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Submission / Angefertigt am
Department of Economics

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8th December 2023

Stock Returns over the FOMC Cycle Revisited

Bachelor Thesis

to obtain the academic degree of

Bachelor of Science

in the Bachelor's Program

Economics and Business

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To myself.

I would like to express my gratitude to Dr. Jochen Güntner, Professor of Macroeconomics at Johannes Kepler University Linz, for providing me with the opportunity to write this bachelor's thesis in a field I haven't been exposed to academically beyond introductory level courses.
I appreciate his valuable comments on the original version of my submitted bachelor thesis.

I also want to take this opportunity to mention Dr. Helga Wagner from the Institute of Applied Statistics, Dr. Martina Zweimüller, Dr. Matthias Fahn from the Department of Economics, and Dr. Florin Ciucu from the Computer Science Department at the University of Warwick. Their courses on Time Series Analysis, Intermediate Econometrics, Behavioural Economics, and Data Analytics have greatly influenced my current understanding in the field of Economics during my undergraduate studies.

Declaration of Academic Honesty

Hereby, I declare that I have composed the presented bachelor thesis independently on my own and without any other resources than the ones indicated. All thoughts taken directly or indirectly from external sources are properly denoted as such.

(Reichel F.)

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1. Motivation

This thesis is motivated by recent research that delves into the potential causal relationship between the monetary policy decisions of the Federal Reserve (FED) and the U.S. stock market. Building upon existing studies, which primarily examine this connection retrospectively, the focus extends to exploring both ex-post and ex-ante perspectives.

Cieslak et. al (2019) finds a pattern in financial markets around the world that suggests that stock market excess returns in the last 23 were entirely earned in even weeks (0, 2, 4 and 6) starting from the last FOMC meeting. The authors tie their findings to a known phenomenon called "FED Put", by which they mean accommodating monetary policy.

Cieslak and Vissing-Jorgensen (2021) use textual analysis of FOMC (Federal Open Market Commitee) scripts to identify that policymakers indeed pay attention to the stock market, especially since the mid-1990s and stock market performance is linked with updates of the FED's internal growth projections. The authors further claim that even if the policymakers seem to be aware that a dynamic like the FED Put could cause overly risky investing behavior leading to moral-hazard implications, it does not particularly change their decision-making in an ex-ante sense.

In my thesis, my goal is to explore whether the financial pattern concerning excess returns in FOMC even weeks remains pertinent after 2016 or from that year onward. (probably complicated by the COVID-19 crisis) This is significant as one would anticipate a decrease in relevance, particularly after the market became aware of the pattern. Cieslak et al. (2019) exclusively examines this pattern before 2016. Furthermore, the authors assess the global significance of this financial pattern by examining exchange-traded funds (ETFs) containing European stocks. I aim to incorporate additional findings, with a particular emphasis on the returns of European stock excess returns.

2. What is the "FED Put" and how can it be explained?

2.1. The FED Put

The FED Put in general refers to (or, moreover, to the expectation of) a strong accommodating monetary policy by the FED, by which, in case of a sharp decline in asset prices, the FED is expected by the market (its investors) to intervene. The term is coined from the concept of a "put option" in asset markets, which gives the buyer the option to sell at a predetermined price. Thus, the FED would protect an investor from the decline in the value of an asset.[1]

Central banks have gained credibility ever since the mid-1980s by keeping inflation low Hall (2011) . The related term "Greenspan Put" is often used to describe the monetary policy under former Federal Reserve Chairman Alan Greenspan to intervene in financial markets in order to prevent significant declines or disruptions.

While some argue that market interventions are necessary to prevent financial crises (like the Dot-com bubble burst in 2001 or Lehman Brothers in 2008), others believe that these interventions distort the market and create unnecessary moral hazard Cieslak and Vissing-Jorgensen (2021), meaning that investors are willing to take on excessive risks because they believe that the FED will always come to rescue them arguing that such "too big to fail" beliefs or mentality can lead to financial crises in the long run.

2.2. Stock Returns over the FOMC Cycle

Diving further into dynamics like the FED Put, Cieslak et. al (2019),focuses on a FOMC cycle specific pattern of the equity premium since 1994. The stock returns exhibit a distinct, statistically significant

[1] **https://corporatefinanceinstitute.com/resources/economics/FED-Put/**

pattern over the FOMC cycle. Notably, it primarily accrues in even weeks of the FOMC cycle time (for a graphical explanation of the FOMC cycle, see figure 3.1 on page 8). For calculation of stock excess returns the authors use research portfolio data provided by Kenneth R. French for convenience[2].

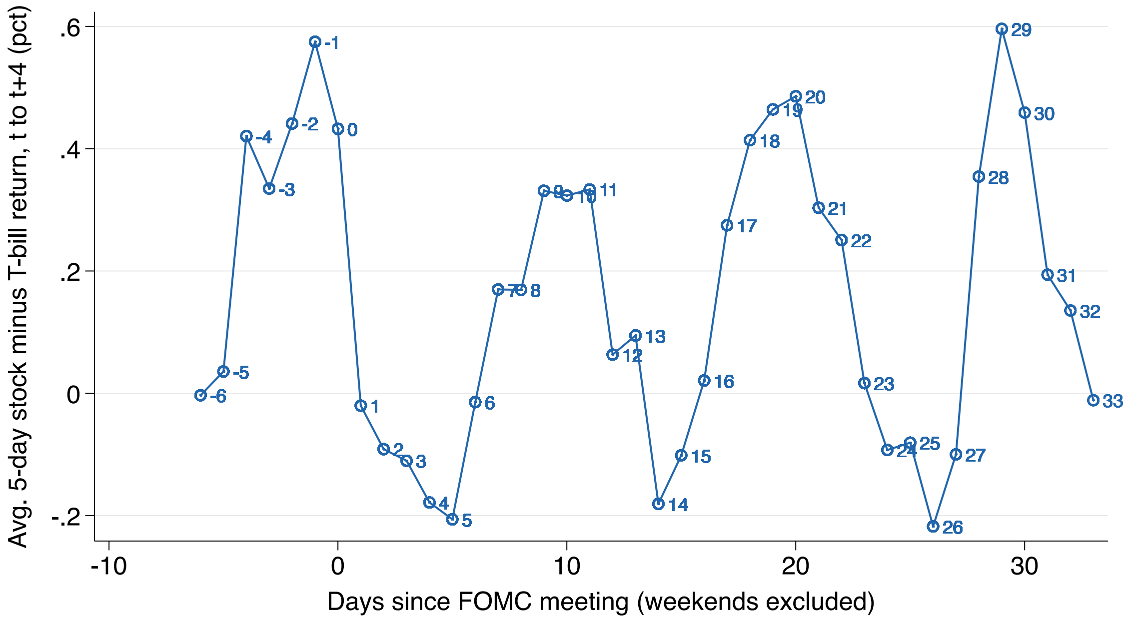

Figure 2.1.: Average 5-day stock excess returns over FOMC cycle time (pct) (Cieslak et. al, 2019)

The authors present three different trading strategies (A, B, and C) that demonstrate the influence of the FOMC cycle on stock market returns. Of particular note is Strategy A, which involves exclusively holding stocks during even FOMC cycle weeks (and investing in a risk-free rate during odd FOMC cycle weeks). This strategy demonstrates that the average annual return more than doubles compared to holding for example an ETF throughout the entire FOMC cycle. Conversly, the authors find that holding an ETF during uneven FOMC weeks (compared to a risk-free rate) resulted in financial losses over the examined period from 1994 to 2016. This results have also been covered by the media.[3]

The authors extend their analysis to explore whether the FOMC cycle return pattern extends beyond the United States, potentially influenced by movements of the dollar currency. To investigate this, they use ETFs containing globally diversified stocks. To establish causality, the authors compare FOMC cycles with other macroeconomic news calendars (e.g., Bloomberg macroeconomic news), dispelling the notion that macroeconomic news significantly correlates with FOMC cycle calendars. They also provide evidence that the release of quarterly firm profits does not substantially account for the observed equity premium patterns over the FOMC cycle.

[2]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#research
[3]https://www.economist.com/finance-and-economics/2016/09/03/the-long-arm-of-the-FED

2. *What is the "FED Put" and how can it be explained?*

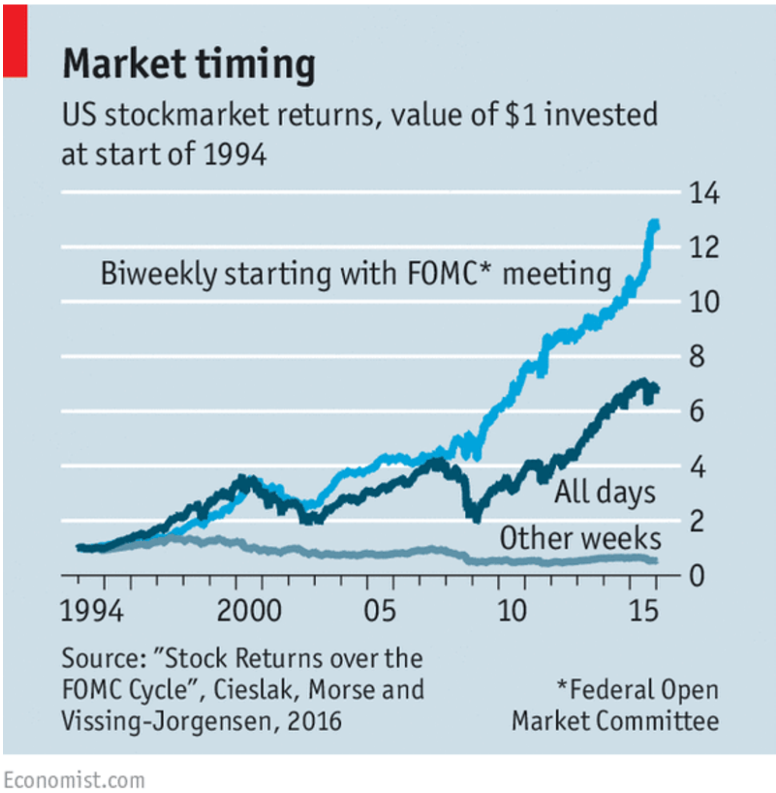

Figure 2.2.: "The long arm of the FED", *TheEconomist* (2016)

The authors examine a causal link between the FED's policy actions and the behavior of the stock market by analyzing in the Federal Fund target changes between meetings, FED funds futures and internal meetings of the Board of Governors. They propose that the FED's anticipated accommodative policies have a substantial impact on the stock market, resulting in a increase of the overall equity premium. Additionally, they contend that there is evidence of informal communication channels between FED officials, the media, and the financial sector, which serve as a means for disseminating information about monetary policy to the market.

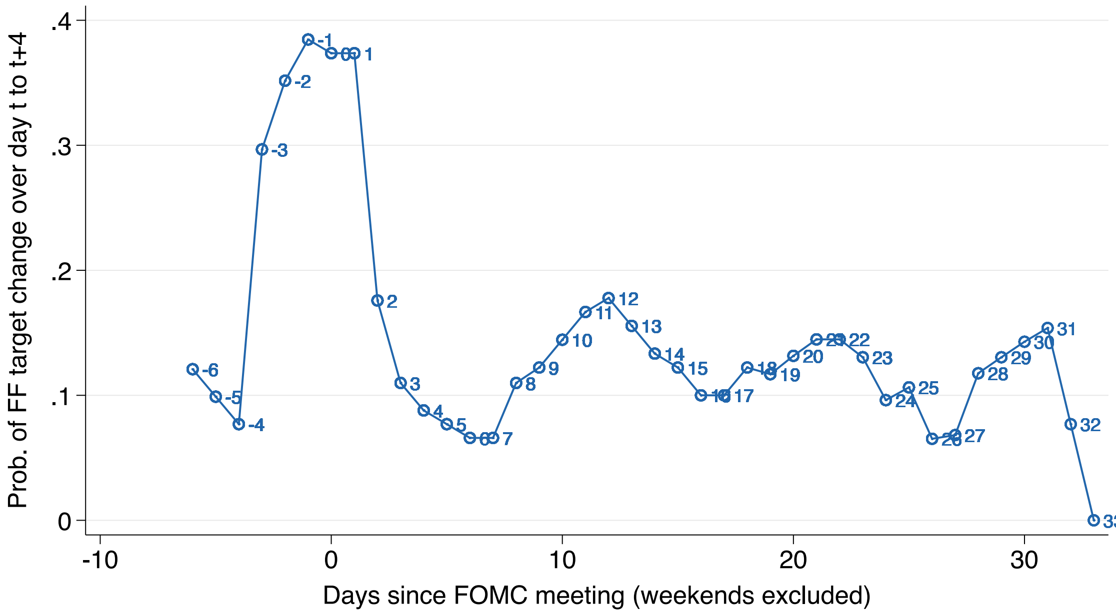

Figure 2.3.: Probability of FFR target changes within FOMC cycle time (Cieslak et. al, 2019)

2.3. The Economics of the FED Put

(2021) further attempts to study the economics of the relationship between FED policy and the stock market. The authors compare the stock market's predictive power to other economic indicators to forecast changes in the Federal Funds Rate (FFR) using textual analysis from former FOMC meeting transcripts.[4] Their findings affirm that the FED indeed pays a lot of attention to the stock market during market downturns.

They argue that the FED Put is fueled by the Federal Reserve's concerns about wealth effects on consumption. Conversely, strong stock market performance corresponds to updates of the FED's internal growth projections. Empirical evidence substantiates their claims, as multiple regressions of changes in the FFR demonstrate that the stock market explains a higher proportion of the variance (R-squared) compared to other macroeconomic indicators. Importantly, this relationship appears to be less pronounced before the 1990s period.

During the third European Central Bank (ECB) annual research conference (European Central Bank, 2018), valuable comments on the econometric approach by the authors were made by the discussant, Emmanuel Moench, the former head of research at the Bundesbank. Moench suggests that the correlation between stock excess returns and the FFR is heavily influenced by two specific FOMC meetings (during financial crises like the dot-com bubble burst in 2001 and the 2008 financial crisis).

[4] **https://www.federalreserve.gov/monetarypolicy/fomc_historical.htm**

2. *What is the "FED Put" and how can it be explained*?

Furthermore, he recommended incorporating additional covariates, including consumer confidence news and credit spreads, into the regression models to enhance their explanatory power. Moench sees the stock market as one of several co-factors influencing Federal Reserve policy (presumably over the updates of the FED's growth projections as stated by the authors), rather than a dominant driver of the FED's policy.

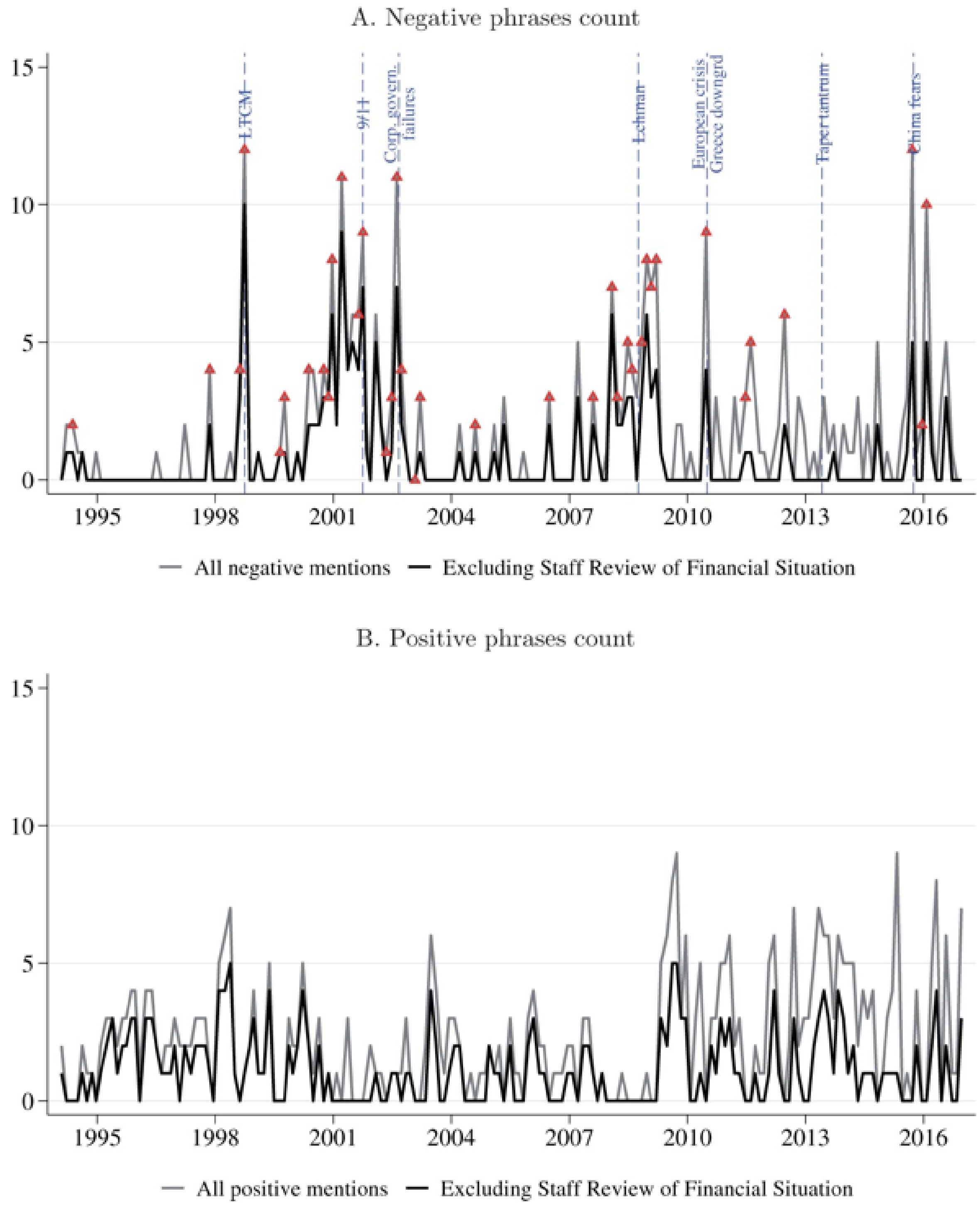

Figure 2.4.: Negative and positive phrases of the stock market count Cieslak and Vissing-Jorgensen (2021)

3. Stock Returns over the FOMC Cycle Revisited

3.1. The FOMC Cycle

The FOMC meets approximately every eight weeks during the year, resulting in an FOMC cycle time of approximately 7 weeks (excluding weekends) most of the time since a year has 52 weeks. The authors, therefore, define FOMC cycle time week dummy variables for week 0 as days -1 to 3, week 1 as days 4 to 8, week 2 as days 9 to 13, week 3 as days 14 to 18, week 4 as days 19 to 23, week 5 as days 24 to 28 and week 6 as days 29 to 33. It is worth mentioning that the authors drop 3 days which would be beyond FOMC cycle week 7 from their investigation for simplicity purposes. Furthermore that the number of available data points decreases for FOMC dummies (meaning 920 days in week 0, 924 days in week 2, 831 days in week 4, 120 days in week 6 for the relevant timespan from 1994 to 2016).

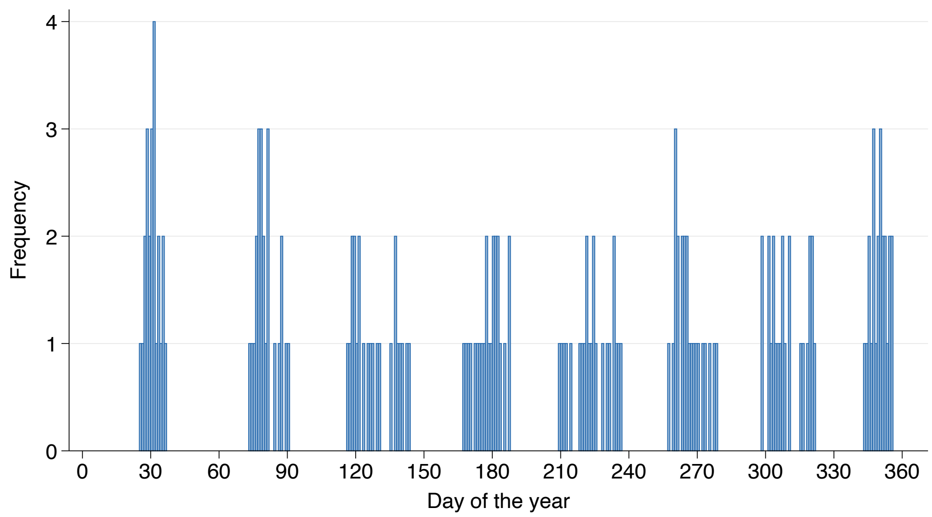

Figure 3.1.: Frequency of FOMC meetings during the year from 1994 to 2016 (Cieslak et. al (2019))

3.2. Institutional Setting

The Federal Reserve System is comprised of the Board of Governors, 12 Federal Reserve Banks, and the FOMC. The FOMC's 12 members are responsible for implementing monetary policy to achieve macroeconomic goals, such as adjusting FFR and conducting large-scale purchases of treasury securities and Federal agency-issued or guaranteed securities since the 2008 financial crisis as policy tools to lower long-term interest rates, ensuring the functioning of the U.S. economy.[1].

3.3. FOMC Data

The FOMC publishes detailed records of its meeting proceedings on the Federal Reserve's webpage[2]. The transcripts are produced by the FOMC Secretariat shortly after every meeting since the year 1994. The meeting participants have the opportunity to review the transcripts for accuracy within the subsequent weeks. These transcripts are available on the Federal Reserve's webpage and contain a very small amount of confidential information that may be deleted. The FOMC also issues a policy statement after each meeting, summarizing the economic outlook and their policy decisions. The Chairman holds press briefings to discuss policy decisions and economic projections. The minutes of the meetings are released three weeks after every regular meeting, and the meeting transcripts are accessible for up to five years after the meeting.

3.4. Econometric Approach

In order to conduct my analysis whether the FOMC cycle pattern is still relevant concerning financial market returns, I re-estimate a linear regression model as defined in Cieslak et. al (2019) and extend their analysis till november 2023 for various sample periods.

3.4.1. Linear regression model

Cieslak et. al (2019) estimates a linear regression model as:

$$ex1_i = \beta_0 + D_0 * \gamma_1 + D_1 * \gamma_2 + \epsilon_i \tag{3.1}$$

[1]**https://www.Federalreserve.gov/abouttheFED.htm**
[2]**https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm**

where

$$D_0 = \begin{cases} 1 & \text{in week 0 of FOMC cycle time} \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

is a dummy equal to 1 if the FOMC cycle is in week 0,

$$D_1 = \begin{cases} 1 & \text{in week 2,4 or 6 of FOMC cycle time} \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

is a dummy equal to 1 if the FOMC cycle is in week 2, 4 or 6, $ex1_i$ are the 1-day risk-free excess returns on stocks, $\hat{\beta_0}$ is the OLS-estimated intercept, $\hat{\gamma_1}, \hat{\gamma_2}$ are OLS-estimated coefficients on the dummies and $\epsilon_i \sim i.i.d.\ \mathcal{N}\left(0, \sigma^2\right)$ are independent identically distributed OLS-estimated residuals. The coefficient $\hat{\gamma_1}$ is of more importance with subject to the probability of target changes between meetings. (see figure 2.3)

3.4.2. FOMC dummies

The R Code in `generate_fomc_dummies_cycle_dummies.R` (see Appendix) generates FOMC week dummy variables by using the `"FOMC_Cycle_dates_1994_nov2023.xlsx"` file containing FOMC meeting dates for later estimation of the influence of the FOMC cycle on excess stock returns.

3.4.3. Data Preprocessing

The analysis commences with the importation and organization of two datasets. The first dataset, identified as `fomc_data`, is loaded from the file `fomc_week_dummies_1994_nov2023.csv`. This dataset includes information related to FOMC week dummies spanning November 1994 to November 2023. The data is sorted by date, and is then saved as `d:fomc_data`, thereby replacing any pre-existing file.

Following this, the second dataset, labeled as `us_returns_data`, is imported from the file `us_returns_df_1994_oct2023.csv`. This dataset contains information about/on the Fama-French factors for the U.S. market, covering the period from October 1994 to October 2023. Similar to the first dataset, it undergoes sorting by date, and the sorted dataset is saved as `d:us_returns_data`, replacing any existing file.

To consolidate the information, a merge operation is executed using the "date" variable as the key. This operation combines the `fomc_data` and `us_returns_data` datasets into a new dataset named `FED_Put_datamerged_data`. The merged dataset is saved as `d:FED_Put_datamerged_data`, effectively replacing any prior file.

Finally, a new variable named `date2` is generated by transforming the existing "date" variable using the `date()` function with the "YMD" (year-month-day) format. The resulting dataset then is used for further analysis, incorporating information from both the FOMC week dummies and U.S. market returns datasets.

3.4.4. Calculation of stock excess returns

Excess stock returns are calculated using the Fama-French 3-factors US research data provided by Kenneth R. French. Data for US market returns for this model and also for various other markets (e.g., European, Asia) are regularly published regularly on Kenneth R. French's webpage[3].

If m represents $1 +$ stock return and r denotes $1 +$ bill return, the 1-day excess return (ex1) is calculated by subtracting r from m and multiplying the result by 100, which can be expressed as $\text{ex}1 = 100 \times (m - r)$. The 5-day excess return (ex5) is computed over a rolling 5-day window, involving the product of five consecutive values of m and r, respectively. The formula is given by $\text{ex}5 = 100 \times (m \times m_{t+1} \times m_{t+2} \times m_{t+3} \times m_{t+4} - r \times r_{t+1} \times r_{t+2} \times r_{t+3} \times r_{t+4})$. Furthermore, t represents the observation number in the dataset.

Accordingly, the calculation of stock excess returns provides insight into their performance relative to the risk-free rate (using 1-day excess returns and 5-day excess returns graphically).

3.4.5. Regression Results

The regression coefficients in Table 3.1, 3.2, 3.3 and 3.4 are reported with t-Statistics robust to heteroskedasticity in parentheses. The coefficients for dummy variables in Table 3.5 show distinct patterns between US and European stock 1-day excess returns over the FOMC cycle time. In the pre-covid sample period 2016-2019 (1), the coefficient on the week-0 dummy is -0.211 (statistically significant at the 5%-level) for US stocks compared to -0.106 (statistically insignificant) for European stock returns. For the coefficient on the dummy for weeks 2, 4, 6, the US coefficient is -0.0487 compared to 0.00678 (both statistically insignificant) for European stock excess returns. Similar contrasting patterns in coefficients persist in the subsequent periods 2019-2022 (2), 2016-2023 (3), and 1994-2023

[3] **https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html**

	(1)	(2)	(3)
	2014-2016	1994-2014	1994-2016
Dummy = 1 in Week 0	0.174*	0.138***	0.143***
	(1.92)	(2.80)	(3.21)
Dummy = 1 in Week 2, 4, 6	0.166**	0.0890**	0.0990***
	(2.55)	(2.38)	(2.95)
Intercept	-0.0486	-0.0164	-0.0206
	(-1.14)	(-0.76)	(-1.05)
Observations	782	5224	6006
significant at 1%-level (***), 5% level (**), 10% level (*)			

Table 3.1.: Replication results of Table 1 Panel A as in Cieslak et. al (2019) using as above specified econometric approach and from FOMC meeting dates generated FOMC dummies using R code matching FOMC Cycle definitions as in Cieslak et. al (2019).

(4), emphasizing the slightly nuanced responses of US and European stock markets with respect to FOMC cycle-related events.

In the first sample from 2016 onwards (1) the coefficient on the week-0 dummy is statistically significant on the 5%-level, the sign of the coefficient turned negative, which is in consonant with a market dynamic labeled by the media as a so-called "FED Call".[4] Looking at the whole period from 1994 to 2023 (4), the regression coefficient of the FOMC cycle pattern turns out to be significantly smaller. All samples from COVID-19 onwards seem to be statistically insignificant so far, suggesting that the FOMC cycle pattern has probably decreased or vanished.

[4]**https://www.economist.com/finance-and-economics/2022/07/21/the-fed-put-morphs-into-a-fed-call.**

	(1) 2014-2016	(2) 1994-2014	(3) 1994-2016
Dummy = 1 in Week 0	0.191*	0.131***	0.138***
	(1.83)	(2.65)	(3.08)
Dummy = 1 in Week 2, 4, 6	0.146*	0.0420	0.0555
	(1.89)	(1.12)	(1.63)
Intercept	-0.0819	-0.00213	-0.0124
	(-1.61)	(-0.09)	(-0.60)
Observations	782	5223	6005
significant at 1%-level (***), 5% level (**), 10% level (*)			

Table 3.2.: European Stock Returns over the FOMC cycle

	(1) 2016-2019	(2) 2019-2022	(3) 2016-2023	(4) 1994-2023
Dummy = 1 in Week 0	-0.211**	-0.0952	-0.125	0.0800**
	(-2.29)	(-0.57)	(-1.40)	(2.01)
Dummy = 1 in Week 2, 4, 6	-0.0487	0.0578	0.0256	0.0828***
	(-0.74)	(0.48)	(0.41)	(2.81)
Intercept	0.0960**	0.0108	0.0434	-0.00622
	(2.48)	(0.12)	(0.94)	(-0.34)
Observations	762	779	1752	7772
significant at 1%-level (***), 5% level (**), 10% level (*)				

Table 3.3.: US Stock Returns over the FOMC Cycle from 2016 onwards

	(1) 2016-2019	(2) 2019-2022	(3) 2016-2023	(4) 1994-2023
Dummy = 1 in Week 0	-0.106	-0.0641	-0.0612	0.0911**
	(-1.35)	(-0.43)	(-0.78)	(2.34)
Dummy = 1 in Week 2, 4, 6	0.00678	0.111	0.0759	0.0599**
	(0.12)	(1.03)	(1.36)	(2.05)
Intercept	0.0596*	-0.0165	0.00995	-0.00743
	(1.79)	(-0.21)	(0.25)	(-0.41)
Observations	762	779	1753	7772
significant at 1%-level (***), 5% level (**), 10% level (*)				

Table 3.4.: European Stock Returns over the FOMC Cycle from 2016 onwards

Table 3.5.: Comparison of Dummy Coefficients between US and European Stock Returns

	Dummy = 1 in Week 0	Dummy = 1 in Week 2, 4, 6
(1) Pre COVID-19		
2016-2019 (US)	-0.211**	-0.0487
2016-2019 (Europe)	-0.106	0.00678
(2) Post/During COVID-19		
2019-2022 (US)	-0.0952	0.0578
2019-2022 (Europe)	-0.0641	0.111
(3) Full sample from 2016		
2016-2023 (US)	-0.125	0.0256
2016-2023 (Europe)	-0.0612	0.0759
(4) Full sample revisited		
1994-2023 (US)	0.0800**	0.0828***
1994-2023 (Europe)	0.0911**	0.0599**

4. Conclusion

In conclusion, the examination of stock excess returns during Federal Open Market Committee (FOMC) even weeks (0, 2, 4, 6) from 2016 onwards show patterns that are distinct from previous sample periods, also when comparing US and European stock markets. The comparison on the coefficients on the dummy variables in Table 3.5 display the differences in the responses of the two markets during the FOMC cycle.

In the period before COVID-19 (2016-2019), US stocks exhibited a negative "FED Call" with a coefficient of -0.211, statistically significant at the 5%-level in FOMC week 0, while European stocks showed a less pronounced negative response with a statistically insignificant (indifferent from 0 for all significance-levels) coefficient of -0.106. Similarly, during FOMC week 2, 4, 6, US stocks display a statistically insignificant coefficient of -0.0487, contrasting the statistically insignificant positive coefficient of 0.00678 for European stocks.

Focussing on the entire revisited sample period (1994-2023) results in statistically significantly smaller regression coefficients for the FOMC cycle pattern. Overall, samples from COVID-19 onwards exhibit a lack of statistical significance, suggesting a potential decrease or disappearance of the FOMC cycle pattern.

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A. Appendix

A.1. R Code: FOMC Dummy Generation

The R code in this section, provided in listing A.1, generates FOMC week dummy variables based on the defined week pattern over the FOMC cycle. The resulting data frame is then saved to a CSV file.

```
# Load required libraries
library(readxl)
library(lubridate)

current_path = rstudioapi::getActiveDocumentContext()$path
setwd(dirname(current_path))

# Define constants
monday <- 1
saturday <- 6
sunday <- 7
weekend_duration <- 2

# Define FOMC cycle patterns
fomc_wm1 <- c(-6:-2)
fomc_w0 <- c(-1:3)
fomc_w1 <- c(4:8)
fomc_w2 <- c(9:13)
fomc_w3 <- c(14:18)
fomc_w4 <- c(19:23)
fomc_w5 <- c(24:28)
fomc_w6 <- c(29:33)

# Combine FOMC patterns into a cycle
fomc_cycle <- c(fomc_wm1, fomc_w0, fomc_w1, fomc_w2, fomc_w3, fomc_w4, fomc_w5, fomc_w6)

# Function to calculate time difference in weeks
get_difftime_weeks <- function(fomc_meeting_date, date) {
  weekday_of_fomc_meeting_date <- wday(fomc_meeting_date, week_start = monday)
  adjusted_fomc_meeting_date <- fomc_meeting_date - days(weekday_of_fomc_meeting_date)
  return(floor(difftime(date, adjusted_fomc_meeting_date, units = "weeks")))
}

# Function to get FOMC day within the cycle
get_fomc_day_within_fomc_cycle <- function(fomc_meeting_date, date) {
  weekday_of_date <- wday(date, week_start = monday)
```

```
  if (weekday_of_date %in% c(saturday, sunday)) return(NULL)
  weekday_of_fomc_meeting_date <- wday(fomc_meeting_date, week_start = monday)
  difftime_days <- as.integer(difftime(date, fomc_meeting_date, units = ”days”))
  occurred_weekends <- get_difftime_weeks(fomc_meeting_date, date)
  as.integer(difftime_days - (weekend_duration * occurred_weekends))
}

# Function to get next dummy value
get_next_dummy_value <- function(fomc_cycle_day, fomc_w) as.integer(fomc_cycle_day %in% fomc_w)

# Set working directory
current_path <- rstudioapi::getActiveDocumentContext()$path
setwd(dirname(current_path))

# Read FOMC data
fomc_data <- read_excel(
  'FOMC_Cycle_dates_1994_nov2023.xlsx',
  sheet = 1,
  col_names = c(”Startdate”, ”Enddate”, ”start_less_end_bool”),
  col_types = c(”date”, ”date”, ”logical”),
  skip = 10
)

# Initialize vectors for FOMC cycle week dummies
dates <- w_t0 <- w_t1 <- w_t2 <- w_t3 <- w_t4 <- w_t5 <- w_t6 <- w_tm1 <- w_cluster <- fomc_d <-
    w_even <- w_t2t4t6 <- c()

# Process FOMC start dates
fomc_start_dates <- rev(fomc_data$Enddate)
first_fomc_start_date <- as.Date(fomc_start_dates[1])
adj_first_fomc_start_date <- ymd(first_fomc_start_date) -
    days(as.integer(wday(first_fomc_start_date, week_start = monday))) - days(7)
prev_fomc_start_date <- first_fomc_start_date
length <- length(fomc_start_dates)
remaining_fomc_start_dates <- as.Date(fomc_start_dates[2:length])

# Loop through FOMC start dates
for (next_fomc_start_date in remaining_fomc_start_dates) {
  next_fomc_start_date <- as.Date(next_fomc_start_date, origin = lubridate::origin)
  prev_fomc_start_date <- as.Date(prev_fomc_start_date, origin = lubridate::origin)
  adj_prev_fomc_start_date <- ymd(prev_fomc_start_date) - days(as.integer(wday(prev_fomc_start_date,
      week_start = monday))) - days(7)
  adj_next_fomc_start_date <- ymd(next_fomc_start_date) - days(as.integer(wday(next_fomc_start_date,
      week_start = monday))) - days(7)

  # Generate sequence of days between FOMC meetings
  days_between_fomc_meetings_seq <- seq(adj_prev_fomc_start_date + days(1), adj_next_fomc_start_date
      + days(1), ”day”)

  # Loop through days between FOMC meetings
  for (date in days_between_fomc_meetings_seq) {
    date <- as.Date(date, origin = lubridate::origin)
    fomc_cycle_day <- get_fomc_day_within_fomc_cycle(prev_fomc_start_date, date)

    # Check conditions for dummy values
    if (!is.null(fomc_cycle_day) && fomc_cycle_day %in% fomc_cycle) {
```

```
      dates <- c(dates, date)
      fomc_d <- c(fomc_d, fomc_cycle_day)
      w_cluster <- c(w_cluster, get_difftime_weeks(first_fomc_start_date, date) + 1)
      w_even <- c(w_even, get_next_dummy_value(fomc_cycle_day, c(fomc_w0, fomc_w2, fomc_w4,
          fomc_w6)))
      w_t2t4t6 <- c(w_t2t4t6, get_next_dummy_value(fomc_cycle_day, c(fomc_w2, fomc_w4, fomc_w6)))
      w_t0 <- c(w_t0, get_next_dummy_value(fomc_cycle_day, fomc_w0))
      w_t1 <- c(w_t1, get_next_dummy_value(fomc_cycle_day, fomc_w1))
      w_t2 <- c(w_t2, get_next_dummy_value(fomc_cycle_day, fomc_w2))
      w_t3 <- c(w_t3, get_next_dummy_value(fomc_cycle_day, fomc_w3))
      w_t4 <- c(w_t4, get_next_dummy_value(fomc_cycle_day, fomc_w4))
      w_t5 <- c(w_t5, get_next_dummy_value(fomc_cycle_day, fomc_w5))
      w_t6 <- c(w_t6, get_next_dummy_value(fomc_cycle_day, fomc_w6))
      w_tm1 <- c(w_tm1, get_next_dummy_value(fomc_cycle_day, fomc_wm1))
    }
  }
  prev_fomc_start_date <- next_fomc_start_date
}

# Create a data frame with the results
df <- data.frame(
  date = as.Date(dates, origin = lubridate::origin),
  w_t0 = w_t0,
  w_t1 = w_t1,
  w_t2 = w_t2,
  w_t3 = w_t3,
  w_t4 = w_t4,
  w_t5 = w_t5,
  w_t6 = w_t6,
  w_cluster = w_cluster,
  w_tm1 = w_tm1,
  fomc_d = fomc_d,
  w_even = w_even,
  w_t2t4t6 = w_t2t4t6
)

# Write the results to a CSV file
write.csv(df, 'fomc_week_dummies_1994_nov2023.csv', row.names = FALSE)

# Run tests
testthat::test_dir('tests')
```

Listing A.1: R code for FOMC Week Dummy Generation

A.1.1. CSV File: Example structure of generated FOMC dummy variables

The listing A.2 displays the first 35 examples of the generated FOMC dummies in the CSV file, containing approximately one FOMC cycle consisting of 7 work-weeks:

```
1993-12-13,0,0,0,0,0,0,0,0,1,-6,0,0
1993-12-14,0,0,0,0,0,0,0,0,1,-5,0,0
```

```
1993-12-15,0,0,0,0,0,0,0,0,1,-4,0,0
1993-12-16,0,0,0,0,0,0,0,0,1,-3,0,0
1993-12-17,0,0,0,0,0,0,0,0,1,-2,0,0
1993-12-20,1,0,0,0,0,0,0,1,0,-1,1,0
1993-12-21,1,0,0,0,0,0,0,1,0,0,1,0
1993-12-22,1,0,0,0,0,0,0,1,0,1,1,0
1993-12-23,1,0,0,0,0,0,0,1,0,2,1,0
1993-12-24,1,0,0,0,0,0,0,1,0,3,1,0
1993-12-27,0,1,0,0,0,0,0,2,0,4,0,0
1993-12-28,0,1,0,0,0,0,0,2,0,5,0,0
1993-12-29,0,1,0,0,0,0,0,2,0,6,0,0
1993-12-30,0,1,0,0,0,0,0,2,0,7,0,0
1993-12-31,0,1,0,0,0,0,0,2,0,8,0,0
1994-01-03,0,0,1,0,0,0,0,3,0,9,1,1
1994-01-04,0,0,1,0,0,0,0,3,0,10,1,1
1994-01-05,0,0,1,0,0,0,0,3,0,11,1,1
1994-01-06,0,0,1,0,0,0,0,3,0,12,1,1
1994-01-07,0,0,1,0,0,0,0,3,0,13,1,1
1994-01-10,0,0,0,1,0,0,0,4,0,14,0,0
1994-01-11,0,0,0,1,0,0,0,4,0,15,0,0
1994-01-12,0,0,0,1,0,0,0,4,0,16,0,0
1994-01-13,0,0,0,1,0,0,0,4,0,17,0,0
1994-01-14,0,0,0,1,0,0,0,4,0,18,0,0
1994-01-17,0,0,0,0,1,0,0,5,0,19,1,1
1994-01-18,0,0,0,0,1,0,0,5,0,20,1,1
1994-01-19,0,0,0,0,1,0,0,5,0,21,1,1
1994-01-20,0,0,0,0,1,0,0,5,0,22,1,1
1994-01-21,0,0,0,0,1,0,0,5,0,23,1,1
1994-01-24,0,0,0,0,0,1,0,6,0,24,0,0
1994-01-27,0,0,0,0,0,0,0,6,1,-6,0,0
1994-01-28,0,0,0,0,0,0,0,6,1,-5,0,0
1994-01-31,0,0,0,0,0,0,0,7,1,-4,0,0
1994-02-01,0,0,0,0,0,0,0,7,1,-3,0,0
```

Listing A.2: First 35 examples of the generated FOMC dummies

A.2. R Code: Tests

The provided test (see listing A.3), implemented with the `testthat` package in R, is designed to assess the accuracy of the `get_fomc_day_within_fomc_cycle` function. In this test scenario, a reference FOMC meeting date, set to "2014-01-28" (`fomc_test_date`), serves as the basis for evaluating the function's output for various input dates. The expectations are explicitly defined for different scenarios, encompassing dates preceding, matching, and succeeding the FOMC meeting date. The function is expected to return negative values for dates before the meeting, indicating the number of days prior, 0 for the meeting date itself, and positive values for dates afterward, denoting the days post-meeting. Importantly, the test accounts for weekends, with the function expected to return `NULL` for input dates falling on Saturdays or Sundays. By assessing the function's behavior across this range of conditions, the test aims to ensure the accurate functioning of `get_fomc_day_within_fomc_cycle` in relation to FOMC meeting dates and weekends, contributing to the overall verification of its correctness and robustness.

```
library(testthat)

test_that("get_fomc_day_within_fomc_cycle returns expected values", {

  fomc_test_date <- as.Date("2014-01-28")

  expected_values <- c(
    -5, -4, -3, -2, NULL, NULL, -1, 0, 1, 2, 3,
    NULL, NULL, 4, 5, 6, 7, 8, NULL, NULL, 9, 10)

  dates <- as.Date(
    c("2014-01-21", "2014-01-22", "2014-01-23", "2014-01-24",
      "2014-01-25", "2014-01-26", "2014-01-27", "2014-01-28",
      "2014-01-29", "2014-01-30", "2014-01-31", "2014-02-01",
      "2014-02-02", "2014-02-03", "2014-02-04", "2014-02-05",
      "2014-02-06", "2014-02-07", "2014-02-08", "2014-02-09",
      "2014-02-10", "2014-02-11"))

  for (i in dates) {
    expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, dates[i]), expected_values[i])
  }
})
```

Listing A.3: R code for FOMC Cycle Dummy Generation Tests

A.3. R Code: Fama-French Daily Factors Data Extraction

The following R Code in listing A.4 reads the Fama-French daily factors data from a CSV file, extracts data within a specified date range, and writes the subsetted data to a new CSV file named `us_returns_df_1994_oct2023.csv`.

```
library(readxl)

current_path <- rstudioapi::getActiveDocumentContext()$path
setwd(dirname(current_path))

# Read the Fama-French daily factors data from CSV file
us_returns <- read.csv('F-F_Research_Data_Factors_daily_nov2023.CSV', col.names = c("DATE",
    "Mkt-RF", "SMB", "HML", "RF"), skip = 4)

# Extract relevant date range
date_format <- "%Y%m%d"
us_returns$DATE <- as.Date(as.character(us_returns$DATE), format = date_format)
start_date <- as.Date("1993-12-31", format = "%Y-%m-%d")
end_date <- as.Date("2023-10-31", format = "%Y-%m-%d")
us_returns_df <- subset(
  us_returns,
  DATE >= start_date & DATE <= end_date
```

```
)

# Change the date format to yyyy-mm-dd
new_date_format <- "%Y-%m-%d"
us_returns_df$DATE <- format(us_returns_df$DATE, format = new_date_format)

# Write the subsetted data frame to a new CSV file
write.csv(
  us_returns_df,
  'us_returns_df_1994_oct2023.csv',
  row.names = FALSE
)
```

Listing A.4: R Code for Fama-French Daily Factors Data Extraction

A.4. STATA Code: Statistical Analysis

This STATA code provided in listing A.5 conducts an analysis of stock returns in relation to FOMC meetings. The focus extends to both U.S. and European stock returns, with the code structured into following sections:

Setup

- Clears existing data and configures preferences.
- Initializes a log file for documentation.

Data Import and Preprocessing

- Imports FOMC meeting dates and U.S. stock return data.
- Merges datasets based on the date variable.
- Converts the date variable to a standardized format.

Calculation of Excess Stock Returns

- Computes excess stock returns using the methodology from Cieslak et al. (2019).

Statistical Analysis

- Performs regression analyses on excess stock returns for various time periods.
- Utilizes the `eststo` command to store regression results.

Output Generation

- Outputs regression results in LaTeX format, generating tables for different analysis periods.

- Replicates the statistical analysis for European stock returns.

```
// U.S. Stock Returns over the FOMC Cycle - Statistical Analysis
clear
set more off
set cformat %5.3f
capture log close
cd "<insert-working-directory-here>"
cap mkdir stata_log
log using "stata_log/stata_log", replace

import delimited "FOMC_dummy_generation/fomc_week_dummies_1994_nov2023.csv", clear
sort date
save d:fomc_data, replace

import delimited "F-F_Factors_daily_US/us_returns_df_1994_oct2023.csv", clear
sort date
save d:us_returns_data, replace

merge date using d:fomc_data d:us_returns_data
save d:fed_put_datamerged_data, replace
gen date2 = date(date, "YMD")

gen m = (mktrf + rf) / 100 + 1
gen r = rf / 100 + 1
replace m = 1 if m ==.
replace r = 1 if r ==.
label var m "1+stock return"
label var r "1+bill return"
gen ex1 = 100 * (m - r)
label var ex1 "1-day excess return, day t, pct"
gen t = _n
label var t "Observation number"

eststo mlr1: reg ex1 w_t0 w_t2t4t6 if t >= 5307 & t <= 6089, robust
eststo mlr2: reg ex1 w_t0 w_t2t4t6 if t >= 16 & t < 5307, robust
eststo mlr3: reg ex1 w_t0 w_t2t4t6 if t >= 16 & t <= 6089, robust
esttab mlr1 mlr2 mlr3 using "stata_out/Stock Returns over the FOMC cycle.tex", ///
  r2(%9.4g) ar2(%9.4g) stats(N) starlevel(* 0.1 ** 0.05 *** 0.01) noobs ///
  mlabels("2014-2016" "1994-2014" "1994-2016") ///
  postfoot("significant at 1\%-level (***), 5\% level (**), 10\% level (*)")

eststo mlr1: reg ex1 w_t0 w_t2t4t6 if t >= 6089 & t < 6872, robust
eststo mlr2: reg ex1 w_t0 w_t2t4t6 if t >= 6872 & t < 7658, robust
eststo mlr3: reg ex1 w_t0 w_t2t4t6 if t >= 6089, robust
eststo mlr4: reg ex1 w_t0 w_t2t4t6, robust // 1994-2023
esttab mlr1 mlr2 mlr3 mlr4 using "stata_out/Stock Returns over the FOMC cycle Revisited.tex", ///
  r2(%9.4g) ar2(%9.4g) stats(N) starlevel(* 0.1 ** 0.05 *** 0.01) noobs ///
  mlabels("2016-2019" "2019-2022" "2016-2023" "1994-2023") ///
  postfoot("significant at 1\%-level (***), 5\% level (**), 10\% level (*)")

// European Stock Returns over the FOMC Cycle - Statistical Analysis
clear
import delimited "FOMC_dummy_generation/fomc_week_dummies_1994_nov2023.csv", clear
sort date
save d:fomc_data, replace
```

```
import delimited "F-F_Factors_daily_European/european_returns_df_1994_sept2023.csv", clear
sort date
save d:eur_returns_data, replace

merge date using d:fomc_data d:eur_returns_data
save d:fomc_eur_ret_datamerged_data, replace
gen date2 = date(date, "YMD")

gen m = (mktrf + rf) / 100 + 1
gen r = rf / 100 + 1
replace m = 1 if m ==.
replace r = 1 if r ==.
label var m "1+stock return"
label var r "1+bill return"
gen ex1 = 100 * (m - r)
label var ex1 "1-day excess return, day t, pct"
gen t = _n
label var t "Observation number"

eststo mlr1: reg ex1 w_t0 w_t2t4t6 if t >= 5307 & t <= 6089, robust
eststo mlr2: reg ex1 w_t0 w_t2t4t6 if t >= 16 & t < 5307, robust
eststo mlr3: reg ex1 w_t0 w_t2t4t6 if t >= 16 & t <= 6089, robust
esttab mlr1 mlr2 mlr3 using "stata_out/European Returns over the FOMC cycle.tex", ///
  r2(%9.4g) ar2(%9.4g) stats(N) starlevel(* 0.1 ** 0.05 *** 0.01) noobs ///
  mlabels("2014-2016" "1994-2014" "1994-2016") ///
  postfoot("significant at 1\%-level (***), 5\% level (**), 10\% level (*)")

eststo mlr1: reg ex1 w_t0 w_t2t4t6 if t >= 6089 & t < 6872, robust
eststo mlr2: reg ex1 w_t0 w_t2t4t6 if t >= 6872 & t < 7658, robust
eststo mlr3: reg ex1 w_t0 w_t2t4t6 if t >= 6089, robust
eststo mlr4: reg ex1 w_t0 w_t2t4t6, robust // 1994-2023
esttab mlr1 mlr2 mlr3 mlr4 using "stata_out/European Stock Returns over the FOMC cycle Revisited.tex", ///
  r2(%9.4g) ar2(%9.4g) stats(N) starlevel(* 0.1 ** 0.05 *** 0.01) noobs ///
  mlabels("2016-2019" "2019-2022" "2016-2023" "1994-2023") ///
  postfoot("significant at 1\%-level (***), 5\% level (**), 10\% level (*)")
```

Listing A.5: STATA code for Statistical Analysis