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U.S. Stock Returns over the FOMC Cycle

An exploration and empirical analysis of whether previously discovered patterns have persisted

Master's thesis in Financial Economics
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Preface

This Master thesis concludes my MSc in Financial Economics at the Norwegian University of Science and Technology – two wonderful years with interesting, albeit challenging, subjects and great friends. Thank you to my supervisor Professor Knut Anton Mork for valuable guidance and good advice. I would also like to thank my parents Kolbjørn and Eva Grete, and my fiancé Alexander, for their love and support.

Kari Elise Storengen Skaar

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Abstract

An intriguing pattern has been observed in stock returns over the FOMC cycle, i.e. the time periods between the scheduled meetings of the Federal Open Market Committee (FOMC). The even weeks over the FOMC cycle observe positive excess returns, whilst the odd weeks exhibit excess returns that are negative or close to zero. This pattern has been present since 1994, when the Fed started making public announcements of decisions immediately after scheduled FOMC meetings. Cieslak et al. have investigated this pattern over several years, and their most recent article on the topic was published in February 2018, containing data and statistical analyses on the sample 1994 – 2016. This master thesis has its focus on U.S. stock returns, replicating Cieslak et al.'s analyses on their 1994 – 2013 and 1994 – 2016 samples, before applying the same procedures to my more recent sample 1994 – April 2018. Analyses find that the biweekly stock return pattern does indeed persist, suggesting that it is still financially rewarding to hold stocks in even weeks over the FOMC cycle.

Sammendrag

Det er funnet et interessant mønster i aksjeavkastningene i FOMC-syklusen, altså periodene mellom de planlagte møtene til Federal Open Market Committee (FOMC). Partallsukene i FOMC-syklusen har meravkastninger som er positive, mens oddetallsukene har meravkastninger som er negative eller tilnærmet lik null. Dette mønsteret har vært til stede siden 1994, da sentralbanken i USA begynte å offentliggjøre beslutninger umiddelbart etter de planlagte FOMC-møtene. Cieslak et al. har undersøkt dette mønsteret i meravkastningene over flere år, og deres siste artikkel om emnet ble publisert i februar 2018, med data- og statistikkanalyser fra utvalget 1994 – 2016. Denne masteroppgaven har sitt fokus på amerikanske aksjeavkastninger, hvor jeg først replikerer Cieslak et al. sine analyser fra utvalgene 1994 – 2013 og 1994 – 2016, og deretter anvender de samme metodene på mitt nyere utvalg 1994 – April 2018. Analysene bekrefter at ukemønsteret i meravkastningene fortsatt er til stede i markedet, og at det fortsatt er lukrativt å investere i aksjer i partallsukene i FOMC-syklusen.

Contents

Introduction

This master thesis looks at the excess return on U.S. stocks[1] over Treasury bills over the FOMC cycle.[2] It is an exploration of the results from articles by Anna Cieslak (Duke University), Adair Morse and Annette Vissing-Jorgensen (University of California Berkeley).

The FOMC, the Federal Open Market Committee, is a committee within the Federal Reserve in the United States. It is the main decision-making body for monetary policy within the Federal Reserve, and has the responsibility for deciding upon open market operations and adjusting the federal funds rate.[3] The FOMC consists of twelve voting members, where the Chairman of the Federal Reserve, currently Jerome H. Powell, serves as the Chairman of the Board of Governors and the Chairman of the FOMC. The remaining six members of the Board of Governors and the president of the Federal Reserve Bank of New York are also permanent voting members of the FOMC. The final four voting members of the FOMC are presidents from the other eleven Reserve Banks in the U.S., chosen on a rotating basis where they serve one-year terms.[4] The rotating members of the FOMC do not have permanent voting rights, where the presidents of the Federal Reserve Banks of Chicago and Cleveland are voting members in alternate years and the other nine Reserve Bank presidents are voting members during one out of three years. If a regional Fed president with voting rights is not present at an FOMC meeting, another Reserve Bank president votes in their place as the regional Fed presidents that are currently not voting members of the FOMC are still present at the FOMC meetings. The voting rights in the absence of the president of the Federal Reserve Bank of New York at an FOMC meeting is somewhat different, as in this case their vote is transferred to the first vice president of the New York Federal Reserve.[5] All the regional Fed presidents get to voice their opinion during the FOMC meetings. Hence, despite the regional Fed presidents not all getting a vote during an FOMC meeting, they might still influence the opinions and decisions of the voting members. The non-voting regional Fed

[1] When referring to stocks in this thesis it will be U.S. stocks.
[2] Data in this thesis (and the data used by Cieslak et al.) comes from the Fama/French Daily Factors File from Kenneth R. French's website. He has the following description of the excess return used in his data: "the excess return on the market, value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t minus the one-month Treasury bill rate (from Ibbotson Associates)," where CRSP is the Center for Research in Security Prices.
[3] Board of Governors of the Federal Reserve System
[4] Board of Governors of the Federal Reserve System
[5] Federal Reserve Bank of New York

presidents can therefore be considered members of the FOMC along with the members who can vote, as they have the power to influence the decision making that takes place during the FOMC meetings.

In this thesis we are particularly interested in the period between the scheduled FOMC meetings, called the FOMC cycle. There are 8 scheduled FOMC meetings annually, and the FOMC cycle has an average length of around 6 weeks,[6] and can be as short as 4.6 weeks or as long as 8.4 weeks.[7] According to Cieslak et al. the equity premium has been earned entirely in the even numbered weeks of this FOMC cycle, whilst the excess returns in the odd numbered weeks are usually negative or close to zero. Whenever mentioning even or odd weeks in this thesis, it will always be in referral to the even or odd numbered weeks over the FOMC cycle, and not in relation to calendar time. The even numbered weeks here refer to weeks 0, 2, 4 and 6 over the FOMC cycle, whilst the odd numbered weeks refer to weeks –1, 1, 3, and 5. The FOMC meetings take place during week 0, where the FOMC announcement and scheduled meeting day is set as day number 0. Week 0 consists of days –1 to 3 as we think of each week as a 5-day week where weekends are excluded. The rest of the weeks follow from their relation to week 0, where week –1 is days –6 to –2 and week 1 is days 4 to 8 etc. We will get back to the specific numbering of the days of the weeks in the next section. It is important to emphasize that the FOMC cycle periods vary in length as the lengths of the time periods between the meetings vary. To find the length of each FOMC cycle, we mark the end of a cycle where the next cycle's week –1 begins. Consequently, the beginning of a cycle is on day –6, which is the first day of week –1.

This thesis replicates Cieslak et al.'s data and statistical analyses, before applying those methods to more current data to see whether the biweekly excess return pattern still persists. It is thought that this biweekly excess return pattern has something to do with decision making and information processing happening within the Fed, where meetings of the Board of Governors take place in the even numbered weeks. Informal information leaks from the Fed in addition to anticipation before FOMC announcements contribute to the effect. There is

[6] According to my own calculations of the average of all FOMC cycle periods, regardless of being in sample 1994 – 2013, sample 1994 – 2016 or sample 1994 – April 2018, the average length of an FOMC cycle is approximately 6 weeks.

[7] From calculating the number of working days between two consecutive scheduled FOMC meetings and dividing by 5-day weeks. When there are 2-day meetings we here refer to the final day which is the announcement day. Hence, we are looking at the period between two consecutive FOMC meeting announcement days.

for example a pattern of high stock returns during the 24-hour period before a scheduled FOMC announcement.[8] Cieslak et al.'s initial article on the topic was published in 2014, where they studied a sample period between 1994 – 2013. A reason for the sample period beginning in 1994 is that from this year the Fed has mainly changed the federal funds target at the scheduled FOMC meetings, and made announcements about the changes immediately after. Pre-1994 the federal funds target change happened more commonly between the FOMC meetings, and with discretion, i.e. without any public announcement.[9] Cieslak et al. have updated their article a few times since its first publication, with the last one being published in February 2018. They only published results up to 2016 in this latest version, leaving me to proceed with my initial plan of an analysis of a more recent sample period including data from all of 2017 and a few months into 2018. From my analysis the pattern does indeed persist in this newer sample, where I obtain excess returns that are positive in the even numbered weeks and negative or close to zero in the odd numbered weeks. Statistical tests strongly support the hypothesis that excess returns in the even numbered weeks are statistically significantly higher than the excess returns in odd numbered weeks.

The motivation for choosing this topic was the opportunity to work independently on a problem that required me to replicate someone else's data and statistical analyses and understand the process behind such a task. This has involved a lot of careful thinking about which assumptions to make for points that were not explained in the articles by Cieslak et al. After replicating Cieslak et al.'s analyses, I wanted to make my own contribution to the research in this field by applying the same methods to more recent data. To control for the robustness of my results, I performed tests on parameter stability which will be discussed in chapter 2 of this thesis. Beyond the theoretical scope, the results from this thesis have real world implications which will be discussed as well, such as the effect that governmental bodies can have on financial systems and how we can take advantage of the stock return pattern in the stock market.

The next chapters explain the process of replicating Cieslak et al.'s analysis and the assumptions made along the way. This includes a discussion of the procedures used in both

[8] Lucca, David O. and Moench, Emanuel., p. 2
[9] Cieslak et al. (February 12, 2018), pp. 10 – 11

the data and statistical analyses of the following samples: 1994 – 2013, 1994 – 2016[10] and 1994 – April 2018. The two former samples will be discussed first as they form the foundation of the work in this thesis, namely the replication of Cieslak et al.'s analysis. The most recent data, represented by the latter sample, will follow in a separate discussion answering the question raised in the master thesis title, about whether the excess return pattern has persisted. The results of parameter stability testing are discussed in chapter 2, in addition to the implications that these results have for the analyses of the most recent sample period 1994 – April 2018. Subsequently, there will be a discussion of adapting the knowledge gained from this topic to the stock market when investing, and whether there could be natural explanations to the curious patterns in the excess returns over the FOMC cycle in the form of for example governmental interference in financial markets.

[10] When referring to sample 1994 – 2013 or sample 1994 – 2016 I will be referring to my samples, and not to those of Cieslak et al. When referring to the analysis done by Cieslak et al. I will mention this explicitly.

1 Methodology: Replication of Cieslak et al.'s analysis

1.1 Sample 1994 – 2013

The following section includes a detailed description of how the replication of Cieslak et al.'s data and statistical analyses was carried out. This involves an explanation of the assumptions that have been deemed necessary to make throughout the thesis and the decisions made on how to best organize the data.

1.1.1 Data analysis procedure and results

When it comes to the data analysis, the most critical point is seeing whether the pattern we expect to see is present in the results, namely the positive excess returns in the even weeks and the negative or approximately zero excess returns in the odd weeks. Cieslak et al. have focused on looking at the weekly averages and annual averages of the various weeks over the FOMC cycle, whilst I have also chosen to include the daily averages. The calculations of the averages will be explained using the example of the excess returns that belong to week 0 of the FOMC cycle. The averages of week 0 are calculated using the sum of all the excess returns belonging to week 0 in the sample that we are studying. For the daily average of week 0, this sum is divided by the total number of excess returns, i.e. days, that fall in week 0 in that sample. When it comes to the weekly average of week 0 the sum is divided by the number of 5-day weeks that are in week 0 in the sample in question. The daily average can also be thought of as one fifth of the weekly average. When calculating the annual average of week 0, the sum of excess returns in week 0 is divided by the number of years in the sample period we are looking at. The same procedure for calculating averages applies to all weeks over the FOMC cycle. I have chosen to include these three averages in my thesis to illustrate the magnitude of the values in daily, weekly and annual terms, rather than just illustrating it using one of them such as the weekly average. This allows us to directly see the profitability of holding stocks in different weeks over the FOMC cycle when choosing to hold them over different lengths of time. The weekly average is the average that is of main interest when comparing my results to those of Cieslak et al. as this is the main average they use for the individual weeks over the FOMC cycle. When finding the averages of combined weeks over the FOMC cycle, Cieslak et al. tend to use the annual average. We will begin by looking at my results of the averages before comparing them to those of Cieslak et al.

Table 1. U.S. excess return averages by individual week, combined week or all weeks; illustrating the profitability of different trading strategies, sample 1994 – 2013

	Week –1	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 2,4,6	Week 0,2,4,6	Week –1,1,3,5	All Weeks
Daily Average	0.02	0.12	-0.05	0.07	-0.05	0.07	0.02	0.10	0.07	0.09	-0.02	0.03
Weekly Average	0.09	0.58	-0.27	0.37	-0.24	0.33	0.09	0.49	0.36	0.44	-0.11	0.14
Annual Average	0.71	4.67	-2.12	2.98	-1.89	2.15	0.28	0.39	5.53	10.20	-3.03	7.15

Note: All the values in the table are in percent. The holding of stocks in different weeks refer to the different trading strategies, where for example column Week 0 refers to holding stocks in week 0 only.

Table 1 gives my data analysis results from the first sample. When separating the various weeks, I sorted all the individual daily excess returns from Kenneth R. French's data into the weeks that they belong to according to the FOMC cycle structure outlined by Cieslak et al. using Microsoft Excel. This structure assigns day 0 to be the FOMC announcement day. This is also the day of the scheduled FOMC meeting, or in the case of a 2-day meeting it is the final day of a scheduled FOMC meeting. The FOMC cycle structure sees days –6 to –2 inclusive in week –1 and days –1 to 3 inclusive in week 0. Hence, the high excess return obtained in week 0 already starts to accumulate on day –1, before the FOMC announcement. This is in anticipation of news about to reach the public, and corresponds well to Lucca and Moench's findings of a high excess return in the 24-hour period leading up to the Fed announcement following a scheduled FOMC meeting. Continuing the rest of the FOMC cycle structure; week 1 is day 4 to 8 inclusive, week 2 is day 9 to 13 inclusive, week 3 is day 14 to 18 inclusive, week 4 is day 19 to 23 inclusive, week 5 is day 24 to 28 inclusive and week 6 is day 29 to 33 inclusive. Assigning each daily excess return from the Fama/French data to one of these outlined days, and then sorting that specific day into the correct odd or even week gives us the data in the organized form that is used in both the data and statistical analyses in this thesis. The list of scheduled FOMC meeting dates that I used was from the Federal Reserve Bank of St. Louis.[11]

To make sure that each individual daily excess return got assigned to only one specific day in the various samples, and that it got assigned to the correct day in the correct FOMC cycle week, I assigned them all manually. Hence, instead of programming a code to assign all the excess returns to certain days, I assigned them all individually to make sure that they ended in the correct place. This was especially important because the FOMC cycle periods vary in length, and we do not want the cycle periods to overlap. Thus, all the excess returns were manually divided into different columns in Excel, where each column contained excess returns for one specific week of the FOMC cycle. I added all the excess returns together in their respective weekly columns before dividing by the number of excess returns in each column to obtain the daily average seen in the first row of Table 1. To obtain the weekly average in the second row, I divided the sum of excess returns by the number of 5-day weeks in that column. Finally, the annual average was obtained by dividing the sum of excess returns by the number of years represented in the column which is also the number of years in the sample. Table 1 shows that all the averages correspond to our expectations of positive returns in even weeks and negative or zero returns in odd weeks. All the even weeks exhibit strong positive returns, whilst the odd weeks have returns that are strongly negative or close to zero. These results apply equally to the combined week averages of week 0, 2, 4, 6; week 2, 4, 6 and week –1, 1, 3, 5.

[11] Federal Reserve Bank of St. Louis website

Table 2. U.S. excess return averages by individual week, combined week or all weeks; illustrating the profitability of different trading strategies, Cieslak et al.'s results from sample 1994 – 2013

	Week –1	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 2,4,6	Week 0,2,4,6	Week –1,1,3,5	All Weeks
[12]Weekly Average	≈ 0	0.57	-0.17	0.30	-0.17	0.42	-0.12	0.61				
[13]Annual Average		4.76		2.44		3.02		0.93		11.58	-2.67	8.47

Note: All the values in the table are in percent. The holding of stocks in different weeks refer to the different trading strategies, where for example column Week 0 refers to holding stocks in week 0 only. The daily average row included when displaying the data results from my samples has been omitted here as Cieslak et al. have not included this in their articles.

Table 2 shows the results from Cieslak et al.'s data analysis. When comparing Table 1 and Table 2, we see that our results are very similar for the first two weeks. The values for the other individual weeks are not as similar although they all exhibit the pattern expected, whilst the combined weeks show quite similar results. Reasons for differences in values will be discussed below. What I deem most important is that the averages from my samples follow the pattern expected, and some variations in the absolute values between my sample and Cieslak et al.'s sample is only natural.

The differences in the values in my sample compared to those in Cieslak et al.'s sample could be due to a difference in setting holiday returns equal to zero or leaving the holidays out of the data. Cieslak et al. have chosen to set holiday returns equal to zero, whilst I have chosen to do a combination of setting some of them equal to zero, whilst leaving some out. It seemed superfluous to add holidays that had already been removed from the Fama/French data, only to set these holiday returns equal to zero. Especially since Cieslak et al. mention that setting holiday returns equal to zero or omitting them altogether give almost the same results in the regressions.[14] Hence, before organizing my data into different weeks as explained above, I programmed Excel to assign a return equal to zero to all the holidays that were still in the data. To do this I used a list of U.S. public holidays[15] that I transferred as a list into Excel, and checked the holidays against several other sources to see that they were complete. After

[12] Cieslak et al. (June 25, 2014), p. 3
[13] Cieslak et al. (June 25, 2014), p. 54
[14] Cieslak et al. (February 12, 2018), p. 40
[15] Robert Mundigl

checking some of the Fama/French stock market dates in Excel, I found that some of them were holidays that were not included in the holiday list I was already using. These were unique and sudden public holidays such as the day of mourning for President Ford on the 2nd of January 2007 and Wall Street being hit by Hurricane Sandy on the 29th and 30th of October 2012. Additionally, some Mondays after holidays, Fridays before holidays and some Good Friday dates had not been counted as holidays. I added all the above-mentioned holidays and other dates discovered as holidays to my holiday list in Excel. Another reason for not removing all of the holidays from the Fama/French data is that this would reduce the number of observations for the different weeks, and therefore reduce the validity of some of the statistical results if variables have small sample sizes.

Logically one would perhaps also want the highest possible number of total observations as these lead to higher degrees of freedom. The higher the degrees of freedom, the lower the critical value, and hence, the more likely it is that a variable will be statistically significant to a higher level. However, when looking at the sample sizes we are dealing with, where the lowest is 5030 for my sample of 1994 – 2013 and the highest is 6102 for my sample of 1994 – April 2018, these are all fairly high. Hence, a difference of a few hundred observations caused by omitting holidays rather than setting them equal to zero, will seemingly only have a very small effect on degrees of freedom when we have samples sizes of around 5000 – 6000.

A reason for slight differences in my results compared to those of Cieslak et al. could also be the choices of which FOMC cycle periods to include at the beginning and at the end of a sample period. Cieslak et al. have not mentioned their choices regarding this, so I made decisions that I considered appropriate. I have chosen to start within the year of 1994, on the 27th of January 1994, as this is the date marking the very first start date of week –1 in 1994. Since we have a sample of 20 whole years in 1994 – 2013, the very final date of this sample is 17th of January 2014, which is the closest end date of a cycle that I found around the 20-year sample period mark. In the case of sample 1994 – 2016 and sample 1994 – April 2018, they also follow the same structure as the first sample, starting on the 27th of January 1994 and ending on the 23rd of January 2017 and the 23rd of April 2018 respectively. Sample 1994 – 2016 encompasses a period of 23 whole years, whilst sample 1994 – April 2018 lasts around 24.25 years. We are not dealing with whole years in this latter sample, as we have three extra months into 2018 in addition to the 24 whole years from 1994 – 2017. This add up to 24.25 years and is the reasoning behind the sample ending on the 23rd of April 2018.

Cieslak et al. mention in their articles that it does not constitute much of a difference to results whether one chooses to set holiday excess returns equal to zero or omit them altogether. This is the reason why I chose to set some holiday returns equal to zero and omit other holidays. Hence, it could appear that the differences in our data results are due to other reasons, such as the possibility that we have chosen different start and end dates for sample periods. However, including or excluding holidays in the dataset could have an impact on the calculated averages as Cieslak et al. will most likely have smaller averages than I have in most of the weeks of the FOMC cycle because they divide the sum of excess returns by a larger number of days in their sample. This is simply due to their sample size being bigger than mine because they include all holidays in their dataset which gives a larger number of days in the sample period than if we omit some holidays like I have done. We should logically have the same sum of excess returns as the included holiday returns are set equal to zero. Hence, Cieslak et al. should in theory have smaller and different averages than I have, and this is also the case if we compare Table 1 and Table 2 for all weeks except week 4 and week 6. In week 4 and week 6 I have smaller averages than Cieslak et al. have, which could be due to choosing different start and end dates for our samples.

1.1.2 Statistical analysis procedure and results

Table 3 below shows the descriptive statistics for the first sample, where the mean of the various weeks is the daily average that is given in Table 1. I have rounded the daily averages to two decimal places in Table 1, whilst Table 3 gives them with more decimal places. The statistical analysis in this thesis is done in Stata by importing the data that has been organized in Excel. We can see that the first four weeks over the FOMC cycle have the same number of observations, whilst the weeks after have a declining number of observations. Week 6 has as few as 80 observations, indicating that this week may not be of the same importance when looking at statistical significance as for example week 0 which has ten times the amount of observations.

Table 3. Descriptive statistics for weekly variables, sample 1994 – 2013

Variable	Observations	Mean	Standard deviation	Min. value	Max. value
Week –1	800	0.017625	1.114326	-5.76	6.35
Week 0	800	0.11675	1.259407	-6.97	9.77
Week 1	800	-0.0530625	1.13061	-5.05	4.47
Week 2	800	0.0744875	1.216497	-8.26	6.79
Week 3	781	-0.0484891	1.275553	-7.36	6.27
Week 4	662	0.0650906	1.262221	-8.95	5.43
Week 5	306	0.0181373	1.119107	-4.21	4.55
Week 6	80	0.097875	0.9617925	-2.38	2.95
Week 2,4,6	1542	0.0716667	1.223999	-8.95	6.79
Week 0,2,4,6	2342	0.0870666	1.236124	-8.95	9.77
Week –1,1,3,5	2687	-0.0225791	1.168528	-7.36	6.35

Using the data organized in Excel I continued organizing it for statistical analysis in Stata. The columns I had created with the excess returns separated for the individual weeks were left as they were, as these could be used to create the odd and even week dummy variables when importing the data into Stata. Some of the weeks were combined to create the dummy variables for week 0, 2, 4, 6; week 2, 4, 6 and week –1, 1, 3, 5. It seemed like it was best to organize these combined weeks in Excel before importing them to Stata, rather than creating combined week dummies from the data for the individual weeks in Stata. Once columns with the individual weekly excess returns and the combined weekly excess returns had been created in Excel, this data was imported to Stata. Dummy variables were then programmed in Stata, where the individual dummies where set equal to 1 if there was a data point for that week and set to 0 if there was not. After all the binary variables were created, I ran regressions on different combinations of independent variables where the dependent variable was the excess return on U.S. stocks over Treasury bills. These regressions were all run with standard errors robust to heteroskedasticity. I ran diagnostic tests in Stata testing for the presence of heteroskedasticity in the residuals for all of the regressions using the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity. We use the chi-square distribution for the Lagrange Multiplier statistic in these tests, and most of these tests returned statistically significant results where the null hypothesis was that there was constant variance in the residuals. Thus, heteroskedasticity in the residuals appeared to be an issue, which is the reason for my decision to run the regressions with standard errors robust to heteroskedasticity. When running regressions that included all of the odd weeks and all of the even weeks, I omitted the constant term so there would be no problem with the dummy variable trap. The regressions that I ran for the sample of 1994 – 2013 are displayed in Table 4 below.

Table 4. Regressions of U.S. daily excess stock returns on FOMC cycle dummies, sample 1994 – 2013

	(1)	(2)	(3)	(4)	(5)
Dummy=1 in Week 0, 2, 4, 6	0.111*** (3.24)				
Dummy=1 in Week 0		0.140*** (2.80)	0.140*** (2.80)	0.117*** (2.62)	0.117*** (2.62)
Dummy=1 in Week 2, 4, 6		0.095** (2.46)		0.073** (2.30)	
Dummy=1 in Week 2			0.098** (2.00)		0.076* (1.73)
Dummy=1 in Week 4			0.088 (1.62)		0.066 (1.33)
Dummy=1 in Week 6			0.121 (1.10)		0.099 (0.92)
Dummy=1 in Week -1, 1, 3, 5				-0.023 (-1.00)	-0.023 (-1.00)
Constant	-0.022 (-1.00)	-0.022 (-1.00)	-0.022 (-1.00)		
No. of days	5030	5030	5030	5030	5030

Note: The significance level is indicated by the asterisks, where *** is significance at the 1 percent level, ** is significance at the 5 percent level, and * is significance at the 10 percent level. The dependent variable, i.e. the variable on the left hand side, is the excess return on U.S. stocks over Treasury bills, and is given in percent where for example 0.1 is 10 basis points per day. The t-statistics are robust to heteroskedasticity and are in parentheses.

Throughout this thesis I have used the calculations in Stata for t-tests with null hypotheses that the coefficients of the variables are equal to zero, and these are quoted directly in the various statistical regression tables with asterisks for their respective levels of significance. The formula for calculating t-statistics is:[16]

$$t - statistic = \frac{\widehat{\beta_j} - \beta_j}{se\left(\widehat{\beta_j}\right)} \sim t_{n-k-1} \qquad (1.1.2.1)$$

[16] Wooldridge, p. 108

In the above equation, $\widehat{\beta_j}$ is the estimated coefficient for the jth variable; β_j is the hypothesized value for the coefficient for the jth variable and $se\left(\widehat{\beta_j}\right)$ is the standard error of the estimated coefficient for the jth variable. The t-statistic is distributed with $n - k - 1$ degrees of freedom.

The t-tests in this thesis are all two-sided, where the null hypothesis is that β_j is equal to zero, whilst the alternative hypothesis is that β_j is not equal to zero. The t-statistic can be calculated from formula (1.1.2.1) using the coefficient estimate and standard error returned when running a regression in Stata. This t-statistic is then compared to the critical value of the t-distribution at the 1 percent, 5 percent and 10 percent level. If the absolute value of the t-statistic exceeds that of the critical value, we can reject the null hypothesis at that level and conclude that the coefficient is significantly different from zero at that significance level.

We will now compare my regression results in Table 4 to those of Cieslak et al. in Table 5. The signs of my coefficients are the same as those for Cieslak et al., which is also the case when comparing Cieslak et al.'s coefficient results to mine in sample 1994 – 2016, as we shall see in the next section. My sample above shows similar results for the week 0 dummy to that of Cieslak et al. in all regressions, where the coefficients are very similar and the dummy is significant at the 1 percent level. The constant term in my regressions is similar to that of Cieslak et al., both in terms of coefficient and not being significant. The same applies to the cases when we omit the constant term in regressions (4) and (5), and get similar results for the dummy representing all the odd weeks. The dummy of week 2, 4, 6 is of a similar coefficient value in both samples, however in my sample the t-statistics are somewhat lower than in Cieslak et al.'s results, making the dummy significant at the 5 percent level rather than at 1 percent. The week 2 dummy in Cieslak et al.'s sample in regression (3) is significant at the 10 percent level whilst mine is significant at the 5 percent level. The same dummy in regression (5) is not significant in Cieslak et al.'s sample, but is significant at the 10 percent level in mine. My dummies of week 4 and 6 are not significant, whilst Cieslak et al.'s dummies are significant at the 5 or 10 percent level. This distinction in significance levels could be due to a low number of observations in these weeks. This makes my results for these weeks not as important as in the other weeks. We can see in Table 3 that I only have 80 observations in week 6 and 662 observations in week 4. Although it does not say exactly how many observations the different weeks in Cieslak et al.'s 1994 – 2013 sample have,[17] it is clear that these numbers are larger than in my sample since Cieslak et al. have included more holidays in their dataset than I have in mine. This can be seen when comparing my sample size of 1994 – 2013 to that of Cieslak et al., where mine has 5030 observations and Cieslak et al.'s has 5214.

Table 5. Regressions of U.S. daily excess stock returns on FOMC cycle dummies, Cieslak et al.'s results from sample 1994 – 2013[18]

	(1)	(2)	(3)	(4)	(5)
Dummy=1 in Week 0, 2, 4, 6					
Dummy=1 in Week 0		0.136*** (2.76)	0.136*** (2.76)	0.115*** (2.59)	0.115*** (2.59)
Dummy=1 in Week 2, 4, 6		0.101*** (2.68)		0.079*** (2.59)	
Dummy=1 in Week 2			0.083* (1.75)		0.062 (1.46)
Dummy=1 in Week 4			0.108** (2.00)		0.086* (1.75)
Dummy=1 in Week 6			0.179** (1.99)		0.157* (1.81)
Dummy=1 in Week -1, 1, 3, 5				-0.021 (-0.98)	-0.021 (-0.98)
Constant		-0.021 (-0.98)	-0.021 (-0.98)		
No. of days		5214	5214	5214	5214

Note: The significance level is indicated by the asterisks, where *** is significance at the 1 percent level, ** is significance at the 5 percent level, and * is significance at the 10 percent level. The dependent variable, i.e. the variable on the left hand side, is the excess return on U.S. stocks over Treasury bills, and is given in percent where for example 0.1 is 10 basis points per day. The t-statistics are robust to heteroskedasticity and are in parentheses.

We will see in the next sections that all my other samples give stronger significance results, and my sample of 1994 – 2016 is much more similar to Cieslak et al.'s results. This could be tied to the number of observations increasing in the different weeks as we expand our samples, increasing the importance of the individual weeks and their results.

[17] This specific information is not given in the articles by Cieslak et al. that contain information for the sample 1994 – 2013. However, as will be mentioned later on, the most recent article does contain this information for sample 1994 – 2016.

[18] Cieslak et al. (June 25, 2014), p. 51

1.2 Sample 1994 – 2016

The procedures outlined in the previous section apply to all of the samples studied in this thesis. There will however be additional points to add to what has already been explained depending on which sample we are focusing on. For order and simplicity, the sections discussing the analyses of the various samples have the same structure.

1.2.1 Data analysis procedure and results

Looking at Table 6 below, we can see that the excess return pattern in my sample of 1994 – 2013 still persists. There are slight differences between the two samples, but the general interpretation of Table 1 and Table 6 are the same.

Table 6. U.S. excess return averages by individual week, combined week or all weeks; illustrating the profitability of different trading strategies, sample 1994 – 2016

	Week –1	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 2,4,6	Week 0,2,4,6	Week –1,1,3,5	All Weeks
Daily Average	0.006	0.12	-0.05	0.08	-0.05	0.09	0.02	0.08	0.08	0.09	-0.03	0.03
Weekly Average	0.03	0.59	-0.26	0.39	-0.25	0.43	0.09	0.40	0.41	0.47	-0.13	0.15
Annual Average	0.23	4.72	-2.05	3.09	-1.95	2.88	0.28	0.29	6.27	10.98	-3.49	7.48

Note: All the values in the table are in percent. The holding of stocks in different weeks refer to the different trading strategies, where for example column Week 0 refers to holding stocks in week 0 only.

When comparing Table 6 and Table 7 we see that the weekly averages are very similar for the first two weeks and for week 4. Week 2 also has similar results between the two samples. There are some differences in the other weeks, where a possible reason for differences in averages is that there could have been revisions in retrospect by Kenneth R. French to the excess returns that Cieslak et al. have used. This could result in slight differences in the excess returns that I have used in my analyses compared to those used by Cieslak et al. These differences are likely to be small though, so more probable reasons for differences are the ones discussed in the previous section concerning start and end dates of sample periods, and differences in whether holiday returns are omitted from the data or set equal to zero. The combined week annual averages are similar in both the samples, with a week 0, 2, 4, 6 annual average of 12.15 percent in Cieslak et al.'s sample and a 10.98 percent in mine. The annual average of week –1, 1, 3, 5 is –3.13 percent in Cieslak et al.'s sample and –3.49 percent in mine, whilst the annual average of all the even and odd weeks combined is 8.48 percent in Cieslak et al.'s sample and 7.48 percent in mine.

Table 7. U.S. excess return averages by individual week, combined week or all weeks; illustrating the profitability of different trading strategies, Cieslak et al.'s results from sample 1994 – 2016

	Week –1	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 2,4,6	Week 0,2,4,6	Week –1,1,3,5	All Weeks
[19]Weekly Average	≈ 0	0.57	-0.18	0.33	-0.18	0.46	-0.09	0.60				
[20]Annual Average										12.15	-3.13	8.48

Note: All the values in the table are in percent. The holding of stocks in different weeks refer to the different trading strategies, where for example column Week 0 refers to holding stocks in week 0 only. The daily average row included when displaying the data results from my samples has been omitted here as Cieslak et al. have not included this in their articles.

1.2.2 Statistical analysis procedure and results

Table 8 below gives an overview of the descriptive statistics for the second sample period, where we can see that the number of observations in each of the first four weeks has increased by 120 from the last sample period displayed in Table 3. Week 6 has only increased with 4 observations, whilst week 4 and week 5 have increased with 106 and 48 observations respectively.

[19] Cieslak et al. (February 12, 2018), pp. 4 – 5
[20] Cieslak et al. (February 12, 2018), p. 41

Table 8. Descriptive statistics for weekly variables, sample 1994 – 2016

Variable	Observations	Mean	Standard deviation	Min. value	Max. value
Week –1	920	0.0057283	1.077989	-5.76	6.35
Week 0	920	0.1179022	1.216059	-6.97	9.77
Week 1	920	-0.0511848	1.09995	-5.05	4.47
Week 2	920	0.0772826	1.170714	-8.26	6.79
Week 3	901	-0.0498557	1.236901	-7.36	6.27
Week 4	768	0.0863672	1.208115	-8.95	5.43
Week 5	354	0.0181921	1.087079	-4.21	4.55
Week 6	84	0.079881	0.9910679	-2.47	2.95
Week 2,4,6	1772	0.0813431	1.178717	-8.95	6.79
Week 0,2,4,6	2692	0.0938373	1.191511	-8.95	9.77
Week –1,1,3,5	3095	-0.0259451	1.133697	-7.36	6.35

Looking at Table 9 and Table 10 below, we see that these two sample results are very similar and they exhibit a strong result in terms of replicating Cieslak et al.'s analysis as accurately as possible.

Table 9. Regressions of U.S. daily excess stock returns on FOMC cycle dummies, sample 1994 – 2016

	(1)	(2)	(3)	(4)	(5)
Dummy=1 in Week 0, 2, 4, 6	0.121*** (3.93)				
Dummy=1 in Week 0		0.144*** (3.20)	0.144*** (3.20)	0.119*** (2.94)	0.119*** (2.94)
Dummy=1 in Week 2, 4, 6		0.109*** (3.11)		0.083*** (2.90)	
Dummy=1 in Week 2			0.105** (2.36)		0.079** (2.00)
Dummy=1 in Week 4			0.113** (2.33)		0.088** (1.98)
Dummy=1 in Week 6			0.107 (0.96)		0.081 (0.74)
Dummy=1 in Week -1, 1, 3, 5				-0.026 (-1.27)	-0.026 (-1.27)
Constant	-0.026 (-1.28)	-0.026 (-1.28)	-0.026 (-1.28)		
No. of days	5788	5788	5788	5788	5788

Note: The significance level is indicated by the asterisks, where *** is significance at the 1 percent level, ** is significance at the 5 percent level, and * is significance at the 10 percent level. The dependent variable, i.e. the variable on the left hand side, is the excess return on U.S. stocks over Treasury bills, and is given in percent where for example 0.1 is 10 basis points per day. The t-statistics are robust to heteroskedasticity and are in parentheses.

The regression results in Table 9 and Table 10 are indeed very similar as already mentioned, both when it comes to coefficient values and significance levels. Furthermore, the signs of my coefficients are the same as those in Cieslak et al. The difference between my sample and Cieslak et al.'s sample is the significance results of week 6, where my individual dummy of week 6 is not significant and Cieslak et al.'s is significant at the 5 percent level. Cieslak et al. have not included the regression results for columns (4) and (5) in their article for this particular sample, which is why these columns are left blank in Table 10. Hence, I can only comment on the significance of week 6 in relation to regression (3) here. All the other dummy variables and constant terms exhibit results that seem quite satisfactory in terms of replicating Cieslak et al.'s statistical analysis.

Table 10. Regressions of U.S. daily excess stock returns on FOMC cycle dummies, Cieslak et al.'s results from sample 1994 – 2016[21]

	(1)	(2)	(3)	(4)	(5)
Dummy=1 in Week 0, 2, 4, 6	0.120*** (4.00)				
Dummy=1 in Week 0		0.141*** (3.17)	0.141*** (3.17)		
Dummy=1 in Week 2, 4, 6		0.109*** (3.24)			
Dummy=1 in Week 2			0.090** (2.10)		
Dummy=1 in Week 4			0.120** (2.52)		
Dummy=1 in Week 6			0.187** (2.07)		
Dummy=1 in Week -1, 1, 3, 5					
Constant	-0.025 (-1.25)	-0.025 (-1.25)	-0.025 (-1.25)		
No. of days	5997	5997	5997		

Note: The significance level is indicated by the asterisks, where *** is significance at the 1 percent level, ** is significance at the 5 percent level, and * is significance at the 10 percent level. The dependent variable, i.e. the variable on the left hand side, is the excess return on U.S. stocks over Treasury bills, and is given in percent where for example 0.1 is 10 basis points per day. The t-statistics are robust to heteroskedasticity and are in parentheses.

[21] Cieslak et al. (February 12, 2018), p. 40

The total number of observations in my sample is 5788, whilst that in Cieslak et al.'s is 5997. The number of observations for week 6 in my sample is 84, whilst it is 120 in Cieslak et al.'s sample.[22] The number of daily returns in week 6 in my sample that have been set equal to zero due to being holidays is only one.[23] Hence, all holidays in week 6 have been omitted with the exception of one which has a return set to zero. This very much seems to be a contributing factor to why my week 6 dummy is not statistically significant, as an already low week 6 sample size in Cieslak et al. is reduced even further in mine when most holidays in week 6 are omitted. In fact, my sample size of week 6 is only about two thirds of Cieslak et al.'s. This makes this week much less important than the other weeks. Hence, week 6 not returning statistically significant results does therefore not seem too important here.

When comparing the number of observations for each individual week in Cieslak et al.'s sample versus mine, we see that mine are all of a smaller magnitude. Mine are given in Table 8 and in the consecutive order of week –1 to week 6 they are: 920, 920, 920, 920, 901, 768, 354 and 84. Cieslak et al.'s number of observations are in comparison, in the consecutive order for week 0, 2, 4, 6[24]: 920, 924, 831 and 120.[25] Cieslak et al. and I both have 920 observations for week 0. I do find it puzzling that Cieslak et al.'s week 2 has more observations than week 0, as I would assume that week 0 and week 2 have the same number of observations as they are both present in every FOMC cycle, and they are both 5-day weeks. None of these weeks have an FOMC cycle that ends on either of them, as all FOMC cycle weeks are more than 4 weeks in length.

The validity of the statistical regressions on week 6 appear to be more questionable compared to for example the validity of the statistical regressions on week 0, as the latter week has a much larger number of observations in all samples. Cieslak et al. also comment upon this, that the lower number of observations for week 6 make it less important than the other even weeks.[26] This shines some light on another matter, namely that all FOMC cycle periods include weeks –1, 0, 1 and 2. This can be seen from the descriptive statistics of all my samples, namely Table 3, Table 8 and Table 21. These weeks all have the same number of observations in their respective samples. From week 3 onwards, however, the number of

[22] Cieslak et al. (February 12, 2018), p. 5
[23] From looking at my week 6 column of my Excel spreadsheet.
[24] Cieslak et al. have not included these details when it comes to the odd weeks.
[25] Cieslak et al. (February 12, 2018), p. 5
[26] Cieslak et al. (February 12, 2018), p. 5

observations start declining. When combining all the even weeks into one dummy, or just combining week 2, 4, and 6 into one dummy, these dummy variables are strongly statistically significant in regressions. Hence, the week 6 dummy not being individually statistically significant in regressions does not affect the statistical significance of dummies that consist of a combination of week 6 and other weeks. This reason, in addition to week 6 being the least important variable in the sense of having the smallest number of observations, makes the situation of the week 6 dummy not being individually statistically significant in regressions appear to be less of an issue.

1.3 Summary and thoughts on the replication process

In the replication of the first sample of 1994 – 2013, the results I obtained exhibited some differences to Cieslak et al.'s sample when it came to the significance of week 4 and week 6. Possible reasons for these distinctions are the choices of start and end dates for the sample period together with choosing a combination of setting some holiday returns equal to zero, whilst leaving others out of the sample.

The results of the replication of the second sample of 1994 – 2016 gave more satisfactory results as the statistical results of these were very similar to those of Cieslak et al. The only exception was the week 6 dummy which did not exhibit a statistically significant result in my regression. However, this did not seem to affect the results concerning the combined week dummies consisting of even weeks over the FOMC cycle. As these two dummies, namely week 0, 2, 4, 6 and week 2, 4, 6 were both statistically significant at the 1 percent level in all my regressions, it seems reasonable to conclude that the week 6 dummy is not a big problem as it is not affecting the other results.

The data analyses in both my 1994 – 2013 and 1994 – 2016 samples exhibit results according to our expectations of positive excess returns in even weeks, and negative or approximately zero returns in odd weeks. Although there are some differences in the magnitude of these values, the pattern that is consistent with biweekly excess returns is strong. When looking at my combined week averages of all the odd weeks, all the even weeks, or all of the weeks, the values exhibited are in fact very similar to those in the analysis by Cieslak et al. in both the 1994 – 2013 and 1994 – 2016 samples.

It is particularly the statistical results from my sample of 1994 – 2016, which appear strong and very similar to Cieslak et al.'s sample, that suggest that we can now go ahead with the analysis of the new sample of 1994 – April 2018. However, before doing this we will investigate parameter stability when expanding the samples 1994 – 2013 and 1994 – 2016 with data up to and including April 2018.

2 Looking at parameter stability when expanding initial samples to include more recent data

In this section we will investigate parameter stability when expanding the initial sample periods of Cieslak et al. to include the most recent data up to and including April 2018. This will be explored in two different parts where the first expansion consists of adding 2014 – April 2018 to the initial sample of 1994 – 2013, and the second expansion consists of adding 2017 – April 2018 to the initial sample of 1994 – 2016. We wish to see whether the initial sample periods dominate the results we obtain for the stock return pattern when looking at sample 1994 – April 2018. Adding more recent data spanning a mere time period of 1.25 years (2017 – April 2018) or 4.25 years (2014 – April 2018), might not change the stock return pattern due to these new datasets only contributing with a few years of data compared to the 20 years of 1994 – 2013 or 23 years of 1994 – 2016. Investigating parameter stability will help us determine whether to go ahead and use the replication methods outlined above in analyses on a sample including more recent data. This is because parameter stability test results will indicate whether analyses on a more recent sample will lead to reliable results in terms of determining whether the stock return pattern is still present.

2.1 Expanding sample 1994 – 2013 to include 2014 – April 2018

Table 11 below shows the results from running the same regressions as those run in previous sections, but this time also including parameter stability dummies for the different weeks. These new dummies consist of the original weekly dummies that have been used previously, multiplied by a new dummy *d* separating the time periods 1994 – 2013 and 2014 – April 2018. This new dummy *d* is set equal to 1 for the most recent time period of 2014 – April 2018 and set equal to 0 for 1994 – 2013. When running these new regressions, we wish to see whether the coefficients of the parameter stability dummies are close to zero when it comes to both magnitude and statistical significance. If they are, then we can be fairly confident that the stock return pattern is still present, i.e. that the stock return pattern remains unchanged.

Table 11. Testing parameter stability with regressions on sample 1994 – April 2018 of U.S. daily excess stock returns on FOMC cycle dummies *and* parameter stability dummies for 2014 – April 2018

	(1)	(2)	(3)	(4)	(5)
Dummy=1 in Week 0, 2, 4, 6	0.109*** (3.37)				
Dummy=1 in Week 0		0.138*** (2.83)	0.138*** (2.83)	0.117*** (2.62)	0.117*** (2.62)
Dummy=1 in Week 2, 4, 6		0.094** (2.52)		0.073** (2.30)	
Dummy=1 in Week 2			0.097** (2.02)		0.076* (1.73)
Dummy=1 in Week 4			0.087 (1.62)		0.066 (1.33)
Dummy=1 in Week 6			0.120 (1.09)		0.099 (0.92)
Dummy=1 in Week -1, 1, 3, 5				-0.023 (-1.00)	-0.023 (-1.00)
Week 0246 x d	0.027 (0.59)				
Week 0 x d		-0.061 (-0.74)	-0.061 (-0.74)	-0.061 (-0.74)	-0.061 (-0.74)
Week 246 x d		0.073 (1.36)		0.073 (1.36)	
Week 2 x d			0.040 (0.53)		0.040 (0.53)
Week 4 x d			0.122 (1.55)		0.122 (1.55)
Week 6 x d			-0.098 (-0.24)		-0.098 (-0.24)
Week -1135 x d				0.010 (0.24)	0.010 (0.24)
Constant	-0.021 (-1.07)	-0.021 (-1.07)	-0.021 (-1.07)		
No. of days	6102	6102	6102	6102	6102

Note: The significance level is indicated by the asterisks, where *** is significance at the 1 percent level, ** is significance at the 5 percent level, and * is significance at the 10 percent level. The dependent variable, i.e. the variable on the left hand side, is the excess return on U.S. stocks over Treasury bills, and is given in percent where for example 0.1 is 10 basis points per day. The t-statistics are robust to heteroskedasticity and are in parentheses.
The parameter stability dummies are interaction terms, where each of the weekly dummies we have used in previous regressions are multiplied by a dummy *d* separating the sample 1994 – April 2018 into the two time periods 1994 – 2013 and 2014 – April 2018. In these interaction terms, the dummy *d* is set equal to 1 for the most recent time period of 2014 – April 2018 and set equal to 0 for the time period 1994 – 2013. Hence, the interaction term for week 0 is written as *Week 0 x d*, the term for week 2 is *Week 2 x d* etc.

The coefficients of the initial weekly dummy variables in Table 11 are approximately of the same magnitude as they were in the regressions on sample 1994 – 2013 in Table 4. This is due to explanatory variables being independent, or orthogonal, to one another in a regression. The statistical significance results for the initial weekly dummy variables are also the same as they were in sample 1994 – 2013. What is of particular interest in Table 11 is whether the interaction terms of the various weeks are statistically significant. None of these parameter stability dummies appear to be significant, even at the 10 percent level, and therefore their coefficient values do not appear to be different from zero at either the 1 percent, 5 percent or 10 percent level. These interaction terms can therefore be omitted from the regressions for the purposes of obtaining accurate results concerning the stock return pattern. This pattern previously discovered by Cieslak et al. does not seem to have changed as the interaction terms are not statistically significant. The data from sample 1994 – 2013 does therefore not appear to dominate the sample 1994 – April 2018 in terms of recreating former patterns simply due to the larger sample size of 1994 – 2013 compared to that of 2014 – April 2018. Hence, investigations of parameter stability so far suggest that analyses of sample 1994 – April 2018 will return reliable results. Analyses of this more recent sample will follow in the next chapter, along with tables exhibiting its results such as Table 22 exhibiting regression results for sample 1994 – April 2018. I will include references to Table 22 in this chapter as the information in this table is necessary for the F-tests carried out below.

None of the individual interaction terms are statistically significant when doing two-sided t-tests where the null hypothesis is that their respective coefficients are equal to zero. We will investigate the matter of statistical significance further by running an F-test for each of the five regressions in Table 11 to test for joint significance of the interaction terms. We could either look at the R-squared or the sum of squared residuals given in Stata for the regressions in Table 11 and Table 22 when carrying out F-tests. The F-statistic has the following two formulas:[27]

$$F - statistic = \frac{\frac{SSR_r - SSR_{ur}}{q}}{\frac{SSR_{ur}}{n-k-1}} = \frac{\frac{R_{ur}^2 - R_r^2}{q}}{\frac{1 - R_{ur}^2}{n-k-1}} \sim F_{q,n-k-1} \qquad (2.1.1)$$

[27] Wooldridge, pp. 129 – 130 and p. 133

In the above equation SSR_r is the sum of squared residuals for the restricted regression, i.e. the regression without the interaction terms; SSR_{ur} is the sum of squared residuals for the unrestricted regression, i.e. the regression including interaction terms; q is the number of restrictions, i.e. the number of interaction terms; n is the number of observations and k is the number of variables in the unrestricted regression. In the second formula above, R_{ur}^2 is the R-squared for the unrestricted regression whilst R_r^2 is the R-squared for the restricted regression. The F-statistic is distributed with $(q, n - k - 1)$ degrees of freedom.

We may use either of the formulas in equation (2.1.1). The F-statistics obtained from the two different formulas may vary slightly due to the rounding of values, but this should not have any consequences for our results. The null hypothesis is that all coefficients of the interaction terms are jointly equal to zero, whilst the alternative hypothesis is that they are jointly not equal to zero. Under the null hypothesis, the F-test is distributed as an $F_{q,n-k-1}$. The critical values for the 1 percent, 5 percent and 10 percent levels are denoted as $F_{0.01}^{CRIT}$, $F_{0.05}^{CRIT}$ and $F_{0.10}^{CRIT}$ respectively, where I have used the F-distribution tables from Wooldridge.[28] We use the second formula in (2.1.1) containing R-squared and obtain the F-statistics for regressions (1) – (5) which are given in Table 12 below. The critical values are also given in Table 12.

Table 12. Statistical information for carrying out F-tests, where the null hypothesis is that all coefficients of the interaction terms for 2014 – April 2018 are jointly equal to zero

	(1)	(2)	(3)	(4)	(5)
$F_{q,n-k-1}$	$F_{1,6099}$	$F_{2,6097}$	$F_{4,6093}$	$F_{3,6095}$	$F_{5,6091}$
F-statistic	0.6114	0.6114	0.4583	0.4074	0.3665
$F_{0.01}^{CRIT}$	6.63	4.61	3.32	3.78	3.02
$F_{0.05}^{CRIT}$	3.84	3.00	2.37	2.60	2.21
$F_{0.10}^{CRIT}$	2.71	2.30	1.94	2.08	1.85

[28] Wooldridge, pp. 746 – 748

Comparing the F-statistic to the critical values at the various significance levels in Table 12 tells us whether we can reject the null hypothesis and at which certainty this can be rejected. The absolute value of the F-statistic must be higher than the critical value in order to reject the null hypothesis at that particular level. Hence, we quite clearly fail to reject the null hypothesis at any percentage level, and the coefficients of the interaction terms are jointly equal to zero. Thus, both t-tests and F-tests indicate that the stock return pattern has not changed.

Although the t-tests and F-tests do not suggest that the stock return pattern has changed, it could still be of interest looking directly at the coefficients of the weekly variables for the new sample period of 2014 – April 2018 to see whether these coefficients look very different to those in the other samples. The coefficients of the weekly variables for the new sample period 2014 – April 2018 are the *sum* of the coefficient of the initial weekly dummy variable (for example *Week 0246*) and the coefficient of the respective interaction term (for example *Week 0246 x d*), i.e. the coefficient for week 0 is the sum of *Week 0* and *Week 0 x d*. The first of these two dummies gives the coefficient for that week for the sample 1994 – 2013, whilst the second dummy gives the change in coefficient estimate from the sample 1994 – 2013 to the sample 2014 – April 2018. Any large differences in the sum of these coefficients to the coefficients in samples 1994 – 2013 or 1994 – April 2018 could help illustrate whether there have been any changes in the stock return pattern. Tables 13 – 17 below give the coefficient estimates for samples 2014 – April 2018 and 2017 – April 2018. In order to compare these coefficients to those that are in samples 1994 – 2013, 1994 – 2016 and 1994 – April 2018, the coefficients from the three latter samples have been added to the tables as well. I have not included the usual asterisks indicating levels of statistical significance in these tables as I am focusing on the values of the coefficient estimates in this particular instance.

Table 13. Coefficients of weekly variable in regression number (1)[29] for all sample periods

	1994 – 2013	1994 – 2016	1994 – April 2018	2014 – April 2018	2017 – April 2018
Week 0, 2, 4, 6	0.111	0.121	0.114	0.136	0.073

Note: The dependent variable in the regression is the daily excess return on U.S. stocks over Treasury bills and is given in percent where for example 0.1 is 10 basis points per day.

[29] Using the same numbering of regressions as in Tables 4, 5, 9, 10 and 22

Table 14. Coefficients of weekly variables in regression number (2)[30] for all sample periods

	1994 – 2013	1994 – 2016	1994 – April 2018	2014 – April 2018	2017 – April 2018
Week 0	0.140	0.144	0.127	0.077	-0.093
Week 2, 4, 6	0.095	0.109	0.106	0.167	0.157

Note: The dependent variable in the regression is the daily excess return on U.S. stocks over Treasury bills and is given in percent where for example 0.1 is 10 basis points per day.

Table 15. Coefficients of weekly variables in regression number (3)[31] for all sample periods

	1994 – 2013	1994 – 2016	1994 – April 2018	2014 – April 2018	2017 – April 2018
Week 0	0.140	0.144	0.127	0.077	-0.093
Week 2	0.098	0.105	0.104	0.137	0.178
Week 4	0.088	0.113	0.109	0.209	0.119
Week 6	0.121	0.107	0.111	0.022	0.303

Note: The dependent variable in the regression is the daily excess return on U.S. stocks over Treasury bills and is given in percent where for example 0.1 is 10 basis points per day.

Table 16. Coefficients of weekly variables in regression number (4)[32] for all sample periods

	1994 – 2013	1994 – 2016	1994 – April 2018	2014 – April 2018	2017 – April 2018
Week 0	0.117	0.119	0.107	0.056	-0.113
Week 2, 4, 6	0.073	0.083	0.086	0.146	0.136
Week -1, 1, 3, 5	-0.023	-0.026	-0.021	-0.013	0.076

Note: The dependent variable in the regression is the daily excess return on U.S. stocks over Treasury bills and is given in percent where for example 0.1 is 10 basis points per day.

[30] Using the same numbering of regressions as in Tables 4, 5, 9, 10 and 22
[31] Using the same numbering of regressions as in Tables 4, 5, 9, 10 and 22
[32] Using the same numbering of regressions as in Tables 4, 5, 9, 10 and 22

Table 17. Coefficients of weekly variables in regression number (5)[33] for all sample periods

	1994 – 2013	1994 – 2016	1994 – April 2018	2014 – April 2018	2017 – April 2018
Week 0	0.117	0.119	0.107	0.056	-0.113
Week 2	0.076	0.079	0.083	0.116	0.157
Week 4	0.066	0.088	0.088	0.188	0.099
Week 6	0.099	0.081	0.090	0.001	0.283
Week -1, 1, 3, 5	-0.023	-0.026	-0.021	-0.013	0.076

Note: The dependent variable in the regression is the daily excess return on U.S. stocks over Treasury bills and is given in percent where for example 0.1 is 10 basis points per day.

Looking at Tables 13 – 17, the coefficients in sample 2014 – April 2018 do differ from the coefficients in sample 1994 – 2013 and 1994 – April 2018. In Table 13 the difference in coefficient value between sample 2014 – April 2018 and sample 1994 – 2013 is 0.136 – 0.111 = 0.025 for the weekly variable *Week 0246*. The difference in coefficient values is larger for weekly variables in the other tables, where in Table 14 and Table 15 *Week 0* has a difference in coefficient value of 0.077 – 0.140 = -0.063 between the samples 2014 – April 2018 and 1994 – 2013. The biggest difference between coefficient values in these two samples is coefficient *Week 4* in Table 17 with a value of 0.188 – 0.066 = 0.122. Here the coefficient in sample 2014 – April 2018 is more than double the value of the coefficient in sample 1994 – 2013. Hence, the week 4 effect on the dependent variable appears to be much stronger in sample 2014 – April 2018 than in sample 1994 – 2013. The same applies to the week 2 effect, whilst the week 0 and week 6 effects are much weaker in sample 2014 – April 2018 than in sample 1994 – 2013. The effect of the coefficient for the odd weeks on the dependent variable is slightly weaker in sample 2014 – April 2018 than in sample 1994 – 2013. The effect of the coefficient for week 2, 4, 6 on the dependent variable in sample 2014 – April 2018 is exactly double of what it is in sample 1994 – 2013 in Table 16. Although the difference in effect that week 2, 4, 6 has on the dependent variable in sample 2014 – April 2018 and sample 1994 – 2013 is not quite as strong in Table 14, it is still strong. As for the effect of the coefficient for all the even weeks on the dependent variable in Table 13, there is not too much of a difference between sample 2014 – April 2018 and sample 1994 – 2013, although the most recent sample exhibits a stronger effect.

[33] Using the same numbering of regressions as in Tables 4, 5, 9, 10 and 22

When looking at the coefficients in sample 1994 – April 2018 in Tables 13 – 17 we see that these are predominantly somewhere in between the values of the coefficients in sample 2014 – April 2018 and sample 1994 – 2013 as we would expect them to be. The coefficients in sample 1994 – April 2018 are closest in value to those in sample 1994 – 2013. This is not surprising as we might consider it a natural consequence of the sample 1994 – 2013 being dominant in terms of spanning 20 years in contrast to sample 2014 – April 2018 which spans approximately 4.25 years. The differences in coefficient values between samples could suggest that there has been a change in the stock return pattern. However, this potential change does not appear to be very large as none of the t-tests or F-tests return statistically significant results.

2.2 Expanding sample 1994 – 2016 to include 2017 – April 2018

In this section we carry out the same analysis on sample 2017 – April 2018 as has been done in the previous section on sample 2014 – April 2018. The sample studied in this section only spans a time period of 1.25 years, which is less than one third of the sample size of 2014 – April 2018, so naturally this could have an impact on our findings.

Table 18 below shows the results from running regressions that include parameter stability dummies for 2017 – April 2018 for the different weeks. These interaction terms consist of the original weekly dummies multiplied by a new dummy *d* separating the time periods 1994 – 2016 and 2017 – April 2018. This new dummy *d* is set equal to 1 for the most recent time period of 2017 – April 2018 and set equal to 0 for 1994 – 2016.

Table 18. Testing parameter stability with regressions on sample 1994 – April 2018 of U.S. daily excess stock returns on FOMC cycle dummies *and* parameter stability dummies for 2017 – April 2018

	(1)	(2)	(3)	(4)	(5)
Dummy=1 in Week 0, 2, 4, 6	0.116*** (3.83)				
Dummy=1 in Week 0		0.139*** (3.12)	0.139*** (3.11)	0.119*** (2.94)	0.119*** (2.94)
Dummy=1 in Week 2, 4, 6		0.104*** (3.01)		0.083*** (2.90)	
Dummy=1 in Week 2			0.100** (2.27)		0.079** (2.00)
Dummy=1 in Week 4			0.108** (2.24)		0.088** (1.98)
Dummy=1 in Week 6			0.101 (0.92)		0.081 (0.74)
Dummy=1 in Week -1, 1, 3, 5				-0.026 (-1.27)	-0.026 (-1.27)
Week 0246 x d	-0.043 (-0.61)				
Week 0 x d		-0.232 (-1.63)	-0.232 (-1.63)	-0.232 (-1.63)	-0.232 (-1.63)
Week 246 x d		0.053 (0.71)		0.053 (0.71)	
Week 2 x d			0.078 (0.67)		0.078 (0.67)
Week 4 x d			0.011 (0.11)		0.011 (0.11)
Week 6 x d			0.202 (0.75)		0.202 (0.75)
Week -1135 x d				0.102* (1.84)	0.102* (1.84)
Constant	-0.021 (-1.07)	-0.021 (-1.07)	-0.021 (-1.07)		
No. of days	6102	6102	6102	6102	6102

Note: The significance level is indicated by the asterisks, where *** is significance at the 1 percent level, ** is significance at the 5 percent level, and * is significance at the 10 percent level. The dependent variable, i.e. the variable on the left hand side, is the excess return on U.S. stocks over Treasury bills, and is given in percent where for example 0.1 is 10 basis points per day. The t-statistics are robust to heteroskedasticity and are in parentheses.

The parameter stability dummies are interaction terms, where each of the weekly dummies we have used in previous regressions are multiplied by a dummy *d* separating the sample 1994 – April 2018 into the two time periods 1994 – 2016 and 2017 – April 2018. In these interaction terms, the dummy *d* is set equal to 1 for the most recent time period of 2017 – April 2018 and set equal to 0 for the time period 1994 – 2016. Hence, the interaction term for week 0 is written as *Week 0 x d*, the term for week 2 is *Week 2 x d* etc.

What is of interest in Table 18 is whether the coefficients of the parameter stability dummies are close to zero when it comes to magnitude and statistical significance. The coefficients of the initial weekly dummy variables in Table 18 are of a similar magnitude to what they were in the regressions on sample 1994 – 2016 in Table 9. This is as expected and is due to the orthogonality of the explanatory variables. The statistical significance results for the initial weekly dummy variables are the same as in samples 1994 – 2016 and 1994 – April 2018 in Table 9 and Table 22 respectively. The only parameter stability dummy in Table 18 that is significant is the interaction term for the odd weeks, which is significant at the 10 percent level in regressions (4) and (5). Hence, the coefficient values of these dummies appear to be different from zero at the 10 percent level. None of the even week interaction terms are significant in Table 18, and these are the most important in terms of predicting the dependent variable. It is possible that the statistically significant results of the interaction terms for the odd weeks are false positives, where a t-test at the 5 percent significance level can be expected to return a false positive for every 20 tests, i.e. 5 percent of the time. For a t-test at the 10 percent significance level we can expect a false positive for every 10 tests, i.e. 10 percent of the time. We carry out t-tests on many coefficients in this thesis, and it is therefore reasonable to expect that some of these t-tests will return statistically significant results that are false. If this does occur, it is regarded as a Type I error, where a true null hypothesis is falsely rejected.

The only individual interaction terms that are statistically significant when doing two-sided t-tests where the null hypothesis is that coefficients are equal to zero, are the odd week dummies in regressions (4) and (5). We will look at the joint significance of the interaction terms and run an F-test for each of the five regressions in Table 18, to see whether the significant odd week interaction terms affect the joint significance of all the interaction terms. The null hypothesis in the F-tests is that all coefficients of the interaction terms are jointly equal to zero, whilst the alternative hypothesis is that they are jointly not equal to zero. Under the null hypothesis, the F-test is distributed as an $F_{q,n-k-1}$. The critical values for the 1 percent, 5 percent and 10 percent levels are denoted as $F_{0.01}^{CRIT}$, $F_{0.05}^{CRIT}$ and $F_{0.10}^{CRIT}$ respectively, where I have used the F-distribution tables from Wooldridge.[34] We use the second formula in (2.1.1) containing R-squared and obtain the F-statistics for regressions (1) – (5) which are given in Table 19 below. The critical values are also given in Table 19, and are the same as those in

[34] Wooldridge, pp. 746 – 748

Table 12. The degrees of freedom for the various regressions are equal to those in the sample of 2014 – April 2018, i.e. the $F_{q,n\text{-}k\text{-}1}$ here are the same as in each of the corresponding regressions from sample 2014 – April 2018 in Table 12.

Table 19. Statistical information for carrying out F-tests, where the null hypothesis is that all coefficients of the interaction terms for 2017 – April 2018 are jointly equal to zero

	(1)	(2)	(3)	(4)	(5)
$F_{q,n\text{-}k\text{-}1}$	$F_{1,6099}$	$F_{2,6097}$	$F_{4,6093}$	$F_{3,6095}$	$F_{5,6091}$
F-statistic	0.6114	0.9171	0.6111	1.0189	0.7332
$F_{0.01}^{CRIT}$	6.63	4.61	3.32	3.78	3.02
$F_{0.05}^{CRIT}$	3.84	3.00	2.37	2.60	2.21
$F_{0.10}^{CRIT}$	2.71	2.30	1.94	2.08	1.85

Comparing the F-statistic to the critical values at the various significance levels in Table 19 tells us whether we can reject the null hypothesis and at which certainty this can be rejected. The absolute value of the F-statistic must be higher than the critical value in order to reject the null hypothesis at that particular level. Hence, we quite clearly fail to reject the null hypothesis at any percentage level, and the coefficients of the interaction terms are jointly equal to zero.

Although some of the t-tests return statistically significant results in this sample of 2017 – April 2018, the F-tests suggest that potential changes to the pattern previously discovered by Cieslak et al. are not too large. As mentioned earlier, it is also reasonable to expect some false positives when carrying out t-tests on a large number of coefficients as has been done in this thesis. Thus, investigations of parameter stability for 2017 – April 2018 are also in support of the analyses of sample 1994 – April 2018 returning reliable results.

We will now take a look directly at the coefficients of the weekly variables for the sample 2017 – April 2018 to see whether these coefficients look very different to those in the other samples. We follow the same procedure as we did for sample 2014 – April 2018 in the previous section, where Tables 13 – 17 above give the coefficient estimates for samples 2014 – April 2018, 2017 – April 2018, 1994 – 2013, 1994 – 2016 and 1994 – April 2018. Any large differences in the coefficients in sample 2017 – April 2018 to the coefficients in samples 1994 – 2016 or 1994 – April 2018 could help illustrate whether there have been any changes in the stock return pattern. As mentioned in the previous section, the usual asterisks indicating levels of statistical significance are not included in Tables 13 – 17 as the focus here is on the values of the coefficient estimates.

Looking at Tables 13 – 17, the coefficients in sample 2017 – April 2018 appear to differ from the coefficients in samples 1994 – 2016 and 1994 – April 2018 to an even larger degree than sample 2014 – April 2018 differed from samples 1994 – 2013 and 1994 – April 2018 in the previous section. This is perhaps not surprising considering that sample 2017 – April 2018 is of a much smaller size than sample 2014 – April 2018. In Table 13 the difference in coefficient value between sample 2014 – April 2018 and sample 1994 – 2013 is 0.136 – 0.111 = 0.025 for the weekly variable *Week 0246*, whilst the difference in coefficient value between sample 2017 – April 2018 and sample 1994 – 2016 is 0.073 – 0.121 = -0.048 for the same weekly variable. In Table 14 and Table 15 *Week 0* has a difference in coefficient value of 0.077 – 0.140 = -0.063 between the samples 2014 – April 2018 and 1994 – 2013, whilst the difference in coefficient value between sample 2017 – April 2018 and sample 1994 – 2016 is -0.093 – 0.144 = -0.237 for the same weekly variable. This is the biggest difference between coefficient values in samples 2017 – April 2018 and 1994 – 2016. The biggest difference between coefficient values in samples 2014 – April 2018 and 1994 – 2013 is coefficient *Week 4* in Table 17 with a value of 0.188 – 0.066 = 0.122. However, this same weekly variable in the same regression only has a difference in coefficient value of 0.099 – 0.088 = 0.011 for samples 2017 – April 2018 and 1994 – 2016.

As mentioned earlier, the week 4 effect on the dependent variable is much stronger in sample 2014 – April 2018 than in sample 1994 – 2013. The week 4 effect on the dependent variable in sample 2017 – April 2018, on the other hand, is very similar to the week 4 effect in sample 1994 – 2016. Hence, the newer data does not exhibit a much stronger week 4 effect in this case. When it comes to the week 2 effect on the dependent variable, this appears to be much stronger in sample 2017 – April 2018 than it is in sample 1994 – 2016, especially in Table 17. The week 0 and week 6 effects are much weaker in sample 2014 – April 2018 than in sample

1994 – 2013 as mentioned earlier. However, the week 0 effect in sample 2017 – April 2018 is different from what we observe in other samples. It has a negative effect on the dependent variable in Tables 14 – 17 for sample 2017 – April 2018, and has a positive effect for all other samples. The effect of the coefficient for the odd weeks on the dependent variable is positive in sample 2017 – April 2018, which is also different from the results in other samples where this effect is negative. The effect of the coefficient for week 2, 4, 6 on the dependent variable is stronger in sample 2017 – April 2018 than in sample 1994 – 2016 in both Table 14 and Table 16. Finally, the effect of the coefficient for all the even weeks on the dependent variable in Table 13 is weaker in sample 2017 – April 2018 than in sample 1994 – 2016, which is likely to be due to the negative coefficient for week 0 in sample 2017 – April 2018.

When looking at the coefficients in sample 1994 – April 2018 in Tables 13 – 17 we see that these are predominantly somewhere in between the values of the coefficients in sample 2017 – April 2018 and sample 1994 – 2016, which is what we would expect them to be. The coefficients in sample 1994 – April 2018 are closest in value to those in sample 1994 – 2016, which is not surprising considering that the sample 1994 – 2016 spans 23 years in contrast to sample 2017 – April 2018 which spans approximately 1.25 years. The differences in coefficient values between samples suggest that there could be a change in the stock return pattern. However, this potential change does not appear to be very large as only a very small number of the t-tests return statistically significant results, and only at the 10 percent level, and none of the F-tests return statistically significant results. Hence, it appears that we can be confident about results determining the persistence of the stock return pattern in sample 1994 – April 2018 in the next chapter.

2.3 Summary and thoughts on results of parameter stability testing

The main source of differences between the parameter stability results of samples 2014 – April 2018 and 2017 – April 2018 in the previous sections appears to be caused by the difference in sample sizes, where 2014 – April 2018 spans around 4.25 years and 2017 – April 2018 spans approximately 1.25 years. Hence, the sample size of 2014 – April 2018 is over triple that of 2017 – April 2018. However, this does not seem to cause major problems as the only difference between the analyses of the two samples is that two of the t-tests on the parameter stability dummies for 2017 – April 2018 return statistically significant results. These t-tests are on the odd week interaction terms, and they are only significant at the 10 percent level. The t-tests on the parameter stability dummies for 2014 – April 2018 do not return statistically significant results for any weekly interaction term. The F-tests carried out find that the coefficients of the interaction terms are jointly equal to zero at the 1 percent level in both samples.

When comparing and contrasting the coefficients in all samples in this thesis by looking merely at the coefficient values, it does appear that the stock return pattern has been altered slightly. However, this potential change seems to be of a small degree as the statistical tests do not find much evidence to support large changes in the stock return pattern. Hence, the results and conclusions drawn from analyses of samples 1994 – 2013, 1994 – 2016 and 1994 – April 2018 in this thesis are supported by parameter stability testing. The stock return pattern does indeed appear to be present from when the sample periods begin in 1994 to the most recent time period in this thesis of April 2018.

3 Full sample analysis

3.1 Sample 1994 – April 2018

The following section describes the findings of the data and statistical analyses of the final and the most recent sample in this thesis, sample 1994 – April 2018.

3.1.1 Data analysis procedure and results

Table 20. U.S. excess return averages by individual week, combined week or all weeks; illustrating the profitability of different trading strategies, sample 1994 – April 2018

	Week –1	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 2,4,6	Week 0,2,4,6	Week –1,1,3,5	All Weeks
Daily Average	0.007	0.11	-0.05	0.08	-0.04	0.09	0.03	0.09	0.08	0.09	-0.02	0.03
Weekly Average	0.04	0.53	-0.24	0.41	-0.21	0.43	0.16	0.45	0.42	0.46	-0.10	0.16
*Annual Average	0.28	4.24	-1.95	3.25	-1.64	2.92	0.50	0.32	6.49	10.73	-2.80	7.92

*We are not dealing with whole years in this particular sample like in the other samples, but have a few extra months into 2018 in addition to the 24 years from 1994 – 2017. Hence, since this sample ends on the 23rd of April 2018, this is 24 years plus three extra months, i.e. 24.25 years.
Note: All the values in the table are in percent. The holding of stocks in different weeks refer to the different trading strategies, where for example column Week 0 refers to holding stocks in week 0 only.

Table 20 displays the most recent biweekly excess return patterns, where all the weeks have similar values to those of sample 1994 – 2016 in Table 6 with the exception of week 5 which has a weekly average of 0.16 percent in this new sample. This is 0.09 percent more than in the sample of 1994 – 2016. Thus, what could be considered a weekly average stock return close to zero in sample 1994 – 2016, has now become a weekly average stock return more in the category of being positive. Week 5 is therefore the strongest deviation in Table 20 from previous results. This value, although positive, is less than half of the weekly averages in the even weeks. Hence, this result is not dramatic although it does challenge the conventional expected pattern. The combined weekly averages are very similar to those in the previous sample, with a difference in week 0, 2, 4, 6 of merely 0.46 – 0.47 = -0.01, i.e. a 0.01 percent decrease from sample 1994 – 2016 to the new sample period. The difference in the combined weekly average of the odd weeks is an increase of 0.03 percent, whilst the difference in the combined weekly average of all weeks is an increase of 0.01 percent.

3.1.2 Statistical analysis procedure and results

Table 21 below shows the descriptive statistics for the new sample where the first four weeks, which are the weeks with the highest number of observations, have 970 observations each. This is an increase from sample 1994 – 2016 of 50 observations for each week. Week 3 also sees an increase in 50 observations, whilst week 4 has an increase of 45. Week 5 has a small increase of 15, whilst week 6 is the week with the smallest increase of all the weeks with an increase of 4 observations. Week 6 also had this very same increase from sample 1994 – 2013 to 1994 – 2016.

Table 21. Descriptive statistics for weekly variables, sample 1994 – April 2018

Variable	Observations	Mean	Standard deviation	Min. value	Max. value
Week –1	970	0.0071134	1.054661	-5.76	6.35
Week 0	970	0.1061134	1.204549	-6.97	9.77
Week 1	970	-0.0486907	1.089439	-5.05	4.47
Week 2	970	0.0812474	1.153153	-8.26	6.79
Week 3	951	-0.0418402	1.210991	-7.36	6.27
Week 4	813	0.0869496	1.182542	-8.95	5.43
Week 5	369	0.032981	1.073895	-4.21	4.55
Week 6	88	0.0890909	0.9746012	-2.47	2.95
Week 2,4,6	1871	0.0840941	1.157791	-8.95	6.79
Week 0,2,4,6	2841	0.0916121	1.1738	-8.95	9.77
Week –1,1,3,5	3260	-0.0208436	1.114561	-7.36	6.35

When comparing the regression results in Table 22 with those from sample 1994 – 2016 in Table 9, we see that these are equal in terms of levels of statistical significance for all dummy variables and constant terms. In fact, most of the coefficients are very similar in magnitude as well, with the least similar coefficients being the ones for dummy week 0. The differences between these are 0.144 – 0.127 = 0.017 percent and 0.119 – 0.107 = 0.012 percent, which is marginal. All the signs of the coefficients are according to expectations, with positive signs for the even weeks and negative signs for the odd weeks and constant terms.

Table 22. Regressions of U.S. daily excess stock returns on FOMC cycle dummies, sample 1994 – April 2018

	(1)	(2)	(3)	(4)	(5)
Dummy=1 in Week 0, 2, 4, 6	0.114*** (3.85)				
Dummy=1 in Week 0		0.127*** (2.93)	0.127*** (2.93)	0.107*** (2.74)	0.107*** (2.74)
Dummy=1 in Week 2, 4, 6		0.106*** (3.18)		0.086*** (3.14)	
Dummy=1 in Week 2			0.104** (2.44)		0.083** (2.19)
Dummy=1 in Week 4			0.109** (2.35)		0.088** (2.10)
Dummy=1 in Week 6			0.111 (1.04)		0.090 (0.86)
Dummy=1 in Week -1, 1, 3, 5				-0.021 (-1.07)	-0.021 (-1.07)
Constant	-0.021 (-1.07)	-0.021 (-1.07)	-0.021 (-1.07)		
No. of days	6102	6102	6102	6102	6102

Note: The significance level is indicated by the asterisks, where *** is significance at the 1 percent level, ** is significance at the 5 percent level, and * is significance at the 10 percent level. The dependent variable, i.e. the variable on the left hand side, is the excess return on U.S. stocks over Treasury bills, and is given in percent where for example 0.1 is 10 basis points per day. The t-statistics are robust to heteroskedasticity and are in parentheses.

3.2 Summary and thoughts on new results

The most recent sample shows very similar regression results to the ones in sample 1994 – 2016. Hence, the economic implications are the same in both, where the even week dummy variables are all significant to either the 1 percent level or the 5 percent level, with the exception of the dummy week 6 which is not significant in my regressions. All regressions in all samples give non-significant statistical results for the odd weeks. This is important, because although there have been variations in the samples concerning whether week 4 or week 6 have been statistically significant, the odd week dummies have never been significant. Thus, we have strong statistical support of the even weeks being the driving force of high positive excess returns, and strong statistical support that the odd weeks do not contribute to boosting these excess returns.

Results from sample 1994 – April 2018 show that the biweekly pattern outlined by Cieslak et al. appears to still have a strong presence in U.S. excess returns. This is supported by the parameter stability test results in the previous chapter. Hence, there appear to be long term lucrative financial opportunities for investors if they take these findings into consideration. Using the data and statistical analyses concerning the U.S. excess returns over the FOMC cycle, together with knowledge on how the FOMC operates, could be of advantage for an investor not wanting to lose out on high returns during the even weeks of the FOMC cycle. When it comes to knowledge about the FOMC, this is in particular reference to the next chapter where we will be discussing information leaks of Fed decisions before these becoming publicly available. We will also consider governmental interference in financial markets, which is the Fed affecting the market with accommodating policy, or the promise of such policy. The next chapter begins by looking more closely at how we can use results from this thesis when investing in the stock market.

4 Implications of results

4.1 Using findings when investing in the stock market

One might think that the financially lucrative opportunities observed in the even weeks over the FOMC cycle are arbitrage opportunities. However, then it would be unlikely for them to persist 4 years after the initial publication of Cieslak et al.'s results, unless these excess returns are unexploited arbitrage opportunities. Nevertheless, these potential arbitrage opportunities or what might simply be interpreted as equity risk premia for systematic risk factors, appear to be long term. For investors to have an incentive to invest in the stock market during the even weeks of the FOMC cycle, the transaction costs of investing must be less than the compensation that they receive for taking on this risk, i.e. the equity premium. A similar condition applies when taking advantage of a pure arbitrage opportunity. Although a pure arbitrage opportunity is considered riskless, the gains from taking advantage of an arbitrage opportunity must exceed the transaction costs involved in doing so. Hence, unexploited arbitrage opportunities might still be present in the market if transaction costs have been large enough to discourage investors from taking advantage of them. Cieslak et al. document that approximately half of the high stock returns during even weeks are due to stock market mean-reversion,[35] i.e. the tendency for the stock market to "repair" itself, during the even numbered weeks. This is in reaction to substantial stock market declines occurring in the odd weeks. This mean-reversion following low stock returns has not been observed in odd numbered weeks.[36] One can therefore view the even weeks as attempts to smooth the excess returns after losses in the odd weeks. Due to mean-reversion being a type of self-repair mechanism, it could be viewed as a way of incentivizing investors to invest in the stock market by compensating them with high excess returns for taking on the risk of investing after bad periods. In this respect mean-reversion could be viewed as more of a risk factor than an arbitrage opportunity.

The puzzling excess return pattern could also be viewed as the effect of the market responding to the Federal Reserve's interference or the promise of an interference. Accommodating monetary policy by the Fed lowers the risk and uncertainty of investing in

[35] Cieslak et al. (February 12, 2018), p. 2
[36] Cieslak, Anna and Vissing-Jorgensen, Annette., p. 10

the stock market and therefore lowers the equity risk premium.[37] In fact, the Fed does not necessarily have to act for the equity premium to be affected as long as it *promises* to act if needed. Thus, expectations are a powerful force in their own right, and can drive the market. Cieslak and Vissing-Jorgensen discuss the prospect of the stock market driving U.S. Federal Reserve monetary policy in the *Fed put*, where low stock returns can predict accommodating monetary policy.[38] The stock market appears to have too much power, in the sense of not only being a factor for the FOMC to take into concern when forecasting the economy, but being an actual driving force of the choices made concerning the interest rate. Thus, members of a body governing monetary policy might be as affected by expectations and fear from a downturn in the market as an investor could be. This perhaps raises some issues as to the credibility of a body like the FOMC when its members allow themselves to get too affected in their decision making by events and changes in the stock market. As Cieslak and Vissing-Jorgensen point out, bad periods in the stock market are frequently commented upon in FOMC documents to the extent that they appear to predict interest rate cuts.[39]

Thus, we might be looking at a case of perhaps too much interference from the Federal Reserve, where Adam Smith's invisible hand is not allowed to take its “natural” course. The traditional economic viewpoint is that too much interference in the market can sometimes not be a good thing. It does however seem like interference is beneficial here from an investor’s point of view, as it is this interference that helps contribute to a fairly predictable pattern of high excess returns in even weeks. This provides an investor with more security in terms of obtaining financial gains in even weeks. Thus, going long in stocks during even weeks and shorting stocks in the odd weeks appears to be a rather secure strategy when investing in the stock market. This is based on our sample periods where they all start in 1994 and the most recent one ending in April 2018. If we do not merely focus on even and odd weeks over the FOMC cycle, but also look more closely at the days when the FOMC meets, we can look at dates before 1994. Tori[40] says that a sample period from 1980 – 2000 gives a substantially higher mean market return on days when the FOMC met than on the days when it did not meet. In fact, this mean market return is 5.7 times greater on the days the FOMC meets.[41] Thus, if we not only look at whether a week is even or odd, but also look at the relationship

[37] Cieslak et al. (February 12, 2018), p. 2
[38] Cieslak, Anna and Vissing-Jorgensen, Annette.
[39] Cieslak, Anna and Vissing-Jorgensen, Annette.
[40] Tori, p. 170
[41] Tori, p. 170

between FOMC meeting dates and stock returns in a wider context, the effect of the FOMC on the stock market spans an even larger time period.

Tori also mentions that investors risk losing out on large stock returns if they do not invest when the FOMC meets.[42] This naturally also applies to our results of positive excess returns in even numbered weeks and negative or zero excess returns in odd weeks, where investors will lose out on large returns if they do not hold stocks during even weeks. It is equally important that investors then short stocks in odd weeks to not lose their substantial gains from even weeks. In the case of Tori, investors would have to short their stocks on days when the FOMC do not meet.

Something to be aware of is the asymmetric information that could be present in the financial market. Someone with good connections to members of the Fed could have a huge advantage compared to other people due to moral hazard or adverse selection. As an investor, you could be at a disadvantage if others have an informational advantage over you when investing in the stock market. This is illustrated by the example of Laurence H. Meyer, a former Fed governor, who had information from the August 2010 FOMC meeting weeks before it was publicly announced. As an advisor on macroeconomic and monetary policy issues, Meyer charged private sector clients an annual subscription fee of $75 000 for his market updates in his old firm Macroeconomic Advisers.[43] He is currently the president of another advisory firm that also does research within macroeconomics and monetary policy called Monetary Policy Analytics Inc. The example of Meyer highlights several issues, where Meyer as a former official of a governmental body uses his informational advantage for his own and his clients' financial gain. There does not appear to be any law prohibiting former Fed officials from sharing information that they have received and there seem to be no consequences for Meyer for doing so.[44] Many former Fed officials work in consultancy or banking after they finish their official positions within the Federal Reserve. Former staff of the Federal Reserve Board get to keep their access to the central bank building where there are fitness facilities, a barber and a dining room that they can visit in addition to having free access anywhere else in the building.[45] It is natural to assume that these conditions might ease the flow of information between former Fed officials and current officials. However, there are laws prohibiting

[42] Tori, p. 170
[43] Cieslak et al. (June 6, 2014), p. 25
[44] Cooke et al., Reuters
[45] Cooke et al., Reuters

current Fed officials from sharing confidential information with outside parties. This is apparent from a circular on the website of the Federal Reserve Bank of New York[46] issued on the 5th of December 1997, which addresses the improper disclosure of confidential information within the Federal Reserve. Nonetheless, the case of Meyer is not unique as the dissemination of confidential Fed information seems to be a frequent occurrence whether done deliberately or not by the person responsible for the leak. Hence, it is apparent that some people are using Fed connections and information to obtain substantial financial gains, where Meyer's clients in this instance clearly have an informational advantage compared to others.

Table 23. The profitability of different trading strategies when investing 1 U.S. Dollar at the start of 1994*, results from all of my samples and Cieslak et al.'s results from their 1994 – 2016 sample

	Value of 1 U.S. Dollar invested at the start of 1994*			
	Sample 1994 – 2013	Sample 1994 – 2016	Sample 1994 – April 2018	[47]Sample 1994 – 2016 **Cieslak et al.**
Hold stocks on all days	2.91	3.78	4.58	7.68
Hold stocks in weeks 2, 4, 6 only	2.69	3.73	4.25	
Hold stocks in weeks 0, 2, 4, 6 only	6.42	10.32	11.09	15.22
Hold stocks in weeks –1, 1, 3, 5 only	0.45	0.37	0.41	0.51

*The first FOMC cycle period in the sample periods at hand, i.e. from 1994 onwards, starts at the 27th of January 1994. Hence, in referral to the start of 1994, this is the 27th of January 1994 which marks the start of week –1 of the very first 1994 FOMC cycle period. This has been my interpretation of the start date as the FOMC cycle periods are the foundation of the analysis here, so it seemed a natural starting point for me. Cieslak et al. have not stated what their interpretation of the start date is, other than it being towards the beginning of 1994.
Note: Cieslak et al.'s articles with analysis from sample 1994 – 2013 do not give the value of 1 U.S. Dollar invested at the start of 1994, which is why it is not mentioned in the table.

[46] Federal Reserve Bank of New York
[47] Cieslak et al. (February 12, 2018), p. 41

Table 23 looks at the profitability of investing 1 U.S. Dollar when choosing to hold this investment in different weeks. The transaction costs of investing in the stock market are not taken into consideration here. All the samples have a similar result where holding stocks in weeks 0, 2, 4 and 6 only, undoubtedly seems to be the best strategy as it returns the highest yield. Holding stocks in weeks –1, 1, 3 and 5 only, returns the lowest yield and is the worst strategy. This is as expected from our analysis in earlier sections, where yields in week 0 are especially large. The high returns in week 0 are very apparent from the increase in the value of 1 U.S. Dollar when investing in all even weeks compared to choosing to invest only in weeks 2, 4 and 6. The differences in Table 23 between my sample of 1994 – 2016 and Cieslak et al.'s corresponding sample might be due to choosing different start and end dates for our sample periods, and therefore having some different excess returns in our samples. The differences between our results for sample 1994 – 2016 are unlikely to be due to setting some holiday returns equal to zero whilst leaving other holidays out of the sample, as a holiday return equal to zero does not contribute to the value of 1 U.S. Dollar invested at the start of 1994. The numerical results in Table 23, although somewhat different, still strongly correspond with what we are expecting to find.

When looking at Table 1, Table 6 and Table 20 in the data analysis sections of this thesis, we can observe the benefit of holding stocks in certain weeks over the FOMC cycle over different periods of time. From Table 1, we observe that holding stocks in week 2, 4, 6 only returns an annual average of 5.53 percent in sample 1994 – 2013. In comparison for sample 1994 – 2016 in Table 6, holding stocks in this week returns an annual average of 6.27 percent, whilst for sample 1994 – April 2018 in Table 20, holding stocks in this week returns an annual average of 6.49 percent. Thus, the benefit of holding stocks in week 2, 4, 6 increases over time. Including week 0 in the combined week that we just discussed gives us the combined week of all even weeks, week 0, 2, 4, 6. Holding stocks in these weeks gives us an annual average excess return of 10.20 percent, 10.98 percent and 10.73 percent in the periods of 1994 – 2013, 1994 – 2016 and 1994 – April 2018 respectively. Consequently, the magnitude of the benefit of holding stocks in week 0, 2, 4, 6 fluctuates over time. In contrast, when holding stocks in all the odd weeks over the FOMC cycle we obtain a negative annual average return of -3.03 percent, -3.49 percent and -2.80 percent in the periods of 1994 – 2013, 1994 – 2016 and 1994 – April 2018 respectively. Hence, we would lose a certain percentage of our initial investment by holding stocks in odd weeks, and would therefore not choose this strategy. The magnitude of the losses of holding stocks in week –1, 1, 3, 5 fluctuates over time. If an investor decides to hold stocks in all weeks, i.e. both the even and odd weeks, our losses and gains would balance out to an annual average excess return of 7.15 percent, 7.48 percent and 7.92 percent in the periods of 1994 – 2013, 1994 – 2016 and 1994 – April 2018 respectively. Hence, the benefit of holding stocks in all weeks increases over time.

4.2 Explanations of results

4.2.1 Information leaks from the Federal Reserve

As already mentioned in the previous section, the former member of the Federal Reserve Laurence Meyer clearly has informational advantages because of his connections. He is not the only one, and Cieslak et al. give several examples of people who have had access to confidential Fed news before they were supposed to. Another example of this is a live interview on CNBC with Bill Gross from PIMCO where Greenbook content had been leaked to his company before the FOMC meeting in question had taken place.[48] Bill Gross blatantly reveals inside knowledge from the Fed, that they are about to downgrade their forecast of the interest rate from 3 percent to 2 percent. The news anchor then responds that this forecast will not be released before three weeks. This systematic informal communication seems to contribute to the effect of high excess returns in the even weeks, where the Board of Governors have meetings during these weeks. Thus, a lot of the Federal Reserve decision making and information processing happens during the even weeks, and consequently the dissemination of confidential Fed information, in the form of leaks, is likely to occur during this time as well. It is the unofficial news and information about the details of the FOMC meetings that has the biweekly effect on stock returns, and not the actual public announcements from the Fed. Hence, speculation on the content of these meetings helps drive the market.

A downside of providing confidential and potentially profitable information to certain members of the public is that it might threaten the credibility of the Fed as an important governmental body. The Fed should maintain its role as a credible and responsible body whom people can trust. Otherwise the powerful tool of promise of action might not have any, or only very little, effect and the Fed might lose its ability to affect the stock market and drive it in a beneficial direction.

Cieslak et al. mention four reasons[49] why the Fed uses informal communication, i.e. why news not yet made public is spread by various means. The first reason is that informal information gives the Fed flexibility to for example implement more continuous policy.

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[48] Cieslak et al. (February 12, 2018), p. 51
[49] Cieslak et al. (February 12, 2018), p. 3

Having an unofficial dialogue and informal information channel with the public can also be used to explain Fed policy and decision making, as well as assessing how the market will react to certain policies. The Fed is keen to see how its view of the economy is in comparison to the view held by the financial sector, and keen to allow for informal communication to open up to discussions about this. The final reason is the FOMC members all having certain preferences in terms of desired policy outcome and having disagreements about these with one another, where informal communication provides an outlet for these disagreements.

4.2.2 Governmental interference in financial markets

This section discusses unexpectedly accommodating policy by the Federal Reserve in even weeks following a period of low stock returns in odd weeks. News that the Fed will act to alleviate a poor situation on the stock market, or at least a promise to act, may lead to a mean-reversion of the stock market. In other words, accommodating policy by the Fed instigates the stock market to "repair" itself in the sense of smoothing out the low stock returns. Emphasis here is on the accommodating policy being unanticipated by the market, where it will then contribute to the biweekly effect in the stock return pattern. People are generally risk averse and value having some form of insurance in the event of a worst-case scenario. Hence, promises of risk-reducing behaviour and actions if needed may ameliorate a period of poor stock returns even if these promised actions do not need to be realized.

Notable periods where the Fed has had to intervene in the market with significant accommodation policy was following the recession of 2001 and the Great Recession of 2007 – 2009.[50] The stock market crash of 1987, i.e. Black Monday, is believed to be a particular instigator for Fed intervention in the stock market when it is doing badly or when there is news of it perhaps entering a bleak period.[51] This might suggest that intervention in the form of unexpectedly accommodating policy is a frequently used tool so as to avoid experiencing financial turmoil such as Black Monday again. This in turn contributes to the biweekly excess return pattern.

[50] Cieslak et al. (February 12, 2018), p. 22
[51] Cieslak et al. (February 12, 2018), p. 15

5 Conclusion

5.1 Conclusion

The foundation of this thesis is the replication of Cieslak et al.'s analysis of U.S. stock returns over the FOMC cycle, where excess returns are positive in even weeks and negative or close to zero in odd weeks. After replicating their data and statistical analyses using the 20-year sample of 1994 – 2013 and the 23-year sample of 1994 – 2016, and investigating parameter stability when expanding these samples with more recent data, my results seemed sufficient enough to proceed with the analyses of the 24.25-year sample of 1994 – April 2018. Investigations of this new sample resulted in strong statistical support of the hypothesis that the even weeks of the FOMC cycle provide high excess returns, whilst the odd weeks do not. Parameter stability tests controlling for the robustness of the statistical results when expanding the first two samples to include more recent data, also support that the biweekly pattern is still present in the stock market.

The fascinating pattern of stock returns remains, suggesting that the financially lucrative gains in even weeks are long term. Thus, a strategy of going long in stocks in even weeks and shorting stocks in odd weeks seems profitable. Breaking down and looking more closely at information about the FOMC and its actions can help us understand the reasoning behind the biweekly stock return pattern. It is after all the FOMC, with its accommodating policy and informal communication, that forms the building blocks of the pattern we observe.

5.2 Further topics of interest

To continue the research into stock returns over the FOMC cycle on a larger scale one could investigate to what degree the excess return pattern is present in international financial markets. This could be within emerging markets or based specifically on markets in for example Europe. One would have to take into consideration here what role other central banks have, as we have in this instance been dealing exclusively with the Federal Reserve. Does the Federal Reserve's influence on the U.S. stock market transfer to international markets? Do other central banks around the world have such an effect on their respective stock markets? How about leaks to the corporate world or to the media, and what implications they have on markets outside the U.S., i.e. whether other central banks also tend to leak information, giving certain members of the public with the right connections an advantage over others in the financial markets.

Additionally, one could examine alternative sample periods that include older data to see what kind of pattern was present then, if any at all. The Center for Research in Security Prices (CRSP) are currently revising historical data on some stock returns with their Pre-1947 Shares Outstanding Project, and they have recently completed their Pre62 Daily Data Series Project.[52] Some of these revisions could be of interest if examining early FOMC and stock return relationships. The Banking Act of 1935, which was passed by Congress after the Great Depression, saw the establishment of the FOMC as the monetary policymaking body of the Fed.[53] Hence, the FOMC has a history spanning almost six decades prior to the sample periods studied in this thesis, and therefore the CRSP revisions could be of relevance when studying the early days of the FOMC.

[52] Kenneth R. French website
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