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The effect of the United States government shutdown on the stock market

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Abstract:

The objective of this study was to research the effect of the United States government shutdown (December 22, 2018) on the stock market by using daily panel data. Economic policy uncertainty was measured based on the Abnormal Search Volume Index (ASVI) retrieved from the Google Trends search engine. The cumulative abnormal returns (CARs) were negative around the government shutdown announcement and positive around the government reopening announcement, but the anticipation effect diminished the outcome. A panel regression with fixed effects showed a negative association between CARs and the ASVI. A Granger causality test showed that lagged CARs could predict the ASVI but that stock returns were a more ideal measure to predict the ASVI.

Keywords: government shutdown, stock market, S&P 500, US, event study, abnormal returns, panel regression

JEL Codes: B26, B41, C12, C33, C88, E44, G14, G18, N12

Table of Contents

1 Introduction

A government shutdown occurs when a president does not sign the appropriations bills or when Congress fails to appropriate funds for the following fiscal year, which begins on the first of October. During a shutdown, many federal workers are sent home without wages, except for employees who provide essential services and are thus required to work without payment (McCarthy, 2019). Each sector has its own furlough rate, meaning that each industry is affected to a different degree. Workers who do not receive pay do not spend in the economy. Workers who do not receive pay withhold spending. Firms withhold hiring and investments due to economic uncertainty. This slows the economic growth of the country. Another component is that the government plays a significant role in the overall spending of the US, and a shutdown, therefore, causes significant damage to the economy (Amadeo, 2020).

The most recent partial federal government shutdown, occurring under the Trump administration, lasted from December 22, 2018 to January 25, 2019 and was, lasting 35 days, the longest shutdown in history. Parks and museums were closed to visitors. Government labs for research were empty. The Food and Drug Administration partly stopped its inspections, and law enforcement personnel worked without pay. The shutdown affected 800,000 government workers, who had to live without pay and for whom more than half were repaid once the government reopened while the other half was not repaid. At workplaces that remained open, employees called in sick and searched for work elsewhere to recover missed salary payments (Chokshi, 2019). The shutdown cut $1.2 billion of real gross domestic product (GDP) for each week that the government was partially closed. In total, the shutdown reduced GDP by $8 billion, with overall costs of $11 billion. Ironically, Trump had only demanded $5.7 billion of funding for a border wall between the United States (US) and Mexico. The shutdown generally cost the government more money than if congress had acceded to the funding demands (Zarracina & Zhou, 2019).

The economic and political uncertainty during a shutdown is interesting to research. Many empirical papers have researched the effect of policy uncertainty on macroeconomic variables such as employment, growth and inflation (Fernández-Villaverde, Guerrón-Quintana, Kuester & Rubio-Ramírez, 2015). However, relatively limited work has been done on policy shocks and the stock market. The announcement of a government shutdown can be used as an independent policy shock, as a tool to perform an event study on and to detect if there are abnormal returns obtained during these periods of uncertainty. Researchers have additionally discovered a relationship between economic policy uncertainty and the search volume of internet queries of households during times of high uncertainty. One of the most successful results in this directions concerns the epidemic spreading of the influenza virus, where people queried search engines for keywords related to the virus (Ginsberg, Mohebbi, Patel, Brammer, Smolinski & Brilliant, 2009). The same phenomenon may happen during times of financial distress, which makes the search volume of internet queries of households during the US government shutdown appealing to investigate further.

Prior research shows that web search traffic can be used to predict movements in the financial markets. Changes in search volume can be interpreted as early warning signs of stock market movements (Bordino, Battiston, Caldarelli, Cristelli, Ukkonen & Weber, 2012). In the paper by Arouri, Estay, Rault and Rouband (2016) on the impact of economic policy uncertainty on the stock markets for the period from 1900 to 2014, an increase in policy uncertainty significantly reduced returns to the US stock market. These results were confirmed by research on the US government shutdowns in 1995 and 2013, which showed a significant negative market reaction around the event period (Woodard, 2015). When comparing the observed reactions of the 1995 and 2013 shutdown announcements, there were several minor differences between both events. With the government shutdown of 1995, the negative reaction to the shutdown announcement turned out to be somewhat larger and more volatile compared to the shutdown of 2013.

The most recent shutdown in 2018 under the Trump administration is a recent topic that has not been extensively researched. Additionally, the Trump administration is from the Republican Party, whereas the shutdowns in 1995 and 2013 occurred under a Democratic regime. A study conducted by the National Bureau of Economic Research showed that Republican presidencies seem to perform worse than Democratic presidencies. Each year on average, the economy grows by 2.5% with Republican presidencies versus 4.4% with Democratic presidencies (Amadeo, 2020). For this research, this comparison made it interesting to investigate if there were significant differences between the shutdown in 2018 versus the shutdowns of 1995 and 2013. In addition, this paper focused on possible positive announcement effects on the reopening of the government after the shutdown. Furthermore, the effects of economic and political uncertainty on the stock market were assessed by using Google Trends to search for early warning signs in query volume changes. These research topics together led to the following research question:

What was the effect of economic policy uncertainty on the stock market around the period of the United States government shutdown from December 22, 2018 to January 25, 2019?

To answer the main research question, an event study was performed on the stock prices of US firms from the Standard and Poor's (S&P) 500 index around the 30-day period before the government shutdown announcement up until 30 days after. The announcement was on December 22, 2018. Another event study was performed for the reopening announcement of the government shutdown marking the January 25, 2019 date. The event window counted -30 days before the announcement and +30 days after the announcement, with Day 0 as the announcement date in order to be consistent with the paper of Woodard (2015). The abnormal returns were then used in an ordinary least squares (OLS) regression to draw further conclusions. Furthermore, the Google Trends search engine provided the option to see the search volume index (SVI) of keywords related to the government shutdown. This paper chose 17 keywords to represent the SVI. The SVI data could be daily or weekly for a given period scaled by the period's maximum. From here, data was used to uncover the cross-correlations between the search queries of internet users and the fluctuations of the stock market. Here, in particular, the S&P 500 was used as a benchmark for the stock market.

This paper analysed the effects of a government shutdown on stock market returns, which were mainly caused by economic policy uncertainty. The expectations were a significant negative effect on the stock market from the government shutdown announcement and a significant positive effect from the reopening announcement. Furthermore, it was expected that a negative cross-correlation would be seen between the collective intelligence of internet users and the effect on the stock market from the government shutdown. The stock market was expected to decline further as individuals became more aware of the consequences of the shutdown. Individuals would desire more information and start searching on the internet, thus increasing query volume.

To summarize the empirical findings of this paper, the weak form of the efficient market theory was tested with summed lagged serial correlation but hardly any serial correlation was found, meaning that the weak form of the efficient market theory seems to hold. The semi-strong form of the market efficiency theory was tested with an event study. The Patell Z and the Wilcoxon signed-rank test measured the significance of the cumulative abnormal returns (CARs). The event study showed significant negative effects from the government shutdown announcement of -0.008 and positive effects from the government reopening announcement of 0.004. The effects were likely diminished due to the anticipation effect of investors. Another metric that spiked before the government shutdown announcement was trading volume, which could be a sign of insider trading. The panel regressions with fixed effects showed a negative association between CARs and the ASVI, as was seen in the time-lagged cross-correlation. The Granger causality test showed that returns were more ideal predictors of the ASVI than the CARs and that returns and the ASVI had predictive power in both directions. Turnover was insignificant in this model, and the bid-ask spread and volatility had a significant negative association with the CAR while size had a positive association. The ending conclusion was that there was a small effect of economic policy uncertainty on the stock market, but the anticipation effect moderated the effect during the announcement of the shutdown and reopening.

The remainder of the paper is organized as follows. Section 2 presents the literature review on government shutdowns, economic policy uncertainty, stock market returns and efficient market theory. Furthermore, it outlines the hypotheses associated with this study. Section 3 describes the event study and panel regression methodology. Section 4 explains the data collection and transformations. Section 5 discusses the empirical findings and their possible interpretation for the cross-correlation, event study, fixed effects panel regressions and Granger causality tests. Section 6 summarizes and concludes the paper and, finally, provides possible recommendations for future research.

2 Literature review

This section firstly reviews the effects of a government shutdown on the economy and the stock market. Secondly, it discusses previous research on the effect of policy uncertainty on stock market returns. Thirdly, it elaborates on the market efficiency theory and insider trading. Fourthly, this section explains the hypotheses that were formed.

2.1 Effects of the government shutdown

2.1.1 Macroeconomic effects

When the US government shuts down, this has direct and indirect effects on the economy. Directly, a shutdown decreases GDP because the government halts spending. Government spending makes up for roughly 20% of annual GDP. The shutdown further affects government purchases of private-sector goods and services, which are postponed until the end of the shutdown. This has a severe impact on the expected cash flow of firms exposed to government spending (Belo, Gala & Li, 2013). In addition to the decline in government demand, the shutdown reduces government supply, as furloughed federal workers cannot produce government output. The lost working hours and, thus, production cannot be recovered. After the reopening of the government, work is resumed, and government spending and purchases return to their original levels (Labonte, 2013).

Indirectly, other components of GDP (consumption and investment) decrease through multiplier effects greater than the original level of government spending. Consumers and businesses lose confidence in the economy, which can lead to the postponement of purchases and businesses postponing hiring and investments. The multiplier effects are temporary, particularly if the duration of the shutdown is limited, meaning that consumption and investments may simply be delayed rather than permanently reduced. Furthermore, GDP decreases as a result of disrupted exports and imports. Federal imports, mortgages and small business loans are postponed because there are no government employees to verify the process. The delay in salary may cause consumers and firms to fail to pay their required payments, damaging their creditworthiness (Aye, Balcilar, Montasser & Manjezi, 2016). Another macroeconomic variable that is affected by government shutdowns is the exchange rate. Sharma, Phan and Narayan (2019) have found that, on average, the US dollar (USD) depreciates and that exchange rate volatility is high during shutdowns. The authors could not be conclusive about the exchange rate since, in a few cases, the USD has appreciated while volatility decreased. Furthermore, the authors found that the effects of shutdowns were the most significant one day after a shutdown.

The effects of a shutdown depend on the length of the shutdown period and the state of the economy. If the economy is already close to a recession, a shutdown could push the economy directly into an economic downfall. If the state of the economy is in an upward trend, the effects of a shutdown can be less severe (Labonte, 2013). Additionally, the reigning party can alter the effects of a shutdown. Government spending is, on average, lower during Republican presidencies than during Democratic presidencies; consequently, the economic effects of a partial shutdown can be less severe during the regime of a Republican party (Belo et al., 2013). The effects may, additionally, slightly differ for each federal department since each department has its own contingency plan in case of a government shutdown. The nine federal agencies that are most affected are as follows: commerce, interior, agriculture, transportation, state, justice, homeland security, treasury and housing and urban development. Additionally, the furlough rates vary by department. Therefore, homeland security workers are seen as essential and only 14.7% work at home, while at the treasury department, 83.3% of the employees are furloughed (Zarracina & Zhou, 2019).

2.1.2 Stock market effects

Overall, researchers believe that a shutdown does not have a permanent effect on economic growth but that if such an event starts to occur more frequently, it could have a lasting effect on economic uncertainty and consumer confidence. Consumers are more circumspect about spending, firms more reluctant to invest and hire, entrepreneurs more hesitant to attempt startups and banks more cautious about lending. When banks do not lend money, firms cannot invest, and not investing can cause companies to miss profitable business opportunities, which, in the end, causes stock market returns to deteriorate. Additionally, in times of great uncertainty, firms become less sensitive to monetary policy. Changing interest rates do not have the same effect as before, which can lead to an unstable inflation rate that negatively impacts real stock market returns (Labonte, 2013).

Aye et al. (2016) have investigated the predictability of the debt ceiling and a government shutdown for real stock returns for the US between 1985 and 2013 using a bootstrap Granger non-causality test. The debt ceiling and government shutdown variables were constructed from the number of mentions of ‘debt ceiling’ and ‘government shutdown’ in 1,000 relevant US newspapers. The authors found a sharp increase in real stock returns where there were sharp increases in the debt ceiling and government shutdown indexes. This index peak showed a negative correlation between the debt ceiling with government shutdown and real stock returns. News about the debt ceiling and government shutdown could predict movements in stock returns. Another paper by Aye, Deale and Gupta (2016) researched the out-of-sample predictability of the equity risk premium for the S&P 500 using an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) regression model. Here, the government shutdown index could play a significant role in forecasting the US equity risk premium.

Woodard's (2015) research solely examined the effect of the US government shutdown on stock returns. He performed an event study around the two government shutdowns of 1995 to 1996 and 2013 and found a significant negative effect for the government shutdown dates. Nonetheless, before both events, trading had already been on the decline before the announcement of the government shutdowns, suggesting that investors had possibly anticipated the events. After the event, investors could earn an above-normal return by trading on the news of the announcement, exhibiting support for the weak form of the market efficiency theory. Overall, the shutdowns did not seem to severely negatively impact the stock market. The Schwab Center for Financial Research (2019) calculated the returns from the first day of the shutdown compared to the first day the shutdown was over. The results are displayed in

Appendix A. On average, the S&P 500 index return increased by 0.1% in 1995 to 1996, 2.4% in 2013 and 10.3% in 2018 to 2019, indicating that stock markets were affected during the government shutdown but restored themselves before the shutdown was over.

Table 1: Previous papers on the US government shutdown summarized

Author(s) (Publication year)	Time period	Event study	Regression	Results
Labonte (2013)	2014	No, macroeconomic forecasts	No	Each week of a shutdown decreases real GDP approximately with 0.1%
Woodard (2015)	1995 & 2013	Yes, standard risk adjust method	No	Negative announcement effect for the government shutdown
Aye, Balcilar, Montasser, Gypta & Manjezi (2016)	1985-2013	No, Bootstrap Granger non-causality test	No	Government shutdown Granger causes stock returns at the 10% -level
Aye, Deale & Gupta (2016)	1985-2012	No	Yes, bivariate predictive regression model	Government shutdown has predictive power over the equity risk premium
Sharma, Phan & Narayan (2019)	1974-2018	No	Yes, EGARCH regression model	Exchange rates are affected and volatility is high during shutdowns.
Zarracina & Zhou (2019)	2018-2019	No	No	Furlough rates vary for each department. Costs of the shutdown in GDP are higher than Trump demanded funding.

2.2 Economic policy uncertainty and stock prices

The paper by Pastor and Veronesi (2012) provides a framework on how uncertainty about government policy impacts stock prices. The results showed that a change in policy has both a positive cash flow effect (new policies typically increase a firm's future profitability) and a negative discount rate effect (uncertain impact of the new policy on firm's profitability). The cash flow effect generally pushes stock prices up while the discount effect pushes prices down. Eventually, the negative discount rate has a higher weight, resulting in a negative announcement effect on stock market returns. This happens unless the market perceives the old policy of having a negative impact on firm profitability. Then, stock prices increase at the announcement of the policy, but the change in return is smaller compared to the negative announcement reaction. Investors already expect the positive announcement, whereas the negative announcement frequently has the element of surprise.

A change in policy is more likely when the impact of the policy on profitability is anticipated to be higher or less uncertain. If the current policy is perceived as harmful to the economy, there is a greater chance that the policy will be changed. Economic policy uncertainty is not a fully diversifiable risk, which results in investors demanding a higher risk premium, driving up volatilities and correlations on the stock market. These effects are stronger when the economy is weaker (Pastor & Veronesi, 2013). Stock price volatility is positively related to political uncertainty, and local and global political risks affect the volatility differently per industry (Boutchkova, Doshi, Durnev and Molchanov, 2012). Empirical findings between 1985 and 2013 show that correlations between policy uncertainty and stock market returns are consistently negative; an increase in economic policy uncertainty results in a decrease in the stock market. This dynamic correlation was perceptible except during the financial crisis in 2008, wherein correlations turned positive (Antonakakis, Chatziantoniou & Filis, 2013).

There are studies which have found a limited or no effect of uncertainty on the stock market, such as the studies of Bachmann and Bayer (2013), Bekaert, Hoerova and Lo Duca (2013), Chugh (2016) and Popescu and Smets (2010). Nonetheless, in a research study on the US bond and stock market using data from 1986 to 2000, a negative relationship between uncertainty and bond and stock returns was found (Connolly, Stivers & Sun, 2005). A bootstrap Granger causality test was conducted in China and India, with data covering the period from 1995 to 2013. No causality was established for the entire sample, but within a sub-sample, there was a bidirectional causal relationship between economic policy uncertainty and stock returns. A side note was that the relationship was weaker in emerging countries since uncertainty dominated in developing countries (Li, Balcilar, Gupta & Chang, 2016).

Related findings to this research included the effect of government policy uncertainty on uranium firm stock prices from 2005 to 2008 when there was an intense public debate about the private economic benefits and the public externalities of uranium mining (Ferguson & Lam, 2016). A positive relationship was discovered between volatility and periods of intense public debate. However, no significant association between the correlation of stock return and government policy uncertainty proxies was found. The event studies established a significant stock price reaction to important uranium-related policy news. A government shutdown is another form of policy news, and this drove expectations for this paper to see similar event study results on the stock market.

2.3 Efficient market theory

According to the efficient market hypothesis constructed by Fama (1970), a market is efficient when it fully reflects all available information. All information about a company is reflected in the company's stock price, meaning that stock prices are equal to their true fundamental value and investors cannot make above average returns. There are three types of market efficiency: the strong form, the semi-strong form and the weak form. These various forms have different implications for the market's reaction to an event. The strong form dictates that stock prices reflect all available private and public information and that an investor cannot earn an above normal return acting on public or private information. With the semi-strong form, stock prices quickly adjust to available public information, and an investor can earn an above normal return based on private information. This is called insider trading and is illegal. In the weak form, stock prices cannot be predicted by prices from the past, meaning that an investor can earn an above normal return based on public and private information but not on trading rules based on past prices (Woodard, 2015).

Scientifically speaking, the concept of markets fully reflecting all available information has no empirically testable meaning. Therefore, to test these models, there needs to be some form of price definition. For this price formation, the expected return or fair game efficient markets model can be used to calculate the expected returns of financial securities. The three different forms are used to test for market efficiency. In the weak form, technical analysis is useless because there are no price patterns; therefore a majority of the tests are based on random walk theories. Autocorrelation shows the relationships between the price variable and the lagged versions of itself. If there are no price patterns, this should imply that the autocorrelation between the return of a stock and the lagged variables is zero and therefore statistically insignificant. Fama and Blume (1965) found that it was possible to come up with a trading strategy that outperformed the buy-and-hold scheme. This evidence depended on the slightly positive serial correlation for daily returns. However, when the costs of trading are taken into account, the small profits evaporate, leaving the conclusion that there is not a sufficient amount of statistical evidence to call the market inefficient.

In the semi-strong form, the fundamental analysis is not applicable since public information should already have been reflected in stock prices. Here, tests are based on the speed of price adjustments to public news. To test the semi-strong form, whether or not there is abnormal behaviour around the announcement has to be examined. This abnormal behaviour can be examined with an event study. The event study methodology was first introduced by Fama, Fisher, Jensen and Roll (1969). Their paper researched the stock price behaviour around the time of a stock split by comparing stock returns around the event date with a complicated average market return. The main finding of Fama et al.'s (1969) paper was that the stock market is efficient, at least in its ability to adjust to information implicit in a stock split.

The strong form needs to show that no investor has access to private information from which this investor can derive a higher trading profit than others. Niederhoffer and Osborne (1966) have pointed out that insiders of firms could have monopolistic access to information about their corporation that others do not have. Jaffe (1974) tested a trading strategy based upon insider information and found that insiders were able to outperform the market. This conclusion made the strong form of efficient market theory invalid and was, therefore, not further tested in this paper.

The semi-strong form of the market efficiency theory states that all public information is reflected in the market price of a security and that, consequently, only investors with private information can outperform the market. The Securities Exchange Commission (SEC) is present to attempt to prevent illegal insider trading. Despite the SEC's efforts, insider trading is difficult to monitor, and the exact amount of insider trading is unknown (Keown & Pinkerton, 1981). The SEC has convicted investors who have traded on private information in the stock and options market (Chakravarty, Gulen & Mayhew, 2004). An active profitable trading strategy for investors with private information is to go long (short) in the stock market before a positive (negative) announcement. Berkman, McKenzie and Verwijmeren (2017) have found an increase in short selling before surprising negative announcements, probably caused by hedge funds trading on confidential information. Moreover, in the presence of short-sale constraints on underlying stocks, options can be used to trade on the decrease of share prices and corresponding negative information. As argued by Black (1975), investors with private information can prefer option markets due to the leverage advantages options offer.

A substantial amount of informed trading in the options market can affect brokers who need to hedge in the underlying stock. Manaster and Rendleman (1982) have found that price changes in option markets lead to prices changes in stock markets. The bid-ask spread of a stock widens as brokers attempt to protect themselves against informed trading. Important variables to detect insider trading are trading volume, bid-ask spread and stock price volatility. If trading volume drastically increases prior to an announcement, this can be due to trades based on insider information. This is extensively researched before merger and acquisition announcements. However, insider trading can additionally occur for uncertain events such as a government shutdown. During uncertain times, volatility is high, yielding higher abnormal returns. A government shutdown leaves a majority of workers on furlough, consequently including workers with the SEC, which supervises insider trading. This decreases the chance of being caught and might indulge more insider trading (Campoy & Rohrlich, 2019). Brokers are careful when a stock with a wide bid-ask spread suddenly begins to trade at high volume, as this could point to certain traders having private information and knowing something is coming up. Moreover, insiders selling shares has a positive association with volatility, particularly before earnings announcements. Insiders have more information than outsiders, and if they sell their shares, there must be negative news coming (Chiang, Chung & Louis, 2017).

2.4 Testable predictions

Research shows that stock prices should fall at the announcement of a policy change (Pástor & Veronesi, 2012; Arouri et al., 2016; Li et al., 2016; Woodard, 2015). The negative announcement return is larger when there is more uncertainty about government policy. Trump is seen as an unpredictable president, inducing a more than normal negative expected announcement return (Collinson, 2019). Stock prices decline except for when the former policy is perceived as negative for firm profitability – as with a government shutdown (Ferguson & Lam, 2016). The stock market will experience this as a positive announcement, and returns will increase but slightly less compared to a negative announcement. Investors will anticipate the reopening of the government, and the positive announcement return is already priced into a certain degree. When the market finally opens, the effect will be less than that of with the shutdown announcement. Therefore, it is expected that a negative effect from the announcement of the shutdown would be seen and that a slightly less positive announcement effect would be seen on the reopening of the government. This background formed the first two hypotheses:

H1: Stock prices were significantly negatively affected by the announcement of the United States government shutdown on December 22, 2018.

H2: Stock prices were significantly positively affected by the announcement of the United States government reopening on January 25, 2019.

Another finding in the work of Pástor and Veronesi (2012) was that changes in policy should increase volatility among stock returns. During times of uncertainty, investors become less predictable, and deals are called off, which increases the volatility of stocks. The more the market deviates from normal, the higher the abnormal returns. Accordingly, volatility was used as a control variable in the regression and formed the third hypothesis:

H3: Stock price volatility became positively affected during the United States government shutdown from December 22, 2018 to January 25, 2019.

Larger firms are followed more by analysts. Vozlyublennaia (2014) has found that a significant change in investor attention is more likely for large company indexes such as the S&P 500. Larger size indexes seem to respond more quickly to search volume changes than smaller firms. Moreover, prices of small firms may not completely reflect all available information, and using private information could be more profitable, yielding higher abnormal returns for small firms (Elliott, Morse & Richardson, 1984). Furthermore, Ro (1988) has shown that the return is positively associated to firms size in the weeks prior to announcements. Therefore, the fourth hypothesis was as follows:

H4: Firms size is positively affected during uncertain times such as that of the United States government shutdown from December 22, 2018 to January 25, 2019.

Prior literature has found a substantial relationship between trading volume and stock returns (Conrad, Hameed & Niden, 1994). A high trading volume means that a stock is highly liquid. Trading volume can be seen as a proxy for investor attention and generally comes with abnormal stock returns (Barber & Odean, 2008). Additionally, trading volume is significantly correlated with the search queries of companies. During times of economic uncertainty, the stock market is less liquid. Finally, higher trading volume can mean that insiders are taking advantage of leaked information prior to the official announcement of the shutdown. This would result in negative CARs occurring before the official announcement. The bid-ask spread is the difference between the buy and sell price of a stock. If a stock trades infrequently, a broker has to possibly keep the stock longer in his inventory. The lack of liquidity induces a broker to set a wider spread to compensate for this risk. Therefore, it is expected that during times of uncertainty, the bid-ask spread of a stock will increase (Easley, Kiefer, O'Hara & Paperman, 1996). This formed the fifth and sixth hypotheses:

H5: The trading volume of stocks become negatively affected during uncertain times such as the United States government shutdown from December 22, 2018 to January 25, 2019.

H6: The bid-ask spread of stocks becomes positively affected during uncertain times such as the United States government shutdown from December 22, 2018 to January 25, 2019.

Certain industries are more exposed to government spending than others. This affects the free cash flow and volatility of a company. The impact of the shutdown varies in severity depending on the industry. Hence, industry fixed effects were tested for in the regression analysis and formed the seventh hypothesis as follows:

H7: The effects on stock returns were different per industry for the government shutdown from December 22, 2018 to January 25, 2019.

A paper by Da, Engelberg and Gao (2014) used internet queries of households to reveal concerns about the economic conditions between 2004 and 2011. These daily internet searches for keywords such as ‘recession’, ‘unemployment’ and ‘bankruptcy’ were used as an index to reveal the investor sentiment for the market. The sentiment measure showed that days in which households searched for these terms were the same days that equity returns were low, revealing a possible link between the volume of queries and the return in the stock market. The expectations were that during the federal government shutdown, households would once more turn to the internet for answers. This would lead to an increase in Google queries for specific terms during the period of the government shutdown. This formed the eighth hypothesis:

H8: There were more Google queries of specific keywords around the period of the United States government shutdown from December 22, 2018 to January 25, 2019

These Google queries contributed to fluctuations in the stock market according to Bordino, Battiston, Caldarelli, Cristelli, Ukkonen and Weber (2012). When there was an increase in queries, the stock market was affected the next day, and it seemed as if there was a certain kind of correlation between these two factors. This was further confirmed by the results of Da et al. (2014). Irresberger, Mühlnickel and Weiss (2015) showed that bank stock prices were heavily affected by investor sentiment during the financial crisis. The investor sentiment effect was further greater for stock returns of non-financial firms. Joseph, Wintoki and Zhang (2011) have found that increases in search volume for stocks have predictive power over future stock prices and trading volumes. Therefore, the final hypothesis researched the cross-correlation between the stock market and Google search volume and formed the ninth hypothesis:

H9: There was a cross-correlation between the query volume in Google Trends and the cumulative abnormal returns on the S&P 500 around the shutdown period from December 22, 2018 to January 25, 2019.

The cross-correlation between the SVI and the S&P 500 aided in understanding the economic policy uncertainty regarding the event dates and answered the main research question. Bilgin, Demir, Gozgor, Karabulut and Kaya (2019) researched economic policy uncertainty in Turkey and constructed an economic and financial uncertainty index based on search word data from Google Trends. Here, the authors found that the search volumes of Google Trends could successfully capture economic uncertainty in a country.

3 Methodology

The first part of methodology section discusses the market efficiency theory and event study methodology. Here, insider trading is elaborated on, first-order serial correlation for the S&P 500 is shown, the calculations of the CARs are explained and possible robustness tests for the CARs are described. Furthermore, the results of the Patell Z and Wilcoxon signed-rank tests to verify the CARs are depicted. The second part elucidates on the panel regression analyses.

3.1 Event study methodology

Firstly, the weak form of the market efficiency theory was tested. The weak form needs to be valid for the semi-strong form to possibly be true. The test of the weak form needs to show that there is no lagged correlation between the changes in the return of the stocks in the S&P 500 index. To be coherent with the paper of Fama (1970), this paper used various intervals of one, four, nine and 16 days. Fama (1970) used the individual stocks of 30 firms in the Dow Jones, which was significantly less than the 500 firms of the S&P 500 used in this paper. Therefore, instead of 500 individual observations, an average of the index is displayed in Table 2.

Table 2: Weak form of market efficiency test

This table shows the summed up first-order serial correlation coefficients of the natural logarithm of price changes for the S&P 500 for one-, four-, nine-, and 16-day. * Coefficient is twice its computed standard error. The standard error is displayed with brackets.

	Differencing Interval (Days)			
Index	One	Four	Nine	Sixteen
S&P 500	0.109*	-0.005	0.073	-0.077
	(0.047)	(0.054)	(0.051)	(0.045)

The time interval of the used stock prices was from November 1, 2018 to March 29, 2019 to capture the period around the US government shutdown and reopening. The results were similar to those reported by Fama (1970). For the daily returns, the coefficient was 0.109, which was twice its computed standard error of 0.047. Fama (1970) found 11 day-one coefficients from a total of 19 coefficients with more than twice their computed standard errors. When a coefficient is more than twice its computed standard error, there may be serial correlation, meaning that historical stock prices could be used for profitable trading strategies. Nonetheless, this small amount of serial correlation seemed hardly sufficient to create trading rules from which substantial profits could result. As in the results of Fama (1970), the coefficients of daily returns were primarily positive (22 out of 30). For the fourth lag, the coefficient was -0.005, which was slightly negative and close to zero. Here, the results overlapped with Fama (1970), as was visible in the negative magnitudes, as a majority of coefficients here were additionally slightly negative (21/30). The nine-day interval result of this paper was 0.073, and the 16-day interval coefficient was -0.077. Apart from the magnitude of the coefficients, which lay in the same range as the results of Fama (1970), the signs were not coherent with the overall negative coefficients of the ninth day (24/30) and positive of day 16 (17/30). Overall, it could be concluded, as seen in Table 2, that the coefficients of the lagged returns were close to zero and held no linear dependence. So there was not enough evidence for the weak form of the market efficiency theory not to hold.

Secondly, for the semi-strong form of the market efficiency theory, insiders with private information can outperform the market. They need to buy or sell securities at the appropriate moment to engage in a profitable trading strategy. Particularly before positive (negative) news, public announcement investors should purchase (sell) shares of a company. The announcement of the government shutdown is an example of a negative news announcement, and the announcement of the government reopening is an example of a positive news announcement. Figure 1 and Figure 2 show the daily average trading volume of the S&P 500 companies plotted against the event window [-30, 30] around the government shutdown and for the government reopening. Figure 1 shows a large increase in trading volume for day 0 of 8.72e+08. Day 0 was the Monday after the shutdown announcement, and many investors traded on the public release of new information, such as expected for the semi-strong form of the market efficiency theory to be true. There was a small increase in trading volume the days prior to the government shutdown announcement. Days -3, -2 and -1 had higher trading volumes compared to the days before. The trading volumes were 1.71e+09, 1.79e+09 and 2.47e+09, respectively. This could provide evidence of a certain degree of insider trading since the maximum trading volume for [-30,-4] was on day -19 with a volume of 1.63e+09. Figure 2 demonstrates the trading volume for the government reopening, where there was no peak around the announcement date. Only at day 4 was a summit of 1.76e+09 reached. This summit might have been a late response to the reopening announcement or some renewed trust in the markets.

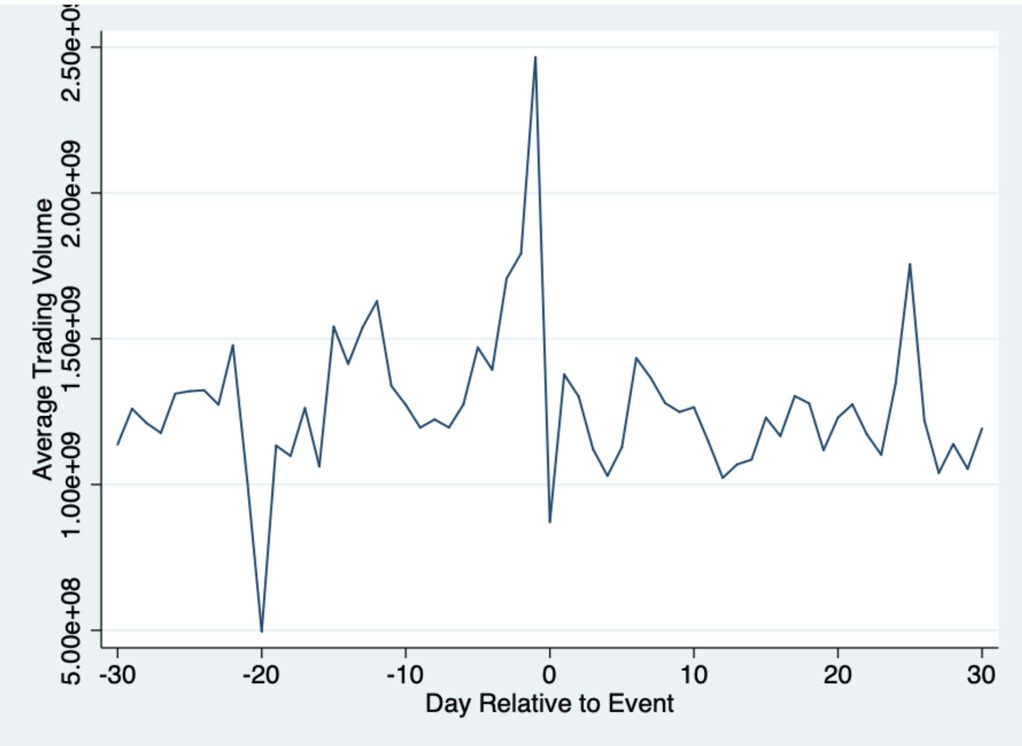

Figure 1: Trading volume for S&P 500 companies around the government shutdown

This figure demonstrates the average trading volume for companies listed on the S&P 500 index relative to the event window [-30,30]. Day 0 marks the date December 24, 2018.

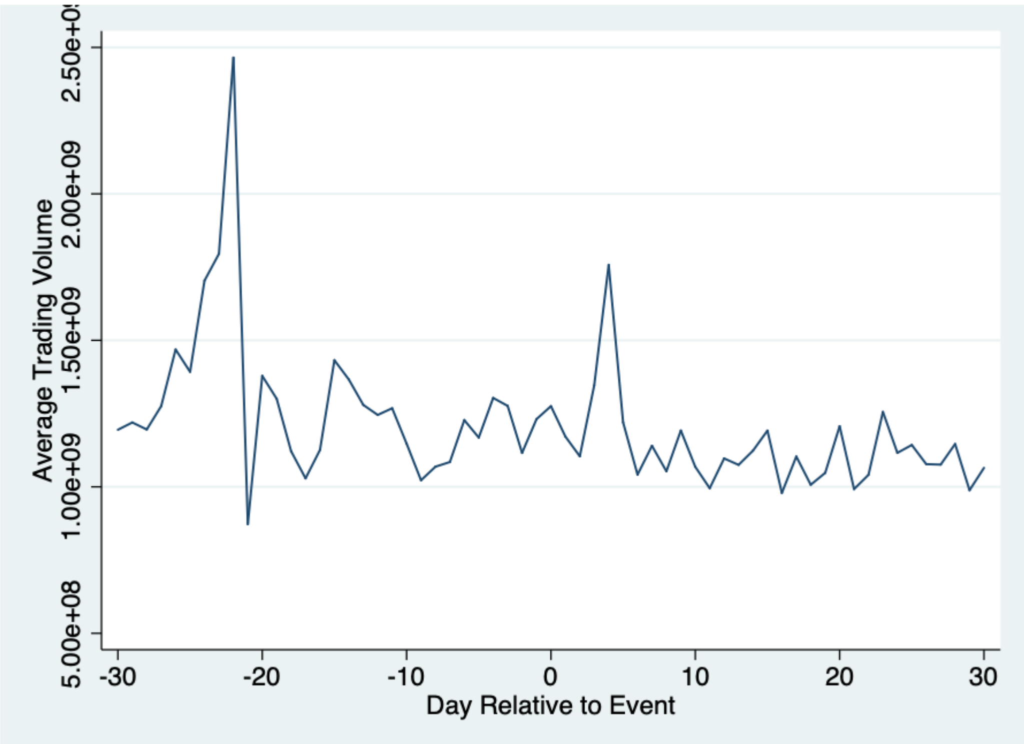

Figure 2: Trading volume for S&P 500 companies around the government reopening

This figure demonstrates the average trading volume for companies listed on the S&P 500 index relative to the event window [-30,30]. Day 0 marks the date January 25, 2019.

Furthermore, the semi-strong form of market efficiency was tested with an event study. An event study uses an event window of a fixed-length with day 0 as the event date. The event window consists of the event date, the pre-event days (T_1) and the post-event days (T_2). The pre-event days are included to capture possible anticipation effects of the market. The post-event days are included to capture price effects of announcements which occur after the stock market is closed. The estimation period is separate from the event window to prevent the event from influencing the normal regression estimates. Figure 3 illustrates the estimation period, the event window, the day of the event 0, and the post-event window.

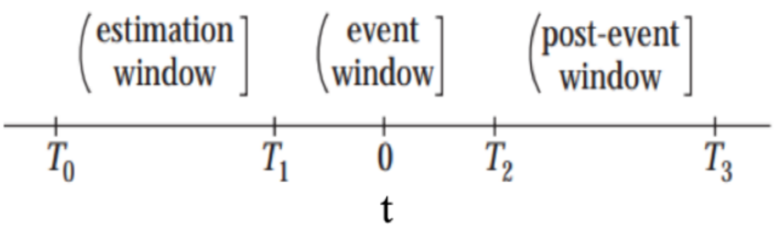

Figure 3: Timeline event study

With the estimation window [-180,-31] and event window [-30,30]. Source (MacKinlay, 1997).

The event window contained 61 trading days and ranged from -30 up to +30. The estimation period began on day -180 and ended on day -31. The event dates were December 22, 2018 and January 25, 2019. December 22, 2018 was a Saturday, and since there were no trades occurring during the weekend, day 0 for the event window was to be December 24, 2018. Since the closing of the US federal government and the reopening were two events with different expected outcomes, the abnormal returns were separately estimated. One would expect a negative announcement effect for the closing of the government and a positive announcement effect for the reopening.

An event study is an empirical analysis performed on securities to detect abnormal returns caused by a specific event. Abnormal returns are the actual returns of a security minus the normal return over a certain event period. The normal return is the expected return of a security. The normal return is fitted with an OLS regression in the estimation period according to the market model. The market model is seen as the most accurate model for short-term event studies and implies a linear relationship between the market return and the security return (Armitage, 1995). The normal return is calculated as follows:

$$R_{i,t} = \alpha_{i,0} + \beta_{i,1} * R_{m,t} + u_{i,t}.$$

where R_{it} captures the return of company i at time t, α_i is the security-specific intercept, β_i is the security-specific slope that determines the movement of the security relative to the market, R_{mt} is the return on the Morgan Stanley capital international world and u_{it} captures the unsystematic component of the return. The underlying assumption is that the residuals are independent of the market return and can be considered to be abnormal returns. The abnormal return is defined as the difference between the predicted and actual return:

$$\widehat{u_{i,t}} = R_{i,t} - \widehat{\alpha_{i,0}} + \widehat{\beta_{i,1}} * R_{m,t}.$$

where $\widehat{u_{i,t}}$ is the abnormal return from security i at time t. If there is unusual behaviour around the announcement date, the abnormal returns will deviate from the expected value of zero. The abnormal returns should only be visible for the day of the event AR(0) and the day following AR(1). The residuals should then quickly adjust and, for AR(2), go back to zero. If this is the case, the semi-strong form of the market efficiency theory holds. If it takes more working days before no abnormal returns remain visible, then the semi-strong form is violated. Adding all these abnormal returns and dividing them by the number of stocks yield the average abnormal returns for day t.

$$AR_t = N^{-1} \sum_{i=1}^{N} u_{i,t}$$

where $AR_{i,t}$ is the average abnormal return for day t, and N is the total number of stocks. CARs are the solution to overcoming problems with uncertainty regarding the event date or regarding whether other information could have triggered the residuals (Fama et al., 1969). The cumulation period, known as the event window, starts at t = 0 and lasts for T number of days. The CARs are expressed in the following formula:

$$CAR_t = \sum_{t=0}^{T} AR_t$$

where CAR_t is the cumulative average abnormal return on day t. The CARs are visualized with the event window [-30,30] in Figure 4 and Figure 5. This shows whether or not the residuals behaved differently around the date of interest. Figure 4 displays the CAR_t of the US government shutdown. As expected, there was a drop in the cumulative residuals around day 0 of -0.008. The graph starts descending a week before the actual announcement. Investors anticipated a possible government shutdown about the funding negotiations of Trump. As a result, investors were selling and shorting stocks, which placed negative pressure on the stock market. After the official announcement of the government shutdown, the CAR_t declined more until it reached its lowest point five trading days after the event date. Thereafter, the cumulative residuals started increasing once more. This increase could be a follow-up anticipation effect of the upcoming government reopening announcement. Figure 5 shows the reopening announcement of the government. There was no clear-cut sharp increase at day 0, as would be expected by a positive announcement. It could be that all information had already been priced in and that the announcement itself no longer had an effect on day 0. The event study showed positive announcement effects from the government reopening of 0.004. As expected, the positive announcement effects were smaller than the negative announcement effects in absolute numbers. The graph of figure 5 rises back to original levels and flattens around the tenth trading day. The conclusion of these two figures was that there may have been announcement effects for the government shutdown and reopening, but there were no clear-cut increases. This might have been due to the anticipation effect that had cancelled out the announcement effect. The markets did not seem efficient, as information from the news of the government shutdown and government reopening was already partially incorporated in the stock price.

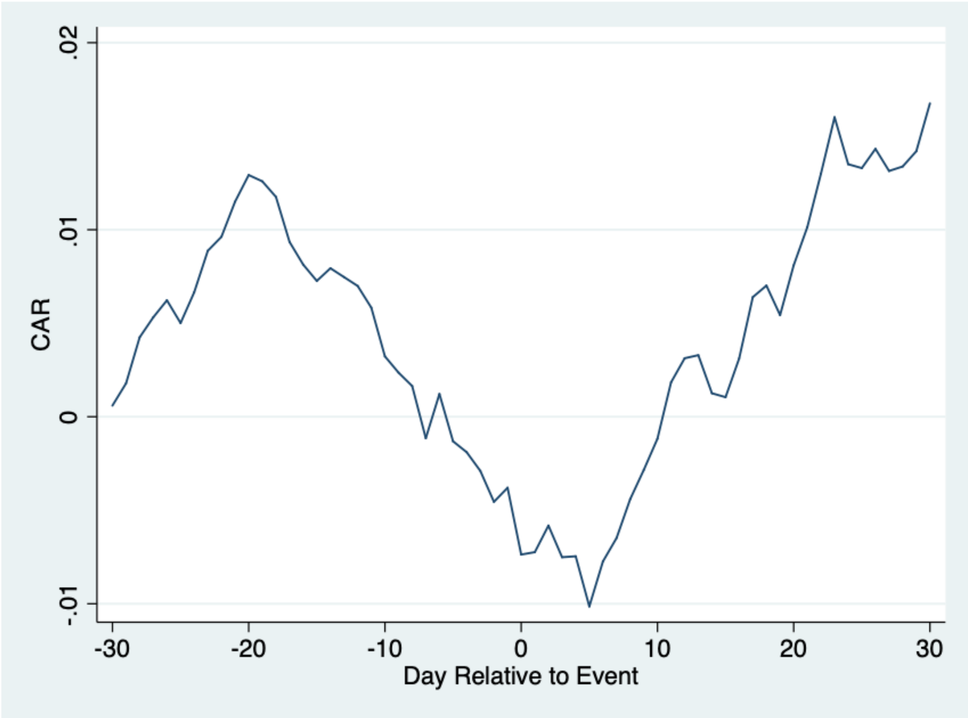

Figure 4: CAR government shutdown

This figure displays the time-series line plots of the CAR and the event window [-30,30] from the government shutdown on December 24, 2018.

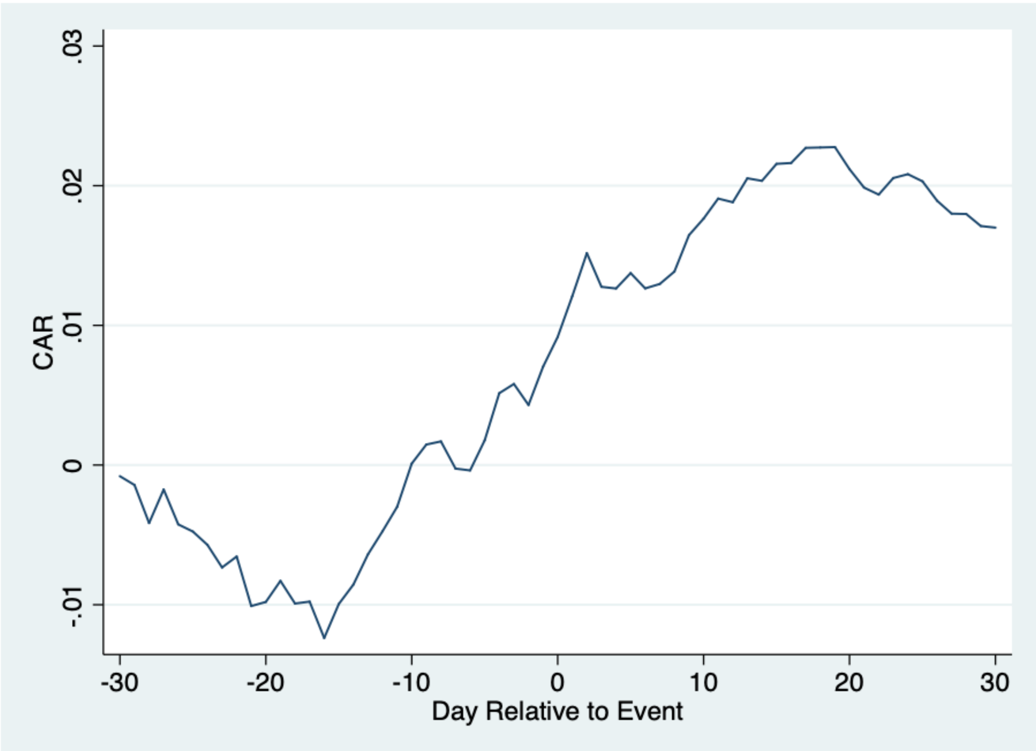

Figure 5: CAR government reopening

This figure shows the time-series line plots of the CAR and the event window [-30,30] from the government reopening on January 25, 2019.

The cumulative average abnormal return is the CAR divided by the total number of stocks in the sample, depicted as follows:

$$CAAR = N^{-1} \sum_{i=1}^{N} CAR_t.$$

The $CAAR$ is the same number for all the observations in the sample. To test the significance of the estimates, a t-test can be done. A t-test is a parametric test that measures the significance of the estimated returns. The null hypothesis states that the $CAAR$ is 0, meaning there is no reaction of the market to the announcement.

Parametric tests assume that returns are normally distributed. The t-test of significance is approved unless abnormal returns indicate significant cross-correlation or increase in variance during the event window (Armitage, 1995). The Patell Z test introduced by Patell (1976) is another parametric test that standardizes the abnormal returns using an estimator of the standard error. This could lead to more power than with a regular t-test. The Patell Z test allows for more ideal control of event-induced volatility and kurtosis or skewness in the data. Cross-correlation can happen when the same event occurs for multiple firms. This could change the event-induced volatility of an event study. The abnormal returns are standardized and summed to find the cumulative standardized abnormal returns:

$$CSAR_i = \sum_{i=1}^{N} \frac{AR_{i,t}}{S_{AR_{i,t}}},$$

$$Z_{Patell} = N^{-1/2} \sum_{i=1}^{N} \frac{CSAR_i}{S_{csar_i}}$$

where Z_{Patell} is the z-statistic with normal distribution, $CSAR_i$ is the cumulative standardized abnormal returns and S_{csar_i} is the standard error adjust by the forecast error. Non-parametric tests do not require assumptions about the probability distribution of returns. The robustness check frequently consists of parametric and non-parametric tests. Some examples of non-parametric tests are the sign test and the rank test. The sign test is based on the sign of the abnormal returns and assumes that positive and negative CARs are equally likely to happen. This assumption is frequently violated with daily data since daily data is often skewed. The rank test is a solution to the possible asymmetric return distribution by ranking all the abnormal returns in the estimation window and the event window. Nonetheless, the rank test is sensitive to changes in the variance of return and the length of the event window. The Wilcoxon signed-rank test takes into account both the sign and the rank of the CAR and has more power than the sign and rank tests (Wilcoxon, 1945).

$$Z_{Wilcoxon} = \frac{\frac{\max(W^{+},W^{-})-N(N-1)}{4}}{\sqrt{\frac{N(N+1)(2N+1)}{12}}}$$

Table 3 reports the p-values of the Patell Z test and the Wilcoxon signed-rank test for the CARs of the federal government shutdown and government reopening. The Patell Z test is calculated at the end of the event window. The Patell Z test was not significant for the three different periods of the government shutdown. The p-value was lower at day 0 than at days -30 and +30, but the p-value remained insignificant. The Wilcoxon signed-rank test was significant at the 5% level for all three chosen time periods. Here, the p-value became higher at day 0, from 0.000 to 0.022. A common problem for parametric tests is the under-rejection symptom that happens with relatively long event windows. Moreover, parametric tests are more sensitive to event-induced volatility, which can further lead to under-rejection of the null hypothesis (Kolari & Pynnonen, 2010). Since non-parametric tests have superior statistical power compared to parametric tests, the first hypothesis could be accepted. *H1: Stock prices were significantly negatively affected by the announcement of the United States government shutdown on December 22, 2018.* Notedly, Appendix C shows the p-values from measuring the CARs with an event window of [-1,1]. Here, the Patell Z test was at the 1%-level significant for day 0 and day 1, both with a p-value of 0.000. Day -1 was not significant and had a p-value of 0.830. The Wilcoxon signed-rank test was then only significant at day 0 with a p-value of 0.005, and day -1 and day 1 had p-values of, respectively, 0.141 and 0.202.

For the reopening of the government, the Patell Z test was once more insignificant. The Wilcoxon signed-rank test was significant at the 10%-level for day -30 and significant at the 1%-level for day 0 but insignificant for day +30. This meant that the second hypothesis could be accepted. *H2: Stock prices were significantly positively affected by the announcement of the United States government reopening on January 25, 2019.* Appendix C displays the p-values for the government reopening with a time window of [-1,1]. Here, the p-values of day -1, 0 and

1 of the Patell Z test were all insignificant. The three days of the Wilcoxon signed-rank test were all significant at the 1%-level with, respectively, p-values of 0.002, 0.000 and 0.000.

Table 3: Patell Z test and the Wilcoxon signed-rank test for the CARs.

This table contains the p-values of the parametric Patell Z test and the non-parametric Wilcoxon signed-rank test for the Cumulative Abnormal Returns on day -30, 0 and +30 of the event window [-30,30]. The first two lines of the table display the p-values of the government shutdown and the second two lines the p-values of the government reopening.

	Patell Z test			Wilcoxon signed-rank test		
			Government shutdown			
Event date	-30	0	+30	-30	0	+30
P-value CAR	0.645	0.196	0.999	0.000	0.022	0.000
			Government reopening			
Event date	-30	0	+30	-30	0	30
P-value CAR	0.418	0.924	0.999	0.092	0.000	0.792

3.2 Panel regression analysis

The assumption is that abnormal returns are normally distributed. An F-test can determine if data needs to be fitted with a pooled OLS or a fixed-effects panel regression to include industry fixed effects. If the F-test is significant, the pooled OLS is rejected, and the fixed effects model needs to be enforced. Secondly, the Hausman test is applied for a random or fixed-effects model. The null hypothesis of the Hausman test says that the random-effects model is appropriate. The alternative hypothesis states that applying the fixed-effects model is appropriate. The data contains significant fixed effects when the p-value is below 5%. Table 4 shows the F-test for the pooled OLS regression and the Hausman test for the fixed-effects model. The p-value of the F-test was 0.00, meaning that the null hypothesis could be rejected and that panel regression with industry effects was the appropriate model to use. The Hausman test provided another p-value of 0.000, with the conclusion that the fixed-effects model was the suitable model to use. These p-values were the same for the government shutdown and the government reopening and are therefore only depicted once.

Table 4: F-test and Hausman test

This table shows the p-values of the F-test for pooled OLS regression or panel regression with fixed effects model and the Hausman test for fixed effects or random effects model.

	F-test	Hausman
P-value	0.000 (F: 155.91)	0.000 (chi2: 2508.05)

This resulted in the following two-panel regressions with fixed effects, where, first, the effect of ASVI on CAR was measured alone and thereafter with the control variables.

$$CAR_{i,t} = \alpha + \beta_1 * ASVI_t + FE + u_{i,t};$$

$$CAR_{i,t} = \alpha + \beta_1 * ASVI_t + \beta_2 * Volatility_t + \beta_3 * Size + \beta_4 * Turnover + \beta_5 * Bid\_Ask + FE + u_{i,t}$$

where $CAR_{i,t}$ is the cumulative abnormal return, coefficient α is a constant, β_x is the beta coefficient before the independent variables, $Volatility_t$ is the volatility of stock return, $Size$ stands for the natural logarithm of market capitalization, $Turnover$ is the natural logarithm of the trading volume divided by the number of shares outstanding, Bid_Ask is the bid-ask spread relative to the share price, FE is the fixed effects model and $u_{i,t}$ is the error term. All these regressions were tested for heteroskedasticity and autocorrelation. Heteroskedasticity was corrected for using robust standard errors, and autocorrelation was corrected with Newey-West standard errors. These problems needed to be accounted for; otherwise, the coefficients, the standard errors and p-values could not be interpreted.

4 Data

The first part of the data section shows the data collection process and demonstrates the return on the index and the SVI against the event window. The second part explains the stock market data with the variables of returns, volume and bid-ask spread. The third part elaborates on the independent variable from Google Trends.

4.1 Data collection

The data used in this paper were obtained from Wharton Research Services (WRDS) and Google Trends. The data obtained from WRDS included index returns, daily stock prices, bid-ask spreads, trading volumes, numbers of shares outstanding and Standard Industrial Classification (SIC) codes. The downloaded stock data were from the S&P 500 companies around the event period from November 1, 2018 to March 31, 2019. The S&P 500 was used due to the size and number of companies in the index. The two events were on December 22, 2018 and January 25, 2019. There were more observations (505) than companies (500) in the dataset. This was caused by companies such as Google, Under Armour, News Corporation, Discovery and Fox that offered two classes of shares. Google, News Corporation and Fox had class A and B shares, and Under Armour and Discovery had class A and C shares. The classes of shares differ by shareholder rights. Class A shares have more voting power compared to class B shares. Certain observations were lost after merging the entire dataset; this left the file with 484 companies. Furthermore, the daily search volume index (SVI) of related search terms on the government shutdown around the event period were downloaded from Google Trends. The SVI data was only downloaded for the US since the S&P 500 includes US companies and since the shutdown happened in the US. Preis et al. (2013) have found that US data is more suitable than global data when using a US stock market.

Figures 6 and 7 demonstrate the probable cause of this paper. Figure 6 clearly shows decreasing stock returns of the S&P 500 index before the announcement of the federal government shutdown, indicating that investors were anticipating the shutdown, which lowered share prices in advance. This anticipation effect could cause the actual announcement return of the shutdown to be small in magnitude since the stock market had already incorporated the effect of the shutdown in the price. The same anticipation effect could be seen with the reopening of the government, as seen in Figure 7. The level of the S&P 500 index increased before the actual announcement of the reopening of the government. The stock market had already increased in anticipation of the good news. A rebound of the stock market after a crash is a phenomenon that is frequently seen in historical data. For a majority of cases, the stock market will return to its original level. Stock markets are led by uncertainty and fear, which is visible in the changing returns of the market (Thooft, 2020).

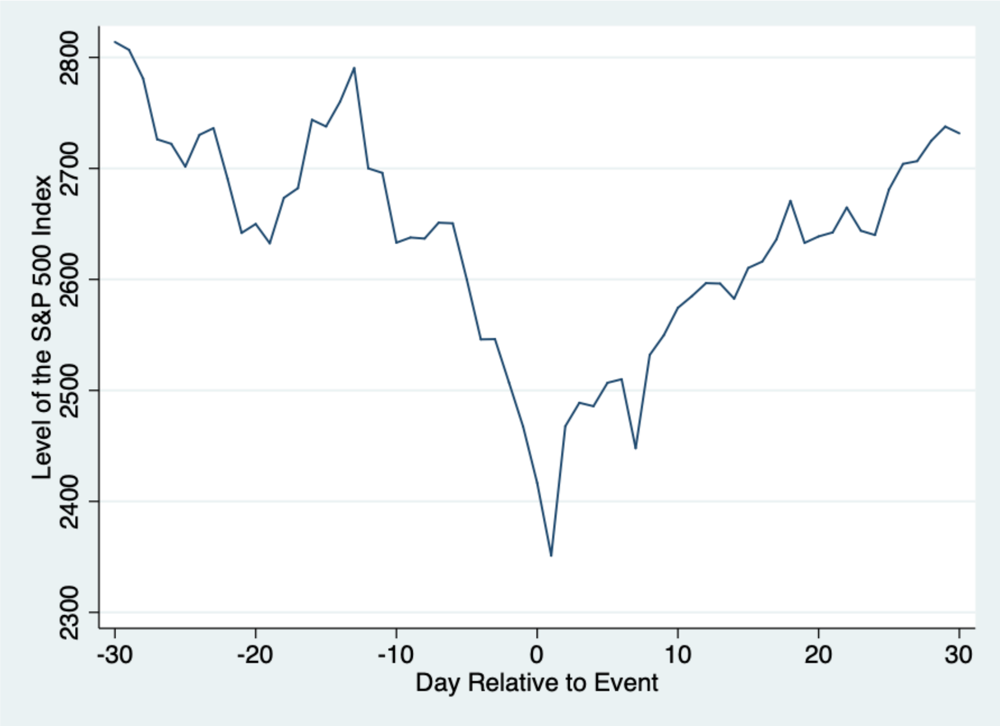

Figure 6: The level of the S&P 500 around the government shutdown

This graph shows the time-series line plots of the level of the S&P 500 index and the event window [-30,30] for the government shutdown with day 0 on December 24, 2018.

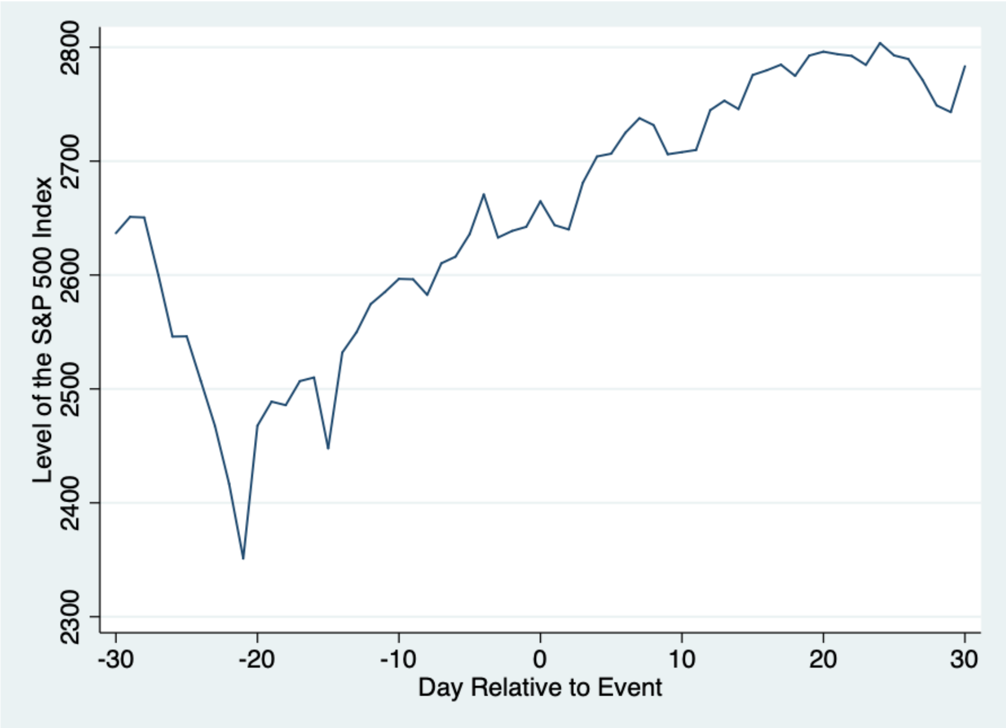

Figure 7: The level of the S&P 500 around the government reopening

This graph shows the time-series line plots of the level of the S&P 500 index and the event window [-30,30] for the government reopening with day 0 on January 25, 2019.

4.2 Google Trends data

Google Trends reports the Google SVI, which is the index of searches for a given term for the total number of searches in a selected time period. Google allows users to download this SVI data freely. The SVI was downloaded as daily data for the US for the time period of November 1, 2018 to March 31, 2019. The SVI was downloaded for 17 query terms. These were keywords related to the event and to the state of the economy and are depicted in Appendix B. All terms were narrowly correlated to the subject of this research. The underlying assumption of the Google Trends uncertainty index is that internet users search online for information when they are uncertain. This assumption implies that search volume increases when there is more uncertainty and vice versa. The Google Trends data ranges between 0 and 100 and is based on historical data of the search term for a chosen time period and region. Since the data is dependent on the time period, the data needs to be standardized.

Figure 8 and Figure 9 display the average SVI of the 17 search terms retrieved from Google Trends in regular week-days. The choice to exhibit the SVI in week-days instead of trading days was deliberate because the event happened over the weekend. Therefore, a peak was expected on that day. In contrast to the stock market, the effect of the shutdown would be incorporated on Monday, December 24, 2018. Figure 8 shows the average SVI for the government shutdown on December 22, 2018. The SVI seemed to increase and decrease in cycles over the event window with three relatively large peaks on day -1, day 18 and day 27 with, respectively, a SVI of 47, 55 and 54. Household online search was relatively high one day before the actual announcement. After day -1, the SVI decreased until day 11 when queries started increasing to higher values than those on day -1. This may have been due to the fact that government shutdowns happen more frequently in the US and that households decided to simply enjoy Christmas and New Year's Eve. Day 11 marked the date of January 2, 2019. Households possibly started to worry more when the holidays were over and increased their Google search queries. Figure 9 visualizes the average SVI around the federal government reopening on January 25, 2018. Here is a clear summit on day 0 with SVI of 62. After this summit, the SVI declined until it reached a steady SVI cycle with a maximum peak at around 35. The cycles visible from day 17 until day 30 appeared similar to the increasing and decreasing cycles of Figure 8 before the announcement of the government shutdown. Perhaps these cycles were the normal average search volume of households for these 17 terms in this chosen time period.

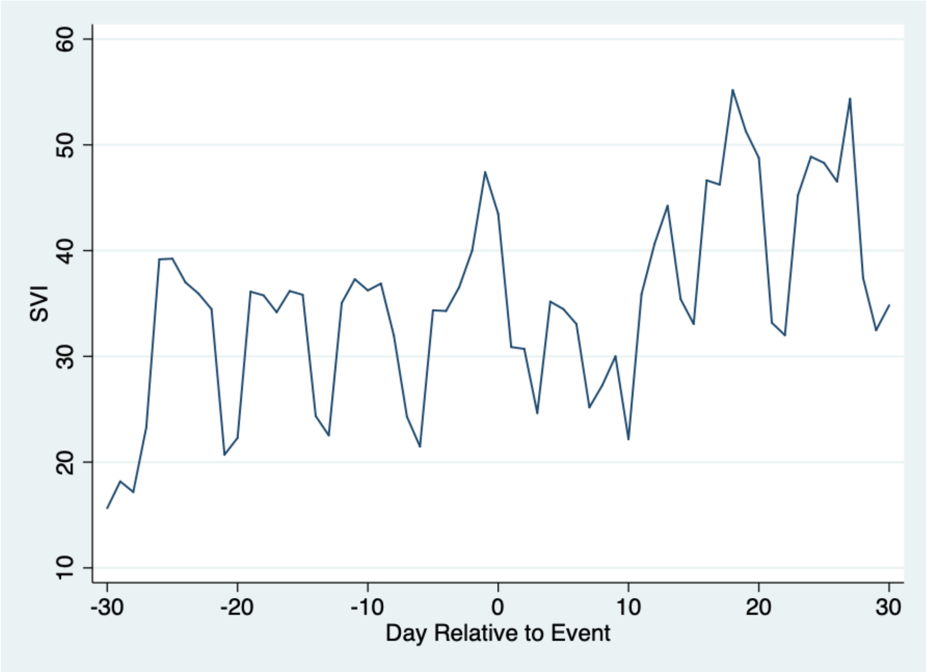

Figure 8: SVI government shutdown

The graphs shows the average SVI of the 17 chosen keywords retrieved from Google Trends relative to 30 days before and 30 days after the government shutdown announcement with day 0 on December 22, 2018.

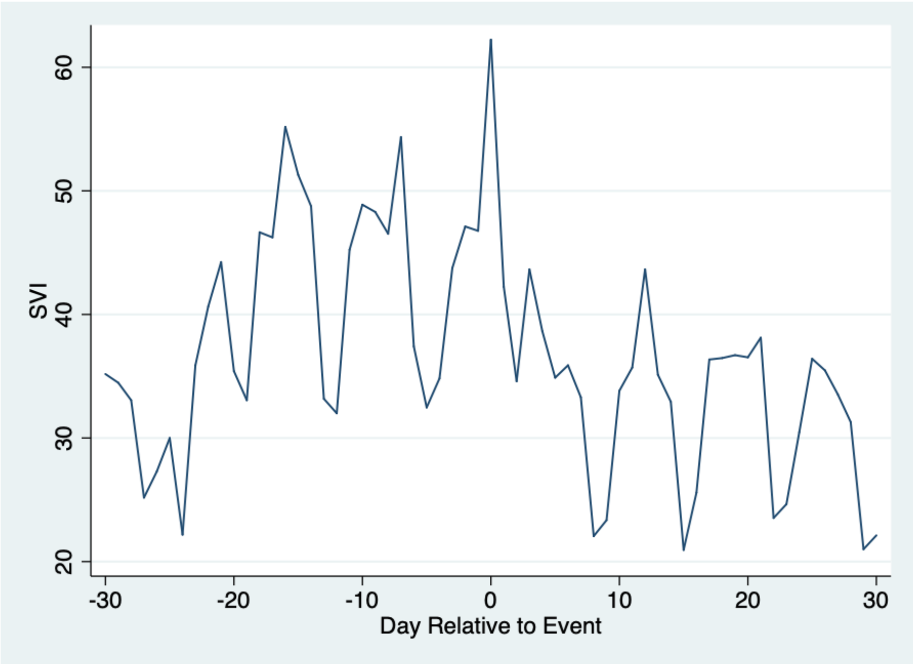

Figure 9: SVI government reopening

The graphs shows the average SVI of the 17 chosen keywords retrieved from Google Trends relative to 30 days before and 30 days after the government reopening announcement with day 0 on January 25, 2018.

The normal trend could be excluded from the data by creating an Abnormal Search Volume Index (ASVI). This paper chose to use two methods. The first method was based on Bijl et al. (2016), who subtracted the average SVI of the previous year from the SVI and divided it with the standard deviation of the previous year. This paper used daily data instead of the weekly data in Bijl et al. (2016). Daily data can only be downloaded up to a certain number of days. Therefore, to attempt to remain coherent, this paper subtracted the SVI of the previous 52 days.

$$ASVI_t = \frac{SVI_t - \frac{1}{52}\sum_{i=1}^{52} SVI_i}{\sigma_{GSV}}$$

where $ASVI_t$ is the abnormal search volume index of at time t, SVI_t is the raw average search volume at time t and σ_{GSV} is the standard deviation over prior 52 days. The second method was based on a paper by Da et al. (2011). Here, the natural logarithm of the average daily SVI is subtracted from the natural logarithm of the median SVI of the past 52 days.

$$M\_ASVI_t = \ln(SVI_t) - \ln\,[Median(SVI_{t-1}, \dots, SVI_{t-52})]$$

where M_ASVI_t is the median abnormal search volume index at time t, and $\ln\,[Median(SVI_{t-1}, \dots, SVI_{t-52})$ is the median of the SVI of the previous 52 days. The correlation between the number of queries and the return on the S&P 500 was examined with time-lagged cross-correlation. Cross-correlation shows the correlation between two time series variables at various lags, which shows if movement in one variable tends to provoke movement in the other. The analysis was performed with the return of the S&P 500 index as the independent variable and the ASVI as the dependent variable. With this method, eventually, conclusions can be drawn about internet activity and movements in the stock market (Bordino et al., 2012).

A Granger causality test was performed to investigate if changes in investor attention caused changes in stock returns or if changes in returns caused the attention of investors to change. The primary literature seemed to find that, firstly, the attention changes, and then the stock prices change with it (Irresberger et al., 2015; Bijl, Kringhaug & Molnar, 2016; Da et al., 2014). In contrast, Vozlyublennaia (2014) has found that the Granger causality between search probabilities and stock returns runs in both directions. She additionally performed a causality test on the return volatility and search probabilities and found that volatility has an effect on searches, but the reverse is less likely. This paper tested the Granger causality between CARs and the ASVI. Moreover, to verify the results of Irresberger et al., 2015 Bijl, et al. (2016), Da et al. (2014) and Vozlyublennaia (2014), another Granger causality test was performed between stock return and ASVI

To perform a Granger causality test, the data needs to be stationary. Since this paper used panel data, the unit root test was a Dickey-Fuller test altered by Levin, Lin and Chu (2002). Non-stationarity of the data would lead to spurious regressions. The assumption for the unit root and Granger causality test was that the panel data set would be balanced and without gaps. Since stock returns are based on trading days, which contains gaps, the data did not fill the requirement. To solve this, a balanced data set without gaps was created by using the event window as the time variable instead of the date. From Figure 4, Figure 6 and Figure 8, that there was no trend in the CAR, the level of the S&P 500 and in the SVI is visible. However, there could, nonetheless, be a drift or autocorrelation in the error terms. The null hypothesis states that the data is a unit root and the alternative hypothesis that the data is stationary. Solving for CAR, return, ASVI and M_ASVI, the p-values were, respectively, 0.002, 0.000, 0.000 and 0.000, meaning that the variable ASVI, return and CAR were stationary. These results are displayed in Table 5.

Table 5: Unit root test

This table contains the p-values of the augmented Dickey-Fuller unit root for panel data, to test for non-stationarity in the data for the CARs [-30,30], the S&P 500 index return, the ASVI and the M_ASVI. ***, ** or * mean that the p-value is significant on the 1%, 5%, or 10%-level.

	CAR [-30,30]	Return	ASVI	M_ASVI
Dickey-Fuller test (p-value)	0.002***	0.000***	0.000***	0.000***

Since the data was stationary, the Granger non-causality test for panel regressions of Dumitrescu and Hurlin (2012) could be performed. The null hypothesis was that the ASVI would not Granger cause CAR. If the null hypothesis was to be rejected, there would be a Granger causality, and past values of the ASVI could predict CARs. The basic idea is written below in the first equation:

$$CAR_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} * CAR_{i,t-k} + \sum_{k=1}^{K} \gamma_{ik} \, ASVI_{i,t-k} + e_{i,t}.$$

This was further tested for the other direction. The null hypothesis that CAR would not Granger cause the ASVI was tested with this second equation:

$$ASVI_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} * ASVI_{i,t-k} + \sum_{k=1}^{K} \gamma_{ik} \, CAR_{i,t-k} + e_{i,t} \ .$$

If the p-value was to be greater than 5%, the null hypothesis would be accepted, and the variables would not Granger cause one another. The same equations could be used to test Granger causality between Return and ASVI. The results of the Granger causality test are shown in Section 5.

4.3 Control variables

More explanatory variables were added to correct for possible biases in the data – variables such as volatility, size, trading volume and bid-ask spread.

3.4.2 Volatility

Volatility is a determinant factor and seen as a proxy for financial uncertainty (Bloom, 2009). During economic policy shocks, uncertainty grows and volatility does as well. Volatility is calculated as the standard deviation of stock returns.

$$Volatility = \sqrt{\frac{\sum_{i=1}^{N}(R_{i,t} - \overline{R_{i,t}})^2}{N-1}}$$

where $R_{i,t}$ is the return of stock i on day t, and $\overline{R_{i,t}}$ is the mean return.

3.4.3 Size

Size was added as a control variable because the size of a firm and the stock return and stock volatility are narrowly related. Size was calculated as the natural logarithm of the market capitalization to control for outliers. Market capitalization is the number of shares outstanding multiplied by the current value of one share:

$$Size = \ln \,(number\ of\ shares\ outstanding * share\ price).$$

3.4.4 Trading volume

Volume is the total number of shares sold on day t and expressed in units of one share. Trading volume can represent the liquidity depth of the stock market (Düz Tan & Taş, 2019). Trading turnover is created by dividing trading volume with the total number of shares outstanding and taking the natural logarithm.

$$Turnover_{i,t} = \ln \left(\frac{Trading\ volume_{i,t}}{Number\ of\ shares\ outstanding_{i,t}}\right)$$

3.4.5 Bid-ask spread

The bid-ask spread is the difference between the buy and sell price of a security. When a stock is more liquid, the bid-ask spread should be small. The ask price is always higher than the bid price; thus, the bid-ask spread should be positive. The bid-ask spread is stated in percentage terms of the stock price to show the real value of the spread.

$$Bid\_Ask = \frac{Ask - Bid}{price} * 100$$

Table 6: List of variable explanations

This shows the variables used in the regressions with their abbreviation and explanation. The dependent variable CAR [-30,30] was retrieved through an event study with the market model. The independent variables ASVI and M_ASVI were constructed with Google Trends data. The control variables were firm size, volatility, turnover volume, bid-ask spread percentage and industry.

Variable	Abbreviation	Explanation
Dependent variables		
Cumulative abnormal return	CAR	CAR is short for cumulative abnormal return and is the sum of all the abnormal returns.
S&P 500 return	Return	The average return of the companies in the S&P 500 index
Independent variables		
Abnormal search volume index	ASVI	ASVI represented the daily abnormal search volume of household based on the paper of Bijl et al. (2016). The ASVI was calculated by subtracting the average SVI of the previous 52 days of the SVI and dividing it by the standard deviation.
Abnormal search volume index	M_ASVI	The median abnormal search volume index was based on the paper of Da et al. (2011) and was calculated by subtracting the median of the previous 52 days from the SVI at time t.
Control variables		
Firm size	Size	Firm size was based on the natural logarithm of the market capitalization (number of shares x share price).
Volatility	Vol	Volatility was based on the standard deviation of daily stock return.
Turnover volume	Turnover	Turnover volume was the natural logarithm of trading volume divided by the number of shares outstanding and simulated the liquidity depth of the market
Bid-ask spread percentage	Bid_ask	Bid-ask spread was a measure for the liquidity tightness on the market. It was the bid-ask spread of a stock relative to the share price.
Industry	Industry	Industry was the specific sector a company earned its operating revenue from based on the SIC code.

5 Results

This section explains the main results and attempts to link the results to the literature. Furthermore, this chapter answers the hypothesis from Section 2 and starts analysing the data with descriptive statistics and the underlying correlation. Next, the various regressions that were performed with a robustness check are presented, and, finally, the time-lagged cross-correlation and Granger causality results are discussed.

5.1 Descriptive statistics

Table 7 demonstrates the descriptive statistics for the CAR, return, SVI, ASVI, M_ASVI, bid-ask spread, volatility, size and turnover volume. The number of observations was 29,524 for all the variables, which consisted of 484 companies. The mean of the CAR was close to 0; therefore, on average, there were hardly any abnormal returns. The S&P 500 market return was 0, which seemed normal across the event period, where the markets decreased and later increased back to original levels. The time series data of the SVI, ASVI and M_ASVI were added to the panel regression data with the data of the S&P 500 companies. This led to the SVI being duplicated for each company at each unique date. Dates that did not match were dropped. These were weekend and holiday dates since S&P 500 data was in trading dates. Table 7 neatly demonstrates the difference between the ASVI and the M_ASVI. The max ASVI was 2.860, which was far away from the downloaded data, where the maximum value was 100. Furthermore, it was interesting to examine the skewness and kurtosis in the data. For a normal distribution, which is assumed with an OLS regression, the skewness would be ideal with a value of zero and be a value close to three for the kurtosis. Here, the ASVI had values of -0.028 and 3.404, and the M_ASVI had values of -0.468 and 4.663. It seemed that the ASVI was more normally distributed than the M_ASVI. The bid-ask spread had a minimum value of 0, meaning that the buy and sell price of that stock was the same and that the stock was highly liquid. The bid-ask spread could not be negative because the ask price is always higher than the bid price; therefore, this appeared accurate. However, there was a certain positive kurtosis in the bid-ask spread. The maximum spread was 20.74%, which seemed to be a reasonable number for large companies as on the S&P 500 index. Size was calculated with the natural logarithm of market capitalization to make the data more normally distrusted. Market capitalization at one point contained negative values, but those were dropped, leaving only positive values. Turnover had some positive kurtosis, indicating a heavy-tailed distribution.

Table 7: Descriptive statistics

This table displays the observations, mean, standard deviation, minimum, maximum, skewness and kurtosis of the CAR [-30,30], the return on the S&P 500, the SVI, the ASVI based on Bijl et al. (2016), the M_ASVI based on Da et al. (2011), the bid-ask spread relative to the stock price multiplied with 100, the volatility of the stock price, the size based on the natural logarithm of market capitalization and the turnover volume based on trading volume.

Variable	Obs.	Mean	Std. Dev.	Min	Median	Max	Skewness	Kurtosis
CAR [-30,30]	29,524	0.003	0.087	-0.483	0.008	0.377	-0.481	5.516
Return	29,524	0.000	0.021	-0.293	0.001	0.202	-0.207	9.594
SVI	29,524	38.338	7.620	17.882	36.118	59.235	0.403	3.214
ASVI	29,524	0.734	0.9111	-1.997	0.746	2.860	-0.028	3.404
M_ASVI	29,524	0.097	0.193	-0.616	0.081	0.509	-0.468	4.663
Bid_ask	29,524	2.712	1.406	0	2.384	20.740	1.867	10.616
Volatility	29,524	0.020	0.006	0.007	0.019	0.055	1.344	6.270
Market cap.	29,524	4.55e+07	8.27e+07	328935.6	1.94e+07	9.89e+08	5.676831	46.13863
Size	29,524	16.995	1.001	12.704	16.780	20.713	0.813	3.633
Turnover	29,524	2.052	0.620	-5.213	2.019	5.788	-0.672	13.610

5.2 Correlation

Table 8 discloses the pairwise correlation between variables that was used in the later regressions. All the correlations were significant between the CAR and the explanatory variables. There was a negative correlation for the CAR with ASVI (-0.032), M_ASVI (-0.020), bid_ask (-0.097), volatility (-0.138) and turnover (-0.089), meaning that when abnormal returns decreased, Google queries increased. Section 5.4 later establishes what occurred – the increase in Google queries or the decrease in abnormal returns. The correlation with the bid-ask spread meant that the spread became wider when the abnormal returns decreased, which seemed accurate. There was a wider spread when the abnormal returns became more negative and times were more uncertain. Additionally, volatility increased during uncertain times with more negative CARs. Furthermore, size experienced positive correlation, as larger firms were less affected and had smaller negative abnormal returns. This was in line with Vozlyublennaia, (2014). Turnover had a negative correlation, meaning that higher trading volume compared to their number of shares outstanding experienced larger negative CARs. This could mean that firms were frequently shorted or sold before this negative announcement, which caused downward pressure on the on stock and therefore caused more negative CARs.

ASVI and M_ASVI were similar variables, and this could be further seen in their significant positive correlation of 0.953. The ASVI was significantly positively correlated at the 1%-level with bid-ask spread (0.034) and turnover (0.109). Both metrics increased when Google query volume increased. This could be due to the fact that during uncertain times, households searched more online and traded based on this information, resulting in a higher turnover. Since times were uncertain, a broker would want a higher premium for its stocks, increasing the bid-ask spread. The paper of Bordino et al. (2012) additionally found a positive correlation between trading volume and online searches.

Size was negatively related to ASVI and significant at the 5%-level. Smaller firms were more affected by an increased Google search volume. Uncertainty increased the Google queries, and smaller firms had higher chances of going bankrupt during those relatively negative economic times. Moreover, smaller firms could yield higher abnormal returns during negative economic times, which raised the attention of investors.

There was a large significant positive correlation between volatility and the bid-ask spread. The bid-ask spread became wider when volatility increased. Both were positively affected when economic policy uncertainty increased. Size was negatively related to the bid-ask spread (-0.111), with a smaller bid-ask spread for larger firms. A broker could readily sell shares of large notable firms with less chance of bankruptcy. Furthermore, this paper found a positive correlation between turnover and volatility (0.451), which is a well-known relationship in the literature, as seen in, for example, Kim et al. (2019). Turnover and size were significantly negatively correlated (-0.277). Large firms were traded less by households. Investors maintained larger company shares in their portfolios and did not expect them to drop in share price or go bankrupt as much as relatively smaller companies. This was complementary to the other results, where smaller firms were more negatively affected by economic uncertainty. Size and volatility were negatively correlated (-0.110). Larger firms were less volatile. The price did not change as much as with smaller firms.

Table 8: Pairwise correlation matrix

This table shows the correlation between the variables in the model. The variables are CAR, ASVI based on Bijl et al. (2016), M_ASVI based on Da et al. (2011), bid-ask spread, trading turnover, stock volatility and firm size. ***, ** or * mean that correlation is significant at the 1%, 5%, or 10%-level

Variables	CAR [-30,30]	ASVI	M_ASVI	Bid-ask	Volatility	Size	Turnover
CAR [-30,30]	1						
ASVI	-0.032***	1					
M_ASVI	-0.020***	0.953***	1				
Bid-ask	-0.097***	0.034***	-0.037***	1			
Volatility	-0.138***	0.000	0.000	0.436	1		
Size	0.059***	-0.012**	-0.008	-0.111***	-0.110***	1	
Turnover	-0.089***	0.108***	0.096***	0.503***	0.451***	-0.277***	1

5.3 Regression

Table 4 shows that a panel regression with fixed effects was the appropriate model to use. The first model consisted of a panel regression with fixed effects for only the CAR and ASVI. The second model added the control variables. The regression had CAR as the dependent variable and ASVI measured with 17 search query terms as the independent variable. The M_ASVI is displayed in Appendix D. All regressions were corrected for heteroskedasticity and autocorrelation. This paper found a negative significant coefficient for the government shutdown, as shown in Table 9 models 1 and 2 of -0.003 for ASVI, meaning that when ASVI increased by 1, the CARs decreased by 0.003. For the government reopening, the ASVI was larger, with -0.005 for Table 10 model 2. This might have been because the ASVI had declined since the end of the shutdown. Consequently, when the CARs increase, the ASVI decrease. Da et al. (2014) examined S&P 500 daily returns and an ASVI called the FEARS index. They reported a negative significant coefficient of -0.005, which lay close to the coefficients found in this paper. The standard deviations were the same as well, being 0.001. Da et al. (2014) concluded that an increase in standard deviation resulted in a decline of 19 basic points for the daily S&P 500 index. The same conclusion could not be drawn for this paper since this paper used CARs as the dependent variable, and Da et al. (2014) indexed returns with lagged returns as control variables.

Volatility was negatively significant, as seen in Table 9 model 3 (-4.146) for the government shutdown. The volatility of the government reopening was insignificant and therefore not interpretable. There were negative CARs for the government shutdown; therefore, an increase in volatility of 1, and, hence, more uncertainty resulted in a -4.146 decrease in the CARs. This was in line with the work of Antonakakis et al. (2013), who found an increase in volatility during policy uncertainty when returns decreased. Hypothesis 3 could be accepted: *H3 – Stock price volatility increased during the United States government shutdown from December 22, 2018 to January 25, 2019.* For the coefficient, firm size had a significant positive effect for the government shutdown (0.010) and an insignificant positive association for the government reopening (0.004) in model 2. If size increased by 1%, the CARs changed upward by 0.010. Larger firms experienced less negative CARs in negative times. Larger firms had a lower chance of going bankrupt and were seen as savers more than small firms during uncertain times. The fourth hypothesis could be accepted: *Firms size is positively affected during uncertain times such as the United States government shutdown from December 22, 2018 to January 25, 2019.*

The coefficient for turnover in Tables 9 and 10 of model 2 was not significant and therefore not interpretable. The fifth hypothesis could not be answered: *H5 – The trading volume of stocks become negatively affected during uncertain times such as the United States government shutdown from December 22, 2018 to January 25, 2019.* There was a positive coefficient between the CAR and the turnover, which would have meant that when the turnover increased by one, the CAR additionally increased, meaning that investors traded more when there were higher positive abnormal returns, which would be in line with the insider trading theory. The bid-ask spread had a significant influence on the CAR. If the bid-ask spread increased by one, then the CAR decreased by 0.004 for the government shutdown, as seen in Table 9 model 2, and by 0.007 for the government reopening, as seen in Table 10. A wider bid-ask spread meant that the stock was less liquid and this provided a negative signal to the market, resulting in negative cumulative abnormal returns, and when there were positive CARs, the bid_ask spread reduced. The sixth hypothesis was accepted: *H6 – The bid-ask spread of stocks is positively affected during uncertain times such as the United States government shutdown from December 22, 2018 to January 25, 2019.*

To examine separate industries, the fixed effects were excluded, and the industry dummy was included. There were 212 industries, which added to an excessive number to display, but a majority of coefficients were significant at the 1%-level, with several having positive coefficients and others negative coefficients. The SIC code 1021 represented copper ores and had a positive significant coefficient at the 1%-level with 0.133. SIC code 2834 represented pharmaceutical preparations and had a significant value of -.187. From this observation, the seventh hypothesis could be accepted. *H7 – The effects on the stock returns were different per industry for the government shutdown from December 22, 2018 to January 25, 2019.* Figure x shows higher spikes of the SVI during the shutdown period before and after. Therefore, the eighth hypothesis was accepted. *H8 – There are more Google queries of specific keywords around the period of the US government shutdown from December 22, 2018 to January 25, 2019.*

Table 9: Panel regression results government shutdown

Two panel regression with fixed effects models and robust standard errors. Model 1 contains the dependent variable CAR [-30,30], for the government shutdown, and the independent variable ASVI measured with 17 search words. Model 2 also contains the control variables: volatility, bid-ask spread, turnover, and firm size. The standard error is displayed in brackets. ***, ** or * mean that the coefficients are significant at the 1%, 5%, or 10%-level.

Variable	Model 1	Model 2
Intercept	0.005***	-0.075
	(0.000)	(0.076)
ASVI	-0.003***	-0.003***
	(0.001)	(0.001)
Volatility	-	-4.146***
		(1.003)
Bid-Ask	-	-0.004***
		(0.001)
Turnover	-	0.001
		(0.003)
Size	-	0.010**
		(0.004)
Industry dummy	No	No
FE	Yes	Yes
Observations	29,524	29,524
Adjusted R^2	0.002	0.097

Table 10: Panel regression results government reopening

Two panel regression with fixed effects models and robust standard errors. Model 1 contains the dependent variable CAR [-30,30], for the government reopening, and the independent variable ASVI measured with 17 search words. Model 2 also contains the control variables: volatility, bid-ask spread, turnover, and firm size. The standard error is displayed in brackets. ***, ** or * mean that the coefficients are significant at the 1%, 5%, or 10%-level.

Variable	Model 1	Model 2
Intercept	0.009***	-0.074
	(0.001)	(0.069)
ASVI	-0.007***	-0.005***
	(0.002)	(0.001)
Volatility	-	0.750
		(1.309)
Bid_ask	-	-0.007***
		(0.001)
Turnover	-	0.005
		(0.004)
Size	-	0.004
		(0.004)
Industry dummy	-	No
FE	Yes	Yes
Observations	29,524	29,524
Adjusted R^2	0.011	0.026

5.4 Cross-correlation and Granger causality

Tables 11 and 12 report the values of a time-lagged Pearson cross-correlation between the two time series market returns and ASVI. The correlation can range from anticorrelation (-1) to positive correlation (1). As in Bordino et al. (2012), the number of lags ranged from -5 to 5. Table 11 contains the cross-correlation results between the return on the S&P 500 and the ASVI. On lag 0, the correlation was at its most with 0.172. The correlation did not slowly fade, as in the paper of Bordino et al. (2012). After lag 0, lags -1 and -2 decreased further to negative correlation values for lag 2 (-0.018). Thereafter, lag 3 increased to 0.151, and then lags 4 and 5 decreased to 0.074 and -0.007. This seemed to be a pattern where the time-lagged cross-correlation first increased and then decreased. For lag 0 to lag 5, the correlation slowly declined from 0.172 to 0.046. Only lag 5 (0.0046) was larger than lag 4 (0.008). The correlation at lag 0 showed that the returns on the S&P 500 and Google searches were positively related. The positive correlation for the negative lags confirmed the idea that internet activity influenced investor behaviour. This effect held for several days since the correlation did not fade quickly. This could have been caused by the anticipation effect. Table 12 reports the lagged cross-correlation between the CAR and the ASVI. The independent variable is the CAR and the dependent the ASVI. The correlation between these two variables was negative. At lag 0, the correlation was -0.383. The correlation slowly decreased when moving to lag -5 and lag 5, with minimal distortions at lag -2 and lag 3. Online activity provoked future abnormal returns. In this case, the abnormal returns were negative since the effect was measured for a negative announcement. Here, the ninth hypothesis could be accepted. *H9 – There was cross-correlation between query volume in Google Trends and the cumulative abnormal returns on the S&P 500 around the shutdown period from December 22, 2018 to January 25, 2019.*

Table 11: Lagged cross-correlation between the S&P500 return and ASVI

Lag	-5	-4	-3	-2	-1	0	1	2	3	4	5
CCF	-0.007	0.074	0.151	-0.018	0.029	0.172	0.103	0.078	0.011	0.008	0.046

Table 12: Lagged cross-correlation between the CAR and ASV

Lag	-5	-4	-3	-2	-1	0	1	2	3	4	5
CCF	-0.198	-0.251	-0.260	-0.367	-0.355	-0.383	-0.186	-0.096	-0.139	-0.084	-0.166

A Granger causality test was performed to research the anticipation effect more and test the significance of the cross-correlation. Table 13 reports the p-value of the Granger causality test. Note that the Granger causality test only gives the direction of a relationship and does not imply causality. The M_ASVI is in the appendix since the results were similar to those of the ASVI. The CAR and ASVI had two lags and returns, and ASVI had one lag since this was the outcome of the lag-order selection previously done. For the first line of Table 13, the null hypothesis states that lagged ASVI did not Granger cause CAR. The p-value was 0.308, which meant that the null hypothesis could be accepted and that ASVI did not Granger cause CAR. Past values of ASVI could not predict the CAR. For the second line of the table, the p-value was 0.000, meaning that CAR did Granger cause ASVI. Past CARs contained information that helped to predict ASVI. This meant that households saw changes in stock market returns and then started searching online for answers. For the return on the S&P 500 and the ASVI, the p-value was 0.000 of the Granger causality for both directions. This was in line with Vozlyublennaia (2014), who found that changes in returns could significantly affect changes in returns. The same conclusion could be drawn from the M_ASVI, shown in appendix E.

Table 13: Granger causality tests

Granger causality test results for CAR and Abnormal Search Volume Index with 1 lag and Return and ASVI with 2 lags. P-values smaller than 5% are significant.

Dependent	Independent	p-value
CAR	ASVI	0.308
ASVI	CAR	0.000
Return	ASVI	0.000
ASVI	Return	0.000

The answer to the main research question of this paper was *'What was the effect of economic policy uncertainty on the stock market around the period of the US government shutdown from December 22, 2018 to January 25, 2019?'* The results revealed a limited effect of economic policy uncertainty on the stock market caused by the event. This limited effect is in line with previous papers written by Bachmann and Bayer (2013), Bekaert, Hoerova and Lo Duca (2013), Chugh (2016) and Popescu and Smets (2010). In Figure 4 with day 0 on December 24, 2018, the average CAR was -0.008, showing a small negative CAR. For Figure 5 with day 0 on January 25, 2019, the average CAR was 0.004 – a small positive announcement effect. These results were in line with those of Woodard (2015), who investigated prior government shutdowns in 1995 and 2013. Similar to Pastor and Veronesi (2012), the anticipation effect diminished the effect on the stock market. From Figures 6 and 7, it is clearly visible how the level of the S&P 500 starts decreasing before the government shutdown announcement and restores itself before the reopening announcement. Furthermore, volatility increased during economic policy uncertainty, and stock returns of larger firms were less affected. The bid-ask spread widened during negative announcements and became smaller with positive announcements, indicating the liquidity of the market.

6 Conclusion

This study attempted to determine the relationship between economic policy uncertainty as revealed by Google search queries and the stock market represented by the S&P 500 during the US government shutdown from December 22, 2018 to January 25, 2019. Table 3 shows that the CAR did have significant negative announcement effects for the government shutdown and significant positive announcement effects for the government reopening, determined with a market model and validated with the non-parametric Wilcoxon signranked test. Nonetheless, there was evidence that the anticipation effect and insider trading possibly diminished the abnormal returns on the actual announcement days. Figure 1 shows a spike in trading volume before the government shutdown announcement, which could be evidence of insiders trading on private information.

Given the cross-correlation results, there was a negative correlation between CARs and ASVI, and the returns and ASVI were inconclusive. The Granger causality test showed significant results for the return on the S&P 500 and the ASVI in both directions, indicating that past returns influenced ASVI and that ASVI influenced returns. For the CAR and the ASVI, only the directions established that CARs Granger caused ASVI. Future ASVI could be determined with past CARs. The panel regression with industry fixed effects showed a small negative coefficient of 0.003 for ASVI during times of economic uncertainty – in line with prior research. Furthermore, bid-ask spread and volatility were negatively associated with the CAR and size significantly positively associated. The main conclusion of the paper is that there was a limited effect of economic policy uncertainty on the stock market around the government shutdown period although this effect was dampened by anticipation effects and possible insider trading.

The limitations of this paper were the relatively small data set. A larger data set with more time periods or more shutdowns could make a more generalized conclusion. Additionally, another index with smaller firms could have made a larger impact to describe the differences in firm size for announcements effects and insider trading. It would be a useful extension for further research to include more indexes with more differentiated firms, such as the broad Wilshire 5000 or the Russel index with smaller companies. Additionally, the calculations of the abnormal returns were limited to the assumptions of the market model and the event window. Different asset pricing models or event windows could change the results of this paper. A similar case could be made for the ASVI, which was based on the 17 chosen search terms and time period. A potential avenue for future research is to examine whether the ASVI has more power for shorter event windows. It would further be interesting to use the ASVI as the dependent variable to see what determines the ASVI or investigate possible insider trading when the employees of the SEC were on furlough around multiple government shutdowns.

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8 Appendix

Appendix A

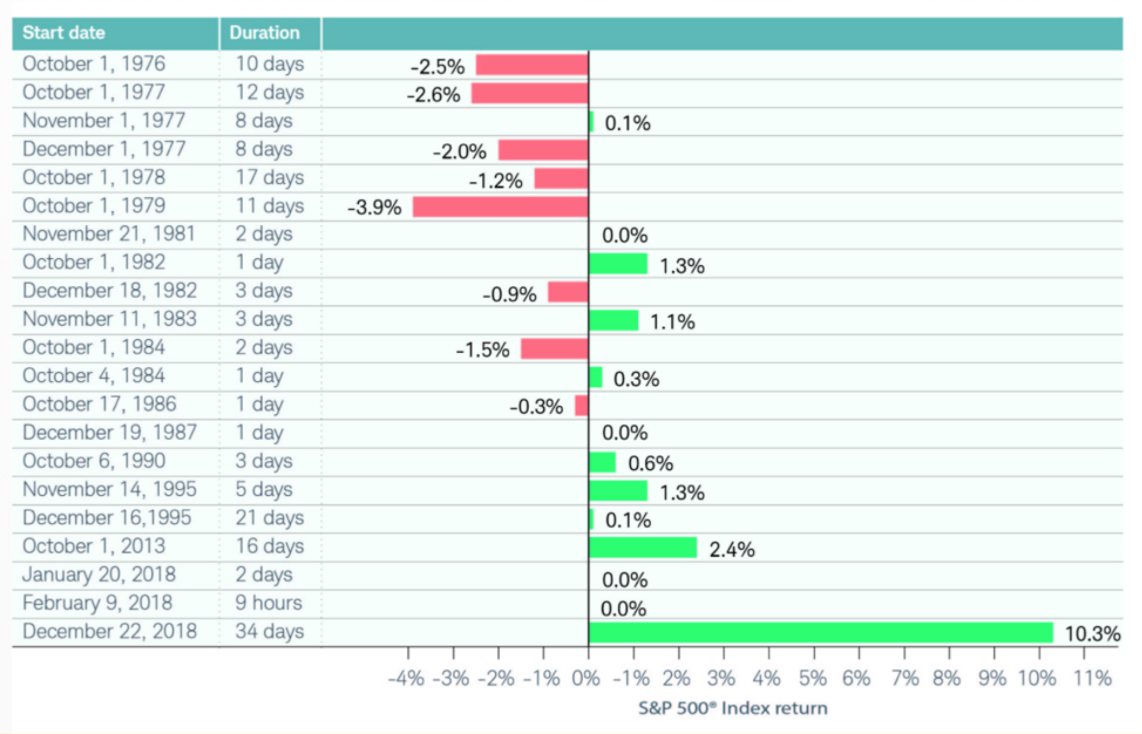

Figure A: S&P 500 Return and government shutdowns

This figure shows the effect of the US government shutdowns and the S&P 500 return. Source: Schwab Center for Financial Research with data provided by Standard & Poor's, and the Congressional Research Service (https://www.schwab.com/resource-center/insights/content/how-government-shutdowns-have-affected-stock-market).

Appendix B

Table B: Search volume index terms

This table shows the 17 chosen search terms retrieved from Google Trends. The search terms consists out of general terms that defined the state of the economy and terms specific for the government shutdown.

Search terms	
Government shutdown	Unemployment
Government reopening	S&P 500
Trump administration	Uncertainty
Federal shutdown	Economy
Federal reopening	Policy
Border wall	GDP
Funding	Government
Donald Trump	Congress
Mexican border	

Appendix C

Table C: Patell Z test and the Wilcoxon signed-rank test for the CARs.

This table contains the p-values of the parametric Patell Z test and the non-parametric Wilcoxon signed-rank test for the CARs on day -1, 0 and +1 of the event window [-1,1]. The first 2 lines of the table display the p-values of the government shutdown and the second 2 lines the p-values of the government reopening.

	Patell Z test			Wilcoxon signed-rank test		
			Government shutdown			
Event date	-1	0	+1	-1	0	+1
P-value CAR	0.830	0.000	0.000	0.141	0.005	0.202
			Government reopening			
Event date	-1	0	+1	-1	0	+1
P-value CAR	0.931	0.993	0.999	0.002	0.000	0.000

Appendix D

Table D1: Panel regression results government shutdown

Two panel regression with fixed effects models and robust standard errors. Model 1 contains the dependent variable CAR [-30,30], for the government shutdown, and the independent variable M_ASVI measured with 17 search words. Model 2 also contains the control variables: volatility, bid-ask spread, turnover, and firm size. The standard error is displayed in brackets. ***, ** or * mean that the coefficients are significant at the 1%, 5%, or 10%-level.

Variable	Model 1	Model 2
Intercept	0.004***	-0.0076
	(0.001)	(0.076)
M_ASVI	-0.009**	-0.010*
	(0.006)	(0.006
Volatility	-	-4.129***
		(1.003)
Bid-Ask	-	-0.004***
		(0.001)
Turnover	-	0.001
		(0.003)
Size	-	0.010**
		(0.004)
Industry dummy	No	No
FE	Yes	Yes
Observations	29,524	29,524
Adjusted R^2	0.001	0.096

Table D2: Panel regression results government reopening

Two panel regression with fixed effects models and robust standard errors. Model 1 contains the dependent variable CAR [-30,30], for the government reopening, and the independent variable ASVI measured with 17 search words. Model 2 also contains the control variables: volatility, bid-ask spread, turnover, and firm size. The standard error is displayed in brackets. ***, ** or * mean that the coefficients are significant at the 1%, 5%, or 10%-level.

Variable	Model 1	Model 2
Intercept	0.007***	-0.075
	(0.001)	(0.069)
M_ASVI	-0.027***	-0.023***
	(0.007)	(0.007)
Volatility	-	0.797
		(1.311)
Bid-Ask	-	-0.007***
		(0.001)
Turnover	-	0.005
		(0.004)
Size	-	0.004
		(0.004)
Industry dummy	No	No
FE	Yes	Yes
Observations	29,524	29,524
Adjusted R^2	0.005	0.097

Appendix E

Table E: Granger causality tests

Granger causality test results for CAR and M_ASVI with 1 lag, and Return and M_ASVI with 2 lags. P-values smaller than 5% are significant.

Dependent	Independent	p-value
CAR	ASVI	0.801
ASVI	CAR	0.000
Return	ASVI	0.000
ASVI	Return	0.000