiveproxy2.activesum,
quintsmlactiveproxy2.activepctl
from quinttempdatawpassive left outer join quintsmlactiveproxy2
on quinttempdatawpassive.permno = quintsmlactiveproxy2.permno
```

```
and quinttempdatawpassive.rdq > quintsmlactiveproxy2.qend and quinttempdatawpassive.rdq-60<quintsmlactiveproxy2.qend")
quinttempdatawpassiveandactive[2] <- NULL
quinttempdatawpassiveandactive2 <-na.omit(quinttempdatawpassiveandactive)
quinttempdatawpassiveandactive2[8] <- NULL
mergedqtemp<-
quinttempdatawpassiveandactive2 %>%
group_by(cqtr) %>%
mutate(pctl = ntile(sue, 10))
mergedqtemp <- subset(mergedqtemp, pctl ==1 | pctl == 10)
mergedqtemp$fordt <- (mergedqtemp$rdq+90)
#cleanup
mergedqtemp2 <- mergedqtemp
[,c("permno","rdq","qend","passivepctl","activepctl","pctl","fordt")]
#merge this with subreturns
mergedqtemp3 <- sqldf("select
mergedqtemp2.permno,mergedqtemp2.rdq,mergedqtemp2.qend,mergedqtemp2.passivepctl,mergedqtemp2.activepctl,mergedqtemp2.pctl,subret.date,subret.dt,subret.ret
from mergedqtemp2 left outer join subret
on mergedqtemp2.permno = subret.permno
and mergedqtemp2.rdq < subret.dt and subret.dt<mergedqtemp2.fordt")
mergedqtemp3$dif<-as.numeric(mergedqtemp3$DATE- mergedqtemp3$rdq)
mergedqtemp4 <- na.omit(mergedqtemp3)
Active1Passive1 <- subset(mergedqtemp4, activepctl ==1 & passivepctl == 1)
Active5Passive5 <- subset(mergedqtemp4, activepctl ==5 & passivepctl == 5)
Active1Passive5 <- subset(mergedqtemp4, activepctl ==1 & passivepctl == 5)
Active5Passive1 <- subset(mergedqtemp4, activepctl ==5 & passivepctl == 1)
#Active1Passive1
aggactive1passive1<-sqldf("select dif,pctl, activepctl , avg(ret) as mret from Active1Passive1
group by dif,pctl")
subport_L_active1passive1<-subset(aggactive1passive1,aggactive1passive1$pctl==1)
subport_H_active1passive1<-subset(aggactive1passive1,aggactive1passive1$pctl==10)
subport_L_active1passive1$pl1<-1+subport_L_active1passive1$mret
subport_H_active1passive1$pl1<-1+subport_H_active1passive1$mret
subport_L_active1passive1$cumretpl1<-cumprod(subport_L_active1passive1$pl1)
subport_L_active1passive1$cumret_l<-subport_L_active1passive1$cumretpl1-1
subport_H_active1passive1$cumretpl1<-cumprod(subport_H_active1passive1$pl1)
subport_H_active1passive1$cumret_h <-subport_H_active1passive1$cumretpl1-1
togoactive1passive1 <- cbind(subport_L_active1passive1[,c("dif","cumret_l")],
subport_H_active1passive1[,c("cumret_h")])
colnames(togoactive1passive1)<-c("EventDate","Low","High")
 #graph high active
plot(togoactive1passive1 $EventDate,togoactive1passive1$Low,type="l",col="red",ylim=c(-0.1,0.3),xlab="Event Date",ylab="Cumulative Returns")
lines(togoactive1passive1 $EventDate,togoactive1passive1$High,type="l",col="green")
#Active5Passive5
```

```
aggactive5passive5<-sqldf("select dif,pctl, activepctl , avg(ret) as mret from Active5Passive5
group by dif,pctl")
subport_L_active5passive5<-subset(aggactive5passive5,aggactive5passive5$pctl==1)
subport_H_active5passive5<-subset(aggactive5passive5,aggactive5passive5$pctl==10)
subport_L_active5passive5$pl1<-1+subport_L_active5passive5$mret
subport_H_active5passive5$pl1<-1+subport_H_active5passive5$mret
subport_L_active5passive5$cumretpl1<-cumprod(subport_L_active5passive5$pl1)
subport_L_active5passive5$cumret_l<-subport_L_active5passive5$cumretpl1-1
subport_H_active5passive5$cumretpl1<-cumprod(subport_H_active5passive5$pl1)
subport_H_active5passive5$cumret_h <-subport_H_active5passive5$cumretpl1-1
togoactive5passive5 <- cbind(subport_L_active5passive5[,c("dif","cumret_l")],
subport_H_active5passive5[,c("cumret_h")])
colnames(togoactive5passive5)<-c("EventDate","Low","High")
 #graph high active
plot(togoactive5passive5 $EventDate,togoactive5passive5$Low,type="l",col="red",ylim=c(-
0.1,0.3),xlab="Event Date",ylab="Cumulative Returns")
lines(togoactive5passive5 $EventDate,togoactive5passive5$High,type="l",col="green")
#Active1Passive5
aggactive1passive5<-sqldf("select dif,pctl, activepctl , avg(ret) as mret from Active1Passive5
group by dif,pctl")
subport_L_active1passive5<-subset(aggactive1passive5,aggactive1passive5$pctl==1)
subport_H_active1passive5<-subset(aggactive1passive5,aggactive1passive5$pctl==10)
subport_L_active1passive5$pl1<-1+subport_L_active1passive5$mret
subport_H_active1passive5$pl1<-1+subport_H_active1passive5$mret
subport_L_active1passive5$cumretpl1<-cumprod(subport_L_active1passive5$pl1)
subport_L_active1passive5$cumret_l<-subport_L_active1passive5$cumretpl1-1
subport_H_active1passive5$cumretpl1<-cumprod(subport_H_active1passive5$pl1)
subport_H_active1passive5$cumret_h <-subport_H_active1passive5$cumretpl1-1
togoactive1passive5 <- cbind(subport_L_active1passive5[,c("dif","cumret_l")],
subport_H_active1passive5[,c("cumret_h")])
colnames(togoactive1passive5)<-c("EventDate","Low","High")
 #graph high active
plot(togoactive1passive5 $EventDate,togoactive1passive5$Low,type="l",col="red",ylim=c(-
0.1,0.3),xlab="Event Date",ylab="Cumulative Returns")
lines(togoactive1passive5 $EventDate,togoactive1passive5$High,type="l",col="green")
#Active5Passive1
aggactive5passive1<-sqldf("select dif,pctl, activepctl , avg(ret) as mret from Active5Passive1
group by dif,pctl")
subport_L_active5passive1<-subset(aggactive5passive1,aggactive5passive1$pctl==1)
subport_H_active5passive1<-subset(aggactive5passive1,aggactive5passive1$pctl==10)
subport_L_active5passive1$pl1<-1+subport_L_active5passive1$mret
subport_H_active5passive1$pl1<-1+subport_H_active5passive1$mret
subport_L_active5passive1$cumretpl1<-cumprod(subport_L_active5passive1$pl1)
subport_L_active5passive1$cumret_l<-subport_L_active5passive1$cumretpl1-1
subport_H_active5passive1$cumretpl1<-cumprod(subport_H_active5passive1$pl1)
subport_H_active5passive1$cumret_h <-subport_H_active5passive1$cumretpl1-1
```

```
togoactive5passive1 <- cbind(subport_L_active5passive1[,c("dif","cumret_l")],
subport_H_active5passive1[,c("cumret_h")])
colnames(togoactive5passive1)<-c("EventDate","Low","High")
 #graph high active
plot(togoactive5passive1 $EventDate,togoactive5passive1$Low,type="l",col="red",ylim=c(-
0.1,0.5),xlab="Event Date",ylab="Cumulative Returns")
lines(togoactive5passive1 $EventDate,togoactive5passive1$High,type="l",col="green")
```

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