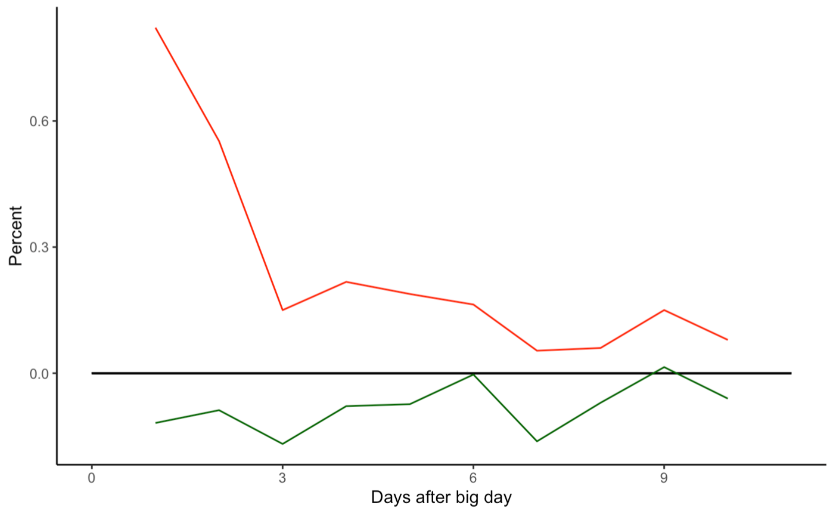

Senior Thesis in Economics

A Reappraisal of Mean Reversion in Dow Stocks

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Abstract

A compelling body of evidence exists to substantiate Keynes' observation that "day-to-day fluctuations in the profits of existing investments, which are obviously of an ephemeral and non significant character, tend to have an altogether excessive, and even absurd, influence on the [stock] market."[9] The current body of literature focuses primarily on long-term price reversion. This paper looks to expand on Smith's [13] analysis of short-term price reversion with a fresh set of CRSP stock return data.

Contents

Chapter 1

Introduction

In 2008 Warren Buffet famously said to, "Be fearful when others are greedy, and be greedy when others are fearful." It is nearly impossible to predict what will happen tomorrow, the next day, a week from now, a month from now, or even five years from now, but in the long run, investing in the market is a very profitable decision. Moreover, daily fluctuations in the stock market are nearly impossible to predict, but the current body of literature contains significant evidence of long term mean reversion. In this paper we extend analysis of mean reversion to short term data.

Regression to the mean is present in all aspects of life, and can be defined as, "the phenomenon that arises if a random variable is extreme on its first measurement but closer to the mean or average on its second measurement"[12]. Regression to the mean can be seen in sports, test taking, medical tests, annual earnings, and much more. Consider what many sports analysts call the "Madden Football Curse." People believe that when a player is on the cover of the video game, Madden NFL, the next year they will perform badly because, "they are cursed." In reality, in order to make the cover, a player needs to have an exceptional season, and therefore their next season will likely not be as good, because they were lucky having such an exceptional season. The following year they will most likely not have this same luck and regress to their mean ability. The curse of course is not real, and the players just had an unbelievable season, and were less fortunate the following year. Using regression to the mean in the context of overreactions, this paper explores its existence in daily returns after a negative and positive big day. Revisiting Warren Buffets quote, investors are irrational, and often overreact to both good and bad news. This study examines Dow Jones Industrial Average daily stock returns from October 1st, 1928, when the Dow was switched from 20 to 30 stocks, until the end of the 2019.

Chapter 2

Previous Work

2.1 Regression

Considered within the framework of the efficient market hypothesis, a large changes in a security's price is by definition, unexpected. Thus, a large change in the price of a stock reflects the presence of new information. In 1982, Kahneman and Teversky found that people tend to overweight new information [6]. Such overweighting often leads to overreactions and an associated mean reversion. This regression to the mean is often unanticipated.

For example, tests are often an imperfect measure of student ability. After a high test score, a student is likely to do worse on the next test because they scored above their ability on the first[8] [10]. On average they will regress to the mean, which reflects their true ability. The same is true for medical tests. [2] show that when using imperfect tests a patient's condition can be overstated by an extreme measurement. This causes recovery to be miss attributed to effective treatment.

Another example is the announcers curse with sports commentators. Consider a setting where a player has made 80 of his last 80 putts inside 10 feet, and he is about to take his 81^{st} putt inside 10 feet. The announcer usually comments, he's 80/80 in has last 80 putts, he then misses the putt, and everyone says "The announcer cursed him, he would have made it if he didn't say anything!" In reality, the golfer is regressing to the mean. He has gotten lucky to make 80 of his last 80 putts, and is not actually that good. Therefore, the announcer didn't curse him, he simply did not get as lucky.

Such overstatements are also present in earnings analysis. In their 2004 paper, [7] found that extreme forecasts from analysts are often exceedingly pessimistic or optimistic. Furthermore [5] found that successive earnings regress to their mean. As overreactions are identified, the initial price dip or jump is reversed.

2.2 Overreaction

According to the random walk hypothesis, stock prices are random and cannot be predicted. Nonetheless, in 1985 De bondt and Thaler concluded that in violation of Bayes' rule, investors tend to overreact to "unexpected or dramatic news events" [3]. Using CRSP data, they discovered that monthly return data is consistent with an overreaction hypothesis.

Moreover, [4] and [11] found autocorrelation in stock prices over long term horizons. This autocorrelation is weak for daily and weekly holding periods, but Fama and French find that mean reversion accounts for a large amount of predictable price variation for 3-5 year holding periods. Ultimately, there exists statistical evidence for discrepancies between prices and fundamental methods.

The current study examines daily returns on stocks in the Dow Jones Industrial Average. Dow stocks were chosen because of their liquidity, small bid-ask spreads and to ensure that stocks are followed by institutional investors [13]. We want to ensure mean reversion is not the result of amateur investors. Daily returns are used to mitigate concerns regarding risk premia as daily risk premiums are roughly zero.

Chapter 3

Data

The present study includes data from the Dow Jones Industrial Average from October 1st, 1928 (when the Dow expanded from 20 stock to 30 stocks) until the end of 2019. The daily returns from 1928-2019 were gathered from the Center for Research in Security Prices Database (CRSP). Because CRSP did not have data for National Cash Register, data were aggregated from "Real Dogs of the Dow."[1].

A data set of returns contains all 83 companies that have been in the Dow. A relative average was calculated as follows: for each company, calculate the average return of the other 29 stocks on a given day and subtract the return of the company being observed from the average of the other 29 stocks. Let the relative return for Company i be R_i. Let the other 29 companies be indexed by $i+1, i+2, ..., i+30$. The average return of the other 29 companies is $\bar{R}_{i+1:i+29}$: $\frac{\sum_{i=i+1}^{i+30} R_{i+1}}{29}$. Now take the average return of the other 29 companies, and subtract it from company i and obtain $\bar{R}_{i+1:i+29} - R_i$. This is the relative average of company i.

It is important to calculate a relative average to isolate excess return from an individual company from the market as a whole having a "really good" or "really bad" day. In this paper a "really good" day is defined as a daily return in excess of 5%, and a "really bad" is defined as a loss greater than 5%. This is the 99^{th} percentile of adjusted daily returns, similar to [13]. In Table 3.1, we provide descriptive statistics regarding our returns.

Table 3.1: Descriptive statistics for adjusted daily returns.

Statistic	**Value**
Mean	0.0002999
Standard Deviation	0.0186214
Skewness	0.2378170
Kurtosis	27.7342700

Table 3.1 includes the mean, standard deviation, skewness, and kurtosis of the distribution of daily returns. The mean is centered very close to 0, with a standard deviation of roughly 0.01. The skewness represents the 3rd moment of the distribution divided by the variance cubed while kurtosis is defined as the 4th moment of a distribution divided by the variance raised to the fourth power. Moreover, skewness is a measure of symmetry, or more precisely, the lack of symmetry. Figure 4.5 displays this lack of symmetry, and is further evidenced by a skewness value of nearly 0. Kurtosis, on the other hand, describes the height and tails of the distribution. Data sets with high Kurtosis tend to have heavy tails or outliers, which is true for this data set and motivates the results section.

Given a normal distribution with mean 0 and a standard deviation of 0.01488, we calculated the expected number of observations greater than 5% to be 267. In this case the number is $3,342$. Similarly, the expected number of observations greater than 10% are 0.0000623, but this data set yields 378 days. Table 3.2 displays these results.

Table 3.2 suggests that our distribution contains fat tails, indicating the stock returns are not normally distributed. In other words, given a return

Table 3.2: Actual number of big days and expected number with normal distribution.

Daily return (%)	**Expected number**	**Actual number**
>10	0.0000623	378
>5	267.9458000	3342
<-5	267.9458000	2652
<-10	0.0000623	288

of 0, and a standard deviation of 0.01488, there should be 0 days where a stock's return is greater than 10% or less than 10%, but this occurred 666 times. This suggests that stock returns are influenced by other factors, such as the emotions of investors, and stock returns are not independent of each other. In other words, daily returns are not distributed normally because they fail to satisfy the critical assumption of independence.

Chapter 4

Results

4.1 Tables

Table 4.1 exhibits the proportion of positive returns after a negative and positive big day. After a positive big day, the proportion of positive returns is smaller in comparison to that of a negative big day. This indicates that after a positive big day returns are less likely to be positive, suggesting mean reversion. Secondly, after a negative big day, stock returns are more likely to be positive as evidenced by the third column. After an individual stock has a return greater than 10%, 42% of stocks average negative returns. The 4^{th} column shows the results of a chi-squared test with a null hypothesis that assumes stocks are equally likely to have a positive or negative return after a positive big day and a negative big day. The minuscule p-values suggest statistically significance evidence that after a positive big day, companies are more likely to have a negative return, and vice versa.

Table 4.2 shows average percentage adjusted daily returns after a positive and negative big day. There is significant evidence that on average, the day after a big positive day, stocks are more likely to have a negative adjusted return. We see a symmetric results for negative big days. Returns

Table 4.1: Percentage of stocks with positive adjusted returns the day after a big day

Cutoff (%)	**After + Big Day**	**After - Big Day**	**p-value**
5	0.435443738	0.511522346	0.000021
6	0.432999523	0.507566204	0.000338
7	0.420516836	0.50377562	0.000423
8	0.409638554	0.54180602	0.067474
9	0.425182482	0.542997543	0.327116
10	0.416243655	0.576666667	0.851264

are more likely to be positive after a negative big day. Moreover, Table 4.2 shows the results of a difference in means test, with with distributions of possibly unequal variance. The small p-values suggest we should reject the null hypothesis, a difference in means of 0. The p-values exhibit a significant difference in mean returns after a positive big day and a negative big day. Again, these results suggest mean reversion.

Table 4.2: Average percentage adjusted daily return on stocks the day after a big day

Cutoff (%)	**After + Big Day**	**After - Big Day**	**p-value**
5	-0.001183166	0.008219263	3.448950×10^{-14}
6	-0.00159944	0.01001222	5.305268×10^{-10}
7	-0.002524473	0.01281827	1.421954×10^{-08}
8	-0.005052967	0.019158814	$1\ .328036 \times 10^{-11}$
9	-0.005589434	0.022671184	9.884375×10^{-10}
10	-0.010011759	0.029484243	1.624419×10^{-12}

Table 4.3 and Figure 4.2 display average adjusted daily returns and aver-

Table 4.3: Percentage adjusted daily returns on stocks after 5% big day

	Average adjusted daily return			**Average adjusted cumulative return**		
day	+ Big Day	- Big Day	p-value	+ Big Day	- Big Day	p-value
1	-0.1183166	0.8219263	$3.448950\text{x}10^{-14}$	-0.1183166	0.8219263	0.000000
2	-0.0879602	0.5521903	$4.187509\text{x}10^{-8}$	-0.2062768	1.3741166	0.000000
3	-0.1682084	0.1501177	0.003889	-0.3744852	1.5242343	0.000000
4	-0.0783441	0.2172801	0.007095	-0.4528293	1.7415144	0.000000
5	-0.0736816	0.1884477	0.014380	-0.5265109	1.9299621	0.000000
6	-0.0031993	0.163374	0.101535	-0.5297103	2.0933361	0.000000
7	-0.1620334	0.0535814	0.034755	-0.6917436	2.1469175	0.000000
8	-0.0702467	0.0600453	0.199482	-0.7619903	2.2069627	0.000000
9	0.014493	0.1501715	0.174719	-0.7474973	2.3571342	0.000000
10	-0.0602982	0.0793229	0.152038	-0.8077955	2.4364571	0.000000

age adjusted cumulative returns for 10 days after a 5% percent big day and a 5% percent negative day. For all 10 days after a big positive day, a stock's average adjusted return slopes downward, while the opposite is observed after a 5% negative day. For all 10 days after a negative big day the sign associated with the average returns is positive. It is also important to note that the day after a big negative day the average return is almost positive one percent. This suggests a major overreaction from investors.

Table 4.3 displays the associated p-values for a difference in means test with a null hypothesis of 0. For the first 5 days after a big day, p-values are statistically significant at the 5% level while for cumulative returns, we observe statistical significance for all 10 days following a big day. We can therefore reject the null hypothesis. While this does not prove our alternative hypothesis, our sample size is quite large. Both the p-values and the signs on of the returns, show that a stock is considerably more likely to have a negative return after a big positive day, and a positive return after a big negative day.

4.2 Figures

In all figures, the red line depicts information after a negative big day while the green line depicts that of a positive big day.

Figure 4.1 exhibits average daily adjusted returns after a 5% big day. It is clear that adjusted returns shift towards their mean of roughly 0, after both positive and negative big days. After a positive big day, returns start negative and trend upwards, and the opposite is true after a negative big day, where returns starts positive and trend downwards.

Figure 4.1: Average daily adjusted return after a 5% big day

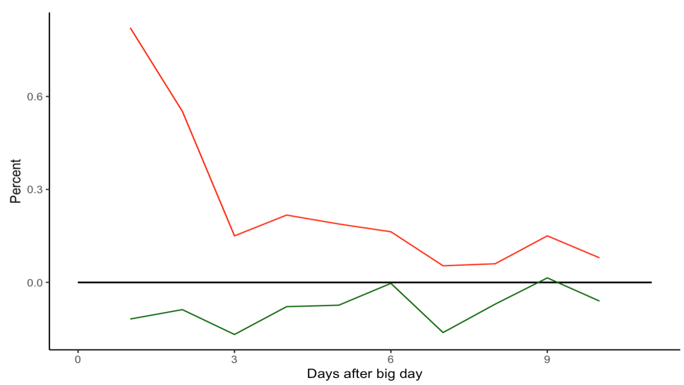


Figure 4.2: Cumulative average daily adjusted return after a 5% big day

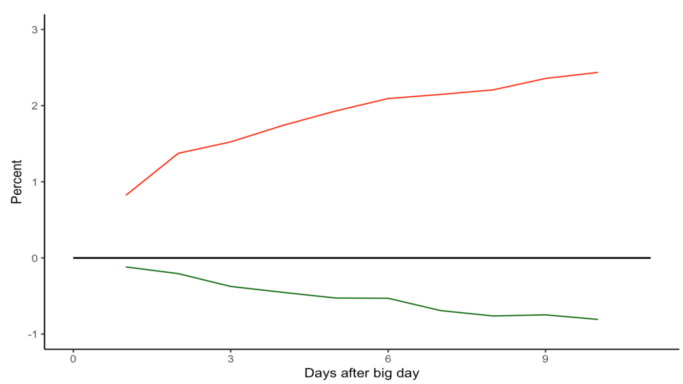


Figure 4.3 presents the standard deviation of daily returns for 10 days proceeding a big day, and 10 days following a big day. In this case, a big day is considered a gain in excess of 5% or a loss less than 5%. The standard deviations of average relative returns increase leading up to a big day and decrease after a big day. Standard deviations also appear to revert to their mean.

Figure 4.3: Standard deviation of daily adjusted returns before and after a 5% big day

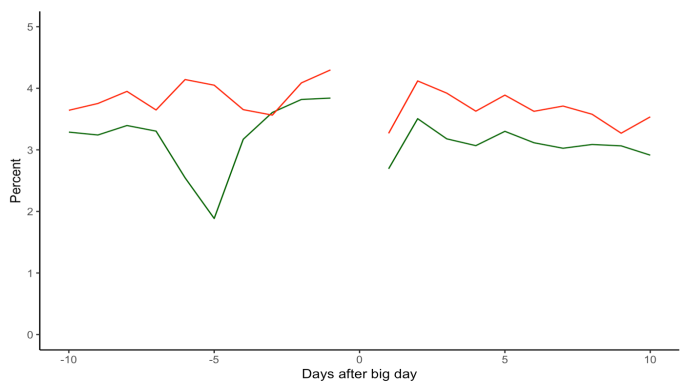


Figure 4.4: Kurtosis of daily adjusted returns before and after a 5% big day.

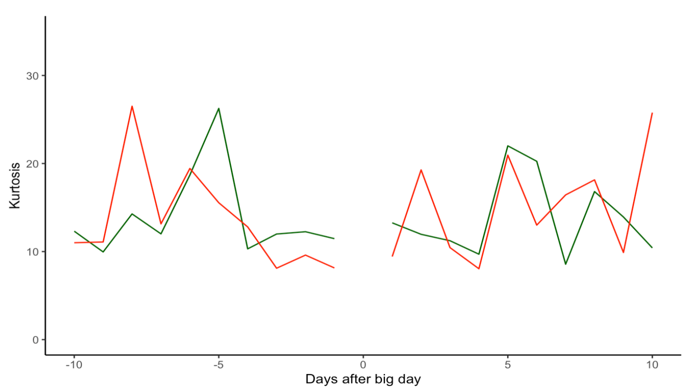
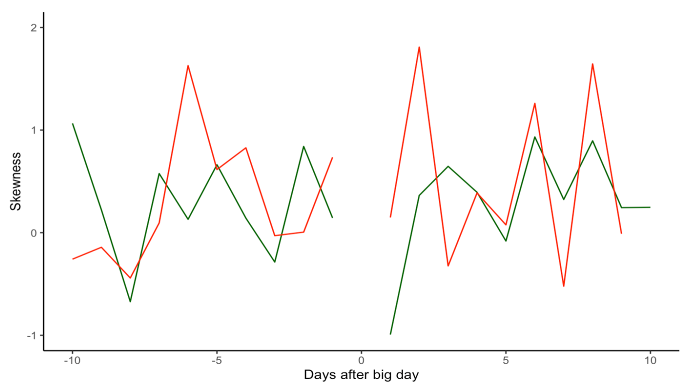


Figure 4.5: Skewness of daily adjusted returns before and after a 5% big day



Chapter 5

Conclusion

This paper adds to the growing body of evidence that investors tend to overreact. Because daily data was used, we ensure that our results are not the consequence of amateur investors; even seasoned investors and analysts underestimate the effects of mean reversion.

We find significant evidence of overreaction in the data. By analysing daily data to alleviate concerns regarding risk premia, we find strong evidence that large positive and negative returns are followed by considerable, statistically significant price reversals.

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