Volatility Analysis of US Equity and Federal Funds Markets Through the Recent Financial Crisis and Recovery Periods, Based on Release of FOMC Meeting Statements and Minutes

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Volatility Analysis of US Equity and Federal Funds Markets
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Hanxiao Yue

Submitted to the Committee on Undergraduate Honors at Baruch College of the City University of New York
in partial fulfillment of the requirements for the degree of Bachelor of Arts in Mathematics with Honors.

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Faculty Sponsor: Professor Sebastiano Manzan

Faculty Reviewer: Professor Hammou Elbarmi

Faculty Reviewer: Professor Barry Ma

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1 Abstract

The Federal Open Market Committee (FOMC) is the principal maker of monetary policy in the United States. The main instrument of monetary policy is the target federal funds rate, which is de facto the base interest rate of the US economy. The FOMC meets around eight times a year to discuss the economic outlook and decide on this metric. Throughout most of its history, the Fed has been opaque about how it decides on monetary policy, but in recent years it has adopted a more transparent disclosure policy. For each FOMC meeting, it currently releases a brief statement immediately after the meeting ends summarizing the economic outlook and target federal funds rate it will be implementing. Three weeks later, it releases the full minutes of the meeting. This paper investigates if and how the release of the statement and the release of the minutes impacts market volatility in the US equities market and the market for the federal funds rate in the sample 2007-2014, encompassing the interesting time period of the recent financial crisis, recession, and recovery years.
2 Introduction

The Federal Reserve System (colloquially known as the Fed, and referred to as such for the rest of the paper) is the central bank of the US and serves the economy through two key objectives established by Congress: maximizing employment and controlling inflation. It makes monetary policy through the Federal Open Market Committee (FOMC), which meets periodically throughout the year to discuss the outlook of the economy and decide on key policy actions. The federal funds rate is the rate that banks lend to each other overnight to satisfy the Fed’s reserve requirements. Although the Fed does not have direct control over this rate, which is officially determined by the market, it can influence it significantly to be within a desired target range through open market operations, or the buying and selling of United States Treasury Securities. In times of economic expansion, the Fed will try to raise the fed fund rate to keep inflation in check by selling securities, and in times of recession, the Fed will buy securities, lowering the fed funds rate. The fed funds rate is also colloquially known as the interest rate, since it serves as the base rate that determines the level of all other interest rates in the US economy.

Since the FOMC meetings determine such key policy actions, naturally, the detail and outcomes of these meetings provide important information to market participants as they trade securities in the markets. Traditionally, the Fed has been a highly opaque institution. Since it is not officially a government agency (to minimize political intervention in the economy), it has not been required to publicly disclose its practices like normal government bodies. For many years, it only released the minutes of the last meeting on the day of the current meeting, which makes the disclosure largely of historic relevance, as the policy effect has already been experienced by the market. Over the years, however, the Fed has adopted an increasingly transparent outlook on its disclosure practices. In the past twenty years, it has started releasing brief statements on the days of meetings summarizing the policy action decided on in the current meeting. While the content of the statement has greatly changed since it was first introduced, it has become more complex throughout the years. In its current form, the one used throughout the sample I studied, it is essentially a press release that briefly summarizes the Fed’s outlook on the current economy and the target rate the Fed aims to achieve in the upcoming months. The Fed also shortened the lag between the meeting and the release of the full minutes from after the next FOMC meeting to only a delay of 3 weeks after the current meeting.
My paper seeks to examine whether the release of these documents has an effect on average stock market volatility and the average volatility in the market for the federal fund rates (also referred to as "fed fund rates"), and compare which document has a greater effect on average market volatility in a series of different timespans.

In the following sections, I study the behavior of volatility in the United States equities market as a consequence of FOMC actions, such as on FOMC meeting days when the FOMC meeting statement is released, and on FOMC minutes release days, which are three weeks after the meeting. Using a methodology similar to Rosa (2013) and Kohn and Sack (2003), I analyze the separate effects on volatility in the equity market and fed funds rate market on meeting days and minutes release days. Then, I compare the effect of FOMC statement releases with that of the FOMC minutes release. The timeframes I analyze over are: overall sample (2007-2014), over each separate year, and over two groups labelled crisis (2007-2010) and recovery (2011-2014). I do this to see whether overall trends are replicated, or differ, in a smaller time frame and under different market psychological conditions. Finally, I analyze whether these events are significant predictors of changes in volatility, and provide a data-supported theory of how volatility trends changed from the crisis years to the recovery years. I also provide historical background on the actual content of the FOMC releases to better explain the statistical results presented.

The rest of my paper is organized as follows: Section 3 is a review of relevant literature, Section 4 provides a description of the data and methodology, and Section 5 provides a discussion of the results presented as a series of questions that I answer. I summarize my findings and conclude in Section 6.

3 Review of Literature

Significant research has been conducted to measure the effect of FOMC communications on market volatility. The 2003 study by Kohn and Sack investigated the effect of three types of Fed communication: FOMC statements, the Chairman’s Congressional Testimony, and the Chairman’s major speeches on asset prices and interest rates. Their sample was from the period January 3, 1989 to April 7, 2003 under Greenspan. During this period, the content in the FOMC statements changed gradually as the Fed adopted a more transparent communications policy, from intermittent releases in 1989-1993, to including a brief description
of the policy rationale in 1994-1998 to including a more nuanced risk assessment from 1999 until the end of the study. The assets they studied are the federal funds futures rate expiring 3 months ahead, eurodollar futures rates expiring 2 quarters and 4 quarters ahead, 2 year and 10 year Treasury yields, 1 year Treasury forward rates ending 1-4 years ahead, the S&P 500 index, and the forex value of the dollar. Using regression analysis on asset price returns, they investigate whether these forms of communication have had any effects on various asset prices that are independent of the effects of the policy actions they announced. They found that the method of communication of the FOMC statements had a significant influence on asset prices, especially short term and intermediate term interest rates, even after controlling for the actual change in the interest rate. After a comparison of the increase in variance of a given asset price attributed to the statement to that induced directly by the realized policy itself, it was found that short term rates were more directly influenced by policy actions, while long term rates were more directly influenced by policy statements. So in the long run, what the Fed says is even more important than what the Fed actually does at the moment. In my study, I examine the federal funds rate and the S&P 500 Index, and use regression analysis to determine if the minutes and the statements are significant predictors of asset price volatility, instead of asset price returns.

The Bomfirm (2003) study shows a trend of US stock prices being influenced by macroeconomic news conveyed by FOMC decisions on the target fed funds rate. The sample he studies is from 1989-1998. The relationship between monetary policy and daily stock market volatility is examined from two perspectives: days around regularly scheduled FOMC meetings, and days of actual policy decisions. This is because before 1994, there was a one-day lag between the decision (the size and type of open market operation conducted, usually in the afternoon right before trading ends) and the announcement, or the market reaction the following day. When examining from the perspective of the days of FOMC meetings, they find statistical evidence that the existence of regularly scheduled policy meetings affects stock market volatility, and the hypothesis of no FOMC meeting day effects across the entire 1989-1998 sample can be rejected with 1% significance. When examining from the the day of actual policy decision, they find evidence that the policy decisions increase volatility regardless of whether they were announced on regularly scheduled meeting days. They find that conditional volatility is about 40% above typical levels on days of FOMC decisions. In fact,
a restricted analysis of only the days of surprise announcements nearly doubles the conditional volatility levels, and the hypothesis of no FOMC meeting day effects on announced/unannounced decision days can be rejected with 1% significance. They also found that positive surprises (higher than expected value of fed funds rate) tend to have a larger effect on volatility than negative surprises, thus the effect of policy news is asymmetric, agreeing with the leverage and volatility-feedback hypotheses. They find that previous day volatility tends to be muted in anticipation of the policy news, while a surprise increase in the fed funds rate at a meeting increase market volatility to unusually high levels. In summary, this paper shows that monetary announcements are an important source of short-run volatility in the stock market. Based on this paper, I hypothesize that meeting days should have significantly higher market volatility levels than control days.

The 2011 study by Farka and Fleissig analyzes a sample period from May 1999 to December 2007. They use an indicator variable that captures the information content in the statements. Their results show that both an unanticipated change in the interest rate and policy statements have a significant impact on the average level of asset prices and asset price volatility. They find that the volatility trend follows a “tent” like pattern, where volatility is unusually low in anticipation of the announcement, peaking right after the information is introduced, and then returning to a lower stable state after the information has been priced in the markets. They also find that FOMC statements have a more visible impact on stock returns and intermediate and long term bond yields, while the short term yield market (the federal funds rate market) is mostly affect by the target federal funds rate decisions. They also find that since the FOMC revised the wording of the statement in 2003 to be more forward looking, this increased transparency and has led to reduced volatility associated with the federal funds rate decision on meeting days. My study shows that the increased transparency of FOMC regarding the federal funds rate led to lower volatility on meeting days for the security BIL, which proxies the federal funds market.

In a 2014 article by Murillo and Shell, the authors noted that Fed statements have grown in complexity in recent years due to the Feds use of unconventional monetary policy, and suggested that the volatility attributed to its release in the markets may be caused by market participants’ confusion and lack of background about these new tools. They used the Flesch-Kincaid Grade Level index to measure the readability
of the statements based on education grade levels. They find that in the early 1990s, the statements ranged from 50-200 words and were comprehensible by high school students. Then in the 2000s until the end of Greenspan’s tenure, they averaged around 210 words and were written at the reading level of a college sophomore. During Bernanke and Yellen’s regimes, the length grew to over 800 words and readers were expected to have a graduate level education to be able to understand them fully. This study warns of the fallacy of associating greater transparency with reduced complexity.

I also examine several papers by Carlo Rosa, senior economist at the Federal Reserve Bank of New York. The paper that I drew most inspiration from is his 2013 publication. In this paper he examines the effect of FOMC Minutes from January 2005 to March 2011 on a variety of asset prices in a shortened time window. He uses a dataset of 5 minute returns and computes the standard deviations of these returns. After statistical testing, he finds that the release of the minutes significantly affect the price volatility of U.S. assets. I also use a similar methodology to organize my data and also examine my data from a shortened time window.

In Rosa’s 2011 paper, he examines the stock market reaction to central bank communication in real time. Using a high frequency event study analysis on the Dow Jones Industrial Index, NASDAQ 100, S&P 500 and the VIX volatility index, he shows that, in a sample from 1999 to 2010, FOMC policy communications and policy actions have a significant impact on volatility of several US stock indices, and that individual stock prices take around 1 hour to fully incorporate the news before reaching a new price equilibrium, while equity indices tend to absorb the effects of the news within 40 minutes from the time of release. I also include his 2010 paper, which studies the high-frequency response of exchange rates to monetary policy actions and statements for reference into other types of securities besides equities. This paper examines the effect of FOMC statements on the exchange rate of the USD with 5 currencies: the Euro, Canadian dollar, British pound, Swiss franc, and Japanese Yen. He finds that the release of the FOMC statement and the actual policy decision highly impact these exchange rates.

Finally, I examine a 2013 study by Jubinski and Tomljanovich examining FOMC minutes from an intraday perspective using individual equity volatility and returns. This paper analyzes a shorter time span of one year, from 2006-2007, but instead of analyzing asset prices from an aggregate index, they create their own index based on the securities of 2832 firms. They also find evidence that volatility is lower before 2PM than
after 2PM on minutes-release days, and that volatility is higher on release days relative to a set of control days taken one week before each release date. Similar to this paper, and the Rosa (2013) paper, I use a set of control days taken one week before and one week after each meeting and minutes release day and I seek to verify if their findings are replicated in my sample period.

Building on the existing literature, my paper studies a more recent period of time, dating from May 2007 to December 2014, which chronicles a very tumultuous time in American economic and financial history. The financial crisis from 2007-2009 was the worst since the Great Depression. This period, and the ensuing recession and recovery make for a very interesting analysis, and I seek to determine if the results of the earlier literature still stand. Using the methodology inspired by earlier studies, my paper aims to use the data to determine if, and how volatility behavior changes throughout the sample through a set of different timeframes, provide a comparison of volatility levels on minutes release days with that of the FOMC meeting/statement release days, and investigate whether the meetings and minutes are significant predictors of market volatility.

4 Hypothesis

Based on reviewing the previous studies, for my analysis in section 6, I expect to see meeting days correspond to higher levels of average volatility when compared to a set of non-event control days. I also expect to see minutes release days induce higher levels of average volatility than a set of control days. When looking at intraday volatility, the difference of volatility before and after 2PM, I expect the difference on meeting and minutes days to be significantly larger than the difference their respective control days control days. When comparing which event release day induces higher intraday volatility, I expect the meeting day to prevail over minutes release day. Finally, when I examine whether how well the event of a meeting day or minutes day predicts market volatility, I expect a model that includes meeting day and minutes day as indicator variables to be more significant than a model without these predictors.
5 Data and Methodology

For the purpose of my analysis, I use the securities SPY and BIL as proxies for the behavior of the US equity market and fed funds market, respectively. SPY is the SPDR S&P 500 ETF Trust, an exchange traded fund that tracks the S&P 500, a stock market index based on 500 companies with the largest market capitalizations on the NYSE or NASDAQ. The movement of the S&P stock index is usually quite similar to the movement of the entire US stock market, so how the price of SPY changes is a good indicator of how price levels in the overall stock market change.

The federal funds rate data was not readily accessible to me, so I used BIL, the SPDR Bloomberg Barclays 1-3 Month T-Bill ETF, as a proxy. It tracks the 1-3 Month T-Bill index. Since short term T-Bill yields are closely and positively correlated with movements federal funds rates, the volatility of BIL can be used as a proxy for the volatility of the federal funds rate. Since the first day BIL started trading was May 30, 2007, this is the day my sample starts. The latest year I have access to from Wharton Research Data Services (WRDS) is 2014, which is where my sample ends. So, the dates of my sample are from May 30, 2007 to December 31, 2014. There were 121 meeting days and 80 minutes release dates over the sample.

The formal definition of the primary metric I study, market volatility, is the standard deviation of 1 minute returns:

\[ s = \sqrt{\frac{\sum_{i=1}^{N} (r_i - \bar{r})^2}{N - 1}} \]  

(1)

where \( r_i \) is the individual 1-minute return of the security, \( \bar{r} \) is the sample mean return of the security, and \( N \) is the number of observations. I calculate this metric for SPY and BIL. To create my dataset, I use high frequency, tick by tick data that records all transactions on an asset, with more than one entry per second. I retrieve the data for SPY and BIL from the WRDS database. I use R’s collection of data cleaning and statistical analysis packages to process the data and conduct hypothesis testing and regression analysis.

To reduce the noise, or random fluctuations that are inherent in high frequency data, I aggregate the original, tick by tick time series into a minute by minute time series. The data cleaning and aggregation process includes converting the original dates used into a format that other functions can process, removing the times that were not part of the time interval considered (keeping only entries from 12:00PM to 4:00PM), and computing summary statistics for minute by minute intervals, such as an approximate minute return,
which will be used to calculate the volatility, by computing the return between each tick, and summing these returns up together over each 1 minute interval.

I have included the summary statistics for SPY and BIL returns below. As a check, I test for normality of returns. I have included the Jarque-Bera test for normality results and summary statistics for the returns in the Appendix, Item 1. The extremely low p-values indicate that the returns of SPY and BIL are not normally distributed, which is consistent with the observation in Rosa (2013).

Now, my entire dataset consists of 1-minute returns of the securities SPY and BIL recorded for each minute of the event window, over the years 2007-2014. After eliminating the values outside of the event window I am considering, from 12:00PM to 4:00PM, I proceed to group my data by hour and minute. I do this with the dplyr data analysis package in R, which has a function that allows me to sort and work with the data in groups. After applying this function, my data would now be sorted into the groups 12:00PM, 12:01PM and 12:02PM, and so on, until 3:59PM. So there would be 60 minutes * 4 hours = 240 groups that all my data would be sorted into. I’ll refer to them as minute-groups for clarity, because there is one for each minute of the event window. So now, each minute-group will consist of the returns of BIL and SPY in that minute for each of the days in the sample. Continuing with our example, for the minute group 12:01PM, one row would contain the returns of BIL and SPY on August 19, 2008 (at 12:01PM), and the following row would contain the returns of BIL and SPY on August 20, 2008 (at 12:01PM). I then proceed to separately calculate the sample standard deviation of the returns of BIL and the returns of SPY with Equation 1 above, for each minute group. I end up with a dataset of 240 standard deviations, one for each minute group. This method works best when there are a large number of observations for each minute-group.

For more qualitative analysis, I look online to find articles in the CNN news series Market Summary and other intraday updates provided by CNN Money. These articles are written on days I identified as having high average volatility levels. Based on these articles, I determine the story behind the volatility trend, or discover the reason why a particular day is an outlier, as explained in the next section.

In order to provide a control set for comparison purposes, I follow the methodology of Rosa (2013) and Jubinski and Tomljanovich (2013) and sample from a subset of days one week before and one week after each meeting day as proxies for normal, non-event days. This is done to isolate the effects of the meeting on
the meeting days as best as possible, and minimize the effect of non-FOMC events on non-meeting days. To illustrate our sampling criteria, if a meeting occurred on June 12, 2007, control dates would be June 5, 2007 and June 19, 2007.

5.1 Investigating and Identifying Outliers

Any dataset with influential outliers would give biased and inaccurate results upon analysis, so I employ the common IQR method to identify and eliminate extreme points in the 1 minute returns of SPY and BIL. I define an outlier as any return that lies more than 3 times the length of the interquartile range. So an outlier is any return that is outside the range:

$$(Q_1 - 3 \times IQR, Q_3 + 3IQR)$$

A summary of the original SPY returns with outliers showed:

```r
> summary(MasterData12to4PMwithOutliers$RET.SPY)

   Min. 1st Qu.  Median        Mean  3rd Qu.       Max.  
-0.0288  -0.0002  0.0000  0.0189 0.0002  2174.0000
```

The interquartile range (IQR) is $Q_3 - Q_1 = 0.0004$. Based on the criteria above, I consider any 1-minute return outside of the range ($-0.0014, 0.0014$), or with an absolute value greater than or equal to .14% to be an outlier for SPY.

A summary of the original BIL returns with outliers showed:

```r
> summary(MasterData12to4PMwithOutliers$RET.BIL)

   Min. 1st Qu.  Median        Mean  3rd Qu.       Max.  
-2.183e-02 -4.366e-05 0.0000+00 1.240e-07 4.368e-05 2.231e-02
```

The interquartile range is $Q_3 - Q_1 = 0.0008734$. Hence I consider any 1-minute return for BIL outside of the range ($-0.0031, 0.0031$), or with an absolute value greater than or equal to 0.031% to be an outlier for BIL.
I then investigate the reasons some extremely large outliers appear in the original dataset by researching journal articles for significant events around these dates and times.

A preliminary analysis of abnormally large 1 minute returns of BIL shows one day with large price volatility: October 3, 2007. The one minute returns for BIL fluctuated in the late afternoon from 2:30-4:00PM with a jump of -2% between 2:38-39PM, a jump of 2% between 2:43-2:44PM, a jump of -2% again between 2:44-2:45PM, and ended with a final jump of 2% at 3:58-3:59PM. I have not found a significant explanation for the large deviation, since it is not a day of meeting and no immediate Fed news was released during this time. The markets may be simply reacting to interest rate volatility occuring around this time due to rising rates of subprime mortgage defaults.

A preliminary survey of abnormally large 1 minute returns of SPY shows the following days with corresponding returns: June 25, 2009 at 3:46-3:47PM, the price went up around 1088 times or 108800%, and at 3:54-3:55PM, the price went up around 2174 times or 217400%, August 10, 2007 at 12:35-12:36PM, the price more than doubled (increased by 213%), May 6, 2010, at 2:44-45PM the price fluctuated by 28%, 8%, 22%, 60%, over each of the minute intervals from 2:45-2:50PM, October 16, 2008, at 3:54-3:55PM, the price fluctuated by 20%, 42%, 50%, 38%, and 49%, in the last minutes of the trading day, November 7, 2008, at 3:25-3:26PM, a jump of 30% occurred, and December 18, 2014, at 3:58-3:59PM a jump of 10% occurred.

I then investigate whether any significant events occurred on those days to warrant the large jumps in volatility. I found that June 25 was not a meeting day, and no significant news occurred, although there was a rally in stock prices that day because investors felt shares in several industries were undervalued after a period of falling prices. I also noted that June is the month of the annual Russell Index Rebalance, giving a reason for some degree of abnormal price movements. However, neither of these reasons is enough to warrant the huge return, so I suspect that the fluctuation was due to an entry error.

For August 10, 2007, I first noted it was a meeting day. Further reading showed that on this day, the Federal Reserve made its discount window ready to provide emergency liquidity as many credit institutions were failing because of the subprime mortgage crisis, and the Dow Jones index closed down 0.2%, a sign of the pessimism in the markets. Some news articles published around the time of the large volatility fluctuation talked of market uncertainty regarding housing prices and the collapse of many subprime mortgage lenders.
For May 6, 2010, market reports showed it is the day of the May 6th flash crash, where an erroneous trade by a mutual fund sparked massive sell-offs in blue-chip stocks, the shares of large and well regarded companies. This occurred around 2:45PM, the time these abnormal returns were observed. Hence the event is also known as the “Crash of 2:45”. However, once the error was apparent, markets were able to quickly recover those losses, thus explaining the large price volatilities observed around those times.

For October 16, 2008, I noted it was not a meeting day, but the stock market saw large price fluctuations as it was near the height of the crisis, and the government started taking aggressive action (after the unexpected bankruptcy of Lehman Brothers in September 2008). On this day in particular, the lowest oil prices this year prompted investors to jump back into the equities market, scooping up many shares at very low prices, which led to large fluctuations in price as demand changed.

On November 7, 2008 a stock rally sparked great movement in prices. Although it was not a meeting day, investors started buying what they felt were undervalued stocks. After several waves of bad news early in the day: an abysmal job report of 10 straight months of job losses, negative investor sentiment about the announcement of Barack Obama’s presidential victory, and a large quarter loss reported for influential company General Motors, they felt prices were already at a low. The rush to buy caused large price movements. A piece of positive news that also may have helped was that then president-elect Obama gave an afternoon conference where he promised a stimulus package upon taking office. Together, the weak economic data and investors’ hope of policy action sparked by Obama’s conference were enough to change the price a lot in a short period of time, explaining the high volatility recorded in the afternoon.

Although December 18, 2014 was itself not a meeting day, it was the day after the December 17th FOMC meeting. The Dow Jones index was at the highest point since 2011 and the S&P also had the biggest increase since the beginning of 2013. The markets reacted positively to the Fed’s announcement that it will not raise rates until mid 2015. It was largely regarded as the best trading day in 2014.

6 Results: Analysis of Volatility

6.1 Background of general volatility trend throughout the sample

Figure 1 below shows the average 1 minute price volatility of SPY and BIL for the event window from 12PM to 4PM, calculated for the entire sample. I derived the volatility metrics using the method in Section 4.

Figure 1: Average 1 Minute Price Volatility of SPY and BIL for the event window from 12PM - 4PM

Without accounting for the effect of a meeting day or minutes release day, it is clear that when considering the entire sample period of years 2007-2014, the graphs show that the volatility of the proxy security for the equity market, SPY, behaves differently from the volatility of the proxy security for the federal funds rate, BIL. SPY volatility levels tend to increase as each trading day progresses towards the end, from noon to afternoon. This may be due to the fast paced and global nature of the equities market. Participants may be anticipating outcomes of economic reports that are released after market hours, and also market events that occur abroad in other time zones. An operational reason for this trend is that day traders, who do not hold shares overnight, need to close their daily positions latest at 4PM.
However, BIL volatility levels tend to fluctuate around a constant mean, and tend to level off as the trading day ends, indicating it is mainly influenced by domestic events in the US. The lack of a clear up or down trend agrees with my expectations, because under normal circumstances, the federal funds rate would have little reason to experience large fluctuations unless the FOMC announces a new target federal funds rate, which only occurs during FOMC meetings. Also, due to the effects of the financial crisis, over most of the sample period, from December 2008 to December 2014, interest rates close to zero prevailed, which is highly unusual considering past history. Therefore, the limited number of days for the target rate to move, and the bad economic conditions driving rates to the lower bound are factors that lead to a lack to a particular trend in the volatility of BIL. Visually the peaks of volatility appear larger than SPY, but this is because the BIL graph’s volatility is plotted on a smaller scale, magnifying even small movements. The spikes indicate some level of volatility visibly different from the surrounding levels, yet not abnormal enough to be eliminated as outliers. This can be attributed to noise, the phenomenon of random variations in data measured at smaller intervals, such as in the 1-minute returns I use. Previous studies used larger intervals, such as a 5-minute, hourly, or even daily return.

Although the above graphs show some general, long term trends that persist throughout the sample period, shorter term trends persisting for a few years or even one year can be missed if I only consider the volatility across the entire sample. To detect any shorter term trends in volatility, I will examine in later sections volatility under smaller time periods: over each individual year of the sample, and over two subsamples: crisis and recovery years.

6.2 Do meeting days have significantly different volatility than non meeting days?

I separate my sample into meeting and non-meeting days via an indicator variable and examine if the volatility of SPY and BIL returns is different in the context of meeting vs non-meeting days. Because the number of non-meeting days far outnumbers the number of meeting days, and the volatility may be influenced by many other external factors, I get control dates via the methodology introduced in the previous section.

Figure 2 shows the average volatility of SPY and BIL during the entire sample period when I differentiate
between meeting and non-meeting days. The red lines denote volatility over meeting days, while the blue line denotes volatility over control days. For SPY, an upward trend in volatility appears over time. It is also evident that volatility appears to be higher on meeting days, denoted by the red line, as opposed to control days, denoted by the blue line. This visually confirms my hypothesis that through the timeframe of the entire sample, the volatility on meeting days is higher than on non-meeting days. However, for BIL the trend is not obvious.

Figure 2: Average volatility of SPY and BIL during entire sample period

I use hypothesis testing to confirm for sure whether the average volatility is significantly different on meeting days than control days. I test the following alternative hypothesis:

\[ H_a : \mu_{\text{Vol, Meeting}} \neq \mu_{\text{Vol, Control}} \]
Table 1 below shows that a two sided t-test for the difference of average volatility confirms that average volatility is significantly different on meeting days than control days. The positive test statistic of SPY shows that average volatility on meeting days is in fact greater than on non-meeting days. However for BIL, the negative test statistic shows that the average volatility on meeting days is actually less than on control days. Further testing showed that BIL volatility is actually significantly less on control days. This is an interesting deviation from previous literature, where evidence mostly suggest larger market movements on meeting days, but a plausible explanation can be the unusually high intraday volatility observed during the height of the financial crisis, active FOMC policymaking on non-scheduled meetings, as well as the unusually long term period of zero interest rates and transparent communication. I will examine smaller timeframes shortly. These observations statistically confirm my hypothesis that the volatility for SPY on FOMC meeting days is significantly different than the volatility on control days due to the introduction of market-moving information provided by the meeting statements. For R output and other relevant statistics, please refer to Appendix Item 2.

<table>
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<th>T-stat</th>
<th>P-value</th>
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<td>0.0005085 *</td>
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<tr>
<td>BIL</td>
<td>-5.6044</td>
<td>5.07e-08 *</td>
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</tbody>
</table>

Although it is evident that when considering the timeframe of the entire sample, the volatility on meeting days is significantly different than on non-meeting days, I would like to examine whether this trend persists throughout each individual year, or a group of years. Thus, I examine the volatility in each separate year in my sample: 2007, 2008, 2009, 2010, 2011, 2012, 2013, and 2014, and in two subsamples: crisis (2007-2010) and recovery (2011-2014).

Table 2 below shows the results of the test of significance of the difference in average volatility over all the years. As a general observation, in the years 2007, 2008, 2009, 2010, market volatility was higher, on average, on control days than on meeting days. This suggests that the events of the financial crisis brought about significant volatility in daily trading, and the meetings of the FOMC were but just one event investors...
needed to watch out for. It may also signify that the FOMC has become more transparent than earlier years, allowing market participants to predict the target rate from past statements and adjust market prices before the actual meeting. As the economy eventually recovered from the crisis, more volatility can be observed, especially in the equity market, on meeting days. Table 3 confirms this observation using the data.

On a technical note, for the years of my sample from 2007 to 2010, I encountered the issue of having some undefined volatility metrics. This is caused by some time intervals (a specific minute-group) having only 1 entry recorded in the sample. For example, only 1 date may have been observed in minute-group 3:14PM. Because the standard deviation of a sample of 1 is undefined, there were gaps in my graph that obscured some trends. To make the trends clearer, I fix this issue by setting the times with undefined standard deviations to having standard deviations equal to 0, which would connect the gaps. This is a common approach I read about in online statistics forums. For other calculations, I used the original dataset with NA values.

Figures 3 and 4 show the FOMC volatility graphs across the different years. I will now go over the results of Tables 2 and 3 and Figures 3 and 4 and discuss some key events affecting market volatility in each of the years of our sample to improve our understanding of the annual volatility trends.

I note that the 2007 graph is sparser than the graphs of the following years because the sample starts on May 30, 2007, the day the BIL security began trading on the market, and ends on December 31 2007. After mid 2007, as the subprime mortgage market collapsed and the effects of the credit crisis were just beginning to unfold, there was uncertainty whether the Federal Reserve will lower rates or inject reserves to help the banking system. The results of Table 2 show that for SPY, volatility on meeting days in the equity markets was less than control days, while for BIL, volatility on meeting days was not significantly different from volatility on control days. This reflect a general uncertainty about interest rates in the beginning of the crisis, since the FOMC still had room to move the relatively high rate at this time. The results for 2007 may not be as strong as the results for the following years because of the smaller dataset.

From this graph, it is evident that there is a difference in trend from the earlier years to the later years. Although volatility during meeting days is surprisingly significantly lower than non-meeting days during the earlier years, during the later years, volatility is reverts to the trend observed in previous literature of being higher on meeting days than non meeting days.
Table 2: Two tailed T-test for difference in average volatility of SPY and BIL results by year

Significant results ($\alpha = 10\%$) denoted *

<table>
<thead>
<tr>
<th>Security</th>
<th>$H_a: \mu_{\text{Meeting}} \neq \mu_{\text{Control}}$</th>
<th>T-stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPY 2007</td>
<td>Yes</td>
<td>-2.7948</td>
<td>0.007984 *</td>
</tr>
<tr>
<td>BIL 2007</td>
<td>No</td>
<td>0.54865</td>
<td>0.5873</td>
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<tr>
<td>SPY 2008</td>
<td>Yes</td>
<td>-2.3478</td>
<td>0.01966 *</td>
</tr>
<tr>
<td>BIL 2008</td>
<td>Yes</td>
<td>-2.7924</td>
<td>0.005628 *</td>
</tr>
<tr>
<td>SPY 2009</td>
<td>Yes</td>
<td>-2.2709</td>
<td>0.02367 *</td>
</tr>
<tr>
<td>BIL 2009</td>
<td>No</td>
<td>-0.67106</td>
<td>0.5026</td>
</tr>
<tr>
<td>SPY 2010</td>
<td>No</td>
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<td>0.6974</td>
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<tr>
<td>BIL 2010</td>
<td>Yes</td>
<td>-1.8802</td>
<td>0.06078 *</td>
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<tr>
<td>SPY 2011</td>
<td>Yes</td>
<td>3.2924</td>
<td>0.001078 *</td>
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<tr>
<td>BIL 2011</td>
<td>No</td>
<td>-0.65854</td>
<td>0.5106</td>
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<tr>
<td>SPY 2012</td>
<td>Yes</td>
<td>5.1657</td>
<td>3.844e-07 *</td>
</tr>
<tr>
<td>BIL 2012</td>
<td>Yes</td>
<td>-4.4666</td>
<td>1.039e-05 *</td>
</tr>
<tr>
<td>SPY 2013</td>
<td>Yes</td>
<td>4.1138</td>
<td>4.771e-05 *</td>
</tr>
<tr>
<td>BIL 2013</td>
<td>Yes</td>
<td>-5.043</td>
<td>6.594e-07 *</td>
</tr>
<tr>
<td>SPY 2014</td>
<td>Yes</td>
<td>6.5477</td>
<td>2.077e-10 *</td>
</tr>
<tr>
<td>BIL 2014</td>
<td>Yes</td>
<td>-3.5361</td>
<td>0.000453 *</td>
</tr>
<tr>
<td>SPY Subsample 1</td>
<td>Yes</td>
<td>-1.8609</td>
<td>0.06349 *</td>
</tr>
<tr>
<td>BIL Subsample 1</td>
<td>No</td>
<td>-0.8394</td>
<td>0.4017</td>
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<td>SPY Subsample 2</td>
<td>Yes</td>
<td>7.6059</td>
<td>1.988e-13 *</td>
</tr>
<tr>
<td>BIL Subsample 2</td>
<td>Yes</td>
<td>-4.6791</td>
<td>3.831e-06 *</td>
</tr>
</tbody>
</table>

For 2008, I note that, as verified by the tests in Table 2, the average annual volatility of SPY and BIL are both significantly lower on meeting days than control days. Table 3 shows that for SPY and BIL, overall volatility levels for this year are higher than the sample average. The higher than average market volatility on control days is a sign of economic uncertainty due to the financial crisis. Many significant events happened over non-meeting days that had greatly affected the markets, such as the unexpected bankruptcy of large
financial firm Lehman Brothers and the bailout of AIG. For BIL, the similar average volatilities on FOMC meeting days vs non-meeting days indicates that investors had trouble predicting the direction of interest rates that year, on average.

In 2009, as the crisis continued, a similar effect can be seen. Table 2 and Table 3 shows the continuation of the trend of higher intraday volatility levels on control days than meeting days in the equity markets, while volatility levels in the federal funds market remained indistinguishable between meeting and control days. In 2009, the FOMC expanded its use of alternative monetary policy, such as the expansion of the quantitative easing program, to assist in economic recovery.

In 2010, signs of recovery can be observed, with average volatility in SPY being lower than the previous two years. However, Table 2 shows that equity markets still experience almost constant levels of volatility on all days. Although markets in the U.S. were doing better, the European economy, which also influences the U.S. economy, was greatly affected by the government debt crisis across Eurozone countries. A June 23 FOMC meeting also warned of a slower pace of economic recovery due to this event, and the high volatility may have been due to worries about international spillover effects. BIL volatility remained higher on non-meeting days because it was clear interest rates would not be raised in the near future since the economy was still quite weak, and the zero interest rate policy gave no room for the FOMC to move it any lower.

In 2011, the effects of the continuation of quantitative easing can be observed, and economic data shows signs of a modest recovery. For the first time since the crisis, equity markets are shown to place more importance in information released on FOMC meeting days. The fact that this trend can be detected is a sign of lower intraday volatility and the restoration of normal market conditions. An important piece of news that may have sped up recovery is a strongly dovish (accommodating) FOMC statement released on the meeting day August 9th 2011 announcing that the committee would keep interest rates low until mid 2013. This, along with a similar statement released in the following year, would greatly reduce interest rate uncertainty for the remainder of the sample period.

For 2012, Table 2 indicates the continued recovery of the economy. A continuation of the pre-crisis results from the previous year can be seen, as described in earlier literature. Average volatility on meeting days for the equities market is now significantly higher than on control days, while the federal funds market remains
relatively calm on meeting days. This may be due to continued dovish FOMC statements protecting the equity market. On September 13, 2012, the FOMC announced a 3rd round of quantitative easing, and also assured investors of its intention to keep rates near 0 until 2015. Both would have an effect on keeping volatility for SPY and BIL low for control days for the remainder of the year.

For 2013, a prevalent question market participants watched out for during meeting days was when, and how, the quantitative easing program was going to end. The equity market benefited from the artificially lowered interest rates brought about by quantitative easing, but investors feared stocks prices would plummet again when the rates go back up after the program ends. Thus, there was uncertainty when the FOMC revealed its plan for tapering, or gradually discontinuing, their stimulative programs. BIL prices fluctuated little, indicating investor confidence in the FOMC statement of the previous year saying that rates would be low until 2015.

For 2014, a continuation of the trend from the prior year can be observed. The dataset shows that the highest volatility spikes for SPY on meeting days occurred at 2:00PM and at 2:32PM for control days. The 2:00PM spike during the meeting can be attributed to a stock price rally after the December 17, 2014 meeting, in which the Fed announced that it would only gradually increase rates after the first two meetings of 2015. This assured investors that the market would remain protected by policy for the short term.

Here, it is evident that the double tailed test revealed an interesting contrasting trend in volatility. In earlier years, there is a significant difference in volatility between meeting and control days, and the negative T-statistics show that volatility on meeting days is actually less than on control days for most years. This is more evidence that the events of the financial crisis proved to be more disruptive to markets than regularly scheduled FOMC policy meetings, and the reaction to the unanticipated daily events of the crisis masked the effects of the meetings. For BIL, in the earlier years, 2008 was a significant year, because of the large fluctuations in interest rate, which decreased from around 5% to 0%. As the crisis resolved itself, a general trend of FOMC events having larger effects in the markets in the later years can be observed. Also, due to the clearly dovish stance taken during the recovery period, when the Fed assured long periods of zero interest rate policy, the federal funds market remained unusually stable on meeting days during the entire sample period.
Table 3: Comparison of volatility levels each year

<table>
<thead>
<tr>
<th>Year and Security and Meeting/Control</th>
<th>Average Volatility</th>
<th>2007-2014 Average Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPY 2007 Meeting</td>
<td>0.00020</td>
<td>0.0003836</td>
</tr>
<tr>
<td>SPY 2007 Control</td>
<td>0.00041</td>
<td>0.0003618</td>
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<td>BIL 2007 Meeting</td>
<td>0.00008</td>
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<td>BIL 2007 Control</td>
<td>0.00007</td>
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<td>0.0003836</td>
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<td>SPY 2008 Control</td>
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<td>0.0003618</td>
</tr>
<tr>
<td>BIL 2008 Meeting</td>
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<td>1.053e-04</td>
</tr>
<tr>
<td>BIL 2008 Control</td>
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<td>SPY 2009 Control</td>
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<tr>
<td>BIL 2011 Control</td>
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<td>SPY 2012 Meeting</td>
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<td>0.0002464</td>
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</tr>
<tr>
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</tbody>
</table>
Figure 3: Annual FOMC Volatility on Meeting Days across the years 2007-2010.

Red = Meeting, Blue = Non-Meeting
Figure 4: Annual FOMC Volatility on Meeting Days across the years 2011-2014.

Red = Meeting, Blue = Non-Meeting
6.3 Do meeting days experience a larger change in volatility before and after 2PM than on control days?

I then analyze the volatility in terms of before and after the release of the statement, which are usually published around 2PM on meeting days, in terms of control days versus meeting days.

I divide my data of volatility on meeting days and control days into pre-2PM and post-2PM and investigate whether the change in average volatility from before 2PM to after 2PM is greater than the change in average volatility from before 2PM to after 2PM on control days. To be able to capture more trends, I test the two tailed alternative hypothesis:

\[ H_a = \mu_{\text{Vol, Meeting, post2PM}} - \mu_{\text{Vol, Meeting, pre2PM}} \neq \mu_{\text{Vol, Control, post2PM}} - \mu_{\text{Vol, Control, pre2PM}} \]

I first test this hypothesis for the overall sample, and then for each of the years of my sample and across subsamples. In Table 4 below, I present the results for each of the years of the sample and discuss some significant observations. The complete printout of the test results is in the Appendix, Item 4.

For the overall sample, I found the difference in volatility before and after 2PM to be indeed significantly greater on meeting days than control days for both BIL and SPY. However, examining the volatility in each year, I note that in the most tumultuous crisis years of 2007-2008, the change in volatility on control days was not significantly different compared to the change in the volatility on meeting days as the markets dealt with dramatic events on a frequent basis. This may be also due to the unusual earlier release time of some statements, such as at 7AM or 8AM, so that investors have already had the chance to price in the effects into the markets by 2PM. For 2009, the data shows that the change in volatility before and after 2PM is significantly greater on meeting days than on non-meeting days for the equity markets. A possible interpretation for this behavior is due to the Fed increasing the size of its quantitative easing program that year. Because quantitative easing has never been implemented before in the United States, investors were uncertain of the effects of this policy and had trouble predicting its impact. For 2010, again for the equity markets, the change in volatility is greater on meeting days than non-meeting days. In 2011, I note that the dovish August FOMC announcement kept the federal funds market relatively stable. In 2012, for BIL, the change in volatility before and after 2PM is significantly greater on meeting days than on non-meeting
days. This may be a sign of uncertainty about Europe and interest rates. Although the market was slowly recovering, investors were worried about the impacts of the European debt crisis on domestic growth and were not sure if this growth can be sustained without accommodating policies from the Fed. In 2013, as the economy visibly improved, markets participants were now interested in when, and how, quantitative easing policies would be tapered. In that year, the continued effects of the strong dovish statement from the FOMC in December 2012 assured investors that interest rates would not be raised until 2015. In 2013 and 2014, the effects of this statement can be observed, as BIL volatility levels before and after 2PM did not change significantly on meeting days when compared to non-meetings days. I provide a discussion of the subsample results in Section 5.8.

Figure 5 below shows volatility before and after 2PM for BIL and SPY. The orange line denotes volatility before 2PM on meeting days, red line denotes volatility after 2PM on meeting days, green denotes volatility before 2PM on control days, and blue denotes after volatility after 2PM on control days.

Figure 5: Volatility for SPY(left) and BIL (right), before and after 2PM on Meeting and Control days
Table 4: Results for test $H_a = \mu_{\text{Vol,Mpost}} - \mu_{\text{Vol,Mpre}} \neq \mu_{\text{Vol,Cpost}} - \mu_{\text{Vol,Cpre}}$

<table>
<thead>
<tr>
<th>Year and Security</th>
<th>$H_a = \mu_{\text{Vol,Mpost}} - \mu_{\text{Vol,Mpre}} \neq \mu_{\text{Vol,Cpost}} - \mu_{\text{Vol,Cpre}}$</th>
<th>T statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
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<td>Overall SPY</td>
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<td>&lt; 2.2e-16 *</td>
</tr>
<tr>
<td>Overall BIL</td>
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<td>0.01062 *</td>
</tr>
<tr>
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<td>BIL 2011</td>
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</tr>
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<td>BIL 2012</td>
<td>Yes</td>
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<td>0.0002404 *</td>
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<tr>
<td>SPY 2013</td>
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<td>8.7514</td>
<td>5.683e-16 *</td>
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<td>BIL 2013</td>
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<td>5.7265</td>
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<td>BIL 2014</td>
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<td>BIL Subsample 1</td>
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<tr>
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<tr>
<td>BIL Subsample 2</td>
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</table>

6.4 Is volatility higher on minutes release days than control days?

Here, I create a new set of control dates in a methodology similar to above: using as controls the day one week before and 1 week after the day the minutes are released. This set of controls is different from the ones
used in the analysis of meeting days. I test the alternative hypothesis:

$$H_a : \mu_{\text{vol, minutes}} \neq \mu_{\text{vol, control}}$$

The table below shows my results throughout the entire sample, with significant results denoted * at \(\alpha = 10\%\). Overall, I observe for SPY that on release of minutes days, the average market volatility is not significantly higher than the average market volatility on control days, but for BIL, the average market volatility during minutes-release days does significantly differ from the average market volatility during control days. The overall sample conclusion for SPY indicates that when considering the entirely of the seven years, the minutes did not, in general, convey as much information to the equity market. The only years where SPY exhibited higher than normal volatility on minutes release days was 2012 and 2013, reflecting market uncertainty about how the beginning of policy tapering and ending of quantitative easing as the economy recovered. The additional information would have helped the markets understand the FOMC’s policy intentions better. The overall sample conclusion for BIL shows that minutes release days was, in general calmer than the surrounding days, with the markets anticipating most of the information released in the minutes.

Looking at the subsamples, during the years 2007-2010, the high intraday volatility and many unexpected events during the crisis mutes the effect of the release of FOMC minutes, with the equity markets showing more volatility on non-minutes release days, while the federal funds markets show constant levels of volatility. However, for the second subsample, a renewed interest in the minutes in equity markets as the economy returned to normal conditions can be observed. For BIL, the volatility on minutes release days does not significantly differ from control days, perhaps as a consequence of strong FOMC statements about keeping interest rates near 0% in the later years of the economic recovery. The below graph plots the volatility of SPY and BIL separated by control vs meeting days. The red line shows minutes-release day volatility and the blue line shows control day volatility. This suggests that the minutes are not as significant a document as the meeting statements, even after the crisis subsided. I investigate this hypothesis in a later section.
Table 5: Two tailed t-test for difference in average volatility on minutes release days and control days

<table>
<thead>
<tr>
<th>Security and Year</th>
<th>$H_a : \mu_{vol, \text{minutes}} \neq \mu_{vol, \text{control}}$</th>
<th>T-statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPY, overall</td>
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<tr>
<td>BIL, overall</td>
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<td>&lt; 2.2e-16 *</td>
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<td>0.0005155 *</td>
</tr>
<tr>
<td>BIL 2009</td>
<td>Yes</td>
<td>-6.8796</td>
<td>2.065e-11 *</td>
</tr>
<tr>
<td>SPY 2010</td>
<td>Yes</td>
<td>-3.1925</td>
<td>0.001512 *</td>
</tr>
<tr>
<td>BIL 2010</td>
<td>Yes</td>
<td>-4.8778</td>
<td>1.493e-06 *</td>
</tr>
<tr>
<td>SPY 2011</td>
<td>Yes</td>
<td>-6.1551</td>
<td>1.7e-09 *</td>
</tr>
<tr>
<td>BIL 2011</td>
<td>Yes</td>
<td>-4.9408</td>
<td>1.118e-06 *</td>
</tr>
<tr>
<td>SPY 2012</td>
<td>Yes</td>
<td>4.128</td>
<td>4.415e-05 *</td>
</tr>
<tr>
<td>BIL 2012</td>
<td>Yes</td>
<td>-3.7377</td>
<td>0.0002086 *</td>
</tr>
<tr>
<td>SPY 2013</td>
<td>Yes</td>
<td>1.8905</td>
<td>0.05947 *</td>
</tr>
<tr>
<td>BIL 2013</td>
<td>Yes</td>
<td>-6.541</td>
<td>1.633e-10 *</td>
</tr>
<tr>
<td>SPY 2014</td>
<td>Yes</td>
<td>-4.391</td>
<td>1.402e-05 *</td>
</tr>
<tr>
<td>BIL 2014</td>
<td>Yes</td>
<td>1.7407</td>
<td>0.08255 *</td>
</tr>
<tr>
<td>SPY Subsample 1</td>
<td>No</td>
<td>-1.178</td>
<td>0.2395</td>
</tr>
<tr>
<td>BIL Subsample 1</td>
<td>Yes</td>
<td>-4.8112</td>
<td>2.133e-06 *</td>
</tr>
<tr>
<td>SPY Subsample 2</td>
<td>Yes</td>
<td>1.6985</td>
<td>0.0902 *</td>
</tr>
<tr>
<td>BIL Subsample 2</td>
<td>No</td>
<td>-0.8781</td>
<td>0.3804</td>
</tr>
</tbody>
</table>
6.5 Do minutes days experience a larger change in volatility before and after 2PM than control days?

I then examine if the change in average volatility on minutes release days before and after 2PM is significantly different from the change in average volatility on control days at 2PM for SPY and BIL. I examine the data through the timeframes of overall sample and by subsample, by before and after 2PM. I test the hypothesis:

$$H_a : \mu_{\text{Minutes, post}} - \mu_{\text{Minutes, pre}} \neq \mu_{\text{Control, post}} - \mu_{\text{Control, pre}}$$

The table below shows the results. I find that overall, for SPY, the volatility change on minutes days is significantly different (and larger) than on control days, particularly for the post-crisis years. The large positive t-statistics for SPY in the later years indicate that average market volatility after the minutes release was higher than before the minutes release under more normal market conditions.
Table 6: Results for $H_a: \mu_{M, \text{post}} - \mu_{M, \text{pre}} \neq \mu_{C, \text{post}} - \mu_{C, \text{pre}}$

<table>
<thead>
<tr>
<th>Year and Security</th>
<th>$H_a: \mu_{M, \text{post}} - \mu_{M, \text{pre}} \neq \mu_{C, \text{post}} - \mu_{C, \text{pre}}$</th>
<th>T-statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPY, overall</td>
<td>Yes</td>
<td>4.8414</td>
<td>2.611e-06 *</td>
</tr>
<tr>
<td>BIL, overall</td>
<td>No</td>
<td>1.3447</td>
<td>0.1801</td>
</tr>
<tr>
<td>SPY 2007</td>
<td>No</td>
<td>-0.3202</td>
<td>0.7491</td>
</tr>
<tr>
<td>BIL 2007</td>
<td>No</td>
<td>-0.39709</td>
<td>0.6917</td>
</tr>
<tr>
<td>SPY 2008</td>
<td>No</td>
<td>-0.98396</td>
<td>0.3262</td>
</tr>
<tr>
<td>BIL 2008</td>
<td>No</td>
<td>0.68778</td>
<td>0.4923</td>
</tr>
<tr>
<td>SPY 2009</td>
<td>Yes</td>
<td>2.3572</td>
<td>0.01927 *</td>
</tr>
<tr>
<td>BIL 2009</td>
<td>No</td>
<td>0.24654</td>
<td>0.8055</td>
</tr>
<tr>
<td>SPY 2010</td>
<td>Yes</td>
<td>2.3276</td>
<td>0.02089 *</td>
</tr>
<tr>
<td>BIL 2010</td>
<td>No</td>
<td>0.99169</td>
<td>0.3224</td>
</tr>
<tr>
<td>SPY 2011</td>
<td>No</td>
<td>0.22584</td>
<td>0.8215</td>
</tr>
<tr>
<td>BIL 2011</td>
<td>No</td>
<td>0.38462</td>
<td>0.7009</td>
</tr>
<tr>
<td>SPY 2012</td>
<td>No</td>
<td>1.6136</td>
<td>0.1082</td>
</tr>
<tr>
<td>BIL 2012</td>
<td>No</td>
<td>0.42389</td>
<td>0.672</td>
</tr>
<tr>
<td>SPY 2013</td>
<td>Yes</td>
<td>6.9882</td>
<td>3.384e-11 *</td>
</tr>
<tr>
<td>BIL 2013</td>
<td>Yes</td>
<td>2.5861</td>
<td>0.01031 *</td>
</tr>
<tr>
<td>SPY 2014</td>
<td>Yes</td>
<td>5.0465</td>
<td>8.953e-07 *</td>
</tr>
<tr>
<td>BIL 2014</td>
<td>No</td>
<td>0.76926</td>
<td>0.4427</td>
</tr>
<tr>
<td>SPY subsample 1</td>
<td>Yes</td>
<td>2.7232</td>
<td>0.007006 *</td>
</tr>
<tr>
<td>BIL subsample 1</td>
<td>No</td>
<td>1.09</td>
<td>0.2769</td>
</tr>
<tr>
<td>SPY subsample 2</td>
<td>Yes</td>
<td>5.5824</td>
<td>7.241e-08 *</td>
</tr>
<tr>
<td>BIL subsample 2</td>
<td>No</td>
<td>1.204</td>
<td>0.2299</td>
</tr>
</tbody>
</table>

However, for BIL the effect is much more muted, and this can be attributed to the statement already clearly announcing the target fed fund rate, the main factor that moves prices in the BIL market. Overall,
it is evident that under normal market conditions, as the minutes are released, they do exert some influence on intraday volatility for equity markets by adding some additional details to provide participants with a more nuanced and accurate understanding of the FOMC’s economic outlook, although during crisis years, the delayed nature of the release makes the information less relevant than usual.

6.6 Is the change in volatility higher on meeting days than minutes release days?

Although I have investigated the relationship of volatility on minutes release days and meeting days when considering the events separately, I now investigate in which of the two FOMC events studied one can observe a higher change in volatility. My original hypothesis is that since the minutes is a more detailed, and delayed, explanation of the rationale behind the policy actions the Fed outlined in the statements, the average change in market volatility on minutes release days ought to be smaller than the average change in market volatility on the meeting days. However, to capture all possible trends, I test a broader, two tailed alternative hypothesis:

\[ H_a : \mu_{Vol, Meeting, post2PM} - \mu_{Vol, Meeting, pre2PM} \neq \mu_{Vol, Minutes, post2PM} - \mu_{Vol, Minutes, pre2PM} \]

Table 7 shows the results at \( \alpha = 10\% \) (denoted with *). I find that, for the timeframe of the entire sample, the change in intraday volatility on minutes days in the federal funds market is not significantly different from the change in volatility on meetings dates. However, for the equities market, I observe intraday volatility on meeting days to be higher than on minutes release days, especially during the crisis years. This observation suggests that both documents influence the markets similarly on the days they are released, while for equities markets during the crisis years, the meeting statements proved to be a bit more useful, probably because of the timely information they conveyed. However, this trend did not persist uniformly throughout the entire sample. A notable exception is in 2013, when the minutes release days were actually observed to have higher intraday volatility than meeting days. This may be the effect of a general concern with tapering, which caused both the equity and federal funds rate markets to consult the minutes for more information, and the delay did not eliminate the usefulness of a more detailed discussion of tapering policies. The table conveys that the statement and minutes ought to be equally important during normal market conditions.
conditions, since they serve different purposes, although the usefulness of the minutes can be diminished in an abnormally fast paced market due to the time lag. In Figure 7 one can visually see that the change in volatility on meeting days is larger than minutes days in subsample 1, for SPY.

Table 7: T-test results comparing volatility on minutes release days with statement release days.

<table>
<thead>
<tr>
<th>Security and Year</th>
<th>$H_a: \mu_{Vol, \text{Meeting, post}} - \mu_{Vol, \text{Meeting, pre}} \neq \mu_{Vol, \text{Minutes, post}} - \mu_{Vol, \text{Minutes, pre}}$</th>
<th>T-statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPY, overall</td>
<td>Yes</td>
<td>1.9504</td>
<td>0.0525 *</td>
</tr>
<tr>
<td>BIL, overall</td>
<td>No</td>
<td>-0.10117</td>
<td>0.9195</td>
</tr>
<tr>
<td>SPY 2007</td>
<td>No</td>
<td>-1.0205</td>
<td>0.3086</td>
</tr>
<tr>
<td>BIL 2007</td>
<td>No</td>
<td>-1.1168</td>
<td>0.2653</td>
</tr>
<tr>
<td>SPY 2008</td>
<td>Yes</td>
<td>1.8196</td>
<td>0.07014 *</td>
</tr>
<tr>
<td>BIL 2008</td>
<td>No</td>
<td>-0.69707</td>
<td>0.4865</td>
</tr>
<tr>
<td>SPY 2009</td>
<td>No</td>
<td>0.27742</td>
<td>0.7817</td>
</tr>
<tr>
<td>BIL 2009</td>
<td>No</td>
<td>-1.4648</td>
<td>0.1445</td>
</tr>
<tr>
<td>SPY 2010</td>
<td>Yes</td>
<td>1.8942</td>
<td>0.05942 *</td>
</tr>
<tr>
<td>BIL 2010</td>
<td>No</td>
<td>-1.1219</td>
<td>0.2631</td>
</tr>
<tr>
<td>SPY 2011</td>
<td>No</td>
<td>1.4004</td>
<td>0.1627</td>
</tr>
<tr>
<td>BIL 2011</td>
<td>No</td>
<td>0.42187</td>
<td>0.6735</td>
</tr>
<tr>
<td>SPY 2012</td>
<td>No</td>
<td>-1.5261</td>
<td>0.1284</td>
</tr>
<tr>
<td>BIL 2012</td>
<td>No</td>
<td>1.0165</td>
<td>0.3105</td>
</tr>
<tr>
<td>SPY 2013</td>
<td>Yes</td>
<td>-2.2718</td>
<td>0.02421 *</td>
</tr>
<tr>
<td>BIL 2013</td>
<td>Yes</td>
<td>-2.8213</td>
<td>0.00529 *</td>
</tr>
<tr>
<td>SPY 2014</td>
<td>No</td>
<td>0.17202</td>
<td>0.8636</td>
</tr>
<tr>
<td>BIL 2014</td>
<td>No</td>
<td>-1.0113</td>
<td>0.3133</td>
</tr>
<tr>
<td>SPY Subsample 1</td>
<td>Yes</td>
<td>2.4292</td>
<td>0.01594 *</td>
</tr>
<tr>
<td>BIL Subsample 1</td>
<td>No</td>
<td>-1.4007</td>
<td>0.1627</td>
</tr>
<tr>
<td>SPY Subsample 2</td>
<td>No</td>
<td>-0.37164</td>
<td>0.7105</td>
</tr>
<tr>
<td>BIL Subsample 2</td>
<td>No</td>
<td>0.16255</td>
<td>0.871</td>
</tr>
</tbody>
</table>
6.7 How good are meeting days and minute release days in predicting the volatility of SPY?

I group my dataset into 3 categories, days of no meeting and no minutes, days of meeting and no minutes, and days of minutes and no meetings. There is no category for days of meeting and minutes because they never occur simultaneously. After calculating the 1-minute standard deviations of each group, I fit the data according to the linear regression model

\[
\text{Volatility of SPY}_t = \beta_0 + \beta_1 \times \text{Volatility of BIL}_t + \beta_2 \times \text{Meeting}_t + \beta_3 \times \text{Minutes}_t + \epsilon_t
\]  

(2) where Meeting is an indicator variable that is 1 when the date is a meeting day and 0 otherwise. Similarly, Minutes is an indicator variable that is 1 when the date is a minutes release day and 0 otherwise. My results show that throughout the entire sample, the volatility of BIL, the Meeting, and the Minutes are significant predictors on their own that influence the volatility of SPY. A partial F-test comparing models that include different combinations of the above predictors shows that a full model with all the predictors: Volatility of BIL, Meetings, and Minutes is significant.

I also analyze the quality of meeting days and minutes release days in predicting the volatility of BIL.
The regression model I use is:

\[
\text{Volatility of BIL}_t = \beta_0 + \beta_1 \cdot \text{Meeting}_t + \beta_2 \cdot \text{Minutes}_t + \epsilon_t
\]  

(3)

The variables Meeting and Minutes are similarly defined. Here, I find that throughout the entire sample, the volatility of BIL is highly impacted by the meeting and the minutes. Since the statement is released on the meeting day, the statement itself is more a significant predictor than the minutes. This indicates that the statements does a good job of clearly announcing the federal funds rate throughout the sample, and the minutes, although helpful, is additional delayed information that is somewhat less important. A partial F test shows that the most significant model using these predictors is the model that includes just the Meetings variable.

As a side note, the overall adjusted \( R^2 \) of the model is very low, indicating that still more of the variability of SPY and BIL must be explained by other factors. The full regression output and partial F test results can be found in Item 8 of the Appendix.

6.8 How do volatility patterns change from the financial crisis years to the recovery years?

Here I summarize the statistics on subsamples presented in earlier samples to form a theory of how average volatility patterns in SPY and BIL change from crisis to recovery years.

In Section 6.2 one can see that, when measured on the subsample level, average volatility on FOMC meeting days in the crisis years significantly differs from average volatility in control days for SPY in the recovery years but is not significantly different for BIL in either of the two phases. In the crisis years, average volatility is significantly higher on control days, while in the recovery years, average volatility is significantly lower on control days. This is most likely due to large market disruptions during the crisis years but relatively calmer markets during the control years that caused FOMC meetings to rise in prominence. For BIL, volatility levels remain indistinguishable between meeting and control days for the crisis years, but calmed considerably during the recovery years as the FOMC adopted a strongly dovish stance to stimulate economic recovery.
In Section 6.3, one sees that the change in volatility on the meetings days was significantly different than the change in volatility on control days for equities throughout both subsamples, but does not seem to have the similar effect on the federal funds market. During the crisis years, the result in the equities market would be likely due to prices moving around investor reactions to emergency FOMC actions designed to provide liquidity and stability in the economic system in the short term. Then, as the economy recovered, investors looked to the FOMC for how these policies were going to "taper", or end. Another factor in the significant reaction of SPY during the recovery years is that the equity market is influenced by factors other than the federal funds rate, and investors of SPY read the statements for other information as well, such as the Fed’s outlook on the economy and its commentary on the European debt crisis. A more subtle observation indicates that the FOMC statements got more significant after the crisis. This is expected because during the crisis years, the FOMC’s economic outlook was just one of many influential economic events they had to react to, but as the crisis subsided, there were less disruptive events that were as influential as the release of the FOMC statements, leading to an increased importance placed on meeting days. For BIL, one can deduce markets expecting, in general, near zero interest rates throughout the crisis years. The clearly accommodative policy taken in the years after the crisis subdued much of the volatility in the federal funds markets even as the economy recovered.

In Section 6.4, the subdued effect of FOMC meetings during crisis years in minutes data is again observed. In the crisis years, minutes information seems to not affect volatility significantly, mostly due to the delayed information not having much use when market conditions are rapidly changing. In fact, for BIL the markets are observed as having completely anticipated the information released in the minutes, so that release days actually experience significantly lower volatility than control days. However, as the markets became calmer in the recovery years, equities market participants were observed to be able to gain more detailed information on the FOMC economic outlook through the FOMC minutes as volatility on minutes release days became significantly higher than on control days. Also, BIL market participants were mostly assured, by the strong dovish policies, that the federal funds rate would not fluctuate by much in the short term, even in the calmer markets of the remainder months of the sample period, illustrated by the observation that average volatility levels were indistinguishable between meeting and control days in the recovery subsample.
In Section 6.5 it is noted that, consistent with past results, the change in intraday volatility levels from before 2PM to after 2PM on minutes release days and control days was not significantly different for BIL during the crisis years, since the statement clearly conveys this rate in both subsamples. However for SPY, in both subsamples it is evident that the release of the minutes does significantly influence intraday volatility levels. The trend appears to grow in significance in the second subsample, indicating that the minutes tend to be more influential in intraday volatility in a calmer market.

In Section 6.6, I compare the change in volatility on minutes release days with that of the meeting days, to see which event was more influential. I found that the change in intraday volatility levels on meeting days is significantly higher than the change in intraday volatility levels on minutes days for the overall sample in SPY, and this trend is mainly supported by the first subsample, not the second. For BIL, the two events seem to induce almost the same levels of intraday volatility. A theory on why this is occurring may be that during the crisis, market disrupting events occurred so frequently that the minutes, released with a three week lag, contained information that was no longer relevant. Investors must rely only on the statements to make their best judgment. However, as the economy recovered, the data shows the minutes beginning to gain more importance, as markets stabilized and influential, unexpected events happened less frequently. So in a more normal economy, markets were able to make some use of the additional information of the detailed economic outlook in the minutes.

7 Conclusion

After answering the questions above, one can see that the results are quite different from what the existing literature concluded about earlier samples. In the tumultuous 8 years of the sample, the financial crisis challenged the FOMC to help the economy in experimental new ways, such as long periods of zero interest rates and using alternative monetary policies like quantitative easing. It is also clear that changing volatility trends reflect the change in the role of communications as monetary policy evolved.

In summary, Section 6.2 shows that, through the entire sample, the volatility on meeting days is higher than on control days. However, the annual trends show two distinct trends between the crisis and recovery years. For the equities market, volatility is observed to be higher on normal (control) days during the crisis
years, while in the recovery years, meeting day volatility becomes significantly higher than control days. Section 6.3 shows that, through the entire sample, the change in volatility before and after the common 2PM release time on meeting days is larger than the change in volatility before and after the 2PM release time on control days for both the equities and fed funds markets. Section 6.4 shows that average volatility on minutes release days is indistinguishable from volatility on control days for SPY, and average volatility on minutes release days is significantly less than control days for BIL when considering the whole sample. However, looking at the subsample results, I note that minutes release day volatility can be more prominently observed as markets recovered from the crisis. Section 6.5 shows that, through the entire sample, the change in volatility before and after the common 2PM release time on minutes release days is larger than the change in volatility before and after the 2PM release time on control days for the equities market, while for the federal funds market, the release of the minutes has an indistinguishable effect. Section 6.6 shows that the change in volatility on meetings days is higher than the change in volatility on minutes-release days during the peak years of the crisis for the equities market, but this trend subsided during the recovery period, largely because both releases were important in different ways, and the time lag of the minutes was less of an issue. Section 6.7 shows that meetings and minutes are important variables that explain variability in SPY and BIL. Section 6.8 provides a summary of the evolution of volatility trends as the economy moved from a state of crisis to gradual recovery.

Statistically, my results are strongest at the overall sample and are not as strong when I analyze according to smaller timeframes, such as over each individual year. This is due to having less observations in each dataset, which allow for random variations to have more influence on my results.

There is room for additional analysis. Further ideas to investigate include investigating if dovish or hawkish statements influences volatility in different ways. Future researchers can also evaluate additional regressors in the volatility model by analyzing other types of Fed communications releases, and other security types, or explore non-linear models to fit the data.
8 Bibliography

8.1 Relevant Literature


8.2 Market Summary Sources


9 Appendix

Item 1

Jarque-Bera statistics showing that returns for SPY are not normally distributed (very low p-value).

```r
> jb.norm.test(MasterData12to4PM_2$RET.SPY)

    Jarque-Bera test for normality

data: MasterData12to4PM_2$RET.SPY

JB = 316640000, p-value < 2.2e-16
```

Jarque-Bera statistics showing that returns for BIL are not normally distributed (very low p-value).

```r
> jb.norm.test(MasterData12to4PM_2$RET.BIL)

    Jarque-Bera test for normality

data: MasterData12to4PM_2$RET.BIL

JB = 167400000, p-value < 2.2e-16
```

Summary returns for SPY and BIL, without outliers.
Item 2

Output for T-test of Difference in Average Volatility on Meeting Days vs Control Days

For SPY, Overall Sample

```r
> t.test(meetings_sd_overall$STD.DEV.SPY, control_meetings_sd_overall$STD.DEV.SPY)
Welch Two Sample t-test
data: meetings_sd_overall$STD.DEV.SPY and control_meetings_sd_overall$STD.DEV.SPY
t = 3.5124, df = 317.72, p-value = 0.0005085
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
9.603831e-06 3.406479e-05
sample estimates:
mean of x  mean of y
0.0003836090 0.0003617747
```

For BIL, Overall Sample

```r
> t.test(meetings_sd_overall$STD.DEV.BIL, control_meetings_sd_overall$STD.DEV.BIL)
Welch Two Sample t-test
data: meetings_sd_overall$STD.DEV.BIL and control_meetings_sd_overall$STD.DEV.BIL
t = -5.6044, df = 275.37, p-value = 5.07e-08
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-6.25471e-06 -3.00286e-06
```
For 2007

> t.test(meetings_sd_2007$STD.DEV.SPY, control_sd_2007$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2007$STD.DEV.SPY and control_sd_2007$STD.DEV.SPY
t = -3.4499, df = 319.09, p-value = 0.0006363
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-6.752542e-05 -1.847828e-05
sample estimates:
  mean of x  mean of y
1.348053e-05 5.648237e-05

> t.test(meetings_sd_2007$STD.DEV.BIL, control_sd_2007$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2007$STD.DEV.BIL and control_sd_2007$STD.DEV.BIL
t = -1.3304, df = 444.99, p-value = 0.1841
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-9.386841e-06 1.808435e-06
sample estimates:
  mean of x  mean of y
5.153739e-06 8.942942e-06

For 2008

> t.test(meetings_sd_2008$STD.DEV.SPY, control_sd_2008$STD.DEV.SPY)

Welch Two Sample t-test
```r
data: meetings_sd_2008$STD.DEV.SPY and control_sd_2008$STD.DEV.SPY
t = -8.3953, df = 474.68, p-value = 5.394e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.0002958216  -0.0001836082
sample estimates:
  mean of x  mean of y
0.0002648793 0.0005045942

> t.test(meetings_sd_2008$STD.DEV.BIL, control_sd_2008$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2008$STD.DEV.BIL and control_sd_2008$STD.DEV.BIL
t = -8.1605, df = 478, p-value = 2.978e-15
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-6.163733e-05  -3.771471e-05
sample estimates:
  mean of x  mean of y
4.788441e-05 9.756043e-05

For 2009

> t.test(meetings_sd_2009$STD.DEV.SPY, control_sd_2009$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2009$STD.DEV.SPY and control_sd_2009$STD.DEV.SPY
t = -2.9205, df = 406.15, p-value = 0.003689
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-7.684670e-05  -1.501429e-05
sample estimates:
  mean of x  mean of y
```

45
> t.test(meetings_sd_2009$STD.DEV.BIL, control_sd_2009$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2009$STD.DEV.BIL and control_sd_2009$STD.DEV.BIL
t = -1.5312, df = 375.32, p-value = 0.1266
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.125383e-05 1.400055e-06
sample estimates:
  mean of x  mean of y
0.0001121467 0.0001170736

For 2010

> t.test(meetings_sd_2010$STD.DEV.SPY, control_sd_2010$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2010$STD.DEV.SPY and control_sd_2010$STD.DEV.SPY
t = -1.7819, df = 395.96, p-value = 0.07553
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-5.976571e-05 2.934934e-06
sample estimates:
  mean of x  mean of y
0.0003119683 0.0003403836

> t.test(meetings_sd_2010$STD.DEV.BIL, control_sd_2010$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2010$STD.DEV.BIL and control_sd_2010$STD.DEV.BIL
t = -3.4959, df = 418.62, p-value = 0.0005229
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
For 2011

> t.test(meetings_sd_2011$STD.DEV.SPY, control_sd_2011$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_2011$STD.DEV.SPY and control_sd_2011$STD.DEV.SPY
t = 3.139, df = 416.87, p-value = 0.001816
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 1.660802e-05 7.225327e-05

sample estimates:
  mean of x  mean of y
0.0004511471 0.0004067165

> t.test(meetings_sd_2011$STD.DEV.BIL, control_sd_2011$STD.DEV.BIL)

Welch Two Sample t-test

data: meetings_sd_2011$STD.DEV.BIL and control_sd_2011$STD.DEV.BIL
t = -0.78931, df = 387.27, p-value = 0.4304
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-8.809213e-06 3.762267e-06

sample estimates:
  mean of x  mean of y
0.0001029706 0.0001054941

For 2012

> t.test(meetings_sd_2012$STD.DEV.SPY, control_sd_2012$STD.DEV.SPY)
Welch Two Sample t-test

data: meetings_sd_2012$STD.DEV.SPY and control_sd_2012$STD.DEV.SPY

t = 5.1657, df = 386.64, p-value = 3.844e-07
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
3.439318e-05 7.666154e-05

sample estimates:
  mean of x  mean of y
0.0003018786 0.0002463512

> t.test(meetings_sd_2012$STD.DEV.BIL, control_sd_2012$STD.DEV.BIL)

Welch Two Sample t-test

data: meetings_sd_2012$STD.DEV.BIL and control_sd_2012$STD.DEV.BIL

t = -4.4666, df = 395.21, p-value = 1.039e-05
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-1.712361e-05 -6.656684e-06

sample estimates:
  mean of x  mean of y
8.248120e-05 9.437135e-05

For 2013

> t.test(meetings_sd_2013$STD.DEV.SPY, control_sd_2013$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_2013$STD.DEV.SPY and control_sd_2013$STD.DEV.SPY

t = 4.1138, df = 381.37, p-value = 4.771e-05
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
1.898305e-05 5.374250e-05

sample estimates:
mean of x  mean of y
0.0002517569 0.0002153941

> t.test(meetings_sd_2013$STD.DEV.BIL, control_sd_2013$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2013$STD.DEV.BIL and control_sd_2013$STD.DEV.BIL
t = -5.043, df = 462.21, p-value = 6.594e-07
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.573478e-05 -6.910562e-06
sample estimates:
mean of x  mean of y
9.011094e-05 1.014336e-04

For 2014

> t.test(meetings_sd_2014$STD.DEV.SPY, control_sd_2014$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2014$STD.DEV.SPY and control_sd_2014$STD.DEV.SPY
t = 6.5477, df = 351.02, p-value = 2.077e-10
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
4.632595e-05 8.610384e-05
sample estimates:
mean of x  mean of y
0.0003143368 0.0002481219

> t.test(meetings_sd_2014$STD.DEV.BIL, control_sd_2014$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2014$STD.DEV.BIL and control_sd_2014$STD.DEV.BIL
t = -3.5361, df = 405.66, p-value = 0.000453
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.241103e-05 -3.542121e-06

sample estimates:

  mean of x  mean of y
0.0001048775 0.0001128541

For Subsample 1

> t.test(meetings_sd_subsample_1$STD.DEV.SPY, control_sd_meetings_subsample_1$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_subsample_1$STD.DEV.SPY and control_sd_meetings_subsample_1$STD.DEV.SPY
t = -1.8609, df = 397.98, p-value = 0.06349
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-4.161294e-05 1.141884e-06

sample estimates:

  mean of x  mean of y
0.0004503169 0.0004705524

> t.test(meetings_sd_subsample_1$STD.DEV.BIL, control_sd_meetings_subsample_1$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_subsample_1$STD.DEV.BIL and control_sd_meetings_subsample_1$STD.DEV.BIL
t = -0.8394, df = 406.2, p-value = 0.4017
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-5.758983e-06 2.312482e-06

sample estimates:

  mean of x  mean of y
0.0001137453 0.0001154686

For Subsample 2
> t.test(meetings_sd_subsample_2$STD.DEV.SPY, control_sd_meetings_subsample_2$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_subsample_2$STD.DEV.SPY and control_sd_meetings_subsample_2$STD.DEV.SPY
t = 7.6059, df = 405.96, p-value = 1.988e-13
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 3.80378e-05 6.44841e-05
sample estimates:
  mean of x  mean of y
0.0003447216 0.0002933505

> t.test(meetings_sd_subsample_2$STD.DEV.BIL, control_sd_meetings_subsample_2$STD.DEV.BIL)

Welch Two Sample t-test

data: meetings_sd_subsample_2$STD.DEV.BIL and control_sd_meetings_subsample_2$STD.DEV.BIL
t = -4.6791, df = 444.44, p-value = 3.831e-06
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-7.892644e-06 -3.223587e-06
sample estimates:
  mean of x  mean of y
0.0001006855 0.0001062436

Item 3

Summary statistics of volatility over meeting and control days for the years of the sample

Over the entire sample 2007-2014

> summary(meetings_sd_overall$STD.DEV.SPY)

     Min.  1st Qu.   Median      Mean   3rd Qu.     Max.     
0.0001806 0.0003140 0.0003841 0.0003836 0.0004530 0.0005852

> summary(control_meetings_sd_overall$STD.DEV.SPY)

     Min.  1st Qu.   Median      Mean   3rd Qu.     Max.     
0.0001806 0.0003140 0.0003841 0.0003836 0.0004530 0.0005852
0.0002948 0.0003356 0.0003538 0.0003618 0.0003844 0.0005082

> summary(meetings_sd_overall$STD.DEV.BIL)

       Min.  1st Qu.   Median      Mean   3rd Qu.     Max.

> summary(control_meetings_sd_overall$STD.DEV.BIL)

       Min.  1st Qu.   Median      Mean   3rd Qu.     Max.
 0.0000989 0.0001075 0.0001100 0.0001100 0.0001124 0.0001181

2007

> summary(meetings_sd_2007$STD.DEV.SPY)

       Min.  1st Qu.   Median      Mean   3rd Qu.     Max.
 0.000000 0.000007 0.000160 0.000200 0.000320 0.000870

> summary(control_sd_2007$STD.DEV.SPY)

       Min.  1st Qu.   Median      Mean   3rd Qu.     Max.
 0.000000 0.000190 0.000280 0.000410 0.000590 0.001210

> summary(meetings_sd_2007$STD.DEV.BIL)

       Min.  1st Qu.   Median      Mean   3rd Qu.     Max.
 0.000000 0.000090 0.000090 0.000080 0.000150 0.000160

> summary(control_sd_2007$STD.DEV.BIL)

       Min.  1st Qu.   Median      Mean   3rd Qu.     Max.
 0.000000 0.000000 0.000050 0.000090 0.000150 0.000160

2008

> summary(meetings_sd_2008$STD.DEV.SPY)

       Min.  1st Qu.   Median      Mean   3rd Qu.     Max.
 0.000002 0.000024 0.000043 0.000048 0.000071 0.001400

> summary(control_sd_2008$STD.DEV.SPY)

       Min.  1st Qu.   Median      Mean   3rd Qu.     Max.
 0.000046 0.000037 0.000059 0.000055 0.000073 0.001319
> `summary(meetings_sd_2008$STD.DEV.BIL)`

    Min. 1st Qu. Median  Mean  3rd Qu.  Max. 
    0.00000  0.00002  0.00010  0.00009  0.00013  0.00027

> `summary(control_sd_2008$STD.DEV.BIL)`

    Min. 1st Qu. Median  Mean  3rd Qu.  Max. 
    0.000000  0.000072  0.000116  0.000107  0.000148  0.000256

---

2009

> `summary(meetings_sd_2009$STD.DEV.SPY)`

    Min. 1st Qu. Median  Mean  3rd Qu.  Max. 
    0.000000  0.000299  0.000431  0.000444  0.000590  0.001079

> `summary(control_sd_2009$STD.DEV.SPY)`

    Min. 1st Qu. Median  Mean  3rd Qu.  Max. 
    0.0001850  0.0003820  0.0004749  0.0004785  0.0005766  0.0008754

> `summary(meetings_sd_2009$STD.DEV.BIL)`

    Min. 1st Qu. Median  Mean  3rd Qu.  Max. 
    0.000000  0.000093  0.000118  0.000115  0.000143  0.000189

> `summary(control_sd_2009$STD.DEV.BIL)`

    Min. 1st Qu. Median  Mean  3rd Qu.  Max. 
### 2010

```r
> summary(meetings_sd_2010$STD.DEV.SPY)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
0.000000 0.000167 0.000299 0.000334 0.000476 0.000911
> summary(control_sd_2010$STD.DEV.SPY)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
> summary(meetings_sd_2010$STD.DEV.BIL)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
0.000001 0.000072 0.000102 0.000100 0.000129 0.000218
> summary(control_sd_2010$STD.DEV.BIL)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
```

### 2011

```r
> summary(meetings_sd_2011$STD.DEV.SPY)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
0.0000348 0.0003253 0.000489 0.0004530 0.0005715 0.0011080
> summary(control_sd_2011$STD.DEV.SPY)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
> summary(meetings_sd_2011$STD.DEV.BIL)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
0.0000000 0.0000808 0.0001051 0.0001034 0.0001321 0.0002160
> summary(control_sd_2011$STD.DEV.BIL)
  Min. 1st Qu. Median Mean 3rd Qu. Max.
```
> summary(meetings_sd_2012$STD.DEV.SPY)

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.

> summary(control_sd_2012$STD.DEV.SPY)

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.
0.0001010 0.0001798 0.0002327 0.0002464 0.0002873 0.0006266

> summary(meetings_sd_2012$STD.DEV.BIL)

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.
0.0000000 5.884e-05 8.616e-05 8.248e-05 1.092e-04 1.722e-04

> summary(control_sd_2012$STD.DEV.BIL)

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.

---

2013

> summary(meetings_sd_2013$STD.DEV.SPY)

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.

> summary(control_sd_2013$STD.DEV.SPY)

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.

> summary(meetings_sd_2013$STD.DEV.BIL)

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.

> summary(control_sd_2013$STD.DEV.BIL)

      Min. 1st Qu. Median   Mean 3rd Qu.   Max.
2.521e-05 8.832e-05 1.025e-04 1.014e-04 1.158e-04 1.477e-04
> summary(meetings_sd_2014$STD.DEV.SPY)

       Min. 1st Qu.  Median      Mean 3rd Qu.    Max.

> summary(control_sd_2014$STD.DEV.SPY)

       Min. 1st Qu.  Median      Mean 3rd Qu.    Max.

> summary(meetings_sd_2014$STD.DEV.BIL)

       Min. 1st Qu.  Median      Mean 3rd Qu.    Max.
1.874e-08 8.692e-05 1.071e-04 1.049e-04 1.253e-04 1.948e-04

> summary(control_sd_2014$STD.DEV.BIL)

       Min. 1st Qu.  Median      Mean 3rd Qu.    Max.

---

**Item 4**

Output for T-test of Difference in Average Volatility before and after 2PM, on meeting days and control days

For entire sample

> t.test(metings_sd_overall_post$STD.DEV.SPY - meetings_sd_overall_pre$STD.DEV.SPY,
        control_meetings_sd_overall_post$STD.DEV.SPY - control_meetings_sd_overall_pre$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_overall_post$STD.DEV.SPY - meetings_sd_overall_pre$STD.DEV.SPY and
        control_meetings_sd_overall_post$STD.DEV.SPY - control_meetings_sd_overall_pre$STD.DEV.SPY

    t = 11.009, df = 150.97, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
  0.0000722081 0.0001037975

sample estimates:
      mean of x     mean of y
t.test(meetings_sd_overall_post$STD.DEV.BIL - meetings_sd_overall_pre$STD.DEV.BIL,
        control_meetings_sd_overall_post$STD.DEV.BIL - control_meetings_sd_overall_pre$STD.DEV.BIL)

Welch Two Sample t-test

data: meetings_sd_overall_post$STD.DEV.BIL - meetings_sd_overall_pre$STD.DEV.BIL and
        control_meetings_sd_overall_post$STD.DEV.BIL - control_meetings_sd_overall_pre$STD.DEV.BIL

t = 2.5903, df = 137.23, p-value = 0.01062
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
 9.829519e-07 7.325487e-06

sample estimates:
mean of x  mean of y
3.680255e-06 -4.739642e-07

2007

t.test(meetings_sd_2007_post$STD.DEV.SPY - meetings_sd_2007_pre$STD.DEV.SPY,
        control_sd_2007_post$STD.DEV.SPY - control_sd_2007_pre$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_2007_post$STD.DEV.SPY - meetings_sd_2007_pre$STD.DEV.SPY and
        control_sd_2007_post$STD.DEV.SPY - control_sd_2007_pre$STD.DEV.SPY

t = -0.91316, df = 156.89, p-value = 0.3626
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-7.490958e-05 2.754405e-05

sample estimates:
mean of x  mean of y
6.714115e-06 3.039688e-05

t.test(meetings_sd_2007_post$STD.DEV.BIL - meetings_sd_2007_pre$STD.DEV.BIL,
        control_sd_2007_post$STD.DEV.BIL - control_sd_2007_pre$STD.DEV.BIL)
Welch Two Sample t-test

data: meetings_sd_2007_post$STD.DEV.BIL - meetings_sd_2007_pre$STD.DEV.BIL and
control_sd_2007_post$STD.DEV.BIL - control_sd_2007_pre$STD.DEV.BIL

t = -1.4972, df = 221.3, p-value = 0.1358

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-2.018860e-05  2.756702e-06

sample estimates:

  mean of x  mean of y

-1.201464e-06  7.514483e-06

---

2008

> t.test(meetings_sd_2008_post$STD.DEV.SPY- meetings_sd_2008_pre$STD.DEV.SPY,
control_sd_2008_post$STD.DEV.SPY - control_sd_2008_pre$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_2008_post$STD.DEV.SPY - meetings_sd_2008_pre$STD.DEV.SPY and
control_sd_2008_post$STD.DEV.SPY - control_sd_2008_pre$STD.DEV.SPY

t = -0.053723, df = 231.57, p-value = 0.9572

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-0.0001172342  0.0001110107

sample estimates:

  mean of x  mean of y
0.0000998608  0.0001029726

> t.test(meetings_sd_2008_post$STD.DEV.BIL- meetings_sd_2008_pre$STD.DEV.BIL,
control_sd_2008_post$STD.DEV.BIL - control_sd_2008_pre$STD.DEV.BIL)

Welch Two Sample t-test

data: meetings_sd_2008_post$STD.DEV.BIL - meetings_sd_2008_pre$STD.DEV.BIL and
control_sd_2008_post$STD.DEV.BIL - control_sd_2008_pre$STD.DEV.BIL
\[ t = -1.0226, \text{ df } = 237.88, \text{ p-value } = 0.3075 \]

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
\[-3.410297 \times 10^{-5} \text{ to } 1.079561 \times 10^{-5} \]

sample estimates:

<table>
<thead>
<tr>
<th>mean of x</th>
<th>mean of y</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.112828 \times 10^{-5}</td>
<td>1.054085 \times 10^{-5}</td>
</tr>
</tbody>
</table>

---

2009

```r
> t.test(meetings_sd_2009_post$STD.DEV.SPY - meetings_sd_2009_pre$STD.DEV.SPY,
       control_sd_2009_post$STD.DEV.SPY - control_sd_2009_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2009_post$STD.DEV.SPY - meetings_sd_2009_pre$STD.DEV.SPY and
control_sd_2009_post$STD.DEV.SPY - control_sd_2009_pre$STD.DEV.SPY
t = 4.1361, df = 216.1, p-value = 5.058 \times 10^{-5}
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
6.085218 \times 10^{-5} \text{ to } 1.716459 \times 10^{-4}

sample estimates:

<table>
<thead>
<tr>
<th>mean of x</th>
<th>mean of y</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.817974 \times 10^{-4}</td>
<td>6.554833 \times 10^{-5}</td>
</tr>
</tbody>
</table>

> t.test(meetings_sd_2009_post$STD.DEV.BIL - meetings_sd_2009_pre$STD.DEV.BIL,
       control_sd_2009_post$STD.DEV.BIL - control_sd_2009_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2009_post$STD.DEV.BIL - meetings_sd_2009_pre$STD.DEV.BIL and
control_sd_2009_post$STD.DEV.BIL - control_sd_2009_pre$STD.DEV.BIL
t = -0.61497, df = 187.64, p-value = 0.5393
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
```
> t.test(meetings_sd_2010_post$STD.DEV.SPY - meetings_sd_2010_pre$STD.DEV.SPY,  
          control_sd_2010_post$STD.DEV.SPY - control_sd_2010_pre$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_2010_post$STD.DEV.SPY - meetings_sd_2010_pre$STD.DEV.SPY and  
control_sd_2010_post$STD.DEV.SPY - control_sd_2010_pre$STD.DEV.SPY

t = 4.8756, df = 206.75, p-value = 2.16e-06
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
8.520983e-05 2.009037e-04

sample estimates:

  mean of x  mean of y
2.116593e-04 6.860256e-05

> t.test(meetings_sd_2010_post$STD.DEV.BIL - meetings_sd_2010_pre$STD.DEV.BIL,  
          control_sd_2010_post$STD.DEV.BIL - control_sd_2010_pre$STD.DEV.BIL)

Welch Two Sample t-test

data: meetings_sd_2010_post$STD.DEV.BIL - meetings_sd_2010_pre$STD.DEV.BIL and  
control_sd_2010_post$STD.DEV.BIL - control_sd_2010_pre$STD.DEV.BIL

t = 1.1103, df = 211.36, p-value = 0.2681
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-6.820472e-06 2.441096e-05

sample estimates:

  mean of x  mean of y
2011

```r
> t.test(meetings_sd_2011_post$STD.DEV.SPY - meetings_sd_2011_pre$STD.DEV.SPY,
control_sd_2011_post$STD.DEV.SPY - control_sd_2011_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2011_post$STD.DEV.SPY - meetings_sd_2011_pre$STD.DEV.SPY and
control_sd_2011_post$STD.DEV.SPY - control_sd_2011_pre$STD.DEV.SPY
t = 2.0836, df = 198.2, p-value = 0.03848
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
3.136467e-06 1.139697e-04
sample estimates:
mean of x mean of y
1.313703e-04 7.281724e-05
```

```r
> t.test(meetings_sd_2011_post$STD.DEV.BIL - meetings_sd_2011_pre$STD.DEV.BIL,
control_sd_2011_post$STD.DEV.BIL - control_sd_2011_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2011_post$STD.DEV.BIL - meetings_sd_2011_pre$STD.DEV.BIL and
control_sd_2011_post$STD.DEV.BIL - control_sd_2011_pre$STD.DEV.BIL
t = 0.11165, df = 196.96, p-value = 0.9112
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.188624e-05 1.331288e-05
sample estimates:
mean of x mean of y
7.873099e-06 7.159780e-06
```

2012
> t.test(meetings_sd_2012_post$STD.DEV.SPY - meetings_sd_2012_pre$STD.DEV.SPY,
  control_sd_2012_post$STD.DEV.SPY - control_sd_2012_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2012_post$STD.DEV.SPY - meetings_sd_2012_pre$STD.DEV.SPY and
  control_sd_2012_post$STD.DEV.SPY - control_sd_2012_pre$STD.DEV.SPY
t = 0.86362, df = 191.44, p-value = 0.3889
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-2.456612e-05 6.283392e-05
sample estimates:
  mean of x mean of y
5.76952e-05 3.85613e-05

> t.test(meetings_sd_2012_post$STD.DEV.BIL - meetings_sd_2012_pre$STD.DEV.BIL,
  control_sd_2012_post$STD.DEV.BIL - control_sd_2012_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2012_post$STD.DEV.BIL - meetings_sd_2012_pre$STD.DEV.BIL and
  control_sd_2012_post$STD.DEV.BIL - control_sd_2012_pre$STD.DEV.BIL
t = 3.7409, df = 196.9, p-value = 0.0002404
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
9.570594e-06 3.091153e-05
sample estimates:
  mean of x mean of y
2.332044e-05 3.079377e-06

> t.test(meetings_sd_2013_post$STD.DEV.SPY - meetings_sd_2013_pre$STD.DEV.SPY,
  control_sd_2013_post$STD.DEV.SPY - control_sd_2013_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2013_post$STD.DEV.SPY - meetings_sd_2013_pre$STD.DEV.SPY and 
control_sd_2013_post$STD.DEV.SPY - control_sd_2013_pre$STD.DEV.SPY

t = 8.7514, df = 219.34, p-value = 5.683e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
9.854454e-05 1.558306e-04
sample estimates:
mean of x  mean of y
1.585191e-04 3.133148e-05

> t.test(meetings_sd_2013_post$STD.DEV.BIL- meetings_sd_2013_pre$STD.DEV.BIL, 
control_sd_2013_post$STD.DEV.BIL - control_sd_2013_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2013_post$STD.DEV.BIL - meetings_sd_2013_pre$STD.DEV.BIL and 
control_sd_2013_post$STD.DEV.BIL - control_sd_2013_pre$STD.DEV.BIL

t = -0.39849, df = 234.22, p-value = 0.6906
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.046876e-05 6.946341e-06
sample estimates:
mean of x  mean of y
3.994494e-06 5.755704e-06

2014

> t.test(meetings_sd_2014_post$STD.DEV.SPY- meetings_sd_2014_pre$STD.DEV.SPY, 
control_sd_2014_post$STD.DEV.SPY - control_sd_2014_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2014_post$STD.DEV.SPY - meetings_sd_2014_pre$STD.DEV.SPY and 
control_sd_2014_post$STD.DEV.SPY - control_sd_2014_pre$STD.DEV.SPY

t = 5.7265, df = 179.43, p-value = 4.244e-08
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

6.295164e-05 1.291463e-04

sample estimates:

mean of x mean of y

1.355974e-04 3.954838e-05

> t.test(meetings_sd_2014_post$STD.DEV.BIL - meetings_sd_2014_pre$STD.DEV.BIL,
  control_sd_2014_post$STD.DEV.BIL - control_sd_2014_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2014_post$STD.DEV.BIL - meetings_sd_2014_pre$STD.DEV.BIL and
control_sd_2014_post$STD.DEV.BIL - control_sd_2014_pre$STD.DEV.BIL
t = -1.4089, df = 209.16, p-value = 0.1604
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-1.465254e-05 2.438404e-06

sample estimates:

mean of x mean of y

9.315326e-07 7.038603e-06

For subsample 1

> t.test(meetings_sd_subsample_1_post$STD.DEV.SPY - meetings_sd_subsample_1_pre$STD.DEV.SPY,
  control_sd_meetings_subsample_1_post$STD.DEV.SPY -
  control_sd_meetings_subsample_1_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_subsample_1_post$STD.DEV.SPY - meetings_sd_subsample_1_pre$STD.DEV.SPY and
control_sd_meetings_subsample_1_post$STD.DEV.SPY -
control_sd_meetings_subsample_1_pre$STD.DEV.SPY
t = 6.4516, df = 213.22, p-value = 7.318e-10
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
8.097763e-05 1.522298e-04

sample estimates:
mean of x mean of y
1.786932e-04 6.208949e-05

> t.test(meetings_sd_subsample_1_post$STD.DEV.BIL - meetings_sd_subsample_1_pre$STD.DEV.BIL, 
control_sd_meetings_subsample_1_post$STD.DEV.BIL - 
control_sd_meetings_subsample_1_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_subsample_1_post$STD.DEV.BIL - meetings_sd_subsample_1_pre$STD.DEV.BIL and 
control_sd_meetings_subsample_1_post$STD.DEV.BIL - 
control_sd_meetings_subsample_1_pre$STD.DEV.BIL
t = -0.50125, df = 204.03, p-value = 0.6167
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-9.741680e-06 5.792449e-06

sample estimates:
mean of x mean of y
-1.517160e-06 4.574558e-07

For subsample 2

> t.test(meetings_sd_subsample_2_post$STD.DEV.SPY - meetings_sd_subsample_2_pre$STD.DEV.SPY,  
control_sd_meetings_subsample_2_post$STD.DEV.SPY - 
control_sd_meetings_subsample_2_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_subsample_2_post$STD.DEV.SPY - meetings_sd_subsample_2_pre$STD.DEV.SPY and 
control_sd_meetings_subsample_2_post$STD.DEV.SPY - 
control_sd_meetings_subsample_2_pre$STD.DEV.SPY
t = 6.1498, df = 201.61, p-value = 4.096e-09
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

4.532169e-05 8.810045e-05

sample estimates:

mean of x  mean of y

1.169841e-04 5.027302e-05

> t.test(meetings_sd_subsample_2_post$STD.DEV.BIL - meetings_sd_subsample_2_pre$STD.DEV.BIL,

control_sd_meetings_subsample_2_post$STD.DEV.BIL -

control_sd_meetings_subsample_2_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_subsample_2_post$STD.DEV.BIL - meetings_sd_subsample_2_pre$STD.DEV.BIL and

control_sd_meetings_subsample_2_post$STD.DEV.BIL -

control_sd_meetings_subsample_2_pre$STD.DEV.BIL
t = 0.079691, df = 226.73, p-value = 0.9366

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-4.497637e-06 4.876758e-06

sample estimates:

mean of x  mean of y

5.514356e-06 5.324796e-06
Item 5

Output for T-test of Difference in Average Volatility on minutes release days and control days

For the entire sample

```r
> t.test(minutes_sd_overall$STD.DEV.SPY, control_minutes_sd_overall$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_overall$STD.DEV.SPY and control_minutes_sd_overall$STD.DEV.SPY
t = 0.49365, df = 390.47, p-value = 0.6218
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.164731e-05  1.945716e-05
sample estimates:
 mean of x  mean of y
 0.0003726875  0.0003687826
```

```r
> t.test(minutes_sd_overall$STD.DEV.BIL, control_minutes_sd_overall$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_overall$STD.DEV.BIL and control_minutes_sd_overall$STD.DEV.BIL
t = -3.4309, df = 424.66, p-value = 0.0006604
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -7.050193e-06 -1.914410e-06
sample estimates:
 mean of x  mean of y
 0.0001063687  0.0001108510
```

For Subsample 1

```r
> t.test(minutes_sd_subsample_1$STD.DEV.SPY, control_minutes_sd_subsample_1$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_subsample_1$STD.DEV.SPY and control_minutes_sd_subsample_1$STD.DEV.SPY
t = -1.178, df = 419.43, p-value = 0.2395
```
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-4.025642e-05  1.008601e-05

sample estimates:
  mean of x  mean of y
0.0004334655  0.0004485507

> t.test(minutes_sd_subsample_1$STD.DEV.BIL, control_minutes_sd_subsample_1$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_subsample_1$STD.DEV.BIL and control_minutes_sd_subsample_1$STD.DEV.BIL
t = -4.8112, df = 398.1, p-value = 2.133e-06
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-1.964416e-05  -8.247232e-06

sample estimates:
  mean of x  mean of y
0.0001052471  0.0001191928

For Subsample 2

> t.test(minutes_sd_subsample_2$STD.DEV.SPY, control_minutes_sd_subsample_2$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_subsample_2$STD.DEV.SPY and control_minutes_sd_subsample_2$STD.DEV.SPY
t = 1.6985, df = 394.07, p-value = 0.0902
alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-2.294814e-06  3.143535e-05

sample estimates:
  mean of x  mean of y
0.0003190340  0.0003044637

> t.test(minutes_sd_subsample_2$STD.DEV.BIL, control_minutes_sd_subsample_2$STD.DEV.BIL)
Welch Two Sample t-test

data: minutes_sd_subsample_2$STD.DEV.BIL and control_minutes_sd_subsample_2$STD.DEV.BIL

t = -0.8781, df = 425.94, p-value = 0.3804
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-4.701114e-06 1.797764e-06
sample estimates:
mean of x  mean of y
0.0001028493 0.0001043009

For 2007

> t.test(minutes_sd_2007$STD.DEV.SPY, control_minutes_sd_2007$STD.DEV.SPY)

Welch Two Sample t-test

data: minutes_sd_2007$STD.DEV.SPY and control_minutes_sd_2007$STD.DEV.SPY

t = -0.9502, df = 477.32, p-value = 0.3425
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-2.675741e-05 9.314083e-06
sample estimates:
mean of x  mean of y
1.497751e-05 2.369917e-05

> t.test(minutes_sd_2007$STD.DEV.BIL, control_minutes_sd_2007$STD.DEV.BIL)

Welch Two Sample t-test

data: minutes_sd_2007$STD.DEV.BIL and control_minutes_sd_2007$STD.DEV.BIL

t = -0.93478, df = 471.22, p-value = 0.3504
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-6.462515e-06 2.295990e-06
sample estimates:
mean of x  mean of y
3.257797e-06  5.341059e-06

For 2008

> t.test(minutes_sd_2008$STD.DEV.SPY, control_minutes_sd_2008$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_2008$STD.DEV.SPY and control_minutes_sd_2008$STD.DEV.SPY
t = -9.0393, df = 452.05, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -0.0003186334  -0.0002048283
sample estimates:
  mean of x  mean of y
  0.0001337798  0.0003955107

> t.test(minutes_sd_2008$STD.DEV.BIL, control_minutes_sd_2008$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_2008$STD.DEV.BIL and control_minutes_sd_2008$STD.DEV.BIL
t = -8.7278, df = 421.5, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -5.948928e-05  -3.761930e-05
sample estimates:
  mean of x  mean of y
  2.129744e-05  6.985173e-05

For 2009

> t.test(minutes_sd_2009$STD.DEV.SPY, control_minutes_sd_2009$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_2009$STD.DEV.SPY and control_minutes_sd_2009$STD.DEV.SPY
\[ t = -3.4987, \text{ df } = 437.54, \text{ p-value } = 0.0005155 \]

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

\[-1.213720e-04 \text{ - } -3.405802e-05\]

sample estimates:

\[
\begin{array}{l}
\text{mean of } x \\
0.0003765238 \\
\text{mean of } y \\
0.0004542388
\end{array}
\]

\[
> \ t.test(minutes\_sd\_2009\$STD.DEV.BIL, control\_minutes\_sd\_2009\$STD.DEV.BIL)
\]

Welch Two Sample t-test

data: minutes\_sd\_2009\$STD.DEV.BIL and control\_minutes\_sd\_2009\$STD.DEV.BIL

t = -6.8796, df = 441.32, p-value = 2.065e-11

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

\[-4.367705e-05 \text{ - } -2.426689e-05\]

sample estimates:

\[
\begin{array}{l}
\text{mean of } x \\
8.442073e-05 \\
\text{mean of } y \\
1.183927e-04
\end{array}
\]

For 2010

\[
> \ t.test(minutes\_sd\_2010\$STD.DEV.SPY, control\_minutes\_sd\_2010\$STD.DEV.SPY)
\]

Welch Two Sample t-test

data: minutes\_sd\_2010\$STD.DEV.SPY and control\_minutes\_sd\_2010\$STD.DEV.SPY

t = -3.1925, df = 439.77, p-value = 0.001512

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

\[-8.676873e-05 \text{ - } -2.064315e-05\]

sample estimates:

\[
\begin{array}{l}
\text{mean of } x \\
0.0002700294 \\
\text{mean of } y \\
0.0003237354
\end{array}
\]
For 2010

```r
t.test(minutes_sd_2010$STD.DEV.BIL, control_minutes_sd_2010$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_2010$STD.DEV.BIL and control_minutes_sd_2010$STD.DEV.BIL
t = -4.8778, df = 448.26, p-value = 1.493e-06
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-3.403272e-05 -1.448493e-05
sample estimates:
  mean of x  mean of y
  8.310155e-05 1.073604e-04
```

For 2011

```r
t.test(minutes_sd_2011$STD.DEV.SPY, control_minutes_sd_2011$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_2011$STD.DEV.SPY and control_minutes_sd_2011$STD.DEV.SPY
t = -6.1551, df = 436.98, p-value = 1.7e-09
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.365293e-04 -7.044069e-05
sample estimates:
  mean of x  mean of y
  0.0002739437 0.0003774288
```

```r
t.test(minutes_sd_2011$STD.DEV.BIL, control_minutes_sd_2011$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_2011$STD.DEV.BIL and control_minutes_sd_2011$STD.DEV.BIL
t = -4.9408, df = 427.76, p-value = 1.118e-06
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-3.212061e-05 -1.383779e-05
```
sample estimates:

mean of x  mean of y

7.929141e-05 1.022706e-04

For 2012

> t.test(minutes_sd_2012$STD.DEV.SPY, control_minutes_sd_2012$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_2012$STD.DEV.SPY and control_minutes_sd_2012$STD.DEV.SPY
t = 4.128, df = 420.46, p-value = 4.415e-05
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
3.124016e-05 8.803559e-05

sample estimates:

mean of x  mean of y
0.0002910815 0.0002314436

> t.test(minutes_sd_2012$STD.DEV.BIL, control_minutes_sd_2012$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_2012$STD.DEV.BIL and control_minutes_sd_2012$STD.DEV.BIL
t = -3.7377, df = 468.98, p-value = 0.0002086
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-2.233421e-05 -6.942545e-06

sample estimates:

mean of x  mean of y
7.881051e-05 9.344888e-05

For 2013

> t.test(minutes_sd_2013$STD.DEV.SPY, control_minutes_sd_2013$STD.DEV.SPY)

Welch Two Sample t-test
**data:** minutes.sd_2013$STD.DEV.SPY and control.minutes.sd_2013$STD.DEV.SPY

\[ t = 1.8905, \text{ df } = 371.8, \text{ p-value } = 0.05947 \]

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

\[-1.089711e-06 \text{ to } 5.539685e-05\]

sample estimates:

<table>
<thead>
<tr>
<th>mean of x</th>
<th>mean of y</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0002394607</td>
<td>0.0002123071</td>
</tr>
</tbody>
</table>

> t.test(minutes.sd_2013$STD.DEV.BIL, control.minutes.sd_2013$STD.DEV.BIL)

Welch Two Sample t-test

**data:** minutes.sd_2013$STD.DEV.BIL and control.minutes.sd_2013$STD.DEV.BIL

\[ t = -6.541, \text{ df } = 459.09, \text{ p-value } = 1.633e-10 \]

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

\[-3.469984e-05 \text{ to } -1.866662e-05\]

sample estimates:

<table>
<thead>
<tr>
<th>mean of x</th>
<th>mean of y</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.141415e-05</td>
<td>9.809738e-05</td>
</tr>
</tbody>
</table>

For 2014

> t.test(minutes.sd_2014$STD.DEV.SPY, control.minutes.sd_2014$STD.DEV.SPY)

Welch Two Sample t-test

**data:** minutes.sd_2014$STD.DEV.SPY and control.minutes.sd_2014$STD.DEV.SPY

\[ t = -4.391, \text{ df } = 458.54, \text{ p-value } = 1.402e-05 \]

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

\[-8.078033e-05 \text{ to } -3.083017e-05\]

sample estimates:

<table>
<thead>
<tr>
<th>mean of x</th>
<th>mean of y</th>
</tr>
</thead>
<tbody>
<tr>
<td>74</td>
<td>74</td>
</tr>
</tbody>
</table>
> t.test(minutes_sd_2014$STD.DEV.BIL, control_minutes_sd_2014$STD.DEV.BIL)

Welch Two Sample t-test

data: minutes_sd_2014$STD.DEV.BIL and control_minutes_sd_2014$STD.DEV.BIL

t = 1.7407, df = 374.69, p-value = 0.08255
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-9.842420e-07 1.617269e-05
sample estimates:
  mean of x  mean of y
1.028865e-04 9.529227e-05

For subsample 1

> t.test(minutes_sd_subsample_1$STD.DEV.SPY, minutes_control_sd_subsample_1$STD.DEV.SPY, alternative = "greater")

Welch Two Sample t-test

data: minutes_sd_subsample_1$STD.DEV.SPY and minutes_control_sd_subsample_1$STD.DEV.SPY

t = -1.1853, df = 409.1, p-value = 0.8817
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
-2.543006e-05 Inf
sample estimates:
  mean of x  mean of y
0.0003100783 0.0003207145

> t.test(minutes_sd_subsample_1$STD.DEV.BIL, minutes_control_sd_subsample_1$STD.DEV.BIL, alternative = "greater")

Welch Two Sample t-test
data: minutes_sd_subsample_1$STD.DEV.BIL and minutes_control_sd_subsample_1$STD.DEV.BIL
t = -1.5788, df = 446.96, p-value = 0.9425
alternative hypothesis: true difference in means is greater than 0

95 percent confidence interval:

-8.244359e-06   Inf

sample estimates:

  mean of x  mean of y

6.012714e-05  6.416055e-05

For subsample 2

> t.test(minutes_sd_subsample_2$STD.DEV.SPY, minutes_control_sd_subsample_2$STD.DEV.SPY,

    alternative = "greater")

Welch Two Sample t-test
data: minutes_sd_subsample_2$STD.DEV.SPY and minutes_control_sd_subsample_2$STD.DEV.SPY
t = 3.7672, df = 417.89, p-value = 9.439e-05
alternative hypothesis: true difference in means is greater than 0

95 percent confidence interval:

1.335481e-05   Inf

sample estimates:

  mean of x  mean of y

0.0002662137  0.0002424679

> t.test(minutes_sd_subsample_2$STD.DEV.BIL, minutes_control_sd_subsample_2$STD.DEV.BIL,

    alternative = "greater")

Welch Two Sample t-test
data: minutes_sd_subsample_2$STD.DEV.BIL and minutes_control_sd_subsample_2$STD.DEV.BIL
t = -0.98363, df = 421.55, p-value = 0.8371
alternative hypothesis: true difference in means is greater than 0

95 percent confidence interval:

-3.43332e-06   Inf

sample estimates:

  mean of x  mean of y
Item 7

Output for T-test of difference in average volatility before and after 2PM on meeting days vs control days

For the entire sample:

```r
> t.test(minutes_sd_overall_post$STD.DEV.SPY - minutes_sd_overall_pre$STD.DEV.SPY,
       control_minutes_sd_overall_post$STD.DEV.SPY - control_minutes_sd_overall_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_overall_post$STD.DEV.SPY - minutes_sd_overall_pre$STD.DEV.SPY and control_minutes_sd_overall_post$STD.DEV.SPY - control_minutes_sd_overall_pre$STD.DEV.SPY
t = 4.8414, df = 195.87, p-value = 2.611e-06
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  3.890447e-05 9.238603e-05
sample estimates:
  mean of x  mean of y
  1.115152e-04 4.586994e-05
```

```r
> t.test(minutes_sd_overall_post$STD.DEV.BIL - minutes_sd_overall_pre$STD.DEV.BIL,
       control_minutes_sd_overall_post$STD.DEV.BIL - control_minutes_sd_overall_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_overall_post$STD.DEV.BIL - minutes_sd_overall_pre$STD.DEV.BIL and control_minutes_sd_overall_post$STD.DEV.BIL - control_minutes_sd_overall_pre$STD.DEV.BIL
t = 1.3447, df = 225.92, p-value = 0.1801
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.605099e-06 8.502390e-06
sample estimates:
  mean of x  mean of y
```

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For subsample 1

```r
> t.test(minutes_sd_subsample_1_post$STD.DEV.SPY - minutes_sd_subsample_1_pre$STD.DEV.SPY,
           control_minutes_sd_subsample_1_post$STD.DEV.SPY -
           control_minutes_sd_subsample_1_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_subsample_1_post$STD.DEV.SPY - minutes_sd_subsample_1_pre$STD.DEV.SPY and
           control_minutes_sd_subsample_1_post$STD.DEV.SPY -
           control_minutes_sd_subsample_1_pre$STD.DEV.SPY
t = 2.7232, df = 211.51, p-value = 0.007006
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  1.844744e-05 1.151699e-04
sample estimates:
  mean of x  mean of y
  1.178919e-04 5.108324e-05

> t.test(minutes_sd_subsample_1_post$STD.DEV.BIL - minutes_sd_subsample_1_pre$STD.DEV.BIL,
           control_minutes_sd_subsample_1_post$STD.DEV.BIL -
           control_minutes_sd_subsample_1_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_subsample_1_post$STD.DEV.BIL - minutes_sd_subsample_1_pre$STD.DEV.BIL and
           control_minutes_sd_subsample_1_post$STD.DEV.BIL -
           control_minutes_sd_subsample_1_pre$STD.DEV.BIL
t = 1.09, df = 211.44, p-value = 0.2769
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-4.824495e-06 1.675984e-05
sample estimates:
```

```
For subsample 2

```r
> t.test(minutes_sd_subsample_2_post$STD.DEV.SPY - minutes_sd_subsample_2_pre$STD.DEV.SPY,
    control_minutes_sd_subsample_2_post$STD.DEV.SPY -
    control_minutes_sd_subsample_2_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: minutes_sd_subsample_2_post$STD.DEV.SPY - minutes_sd_subsample_2_pre$STD.DEV.SPY and
    control_minutes_sd_subsample_2_post$STD.DEV.SPY -
    control_minutes_sd_subsample_2_pre$STD.DEV.SPY
t = 5.5824, df = 211.16, p-value = 7.241e-08
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  5.135463e-05 1.074227e-04
sample estimates:
mean of x  mean of y
1.225090e-04 4.312037e-05
```

```r
> t.test(minutes_sd_subsample_2_post$STD.DEV.BIL - minutes_sd_subsample_2_pre$STD.DEV.BIL,
    control_minutes_sd_subsample_2_post$STD.DEV.BIL -
    control_minutes_sd_subsample_2_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: minutes_sd_subsample_2_post$STD.DEV.BIL - minutes_sd_subsample_2_pre$STD.DEV.BIL and
    control_minutes_sd_subsample_2_post$STD.DEV.BIL -
    control_minutes_sd_subsample_2_pre$STD.DEV.BIL
t = 1.204, df = 215.46, p-value = 0.2299
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-2.584897e-06 1.069964e-05
```
Item 8

Output for T-tests of difference in average volatility between minutes release days and meeting days

For the entire sample:

```r
> t.test(meetings_sd_overall_post$STD.DEV.SPY - meetings_sd_overall_pre$STD.DEV.SPY,
       minutes_sd_overall_post$STD.DEV.SPY - minutes_sd_overall_pre$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_overall_post$STD.DEV.SPY - meetings_sd_overall_pre$STD.DEV.SPY and
       minutes_sd_overall_post$STD.DEV.SPY - minutes_sd_overall_pre$STD.DEV.SPY

t = 1.9504, df = 203.65, p-value = 0.0525
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -2.937821e-07 5.417237e-05

sample estimates:
 mean of x  mean of y
 0.0001384545 0.0001115152
```

```r
> t.test(meetings_sd_overall_post$STD.DEV.BIL - meetings_sd_overall_pre$STD.DEV.BIL,
       minutes_sd_overall_post$STD.DEV.BIL - minutes_sd_overall_pre$STD.DEV.BIL)

Welch Two Sample t-test

data: meetings_sd_overall_post$STD.DEV.BIL - meetings_sd_overall_pre$STD.DEV.BIL and
       minutes_sd_overall_post$STD.DEV.BIL - minutes_sd_overall_pre$STD.DEV.BIL

t = -0.10117, df = 223.14, p-value = 0.9195
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -5.256614e-06 4.743249e-06
```
For 2007

```r
> t.test(meetings_sd_2007_post$STD.DEV.SPY - meetings_sd_2007_pre$STD.DEV.SPY,
        minutes_sd_2007_post$STD.DEV.SPY - minutes_sd_2007_pre$STD.DEV.SPY)
Welch Two Sample t-test
data: meetings_sd_2007_post$STD.DEV.SPY - meetings_sd_2007_pre$STD.DEV.SPY and
        minutes_sd_2007_post$STD.DEV.SPY - minutes_sd_2007_pre$STD.DEV.SPY
t = -1.0205, df = 218.6, p-value = 0.3086
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -4.908315e-05  1.559358e-05
sample estimates:
 mean of x  mean of y
6.714115e-06  2.345890e-05
```

```r
> t.test(meetings_sd_2007_post$STD.DEV.BIL - meetings_sd_2007_pre$STD.DEV.BIL,
        minutes_sd_2007_post$STD.DEV.BIL - minutes_sd_2007_pre$STD.DEV.BIL)
Welch Two Sample t-test
data: meetings_sd_2007_post$STD.DEV.BIL - meetings_sd_2007_pre$STD.DEV.BIL and
        minutes_sd_2007_post$STD.DEV.BIL - minutes_sd_2007_pre$STD.DEV.BIL
t = -1.1168, df = 231.77, p-value = 0.2653
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.418585e-05  3.922108e-06
sample estimates:
 mean of x  mean of y
-1.201464e-06  3.930409e-06
```
For 2008

```r
> t.test(meetings_sd_2008_post$STD.DEV.SPY - meetings_sd_2008_pre$STD.DEV.SPY,
        minutes_sd_2008_post$STD.DEV.SPY - minutes_sd_2008_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2008_post$STD.DEV.SPY - meetings_sd_2008_pre$STD.DEV.SPY and
        minutes_sd_2008_post$STD.DEV.SPY - minutes_sd_2008_pre$STD.DEV.SPY
        t = 1.8196, df = 227.81, p-value = 0.07014
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
     -8.575276e-06 2.154237e-04
sample estimates:
    mean of x    mean of y
              9.986080e-05 -3.563424e-06
```

```r
> t.test(meetings_sd_2008_post$STD.DEV.BIL - meetings_sd_2008_pre$STD.DEV.BIL,
        minutes_sd_2008_post$STD.DEV.BIL - minutes_sd_2008_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2008_post$STD.DEV.BIL - meetings_sd_2008_pre$STD.DEV.BIL and
        minutes_sd_2008_post$STD.DEV.BIL - minutes_sd_2008_pre$STD.DEV.BIL
        t = -0.69707, df = 225.54, p-value = 0.4865
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
     -2.765784e-05 1.320333e-05
sample estimates:
    mean of x    mean of y
              -1.112828e-06 6.114430e-06
```

For 2009

```r
> t.test(meetings_sd_2009_post$STD.DEV.SPY - meetings_sd_2009_pre$STD.DEV.SPY,
        minutes_sd_2009_post$STD.DEV.SPY - minutes_sd_2009_pre$STD.DEV.SPY)
```
Welch Two Sample t-test

data: meetings_sd_2009_post$STD.DEV.SPY - meetings_sd_2009_pre$STD.DEV.SPY and
        minutes_sd_2009_post$STD.DEV.SPY - minutes_sd_2009_pre$STD.DEV.SPY

  t = 0.27742, df = 211.55, p-value = 0.7817
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -6.79823e-05  9.025851e-05
sample estimates:
mean of x  mean of y
0.0001817974  0.0001706622

> t.test(meetings_sd_2009_post$STD.DEV.BIL - meetings_sd_2009_pre$STD.DEV.BIL,
        minutes_sd_2009_post$STD.DEV.BIL - minutes_sd_2009_pre$STD.DEV.BIL)

Welch Two Sample t-test

data: meetings_sd_2009_post$STD.DEV.BIL - meetings_sd_2009_pre$STD.DEV.BIL and
        minutes_sd_2009_post$STD.DEV.BIL - minutes_sd_2009_pre$STD.DEV.BIL

  t = -1.4648, df = 201.09, p-value = 0.1445
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -3.302754e-05  4.873313e-06
sample estimates:
mean of x  mean of y
8.536722e-07  1.493079e-05

For 2010

> t.test(meetings sd 2010 post$STD.DEV.SPY - meetings sd 2010 pre$STD.DEV.SPY,
        minutes sd 2010 post$STD.DEV.SPY - minutes sd 2010 pre$STD.DEV.SPY)

Welch Two Sample t-test

data: meetings_sd_2010_post$STD.DEV.SPY - meetings_sd_2010_pre$STD.DEV.SPY and
        minutes_sd_2010_post$STD.DEV.SPY - minutes_sd_2010_pre$STD.DEV.SPY

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$t = 1.8942, \ df = 236.78, \ p\text{-value} = 0.05942$

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

$-2.722351 \times 10^{-6} \ 1.386780 \times 10^{-4}$

sample estimates:

\[
\begin{align*}
\text{mean of } x & \quad \text{mean of } y \\
0.0002116593 & \quad 0.0001436815
\end{align*}
\]

> t.test(meetings_sd_2010_post$STD.DEV.BIL - meetings_sd_2010_pre$STD.DEV.BIL,

minutes_sd_2010_post$STD.DEV.BIL - minutes_sd_2010_pre$STD.DEV.BIL)

Welch Two Sample $t$-test
data: meetings_sd_2010_post$STD.DEV.BIL - meetings_sd_2010_pre$STD.DEV.BIL and

minutes_sd_2010_post$STD.DEV.BIL - minutes_sd_2010_pre$STD.DEV.BIL

t = -1.1219, \ df = 229.86, \ p\text{-value} = 0.2631

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

$-3.164787 \times 10^{-5} \ 8.684049 \times 10^{-6}$

sample estimates:

\[
\begin{align*}
\text{mean of } x & \quad \text{mean of } y \\
3.467848 \times 10^{-6} & \quad 1.494976 \times 10^{-5}
\end{align*}
\]

---

For 2011

> t.test(meetings_sd_2011_post$STD.DEV.SPY - meetings_sd_2011_pre$STD.DEV.SPY,

minutes_sd_2011_post$STD.DEV.SPY - minutes_sd_2011_pre$STD.DEV.SPY)

Welch Two Sample $t$-test
data: meetings_sd_2011_post$STD.DEV.SPY - meetings_sd_2011_pre$STD.DEV.SPY and

minutes_sd_2011_post$STD.DEV.SPY - minutes_sd_2011_pre$STD.DEV.SPY

t = 1.4004, \ df = 236.85, \ p\text{-value} = 0.1627

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-1.996888e-05 1.181634e-04

sample estimates:

mean of x  mean of y
1.313703e-04 8.227308e-05

> t.test(meetings_sd_2011_post$STD.DEV.BIL - meetings_sd_2011_pre$STD.DEV.BIL,

    minutes_sd_2011_post$STD.DEV.BIL - minutes_sd_2011_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_2011_post$STD.DEV.BIL - meetings_sd_2011_pre$STD.DEV.BIL and

    minutes_sd_2011_post$STD.DEV.BIL - minutes_sd_2011_pre$STD.DEV.BIL
t = 0.42187, df = 223.85, p-value = 0.6735
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:

-1.380203e-05 2.132115e-05

sample estimates:

mean of x  mean of y
7.873099e-06 4.113537e-06

For 2012

> t.test(meetings_sd_2012_post$STD.DEV.SPY - meetings_sd_2012_pre$STD.DEV.SPY,

    minutes_sd_2012_post$STD.DEV.SPY - minutes_sd_2012_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_2012_post$STD.DEV.SPY - meetings_sd_2012_pre$STD.DEV.SPY and

    minutes_sd_2012_post$STD.DEV.SPY - minutes_sd_2012_pre$STD.DEV.SPY
t = -1.5261, df = 226.4, p-value = 0.1284
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:

-1.076211e-04 1.367881e-05

sample estimates:

mean of x  mean of y
> t.test(meetings_sd_2012_post$STD.DEV.BIL - meetings_sd_2012_pre$STD.DEV.BIL, 
  
  minutes_sd_2012_post$STD.DEV.BIL - minutes_sd_2012_pre$STD.DEV.BIL)
Welch Two Sample t-test
data: meetings_sd_2012_post$STD.DEV.BIL - meetings_sd_2012_pre$STD.DEV.BIL and
minutes_sd_2012_post$STD.DEV.BIL - minutes_sd_2012_pre$STD.DEV.BIL

t = 1.0165, df = 226.96, p-value = 0.3105
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-7.05677e-06 2.209558e-05
sample estimates:
  mean of x  mean of y
  2.332044e-05 1.580099e-05

For 2013

> t.test(meetings_sd_2013_post$STD.DEV.SPY - meetings_sd_2013_pre$STD.DEV.SPY, 
  
  minutes_sd_2013_post$STD.DEV.SPY - minutes_sd_2013_pre$STD.DEV.SPY)
Welch Two Sample t-test
data: meetings_sd_2013_post$STD.DEV.SPY - meetings_sd_2013_pre$STD.DEV.SPY and
minutes_sd_2013_post$STD.DEV.SPY - minutes_sd_2013_pre$STD.DEV.SPY
t = -2.2718, df = 191.03, p-value = 0.02421
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-9.873723e-05 -6.963951e-06
sample estimates:
  mean of x  mean of y
  0.0001585191 0.0002113697

> t.test(meetings_sd_2013_post$STD.DEV.BIL - meetings_sd_2013_pre$STD.DEV.BIL, 
  
  minutes_sd_2013_post$STD.DEV.BIL - minutes_sd_2013_pre$STD.DEV.BIL)
Welch Two Sample $t$-test

data: meetings_sd_2013_post$STD.DEV.BIL - meetings_sd_2013_pre$STD.DEV.BIL and

minutes_sd_2013_post$STD.DEV.BIL - minutes_sd_2013_pre$STD.DEV.BIL

t = -2.8213, df = 190.65, p-value = 0.00529

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-3.175660e-05 -5.622735e-06

sample estimates:

mean of x  mean of y

3.994494e-06 2.268416e-05

For 2014

> t.test(meetings_sd_2014_post$STD.DEV.SPY - meetings_sd_2014_pre$STD.DEV.SPY,

minutes_sd_2014_post$STD.DEV.SPY - minutes_sd_2014_pre$STD.DEV.SPY)

Welch Two Sample $t$-test

data: meetings_sd_2014_post$STD.DEV.SPY - meetings_sd_2014_pre$STD.DEV.SPY and

minutes_sd_2014_post$STD.DEV.SPY - minutes_sd_2014_pre$STD.DEV.SPY

t = 0.17202, df = 235.83, p-value = 0.8636

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-3.975927e-05 4.736676e-05

sample estimates:

mean of x  mean of y

0.0001355974 0.0001317936

> t.test(meetings_sd_2014_post$STD.DEV.BIL - meetings_sd_2014_pre$STD.DEV.BIL,

minutes_sd_2014_post$STD.DEV.BIL - minutes_sd_2014_pre$STD.DEV.BIL)

Welch Two Sample $t$-test

data: meetings_sd_2014_post$STD.DEV.BIL - meetings_sd_2014_pre$STD.DEV.BIL and

minutes_sd_2014_post$STD.DEV.BIL - minutes_sd_2014_pre$STD.DEV.BIL

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\[ t = -1.0113, \ df = 168.59, \ p-value = 0.3133 \]

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

\[-2.531594e-05 \, \, 8.164686e-06\]

sample estimates:

\[ \text{mean of } x \, \, \text{mean of } y \]

9.315326e-07 \, \, 9.507161e-06

---

For Subsample 1

\[ t = 2.4292, \ df = 218.25, \ p-value = 0.01594 \]

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

\[ 1.147133e-05 \, \, 1.101313e-04 \]

sample estimates:

\[ \text{mean of } x \, \, \text{mean of } y \]

0.0001786932 \, \, 0.0001178919

\[ t = -1.4007, \ df = 218.32, \ p-value = 0.1627 \]

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:
-1.884012e-05 3.185908e-06

sample estimates:

<table>
<thead>
<tr>
<th>mean of x</th>
<th>mean of y</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.517160e-06</td>
<td>6.309947e-06</td>
</tr>
</tbody>
</table>

For Subsample 2

> t.test(meetings_sd_subsample_2_post$STD.DEV.SPY - meetings_sd_subsample_2_pre$STD.DEV.SPY, minutes_sd_subsample_2_post$STD.DEV.SPY - minutes_sd_subsample_2_pre$STD.DEV.SPY)

Welch Two Sample t-test
data: meetings_sd_subsample_2_post$STD.DEV.SPY - meetings_sd_subsample_2_pre$STD.DEV.SPY and minutes_sd_subsample_2_post$STD.DEV.SPY - minutes_sd_subsample_2_pre$STD.DEV.SPY
t = -0.37164, df = 224.9, p-value = 0.7105

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-3.482004e-05 2.377014e-05

sample estimates:

<table>
<thead>
<tr>
<th>mean of x</th>
<th>mean of y</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0001169841</td>
<td>0.0001225090</td>
</tr>
</tbody>
</table>

> t.test(meetings_sd_subsample_2_post$STD.DEV.BIL - meetings_sd_subsample_2_pre$STD.DEV.BIL, minutes_sd_subsample_2_post$STD.DEV.BIL - minutes_sd_subsample_2_pre$STD.DEV.BIL)

Welch Two Sample t-test
data: meetings_sd_subsample_2_post$STD.DEV.BIL - meetings_sd_subsample_2_pre$STD.DEV.BIL and minutes_sd_subsample_2_post$STD.DEV.BIL - minutes_sd_subsample_2_pre$STD.DEV.BIL
t = 0.16255, df = 209.41, p-value = 0.871

alternative hypothesis: true difference in means is not equal to 0

95 percent confidence interval:

-5.992182e-06 7.069183e-06

sample estimates:

<table>
<thead>
<tr>
<th>mean of x</th>
<th>mean of y</th>
</tr>
</thead>
<tbody>
<tr>
<td>89</td>
<td></td>
</tr>
</tbody>
</table>
Item 8

Regression results on the quality of Meeting and Minutes as predictors

Overall sample, for volatility of SPY

```
Overall_sd <- MasterData12to4PM %>% group_by(HOUR, MINUTE, Meeting, Minutes) %>%
  summarise(STD.DEV.SPY = sd(RET.SPY), STD.DEV.BIL = sd(RET.BIL))

> summary(lm(STD.DEV.SPY ~ STD.DEV.BIL + Meeting + Minutes, data=Overall_sd))

Call:
  lm(formula = STD.DEV.SPY ~ STD.DEV.BIL + Meeting + Minutes, data = Overall_sd)

Residuals:
   Min     1Q Median     3Q    Max
-2.110e-04 -4.478e-05 -5.600e-06 4.990e-05 4.088e-04

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.065e-04  2.834e-05 10.814  < 2e-16 ***
STD.DEV.BIL  4.955e-01  2.530e-01  1.958   0.05059 .
Meeting      2.495e-05  7.596e-06  3.284   0.00107 **
Minutes      1.352e-05  7.560e-06  1.788   0.07425 .

---
Signif. codes:  0 ***  0.001 **  0.01 *  0.05 .  0.1  1

Residual standard error: 8.219e-05 on 716 degrees of freedom
Multiple R-squared: 0.01774, Adjusted R-squared: 0.01362
F-statistic: 4.309 on 3 and 716 DF, p-value: 0.005038
```

Overall sample, for volatility of BIL

```
> summary(lm(STD.DEV.BIL ~ Meeting + Minutes, data=Overall_sd))

Call:
  lm(formula = STD.DEV.BIL ~ Meeting + Minutes, data = Overall_sd)

Residuals:
   Min     1Q Median     3Q    Max
   90
```

90
Residuals:

Min 1Q Median 3Q Max
-5.528e-05 -4.927e-06 4.490e-07 6.174e-06 4.301e-05

Coefficients:

             Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.100e-04  7.831e-07 140.515  < 2e-16 ***
Meeting     -4.703e-06  1.107e-06  -4.247  2.46e-05 ***
Minutes     -3.665e-06  1.107e-06  -3.309  0.000982 ***

---
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Residual standard error: 1.213e-05 on 717 degrees of freedom
Multiple R-squared: 0.02702, Adjusted R-squared: 0.0243
F-statistic: 9.955 on 2 and 717 DF, p-value: 5.44e-05

Partial F-tests

For SPY

> anova(lm(Overall_sd$STD.DEV.SPY~Overall_sd$STD.DEV.BIL),
  lm(Overall_sd$STD.DEV.SPY~Overall_sd$STD.DEV.BIL + Overall_sd$Meeting),
  lm(Overall_sd$STD.DEV.SPY~Overall_sd$STD.DEV.BIL+Overall_sd$Meeting+Overall_sd$Minutes))

Analysis of Variance Table

Model 1: Overall_sd$STD.DEV.SPY ~ Overall_sd$STD.DEV.BIL
Model 2: Overall_sd$STD.DEV.SPY ~ Overall_sd$STD.DEV.BIL + Overall_sd$Meeting
Model 3: Overall_sd$STD.DEV.SPY ~ Overall_sd$STD.DEV.BIL + Overall_sd$Meeting + Overall_sd$Minutes

        Res.Df RSS Df Sum of Sq      F Pr(>F)
1     718 4.9095e-06
2     717 4.8581e-06  1  5.1403e-08  7.6097 0.005954 **
3     716 4.8365e-06  1  2.1588e-08  3.1959 0.074248 .

---
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
For BIL

\begin{verbatim}
> anova(lm(Overall_sd$STD.DEV.BIL ~ Overall_sd$Minutes), lm(Overall_sd$STD.DEV.BIL ~ Overall_sd$Meeting + Overall_sd$Minutes))

Analysis of Variance Table

Model 1: Overall_sd$STD.DEV.BIL ~ Overall_sd$Minutes
Model 2: Overall_sd$STD.DEV.BIL ~ Overall_sd$Meeting + Overall_sd$Minutes

<table>
<thead>
<tr>
<th>Res.Df</th>
<th>RSS</th>
<th>Df Sum of Sq</th>
<th>F</th>
<th>Pr(&gt;F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>718</td>
<td>1.0817e-07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>717</td>
<td>1.0552e-07</td>
<td>2.6541e-09</td>
<td>18.035</td>
</tr>
</tbody>
</table>

---

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
\end{verbatim}