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# Stock Returns over the FOMC Cycle Revisited

Bachelor Thesis

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*To myself, respectivly.*

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# 1 Motivation

The starting point of this thesis is recently conducted research that studies the link and possible causal effects between monetary policy decisions by the FED and the stock market in the U.S., not only in an ex-post but also in an ex-ante sense.

The paper Stock Returns over the FOMC Cycle (Cieslak et al.) 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.

In a follow-up paper, The Economics of the FED Put (Cieslak and Vissing-Jorgensen) the authors use textual analysis of FOMC (Federal Open Market Commitee) scripts to identify and measure the causal effect that policymakers indeed pay intention to the stock market, especially since the mid-1990s and stock market performance is linked with 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 induce risk-taking behavior leading to moral-hazard implications, it does not particularly affect their decision-making in an ex-ante sense.

In my thesis, I aim to find out whether the financial pattern regarding stock excess returns in FOMC even weeks is still relevant from 2016 (which should not be the case, especially once the information has reached the market) onwards (probably complicated by the COVID-19 crisis) since the paper published in 2019 only investigates this pattern before 2016. Additionally, the authors prove the relevance of their financial pattern worldwide using exchange-traded funds (ETFs) containing European stocks. I want to include further results with a specific focus on European stock 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 belief of) a strong accommodating monetary policy by the Federal Reserve (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 holder the right to sell at a predetermined price. Thus, the Fed would protect an investor from the decline in the value of an asset. (“Fed Put”)

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

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 hazards (Cieslak and Vissing-Jorgensen), meaning that investors are willing to take on excessive risks because they believe that the Federal Reserve will always come to rescue them. Some believe that such “too big to fail” beliefs 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, the paper “Stock returns over the FOMC cycle” focusses on a FOMC cycle specific pattern of the equity premium since 1994. The stock returns exhibit a distinct, statistically significant patterns over the FOMC cycle. Notably, it primarily accrues in weeks 0, 2, 4, and 6 within the FOMC cycle weeks (for a graphical explanation of the FOMC cycle, see figure 3.1 on page 7).

For calculation of stock excess returns they authors use research portfolio data provided by Kenneth R. French for convenience. (Kenneth R.)

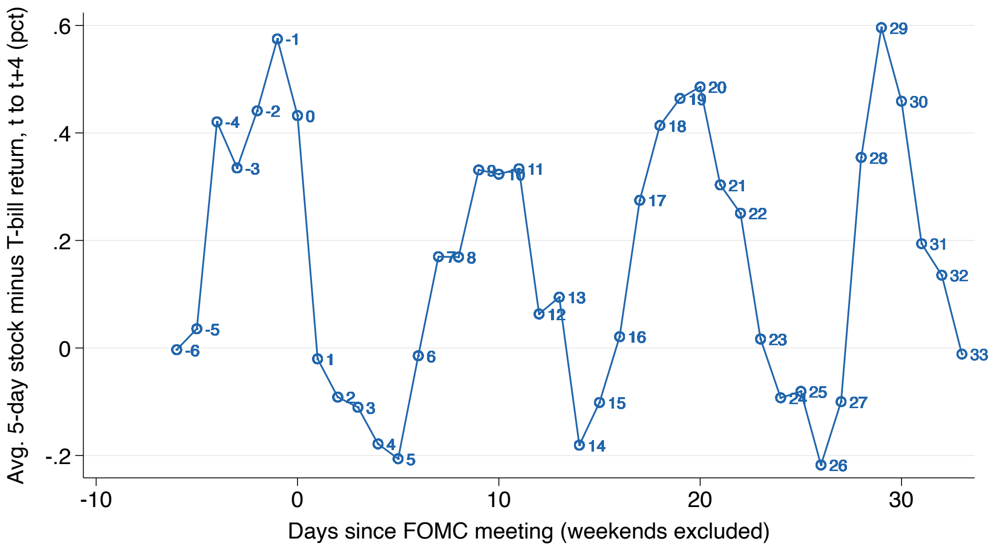


**Figure 2.1:** Average 5-day stock returns minus T-bill returns over the FOMC cycle changes (pct) (Cieslak et al.)

The authors present three distinct trading strategies (A, B, and C) that shed light on 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. This strategy demonstrates that the average annual returns more than double compared to holding an ETF throughout the entire FOMC cycle. Intriguingly, the authors find that holding an ETF during uneven FOMC weeks results in financial losses over the examined period from 1994 to 2016.

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.

To establish a causal link between the Fed's policy measures and stock market behavior, the authors study intermeeting target changes, Fed funds futures, and internal Board of Governors meetings. The authors suggest a significant influence by the Fed over the stock market through its accommodating policies, leading to reductions in the equity premium. Moreover, they argue to uncover evidence of systematic informal communication channels between Fed officials and the media and financial sector, serving as a channel through which news about monetary policy has reached the market.

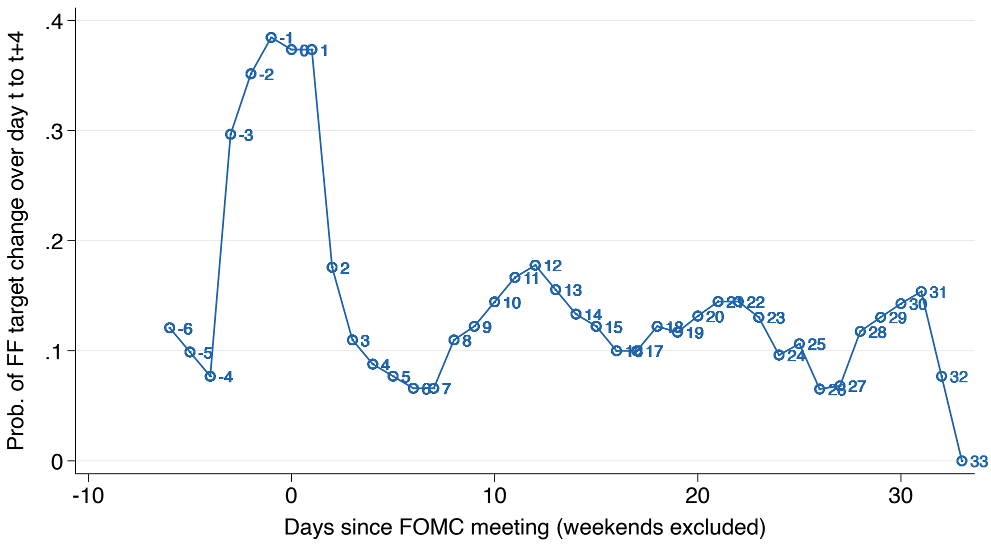


**Figure 2.2:** Probability of Federal Funds rate changes over the FOMC Cycle (Cieslak et al.)

## 2.3 The Economics of the FED Put

"The Economics of FED Put" 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 Federal Open Market Committee (FOMC) meeting transcripts. 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 the consumption wealth effect. Conversely, strong stock market performance corresponds to updates of the Fed's internal growth projections. Empirical evidence substantiates their claims, as multiple regressions on changes in the Federal Funds Rate (FFR) demonstrate that the stock market captures a higher proportion of the variance (R-squared) compared to other macroeconomic indicators. Significantly, this relationship appears to be less pronounced before the 1990s period. (Cieslak and Vissing-Jorgensen)

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

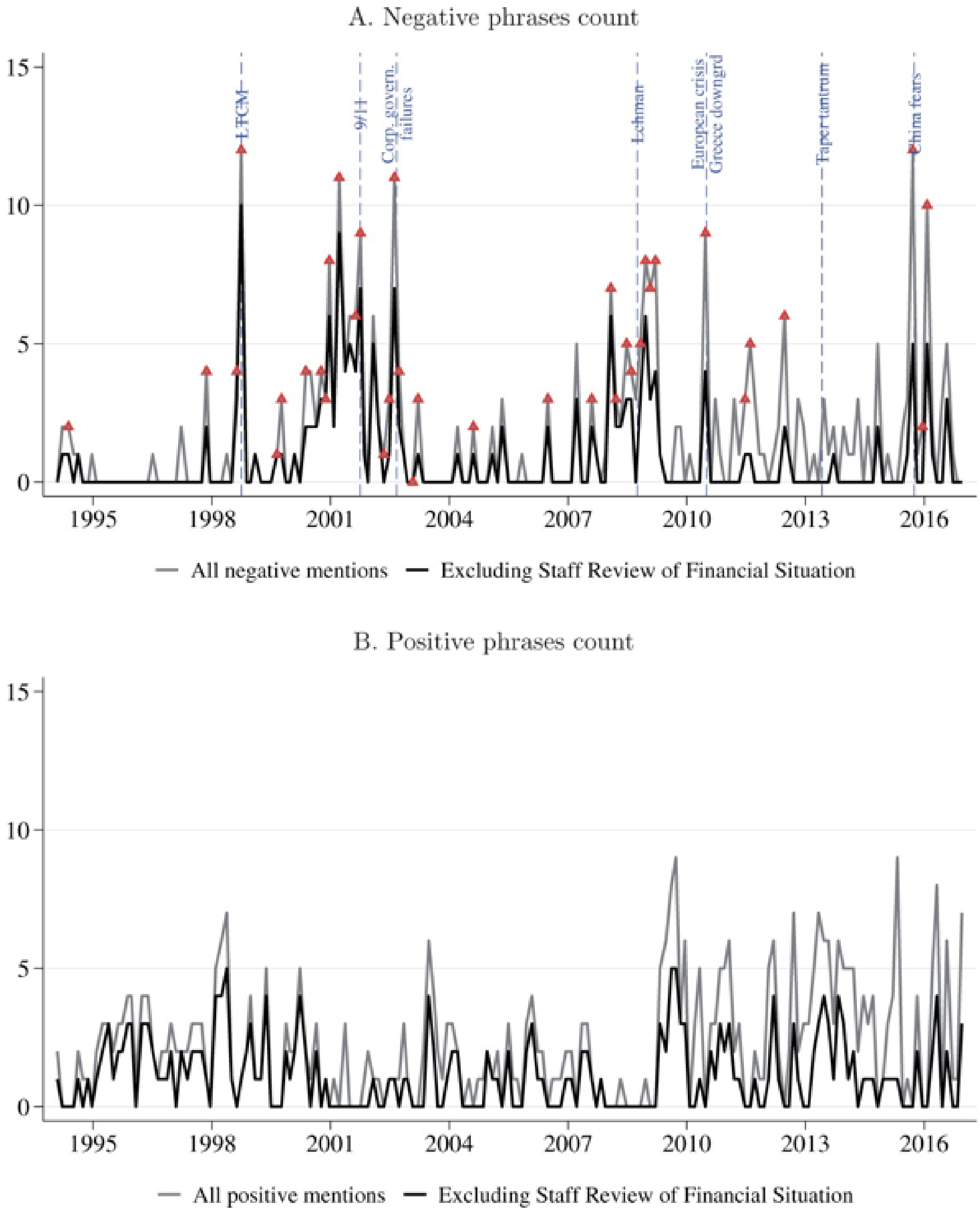


**Figure 2.3:** Negative and positive phrases of the stock market count (Cieslak and Vissing-Jorgensen)

# 3 Stock returns over the FOMC Cycle Revisited

## 3.1 The FOMC cycle

The FOMC (Federal Open Market Committee) 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, and week 6 as days 29 to 33. Worth mentioning is that the authors drop 3 days, which would be in FOMC cycle week 7 from their investigation, and 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).

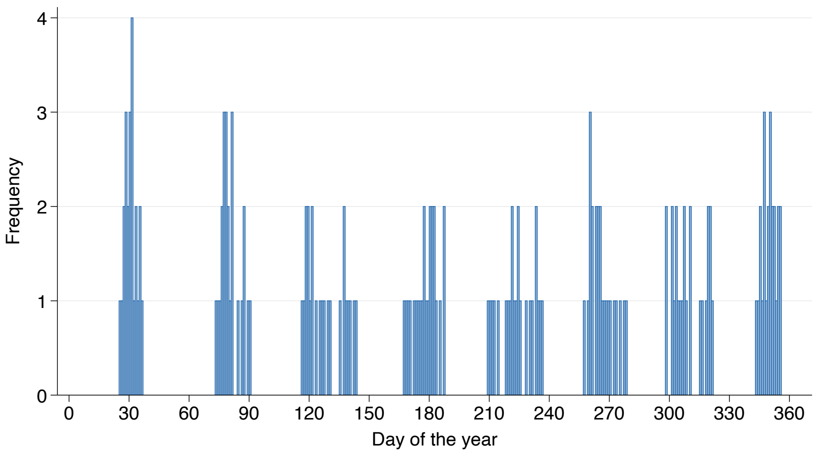


**Figure 3.1:** Frequency of FOMC meetings during the year from 1994 to 2016 (Cieslak et al.)

## 3.2 FOMC data

The FOMC meeting dates get published ...

## 3.3 Measurement and estimation analysis (MEA)

### 3.3.1 MLR model

One relevant multiple linear regression (MLR) model with dummy variables for even FOMC cycle weeks as in (Cieslak et al.) can be defined as:

$$rxpct_i = \hat{\beta_0} + D_0 * \hat{\gamma}_1 + D_1 * \hat{\gamma}_2 + \epsilon_i \tag{3.1}$$

where $\hat{\beta_0}$ is the OLS-estimated intercept, $\hat{\gamma}_1, \hat{\gamma}_2$ the OLS-estimated parameters, $rx_i$ the excess returns as calculated like in chapter 3.3.4.,

$$D_0 = \begin{cases} 1, & \text{if in the 0 week within FOMC cycle time.} \\ 0, & \text{otherwise} \end{cases} \tag{3.2}$$

the FOMC cycle dummy for week 0,

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

the FOMC cycle dummy for week 2, 4, 6 and $\epsilon_i \sim i.i.d.\ \mathcal{N}\left(0, \sigma^2\right)$ are independent identically distributed OLS-estimated standard errors.

### 3.3.2 FOMC dummies

The R Code in `generate_fomc_dummies_cycle_dummies.R` (see R Code Appendix) generates FOMC week dummy variables for later estimation of the influence on FOMC meeting dates on excess stock returns.

### 3.3.3 Data Preprocessing

The analysis commences with the importation and organization of two distinct datasets. The first dataset, identified as `fomc_data`, is loaded from the file `fomc_week_dummies_1994_nov2023.csv`. This dataset encompasses information related to FOMC week dummies spanning from November 1994 to November 2023. The data is sorted by date, and the sorted dataset 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 regarding 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 into Stata date format. This conversion is carried out using the `date()` function with the "YMD" (year-month-day) format. The resulting dataset is now prepared for further analysis, incorporating information from both the FOMC week dummies and U.S. market returns datasets.

### 3.3.4 Calculation of stock excess returns

Excess stock returns are calculated using the Fama-French 3-factor model developed by Kenneth R. French and Eugene Fama. Data for US market returns for this model and also for various other markets (e.g., European, Asia) get published regularly on Kenneth R. French's webpage. (Kenneth R.)

If $m$ represents $1 +$ stock return and $r$ denote $1 +$ 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 $\text{ex1} = 100 \times (m - r)$. The 5-day excess return (ex5) is computed over a rolling

5-day window, involving the product of five consecutive values of $m$ and $r$. The formula is given by $\text{ex5} = 100 \times (m \times m_{t+1} \times m_{t+2} \times m_{t+3} \times m_{t+4} - r \times r_{t+1} \times r_{t+2} \times r_{t+3} \times r_{t+4})$.

Furthermore, $t$ represents the observation number in the dataset. Overall, the calculation for evaluating stock excess returns provides insight into their performance relative to the risk-free rate.

### 3.3.5 Results of the MEA

| | (1) 2014-2016 | (2) 1994-2014 | (3) 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.)

| | (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 3.2:** Stock Returns over the FOMC Cycle from 2016 onwards

In the first sample from 2016 onwards (2016-2019), where the coefficient for the term for FOMC cycle week 0 is statistically significant on the 5%-level, the sign of the coefficient turned negative, which has been labeled by the media as a "Fed Call." (“The Fed put morphs into a Fed call”)

Looking at the whole period from 1994 to 2023, 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 Conclusion

tbd.

# 5 Appendix

## 5.1 R Code: FOMC Cycle Dummy Generation

The R code in this section, provided in Listing 5.3, generates FOMC week dummy variables based on the defined FOMC cycle patterns. The resulting data frame is then saved to a CSV file.

```r
# 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 5.1:** R code for FOMC Week Dummy Generation

### 5.1.1 CSV File of generated FOMC dummies

The listing 5.2 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
```

```
1994-01-20,0,0,0,0,0,1,0,0,5,0,22,1,1
1994-01-21,0,0,0,0,0,1,0,0,5,0,23,1,1
1994-01-24,0,0,0,0,0,0,1,0,6,0,24,0,0
1994-01-27,0,0,0,0,0,0,0,0,6,1,-6,0,0
1994-01-28,0,0,0,0,0,0,0,0,6,1,-5,0,0
1994-01-31,0,0,0,0,0,0,0,0,7,1,-4,0,0
1994-02-01,0,0,0,0,0,0,0,0,7,1,-3,0,0
```

**Listing 5.2:** First 35 examples of the generated FOMC dummies

## 5.2 R Code: FOMC Cycle Dummy Generation Tests

The provided test, 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.

```r
library(testthat)

# Test helper functions
test_that("get_fomc_day_within_fomc_cycle returns expected values", {
  fomc_test_date <- as.Date("2014-01-28")

  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-21")),
      -5)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-22")),
      -4)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-23")),
      -3)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-24")),
      -2)
```

```
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-25")),
      NULL)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-26")),
      NULL)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-27")),
      -1)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-28")), 0)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-29")), 1)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-30")), 2)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-01-31")), 3)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-01")),
      NULL)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-02")),
      NULL)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-03")), 4)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-04")), 5)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-05")), 6)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-06")), 7)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-07")), 8)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-08")),
      NULL)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-09")),
      NULL)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-10")), 9)
  expect_equal(get_fomc_day_within_fomc_cycle(fomc_test_date, as.Date("2014-02-11")),
      10)
})
```

**Listing 5.3:** R code for FOMC Cycle Dummy Generation Tests

## 5.3 R Code: Fama-French Daily Factors Data Extraction

The following R Code 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
```

```r
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 5.4:** R Code for Fama-French Daily Factors Data Extraction

## 5.4 STATA Code: Measurement and Estimation Analysis

The STATA code in this section, provided in Listing 5.5, involves the use of `estab` commands to measure and estimate stock returns over the FOMC cycle. It includes functions to reload data, calculate stock excess returns, and generate graphs for analysis.

```stata
clear
version 11
set more off
set cformat %5.3f
capture log close
set scheme FOMC

cd "<insert-working-directory-here>"

cap mkdir stata_log
log using "stata_log/stata_log", replace

// Import data
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

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

// Calculation of stock excess returns as in Cieslak et al. (2019)
ge m = (mktrf + rf) / 100 + 1
ge r = rf / 100 + 1
replace m = 1 if m ==.
replace r = 1 if r ==.
ge lnm = ln(m)
ge lnr = ln(r)

label variable m "1+stock return"
label variable r "1+bill return"
label variable lnm "ln(1+stock return)"
label variable lnr "ln(1+bill return)"

ge ex1 = 100 * (m - r)
ge ex5 = 100 * (m * m[_n+1] * m[_n+2] * m[_n+3] * m[_n+4] - r * r[_n+1] * r[_n+2] *
    r[_n+3] * r[_n+4])
label variable ex1 "1-day excess return, day t, pct"
label variable ex5 "5-day excess return, day t to t+4 pct"

ge t = _n
label variable t "Observation number"

// Measurement and Estimation Analysis (MEA)
// Stock Returns over the FOMC Cycle Replication results
// Replication of TABLE 1 PANEL A Column 1 (2013 to 2016) as in Cieslak et al. (2019)
eststo mlr1: reg ex1 w_t0 w_t2t4t6 if t >= 5307 & t <= 6089, robust

// Replication of TABLE 1 PANEL B Column 1 (1994 to 2013) as in Cieslak et al. (2019)
eststo mlr2: reg ex1 w_t0 w_t2t4t6 if t >= 16 & t < 5307, robust

// Replication of TABLE 1 PANEL A Column 1 (1994 to 2016) as in Cieslak et al. (2019)
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 (*)")


// Stock Returns over the FOMC Cycle Revisited

// 2016-2019 sample
```

```
eststo mlr1: reg ex1 w_t0 w_t2t4t6 if t >= 6089 & t < 6872, robust

// 2019-2022 covid sample
eststo mlr2: reg ex1 w_t0 w_t2t4t6 if t >= 6872 & t < 7658, robust

// 2016-2023 revisited sample
eststo mlr3: reg ex1 w_t0 w_t2t4t6 if t >= 6089, robust

// 1994-2023 full FOMC Cycle sample
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 (*)")
```

**Listing 5.5:** STATA code for Measurement and Estimation Analysis

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