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Abstract

In this article we study if investor's sentiment measured by an intensity of Google searches may be used to predict future changes of the Effective Federal Funds rate. We find that online searches for “fed funds rate”, “fed interest rate”, “fed reserve”, “fed reserve rate” and “federal interest rate” are associated with next week decrease of the Effective Federal Funds Rate. Google searches for “fed rate hike” and “fed raise rates” are associated with next week increase of the Effective Federal Funds Rate even after we control for a number of macroeconomic indicators. We also find that intensity of Google searches is associated with the future decrease of volatility of the Effective Federal Funds rate. This finding can be explained by the reduction of information asymmetry about future changes that leads to a reduced volatility.

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1. Introduction

Previous literature demonstrates that the intensity of Google searches may serve as a proxy for investors' attention and/or sentiment and can be used to forecast general market conditions such as stock rates of return; mutual fund cash in- and out-flows as in Da, Engelberg, and Gao (2011, 2014); change in indexes as in Vozlyublennaia (2014); unemployment as in Askitas and Zimmermann (2009) and in D'Amuri and Marcucci (2017); and many other economic indicators as in Choi and Varian (2012).

It is natural to extrapolate these ideas to one of the major drivers of capital market fluctuations: the decisions made by the central bank—the Federal Reserve (Fed). However, in contrast to stock rates of return, mutual fund cash flows, and index changes, investors cannot directly affect the decisions made by the Fed with regard to monetary policy. Nevertheless, the Fed uses some market indicators, such as stock rates of return and index levels in its decisions to change interest rates. Since investors affect the overall market condition, they may indirectly affect the Fed's decision about changing the interest rate. In this paper, we demonstrate that Google searches for keywords that reflect investors' sentiment possess predictive power on top of widely used macroeconomic indicators used to predict the Effective Federal Funds Rate (EFFR).

Specifically, we demonstrate that Google searches for specific key phrases possess predictive power during our entire sample period that starts in the first week of 2004 and ends with the 52nd week of 2015. In particular, Google searches for 'fed funds rate,' 'fed interest rate,' 'fed reserve,' 'fed reserve rate,' and 'federal interest rate' are associated with next week decrease of the EFFR. Google searches for 'fed rate hike' and 'fed raise rates' are associated with next week increase of the EFFR.

Our results include macroeconomic indicators widely used in the literature to predict the EFFR such as inflation, expected inflation, unemployment rate, GDP growth rate, and market rate of return. However, we do not find any effect of recent changes of the EFFR on the intensity of online searches for the selected keywords and phrases. So the relation seems to work only in one way: Google searches may be associated with future changes of EFFR, but not vice versa.

We also find that in accordance with the information story, an increase in intensity of Google searches for specific key phrases is associated with next week decrease in volatility of the EFFR. In other words, the more investors search for information online, the lower the next week volatility of the EFFR will be.

2. Literature Review

The EFFR is crucial for U.S. capital market participants as it indirectly affects other interest rates throughout the economy. For the same reason, the Federal Reserve targets the EFFR to implement its monetary policy. Therefore, due to its importance, forecasting the EFFR becomes an urgent need for market participants that has resulted in multiple models being developed. Understandably, many empirical models focus attention on macro indicators such as expected and unexpected inflation; output gap as in Clarida, Gali, and Gertler (1998); futures rate as in Krueger and Kuttner (1996); and other economic aggregates used by the Fed to develop the monetary policy.

Another conceptually different approach to predict changes of the EFFR is to analyze the Federal Open Market Operation committee statements and extract information about expected EFFR changes. Boukus and Rosenberg (2006) study the informational content of the Federal Open Market Committee (FOMC) minutes in the period 1987 - 2005 by using qualitative Latent Semantic Analysis to identify important themes in the minutes that are related to the U.S. economy. Their study suggests that it is possible to use the wording in the FOMC minutes to predict economic conditions. Acosta and Meade (2015) use the tools of computational linguistics to study if content of FOMC minutes has changed across time. The authors argue this approach allows them to get rid of the noise in these statements and identify their hidden meaning.

Additionally, Stewart (2015) argues in an article published in the New York Times that it is important for financial market participants to note whether the Federal Reserve would use the word 'patient' in its discussion of the outlook of the US economy. He argues that the presence or absence of this term in the wording could signal to investors whether the Fed would be raising rates or not. Similarly, Cox (2015) studies if the presence of the word 'some' could be used to predict if the Fed would change rates or not.

However, to our knowledge, investors' sentiment has not been used to predict the EFFR. The current state of information technologies makes it possible to capture investors' sentiment in a timely manner and study if investors anticipate the change of the EFFR in advance. In other words, it is possible that investors in aggregate may be able to predict the change of EFFR ahead of time. To measure investors' sentiment, we use the relative frequency of internet search queries submitted to Google. The idea to measure investors' attention with Google searches belongs to Da, Engelberg, and Gao (2011). To support their instrument choice, the authors argue that the internet becomes a widely popular tool for information collection, and Google is arguably the most popular search engine. Thus, internet searches conducted through Google may serve as an aggregate measure of the attention of millions of internet users which also may reflect their collective intelligence. The authors demonstrate that Google searches are correlated with other measures of investor attention but possess additional power when used to forecast stock prices. Building on the findings of a previous article, Joseph, Wintoki, and Zhang (2011) find that investors' sentiment measured by an intensity of online searches reliably predicts abnormal stock returns and trading volumes for firms included in the S&P 500 index.

In a later study, Da, Engelberg, and Gao (2014) use frequency of Google searches to construct the FEARS[1] index. The authors find that this index, as a measure of investor sentiment, predicts temporary increase in volatility, equity mutual funds run, as well as short-term return reversals.

Choi and Varian (2012) find that Google search data can be used to predict some economic indicators in the short run, which include unemployment claims, consumer confidence, and car sales. Vozlyublennaia (2014) studies whether investor attention measured by Google search frequency can be used to forecast index returns and volatility. She finds that an increase in search frequency is associated with short-term increase of index return. However, change in index return results in a long-term change in investor attention measured by online search activity. In our study, we employ the methodology that is close to the one employed by Vozlyublennaia (2014).

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[1] FEARS index states for Financial and Economic Attitudes Revealed by Search index. For details about the its construction please refer to Da, Engelberg, Gao (2014).

To the best of our knowledge, no study has looked at predicting the EFFR changes with investors' sentiment. Our article fills this gap in the finance and economic literature that attempts to predict future EFFR changes.

3. Methodology, Data, and Empirical Results

The main hypothesis of our research states that investors' attention measured by intensity of search queries submitted to Google may be used to predict changes in the EFFR. However, inherently we make an important assumption: investors will increase their attention when they expect changes of the EFFR. For example, we assume that investors will conduct more online searches for 'fed rate increase' and fewer online searches for 'fed rate decrease' when they expect the EFFR to go up. However, the causality may also work in the opposite direction—a recent actual increase of the EFFR may encourage investors to search more for 'fed rate increase.' This may be explained by investors' desire to evaluate consequences of the recent change in EFFR. To account for this possibility, we hypothesize that not only online searches may predict EFFR, but also past changes in the EFFR may affect current internet search intensity.

To measure investors' attention, we use Google Trends service[2]. This service was introduced by Google in 2006. It provides frequency of Google searches for a specific keyword or a phrase relative to other online searches, which is called Google Search Volume Index (GSVI). For example, if the search phrase is 'fed rate increase,' the value of GSVI represents the relative frequency of online searches for 'fed rate increase' submitted through google.com, relative to the total number of searches submitted to Google over the same time range[3].

Therefore, it is crucial for our research to build a list of keywords and phrases relevant to investors' expectations about change of the EFFR. We use Mishkin and Eakins (2015) and Fabozzi, Modigliani, and Jones (2010) textbooks to identify an initial list of keywords. For each search term in the list, we download weekly GSVI for the period beginning with the first week of 2004 until the last week of 2015. We drop keywords with insufficient data and augment our initial list with keywords and phrases from the 'Related Queries' section provided by Google Trends. Our final list contains search terms and phrases as presented in Table I.

Table I. Full list of keywords used.
In this table, we report all keywords and key phrases we further test for ability to predict EFFR.

fed rate increase	fed rate decrease	contractionary monetary policy
central bank	discount window rate	fed rate hike
the money multiplier	expansionary monetary policy	federal open market committee
fed funds rate	fed interest rate	fed raise rates
fed rate	fed rate change	qualitative easing
discount window	fed reserve	quantitative easing

[2] https://www.google.com/trends/
[3] We use only searches conducted in the United States (thus excluding searches submitted in other countries).

fed chair	federal funds market	federal funds rate
federal funds rates	federal interest rate	fed discount rate
federal reserve	federal reserve banks	federal reserve board
reserve ratio	required reserves ratio	federal reserve rate
federal reserve rates	federal reserve system	fomc
quantitative easing timeline	interest rate increase	m1 money multiplier
mario draghi	monetary base	monetary policy
quantitative easing policy	money multiplier	money supply
multiplier effect	open market operations	overnight rate
district bank	board of governors	

We download daily EFFR from the Federal Reserve Bank of New York website and convert it to weekly data, which provides us with 504 weekly observations[4]. Table II provides summary statistics on the EFFR and a group of control macro variables such as expected inflation, monthly inflation, GDP growth, weekly return on the S&P 500 index, and unemployment rate[5].

Table II. Summary statistics on Google searches for selected terms.
This table represents summary statistics on control variables and the EFFR over the sample period. The EFFR variable is a weekly EFFR measured in percentage points; ΔEFFR represents the first difference of the EFFR variable; Exp_inflation is an expected inflation presented in percentage points; GDP_growth is growth of the GDP presented in decimal form; S&P 500 is a weekly rate of return generated by S&P 500 index presented in the decimal form and used to proxy for the market rate of return; Unemployment is a weekly unemployment rate interpolated from monthly data and is expressed in percentage points.

Variable	N	Minimum	Maximum	Mean	Median	StdDev
EFFR	504	0.06	5.304	1.7722	0.466	1.9662
ΔEFFR	504	-0.9795	0.57	-0.0017	0	0.1025
Exp_inflation	504	0.25	2.6	2.0505	2.19	0.4197
Inflation	504	-0.0192	0.0122	0.002	0.0021	0.0045
GDP_growth	504	-0.0767	0.0825	0.0365	0.0462	0.0315
S&P 500	504	-0.182	0.1203	0.0011	0.0016	0.0255
Unemployment	504	4.4	10	6.8945	6.8608	1.9528

[4] https://apps.newyorkfed.org/markets/autorates/fed%20funds
[5] We do our best to obtain every variable with weekly frequency. However, some control variables (e.g. inflation, GDP_growth) are reported at a lower frequency. Thus, we linearly interpolate their weekly values from monthly observations.

Figure 1 provides visual representation of the temporal behavior of GSVI for keywords ‘fed rate increase’; Figure 2 displays the temporal behavior of GSVI for keywords ‘fed rate decrease.’ Figure 3 shows the temporal changes of the EFFR and the EFFR volatility. All figures cover the entire testing period from the first week of 2014 until 52nd week of 2015.

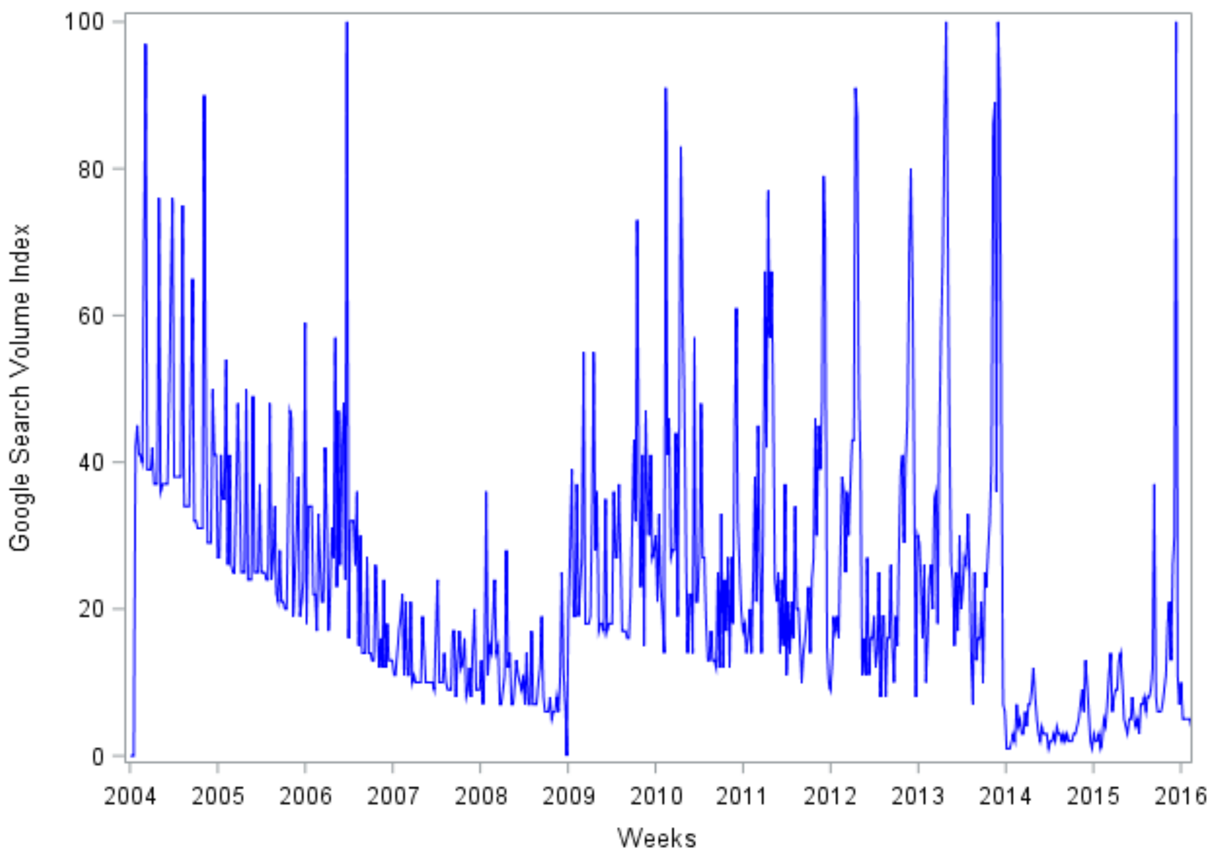

Figure 1. Weekly Google Searches for ‘Fed Rate Increase.’

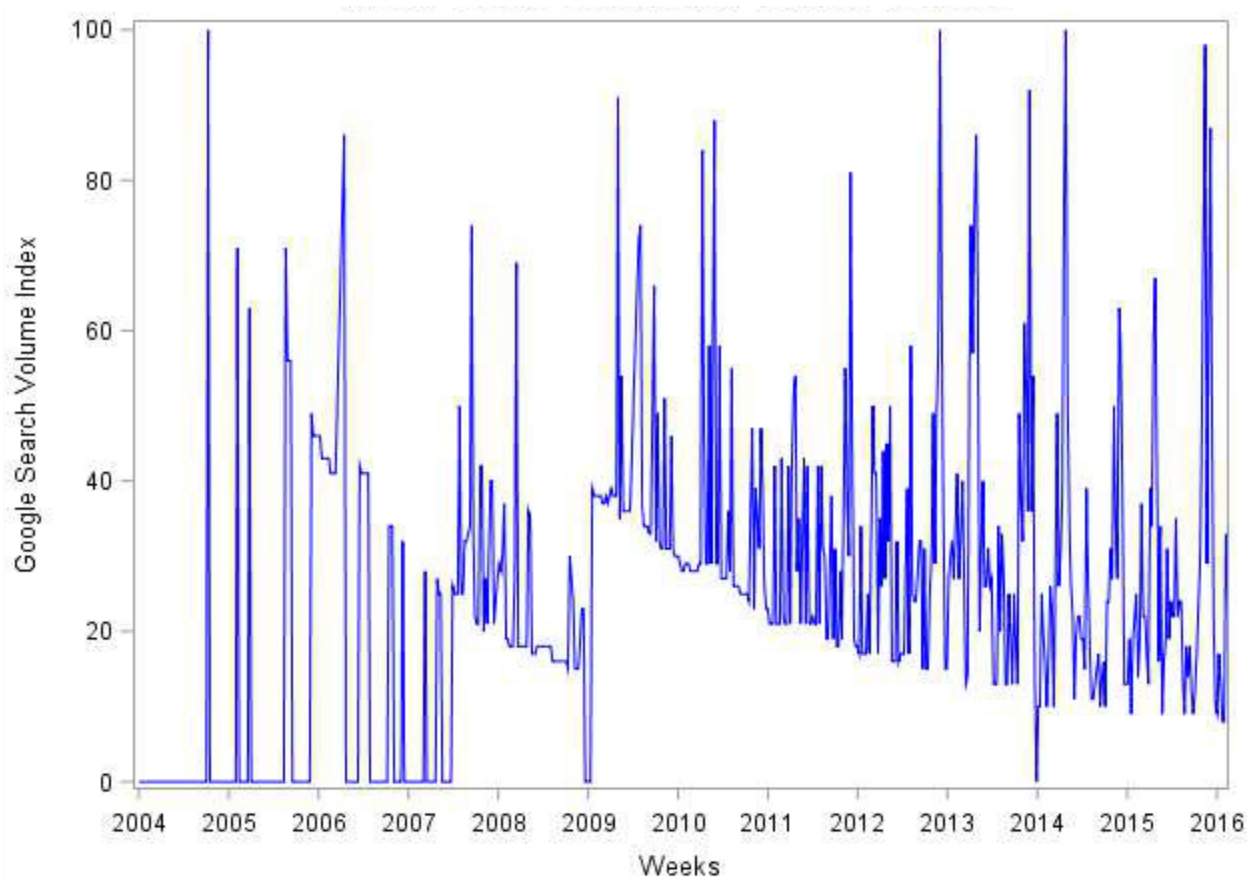

Figure 2. Weekly Google Searches for ‘Fed Rate Decrease.’

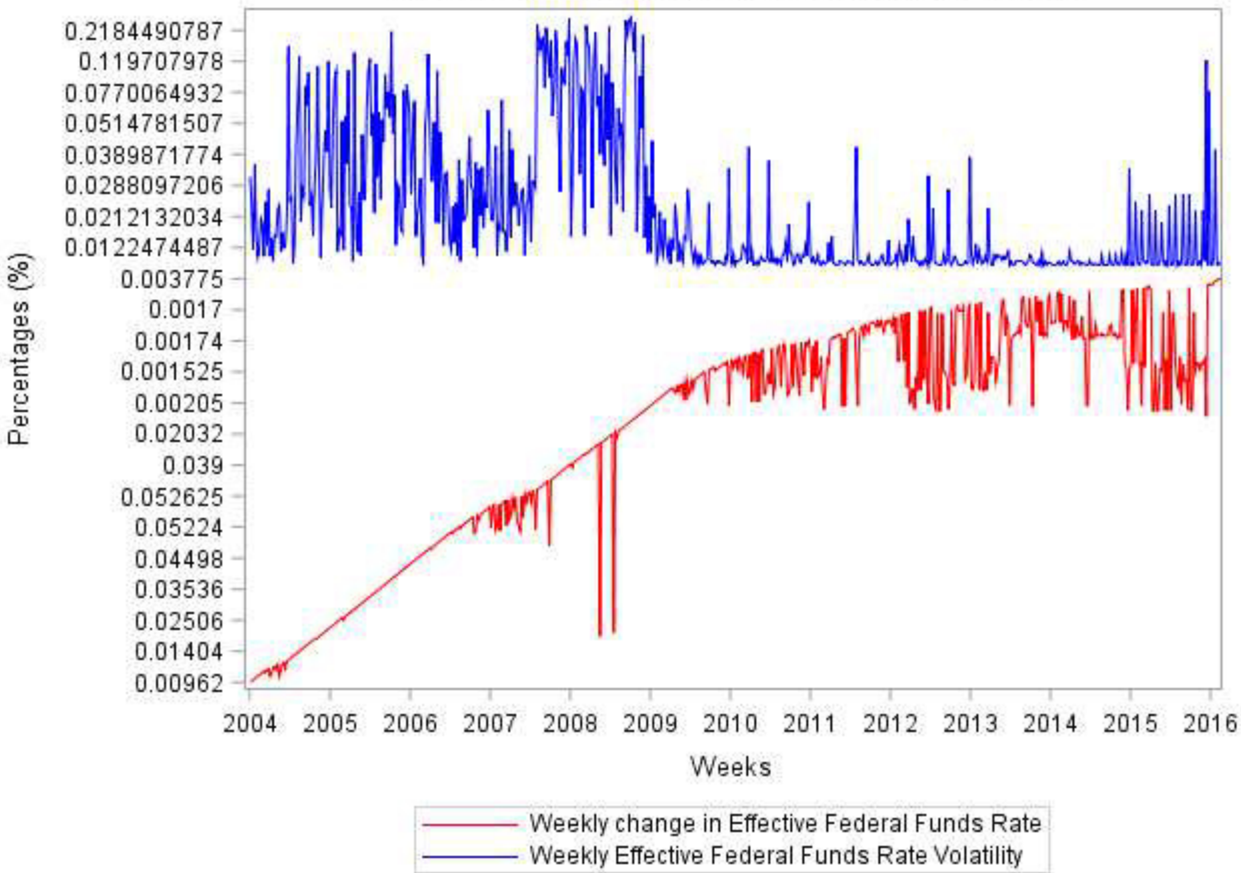

Figure 3. Temporal Behavior of EFFR and Its Volatility.

As shown in the Figures 1, 2 and 3 and since GSVI is a relatively new variable, we check for its stationarity by running the Dickey-Fuller test for each search term from the list. In untabulated results, we find that the Dickey-Fuller test successfully rejects the null hypothesis of non-stationarity, of non-stationarity with a mean, and of non-stationarity with a trend for each keyword at 1% significance level. These results allow us to use raw GSVI measure in our study.

The natural choice to verify an existence of a causal relation is to run the Granger causality test. As we hypothesized above, Google searches may forecast future changes in EFFR, and vice versa, recent changes in EFFR may impact the current Google search intensity. We also control for seasonality by including the weekly dummy variables[6]. Therefore, we specify two models for the Granger causality test:

$$\Delta EFFR_t = \beta_{01} + \propto_{1,t} + \beta_{11}\, GSVI_{t-1} + \gamma_{11}\Delta EFFR_{t-1} + \cdots$$
$$\ldots + \beta_{n1} GSVI_{t-n} + \gamma_{n1}\Delta EFFR_{t-n} + \varepsilon_t \qquad (1)$$

$$GSVI_t = \beta_{02} + \propto_{2,t} + \beta_{12}\, GSVI_{t-1} + \gamma_{12}\Delta EFFR_{t-1} + \cdots$$
$$\ldots + \beta_{n2} GSVI_{t-n} + \gamma_{n2}\Delta EFFR_{t-n} + \varepsilon_t \qquad (2)$$

[6] Following the suggestion of an anonymous referee, we include 52 weekly dummy variables into the Granger causality test and all following regressions to control for seasonality.

In the first model, the null hypothesis is that current change in EFFR is influenced only by its lagged values and not by GSVI. In the second model, the null hypothesis states that current values of GSVI depend only on past values and do not depend on changes in EFFR. We report the results of the Granger causality tests with variables lagged one period in Table III.

Table III. Granger causality test for change in EFFR and Google search intensity.
In this table, we report results of the Granger causality test on Google searches and changes of the EFFR with variables lagged one period (n=1). The Wald's chi-square statistics are reported along with associated p-values in parentheses. Google Search Volume Index and ΔEFFR are obtained at weekly frequencies.

Keyword	ΔEFFR	GSVI
fed funds rate	6.99 (0.0082)	1.23 (0.2683)
fed interest rate	33.29 (<.0001)	0 (0.9584)
fed raise rates	16.78 (<.0001)	0.92 (0.3375)
fed rate hike	17.91 (<.0001)	0.56 (0.4543)
fed rate increase	8.98 (0.0027)	2.55 (0.1100)
fed reserve	10.72 (0.0011)	0.07 (0.7872)
fed reserve rates	0.13 (0.7215)	5.57 (0.0183)
federal interest rate	7.06 (0.0079)	0 (0.9873)
interest rate increase	4.35 (0.0370)	0.13 (0.7225)
open market operations	6.31 (0.0120)	0.95 (0.3298)
the money multiplier	6.75 (0.0094)	0 (0.9753)

In the first column of Table III, we list only search phrases that demonstrate a significant relation with next period change of the EFFR and those that have a significant statistical relation with previous period change of EFFR. In other words, we report search phrases that "Granger-cause" the next period change of EFFR as well as those that are "Granger-caused" by previous week changes of EFFR.

In the second column of the Table III, we report results of the Granger causality test for the model (1) that includes variables lagged one period (n=1). The Wald's chi-square value and associated p-value are reported in the table. For 8 out of 13 search terms, the null hypothesis of no statistical relation can be safely rejected at 1% significance level, for one of them at 5%, and for two at 10% significance level. This test demonstrates the existence of a statistically significant relation between an intensity of online searches and next week change of EFFR. In other words, change of EFFR may depend not only on its past values but also on the volume of Google searches conducted during the previous week. Among neutral searches such as 'fed funds rate,' 'fed interest rate,' and 'federal reserve,' we can see some search phrases with directional meaning (e.g., 'fed rate hike,' 'fed rate increase,' 'fed rate decrease') that are also highly significant. It is of our particular interest to further test the sign of estimated coefficients' for these search terms in the causal relation.

In the third column of Table III, we report test results of the model (2) similarly estimated with variables lagged one period. In this model, we test if past changes of EFFR may influence the intensity of online searches. Unexpectedly, we find that online searches for only two phrases demonstrate a statistically significant relation with lagged changes of EFFR. The statistical significance of the found relationship is also marginal at 10%. In other words, recent changes of EFFR do not "Granger-cause" the volume of online searches in the current period.

We also run the Granger causality test including variables lagged 2, 3, 4, 5, and 6 periods. Expectedly, in unreported results we find that including more lags deteriorates the significance of causal relations compared to the model estimated with variables lagged one period. One possible explanation of the reduced significance is the model overspecification. We also hypothesize that including lags greater than 2 is unjustified since it is hard to imagine that online searches conducted more than 2 weeks ago may have any kind of effect on the current change of EFFR.

The Granger causality test does not provide a direction of a relation, and thus we use this test mainly for filtering purposes. Based on the results, we exclude 34 out of 47 search terms that do not demonstrate any significant relation with changes of EFFR from further tests.

$$EFFR\_Vol_t = \beta_{01} + \propto_{1,t} + \beta_{11}\, GSVI_{t-1} + \gamma_{11} EFFR\_Vol_{t-1} + \ldots$$
$$\ldots + \beta_{n1} GSVI_{t-n} + \gamma_{n1} EFFR\_Vol_{t-n} + \varepsilon_t \quad (3)$$

$$GSVI_t = \beta_{02} + \propto_{2,t} + \beta_{12}\, GSVI_{t-1} + \gamma_{12} EFFR\_Vol_{t-1} + \ldots$$
$$\ldots + \beta_{n2} GSVI_{t-n} + \gamma_{n2} EFFR\_Vol_{t-n} + \varepsilon_t \quad (4)$$

Similar to models (1) and (2), we specify models (3) and (4) to test if there is a relation between EFFR volatility and an intensity of Google searches. We estimate models (3) and (4) with variables lagged one period (n=1) and summarize results in Table IV. Table IV is organized similarly to Table III. In the first column, we report search phrases that demonstrate statistically significant relation with next period EFFR volatility, as well as those that demonstrate the relation with previous week EFFR volatility. According to column 2, Google searches for 11 keywords "Granger-cause" the next week volatility of EFFR. Also, we can see that the volatility of the EFFR "Granger-causes" the intensity of Google searches for 8 keywords. It is worth noting that only five search phrases are mutually included in both Table III and Table IV. In other words, different sets of search phrases demonstrate a statistically significant relation with the actual change of EFFR and its volatility.

Table IV. Granger causality test for EFFR Volatility and Google search intensity.
In this table, we report results of the Granger causality test on Google searches and volatility of the EFFR with variables lagged one period (n=1). The Wald's chi-square statistics are reported

for each keyword and phrase along with associated p-values in parentheses. Google Search Volume Index and EFFR volatility are obtained at weekly frequencies.

Keyword	EFFR Volatility	GSVI
fed raise rates	6.93	3.27
	(0.0085)	(0.0707)
fed rate increase	8.79	8.87
	(0.0030)	(0.0029)
fed reserve rates	2.71	3.23
	(0.0996)	(0.0723)
federal open market committee	19.63	6.84
	(<.0001)	(0.0089)
federal reserve chairman	9.51	3.99
	(0.0020)	(0.0458)
federal reserve rates	7.07	8.69
	(0.0078)	(0.0032)
interest rate increase	14.14	6.42
	(0.0002)	(0.0113)
monetary policy	10.89	0.61
	(0.0010)	(0.4365)
money multiplier	4.95	0.19
	(0.0261)	(0.6626)
open market operations	7.55	0.32
	(0.0060)	(0.5718)
quantitative easing	7.77	1.99
	(0.0053)	(0.1579)
the money multiplier	8.36	6.39
	(0.0038)	(0.0115)
the multiplier effect	16.26	1.99
	(<.0001)	(0.1581)

Since the Granger causality test merely identifies the presence of a statistical relation between variables, we conduct additional tests to determine the direction of the relation and its sign. The natural choice in our setup is to use the vector autoregressive models (VAR) as specified in models (1) and (2) for testing the Granger causality between changes in EFFR and an intensity of Google searches.

In model (1), we test if lagged Google searches possess predictive power for current change in EFFR on top of the EFFR past values. We estimate the model using VAR(1) and VAR(2) specifications and summarize results in Table V(a) and V(b)[7]. In columns of these tables, we report VAR coefficients estimated separately for each search phrase. The variable of interest in model (1) is the lagged GSVI (variable $GSVI_{t-1}$). According to the results, Google

[7] In Table III, we identified 11 search phrases that demonstrate a statistically significant relationship between online searches and changes in EFFR. Table V(a) reports results of estimation of models (1) and (2) for the first six search phrases from Table III; Table V(b) reports results of estimation of models (1) and (2) for the remaining five search phrases from Table III.

searches for 'fed funds rate,' 'fed interest rate,' 'fed reserve,' and 'federal interest rate' conducted in the prior week are significantly negatively related to the current week change in EFFR. In other words, if investors were searching more for these keywords last week, then the current week EFFR will decrease. At the same time, internet searches for 'fed raise rate,' 'fed rate hike,' 'fed rate increase,' 'interest rate increase,' 'open market operations,' and 'the money multiplier' lagged one week are significantly positively related to the current week changes in EFFR and will result in EFFR increase.

As we noted above, search terms 'fed rate increase,' 'fed rate hike,' 'fed raise rate,' and 'interest rate increase' contain a direction of expected changes in EFFR in their meanings. We can see in the respective columns of Tables V(a) and V(b) that estimated coefficients of model (1) for these terms possess anticipated signs: for example, an estimated coefficient on $GSVI_{t-1}$ for the 'fed rate hike' search phrase is 0.002, which means that prior week searches for the phrase are associated with current week increase of the EFFR. Therefore, we can argue that lagged searches for these terms are associated with modern increases and decreases of the EFFR in accordance with the search phrases' literal meanings. It is worth mentioning that including two lags of GSVI variable into the model does not affect the estimation results dramatically: only an estimated coefficient on $GSVI_{t-1}$ for 'fed rate decrease' loses its significance although it preserves the correct sign. On the other hand, the GSVI variable lagged two periods (variable $GSVI_{t-2}$) does not demonstrate any significance except for the 'federal reserve rate' search term. In unreported results, we estimated model (1) with more than two lags included. Additional lags are not significant but reduce significance of variables lagged one period. We link it to the model overspecification problem.

As we mentioned above, it is possible that current week Google search intensity may be influenced by the recent change of EFFR. In other words, in response to an increase of EFFR, investors may start searching more online. We test this hypothesis in model (2) using VAR(1) and VAR(2) specifications and present results along with estimation results of model (1) in Tables V(a) and V(b). The variable of interest in this model is lagged change of EFFR (variable $\Delta EFFR_{t-1}$). According to the results, recent changes of EFFR do not possess much explanatory power for the intensity of Google searches. All estimated coefficients are insignificant with exception of 'fed funds rate,' 'fed interest rate,' 'fed reserve rate,' and 'm1 money multiplier' for which coefficients are just marginally significant at 10%.

In a similar way, we test the relationship between prior week intensity of Google searches and the EFFR volatility in the current week and vice versa. For that we estimate models (3) and (4) respectively using VAR(1) and VAR(2) specifications. In model (3), we look at the effect of lagged Google searches on current week volatility of the EFFR. The estimation results are summarized in Tables VI(a) and VI(b)[8]. We find that lagged intensity of Google searches (variable $GSVI_{t-1}$) in model (3) is significantly negatively related to the current week volatility for 12 out of 13 search terms. In other words, the high volume of Google searches conducted in the prior week is associated with a reduction of the EFFR volatility. The negative sign may be explained as follows. Investors are looking for more information about possible change of EFFR, thus reducing the uncertainty on the market and the EFFR volatility. When we include GSVI lagged two periods into model (3), five search terms lose their significance; however, they

[8] In Table IV we identified 13 search phrases that demonstrate statistically significant relationship between online searches and volatility of the EFFR. Table VI(a) reports results of estimation of models (3) and (4) for the first six search phrases from Table IV; Table VI(b) reports results of estimation of models (3) and (4) for the remaining seven search phrases from Table IV.

preserve the negative sign. In untabulated results, we find that estimation of model 3 using VAR(3)-VAR(6) specifications does not dramatically change the results[9].

Overall, the results of both tests allow us to make two important conclusions: 1) there is a meaningful link between lagged Google searches and modern changes in EFFR and its volatility, and 2) the significant linkage exists only between prior week Google searches and current change in EFFR and its volatility; including more lags does not provide additional explanatory power.

The EFFR is directly affected by the target rates set by the Fed. In its decision to change the target rates, the Fed pays attention to some macroeconomic indicators such as current and expected inflation, GDP growth, stock market state, and unemployment. To account for the effects of the macro indicators, we estimate models (1) and (2) with a vector of control variables. The vector includes current and expected inflation, stock market rate of return, GDP growth rate, unemployment rate, and high limit of the target Federal Funds Rate set by the FOMC.

Tables VII(a) and VII(b)[10] demonstrate results of models (1) and (2) estimation with control variables using VAR(1) specification. The variable of interest in model (1) is a lagged value of Google searches ($GSVI_{t-1}$). Since additional lags did not provide explanatory power in previous estimations, we estimated model (1) including GSVI lagged only one period. According to the results, the inclusion of macro indicators does not dramatically affect the magnitude of estimated coefficients nor their significance compared to the models' estimations without control variables as reported in Tables V(a) and V(b). Prior week Google searches for 'fed raise rate' and 'fed rate hike' are still significantly positively related to the current week changes in EFFR. On the other hand, online searches for 'fed funds rate,' 'fed interest rate,' 'fed reserve,' 'fed reserve rate,' and 'federal interest rate' are all significantly negatively related to the current week change in EFFR similar to the results presented in Tables V(a) and V(b).

Some variables (inflation and GDP growth rate) that we use to control for macroeconomic factors are available only at monthly frequencies. Therefore, we interpolate their weekly values from their lower frequency observations. As it has been suggested to us by an anonymous reviewer, there is a possibility that the GSVI variable simply captures high frequency changes of the aggregate economy. To alleviate concerns of multicollinearity, we included the correlation matrix in the appendix. Table A in Addendum 2 demonstrates that the maximum correlation of 0.28 is achieved between weekly inflation and the weekly GDP growth rate. We can explain this by the interpolation procedure that we use to obtain weekly values from the

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[9] It has been suggested to us by an anonymous referee that the inclusion in our sample of the weeks when FOMC meetings have been held may drive our results since investor attention can be naturally higher shortly before and after FOMC meetings. To correct this issue in models 1, 2, 3, and 4, we employ the following approach: we substitute Google search volume index on weeks with FOMC meetings by the moving average of Google searches conducted during the previous eight weeks. This approach allows us to smooth sharp increases of search activity on weeks with FOMC meetings. The results in Tables V(a), V(b), VI(a), VI(b), VII(a), and VII(b) are presented after implementation of this adjustment. We also verified that using longer periods for calculating moving average (e.g., 12 weeks) do not affect our results. Moreover, since investor attention can increase and drop gradually, we substituted Google search values of the two immediately adjacent weeks (before and after the week with a FOMC meeting) by the moving average value of Google searches. In untabulated results, we confirm that our findings are not materially affected by this adjustment.

[10] In Table III, we identified 11 search phrases that demonstrate a statistically significant relationship between online searches and changes in EFFR. Table VII(a) reports results of estimation of models (1) and (2) with a vector of control variables for the first six search phrases from Table III; Table VII(b) reports results of estimation of models (1) and (2) with a vector of control variables for the remaining five search phrases from Table III.

monthly observations. However, due to the limitation of data, we are unable to provide a deeper analysis of this possibility, and, thus, we include it as a limitation of our study.

In Addendum 1, we present graphs of impulse response functions for selected keywords. All graphs demonstrate that a shock to Google searches results in anticipated change of the EFFR. For example, a shock in 'fed rate hike' results in the positive change of the EFFR.

Table V(a). Estimation of VAR models for changes in EFFR and Google search intensity.

This table summarizes results of VAR(1) and VAR(2) estimations of models (1) and (2) for weekly changes in EFFR and intensity of Google searches for the respective keywords. Standard errors are reported in parentheses; *** , ** , * represent significance at 1, 5, and 10% respectively.

		Variable	fed funds rate	fed interest rate	fed raise rates	fed rate hike	fed rate increase	fed reserve
VAR(1)	Model 1	Constant	0.0079	0.0496**	-0.0458**	-0.0346**	-0.0388**	0.0332*
			(0.0135)	(0.0237)	(0.0126)	(0.0111)	(0.0128)	(0.0180)
		$GSVI_{t-1}$	-0.0012**	-0.006***	0.0015***	0.002***	0.0009**	-0.0014**
			(0.0005)	(0.0011)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
		$\Delta EFFR_{t-1}$	-0.0689	-0.1437**	-0.0758*	-0.0845*	-0.0660	-0.0691
			(0.0452)	(0.0618)	(0.0447)	(0.0449)	(0.0448)	(0.0448)
	Model 2	Constant	6.4916***	6.8789***	8.8112***	3.6958***	8.9067***	13.4016***
			(1.0616)	(1.2247)	(1.2394)	(0.8101)	(1.4973)	(1.5319)
		$GSVI_{t-1}$	0.6343***	0.529***	0.6154***	0.6475***	0.615***	0.6205***
			(0.0349)	(0.0554)	(0.0355)	(0.0346)	(0.0353)	(0.0356)
		$\Delta EFFR_{t-1}$	-3.9362	-1.3924	4.1162	2.4305	7.7334	-1.3820
			(3.5450)	(3.1980)	(4.3782)	(3.2792)	(5.2585)	(3.8192)
VAR(2)	Model 1	Constant	0.0146	0.0799**	-0.0568***	-0.0436***	-0.0475**	0.0396**
			(0.0144)	(0.0257)	(0.0135)	(0.0114)	(0.0136)	(0.0197)
		$GSVI_{t-1}$	-0.001*	-0.0052***	0.0011**	0.0012**	0.0007*	-0.0013**
			(0.0006)	(0.0012)	(0.0005)	(0.0006)	(0.0004)	(0.0005)
		$\Delta EFFR_{t-1}$	-0.0765*	-0.1902**	-0.0913**	-0.1016**	-0.0765*	-0.0766*
			(0.0452)	(0.0627)	(0.0448)	(0.0448)	(0.0449)	(0.0449)
		$GSVI_{t-2}$	-0.0005	-0.0029**	0.0008*	0.0015**	0.0005	-0.0002
			(0.0006)	(0.0013)	(0.0005)	(0.0006)	(0.0004)	(0.0005)
		$\Delta EFFR_{t-2}$	-0.1012**	-0.1818**	-0.1104**	-0.1237**	-0.1006**	-0.0952**
			(0.0453)	(0.0616)	(0.0446)	(0.0447)	(0.0449)	(0.0448)
	Model 2	Constant	5.3382***	5.8585***	6.8012***	2.5472**	6.5262***	11.3296***
			(1.1232)	(1.3522)	(1.2866)	(0.7972)	(1.5535)	(1.6647)
		$GSVI_{t-1}$	0.5457***	0.4736***	0.462***	0.4467***	0.4638***	0.5274***
			(0.0450)	(0.0637)	(0.0438)	(0.0431)	(0.0438)	(0.0446)
		$\Delta EFFR_{t-1}$	-3.8517	-0.0854	2.6728	1.4660	6.8275	-0.6598
			(3.5314)	(3.2944)	(4.2829)	(3.1453)	(5.1374)	(3.7990)
		$GSVI_{t-2}$	0.1396**	0.1222*	0.2333***	0.3007***	0.2287***	0.1467**
			(0.0448)	(0.0663)	(0.0439)	(0.0432)	(0.0437)	(0.0449)
		$\Delta EFFR_{t-2}$	0.8063	1.1525	6.7548	3.5672	7.8111	-3.1837
			(3.5354)	(3.2343)	(4.2663)	(3.1396)	(5.1365)	(3.7905)

Table V(b). Estimation of VAR models for changes in EFFR and Google search intensity.
This table summarizes results of VAR(1) and VAR(2) estimations of models (1) and (2) for weekly changes in EFFR and intensity of Google searches for the respective keywords. Standard errors are reported in parentheses; *** , ** , * represent significance at 1, 5, and 10% respectively.

		Variable	fed reserve rates	federal interest rate	interest rate increase	open market operations	the money multiplier
VAR(1)	Model 1	Constant	-0.0373	0.0405	-0.0402**	-0.041**	-0.0348**
			(0.0265)	(0.0343)	(0.0158)	(0.0145)	(0.0126)
		$GSVI_{t-1}$	0.0002	-0.0028**	0.0007**	0.0007**	0.0007**
			(0.0005)	(0.0011)	(0.0003)	(0.0003)	(0.0003)
		$\Delta EFFR_{t-1}$	-0.0462	-0.0692	-0.0571	-0.0507	-0.0586
			(0.0629)	(0.0628)	(0.0449)	(0.0446)	(0.0447)
	Model 2	Constant	17.6294***	12.3192***	12.3509***	14.9034***	4.7853**
			(2.6585)	(1.6714)	(1.6496)	(1.8417)	(1.4293)
		$GSVI_{t-1}$	0.5489***	0.5429***	0.604***	0.5902***	0.7072***
			(0.0509)	(0.0533)	(0.0358)	(0.0362)	(0.0318)
		$\Delta EFFR_{t-1}$	12.9409**	-1.3724	1.9013	4.8047	1.0561
			(6.3202)	(3.0607)	(4.6795)	(5.6577)	(5.0641)
VAR(2)	Model 1	Constant	-0.0567*	0.0552	-0.0507**	-0.0448**	-0.0319**
			(0.0289)	(0.0387)	(0.0170)	(0.0156)	(0.0130)
		$GSVI_{t-1}$	-0.0003	-0.0025*	0.0004	0.0006*	0.0012**
			(0.0006)	(0.0013)	(0.0004)	(0.0004)	(0.0004)
		$\Delta EFFR_{t-1}$	-0.0544	-0.0787	-0.0645	-0.0573	-0.0585
			(0.0629)	(0.0632)	(0.0449)	(0.0449)	(0.0448)
		$GSVI_{t-2}$	0.0010	-0.0008	0.0006	0.0002	-0.0006
			(0.0006)	(0.0013)	(0.0004)	(0.0004)	(0.0004)
		$\Delta EFFR_{t-2}$	-0.0714	-0.0992	-0.0879*	-0.0813*	-0.0814*
			(0.0633)	(0.0630)	(0.0448)	(0.0446)	(0.0447)
	Model 2	Constant	14.89***	10.5398***	9.8025***	12.339***	4.5926**
			(2.8587)	(1.8816)	(1.7482)	(1.9596)	(1.4726)
		$GSVI_{t-1}$	0.4679***	0.4797***	0.4912***	0.4936***	0.6737***
			(0.0620)	(0.0630)	(0.0443)	(0.0445)	(0.0449)
		$\Delta EFFR_{t-1}$	13.0789**	-0.8040	1.3116	2.4587	0.9261
			(6.2286)	(3.0722)	(4.6237)	(5.6488)	(5.0887)
		$GSVI_{t-2}$	0.1486**	0.1261**	0.1847***	0.1629**	0.0423
			(0.0606)	(0.0636)	(0.0443)	(0.0448)	(0.0451)
		$\Delta EFFR_{t-2}$	14.0481**	1.5177	0.4951	2.7628	5.2703
			(6.2679)	(3.0615)	(4.6195)	(5.6097)	(5.0750)

Table VI(a). Estimation of VAR models for EFFR Volatility and Google search intensity.
This table summarizes results of VAR(1) and VAR(2) estimations of models (3) and (4) for weekly EFFR volatility and intensity of Google searches for the respective keywords. Standard errors are reported in parentheses; *** , ** , * represent significance at 1, 5, and 10% respectively.

		Variable	fed raise rates	fed rate increase	fed reserve rates	federal open market committee	federal reserve chairman	federal reserve rates
VAR(1)	Model 3	Constant	0.0281** (0.0076)	0.0301*** (0.0077)	0.0507** (0.0154)	0.0325*** (0.0071)	0.0309*** (0.0078)	0.0362** (0.0098)
		$GSVI_{t-1}$	-0.0006** (0.0002)	-0.0005** (0.0002)	-0.0005 (0.0003)	-0.0008*** (0.0002)	-0.0007** (0.0002)	-0.0006** (0.0002)
		$\Delta EFFR\_Vol_{t-1}$	0.5052*** (0.0386)	0.4958*** (0.0390)	0.4257*** (0.0568)	0.4616*** (0.0400)	0.4937*** (0.0390)	0.5117*** (0.0382)
	Model 4	Constant	9.3722*** (1.2830)	10.2416*** (1.5625)	19.3607*** (2.7844)	5.49*** (1.1480)	8.1611*** (1.2451)	14.2573*** (1.5593)
		$GSVI_{t-1}$	0.6099*** (0.0354)	0.5975*** (0.0357)	0.5355*** (0.0514)	0.7438*** (0.0302)	0.6305*** (0.0351)	0.6298*** (0.0344)
		$\Delta EFFR\_Vol_{t-1}$	-11.7422* (6.4962)	-23.509** (7.8954)	-18.4334* (10.2574)	-17.0254** (6.5120)	-12.5119** (6.2633)	-18.029** (6.1153)
VAR(2)	Model 3	Constant	0.0225** (0.0080)	0.0264** (0.0082)	0.0509** (0.0170)	0.0277** (0.0073)	0.0268** (0.0081)	0.0335** (0.0102)
		$GSVI_{t-1}$	-0.0001 (0.0003)	-0.0003 (0.0002)	-0.0006* (0.0003)	-0.0004 (0.0003)	-0.0003 (0.0003)	-0.0005* (0.0003)
		$\Delta EFFR\_Vol_{t-1}$	0.233*** (0.0437)	0.2246*** (0.0440)	0.1876** (0.0621)	0.207*** (0.0441)	0.2259*** (0.0438)	0.2372*** (0.0439)
		$GSVI_{t-2}$	-0.0004 (0.0003)	-0.0002 (0.0002)	0.0000 (0.0003)	-0.0004 (0.0003)	-0.0004 (0.0003)	-0.0001 (0.0003)
		$\Delta EFFR\_Vol_{t-2}$	0.3855*** (0.0438)	0.3792*** (0.0438)	0.3371*** (0.0619)	0.3596*** (0.0441)	0.3764*** (0.0439)	0.3821*** (0.0438)
	Model 4	Constant	7.4738*** (1.3405)	7.9028*** (1.6563)	16.3221*** (3.1055)	4.3565** (1.1760)	5.4647*** (1.2716)	12.2125*** (1.6668)
		$GSVI_{t-1}$	0.2333*** (0.0436)	0.2209*** (0.0437)	0.1335** (0.0613)	0.2421*** (0.0438)	0.3045*** (0.0431)	0.1574** (0.0445)
		$\Delta EFFR\_Vol_{t-1}$	-16.5789** (7.3130)	-12.2818 (8.8978)	-0.4876 (11.3408)	-10.4045 (7.1256)	0.4790 (6.8843)	-1.0097 (7.1425)
		$GSVI_{t-2}$	0.4573*** (0.0436)	0.4543*** (0.0439)	0.4742*** (0.0627)	0.5551*** (0.0438)	0.4392*** (0.0430)	0.5308*** (0.0446)
		$\Delta EFFR\_Vol_{t-2}$	0.1083 (7.3290)	-13.2178 (8.8744)	-16.0440 (11.3090)	-8.0395 (7.1261)	-8.0063 (6.9008)	-15.0011** (7.1275)

Table VI(b). Estimation of VAR models for EFFR Volatility and Google search intensity.
This table summarizes results of VAR(1) and VAR(2) estimations of models (3) and (4) for weekly EFFR volatility and intensity of Google searches for the respective keywords. Standard errors are reported in parentheses; *** , ** , * represent significance at 1, 5, and 10% respectively.

		Variable	interest rate increase	monetary policy	money multiplier	open market operations	quantitative easing	the money multiplier	the multiplier effect
VAR(1)	Model 3	Constant	0.0436***	0.0459***	0.0301**	0.0334**	0.0229**	0.0291***	0.0366***
			(0.0095)	(0.0109)	(0.0088)	(0.0088)	(0.0065)	(0.0076)	(0.0079)
		GSVI$_{t-1}$	-0.0008**	-0.0006**	-0.0004**	-0.0005**	-0.0008**	-0.0005**	-0.0006***
			(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
		ΔEFFR_Vol$_{t-1}$	0.4871***	0.4891***	0.5071***	0.4973***	0.499***	0.5009***	0.4756***
			(0.0389)	(0.0392)	(0.0387)	(0.0391)	(0.0389)	(0.0387)	(0.0394)
	Model 4	Constant	13.7211***	11.5504***	14.2056***	15.2669***	1.3263**	5.8534***	8.9257***
			(1.7285)	(1.8253)	(1.8749)	(1.9413)	(0.5798)	(1.4821)	(1.6176)
		GSVI$_{t-1}$	0.5833***	0.7841***	0.6237***	0.586***	0.8335***	0.6924***	0.7573***
			(0.0365)	(0.0285)	(0.0356)	(0.0372)	(0.0248)	(0.0321)	(0.0299)
		ΔEFFR_Vol$_{t-1}$	-17.9216**	-5.0914	-3.5945	-4.8798	-4.8737	-19.1512**	-11.4127
			(7.0758)	(6.5433)	(8.2391)	(8.6318)	(3.4511)	(7.5762)	(8.0863)
VAR(2)	Model 3	Constant	0.0385**	0.0375**	0.0304	0.0258	0.0187	0.0218	0.0315
			(0.0102)	(0.0113)	(0.0093)	(0.0094)	(0.0065)	(0.0078)	(0.0082)
		GSVI$_{t-1}$	-0.0002	-0.0001	-0.0004	0.0001	-0.0007	0.0000	-0.0002
			(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0005)	(0.0002)	(0.0002)
		ΔEFFR_Vol$_{t-1}$	0.2222***	0.2283***	0.2317	0.2408	0.2286	0.2292	0.2179
			(0.0437)	(0.0439)	(0.0436)	(0.0439)	(0.0438)	(0.0439)	(0.0438)
		GSVI$_{t-2}$	-0.0005**	-0.0004	-0.0001	-0.0005	-0.0001	-0.0004	-0.0003
			(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0005)	(0.0002)	(0.0002)
		ΔEFFR_Vol$_{t-2}$	0.3717***	0.3748***	0.3818	0.3760	0.3813	0.3864	0.3650
			(0.0439)	(0.0440)	(0.0438)	(0.0441)	(0.0438)	(0.0438)	(0.0440)
	Model 4	Constant	11.8014***	11.2498***	12.6044	13.3161	1.0834	5.7749	7.9908
			(1.8744)	(1.9422)	(2.0058)	(2.0875)	(0.5887)	(1.5572)	(1.6515)
		GSVI$_{t-1}$	0.1662**	0.0470	0.1266	0.1474	0.1573	0.0338	0.1808
			(0.0444)	(0.0453)	(0.0448)	(0.0448)	(0.0445)	(0.0449)	(0.0437)
		ΔEFFR_Vol$_{t-1}$	-17.4521**	-6.6741	-19.3242	-26.7362	-2.2381	-5.3774	-23.7651
			(8.0017)	(7.5081)	(9.4534)	(9.7746)	(3.9453)	(8.8189)	(8.8533)
		GSVI$_{t-2}$	0.4761***	0.7446	0.5441	0.4976	0.7004	0.6649	0.6091
			(0.0442)	(0.0451)	(0.0446)	(0.0445)	(0.0445)	(0.0450)	(0.0434)
		ΔEFFR_Vol$_{t-2}$	-5.3442	-1.1557	8.4747	11.9411	-2.9885	-15.8775	4.0750
			(8.0434)	(7.5307)	(9.4831)	(9.8275)	(3.9458)	(8.8078)	(8.8969)

Table VII(a). Estimation of VAR models for changes in EFFR and Google search intensity with control variables.

This table summarizes results of VAR(1) estimations of models (1) and (2) for weekly changes in EFFR and intensity of Google searches with control variables. Standard errors are reported in parentheses; *** , ** , * represent significance at 1, 5, and 10% respectively. We include Target FFR variable to control for higher limit of the target Federal Funds rate set by the FOMC as suggested by an anonymous referee.

	Variable	fed funds rate	fed interest rate	fed raise rates	fed rate hike	fed rate increase	fed reserve
Model 1	Constant	-0.0353	-0.1934	-0.0310	-0.0385	-0.0437	0.0064
		(0.0487)	(0.3278)	(0.0485)	(0.0486)	(0.0510)	(0.0498)
	$GSVI_{t-1}$	-0.0009**	-0.0054***	0.0009**	0.0012**	(0.0003)	-0.0013**
		(0.0005)	(0.0011)	(0.0004)	(0.0005)	(0.0003)	(0.0004)
	$\Delta EFFR_{t-1}$	-0.1087**	-0.1937**	-0.1042**	-0.1088**	-0.0977**	-0.1101**
		(0.0450)	(0.0613)	(0.0446)	(0.0448)	(0.0447)	(0.0446)
	$Target\_FFR_t$	-0.0002	0.0065	-0.0021	-0.0021	-0.0008	-0.0027
		(0.0048)	(0.0164)	(0.0047)	(0.0047)	(0.0049)	(0.0047)
	$Unemployment_t$	0.0033	0.0436	-0.0003	0.0018	0.0013	0.0025
		(0.0047)	(0.0498)	(0.0046)	(0.0046)	(0.0046)	(0.0046)
	$S\&P500_t$	-0.4359**	-0.7698**	-0.4368**	-0.4262**	-0.4322**	-0.4382**
		(0.1757)	(0.3293)	(0.1755)	(0.1755)	(0.1765)	(0.1750)
	$GDP\_Growth\_Rate_t$	0.8062***	1.3561**	0.7173***	0.7046***	0.7839***	0.7909***
		(0.1540)	(0.3912)	(0.1620)	(0.1635)	(0.1657)	(0.1533)
	$Inflation_t$	0.6525	1.1342	0.4968	0.6249	0.5299	0.6595
		(1.0345)	(1.9261)	(1.0302)	(1.0314)	(1.0357)	(1.0289)
	$Exp\_Inflation_t$	-0.0068	-0.0320	-0.0118	-0.0115	-0.0083	-0.0092
		(0.0112)	(0.0199)	(0.0111)	(0.0111)	(0.0113)	(0.0111)
Model 2	Constant	-4.4750	41.5503**	3.2979	4.9578	22.4122**	10.9097**
		(3.8866)	(17.5723)	(4.7591)	(3.5552)	(5.9235)	(4.3202)
	$GSVI_{t-1}$	0.591***	0.4887***	0.5423***	0.5699***	0.5015***	0.5679***
		(0.0364)	(0.0579)	(0.0377)	(0.0374)	(0.0389)	(0.0374)
	$\Delta EFFR_{t-1}$	-2.6706	0.0772	1.1532	0.3096	3.5095	-0.4060
		(3.5904)	(3.2884)	(4.3740)	(3.2709)	(5.1899)	(3.8663)
	$Target\_FFR_t$	0.9272**	-1.6074*	-0.2128	-0.1653	-2.2222***	-0.0802
		(0.3822)	(0.8803)	(0.4596)	(0.3422)	(0.5691)	(0.4053)
	$Unemployment_t$	1.0881**	-4.6752*	0.4624	-0.4292	-0.8932*	0.5867
		(0.3758)	(2.6692)	(0.4486)	(0.3332)	(0.5330)	(0.3959)
	$S\&P500_t$	-19.3354	-21.5170	-9.1464	4.9875	27.4380	2.1093
		(14.0368)	(17.6543)	(17.2237)	(12.8293)	(20.4974)	(15.1765)
	GDP_growth_t	-24.4002**	-46.8953**	66.2143***	51.8847***	89.4255***	-30.759**
		(12.3014)	(20.9700)	(15.8979)	(11.9469)	(19.2417)	(13.2966)
	$Inflation_t$	93.1633	-39.9753	115.0675	-29.6205	-68.2177	132.0584
		(82.6329)	(103.2499)	(101.1188)	(75.3857)	(120.2986)	(89.2383)
	$Exp\_inflation_t$	1.6257*	-1.3827	0.7885	0.4472	-1.7022	0.6373
		(0.8964)	(1.0685)	(1.0936)	(0.8136)	(1.3086)	(0.9613)

Table VII(b). Estimation of VAR models for changes in EFFR and Google search intensity with control variables.
This table summarizes results of VAR(1) estimation of models (1) and (2) for weekly changes in EFFR and intensity of Google searches with control variables. Standard errors are reported in parentheses; *** , ** , * represent significance at 1, 5, and 10% respectively. We include Target FFR variable to control for higher limit of the target Federal Funds rate set by the FOMC as suggested by an anonymous referee.

	Variable	fed reserve rates	federal interest rate	interest rate increase	open market operations	the money multiplier
Model 1	Constant	-0.4567	-0.1503	-0.0404	-0.0553	-0.0496
		(0.3394)	(0.3521)	(0.0527)	(0.0531)	(0.0513)
	$GSVI_{t-1}$	-0.0013**	-0.0041**	(0.0002)	(0.0004)	(0.0004)
		(0.0006)	(0.0012)	(0.0004)	(0.0003)	(0.0003)
	$\Delta EFFR_{t-1}$	-0.1358**	-0.1544**	-0.0964**	-0.0935**	-0.097**
		(0.0626)	(0.0619)	(0.0447)	(0.0446)	(0.0446)
	$Target\_FFR_t$	0.0128	0.0027	-0.0016	0.0002	-0.0002
		(0.0177)	(0.0176)	(0.0048)	(0.0051)	(0.0049)
	$Unemployment_t$	0.0767	0.0438	0.0007	0.0017	0.0016
		(0.0514)	(0.0520)	(0.0046)	(0.0046)	(0.0046)
	$S\&P500_t$	-0.9225**	-0.8757**	-0.4343**	-0.428**	-0.4421**
		(0.3411)	(0.3363)	(0.1767)	(0.1764)	(0.1762)
	$GDP\_Growth\_Rate_t$	2.0151***	1.617***	0.82***	0.794***	0.7876***
		(0.4108)	(0.3943)	(0.1601)	(0.1588)	(0.1597)
	$Inflation_t$	1.0850	1.5781	0.5281	0.5970	0.6162
		(2.0142)	(1.9737)	(1.0373)	(1.0376)	(1.0385)
	$Exp\_Inflation_t$	-0.0234	-0.0371*	-0.0076	-0.0081	-0.0080
		(0.0209)	(0.0211)	(0.0118)	(0.0112)	(0.0112)
Model 2	Constant	113.6924**	59.3741**	24.8849***	34.5909***	13.5513**
		(33.8089)	(17.8207)	(5.4510)	(6.6703)	(5.8806)
	$GSVI_{t-1}$	0.2941***	0.4163***	0.4783***	0.4565***	0.6415***
		(0.0612)	(0.0592)	(0.0399)	(0.0405)	(0.0350)
	$\Delta EFFR_{t-1}$	3.9912	-3.0320	-0.7297	1.6808	-0.8576
		(6.2346)	(3.1316)	(4.6193)	(5.6056)	(5.1178)
	$Target\_FFR_t$	-7.2304***	-2.6754**	-1.423**	-3.1293***	-1.5866**
		(1.7597)	(0.8911)	(0.4975)	(0.6361)	(0.5657)
	$Unemployment_t$	-10.9672**	-5.3505**	0.2655	-1.0923*	-0.4649
		(5.1182)	(2.6297)	(0.4729)	(0.5795)	(0.5275)
	$S\&P500_t$	18.7081	-2.0964	13.8950	-8.0606	-16.4997
		(33.9786)	(17.0235)	(18.2619)	(22.1763)	(20.2167)
	GDP_growth_t	83.2871**	-19.1256	54.4231**	57.3084**	49.7786**
		(40.9209)	(19.9581)	(16.5459)	(19.9583)	(18.3290)
	$Inflation_t$	-333.3061*	51.6933	94.4734	12.6666	-3.3172
		(200.6292)	(99.8957)	(107.2245)	(130.4129)	(119.1653)
	$Exp\_inflation_t$	-4.4933**	-3.2469**	-4.6387**	-1.7674	-1.2992
		(2.0802)	(1.0702)	(1.2218)	(1.4131)	(1.2902)

4. Conclusion

In this article, we study whether there is a relationship between Google search intensity and future changes of the EFFR and the EFFR volatility. We find that prior week Google searches for six phrases are statistically related to the current week change of the EFFR. For example, prior week increase of online searches for 'fed rate hike' may result in a current week increase of the EFFR.

Our results are robust and include macroeconomic indicators widely used in the literature to predict the EFFR such as inflation, expected inflation, unemployment rate, GDP growth rate, and market rate of return. However, we do not find any effect of recent changes of the EFFR on the intensity of online searches for the selected keywords and phrases. Thus, the relation seems to work only in one way: Google searches may be associated with future changes of the EFFR, but not vice versa. We also find that in accordance with the information story, an increase of intensity of Google searches is associated with next week decrease in volatility of the EFFR. In other words, the more investors search for information online, the lower the next week volatility of the EFFR will be.

A natural limitation of the study is the frequency of the data that we use, which is weekly. Even though daily data on Google searches may be more interesting to analyze, it is impossible to reach, or it may require an unjustifiable amount of time to collect it. At this point, however, only weekly data are available to us. In a future study, when the higher frequency data become available to us, we plan to conduct a new study to establish the robustness of the results. To ensure the robustness of our findings, we conduct a number of checks that were suggested to us by an anonymous referee.

We also would like to mention another possible limitation of our study. Due to the unavailability of some control variables (inflation and GDP growth rate) at weekly frequency, we interpolate their weekly values from monthly observations. Therefore, as suggested to us by an anonymous reviewer, there is a possibility that weekly observations of Google searches simply pick up the high frequency fluctuations of the aggregate economy. However, due to the data limitation, we are unable to control for such possibility.

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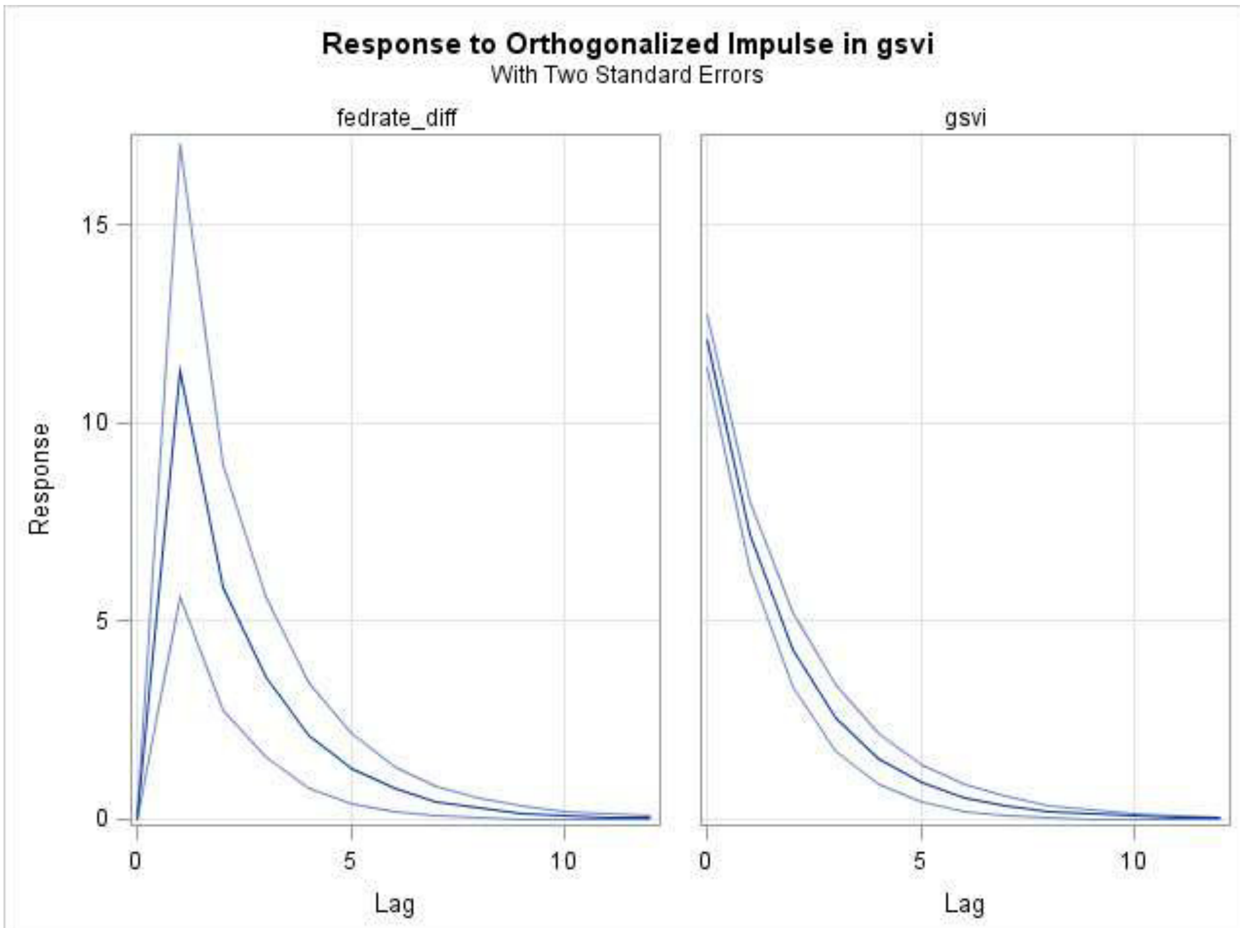
Addendum 1: Impulse Response Functions

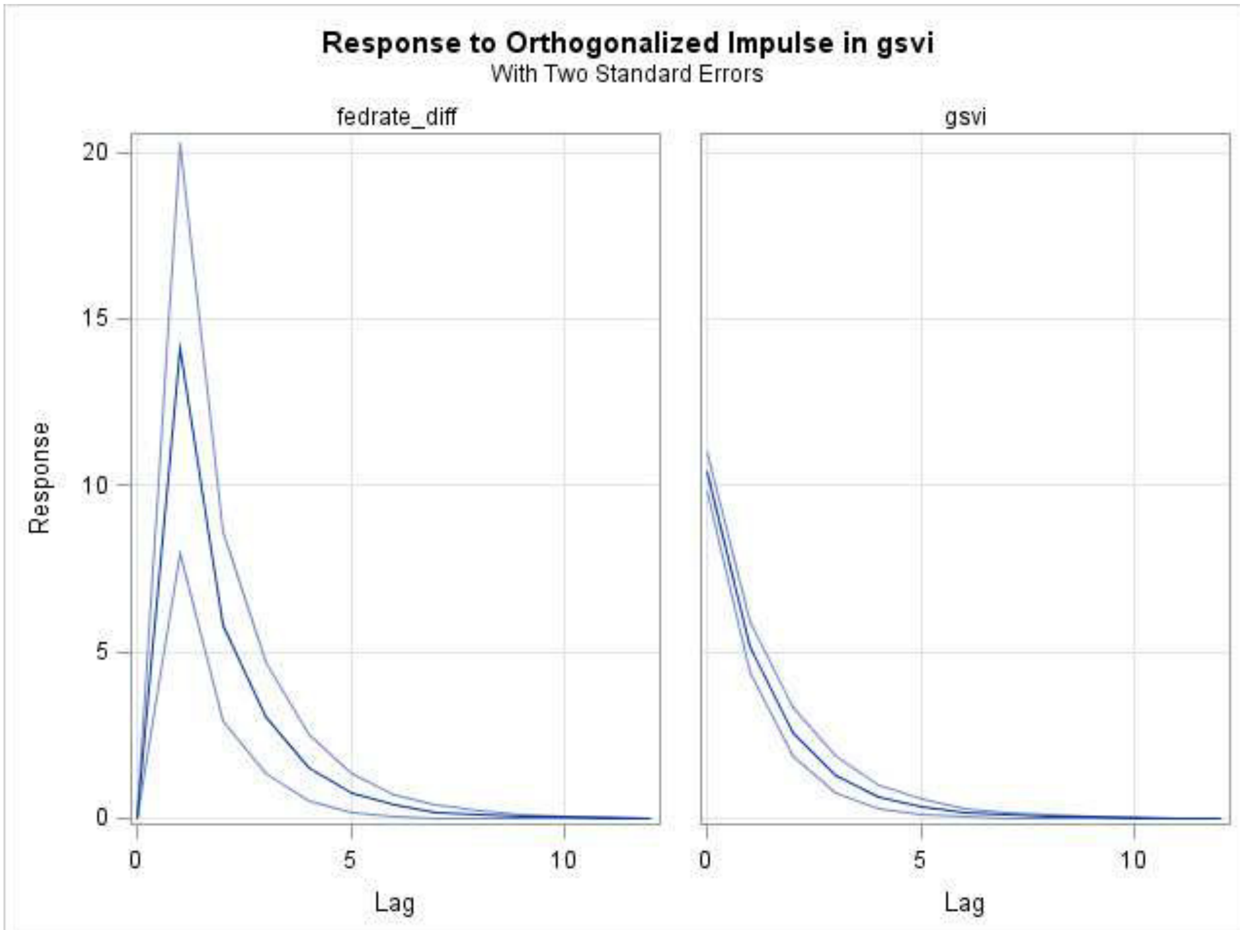
For demonstration purposes, the vertical axis on impulse response function graphs is x1000 the change in EFFR. Otherwise, due to the difference in measurement units of Google searches and changes of EFFR, the response of the EFFR is unnoticeable compared to Google searches.

All impulse response function graphs demonstrate the reaction of the change in EFFR (variable 'fedrate_diff,' first graph) and Google search volume index (variable 'gsvi,' second graph) to the shock in Google search volume index variable.

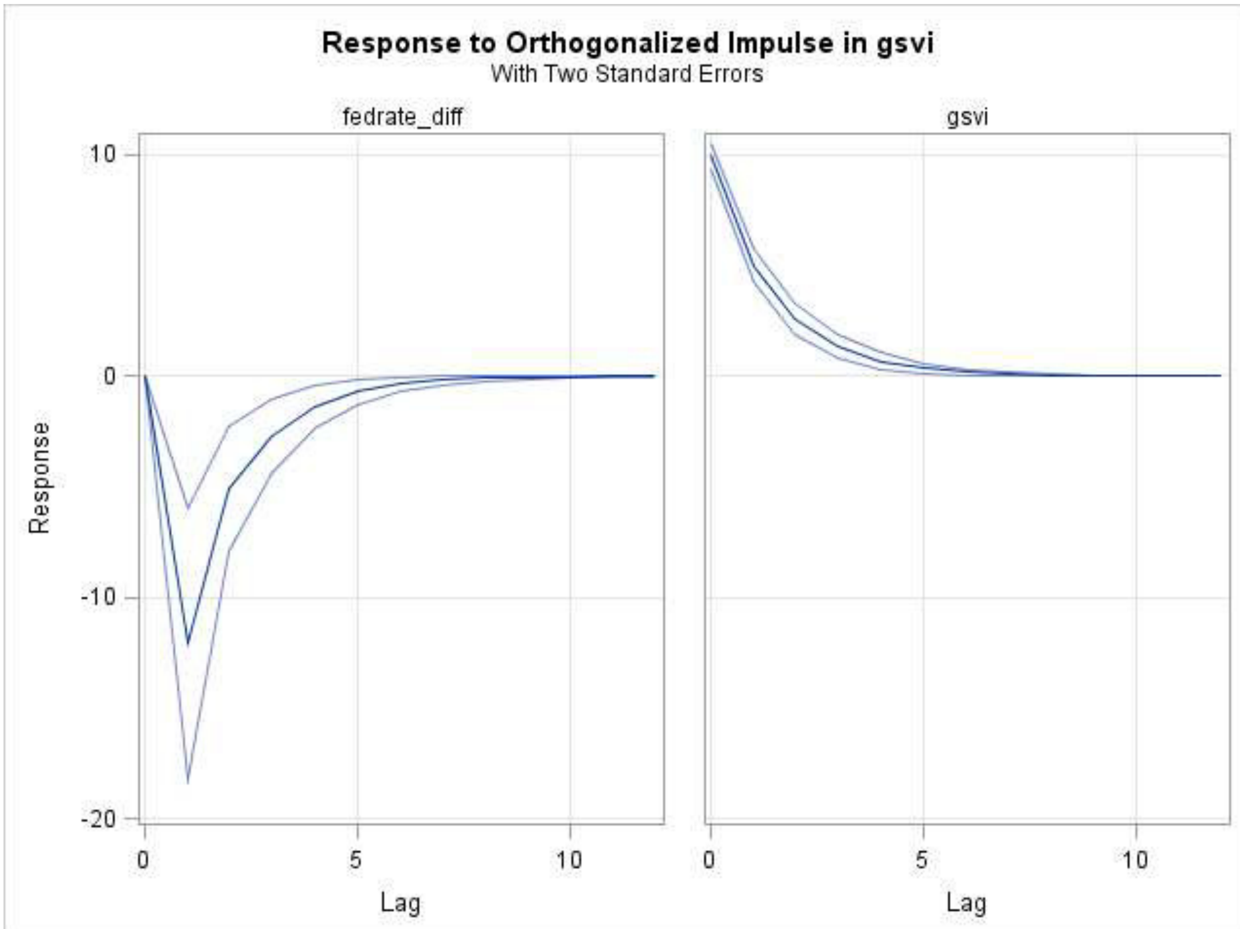
Impulse in Google search for 'fed raise rates'
Response change in EFFR (effective fed funds rate)



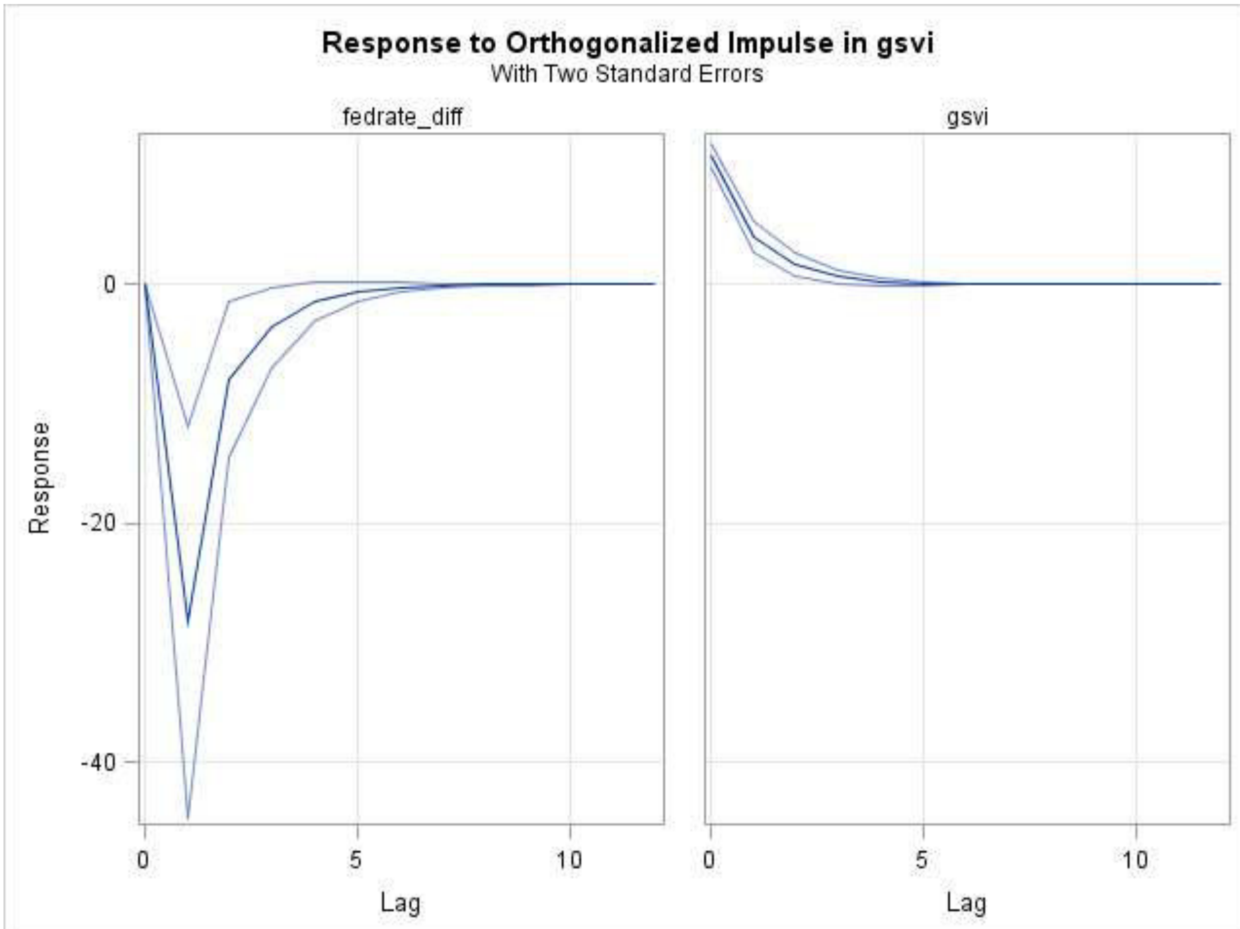
Impulse in Google search for ‘fed rate hike’
Response change in EFFR (effective fed funds rate)



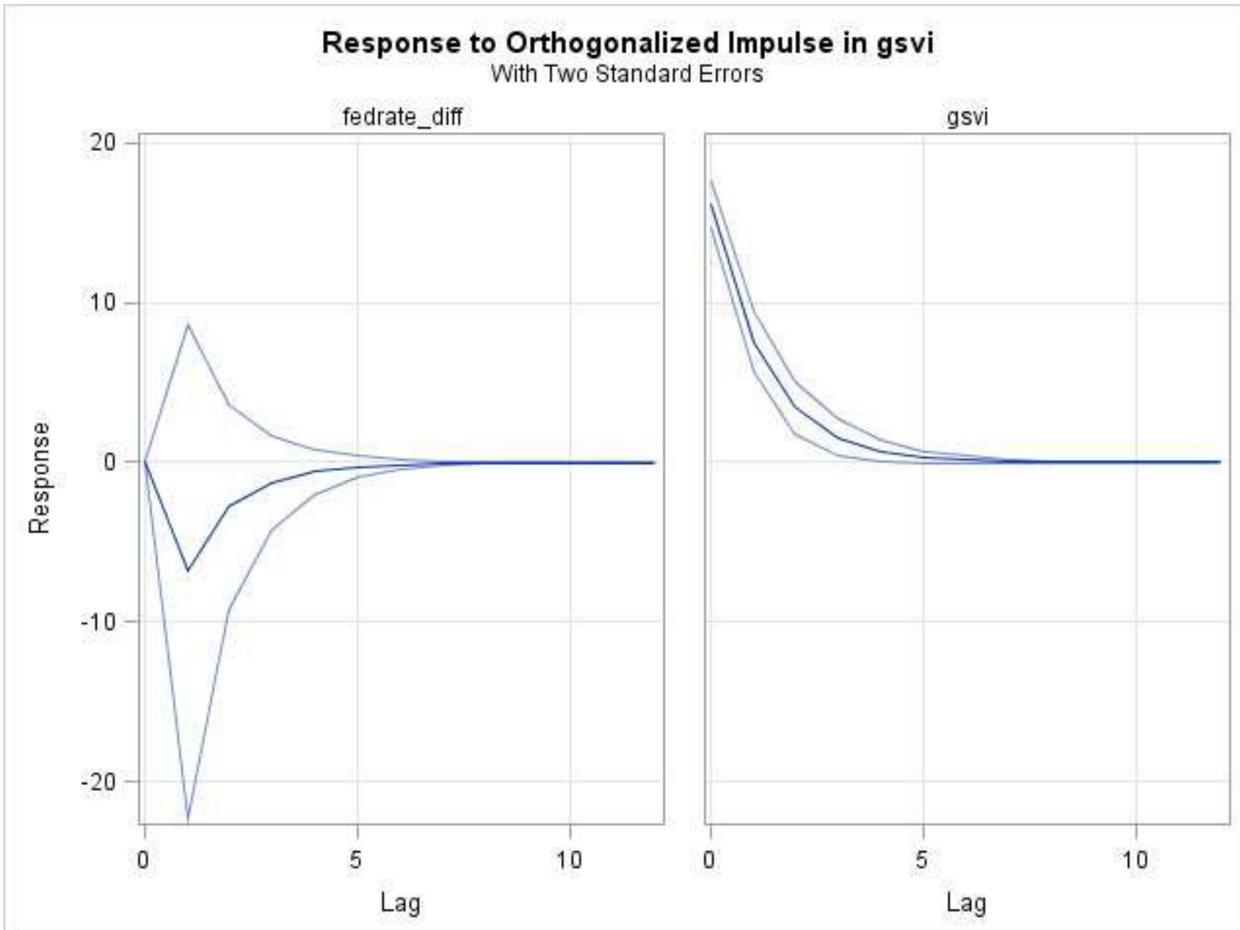
Impulse in Google search for ‘fed funds rate’
Response change in EFFR (effective fed funds rate)



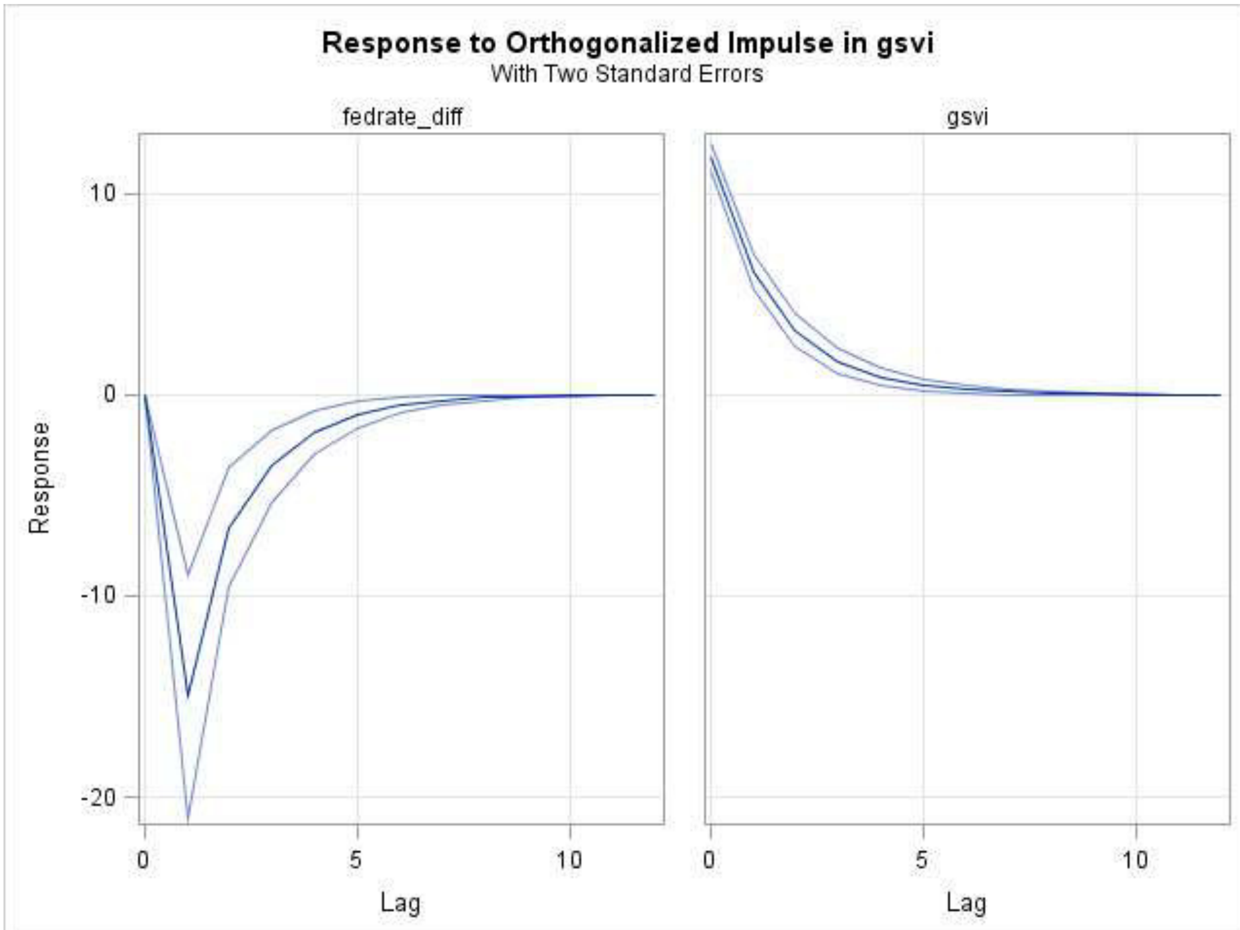
Impulse in Google search for ‘federal interest rate’
Response change in EFFR (effective fed funds rate)



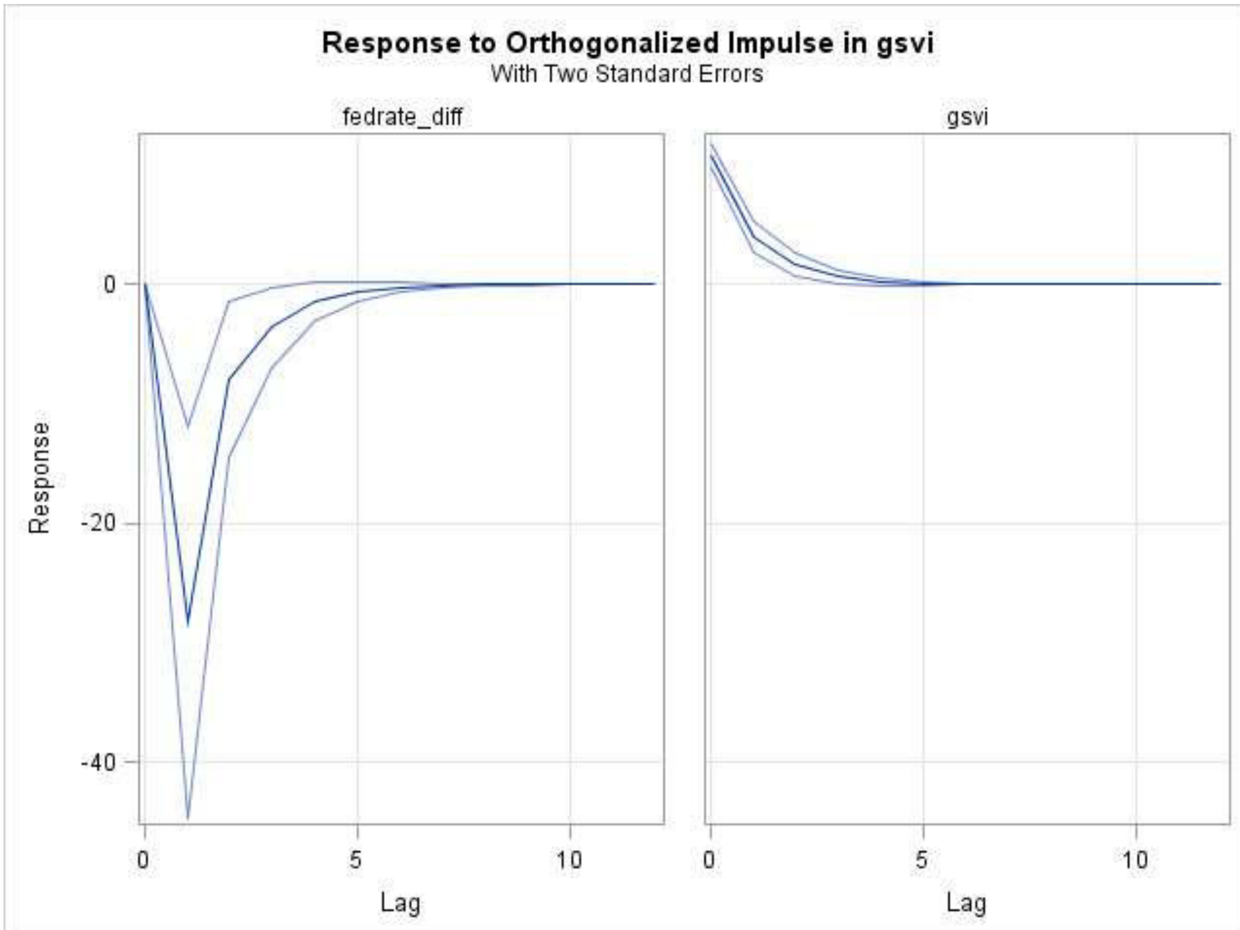
Impulse in Google search for ‘fed reserve rates’
Response change in EFFR (effective fed funds rate)



Impulse in Google search for ‘fed reserve’
Response change in EFFR (effective fed funds rate)



Impulse in Google search for ‘federal interest rate’
Response change in EFFR (effective fed funds rate)



Addendum 2: Independent Variables Correlation Matrix

Table A. Control variables correlation matrix.

In this table, we report Pearson correlation coefficients for pairs of control variables with p-values reported in the parentheses.

	GSVI	Weekly inflation	GDP growth rate	Unemployment rate	S&P 500 weekly return	Expected inflation
GSVI	1	0.0202	0.04024	0.20624	0.029	-0.01058
		(0.0398)	(<.0001)	(<.0001)	(0.0032)	(0.2817)
weekly inflation	0.0202	1	0.2823	-0.12207	0.00637	-0.10552
	(0.0398)		(<.0001)	(<.0001)	(0.5170)	(<.0001)
GDP growth rate	0.04024	0.2823	1	-0.18293	0.11752	0.05399
	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)
Unemployment rate	0.20624	-0.12207	-0.18293	1	0.04725	0.19632
	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)
S&P 500 weekly return	0.029	0.00637	0.11752	0.04725	1	-0.0121
	(0.0032)	(0.5170)	(<.0001)	(<.0001)		(0.2181)
Expected inflation	-0.0106	-0.10552	0.05399	0.19632	-0.0121	1
	(0.2817)	(<.0001)	(<.0001)	(<.0001)	(0.2181)	