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Google Web Searches, Uncertainty and the U.S. Business Cycle

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“It ain't what you don't know that gets you into trouble.
It's what you know for sure that just ain't so.” (**Mark Twain**)

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1. Introduction

After the global financial collapse in 2008, the risk management has widely become an essential aspect of our economies. “Identifying the threat”, “Processing the probabilities”, “Analysing the cost-benefit alternatives” are now vital tasks for producers, investors and consumers too. But are we always able to identify the threats? Events like the terrorist attack of 9/11 or the Pacific tsunami of December 2004, suggest we are not. Can we always correctly process the probabilities? The generalized anxiety following the “Avian Influenza” in 2005, suggests we can’t. Do we always choose the best cost-benefit alternative? Here, a long list of wars suggests we don’t. Behavioural Sciences proved both in empirical and theoretical methods that in reality we often take decisions associated with un-known risk, i.e. characterized by a probability distribution of the outcomes that is undetectable[1]. In other words, “we live in an uncertain world” (Warren Buffet, 2010). Whether we face events which we didn’t even thought they could happen (*Knightian Uncertainty*)[2] or whether we simply can’t process the possible scenarios, uncertainty represents a key factor in our decision-making. Discussions about the pervasiveness of uncertainty—whatever its source and persistence—and, thus, its effects on the financial and economic activity, quickly leads to the need for a quantitative measure of this force. In this study, we introduce novel uncertainty indicators based on the frequency of internet searches and then we investigate the effect of exogenous uncertainty shocks on the US economic activity within a vector auto-regressions (VAR) approach.

From the individual-level to the policy-related, economic uncertainty has been the focus of a large part of the most recent literature. In the wake of the Global Financial Crisis, uncertainty has been recognized as a one of the most critical factors for the depth and the duration of the associated economic downturn, both in the United States and abroad (Caldara et al., 2015). In particular, the extraordinary events surrounding the “Great Recession” have cast considerable doubts on the traditional sources of business cycle fluctuations. In response, a flurry of theoretical and empirical research aimed at

[1] Uncertainty should be distinguished from the related concept of risk. Risk refers to negative outcomes with known probability. For risky situations, one can forecast the likelihood of a negative outcome, while for uncertain situations there is little or no basis for predictions. (Knight 1948).

[2] Former defense secretary Donald Rumsfeld called them “unknown unknowns” and Nassim Taleb’s book, The Black Swan, popularized the concept.

understanding the role of uncertainty within the business cycle has proposed a bag of novel uncertainty measures and tested their impact on the real economy. However, due to its elusive and subjective nature, there is still little consensus among economists on what is the best measure of uncertainty.

Two main stylized facts have emerged from the theoretical literature: first, heightened uncertainty triggers a contraction in real activity; second, uncertainty tends to be higher during economic recessions. The first tenet discerns from the empirical analysis that shows recessionary effects of ambiguity in the presence of real options effects (e.g. Bloom, 2009) or financial frictions (e.g. Motto and Rostagno, 2014). These results are consistent with the theoretical literature, which illustrates how an increase in ambiguity impacts on growth and investment with a twofold action. On the one hand, uncertainty fosters firms "to delay investment and hiring plans when investment projects are costly to undo or workers are costly to hire and fire" (Bernanke, 1983). On the other hand, ambiguity induces household to postpone their consumption (*precautionary saving*); this consumer behavior affects the aggregate demand and therefore the choice of macroeconomic policies (Donadelli, 2015). The second finding refers to the significant amplification of uncertainty shocks' impact on the macroeconomic variables, in situations where a tightening of financial conditions does occur. This latter result may actually release doubts on the nature of the relation between economic distress and uncertainty: as lower economic growth induces greater dispersion at the micro level and higher aggregate volatility, ambiguity could be rather be a consequence, not a cause, of declining economic activity (see Ludvigson et al. 2017). However, recent empirical results suggest that uncertainty is an exogenous source of decline activity, rather than an endogenous response to it (see for instance Angelini et al. 2017). The preliminary evidence in the literature indicates that (i) uncertainty shocks have a significant adverse effect on both investment and consumption, that (ii) their effect is amplified in connection with negative economic conditions and that (iii) uncertainty might be a major cause of declining economic activity, rather than a consequence. At the same time, empirical research is still struggling to find a unique and objective measure of the time-varying economic uncertainty, since it is hardly observable through direct means.

In the spirit of the most recent literature (see e.g. Dzienlinski, 2012 and Donadelli, 2015), the aim of this study is to introduce new indicators based on internet searches, which can provide for a direct and objective measure of uncertainty. In particular, the idea is to isolate

and quantify the degree of uncertainty widespread among economic agents without directly depending on macroeconomic policy-related issues or on financial shocks, in order to test its effect on the U.S. business cycle as a pure exogenous shock. We propose a direct measure of the state of ambiguity in which consumer and investors find themselves following the occurrence of events external to changes within the macroeconomic and financial landscape. Such identification allows us to investigate how uncertainty' shocks at the individual level affects the economic business cycle. The rationale underlying this relationship is in fact straightforward and derives from the conjunction between behavioural findings and macroeconomic literature. Events such as the spread of a serious disease or the approach of new elections trigger uncertainty among agents about the development and the outcome of these events. The difficulty in formulating stochastic scenarios affects both consumers and investors' perceptions. In particular, they lower their expectations as they become pessimistic about the future dynamics. Until the uncertainty is dissolved, consumers prefer to delay consumption of goods or services which might be related to the outcome of these events ("*consumption smoothing*"). The fall in the demand of goods and services reduces firms' revenues and their share prices if listed. In the same way, investors react by postponing the purchase of risky asset at first and demanding a risk premium afterwards. This behaviour should be immediately reflected in a temporary decline in the return of the stocks of the most exposed companies. Next up, the leading sentiment indicators, namely the Consumer Confidence Index (CCI) and the Business Confidence Index (BCI) are negative updated, as a result of the lowering economic expectations. Adverse prospects lead to an increase in the cost of capital through an increase in risk premium. Lastly, manufacturers respond to the fall in the consumer demand and the rise in the cost of capital, adjusting downwards the production volumes and freezing the hiring and investment plans (i.e. "*Wait-and-see*" effect).

The key issue is finding events or new setups that unleash an upsurge in peoples' attention and then building a tool that can quantify this attention. In line with Dzielinski (2011), we argue that the frequency of web searches reported by Google Trends can appropriately capture the appetite for knowledge of economic agents and that the intensity of this appetite reflect the degree of uncertainty about the researched topic. In particular, we rely on the findings in Economic psychology literature (e.g. Da et al., 2011; Liemieux and Peterson, 2011) which points out that consumers respond to greater uncertainty by increasing the search volume. Therefore, by analyzing the search behaviour, we shall get a direct measure

of the aggregate attention addressed to specific events "weighted by its subjective relevance as perceived by individuals" (Bontempi et al. 2016). Within this framework, Google Trends provides a useful and public tool (since 2006) which shows how often a particular keyword or a specific topic is searched relative to the total search-volume across various regions of the world. Since the internet penetration rate in North America now exceeds the 88% (vs 51% World Average)[3] and Google has consistently accounted for an estimated 70% of U.S. search queries, the patterns of searches extrapolated from Google are likely to be representative of the population' general search behavior. Web searches and Google Trends data have already found application within the context of the measurement of economic uncertainty. Dzielinski (2011) for instance, built a first uncertainty indicator based on the single search term "economy" and measured its impact on the S&P 500. Donadelli (2015) extended this research by proposing three uncertainty metrics based on the Google searches for "US stock market", "US politics" and "US Fed" and studied their effects on the US macroeconomic conditions. Bontempi et al. (2016), on the tail of the preliminary realization of Squadrani (2013) rearranged the 210 search terms of Baker et al. (2015) in 184 Google Trends queries, leading to a Google Search-Based metric that is strictly related to the most popular news-based indicator of uncertainty, i.e. the Economic Policy Uncertainty Index. However, all these recent empirical works focused on capturing the attention of investors about policy-related issues that directly derives from the state of the economy; whereas our intent is to obtain the degree of uncertainty, which economic agents *reveal* in front of events *stranger* to the business cycle. In this respect, we decided to study the effect of uncertainty arising out of (i) terrorist attacks (the Google keyword is "Terrorism"); (ii) adverse natural phenomena (the Google keyword is "Natural Disaster"); (iii) cancer diseases (the Google keyword is "Cancer"); (iv) vote opinion poll (the Google keyword is "Opinion poll"). Exploiting the web-search-volume at daily level, we investigate whether an increase in investor attention about the above mentioned topics produce heuristic and psychological biases among the S&P 500 investors. Moreover, we examine whether the effect of these exogenous uncertainty shocks is amplified in connection with a decline in economic activity. In other words, whether an uncertain economic environment in itself strengthen the adverse effects of ambiguity. Subsequently, we employ monthly search volume related to the same topics to study their

[3] Internet World Stats - http://www.internetworldstats.com/stats14.htm, December 2017.

impact on the U.S. business cycle within a VAR framework, both as stand-alone uncertainty shocks and as a composite uncertainty index. Eventually, as robustness check, we compare the extent of the macroeconomic effects our novel indicators with the popular Economic Policy Uncertainty (EPU) index developed by Baker, Bloom and Davis (2013). The study is organized as follows. Section 2 briefly comes back on the literature that has studied uncertainty and proposed relevant measures. Section 3 describes data sources and how we construct Google Search-based metrics. Section 4 analyzes the empirical results obtained from the estimated regressions. Section 5 provides a robustness check by studying the replacement of alternative ambiguity sources (different Google keywords), and the comparison with another uncertainty indicator (EPU). Section 6 offers some concluding remarks.

2. Literature Review

As probability is a luxury that few times we have at disposal, uncertainty is in many cases a binding condition of our state of economy and it seems to play a relevant role at all the levels of the decision-making process. At the micro-level of individual agent or investor, uncertainty has long been subject of behavioural economics studies and laboratory experiments. One of the major findings in this field is referred as the "ambiguity aversion". This concept, first introduced through the Ellsberg Paradox (people prefer to bet on the outcome of a draw from an urn with 50 red and 50 blue balls rather than to bet on one with 100 total balls, but for which the number of blue or red balls is unknown), describes the tendency of people to shy away from choices that involve ambiguity. Ambiguity defines the uncertainty about probability caused by either missing information that is relevant and could be known, either by over-abundance of conflicting and subjective information that requires an increased level of attention from decision-makers (Zio and Pedroni, 2012).

A growing body of research has been studied and proved the connection between ambiguity aversion and psychological biases of economic agents. Among the others, Sarin and Weber (1993) tested the effect of ambiguity aversion on market prices in a sealed bid auction and double oral auction and they found out that individual bid prices as well as market prices for the ambiguous asset were consistently below the corresponding individual bids and market price for the unambiguous asset. They concluded that investors regard ambiguous asset more risky, as the ambiguous has a potential to induce psychological discomfort (since the nature of the stochastic process is unknown) as well as regret due to hindsight. Ambiguity aversion is found to affect the trading volume, as uncertainty about future developments, economic variables or shock dynamics produces greater heterogeneity of opinions among investors (Varian, 1985 and 1989) and investor disagreement cause higher volume trading (Li and Li, 2014). Furthermore ambiguity was held up to be responsible for abnormal returns of certain kind of assets about which little is known, like shares of undersized firms or "initial public-offerings" (IPOs) of small privately held companies, so that the apparent excess returns to small firms and IPOs might be premium paid to investors who dislike ambiguity. Another irrational figure explained by ambiguity seems to be the Equity Home bias puzzle, which describes the fact that individuals and institutions in most countries hold too modest amounts of foreign equity

(French and Porteba, 1991)[4]. In short, micro-level studies revealed that uncertainty affects individual perceptions and preferences. For instance, we know from the work of Kahneman and Tversky (1979) that negative news are given more weight than positive news when attitudes are formed. Camerer and Weber (1992) argue that "not knowing important information is upsetting and scary." Uncertainty is associated not only with the "pessimistic" emotion of fear, but also with the optimistic emotion of hope. However, the association with fear is stronger (Smith and Ellsworth 1985). Thus, uncertain conditions lower expectations (Ilut and Schneider, 2012) since not only people put more effort into assessing the validity of information, but also they put extra weight to worst-case scenarios.

Psychological evidence showed that in order to escape from the state of ambiguity, economic agents react increasing their level of attention and intensifying the information search volume (Liemieux and Peterson, 2011). This finding odds with the traditional paradigm of (subjective) expected utility maximization under rational expectations, as investors' actual choices are often incompatible with the EU (Expected Utility) predictions. A strand of literature has arisen that develops models in which information is not instantaneously incorporated into prices when it arrives, taking into account the fact that many decision makers prefer having additional information concerning the likelihood of the events, even if the information renders the events neither more nor less likely. The demand for more information reflects an increment of the level of attention from investors on the underlying issues, which may vary from macroeconomic, and policy news to firm-specific news[5]. At the individual level, ambiguity has been addressed through different techniques. For instance, Bayesian models consist in replacing rational expectations with beliefs updated through a rational learning rule, for instance Bayes' rule, in the light of the arrival of stochastic signals with non-zero correlation with relevant fundamentals (see, e.g., Pastor, 2000). The class of GARCH models, instead, is based on the mixture of distribution hypothesis (MDH) (see Lamourex and Lastrapes, 1990 or Clark 1973), according to which

[4] People in several countries sacrifice about 3% in annual expected returns - a substantial amount, since stocks rise about 8% per year - by holding too many shares of domestic firms and not enough foreign shares, even accounting for the exchange rate risk. The underlying explanation is that people feel less ambiguity as they have more knowledge about their own country's economy, so that the 3% loss they accept is the premium they pay for avoiding ambiguity about foreign investments (French and Poterba, 1991).

[5] "A wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it", H.Simon, Nobel Laureate in Economics).

a serially correlated mixing variable that measures the rate at which information arrives to the market explains the GARCH effects on asset returns. “Finance-based” approaches tested the relationship between returns, volatility and trading volume, showing either that trading volume can be used as a proxy for information arrival (Lamourex and Lastrapes, 1990) either that extreme returns are an indicator of the investor attention (Barber and Odean, 2008) and either that the option-implied volatility (VIX see Chicago Board Options Exchange, 2009) is a guide to the state of investors' uncertainty. In summary, with regard to the relationship between investors’ attention/information seeking and asset price dynamics, the last few decades of research have produced a large amount of empirical studies, but these studies have by no means reached consensus on the quantitative definition and isolation of uncertainty. Actually, it might seem intuitive to relate inner uncertainty of investors to volatility and volume trading as they directly reflect actions taken by single agents exposed to a certain degree of ambiguity. However, these measures remain strongly bound with the underlying financial assets and markets, meaning that extracting uncertainty estimates from latent processes could be a driver of *endogeneity* issues. Moreover, gauging aggregate consumer uncertainty through finance-related indicators is not entirely correct, since not all individuals invest in the stock market (Romer, 1990), or share the same information that financial market actors have access to.

To quantify the role of uncertainty in shaping the economic conditions, different measures not directly related to the stock market have been proposed. Briefly, excluding the “finance-based” measures which are determined by the fluctuations of the underlying assets, empiricists broadly followed three alternative approaches. One approach is “forecasted based” as it builds on the measurement of the divergence between professional forecasts, under the assumption that the lack of predictability and a large discrepancy between economists’ views are both signs of a more uncertain economy. For example, Rich and Tracy (2010) proposed a proxy for time-varying macroeconomic uncertainty that relied on both ex ante disagreement and ex post forecast errors from the Survey of Professional Forecasters conducted by the European Central Bank.

A second approach may be identified as “news-based” since it estimates the degree of uncertainty by mean of the frequency with which a “bag of keywords” occurs in the news media within a specific length of time. The rationale behind this idea, builds upon the well-established tendency of journalists to report the sources of uncertainty through the recurrent use of certain, specific words. As media represent the channel whereby “the

average citizen comprehend the implication of stock market volatility and economic predictability underlying his/her uncertainty" (Alexopoulos and Cohen, 2009), it sounds reasonable to proxy the state of ambiguity of economic agents by analyzing the frequency of newspaper articles that reference economic uncertainty. Empirical work began testing the relationship between news and economic fluctuations with studies like Cutler et al. (1989), who reported a faint relationship between macroeconomic news, world political events and stock market activity. However, it is only relatively recently that text search methods have been applied to gauge economic uncertainty. Examples include the work of Alexopoulos and Cohen (2009), Shapiro (2010), Knotek and Khan (2011) and Baker et al. (2013 and 2015). In particular, in an influential paper Baker, Bloom and Davis (2013) developed an uncertainty' index (EPU)[6], which "reflects the frequency of articles in 10 leading US newspaper that contain the triple "economic" or "economy"; "uncertain" or "uncertainty" and one or more of "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House", scaled by the smoothed number of articles containing 'today'"[7].

A third approach is "survey based" as it follows the same methodology of the consumer confidence index (CPI, published by The Conference Board), that is investigating agents' opinions, directly by means of a survey. The more divergent are the participants' opinions and greater it is the degree of uncertainty. Bachman et al. (2013) constructed a survey-based measure of ambiguity from the disagreement in business expectations regarding outcome variables such as sales, employment and hours worked. The use of dispersion of expectations as a measure of uncertainty has a long tradition in the literature, mostly in the context of inflation expectations and inflation uncertainty (see Zarnovitz and Lam- bros, 1987). Nevertheless, this interpretation is not unanimous, D'Amico and Orphanides (2008) for instance, showed that the disagreement about the mean forecast can be a poor proxy for the actual forecast uncertainty.

The three previous approaches are easy to perceive and economically sound, but they are still quantitative results that rely on subjective estimates of individuals (in the case of survey-based approaches), or on not-directly related events (as in the case of forecasted

[6] Freely available at http://www.policyuncertainty.com/.

[7] The index is composed of three sets of measures, in addition to the textual data that count the frequency of policy-related terms, also the number of tax laws expiring in coming years and a composite of quarterly forecasts of government expenditures and one-year CPI (consumer price index) from the Philadelphia Fed Survey of Forecasters are included.

and news based methodologies). The survey-based measures have the merit of focusing directly on the individuals' expectations, but their effectiveness is limited by the small sample size and by the possible problems with the honesty of the answers. Conversely, the forecasted and news based approaches have often a large scale and they are less prone to individual subjectivity, however, they are incapable to immediately capture the state of ambiguity in which the economic agents find themselves. In particular, the forecasted-based methodologies can well assess the uncertainty among economists and policy-makers, but they are likely to be affected by many factors other than the one in question. The news-based measure is arguably a good proxy of the degree of uncertainty pervading the economies, yet it focuses on the channel through which the message is conveyed rather than on the individuals themselves. In other words, a news article in the Wall Street Journal does not guarantee attention and it is not a vector of ambiguity unless people actually read it. Moreover, the underlying assumption that the news-media are able to communicate any uncertainty indicated by political debates, economists or market outcomes only through pre-specified words, might be too strong.

The worldwide spread of internet offered an invaluable source of attention predictors: every internet user leaves behind data on what he was looking, if analyzed on a large scale, such data represent an ideal tool to track information seeking behavior and to gauge the amount of attention which any topic receive. Since these data have been made accessible, the empirical literature rapidly produced a large number of works that tested the effect of web-searches on a wider range of disciplines and frameworks. Recent publications used message postings in Yahoo! Finance (Kim and Kim, 2014) as predictor of stock returns, volatility, and trading volume; Siganos et al. (2014) used Facebook user searches [8] as investor sentiment; Meinusch and Tillmann (2016) employed Twitter volume to examine the effect of users' tapering beliefs on interest rates and exchange rates. Among the other data collectors, Google launched in 2006 the public application Google Trends[9] that, by mean of an effective interface, allows to retrieve the aggregate search volume of Google users about any term or topic over time. To the best of our knowledge, the first article to use Google data was "Detecting influenza epidemics using search engine query data" by Ginsberg et al. (2009). The authors estimated the weekly influenza activity in the US

[8] Facebook's gross national happiness index.
[9] http://trends.google.com.

employing an index of health-seeking behaviour that matched with the frequency of influenza-related queries. They found out that search data for 45 terms related to influenza predicted flu outbreaks 1 to 2 weeks before the Center for Disease Control and Prevention reports. This led them to conclude that "harnessing the collective intelligence of millions of users, Google web search logs can provide one of the most timely, broad-reaching influenza monitoring system available today". Taking up the suggestion of Google's Chief Economist Hal Varian, namely that Google Trends data have the potential to describe interest in a variety of economic activities, Choi and Varian (2009) provided evidence that search volume can predict home sales, automotive sales and tourism. Since then, the use of Google Search-based metrics has been quickly extended in estimating their impact on both financial markets and economic variables. For instance, Da et al. (2011) proposed a direct measure of investor attention finding that an increase of the search volume predicts higher stock prices in the next 2 weeks and an eventual price reversal within the year. Vlastakis and Markellos (2012) showed that information demand is positively related to volatility in a GARCH framework. On the other side, Baker and Fradkin (2011) developed a job search activity index to analyze the reaction of job-search intensity to changes in the duration of unemployment benefits in the US, with D'Amuri and Marcucci (2012) suggesting that Google Trends related to job-searches are the best indicators of the US monthly unemployment rate. Koop and Onorante (2013) applied the search volume in a dynamic model selection approach for macroeconomic nowcasting; Vosen and Schmidt (2011) showed that in forecasting Private consumption, Google indicator outperforms the survey-based indicators (the University of Michigan Consumer Sentiment Index and the Conference Board Consumer Confidence Index).

As a matter of fact, this study bears most direct resemblance to Dzielinski (2011), Donadelli (2015), Bontempi et al. (2016) and Castelnuovo and Tran (2017): in their works the volume of a number of economy-related search terms[10] are said to capture the degree of agents' uncertainty and the resulting indexes are tested in a macroeconomic context against the alternative measures of uncertainty. Although the methodology point in the same direction, the motivation in our approach is slightly different as we intend to catch

[10] The single term "Economy" in Dzielinski (2011), the queries "US stock market", "US politics" and "US Fed" in Donadelli (2015), the list of the 184 keywords developed by Baker et al. (2013) in Bontempi et al. (2016). While writing this study, we became aware of the empirical work by Castelnuovo and Tran (2017). They construct Google Trend Uncertainty indices for the United States and Australia based on keywords that are most often cited by the respective central banks under uncertain economic conditions (e.g. "bankruptcy", "White House", "Australian Security Exchange").

the attention of consumers and investors about events or set-ups not directly related to economic issues.

Using aggregate web search volume as a measure of uncertainty has two immediate advantages. First, internet is globally replacing any other source of information therefore web providers are gradually collecting an increasing number of data ("the so-called big data") and this is being done at higher level of frequency. Above all, the search engine Google, which as of December 2017 dominates the search engine market with an 87 percent, tracks user searches from minute to monthly level. Since web users commonly utilize a search engine to gather information and Google continues to be the favourite, the search volume collected by Google[11] is a powerful tool capable to describe the general search behaviour in detail. In the second place, whether it is a message on a Social Network, a comment on a Blog or a query on a Search Engine, internet data represent a spontaneous action directly done by users. In other words, a measure based on the intensity of Internet searches focuses directly on individuals and their need of awareness, rather than on a channel through which the information is conveyed. In this sense, web searches are a *revealed* attention measure of users (da et al., 2011) and the frequency through which they take place indicates the degree of concern about a particular topic. If you search for an event in Google, you are undoubtedly paying attention to it and if you and other users, repeat that action with greater/less frequency a greater/smaller degree of uncertainty about that event arises. The "Web search" approach comes as an uncertainty measure that possesses a relatively large scale and the same "directness" of "survey based" approach, yet without the issue of potential lack of sincerity of the participants. One objection that could be raised against this approach, is the fact that it is a measure of retail investors' attention rather than professional investors' attention. Indeed, Da et al. (2011), using retail order execution from SEC Rule 11Ac1-5 reports, found a stronger link between search volume changes and trading by less sophisticated individuals rather than institutional investors. However, individual investing is becoming more and more prevalent: according to Aite Group[12], about a quarter of all U.S. adults with internet access are retail online traders (51 million), managing $2,8 trillion of trading assets and consistently representing the 25-30% of the total value market size (median value). In short, the behaviour of such

[11] Made available to the public in 2006 through the application Google Trend, https://trends.google.com/trends.

[12] Aite Group, report dated September 2017.

investors can have a significant impact on the stock market, especially in volatile periods (Dzielienski, 2011).

So far, our brief review of empirical and theoretical works focused on economic uncertainty, has disclosed a quite fragmented framework, with little consensus among economists on what is the best measure of economic uncertainty. Given this, it might be useful to shortly analyze the different approaches above-mentioned comparing four uncertainty measures, representative of each methodology. We want to figure out if the numerous proxies proposed by the empirical studies point in the same direction or not. Therefore, we consider the measure of the stock market's expectation of volatility implied by S&P 500 index options[13], known by its ticker symbol VIX, as the uncertainty measure based on the finance approach. As "survey based" approach, we reconstruct the measure of expectations dispersion using the Philadelphia Fed's Business Outlook Survey following the methodology illustrated in Bachmann et al. (2013). We consider the Economic Policy Uncertainty Index for US developed by Baker et al. (2013) publicly available at FRED[14] as measure representative of the "news-based" and the "forecast-based" approaches since it's a composite index which takes into account both methods. And lastly, we also include the measure of uncertainty proposed by Dzielienski (2011) and based on the Google searches of the term "economy". (Details concerning the construction of the various uncertainty measures are contained in Appendix A1).

Table 1 – Panel (A)

	Summary Statistic			
Variable	a_1	a_2	a_3	Q-stat
VIX	0.852	-0.048	0.141	261.19***
BOS	0.175	0.024	0.004	5.394
EPU	0.819	0.083	0.220	253.89***
GT	0.846	0.097	0.146	278.62***

The entries in Panel (A) denote the specific summary statistic: a_k = partial autocorrelation at lag k; Q-stat= the Ljung-Box Q-statistics test for the null hypothesis that there is no autocorrelation up to order 3; * p < 0.10, ** p < 0.05, *** p < 0.01. Sample: each time series is composed by monthly data from 2004 M01 to 2017 M12, T=156

VIX: option-implied volatility on the S&P 500 index, source FRED; BOS: Uncertainty measure based on expectations' dispersion of the Business Outlook Survey (Bachmann et al., 2013), source Philadelphia Fed; EPU: Uncertainty measure based on Baker et al. (2013), source FRED; GT: Uncertainty measure based on Google search volume for the term "Economy" (Dzielienski, 2011), source Google Trends.

[13] Calculated and published by the Chicago Board Options Exchange (CBOE), colloquially referred to as the fear index or the fear gauge.

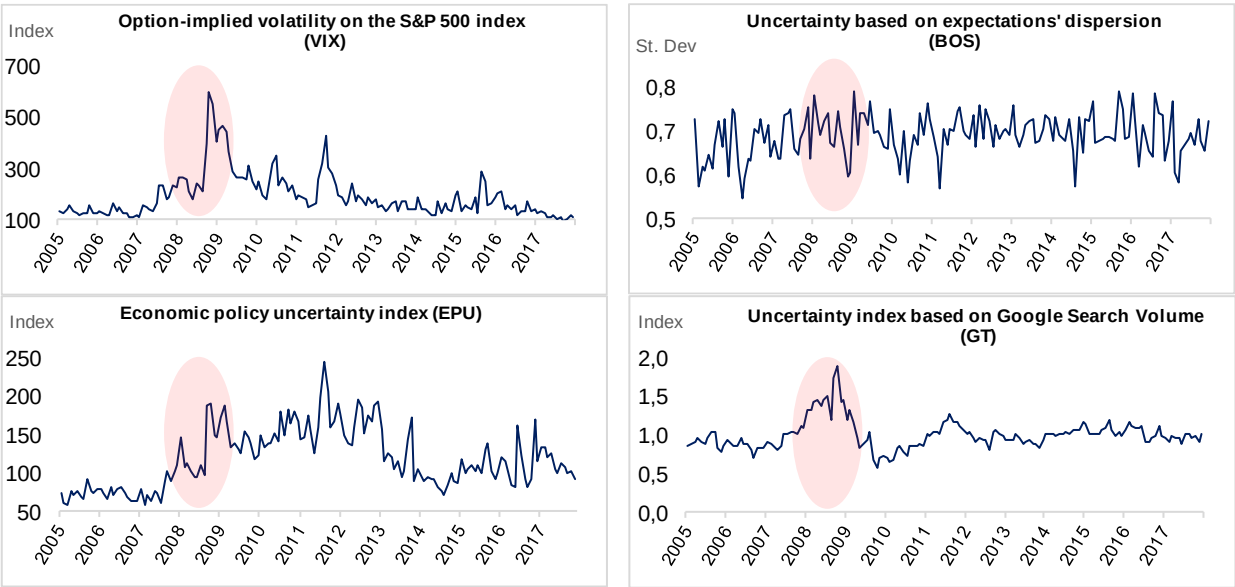
[14] https://fred.stlouisfed.org/series/USEPUINDXM.

Panel (B)

	Pairwise Correlations			
Variable	VIX	BOS	EPU	GT
VIX	1,00	0,09	0,56***	0,50***
BOS		1,00	0,16**	0,09
EPU			1,00	0,25***
GT				1,00

The top panel of Table 1 provides some summary statistics for the four uncertainty measures considered in our analysis. As evidenced by the partial correlogram, most of the series exhibit significant positive first-order autocorrelation; the exception is represented by BOS, which is governed by a much lower serial correlation. However, the degree of serial correlation diminishes rapidly in every case. Choosing a lag (3), there appears to be evidence of serial correlation; according to the Ljung–Box test we reject the null hypothesis of independently distributed data for all the measures –at 1 percent significance level- except for BOS. As shown by the entries in the second panel, the four measures in general exhibit positive contemporaneous correlation, however the coefficient never exceeds 60 percent. The highest degree of co-movement is between VIX, EPU and GT, whereas the "survey-based" uncertainty proxy (BOS) shows a lower correlation with the other measures and statistically significance only with EPU. Consistent with the lack of consensus, although the information contained within the various indicators appears to be somewhat mixed, the evidence suggests that the measures cannot be considered as substitute proxies.

Figure 1



3. Data and Indicators construction

This chapter explains our novel uncertainty indicators (Section 3.1) and illustrates the step taken to create them (Section 3.2). Our first goal is to construct and introduce new indicators that are able to describe properly the state of uncertainty of economic agents when confronted with external (i.e. "Not economy-related") events. Given the long standing theoretical tenet in the behavioural literature that agents respond to greater uncertainty by increasing the information search, we decided to extract a measure of uncertainty towards a particular event by analyzing the web search volume associated with it. In particular, we collected the search volume (monthly and daily) performed in the US through the search engine Google with four different queries[15]: "Terrorism", "Natural Disaster", "Cancer" and "Opinion Poll".

Since 2006, Google makes publicly and freely available the aggregate web traffic via the application Google Trends (https://trends.google.com/trends/). Trends series show how often a particular search-term is entered relative to the total search-volume across various regions of the world, and in various languages. Searches are anonymized (no one is personally identified), categorized (determining the topic for a search query) and aggregated (grouped together). This allows to measure the need for information about a particular topic across search, from around the globe, right down to city-level geography. Through the new interface introduced in 2012[16] it is possible to refine the data not only by region, but also by time period: Real time is a random sample of searches from the last seven days, while non-real time is another random sample of the full Google dataset that can go back anywhere from 2004 to ~36 hours ago. Search volume series can be displayed at monthly, weekly, daily, hourly or minute level; however, the frequency of data is conditioned at the time-span selection. Meaning that you can extract search volume at the minute level only if you choose a time span within last 4 hours, hourly within last 7 days, daily within last 3 months, weekly within last 5 years, otherwise (for periods longer than 5 years) data are presented at monthly basis. Moreover, Trends series can be filtered by

[15] A web search query is a query that a user enters into a web search engine to satisfy his or her information needs.
[16] In 2012, the Insights for Search, a more sophisticated and advanced service displaying search trends data, has been merged into Google Trends.

category and subcategory, in order to determine what users searching for a specific term were actually interested in. The data set does not provide the absolute volume of Google searches, but rather the search interest defined as the number of queries for specific terms scaled by the total Google search traffic. Search interest is then both indexed and normalized, taking value within the interval [0,100] of the Natural Numbers, where 100 is the maximum search interest for the time and location selected. The resulting index, called Search Volume Index (SVI_{st}^{i}) describes the interest for specific keywords (i) in a given region (s), relative to highest point of interest for the selected date range ($X = [0,..,t,..,T]$).

$$SVI^{i}{}_{st} = \begin{cases} 100 \quad if \quad \dfrac{sv_{st}^{i}}{sv_{st}^{tot}} = \max\limits_{t \in X}\left\{\dfrac{sv_{sX}^{i}}{sv_{sX}^{tot}}\right\} \\ \dfrac{sv_{st}^{i}}{sv_{st}^{tot}} \cdot \dfrac{100}{\max\limits_{t \in X}\left\{\dfrac{sv_{sX}^{i}}{sv_{sX}^{tot}}\right\}} \quad otherwise \end{cases} \tag{1}$$

Where sv_{st}^{i} is the volume of searches for a generic term i, in a location s, at the time t and sv_{st}^{tot} is the total Google search volume performed at the same location s and time t. The normalization $\frac{sv_{st}^{i}}{sv_{st}^{tot}}$ is applied to prevent SVI_{st}^{i} from being affected by the overall increase in Google users over time; this should facilitate the comparison among different dates, different countries or different cities. Moreover, the maximum value of the downloaded time-series is set equal to 100, whereas the remaining observations are proportionally scaled (i.e. multiplied by $\frac{100}{\max\limits_{t \in X}\left\{\frac{sv_{sX}^{i}}{sv_{sX}^{tot}}\right\}}$). Google Trends also allow to compare and download together the Search Volume Indexes of different terms (up to five). In this case the observations of the selected time series are scaled by the maximum value which the relative search interest $\frac{sv_{st}^{i}}{sv_{st}^{tot}}$ assume along the time span X *and* across the different SVI. In other words, when the search volume indexes of two or more terms are extracted jointly, the greatest observation within the whole dataset takes value 100 and all the remaining data are scaled accordingly to that observation.

One limitation of Google Trend engineering is sampling variability. To increase the response of speed, Google currently computes $SVIs$ drawing from a random subset of the actual historical full data set. This implies that, when downloaded in different days, $SVIs$

on the same search term could be slightly different. However, as in Da et al. (2011), we believe that the impact of such sampling variability is marginal for our study. Indeed, we find that the correlations for series downloaded several times are usually above 98%. Another limit of Google Trends is the fact that it only provides observation for those search terms exceeding a minimum threshold of relative popularity, otherwise they are set to zero. This becomes relevant, especially when different $SVIs$ are extracted together and the interest towards one of the selected term is greater enough to set to zero most of the observations.

On the other side, $SVIs$ are freely available indicators, measured at high frequency and early released. Furthermore, peak indexation reduces the sensitivity to extreme values, while other manipulation such as outlier trimming can bias the original data structure (Koning and Ohr, 2012). Most importantly, $SVIs$ appear to capture agents' attention accurately. Figure 2 plots the monthly SVI performed in the United States of the two search terms "Cookie" and "Diet", from January 2013 to December 2017.

The SVI for "Cookie" spikes in November and December, coinciding with the winter holidays of Thanksgiving and Christmas. While the Search Volume Index for "Diet" decreases during the holiday season and peaks at the beginning of the year, consistent with the notion that individuals pay more attention to dieting in January as part of a New Year's resolution but less and less over the year.

Figure 2

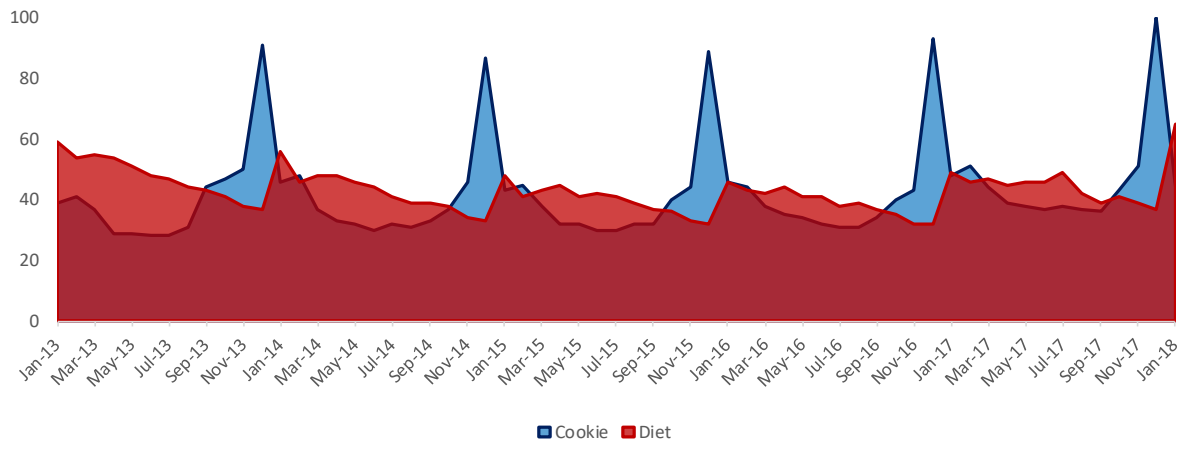


Figure 2: Search Volume Index for the term "Cookie" and the term "Diet", extracted together from Google Trends https://trends.google.com/trends/

3.1 Introducing new uncertainty indicators

As stated above, we intend to measure the degree of uncertainty among economic agent in the wake of changing circumstances or events that do not stem from Economic or Financial conditions. The key issue is how to select relevant topics that might exacerbate ambiguity and therefore enhance the level of information that individuals need in order to increase their awareness. In the context of "Google-search based" metrics, this task boils down to selecting the appropriate keywords. These keywords shall meet some basic criteria. Firstly, they should reflect topics of general interest and be relevant enough to potentially affect the decisions of any economic agent. Secondly, we should avoid to select polysemous terms (i.e. words with multiple meanings) to make clear the intention of Google users (this might be questioned for instance with the selection of the term "depression", which could be associated either with the medical illness, either with the prolonging of an economic recession). Lastly, the keywords should not coincide with the name of a unique event to prevent potential hindsight biases: today we know that "Haiti Earthquake" has been an important topic in Google Trends over the months following the occurrence in 2010, but back in 2000s the choice wouldn't be the same.

Our proposal to the aforementioned requirements are the terms "Natural Disaster", "Terrorism", "Cancer" and "Opinion Poll". They all represent topics that give rise for wide concern, yet on different levels and aspects. The SVI "Natural Disaster[17]" shall catch the uncertainty about the adverse events and their aftermaths, from the short-term damages to the longer-term developments (e.g. Climate change). "Terrorism" encompasses the general fear of the repeat of violent attacks within a short time as well as a substantial uncertainty about long run changes (e.g. National security). "Cancer" represent the concern of individuals for health (and economical) damages generated by a group of serious diseases. The keyword "Opinion Poll" expresses the significant uncertainty about the result of an imminent vote, but also the ambiguity regarding the implications of each outcome, whether it's a political election or a national referendum. Moreover, the selected terms appear to be specific enough to contain noise that is either relatively small or at least constant over the time, since we picked keywords associated with a single meaning. We address the case of

[17] Natural disaster is intended to identify natural adverse phenomena such as floods, earthquake, hurricanes, tsunamis, and other geologic processes, which can cause loss of life or property damage, and typically leaves large economic damages. Recent studies suggest that the increasing number of natural disasters is caused by the impact of climate change (see for instance the Earth Observatory, Nasa, https://earthobservatory.nasa.gov/Features/RisingCost/rising_cost5.php).

constant noise assuming that the trend component actually provides the relevant part of information seeking. Therefore, as in Dzielinski (2011), we identify the trend by dividing the current SVI_{st}^{i} value by the value of the corresponding period (month) one year ago. This transformation (T_SVI), in practice turns out to be very useful to deal with the observed seasonality of the term "Cancer". The dynamics of these modified measures are shown in the following graphs.

Figure 3

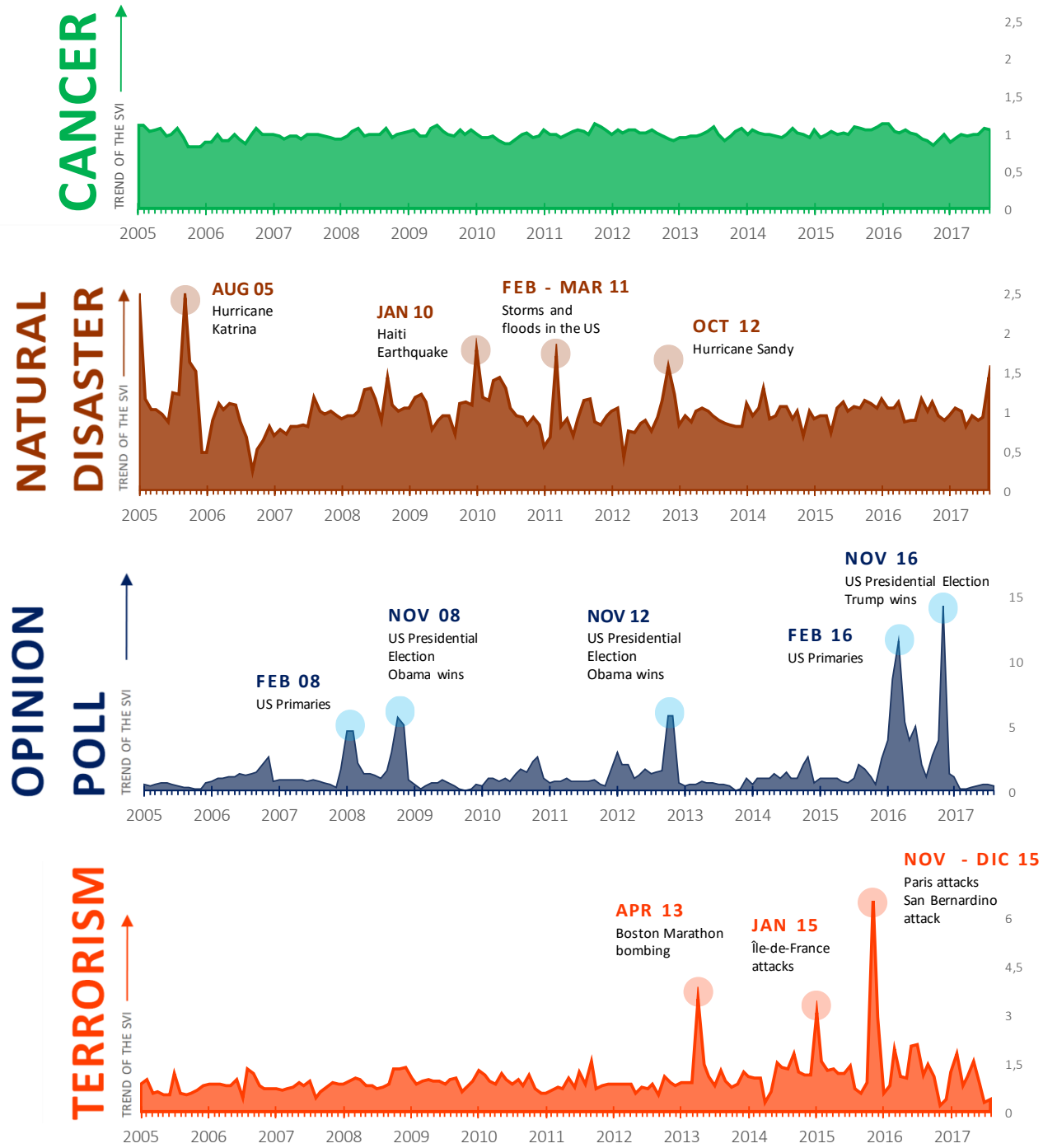


Figure 3: Trend Year-on-Year of the SVI for "Cancer", "Natural Disaster", "Opinion Poll" and "Terrorism". Monthly data from Jan-04 to Sep-17, T=153 obs. (reduced by 12 obs. when computing trends). Location: United Sates; Category: All categories.

3.2 The Making of new uncertainty indicators

Once we have identified the terms and sources of uncertainty, we proceed to describe the step we have taken to construct the different measures that we tested in our empirical frameworks.

We might divide our dataset in two sections. The first section contains time-series downloaded at monthly frequency for the United States from January 2004 (since Google Trends provides data on search term frequency only from this date) to September 2017. In addition to our "search-based" uncertainty measures, the data-book includes monthly returns of the S&P 500 (source: Yahoo! Finance), monthly rates of 3-Month Treasury Bill (source: FRED), monthly levels of Consumer Confidence Index (CCI) and Business Confidence Index (BCI) (source: OECD) and lastly monthly levels of the Industrial Production Index (source: FRED). The second section is composed of time series expressed on a daily basis for the United States, discarding the days when the stock markets are closed, from the 2nd of January 2004 to the 30tth of September 2017. Daily prices of the S&P 500 (source: Yahoo! Finance), daily prices of VIX (source: FRED), daily levels of Volume Trading for the S&P 500 (source: Yahoo! Finance) and the Aruoba-Diebold-Scotti (ADS[18]) business conditions index (source: Federal Reserve Bank of Philadelphia) are included along with our uncertainty indicators.

3.2.1 Monthly Indicators

With regard to monthly data, we downloaded the $SVIs$ Series for each aforementioned term following different specifications. At first, we simply extracted the series one by one, as presented by Google Trend (no category is chosen), we will refer to these as "*Original*". Next, we downloaded one by one the $SVIs$ selecting the sub-category "Finance & Insurance" >> "Investment"; we will refer to these as "*Inv*". The category assignment is carried out by Google Trend exploiting other keywords used in the search along with the one in question, or other searches performed before and after. This technique is meant to reflect the context of the searches; therefore refining the SVI by the category "Investment", we should capture the Search Volume of users determined or at least interested to invest.

[18] The daily time-series data of the ADS index are available from the Real-Time Data Research Center of the Federal Reserve Bank of Philadelphia. See Aruoba, Diebold, and Scotti (2009) for a detailed description of the ADS index.

Afterwards, we repeat the above approaches, i.e. selecting no category and sub-category "Investment", but this time downloading the $SVIs$ together. In such a way, we obtain Search Volume series that are comparable with each other; we will refer to these as "*Comp*." The primary aim of obtaining comparable $SVIs$ is to create a single, composite indicator by mean of the principal component analysis; that is a linear combination of the Search Volume Indexes of the four different keywords.

To sum up, we extracted from Google Trends the SVIs of four terms with four different specifications. The following table might help to lay out better the specified time-series.

Table 2

Download Method		Category Selection									
		Original					Investment				
	One by One	SVI^{orig}	Cancer	Natural Disaster	Opinion Poll	Terrorism	SVI^{inv}	Cancer	Natural Disaster	Opinion Poll	Terrorism
	Together	SVI^{orig}_{comp}	Cancer	Natural Disaster	Opinion Poll	Terrorism	SVI^{inv}_{comp}	Cancer	Natural Disaster	Opinion Poll	Terrorism

Once obtained the Google Trends data, we constructed the uncertainty indicators in accordance with three methodologies. The first uncertainty indicators are simply based on the Search Volume Indexes that we retrieved directly from Google. Therefore SVI^{orig}, SVI^{inv}, SVI^{orig}_{comp} and SVI^{inv}_{comp} are intended to capture the state of ambiguity of economic agents by the magnitude of their search interest, that is their need of information[19]. The second group of uncertainty measures is based on the assumption of constant noise within the series, meaning that the relevant part of the information seeking is the trend that each SVI displays. We isolate this trend following the approach of Dzielienski (2011), namely we divided each monthly observation of the year t by the corresponding monthly observation of the year $t-1$. Although this transformation reduces our sample by cutting out the observations of the year 2004, it appears to be useful to get rid of the series' seasonality, clearly observable in the Search Volume Indexes for the term "Cancer". Applying this approach on each of the four SVI specifications, we obtain the following trends: T_SVI^{orig}, T_SVI^{inv}, $T\_SVI^{orig}_{comp}$ and $T\_SVI^{inv}_{comp}$. These year-on-year trends are designed to measure the degree of uncertainty of individuals by analyzing their relative

[19] The dynamics of these indicators are shown in the Appendix A2.

increase or decrease level of attention towards a particular topic.

The third group of uncertainty indicators are dummy variables developed using the same framework showed in Bloom (2009) and Donadelli (2015), namely we assign value 1 if an extraordinary event occurs and 0 otherwise. These extraordinary events essentially are represented by abnormal flows of attention or interest, which we identify as those observations greater than 1.65[20] the standard deviation of the whole series plus the mean of the series. Formally:

$$(2) \quad Dummy\ Uncertainty\ Indicators = \begin{cases} 1 & if \quad SVI_t > \mu^{SVI} + 1.65\ \sigma^{SVI} \\ 0 & if\ SVI_t < \mu^{SVI} + 1.65\ \sigma^{SVI} \end{cases}$$

This transformation is applied both to the group of indicators directly extracted from Google Trends and to the "Trends" obtained following the approach of Dzielinski. The result are 8 new *Dummy* indicators: D_SVI^{orig}, D_SVI^{inv}, $D\_SVI_{comp}^{orig}$, $D\_SVI_{comp}^{inv}$, $D\_T\_SVI^{orig}$, $D\_T\_SVI^{inv}$, $D\_T\_SVI_{comp}^{orig}$ and $D\_T\_SVI_{comp}^{inv}$. This third group of indicators aims to gauge the uncertainty of individuals when they exhibit extreme need of information.

It should be recalled that every metric we introduced, is constructed for each of the four terms; meaning that, for instance we built a metric T_SVI^{orig} based on the Google queries of the term "Cancer", as well as metrics T_SVI^{orig} which argument is the search volume of "Natural Disaster", "Opinion Poll" and "Terrorism". However, the metrics based on comparable $SVIs$ (*comp)* are designed to create a single indicator by mean of the principal component analysis[21]. We obtain the principal components out of the set of the four variables (i.e. "Cancer", "Natural Disaster", "Opinion Poll" and "Terrorism") by computing the eigenvalue decomposition of the observed variance matrix. The first principal component is the unit-length linear combination of the original variables with maximum variance. Subsequent principal components maximize variance among unit-length linear combinations that are orthogonal to the previous components. The rationale behind forming a linear combination of variables built on different terms is the creation of

[20] 1.65 represent the z-score of the 5th percentile for the normal distribution.
[21] Implemented via EViews.

a composite indicator that describe the uncertainty prompted by multiple and distinct events. To recap, the monthly dataset contains $4\ (number\ of\ terms) * 8\ (stand\ alone\ indicators) + 8\ (composite\ indicators) = 40$ different uncertainty measures[22].

3.2.2 Daily Indicators

Our second contribution consists in the development of uncertainty measures on a daily basis; to the best of our knowledge, this is the first time that "search-based" indicators are constructed at daily frequency and employed within the context of the measurement of uncertainty[23].

Google restricts access to daily data or intervals longer than 90 days, but allows daily data to be gathered for pre-defined intervals, like a specified week or month. The series covering our sample period of 13 years (2004-2017) is therefore available with a monthly aggregation only. We reconstructed the daily search volume series for the whole sample, which comprises the search volume indexes of the four terms "Cancer", "Natural Disaster", "Opinion Poll" and "Terrorism" with both the specifications of no category and category "Investment". The aim is to gather all the series that are going to constitute an entire indicator, and rescale them making the observations comparable each other.

Hence, the first step of this procedure is the collection the set of daily series of each month $SVI\_Daily_{d,m}$: 163 series, (one for each month from January 2004 to July 2017, with the observations in each series equalling the number of days in the month) per each of the eight indicators. In other words, we shall extract 1304 series; to speed up the process we implemented a code in R[24] capable to automate the download of the series under different specifications. (The full script that we used can be found in the Appendix A3). It has to be noted that each series we downloaded are composed by daily observations scaled to the maximum of 100 during the month. This means that, as in the case of monthly SVI (see

[22] This number rises to 72 if we include the indicators based on the search terms "Carcinoma", "C Natural Catastrophe", "Opinion Poll" and "Organized Crime" which we also built in a parallel manner. We did not constructed composite indicators based on these four terms.

[23] Caporin and Poli (2017) developed an Investor Attention Index using daily Google Trends data based on the queries of the stocks' tickers of the S&P 100.

[24] The script we used, exploits the package "gTrendsR" developed by Massicotte (2016), we modified the CRAN version of the package which was no longer working due to changes to Google Trends API.

formula (1)), the observation with the greatest value within the selected time range (in our case a month) takes value 100, while all the other observation of the same series are proportionally scaled. Therefore, observations are not comparable across different months. In reconstructing the series, we applied a three-step procedure, exploiting both the daily series and the monthly series we previously extracted.

1. We compute the relative contribution of day d to the search volume of month m $SVI\_DailyRel_{dm}$, dividing the daily observation of the day d (SVI_Daily_{dm}) by the sum of all the daily observations of that month:

(3) $$SVI\_DailyRel_{dm} = \frac{SVI\_Daily_{dm}}{\sum_{d=1}^{M^m} SVI\_Daily_{dm}}$$

   Where M^m is the number of days of the month m

2. Next, we find the daily observations relative to the whole sample SVI_Row_{dm} , multiplying the relative contribution of day d to the search volume of month m $SVI\_DailyRel_{dm}$ by the monthly observation of the month m $SVI\_Monthly_{dm}$:

(4) $$SVI\_Row_{dm} = SVI\_DailyRel_{dm} \cdot SVI\_Monthly_{dm}$$

3. Finally, we get the adjusted search volume at daily level observations $ASVI_{dm}$ dividing $SVI\_DailyRel_{dm}$ by the maximum value of the whole sample max($SVI\_DailyRel_{dm}$) and multiplying by 100:

(5) $$ASVI_{dm} = \frac{SVI\_DailyRel_{dm}}{\max(SVI\_DailyRel_{dm})} \cdot 100$$

As last task, we discard the observation of the novel $ASVI_{dm}$ indicator, which refer to the days when the stock markets (in our case the S&P 500) are closed, that means the weekends and the market holidays. Ultimately, we obtain a sample composed by 3418 daily observations[25], from the 2nd of January 2004 to the 31st of August 2017.

This procedure allows us to test the impact of uncertainty indicators on daily returns and realized volatility of the most popular American stock market index. Although some studies suggest that investors use the information from the weekend during the following

[25] By including all the observations of $ASVI_{dm}$ we get a sample made of 4960 observations.

trading days (Daniel and Hasler, 2015), we assume that the immediate availability of Google provides (retail) investors pieces of information that could easily affect their financial attitude. Hence, as we will describe in the next section, we match the daily changes in our brand new uncertainty measures with daily returns computed on adjusted closing prices. The dynamics of daily Adjusted SVI (no category specification) are shown in the following pictures.

Figure 4

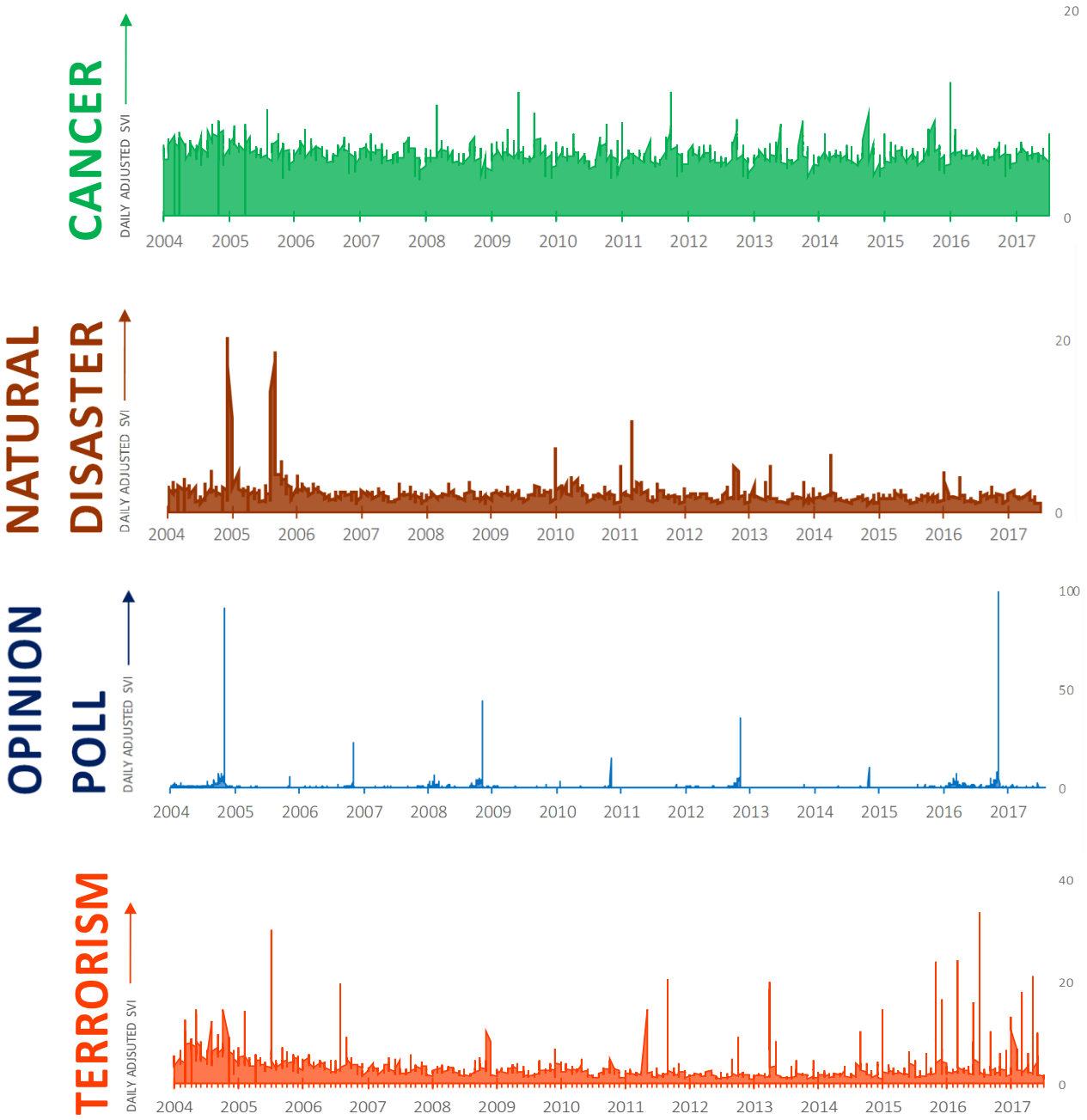


Figure 4: Daily Adjusted SVI for "Cancer", "Natural Disaster", "Opinion Poll" and "Terrorism". Daily data from Jan-04 to Sep-17, T=3418 obs. (1542 obs. discarded, following the Stock Market agenda). Location: United Sates; Category: No specification

The descriptive statistics for our daily Adjusted Search Volume Indexes are presented below; Table 2 summarizes $ASVI$ with no category specification. The mean and the median stat give us an idea of the attention habitually paid to each topic. As expected "Cancer" seems to attract a sustained level of attention for the whole period considered (January 2004 to August 2017), with a mean of 6.11 and a median value of 6.03. This finding shall reflect the fact that "Cancer" is an argument of general interest, which affects individuals' decisions on a daily level. "Natural Disaster", "Terrorism" and "Opinion Poll" show a lower degree of average attention paid to these topics. Intuitively, these latter Search Volume Indexes live by occasional events that may occur within a specific and restricted time span, without which people would not exhibit a fast-paced need for information. The maximum stat provides the greatest value taken by the Indexes. Since we re-scaled to 100 the peak of each series, we should expect that the maximum always coincides with 100, however, in the case of "Natural Disaster", "Terrorism" and "Cancer" the peak did not occur on trading-days, hence their observations were discarded.

All the four indexes are not normally nor independently distributed, as shown by the Jarque-Bera and Ljung Box tests. The Augmented Dickey-Fuller test indicates that the series are stationary on levels.

Table 3

Descriptive Statistics for Adjusted Search Volume Indexes, category: no selection

***ASVI* Statistics**	NATURAL DISASTER	TERRORISM	CANCER	OPINION POLL
Mean	2.082307	2.943937	6.117668	0.759330
Median	1.900764	2.358202	6.032651	0.395660
Maximum	20.37789	33.66029	13.11325	100.0000
Minimum	0.000000	0.000000	0.000000	0.000000
Std. Dev.	1.101674	2.177053	0.840950	2.943908
Skewness	7.714423	4.673731	0.297379	24.12025
Kurtosis	97.03042	40.43629	12.76930	707.4789
Jarque-Bera	1293110 (0.000000)	212037.1 (0.000000)	13642.52 (0.000000)	71011469 (0.000000)
Ljung - Box Q	7566.8 (0.000000)	4416.8 (0.000000)	4677.0 (0.000000)	1311.3 (0.000000)
Aug. Dickey-Fuller	-11.18311 (0.000000)	-24.11579 (0.000000)	-8.579.539 (0.000000)	-5.253.120 (0.000000)
Observations	3418	3418	3418	3418

The following Table displays the same descriptive statistics for $ASVI$ with category specification "Investment". Interestingly, we find that when filtering the search volume for those individuals that are somehow concerned about investments, the average degree of attention paid to "Cancer" is much lower (2,7 against 6,1 without category specification), whereas "Terrorism" attracts a higher average level of attention among investors than among general agents (4,9 against 2,9 without category specification).

Table 4

Descriptive Statistics for Adjusted Search Volume Indexes, category: Investment

***ASVI* Statistics**	NATURAL DISASTER *Investment*	TERRORISM *Investment*	CANCER *Investment*	OPINION POLL *Investment*
Mean	2.093039	4.948431	2.709022	0.843937
Median	1.720032	3.310832	1.894486	0.378950
Maximum	54.76496	59.19692	87.92453	73.04075
Minimum	0.000000	0.000000	0.000000	0.000000
Std. Dev.	2.139195	6.203874	4.591842	2.302765
Skewness	6.390084	3.195362	6.608740	16.81301
Kurtosis	119.5706	18.13119	87.45372	426.9656
Jarque-Bera	1958518. (0.000000)	38423.19 (0.000000)	1040657. (0.000000)	25759981 (0.000000)
Ljung - Box Q	489.43 (0.000000)	956.79 (0.000000)	56.117 (0.000000)	1952.2 (0.000000)
Aug. Dickey-Fuller	-22.88884 (0.000000)	-5.498752 (0.000000)	-6.613993 (0.000000)	-20.62723 (0.000000)
Observations	3418	3418	3418	3418

NOTE: The entries in Table 3 and 4 denote the specific summary statistics (mean, median, maximum, minimum, standard deviation, skewness, kurtosis and the Jarque- Bera statistic) for Adjusted Search Volume Indexes without category specification and with "Investment" category specification, respectively. The Ljung-Box Q-statistics test for the null hypothesis that there is no autocorrelation up to order 5. The Augmented Dickey-Fuller tests the null hypothesis that a unit root is present in a time series sample. P-values are shown in parentheses. Sample: each time series is composed by daily data from 02.01.2004 to 31.07.2017, filtered for trading days, T=3418.

4. Empirical applications

In the previous section, we identified a set of concepts/ events to be used for the development of related variables, we extracted aggregate Google search volume for U.S. users, distinguishing those interested in investing (we will refer to them as investors), and finally we built uncertainty measures on daily and monthly basis, following different approaches.

In this section, we want to employ our novel uncertainty metrics in two empirical frameworks in order to shed light on the link between ambiguity shocks and business cycle. At first, we study the impact of daily changes in Adjusted Search Volume Indexes $ASVI_{dm}$ on the variation of volume trading and on the stock market' returns. In particular, we want to investigate whether an increase in the aggregate degree of uncertainty produces behavioural biases and heuristic choices within the financial context. At the same time, we want to understand the relative importance of each concept/events that trigger ambiguity aversion among individuals and the magnitude of the relative shocks.

Thereafter, we employ monthly uncertainty indicators based on the same concepts/ terms of the daily metrics to investigate their impact on four main macroeconomic variables. In other words, we intend to find out whether the same ambiguity shocks that might produce behavioural biases and affect the capital market participation, do indeed affect the economic activity, eliciting a tightening of the business cycle conditions as suggested by the Real Options theories (see e.g. Bernake, 1983 and Bloom, 2009).

4.1 Search-based uncertainty and Stock Market Activity

We use a vector autoregressive (VAR) framework to examine the relationship between daily changes of $ASVIs$ and daily stock market activity. The VAR model enables us to simultaneously estimate the bidirectional causal relationship between stock market measures and our brand new uncertainty measures. The model takes the following form:

(6) $$y_t = a + \sum_{i=1}^{5} \beta_i \cdot y_{t-i} + \sum_{i=0}^{5} \theta_j \cdot x_{t-j} + \varepsilon_t$$

Where y_t denotes the following endogenous variables in the system: $d\_ASVI_t\{n\}$, $SP500\_Rets_t$ and d_Volume_t. $d\_ASVI\{n\}$ represents the daily change of Adjusted Search Volume Index for the term{n}; $SP500\_Rets_t$ identifies the daily returns of the Standard and Poor 500 Index $SP500\_Rets_t = \log\left(\frac{p_t}{p_{(t-1)}}\right)$ where p_t denotes price on day t; $d_{Volumet}$ stands for the daily change of the trading volume of the S&P 500, on day t [26]. All VAR estimates include all lags of up to 5 days, that means one week of calendar time for the stock market, prior to market activity. The choice of lag length is based on the Akaike (1974) information criteria[27], starting from p = 15. The rest of the equation is composed by a which is a constant and x_t that represents the vector of exogenous control variables in the model. The exogenous variables include the daily changes of CBOE Volatility index VIX up to five lags to control for past volatility and the five lags of the first difference of ADS index proxy for general economic and business conditions. The ADS index, developed by Aruoba, Diebold, and Scotti (2009), is designed to track macroeconomic conditions with high frequency in the US. More specifically, ADS is constructed upon a wide variety of macroeconomic indicators at different frequencies, namely seasonally adjusted weekly jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales and quarterly real GDP. The average value of the ADS index is zero, and values larger (smaller) than zero indicate better (worse) than average economic conditions. Finally, the vector of exogenous variables also contains a dummy variable crisis_dummy to control for the bankruptcy of Lehman Brothers and the associated turbulence in the financial markets. The dummy variable takes value 1 for the fourth quarter of 2008 and the first quarter of 2009: the dates of the financial crisis are chosen in an arbitral way because there is no consensus on the length of the crisis, but selecting the peak period should avoid mistakes. The inclusion of this latter variable is motivated by our aim to determine whether negative financial conditions amplify the effect of uncertainty resulting from external events, i.e. Not economy-related. In other words, we want to test the psychological bias that in the presence of an uncertain environment (in our case it is triggered by the collapse of the US financial

[26] Because trading volume in levels is not stationary, we detrend it using first-order differencing. It is also important to note that we obtain qualitatively similar results when we use alternative detrending procedures such moving average detrending as in Campbell, Grossman, and Wang (1993) and Tetlock (2007).

[27] The AIC criterion for VARs testing the impact of d_ ASVI{Cancer} and d_ ASVI{Cancer_Investetment} suggests a lag length equal to 4 and 3 respectively, however we maintain our choice of 5 lags even for these VARs in order to be coherent with the other regressions.

system) individuals tend to over-react to additional ambiguity shocks (see e.g. Sarin and Weber, 1993). Each series entering in our regression estimates is stationary. Except for the S&P500 returns, all the other variables are inserted in the first difference. Using daily changes of trading volume instead of the absolute values allows us to de-trend the series (ACF analysis). Daily economic activity is approximated by the ADS index (Aruoba et al., 2009). Due to the presence of a unit root[28], we take the first difference and we include the daily increment/decrement of economic activity up to the last five days. To control for past volatility we use VIX up to 5 lags. The inclusion of these latter exogenous variables enables us to determine whether web searches do indeed have explanatory power in measuring the uncertainty within the stock market activity or conversely their impact is subsumed by the ADS and the VIX.

The analysis using the VAR (6) model offers a flexible way to model interdependencies among the variables included in the system, as each variable y_t is expressed as a linear function of its own lags and lags of every other variable in the system. A Vector Auto Regression is actually a set of reduced form equations similar to what might be derived from a structural econometric model. Such models make highly restrictive assumptions on the values estimated their reduced form equations. These restrictions most often take the form of exclusions of variables or lags of variables from these models, which in effect restricts the estimated parameters of these “discarded" variables to zero. This implies that these variables have no predictive or explanatory power in the model. A VAR, instead, include these variables, relying on a much less restrictive concept of economic theory as it applies to these reduced form equations. Data is then allowed to determine the contribution of variables instead of *a priori* structure. This framework has proven to be especially useful for describing the dynamic behaviour of economic and financial time series and for forecasting. It is indeed intuitively appealing to let market data show how particular components of the market, the variables, interact.

[28] Augmented Dickey-Fuller with Null Hypothesis ADS has a unit root: t-Statistic= 1.268849, P-value= 0.9986.

Our 5 lags model can be rewritten in the following simultaneous equation (reduced form):

$$\beta_0^1\, y_{1t} = a_1 + \sum_{i=1}^{5} \beta_{1i}^1 y_{1,t-i} + \sum_{i=1}^{5} \beta_{2i}^1 y_{2,t-i} + \sum_{i=1}^{5} \beta_{3i}^1 y_{3,t-i} + \sum_{i=0}^{5} \theta_j^1 X_{t-j} + \varepsilon_{1t}$$

$$\beta_0^2 y_{2t} = a_2 + \sum_{i=1}^{5} \beta_{1i}^2 y_{1,t-i} + \sum_{i=1}^{5} \beta_{2i}^2 y_{2,t-i} + \sum_{i=1}^{5} \beta_{3i}^2 y_{3,t-i} + \sum_{i=0}^{5} \theta_j^2 X_{t-j} + \varepsilon_{2t}$$

$$\beta_0^3 y_{3t} = a_3 + \sum_{i=1}^{5} \beta_{1i}^3 y_{1,t-i} + \sum_{i=1}^{5} \beta_{2i}^3 y_{2,t-i} + \sum_{i=1}^{5} \beta_{3i}^3 y_{3,t-i} + \sum_{i=0}^{5} \theta_j^3 X_{t-j} + \varepsilon_{3t}$$

Where X_t is actually the vector of the three exogenous variables aforementioned (d_VIX, d_ADS and crisis_dummy) $X'_t = [x_{1t}, x_{2t}, x_{3t}]$. Note that the key condition for correctness of this model is that $E\left[\varepsilon_t \middle| \{y_{t-i}\}_{i=1}^{5}, \{x_{t-i}\}_{j=0}^{5}\right] = 0\ (\in R^3)$, where ε_t is identified as a 3 x 1 white noise innovation process, with $E(\varepsilon_t) = 0$, $E(\varepsilon_t, \varepsilon_t') = \sum_t$, $E(\varepsilon_t, \varepsilon_s') = 0$ for $t \neq s$[29].

In matrixes, the system of the previous equations boils down to the following companion form:

$$B_0 \begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} + \begin{pmatrix} \beta_{1,1}^1 & \beta_{2,1}^1 & \beta_{3,1}^1 \\ \beta_{1,1}^2 & \beta_{2,1}^2 & \beta_{3,1}^2 \\ \beta_{1,1}^3 & \beta_{2,1}^3 & \beta_{3,1}^3 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{pmatrix} + \cdots + \begin{pmatrix} \beta_{1,5}^1 & \beta_{2,5}^1 & \beta_{3,5}^1 \\ \beta_{1,5}^2 & \beta_{2,5}^2 & \beta_{3,5}^2 \\ \beta_{1,5}^3 & \beta_{2,5}^3 & \beta_{3,5}^3 \end{pmatrix} \begin{pmatrix} y_{1t-5} \\ y_{2t-5} \\ y_{3t-5} \end{pmatrix}$$

$$+$$

$$+ \begin{pmatrix} \theta_{1,1}^1 & \theta_{2,1}^1 & \theta_{3,1}^1 \\ \theta_{1,1}^2 & \theta_{2,1}^2 & \theta_{3,1}^2 \\ \theta_{1,1}^3 & \theta_{2,1}^3 & \theta_{3,1}^3 \end{pmatrix} \begin{pmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \end{pmatrix} + \cdots + \begin{pmatrix} \theta_{1,5}^1 & \theta_{2,5}^1 & \theta_{3,5}^1 \\ \theta_{1,5}^2 & \theta_{2,5}^2 & \theta_{3,5}^2 \\ \theta_{1,5}^3 & \theta_{2,5}^3 & \theta_{3,5}^3 \end{pmatrix} \begin{pmatrix} x_{1t-5} \\ x_{2t-5} \\ x_{3t-5} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{pmatrix}$$

The endogenous variables enter in the vector $y' = [y_1, y_2, y_3]$ in the following order: y_1 is the first difference of our uncertainty indicator $ASVI\{n\}$, y_2 is the daily change of the volume trading d_ Volume and y_3 is the daily return of the S&P 500, $SP500\_Rets_t$. The ordering of y_t is based on the assumption that uncertainty shocks cause at first fear among investors about the nearest future, hence ambiguity aversion leads investors to increase their information searches about the source of uncertainty. Once the need for information

[29] The last statement implies that the vector of innovations are contemporaneously correlated with full rank matrix Σ_t, but are uncorrelated with their leads and lags of the innovations and (assuming the usual $x_t$orthogonality) uncorrelated with all of the right-hand side variables.

is fulfilled and the relevant content is processed by individuals (here *heuristics* decisions are often observed[30]), a wider heterogeneity of beliefs and guesses spreads among investors. As a consequence, an increase in the number of total transactions should occur (see e.g. Odean, 1998). Following the changes of volume trading, uncertainty initially lowers returns and subsequently investors should demand an uncertainty premium, leading to an increase in the stocks' prices. The concern about ordering our VAR is actually prompted by the impulse response function (IRF). Since we are going to employ a Cholesky decomposition, we need to order our variables with an exogeneity criterium. Cholesky factorization is built on a lower triangular matrix to orthogonalize the impulses. This option imposes an ordering of the variables in the VAR and attributes all of the effect of any common component to the variable that comes first in the VAR system. Hence we put first the most exogenous of our variables i.e. $\mathrm{ASVI\{n\}}$, then the daily change of volume trading and as last the variable for which the all the other variables have an effect on it, that is $\mathrm{SP500\_Returns_t}$.

The right hand sides of each of three equations contains exactly the same variables and the same lags of variables. Consequently, the moment matrix (XX') will be the same for every equation. In this case, where the right hand sides are the same and are predetermined the system can be estimated equation-by-equation using ordinary least squares (OLS) with no simultaneous equation bias (Ford, 1986). In other words, since the error terms are assumed to be independent of the lagged values of the endogenous variables in the system, each equation can be estimated independently using OLS with exactly the same results.

We can therefore examine the relationship between daily Adjusted Search Volume Indexes and the stock Market activity in two strands. At first we focus on the impact of uncertainty shocks on the quantity of S&P 500' transactions. The forecasting regressions are similar to those used by Tetlock (2007) and Garcia (2013) to predict future stock market activity using media news sentiment. Throughout the empirical analysis, we will focus on the estimates of the coefficients on the variable $\mathrm{d\_ASVI\{n\}}$, (i.e., $\boldsymbol{\beta_{1i}}$) which describe the dependence of the stock market measures on uncertainty implied by the Google Search

[30] The mental shortcuts in the "decision making" process, as opposed to a thorough information gathering and analysis, are referred to as "heuristics". Although heuristics can be helpful in many situations, they often lead to biased decisions (see e.g. Tversky & Kahneman, 1974). The use of heuristics and their effects on financial decision making is well recognized in behavioral economics/finance literature which provides many examples of poor decision making, such as selling the winners too early and holding the losers for too long, excessive trading (Odean, 1998), and under-diversification (Goetzmann & Kumar, 2008).

Volume. The analysis of the relationship between trading volume and uncertainty is motivated both by recent empirical evidence provided by Dinh and Gajewski (2015) and by the theoretical model of Campbell, Grossman, and Wang (1993). In their paper, Campbell, Grossman, and Wang (1993) demonstrate that unusually high or low values of investor beliefs will generate higher trading volume in financial markets. Specifically, when noise investors experience a negative (positive) belief shock, they will sell (buy) securities. To restore market equilibrium, market makers will absorb rising demand (supply) from noise traders, which will result in higher trading volume (Tetlock, 2007). Likewise, Dinh and Gajewski (2015) provided evidence that the dispersion of beliefs is the main driver behind trading volume and that heterogeneity of expectations does not decrease when investors have more information about the final results. However, wide ambiguity in expectations dissuades investors from trading. Thus, we test whether $\Delta\ \mathrm{ASVI}\{n\}$ forecasts future daily volume changes by estimating the following model:

$$y_{2t} = a_2 + \sum_{i=1}^{5} \boldsymbol{\beta_{1i}^2} y_{1,t-i} + \sum_{i=1}^{5} \beta_{2i}^2 y_{2,t-i} + \sum_{i=1}^{5} \beta_{3i}^2 y_{3,t-i} + \sum_{i=0}^{5} \theta_j^2 X_{t-j} + \varepsilon_{2t}$$

(6.1)

Or

$$d\_\mathrm{Volume}_t = a_2 + \sum_{i=1}^{5} \boldsymbol{\beta_{1i}^2} d\_\,\mathrm{ASVI}_t\{n\}_{t-i} + \sum_{i=1}^{5} \beta_{2i}^2 d\_\,\mathrm{Volume}_{t-i} + \sum_{i=1}^{5} \beta_{3i}^2 \mathrm{SP500\_Rets}_{t-i} + \sum_{i=0}^{5} \theta_j^2 X_{t-j} + \varepsilon_{2t}$$

Here below we present the regressions' results for each of the $\mathrm{ASVI}\{n\}$ terms and specifications: *Natural Disaster, Terrorism, Cancer, Opinion Poll* both with no category selection and with category selection "Investment". Due to the large extent of the estimations output, we summarize in the following tables the $\boldsymbol{\beta_{1i}}$ coefficient estimates in absolute values (with the related $t-\mathrm{statistics}$). Nonetheless, a complete version of our results can be found in the Appendix A4.

The following four tables report the coefficient estimates in absolute value for both the $\mathrm{ASVI}\{n\}$ measure (i), (ii) and the $\mathrm{ASVI}\{n\_\mathrm{Investment}\}$ measure (iii), (iv). Furthermore, each uncertainty indicator is tested with (ii), (iv) and without the inclusion of the Financial Crisis dummy variable (i), (iii). The last entry of the tables, displays the results of the null hypothesis that the sum of the standardized coefficients of the Adjusted Search Volume

Indicator from lag one to lag five is equal to zero (Wald coefficient test). In other words, we shall investigate whether the initial decrease or increase in trading volume is followed by a full reversal in the following five days

Table 5:

Predicting Daily Trading Volume Using ASVI{Cancer} *and* ASVI{Cancer_Investment}

	CANCER				CANCER *Investment*			
	(i)		(ii)		(iii)		(iv)	
	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*
Δ *ASVI* $_{t-1}$	77,870***	[3.98785]	80,082***	[4.09112]	2,280	[1.00554]	2,227	[0.98267]
Δ *ASVI* $_{t-2}$	3,094	[0.14816]	3,727	[0.17843]	1,518	[0.51968]	1,519	[0.52040]
Δ *ASVI* $_{t-3}$	4,329	[0.19948]	5,212	[0.24016]	3,482	[1.08289]	3,477	[1.08198]
Δ *ASVI* $_{t-4}$	-30,016	[-1.45748]	-29,724	[-1.44373]	4,432	[1.52207]	4,445	[1.52744]
Δ *ASVI* $_{t-5}$	-5,728	[-0.29855]	-5,174	[-0.26982]	2,559	[1.14706]	2,547	[1.14237]
Inclusion of Crisis Dummy	No		Yes		No		Yes	
No. Obs.[1]	2702		2702		2702		2702	
Adj. R^2 (%)	25,397		25,693		24,007		24,117	
$\sum_{i=1}^{5} \beta_{1t-i} = 0$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$
	0.490351	0.4838	0.583732	0.4449	1,77	0.1837	1,76	0.1852

[1] After adjustment
* Significance at the 10% level
** Significance at the 5% level
*** Significance at the 1% level

The table summarizes the coefficient estimates of the first difference of the Adjusted Search Volume Index for Cancer and Cancer – category specification Investment. The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED.

Table 5 displays the relationship between the daily changes of the search volume of the term Cancer and the daily variation of the total number of transactions performed within the S&P 500. As we can see, a change in the level of web-searches for the term "Cancer" has a statistical and economical effect on the next day's volume trading (regression (i): $t - stat = 3.98,\ p - value \leq 0.01$). The sign of the coefficient of $\Delta\,ASVI_{t-1}\{Cancer\}$ is positive, which seems to run counter to what is generally postulated as the impact of uncertainty, namely to decrease the short-term volume of transactions as result of a "blocking" fear for the near future (see e.g. Laakkonen, 2015). However, an increased level of attention towards this serious disease might reflect not only anxiety and fear, but also the release of conflicting

pieces of information (e.g. a new controversial treatment) which elicit different beliefs among investors. Hence, this heterogeneity of views quickly produces a higher volume of equity trades. The sum of the standardized coefficients estimates for lag one to lag five is not significantly different from zero ($\chi^2 - \text{test} = 0.49$ and $p - \text{value} > 0.1$, (i) regression). Thus, we can't reject the hypothesis that the reversal in lags 1 through 5 exactly offsets the initial increase in market volume trades. Changes of the Adjusted Search Volume with lags greater than one, do not appear to affect significantly the Volume Trading, meaning that stock market' activity is influenced by web searches of the day before, but not by those of the prior days. The category specification "Investment" does not lead to significant results, most likely due to the difficult combination of web-searches for the term "cancer" in the context of stocks' portfolios selection. Interestingly, the inclusion of the crisis dummy variable slightly improves our regression (greater t-statistics and R squared).

Table 6:

Predicting Daily Trading Volume Using ASVI{Natural Disaster} *and* ASVI{Natural Disaster_Investment}

	NATURAL DISASTER				NATURAL DISASTER *Investment*			
	(i)		(ii)		(iii)		(iv)	
	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*
Δ *ASVI* $_{t-1}$	78,099***	[3.19941]	77,935***	[3.19413]	4,039	[0.77990]	3,874	[0.74807]
Δ *ASVI* $_{t-2}$	23,464	[0.94365]	22,906	[0.92135]	2,573	[0.39752]	2,377	[0.36740]
Δ *ASVI* $_{t-3}$	-4,904	[-0.18338]	-5,613	[-0.20994]	-0,315	[-0.04533]	-0,496	[-0.07131]
Δ *ASVI* $_{t-4}$	-1,142	[-0.43778]	-1,101	[-0.42233]	-0,592	[-0.09020]	-0,839	[-0.12799]
Δ *ASVI* $_{t-5}$	-1,152	[-0.47428]	-1,272	[-0.52372]	-2,630	[-0.49613]	-2,835	[-0.53509]
Inclusion of Crisis Dummy	No		Yes		No		Yes	
No. Obs.[1]	2702		2702		2702		2702	
Adj. R^2 (%)	25,00		25,27		24,69		24,97	
	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$
$\sum_{i=1}^{5} \beta_{1t-i} = 0$	1,24	0.2653	1,17	0.2800	0.017496	0.8948	0.008011	0.9287

[1] After adjustment
* Significance at the 10% level
** Significance at the 5% level
*** Significance at the 1% level

The table summarizes the coefficient estimates of the first difference of the Adjusted Search Volume Index for Natural Disaster and Natural Disaster – category specification Investment. The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED.

The coefficient estimates for both Δ ASVI{Natural Disaster} and Δ ASVI{Natural Disaster_Investment} are presented in Table 6. Consistent with the previous results, we find that daily variability of web-searches for the term "Natural Disaster" has a statistical and economic effect on the next day's volume trading (regression (i): $t-\text{stat} = 3.19,\ p-\text{value} \leq 0.01$). The sign of the day before coefficient i.e. $\Delta\ \text{ASVI}_{t-1}$\{Natural Disaster\} is positive, however older variations' coefficients (i.e. lags greater than two) exhibit negative signs. In other words, an increased level of attention towards natural adverse events immediately raises the volume of transactions, but in a matter of two days this effect is reversed. The sum of the standardized coefficients estimates for lag one to lag five is not significantly different from zero ($\chi^2 - \text{test} = 1{,}24$ and $p - \text{value} > 0.1$, (i) regression). Therefore, the initial variation of market volume trades is at least partially reversed within a week. The regressions that include crisis dummy variable, display slightly better estimates. This finding suggests that the impact of uncertainty, implied by the Google searches "Natural Disaster", is even more significant in combination with a distressed economic environment.

Table 7:

Predicting Daily Trading Volume Using ASVI{Opinion Poll} *and* ASVI{Opinion Poll_Investment}

	OPINION POLL				OPINION POLL *Investment*			
	(i)		(ii)		(iii)		(iv)	
	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*
Δ *ASVI* $_{t-1}$	14,419***	[3.82459]	15,434***	[3.83123]	16,831***	[3.14488]	16,856***	[3.15178]
Δ *ASVI* $_{t-2}$	10,251**	[2.52477]	10,225**	[2.52009]	17,487**	[3.14456]	17,410**	[3.13291]
Δ *ASVI* $_{t-3}$	11,609**	[2.70399]	11,599**	[2.70356]	16,406**	[2.79987]	16,409**	[2.80237]
Δ *ASVI* $_{t-4}$	6,364	[1.56988]	6,368	[1.57209]	17,782***	[3.20095]	17,785***	[3.21662]
Δ *ASVI* $_{t-5}$	4,828	[1.21887]	4,805	[1.21396]	12,006**	[2.23549]	12,027**	[2.24097]
Inclusion of Crisis Dummy	No		Yes		No		Yes	
No. Obs.[1]	2702		2702		2702		2702	
Adj. R^2 (%)	25,17		25,45		25,20		25,48	
	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$
$\sum_{i=1}^{5} \beta_{1t-i} = 0$	13,3	0.0003	8,19	0.004	8,19	0.004	18,18	0.000

[1] After adjustment
* Significance at the 10% level
** Significance at the 5% level
*** Significance at the 1% level

The table summarizes the coefficient estimates of the first difference of the Adjusted Search Volume Index for Opinion Poll and Opinion Poll – category specification Investment. The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED.

Table 7 displays the relationship between the daily changes of the search volume of the term "Opinion Poll" and the daily variation of the total number of transactions executed within the S&P 500. As we can notice, the change in the volume of web-searches of "Opinion Poll" has highly significant effects on the next days' volume trading. The coefficient estimates are significant not only on the first lag (i.e. the day before), but until lag three in the regressions (i), (ii) and lag 5 in the regression (iii), (iv). In other words, the number of stock market transactions is affected by the variation of "Opinion Poll" searches of five (and three) days before. The sign of the coefficients $\boldsymbol{\beta_{1i}}$ is positive for all the regressions, denying the presence of a "blocking fear". That is, investors do not appear to stop market transaction as uncertainty regarding the outcome of a vote takes place. Their trades rather reflect the amount of information they collect in order to increase their awareness. Uncertainty leads to different (*ambiguous)* views about future outcomes and in turn, this translates to different market positions among investors. The final entries of the table indicate that the sum of the standardized coefficients estimates for first five days of change in the aggregate web-searches is significantly different from zero ($\chi^2 - \text{test} = 13{,}3$ and $\text{p} - \text{value} < 0.01$, (i) regression). Hence, we can reject the null hypothesis that the effect of Δ ASVI on volume trading fades away in five days and we can reasonably assume that a full reversal of the initial increment of volume trading does not occur within a week. Remarkably, the category specification "Investment" does lead to highly significant results, disclosing a strong interest among investors about the outcome of a vote. This is understandable given that web searches of "Opinion Poll" are reasonably in line with the context of stocks' portfolios selection. In this case too, the inclusion of the crisis dummy variable improves our regression' estimates.

Table 8:

Predicting Daily Trading Volume Using ASVI{Terrorism} *and* ASVI{Terrorism_Investment}

	TERRORISM				TERRORISM *Investment*			
	(i)		(ii)		(iii)		(iv)	
	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*
Δ *ASVI* $_{t-1}$	-2,053	[-0.02708]	-0,418	[-0.05515]	-0,802	[-0.40117]	-0,732	[-0.36623]
Δ *ASVI* $_{t-2}$	-3,104	[-0.40025]	-3,219	[-0.41540]	-1,378	[-0.55112]	-1,267	[-0.50706]
Δ *ASVI* $_{t-3}$	-2,727	[-0.34071]	-2,866	[-0.35830]	-2,270	[-0.86343]	-2,155	[-0.82013]
Δ *ASVI* $_{t-4}$	2,434	[0.32055]	2,330	[0.30693]	-0,407	[-0.16500]	-0,441	[-0.17890]
Δ *ASVI* $_{t-5}$	4,467	[0.61738]	4,362	[0.60332]	-0,414	[-0.20785]	-0,391	[-0.19648]
Inclusion of Crisis Dummy	No		Yes		No		Yes	
No. Obs.[1]	2702		2702		2702		2702	
Adj. R^2 (%)	24,69		24,97		25,20		24,97	
	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$
$\sum_{i=1}^{5} \beta_{1t-i} = 0$	0.001196	0.9724	5.67E-05	0.9940	0.341609	0.5589	0.306081	0.5801

[1] After adjustment
[*] Significance at the 10% level
[**] Significance at the 5% level
[***] Significance at the 1% level

The table summarizes the coefficient estimates of the first difference of the Adjusted Search Volume Index for Terrorism and Terrorism – category specification Investment. The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED.

The coefficient estimates for both Δ ASVI{Terrorism} and Δ ASVI{Terrorism_Investment} are displayed in Table 8. Contrary to the previous results, we don't find that daily changes in web-searches for the term "Terrorism" has a statistical and economic effect on the next day's volume trading. Still, we can observe that the sign of Δ ASVI coefficients up to three lags (namely up to three days before), are negative. This finding suggests that the uncertainty addressing to terrorist attacks, leads investors to freeze their trades. As a matter of fact, investor sentiment literature consistently finds that the occurrence of major adverse events as a terrorist attack, exerts strong psychosocial effects among investors who react lowering their market expectations and their activity (see e.g. Drakos, 2009).

So far, we found out that the changes of Adjusted Search Volume for the terms "Cancer", "Natural Disaster" and "Opinion Poll" have a positive influence on the variation of Volume trading; on the contrary, an increase in web-searches of "Terrorism" negatively affects the

number of stocks' transactions. In all the cases the initial increment (decrement) in trading volume is not followed by a reversal in the following five days, meaning that the uncertainty effects' are not fully incorporated by the Stock Market activity within a trading week.

Next, we consider the effect of changes in ASVI on future daily market returns. To test whether Δ ASVI forecasts future daily returns, we estimate the following model:

$$y_{3t} = a_3 + \sum_{i=1}^{5} \boldsymbol{\beta_{1i}^{3}} y_{1,t-i} + \sum_{i=1}^{5} \beta_{2i}^{3} y_{2,t-i} + \sum_{i=1}^{5} \beta_{3i}^{3} y_{3,t-i} + \sum_{i=0}^{5} \theta_{j}^{3} X_{t-j} + \varepsilon_{3t}$$

(6.2) or

$$d\_\text{Returns} = a_3 + \sum_{i=1}^{5} \boldsymbol{\beta_{1i}^{3}} d\_\text{ASVI}_t\{n\}_{t-i} + \sum_{i=1}^{5} \beta_{2i}^{3} d\_\text{Volume}_{t-i} + \sum_{i=1}^{5} \beta_{3i}^{3} \text{SP500\_Rets}_{t-i} + \sum_{i=0}^{5} \theta_{j}^{3} X_{t-j} + \varepsilon_{3t}$$

Table 9:

Predicting *Daily Market Returns* *Using* ASVI{Cancer} *and* ASVI{Cancer_Investment}

	CANCER				CANCER *Investment*			
	(i)		(ii)		(iii)		(iv)	
	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*
Δ *ASVI* $_{t-1}$	-0.000122	[-0.56437]	-0.000216	[-0.32462]	1.21E-05	[0.48100]	1.05E-05	[0.41978]
Δ *ASVI* $_{t-2}$	-0.000108	[-0.46669]	-0.000231	[-0.42776]	4.83E-05	[1.49584]	4.79E-05	[1.49282]
Δ *ASVI* $_{t-3}$	0.000266	[1.10452]	0.000240	[1.194579]	1.85E-05	[0.52053]	1.81E-05	[0.51343]
Δ *ASVI* $_{t-4}$	-1.87E-05	[-0.08197]	-0.000227	[0.196839]	-5.14E-06	[-0.15972]	-5.24E-06	[-0.16365]
Δ *ASVI* $_{t-5}$	-0.000378*	[1.87469]	-0.000212**	[2.072259]	-1.25E-05	[-0.50833]	-1.35E-05	[-0.54838]
Inclusion of Crisis Dummy	No		Yes		No		Yes	
No. Obs.[1]	2702		2702		2702		2702	
Adj. R^2 (%)	70,04		70,34		70,29		70,38	
$\sum_{i=1}^{5} \beta_{1t-i} = 0$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$
	0.490351	0.4838	0.483444	0.4869	0.322535	0.5672	0.332535	0.5642

[1] After adjustment
* Significance at the 10% level
** Significance at the 5% level
*** Significance at the 1% level

The table summarizes the coefficient estimates of the first difference of Adjusted Search Volume Index for Cancer and Cancer – category specification Investment. The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED.

Here above we summarize the estimates in absolute value of the coefficients of the daily changes in the Adjusted Search Volume Index for the term "Cancer" from the return predictability regressions. As we can see, a change in the level of web-searches for the term "Cancer" has a statistically low effect on the next day's market returns (regression (i): $t-\text{stat} = 0.56,\ p-\text{value} > 0.10$). We find a relative higher significance in the coefficient estimates of Δ ASVI with five days lags (regression (i) $t-\text{stat} = 1.87,\ p-\text{value} \leq 0.10$) suggesting that stock prices respond to uncertainty variation with a certain degree of delay. Consistent with our expectations, the sign of the coefficients of Δ ASVI{Cancer} are all negative, except for lag three. Therefore, an increase in uncertainty leads to lower stock prices within a trading week. The results of regression (ii) give evidence that the explanatory power of the daily variations in $ASVI$ for future returns is higher during the peak of the financial crisis (regression (ii) $t-\text{stat} = 2.07,\ p-\text{value} \leq 0.05$). The sum of the coefficients up to five lags is not significantly different from zero ($\chi^2 - \text{test} = 0{,}49$; $p-\text{value} > 0.1$, (i) regression). In other words, we cannot reject the hypothesis that a reversal in stock prices initial variation, does occur within a week. In a similar fashion to the volume trading prediction (Table 4), the category specification "Investment" does not lead to significant results.

Table 10:

Predicting Daily Market Returns Using ASVI{Natural Disaster} *and* ASVI{Natural Disaster_Investment}

	NATURAL DISASTER				NATURAL DISASTER *Investment*			
	(i)		(ii)		(iii)		(iv)	
	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*
Δ *ASVI* $_{t-1}$	0.000401	[1.48477]	0.000399	[1.48434]	4.47E-05	[0.78054]	4.02E-05	[0.70514]
Δ *ASVI* $_{t-2}$	0.000327	[1.18805]	0.000319	[1.16574]	0.000101	[1.40631]	9.60E-05	[1.34940]
Δ *ASVI* $_{t-3}$	0.000408	[1.37844]	0.000408	[1.38395]	0.000100	[1.30267]	9.62E-05	[1.25742]
Δ *ASVI* $_{t-4}$	0.000162	[0.56111]	0.000164	[0.57226]	9.90E-05	[1.36511]	9.33E-05	[1.29328]
Δ *ASVI* $_{t-5}$	0.000178	[0.66091]	0.000157	[0.58580]	4.99E-05	[0.85176]	4.52E-05	[0.77586]
Inclusion of Crisis Dummy	No		Yes		No		Yes	
No. Obs.[1]	2702		2702		2702		2702	
Adj. R^2 (%)	70,00		70,39		70,30		70,36	
	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$
$\sum_{i=1}^{5} \beta_{1t-i} = 0$	4.05992	0.0439	3.938715	0.0472	0.670912	0.4127	2.056208	0.1516

[1] After adjustment
* Significance at the 10% level
** Significance at the 5% level
*** Significance at the 1% level

The table summarizes the coefficient estimates of the first difference of the Adjusted Search Volume Index for Natural Disaster and Natural Disaster – category specification Investment. The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED.

Table 10 presents the relationship between the daily changes of the search volume of the term "Natural Disaster" and the daily variation of the Standard and Poor 500 Stock prices. Contrary to our expectations, we don't find statistical significance in the estimates of Δ ASVI{Natural Disaster} and Δ ASVI{Natural Disaster_Investment}. One possible explanation is that the impact of uncertainty fluctuations triggered by the occurrence of Natural Disasters is already subsumed by the implied volatility index.

Table 11:

Predicting Daily Market Returns Using ASVI{Opinion Poll} *and* ASVI{Opinion Poll_Investment}

	OPINION POLL				OPINION POLL *Investment*			
	(i)		(ii)		(iii)		(iv)	
	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*
$\Delta\ ASVI_{t-1}$	-5.37E-05*	[-1.89791]	-5.33E-05*	[-1.97911]	-6.67E-05**	[-2.23549]	-6.61E-05**	[- 2.52477]
$\Delta\ ASVI_{t-2}$	2.04E-06	[0.04529]	1.61E-06	[0.03592]	-4.86E-05	[-0.78722]	-4.95E-05	[-0.80650]
$\Delta\ ASVI_{t-3}$	-1.04E-05	[-0.21815]	-1.07E-05	[-0.22497]	-3.15E-05	[-0.48512]	-3.13E-05	[-0.48489]
$\Delta\ ASVI_{t-4}$	2.18E-05	[0.48397]	2.16E-05	[0.48365]	5.03E-05	[0.81592]	5.24E-05	[0.85554]
$\Delta\ ASVI_{t-5}$	2.93E-06	[0.06671]	2.13E-06	[0.04886]	2.93E-05	[0.49138]	3.09E-05	[0.52142]
Inclusion of Crisis Dummy	No		Yes		No		Yes	
No. Obs.[1]	2702		2702		2702		2702	
Adj. R^2 (%)	69,99		70,35		70,01		70,07	
	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$
$\sum_{i=1}^{5} \beta_{1t-i} = 0$	0.009655	0.9217	0.069200	0.7925	0.102978	0.7483	0.0472	0.670912

[1] After adjustment
* Significance at the 10% level
** Significance at the 5% level
*** Significance at the 1% level

The table summarizes the coefficient estimates of the first difference of the Adjusted Search Volume Index for Opinion Poll and Opinion Poll – category specification Investment. The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED.

Examining the coefficient estimates of daily changes of "Opinion Poll" Google searches, we find that Δ ASVI has statistically significant effects on the next days' market returns, and the estimates' explanatory power increases when we consider the category specification "Investment" (regression (iv) $t-\text{stat} = -2.52,\ p-\text{value} \leq 0.05$). Changes of the Adjusted Search Volume with lags greater than one do not appear to affect significantly the S&P500 returns. Thus, an increment of uncertainty about the outcome of a vote, immediately affect investors' expectations, which in turn lead to lower stock prices. Consistent with the results of the regressions displayed in Table 6 (Volume Trading Prediction), we find a relative strong link between investment choices and Opinion poll searches. Moreover, the results of regression (ii) and (iv) gives evidence that our uncertainty indicator is most influential (and most useful) during periods of market turmoil. The Wald coefficient test results lead us not to reject the hypothesis that the effect of Δ ASVI on market returns is reversed within a trading week ($\chi^2 - \text{test} = 0{,}109;\ p-\text{value} > 0.1$, (iii) regression).

Table 12:

Predicting <u>*Daily Market Returns*</u> *Using* ASVI{Terrorism} *and* ASVI{Terrorism_Investment}

	TERRORISM				TERRORISM *Investment*			
	(i)		(ii)		(iii)		(iv)	
	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*	β_1	*t-stat*
$\Delta\ ASVI_{t-1}$	-2.13E-07	[-0.00254]	-4.32E-06	[-0.05180]	3.51E-05	[1.58793]	3.69E-05	[1.68025]
$\Delta\ ASVI_{t-2}$	-9.32E-05	[-1.08667]	-9.67E-05	[-1.13399]	6.82E-06	[0.24665]	1.02E-05	[0.37038]
$\Delta\ ASVI_{t-3}$	-3.96E-05	[-0.44753]	-4.31E-05	[-0.48996]	5.97E-06	[0.20529]	8.92E-06	[0.30877]
$\Delta\ ASVI_{t-4}$	-1.71E-05	[-0.20412]	-1.94E-05	[-0.23202]	-5.09E-06	[-0.18654]	-5.62E-06	[-0.20741]
$\Delta\ ASVI_{t-5}$	-2.31E-05	[-0.28832]	-2.45E-05	[-0.30844]	8.67E-06	[0.39353]	7.95E-06	[0.36321]
Inclusion of Crisis Dummy	No		Yes		No		Yes	
No. Obs.[1]	2702		2702		2702		2702	
Adj. R^2 (%)	69,99		70,35		70,02		70,38	
	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$	$\chi^2 - test$	$p - value$
$\sum_{i=1}^{5} \beta_{1t-i} = 0$	0.341609	0.5589	0.306081	0.5801	0.490351	0.4838	0.583732	0.4449

[1] After adjustment
[*] Significance at the 10% level
[**] Significance at the 5% level
[***] Significance at the 1% level

The table summarizes the coefficient estimates of the first difference of the Adjusted Search Volume Index for Terrorism and Terrorism – category specification Investment. The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five

lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED.

Table 12 presents the relationship between the daily changes of the search volume of the term "Terrorism" and the daily variation of the Standard and Poor 500 Stock prices. Consistent with the results obtained in Table 7, we find that an increment in terrorism' uncertainty produces a contraction of stocks' prices as pointed out by the negative sign of the coefficient estimates. However the results are blurred by low or no statistical significance in the estimates of Δ ASVI{Terrorism} and Δ ASVI{Terrorism_Investment}. A possible explanation lies in the fact that our uncertainty indicator contains low levels of relevant information utilized by investors. Alternatively the effect of Δ ASVI{Terrorism} might be incorporated in the daily changes of the implied volatility index or daily changes of macroeconomic fundamentals.

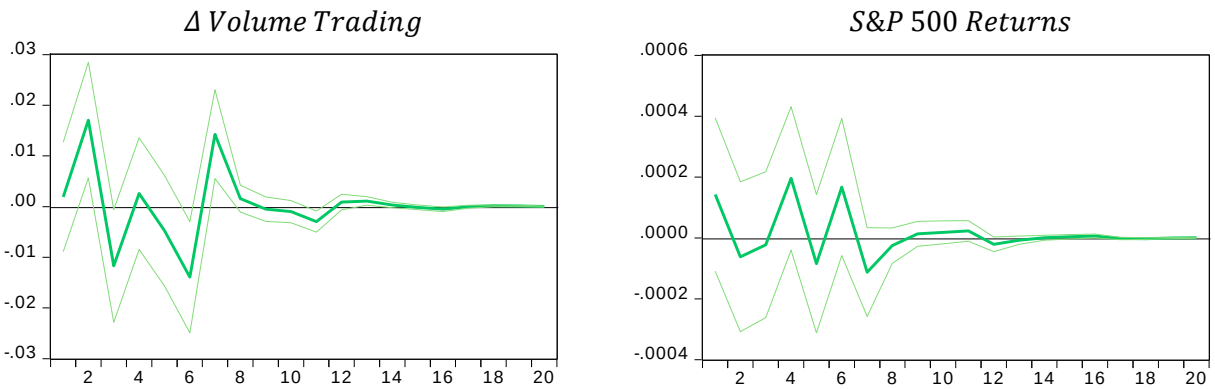
Up to this point in the discussion, we have interpreted ASVI as a measure of investors' uncertainty. The results provide evidence that is consistent with this interpretation. First, we find that increments in ASVI significantly predict higher market trading volume in the immediate following days (except for Δ ASVI{Terrorism}); secondly, we observe that positive variation of uncertainty indicators is associated with a downturn of stock prices. To better understand the scope of Δ ASVI on the stock market activity, we implement the (orthogonalized) impulse response function[31] for each regression. The previous tables contain estimates using non-scaled data. This produces some very large (in magnitude, not statistical significance) estimates which are the result of two variables having very different scales. The IRF approach allows us to deal with standardized coefficients, which have been obtained by subtracting to each observation the mean of the whole series and dividing it by its standard deviation. This makes the magnitude of all coefficients approximately comparable. Despite this transformation and very different parameter estimates, the p-values remain unchanged, since OLS stats are invariant to kind of scaling. Moreover, the eigenvalues of the two parameter matrices are identical and so both sets of parameter

[31] Generalized IRFs assume that a shock occurs only in one variable at time; such an assumption may be reasonable if the shocks in different variables are independent. However, since we expect them to be dependent, we argue that the errors terms consist of all the influences and variables that are not directly included in the set of y variables. Thus, we address to this issue employing the Cholesky decomposition, which consists in decomposing the estimated variance-covariance matrix, into a lower triangular matrix. This type of decomposition isolates the contemporaneous response of y_1 arising solely because of an impulse in the same equation. Nonetheless, the impulse on the first equation will still contemporaneously affect y_2.

estimates indicate the same persistence.

Therefore, after having verified the stability of the models (AR Roots Table[32]), we proceed to trace the effect of a one-time shock to the innovations ε_{1t}, that is a shock to the Δ ASVI , on current and future values of the endogenous variables $\Delta\, Volume$ and $SP500\ Returns$. We stress out that the Choleski decomposition, makes crucial the ordering of the variables, since it attributes the effect of any common component to the variable that comes first. Thus we order the Impulse function, imposing as first Δ ASVI, (the most exogenous variable), followed by Δ Volume Trading and as last, SP500 Returns, which we assume to be affected by both the previous variables. Hereafter, we present the graphs of the IRF for regressions (ii) and (iv), i.e. including the crisis dummy variable[33]. The horizontal axis of each graph shows the effect of a shock over a 20 days period (a trading month), the vertical axis measures the endogenous variations in percentage points. Solid and light lines identify point estimates and 95% level bootstrap confidence intervals, respectively.

Figure 5 - Panel (A): *Response to Cholesky One S.D. Innovations* Δ ASVI{Cancer}



[32] Reports the inverse roots of the characteristic AR polynomial; see Lütkepohl (1991). The estimated VAR is stable (stationary) if all roots have modulus less than one and lie inside the unit circle. If the VAR is not stable, certain results (such as impulse response standard errors) are not valid. There will be kp roots, where k is the number of endogenous variables and p is the largest lag. AR Roots Table results are displayed in the Appendix A5.

[33] Impulse Response Functions of regression (i) and (iii) are also performed and presented in the Appendix A6. Nonetheless, the inclusion of the calendar dummy, does not appear to modify the pattern of IRFs graphs.

Panel (B): *Response to Cholesky One S.D. Innovations* Δ ASVI{Cancer_Investment}

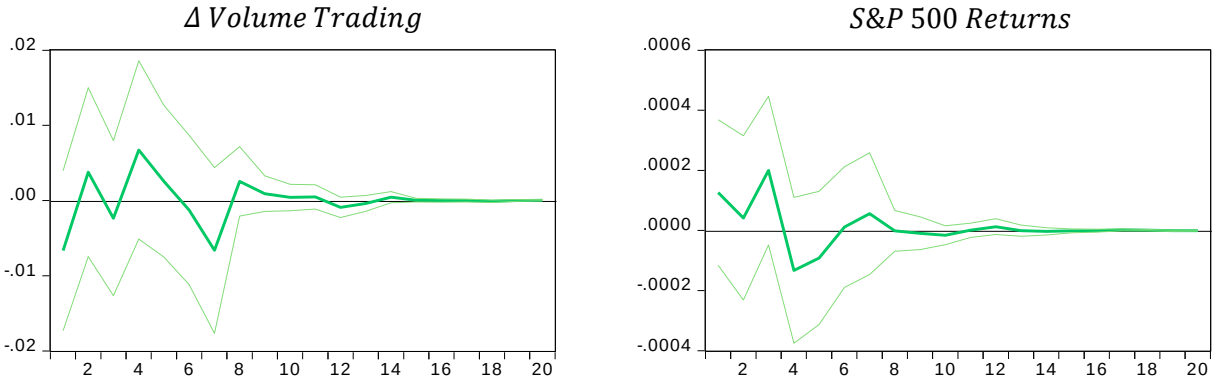
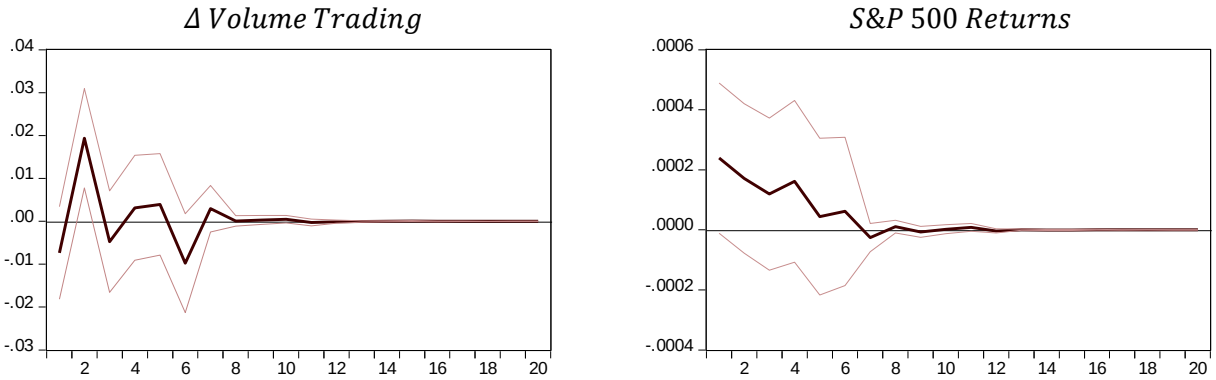


Figure 5 displays the endogenous responses of each variable following an unexpected increase of uncertainty about cancer diseases. The first row shows the effect of a one-standard-deviation impulse to the variation of ASVI{Cancer}. After two days, the uncertainty' shock raises Δ Volume trading up to +1,7%. This increment is immediately followed by various up-and-downs, until reaching stability after 10 days. Daily market returns broadly follow an opposite pattern. An unexpected increase in uncertainty is at first associated with a decline of stock prices (-0,006% within two days). Thereafter, the returns appear to increase (decrease) whenever an increment (decrement) of volume trading does occur. The impact of one-standard-deviation shock to ASVI{Cancer} is fully absorbed by the stock market after two weeks. Although there is no statistical significance at 95 % confidence intervals (the band errors include zeros), the patterns displayed by the IRFs are consistent with our previous results. An increased level of uncertainty produce, within a very short term (2-3 days), a positive variation of trading volume and a slight fall in stock prices. Moreover, these effects are fully absorbed only after ten days. Panel B confirms the opposite behaviour of Volume variations and market returns in the case of a shock to ASVI{Cancer Investment}.

Figure 6 - Panel (A): *Response to Cholesky One S.D. Innovations* Δ ASVI{Natural Disaster}



Panel (B): *Response to Cholesky One S.D. Innovations* Δ ASVI{Natural Disaster_Investment}

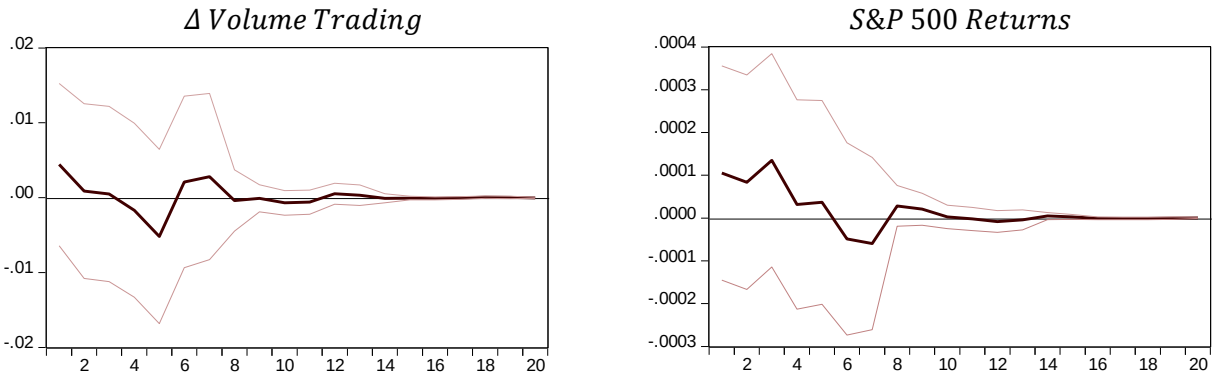
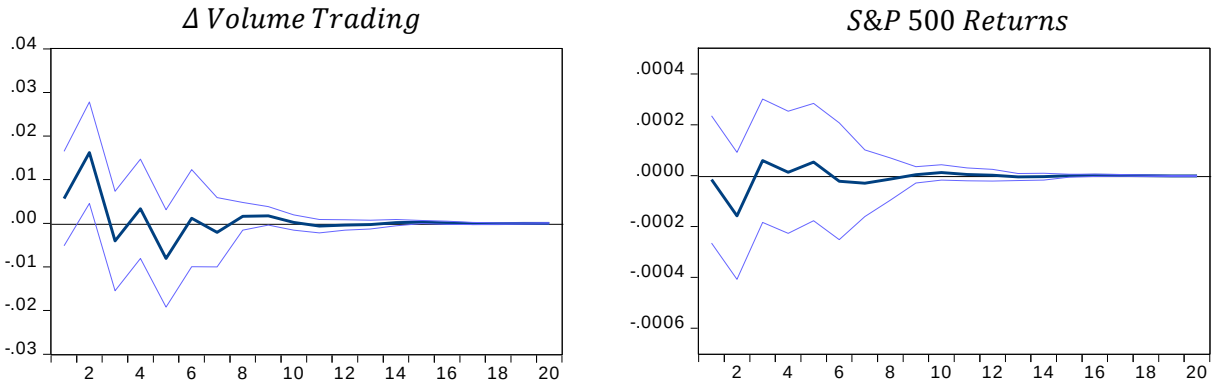
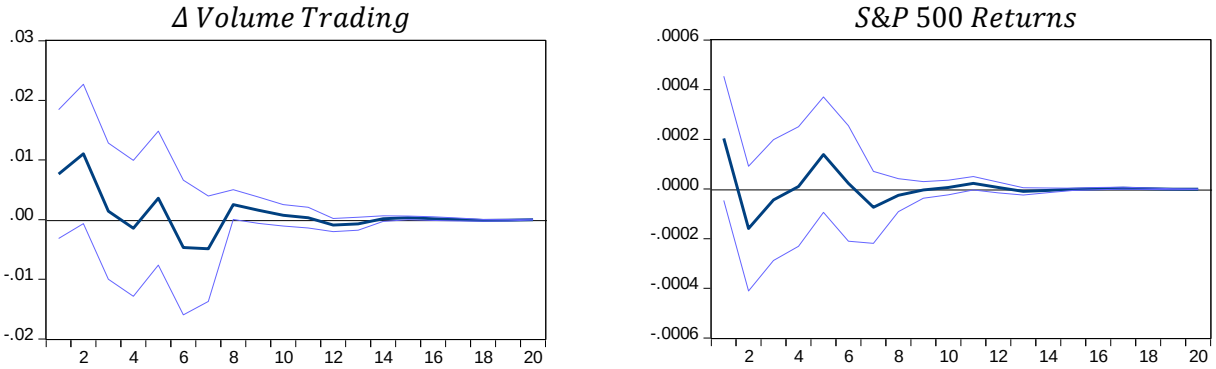


Figure 6 plots the impulse response functions (IRF) of daily changes in Volume trading and in stock market prices to uncertainty shocks based on Google searches of "Natural Disaster". Even though the standard error bands reveal low significance of the IRFs dynamics at 95% confidence intervals, it is worth to note that the pattern of Δ *Volume Trading* displayed in Panel A is quite similar to the one displayed in Table 11. Indeed, a one standard-deviation impulse to the Δ ASVI{Natural Disaster} shock raises the quantity of daily executed transactions to +1,9% after two days (vs +1,7% in the case of Δ ASVI{Cancer}), returning back to zero only after some fluctuations in period 10. The right figure of panel (A) suggests a contemporaneous positive reaction of market returns, becoming negative after seven days and back to zero within two trading weeks. However, also in light of previous coefficient estimates (see Table 9), this latter dynamic appears to be statistically insignificant. Similarly, the IRFs' graphs displayed in the panel (B) (category specification "Investment") reflect the low significance of coefficient estimates of regression (iii) and (iv) (Table 6 and Table 10).

Figure 7 - Panel (A): *Response to Cholesky One S.D. Innovations* Δ ASVI{Opinion Poll}

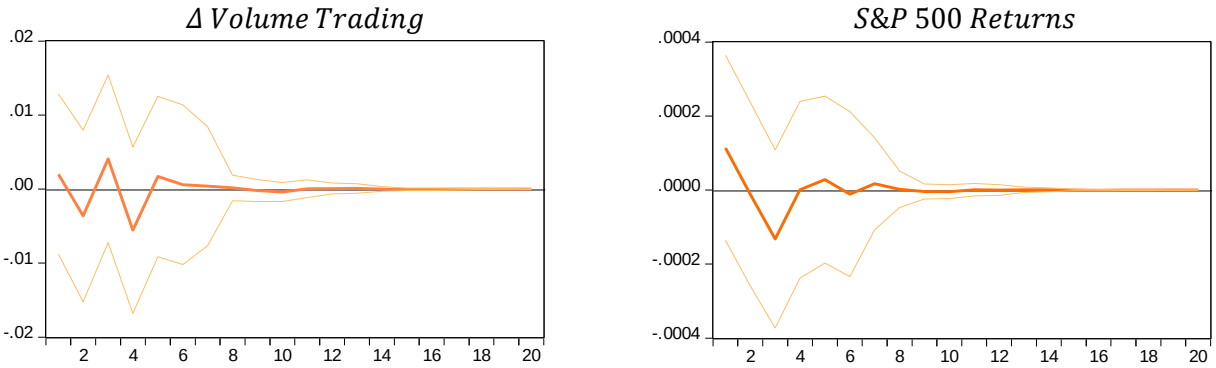


Panel (B): *Response to Cholesky One S.D. Innovations* Δ ASVI{Opinion Poll_Investment}

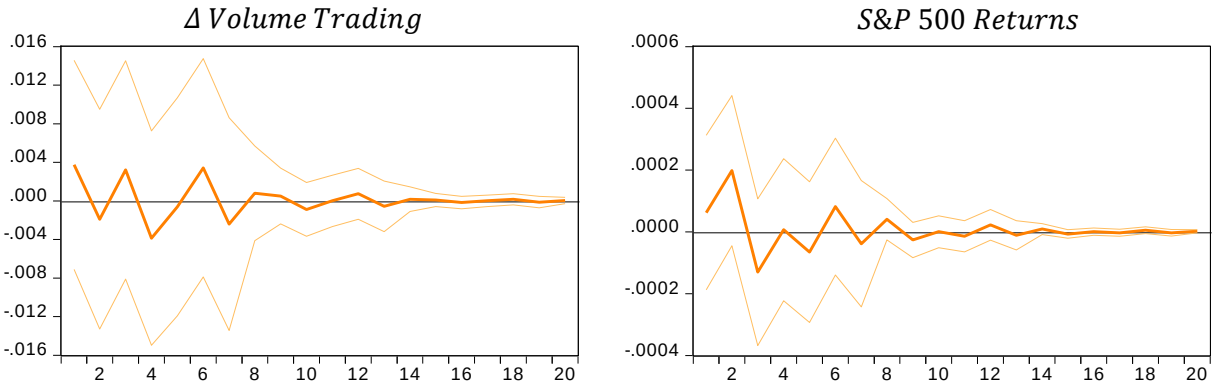


In the top panel of Figure 7, a one standard deviation impulse to the daily change in web searches for the term "Opinion Poll". In this case as well, an increase in the need for information about the outcome of a vote produces a +1,6% growth of Volume Trading in a matter of two days. The initial increase is followed by some minor swings in the subsequent days, until it fades away around the 10th period. Stock prices react in the opposite direction of volume trading, experiencing a decrease peak of -0,016 percentage points in the second day. Thereafter, the negative price pressure gradually dissipates over the course of two trading weeks. A shock based on "Opinion Poll" web-searches with category specification "Investment", leads to impulse response functions similar to those expressed in Panel (A): the uncertain outcome of a vote attracts a greater level of investors' attention, resulting in an immediate increase of daily trades and a rapid decline in stock market' returns. These initial reactions are partially reversed in the following days and vanishes only after a period of ten days. Though the effects are imprecisely estimated (the 95 percent confidence interval includes zeros), the behaviour exhibited by the variables of interest in presence of an uncertainty shock is consistent with our previous findings displayed in Table 7 and 11 (i.e. *beliefs heterogeneity* and *negative price pressure*).

Figure 8 - Panel (A): *Response to Cholesky One S.D. Innovations* Δ ASVI{Terrorism}



Panel (B): *Response to Cholesky One S.D Innovations* Δ ASVI{Terrorism_Investment}



As predicted by Δ ASVI{Terrorism} coefficient estimates in the previous regressions (see Table 8 and Table 12), the short term impact of an uncertainty shock based on Terrorism Google-searches results in a temporary decrease in Volume Trading by -0,4% (day 2) and a drop in Returns by -0,013% (day 2). Afterwards, the effects gradually fade, with some fluctuations in the case of Volume trading, until becoming void around the period 12. Both the low t-statistics (in absolute value) displayed in the prior VAR estimates[34] and the dynamics of the Standard Errors bands, suggest low explanatory power of the uncertainty indicator in question. However, it might be worth to note that an increase in uncertainty somehow led by a terrorist threat tends to decrease the number of transactions executed in the following two days, rather than raise them. A possible interpretation of the divergence between Volume trading' response to a shock based on Δ ASVI{Terrorism} and to shocks based on the other Δ ASVI, may reside in the original source of uncertainty. Since the occurrence of a terrorist attack is undoubtedly associated with the spread of fear and anxiety

[34] See Table 8: Predicting Daily Trading Volume Using ASVI{Terrorism} and Table 11: Predicting Daily Market Returns Using ASVI{Terrorism}.

among the population, investment decisions might be affected by the generalized negative mood, which in turn induces investors to freeze their financial activities. This explanation is consistent with investment sentiment theory, which predicts lower stock market activity in connection with negative sentiments[35]. On the other hand, the occurrence of natural disasters, cancer diseases or votes might as well elicit anxiety among investors, however divergence of opinions and market positions appear to be predominant over blocking thrills. In short, our uncertainty indicators built on the frequency of web-searches of the term "Terrorism" seem to capture a particular investors' behaviour: under the stressful conditions generated by a terrorist threat, the optimal decision of ambiguity-averse investors might be not to trade at all. The severe uncertainty does not allow investors to have complete preferences over portfolios. The lack of ability to rank all the portfolios leads to absence of trading, as the investor changes his portfolio only if the trade improves his expected utility for every belief in the set of beliefs representing his preferences (Easley and O'Hara, 2010). This hypothesis imply a certain degree of irrationality among economic agents since it assumes that (negative) emotions affect the participation in the stock market activity.

4.1.1. Concluding remarks

In section 4.1, we employed our daily uncertainty metrics in a vector autoregressive framework to shed light on the link between ambiguity shocks and financial activity. For convenience, we first presented the effect of daily changes in Adjusted Search Volume Indexes on future Δ volume trading. The model described by the equation (6.1) allowed us to study the effect of different sources of uncertainty on the investors' participation in the stock market. The estimation results (from Table 5 to Table 8) give us the opportunity to identify which of the covered concepts or events significantly drives investors' attention. We found out that increased web-searches for cancer diseases and natural disasters significantly predicts higher trading volume over the next day. The uncertainty arising from the occurrence of a vote seems to have a larger impact on the stock market activity, as increments in the "Opinion Poll" web-searches significantly increase volume trading up to three days after (five in the case of the category specification "Investment"). Conversely,

[35] Several papers study the effect of investor sentiment on stock returns. See, for example, Saunders (1993), Hirshleifer and Shumway (2003), Kamstra et al. (2003), and Edmans et al. (2007) for studies on exogenous mood variables pertaining to weather, lunar phases, or results; see Tetlock (2007) and Garcia (2013 others for studies on sentiment extracted from newspaper columns.

the frequency of "Terrorism" queries does not appear to have explanatory power about the volume of market transactions executed in the following days. Analyzing the relationship between internet traffic volume and daily returns (equation (6.2)), we found out that the uncertainty related to the outcome of an election, significantly affects the stock prices. In particular, an increase in Google searches of "Opinion Poll" produce a significant decline in the next day returns. Likewise, cancer diseases, terrorist threats and natural disasters do have a negative impact on the S&P 500 returns, however their effects is statistically lower as indicated by the regressions' summary tables. The impulse response functions analysis revealed that the uncertainty indicator with the largest impact (in absolute value) on volume trading is the one built upon the web-searches of "Natural Disasters". Indeed, a one standard deviation increase in Δ ASVI{Natural Disaster} rises the number of trades to +1,9% after two days. On the other side, an uncertainty shock about the results of a vote reduces daily returns by -0,016% in the space of two trading days.

From our first empirical application, we gained some remarkable findings. In the first place, we found out that increasing uncertainty about concepts or events, whose occurrence is likely to worsen the state of investors, produce higher volume trading. In particular, once uncertainty is triggered, economic agents react by increasing their information searches. In turn, a higher quantity of information' searches leads to greater chances of different interpretations and different views about the relative importance of pieces of information. Therefore, uncertainty shocks produce divergence of opinions among investors and this effect translates to a greater number of daily trades. On the other hand, the need for information about terrorism seems to be negatively related to volume trading. This finding suggests that, when confronted with severe uncertainty and fear, investors conditioned by their sentiments prefer not to trade at all ambiguous assets (*flight-to-safety* phenomenon). Secondly, consistent with our expectations, increments in uncertainty are followed by declining stock prices. The rationale lies in the behavioural bias displayed by investors under ambiguous conditions. Indeed, under uncertainty, economic agents are not able to trace well-defined probability distributions about the different outcomes of an asset value. Economic psychology evidence consistently finds that retail investors frequently try to overcome the lack of precise probabilities, by employing the heuristic rule of acting according to a worst case scenario. In other words, they tend to maximize their minimum

expected utility[36]. As increasing uncertainty makes the worst-case scenario even worse, aggregate expected values decrease, hence stock prices fall downward. Therefore, the initial increment in the volume trading occurs in the light of investors' willingness to move away from equities in favor of risk-free assets (investors are *net-sellers*). In addition, we found out that the early uncertainty shocks' effects on the stock market activity are likely to be reversed within a week, except for Opinion Poll ASVI, whereas the Impulse response functions show that ambiguity impact completely fades away only after two trading weeks.

[36] MaxMin theory developed by Gilboa and Schmeidler, 1989.

4.2 Search-based uncertainty and Macroeconomic conditions

To put the above results into a business cycle perspective, our next empirical application examines the role of search-behaviour shocks in economic fluctuations over a sample data that goes from January 2004 to July 2017. That is, we employ monthly uncertainty indicators based on the same concepts/ terms of the daily metrics to investigate their impact on four main macroeconomic variables of the U.S. system. After finding that Google-search based uncertainty shocks induce a short-term decline in returns, we shall investigate how ambiguity influences the interest rates, the consumer and business confidence and eventually the industrial production. Both theoretical and empirical literature (see e.g. Stivers and Sun, 2002 and Donadelli, 2015) have shown that under uncertainty the positive co-movement between stocks and Treasury bond returns subsides or even it becomes negative. The rationale behind is that a higher level of uncertainty leads investors to sell risky equities and buy risk-free bonds such as the three-months Treasury Bill. Thus, a drop in the interest rates would detect this "*flight-to-quality*" approach implemented by economic agents. On the other hand, it appears straightforward that a spread of ambiguity is negatively related with the degree of optimism about the state of the economy, which consumers express through savings and spending. Likewise, we expect uncertainty to undermine enterprise's assessment of production, orders and stocks, as well as its current position and expectations for the immediate future. As a final result, uncertainty should pour its effect on the Industrial Production, as consumers react postponing their expenses and businesses react lowering their investments and production plan ("precautionary-saving").

This empirical study strongly relates to the works of Baker et al (2016) and Donadelli (2015), in the aim to test in a vector autoregressive framework, whether innovations in uncertainty foreshadow declines in investment, confidence and output. However, while their works employ uncertainty measures entirely based upon economic-related terms, our study take up the challenge of testing whether the ambiguity provoked by external events or concepts produce as well a decline of economic activity.

Overall, we intend to find out whether the same exogenous shocks that might produce behavioural biases among investors and affect the daily stock market activity, do indeed undermine the real economy, eliciting a tightening of the business cycle conditions as suggested by the recent literature.

As in the previous empirical application, the dynamic relationships between our uncertainty indicators can be assessed within the context of the vector autoregressive model. Supposing that the k −dimensional stationary VAR(p) process Y_t consists in a vector of constants A_t, an autoregressive lag-polynomia $C(L)$ and a vector of structural innovations V_t, the equation takes the following representation:

$$C_0 Y_t = A_t + C(L) Y_{t-p} + V_t \tag{7}$$

Where Y is the vector including all the endogenous variables, namely the uncertainty indicator built upon search volume index (SVI), monthly Standard & Poor 500's returns $(SP500)$, monthly average of the interest rate at which Treasury Bills with a three months maturity are sold on the secondary market $(3TBILL)$, the consumer confidence index $CCI)$, the business confidence index $(BCI)$and the industrial production (IP). All the variables are entered in the logarithmic form, except for the SVI and the $3TBILL$. C denotes the coefficient matrix of the endogenous variable. The lag length (p) is first set by using the SC and HQ criterion (starting from p=8): as the criteria suggest one lag in most of the VAR regressions[37]; our baseline model specification includes one lag of all variables. To recover orthogonal shocks, we use the Cholesky decomposition with the following ordering: the uncertainty indicator, the market returns, the short-term interest rate, the log consumer confidence, the log business confidence and the log industrial production. In a backward reasoning, the manufacturing output is likely to be affected by all the other variables, in particular the leading sentiment indicators have a significant impact on the production and sales plan, whereas stock market and governmental bonds influence, respectively, the cost of equity and the cost of debt by mean of which businesses are financed. On the other hand, consumer and business confidence index are deeply exposed to the financial fluctuations and market sentiment. Stock and bond prices are shaken by the investors' expectations and behavioural biases as ambiguity aversion. At the end of the day, the demand for information of economic agents about certain external events or concepts is the trigger of the whole cycle. Drawing causal inferences from VARs might be challenging, in part because the dynamics of the information search process are not always linear (see e.g. Koop and Onorante, 2013). Despite the challenges, VARs are

[37]SC and HQ criteria applied to the regressions including $SVI\{Cancer\}$ and $SVI\{Cancer\_Investment\}$ suggest a lag choice equal to 3.

extremely useful for characterizing dynamic relationships, as they let us gauge whether unexpected uncertainty innovations foreshadow weaker macroeconomic performance conditional on standard macro and policy variables. In addition, our models have the invaluable advantage to employ ambiguity indicators that are by no means exposed to past or current economic conditions and policy settings, as in the case of Baker et al. (2013). Since the sources of uncertainty are given by the occurrence of a terrorist attack or a natural disaster, we do not have to worry about the chance that ambiguity is an endogenous response to the decline of economic activity, rather than an exogenous source of it.

Here below we present the main results produced by employing a VAR framework for each monthly uncertainty indicator that we previously built (see section 3.2.1). For convenience, we display only the coefficient estimates of the respective SVI metric for all the (dependent) endogenous variables[38]. Indeed, as in the former empirical application, we can represent (7) in the following system of equations[39]:

(7.1) $$c_0^1 SVI_t = a_1 + c_1^1 SVI_{t-1} + c_1^2 SP500_{t-1} + c_1^3 3TBILL_{t-1} + c_1^4 CCI_{t-1} + c_1^5 BCI_{t-1} + c_1^6 IP_{t-1} + \varepsilon_{1t}$$

(7.2) $$c_0^2 SP500_t = a_2 + c_2^1 SVI_{t-1} + c_2^2 SP500_{t-1} + c_2^3 3TBILL_{t-1} + c_2^4 CCI_{t-1} + c_2^5 BCI_{t-1} + c_2^6 IP_{t-1} + \varepsilon_{2t}$$

(7.3) $$c_0^3 3TBILL_t = a_3 + c_3^1 SVI_{t-1} + c_3^2 SP500_{t-1} + c_3^3 3TBILL_{t-1} + c_3^4 CCI_{t-1} + c_3^5 BCI_{t-1} + c_3^6 IP_{t-1} + \varepsilon_{3t}$$

(7.4) $$c_0^4 CCI_t = a_4 + c_4^1 SVI_{t-1} + c_4^2 SP500_{t-1} + c_4^3 3TBILL_{t-1} + c_4^4 CCI_{t-1} + c_4^5 BCI_{t-1} + c_4^6 IP_{t-1} + \varepsilon_{4t}$$

(7.5) $$c_0^5 BCI_t = a_5 + c_5^1 SVI_{t-1} + c_5^2 SP500_{t-1} + c_5^3 3TBILL_{t-1} + c_5^4 CCI_{t-1} + c_5^5 BCI_{t-1} + c_5^6 IP_{t-1} + \varepsilon_{5t}$$

(7.6) $$c_0^6 IP_t = a_6 + c_6^1 SVI_{t-1} + c_6^2 SP500_{t-1} + c_6^3 3TBILL_{t-1} + c_6^4 CCI_{t-1} + c_6^5 BCI_{t-1} + c_6^6 IP_{t-1} + \varepsilon_{6t}$$

[38] The relevant coefficient estimates are red-circled.

[39] The representation of the equations may vary as we introduce the crisis dummy variable in the principal component' regressions.

Table 13: *Predicting Monthly Macroeconomic Conditions Using* ***Cancer Google searches*** *as source of uncertainty*

Term: CANCER								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	0.000392	0.000513	-0.025547	0.012041	-0.000220	0.004177	-0.014327	-0.038574**
	[0.84345]	[0.03885]	[-0.44865]	[0.76646]	[-0.68388]	[0.31510]	[-1.49461]	[-2.32482]
3TBILL	0.001838	-0.033777	0.044033	0.050084	-0.001247	-0.067222	-0.057051	0.000799
	[1.04324]	[-0.67504]	[0.20316]	[0.83836]	[-1.02264]	[-1.34333]	[-1.56572]	[0.01243]
CCI	2.37E-05	0.000996	-0.004914	0.000648	-4.85E-06	-0.000953	-0.001143**	-0.001183
	[0.91928]	[1.36500]	[-1.54267]	[0.73150]	[-0.27053]	[-1.30036]	[-2.13122]	[-1.24877]
BCI	-3.52E-05	-0.000843	0.000147	0.000592	-9.71E-06	0.000222	-4.78E-05	-0.001037
	[-1.53520]	[-1.29417]	[0.05284]	[0.76991]	[-0.60802]	[0.33791]	[-0.10117]	[-1.25979]
IP	2.31E-05	0.001457	0.000995	0.000894	-8.04E-05	-0.002287	-0.000139	-0.001912
	[0.30959]	[0.68995]	[0.11427]	[0.37191]	[-1.56976]	[-1.08075]	[-0.09390]	[-0.74172]

The table displays the coefficient estimates of each uncertainty measure lagged 1 and based upon the Search Volume Index for Cancer and Cancer category specification Investment. Numbers in parenthesis indicate the respective t-statistics of each coefficient estimate. Three stars denote significance at 1% or less; two stars denote significance at 5% or less; one star denotes significance at 10% or less. The regressions are based on 163 observations from January 2004 to July 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to one lag are used. The table data come from Google, Yahoo! Finance, OECD and FRED. The circled uncertainty metric is the one employed in the regression whose Impulse Response Function is plotted in Figure 12.

Table 14: *Predicting Monthly Macroeconomic Conditions Using* ***Natural Disaster Google searches*** *as source of uncertainty*

Term: NATURAL DISASTER								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	-0.000296	-0.027726**	-0.003158*	-0.046618***	-0.000255	-0.022895*	-0.004213*	-0.023608**
	[-1.32097]	[-1.91519]	[-1.66956]	[-2.83883]	[-0.97584]	[-1.67392]	[-1.61190]	[-1.95809]
3TBILL	0.001019	0.065977	0.009060	0.006793	0.001903**	0.049357	0.020471**	0.072950
	[1.19835]	[1.19213]	[1.25399]	[0.10581]	[1.93281]	[0.94494]	[2.07102]	[1.58332]
CCI	-4.97E-06	0.000306	-0.000210**	-0.002301***	-2.65E-06	-0.000861	-0.000166	-0.000221
	[-0.39704]	[0.37567]	[-1.97576]	[-2.46998]	[-0.18166]	[-1.12711]	[-1.11946]	[-0.32082]
BCI	-1.08E-05	-0.000966	-7.63E-05	-0.001587**	-4.79E-06	9.14E-05	-0.000144	-0.001214**
	[-0.96850]	[-1.33705]	[-0.81823]	[-1.94639]	[-0.36847]	[0.13353]	[-1.11853]	[-2.05870]
IP	2.27E-05	0.004519**	0.000205	0.003897	4.41E-05	0.002673	0.000110	0.002453
	[0.63100]	[1.94936]	[0.70264]	[1.52309]	[1.05219]	[1.21488]	[0.27199]	[1.32145]

The table displays the coefficient estimates of each uncertainty measure lagged 1 and based upon the Search Volume Index for Natural Disaster and Natural Disaster category specification Investment. Numbers in parenthesis indicate the respective t-statistics of each coefficient estimate. Three stars denote significance at 1% or less; two stars denote significance at 5% or less; one star denotes significance at 10% or less. The regressions are based on 163 observations from January 2004 to July 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to one lag are used. The table data come from Google, Yahoo! Finance, OECD and FRED. The circled uncertainty metric is the one employed in the regression whose Impulse Response Function is plotted in Figure 13.

Table 15: *Predicting Monthly Macroeconomic Conditions Using* ***Opinion Poll Google searches*** *as source of uncertainty*

Term: OPINION POLL								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	-0.000138	-0.006014	-0.001081	-0.015545	-0.000192	0.009045	-0.004236***	-0.016613
	[-0.46964]	[-0.25568]	[-0.93001]	[-1.14969]	[-0.75074]	[0.48992]	[-2.48647]	[-1.14924]
3TBILL	-0.000707	-0.001768	-0.008574**	-0.069629	-0.001027	0.023833	-0.021983***	-0.183719***
	[-0.62857]	[-0.01979]	[-1.95823]	[-1.35616]	[-1.06185]	[0.33996]	[-3.45738]	[-3.46221]
CCI	1.79E-05	0.001271	-2.20E-05	-0.000638	9.74E-06	0.001278	-8.85E-05	-0.000750
	[1.09442]	[0.97475]	[-0.33509]	[-0.83563]	[0.68643]	[1.25084]	[-0.90516]	[-0.91892]
BCI	-1.72E-05	-0.001082	-5.86E-05	-0.000707	-1.78E-05	-0.000225	-0.000230***	-0.001020
	[-1.17431]	[-0.93004]	[-1.03088]	[-1.06681]	[-1.41006]	[-0.24608]	[-2.76582]	[-1.44436]
IP	3.15E-05	0.000475	0.000211	0.003771*	3.99E-05	0.000176	0.000447*	0.003242
	[0.66453]	[0.12599]	[1.18725]	[1.83759]	[0.97717]	[0.05948]	[1.69959]	[1.47193]

The table displays the coefficient estimates of each uncertainty measure lagged 1 and based upon the Search Volume Index for Opinion Poll and Opinion Poll category specification Investment. Numbers in parenthesis indicate the respective t-statistics of each coefficient estimate. Three stars denote significance at 1% or less; two stars denote significance at 5% or less; one star denotes significance at 10% or less. The regressions are based on 163 observations from January 2004 to July 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to one lag are used. The table data come from Google, Yahoo! Finance, OECD and FRED. The circled uncertainty metric is the one employed in the regression whose Impulse Response Function is plotted in Figure 14.

Table 16: *Predicting Monthly Macroeconomic Conditions Using* ***Terrorism Google searches*** *as source of uncertainty*

Term: TERRORISM								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	-0.000388	-0.015914	-0.004527	-0.004109	-0.000424*	-0.012006	-0.001916	-0.004101
	[-1.34960]	[-1.23296]	[-0.81476]	[-0.19480]	[-1.70235]	[-0.85556]	[-0.28538]	[-0.24983]
3TBILL	0.001974*	0.037478	0.011217	0.026492	0.001768*	0.071403	-0.008262	-0.096041
	[1.81698]	[0.76268]	[0.52992]	[0.33027]	[1.87421]	[1.34510]	[-0.32358]	[-1.55038]
CCI	1.66E-05	0.000159	0.000220	0.001340	9.44E-06	-7.93E-05	0.000436	0.000976
	[1.03506]	[0.22097]	[0.70144]	[1.13227]	[0.67659]	[-0.10148]	[1.15705]	[1.05850]
BCI	-3.92E-05***	-0.001030*	-0.000300	-0.000698	-3.71E-05***	-0.001459**	-0.000204	-0.000745
	[-2.79893]	[-1.61532]	[-1.10556]	[-0.67697]	[-3.06834]	[-2.12099]	[-0.61998]	[-0.92886]
IP	-0.000101**	-0.002059	-0.000120	0.001219	-0.000137***	-0.005015**	3.18E-05	-0.002463
	[-2.22188]	[-0.99423]	[-0.14067]	[0.37821]	[-3.52755]	[-2.26205]	[0.03103]	[-0.98489]

The table displays the coefficient estimates of each uncertainty measure lagged 1 and based upon the Search Volume Index for Terrorism and Terrorism category specification Investment. Numbers in parenthesis indicate the respective t-statistics of each coefficient estimate. Three stars denote significance at 1% or less; two stars denote significance at 5% or less; one star denotes significance at 10% or less. The regressions are based on 163 observations from January 2004 to July 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to one lag are used. The table data come from Google, Yahoo! Finance, OECD and FRED. The circled uncertainty metric is the one employed in the regression whose Impulse Response Function is plotted in Figure 15.

The above tables display the coefficient estimates of each uncertainty measure for all the (dependent) endogenous variables. In the first place, we notice that the metrics based on the Google search volume of the terms "Natural Disaster" and "Terrorism" appear to have greater explanatory power, as they present the largest number of significant coefficient estimates. Analyzing the most relevant results, we find that increments in ambiguity predict a decline in the next month macroeconomic conditions. Consistent with our expectations and the previous findings at daily level, we capture an adverse effect of uncertainty on the future stock market returns, among the regressions of all the four terms. The short term interest rates appear to decrease in presence of an ambiguity about the outcome of a vote, whereas the occurrence of a natural disaster or a terrorist attack are not followed by an increment in the bond' prices. The uncertainty arising from the Cancer and Natural Disasters web-searches significantly deteriorates the next month's consumer confidence; whilst the business confidence is negatively influenced especially by the ambiguity implied by the Opinion Poll Google queries (Trend SVI, category Investment: t-stat= -2,76) and by the Terrorism web searches (SVI, category Investment: t-stat= -3,06). The industrial production seems to decline already one month after the enhanced level of uncertainty about a terrorist threat (SVI, category Investment: t-stat= -3,52). Opinion poll and Natural disaster search volume appear to have a subtle positive effect on the economic output, but the reason is likely to be the delay whereby the industrial production is adjusted downward by the postponement of investment plans and lower consumer demand.

At this stage, we analysed the short-term relationship (one month) between agents' uncertainty and macroeconomic variables by mean of the coefficient estimates' sign. But what are the impacts on the U.S. economic activity over the course of twenty months? Does a search behaviour shock negatively affect the macroeconomic conditions for the entire period, or the initial decline is followed by a positive rebound? From a theoretical perspective, uncertainty shocks shall influence business cycle dynamics in a variety of ways. For instance, we argued before that uncertainty might put pressure on investors to delay investment decisions resulting in a postponement of increases in production and hiring decisions. This argument, known as "Real options", follows from the intuition that facing uncertain settings and important irreversible costs, the "*wait-and-see*" option becomes the best choice for investors. However, after uncertainty has been "absorbed" by the economic system: (i) investors have an incentive to make investments and (ii) firms have an incentive to hire personal and take production decisions, implying a rapid recovery

of economic activity after an uncertainty shock (Bernanke, 1983; Bloom, 2009). Uncertainty could also contribute to the risk premium effect (Arellano et al., 2012; Gilchrist et al., 2014). An increase in the risk premium due to higher uncertainty is expected to occur in the stock market such as the S&P 500 as a result of the higher compensation required by investors for holding riskier asset. Similarly, an augmented ambiguity level might raise interest rates, hence a drop in bond prices should simultaneously occur. Broadly speaking, as uncertainty increases, banks are unsure if the borrowers who previously were going to pay surely will be able to repay their debt and thus are resilient to make loans. In response to this scenario, banks will increase the interest rate to include the greater risk to which they are exposed. As a result, both the cost equity and the cost of debt cost increases, making more expensive to start a new project, thus decreasing investment plans. Nonetheless, uncertainty may also enhance economic activity. For instance, Kraft et al. (2013) considered the growth options effect. In the presence of higher uncertainty, the returns of a given investment become more volatile. This possibility allows the returns of an investment to be, although with low probability, higher than in a "normal" world where volatility is relatively low. This increase in potential gains creates incentives for firms to invest and hence to expand production. As argued by Bloom (2014), this could have been the reason behind the dot-com bubble: the dispersion in gains contributed to the massive entry of new firms that expanded aggregate investment and production in the years before the dot-com bubble exploded.

In order to have a clear view of the business cycle dynamics after that an unexpected uncertainty shocks does occur, we implement the impulse response functions for each regression[40]. For the sake of brevity, we present only the most relevant results for each source of ambiguity, namely for each of the four Google queries[41].

[40] We first verified the stability of the models: AR Roots Table for each Impulse Response Functions that we implemented (from monthly VARs) can be found in the Appendix A7.

[41] In the Appendix A8 we also show the IRFs to the SVI, Trend SVI and Dummy SVI Uncertainty metric (no category specifications). Other estimates and graphs are available upon request.

Figure 9: *Response to Cholesky One S.D. Innovations* Dummy Trend SVI $\{Cancer\_Investment\}$

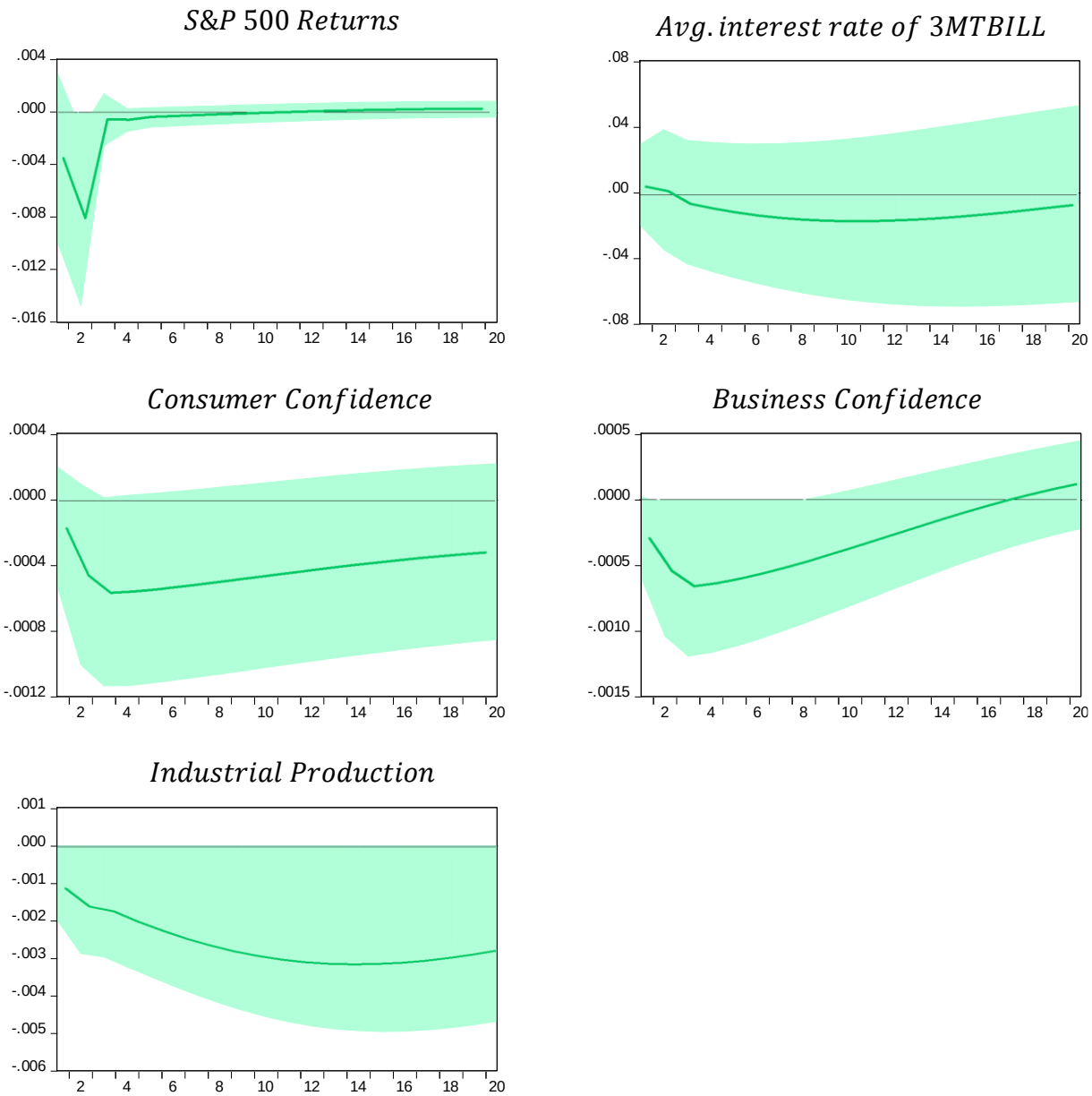


Figure 9 displays the dynamic responses of each endogenous variable to a Trend SVI $\{Cancer\_Investment\}$ shock. The latter metric metric is a dummy variable developed by assigning value 1 to the observations greater than 1.65 the standard deviation of the whole series plus the mean of the series. The series is already manipulated by dividing the current value of the search volume for the term "Cancer", category Investment by the value of the corresponding month one year ago. The Cholesky decomposition (orthogonalized) is used to compute the responses to one standard deviation innovations. The ordering of the lower triangular matrix is as follows: the uncertainty metric, the stock market returns, the average interest of 3-months Treasury Bill, the consumer confidence index, the business confidence index and the industrial production. All the variables, except for the uncertainty metric and the 3TBILL are entered in the regression estimation in log form. Solid lines identify the estimated impulse response function; shaded areas represent the 95% level bootstrap confidence intervals

Figure 10: *Response to Cholesky One S.D. Innovations* Dummy Trend SVI $\{Natural\ Disaster\}$

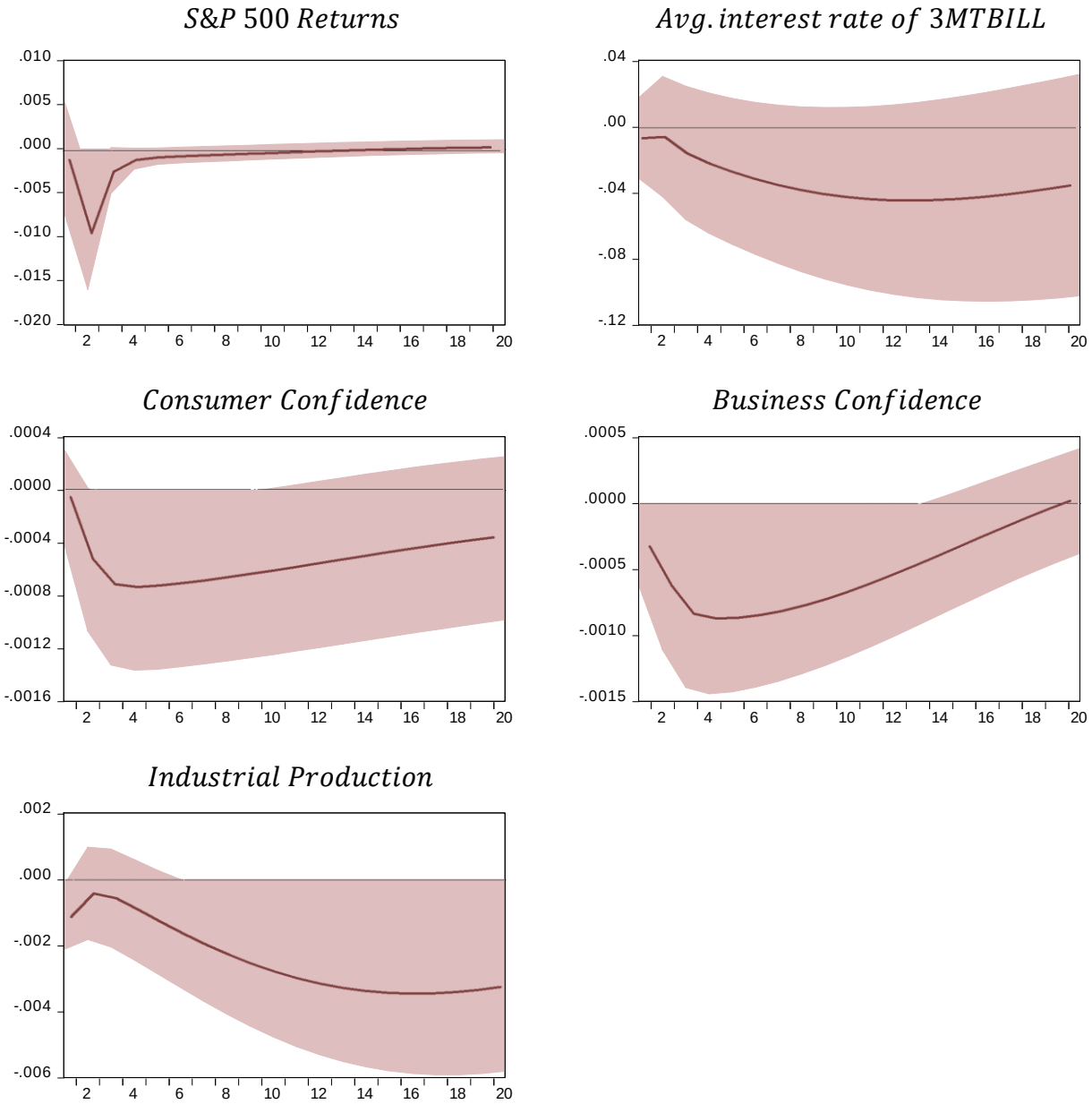


Figure 10 displays the dynamic responses of each endogenous variable to Dummy Trend SVI $\{Natural\ Disaster\}$ shock. The latter metric is a dummy variable developed by assigning value 1 to the observations greater than 1.65 the standard deviation of the whole series plus the mean of the series. The series is already manipulated by dividing the current value of the search volume for the term "Natural Disaster", by the value of the corresponding month one year ago. The Cholesky decomposition (orthogonalized) is used to compute the responses to one standard deviation innovations. The ordering of the lower triangular matrix is as follows: the uncertainty metric, the stock market returns, the average interest of 3-months Treasury Bill, the consumer confidence index, the business confidence index and the industrial production. All the variables, except for the uncertainty metric and the 3TBILL are entered in the regression estimation in log form. Solid lines identify the estimated impulse response function; shaded areas represent the 95% level bootstrap confidence intervals

Figure 11: *Response to Cholesky One S.D. Innovations* Trend SVI $\{Exit\ Poll\_Investment\}$

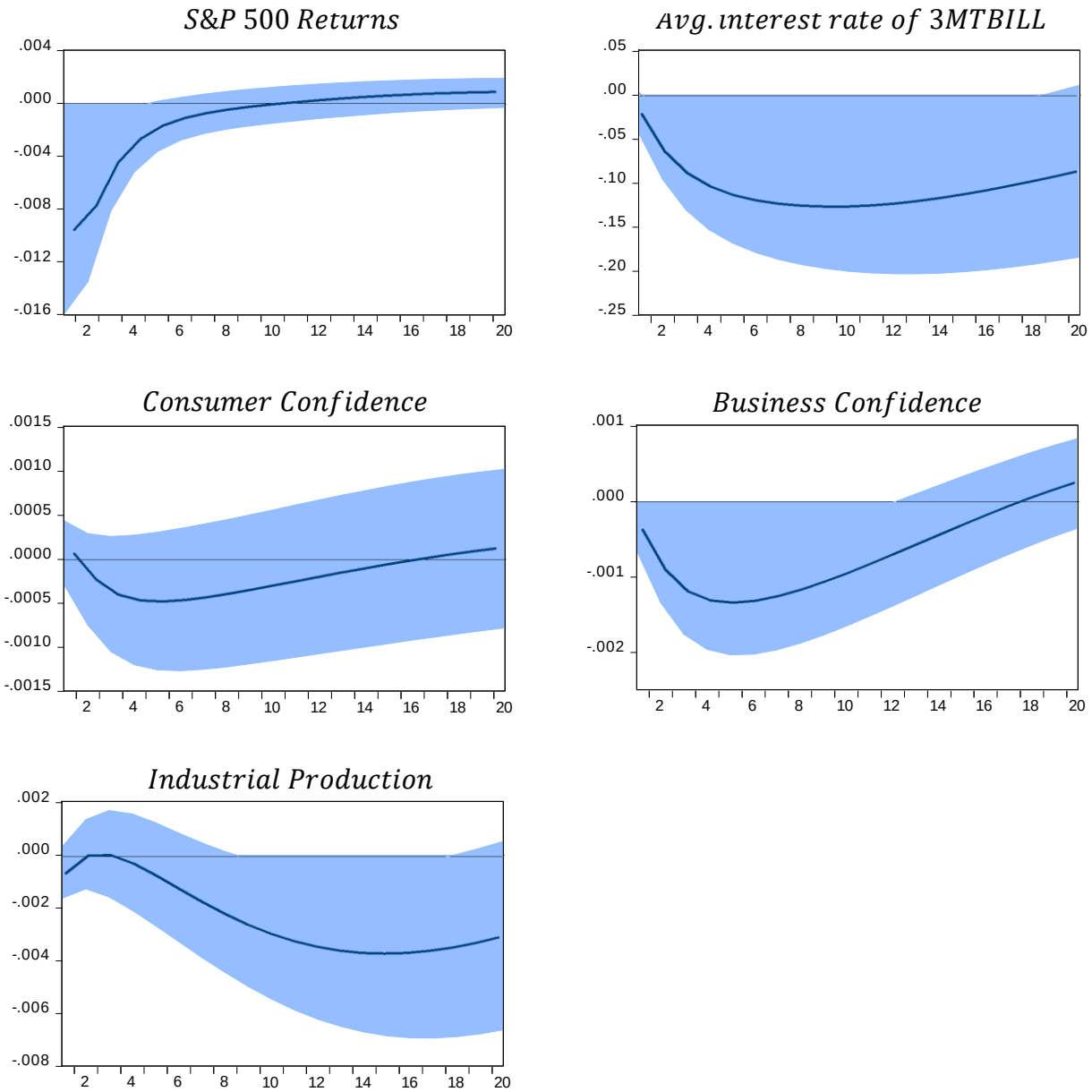


Figure 11 displays the dynamic responses of each endogenous variable to Dummy Trend SVI $\{Exit\ Poll\_Investment\}$ shock. The latter metric is a dummy variable developed by assigning value 1 to the observations greater than 1.65 the standard deviation of the whole series plus the mean of the series. The series is already manipulated by dividing the current value of the search volume for the term "Opinion Poll", category Investment, by the value of the corresponding month one year ago. The Cholesky decomposition (orthogonalized) is used to compute the responses to one standard deviation innovations. The ordering of the lower triangular matrix is as follows: the uncertainty metric, the stock market returns, the average interest of 3-months Treasury Bill, the consumer confidence index, the business confidence index and the industrial production. All the variables, except for the uncertainty metric and the 3TBILL are entered in the regression estimation in log form. Solid lines identify the estimated impulse response function; shaded areas represent the 95% level bootstrap confidence intervals

Figure 12: *Response to Cholesky One S.D. Innovations* SVI $\{Terrorism\_Investment\}$

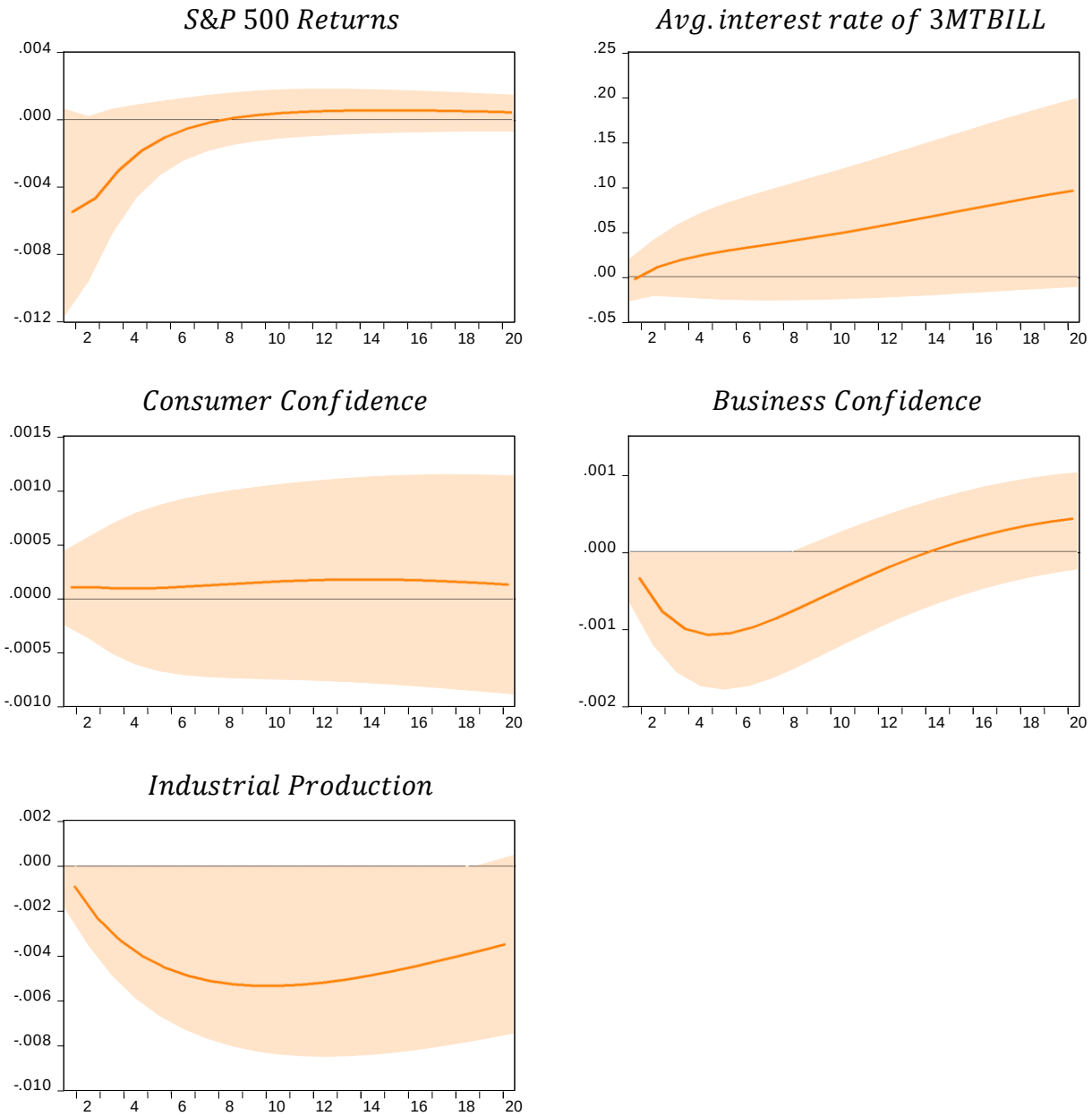


Figure 12 displays the dynamic responses of each endogenous variable to SVI $\{Terrorism\_Investment\}$ shock. The latter metric is based on the Google Search Volume Index for the term "Terrorism", category Investment. The Cholesky decomposition (orthogonalized) is used to compute the responses to one standard deviation innovations. The ordering of the lower triangular matrix is as follows: the uncertainty metric, the stock market returns, the average interest of 3-months Treasury Bill, the consumer confidence index, the business confidence index and the industrial production. All the variables, except for the uncertainty metric and the 3TBILL are entered in the regression estimation in log form. Solid lines identify the estimated impulse response function; shaded areas represent the 95% level bootstrap confidence intervals

Figure 9 presents the impulse responses to an unexpected shock in the uncertainty metric based on "Cancer" Google searches, by users who are willing to invest. In particular, Dummy Trend SVI $\{Cancer\_Investment\}$ reflects the rising of abnormal level of attention directed to the group of the severe diseases. As expected, the shock produces a short term decline in the stock prices: market returns reach the bottom peak after 2 months (-0,8%), followed by an equally rapid rebound the month after. Conversely, the short-term Treasury Bills market prices experience an increase, as the related interest rate appears to mildly subside[42] throughout the whole period. This finding is consistent with the notion of "flight to quality" which explains the tendency of economic agents to close their risky position on equity assets, in favor of safer investment such as AAA bonds. Both consumer and business confidence are found to diminish until the third month, however the rate of recovery is quite different as BCI experience a positive reversal from the 16th month, whereas CCI does not appear to fully recover within the covered period. This latter finding indicates that consumers update their beliefs more slowly than entrepreneurs do. One possible explanation could be found in the nature of the ambiguity effects on the leading confidence indicators. In the case of the businesses, the shock is likely to delay the supply orders and the capital expenditures until the uncertainty fades away; on the other hand, consumers might await for some positive signals from the economic activity before increasing their spending. As a result, the industrial production steeply decreases the whole first year due to the combined effects of lower consumer demand and business plan contraction. In addition, the latter index does not display any positive reversal within the considered period of 20 months.

A similar business cycle reaction to an ambiguity shock is found when considering the uncertainty metric based on "Natural Disaster" Google Trends. As in the previous case, Dummy Trend SVI $\{Natural\ Disaster\}$ is by design built to capture the occurrence of attention upsurges. In our series, these upsurges in fact coincide with some well-known adverse events that have taken place from January 2004 to July 2017, e.g. Hurricane Katrina (August 2005), Haiti Earthquake (January 2010) and Floods (February-March 2011). Figure 10 illustrates the impact of the occurrence of a Natural Disaster on the S&P500, which experiences a drop in the stock prices in the early 2 months (-1%) followed by a full reversal in the fourth month. The declining trend expressed by the interest rate' IRF suggests a

[42] It should be noted that in Figure 9, S&P500, 3TBILL and Consumer Confidence Impulse response functions dynamics display little significance at 95% confidence intervals.

decisive shift among investors to safer assets. In addition, the short-term Treasury Bill interest rate does not come back to pre-shock levels in the considered period. This "sticky" pattern might be due the strong influence exerted by the Fed funds rate on the 3TBILL prices: as uncertainty arises policymakers are persuaded to update upward the money supply in order to reduce eventual lending contraction. In return, this strategy keeps bond's prices elevated for a longer period. Consumer and Business confidence[43] appear to experience a decrease in the three months following the uncertainty shock. As before, the rate of recovery is distinct between the two variables, as Consumer displays a slower recovery rate than Business Confidence. Eventually, the uncertainty produced by the occurrence of natural disasters appears to reduce the economic output throughout the whole period.

Analyzing figure 10, we find that the uncertainty implied by the need of information among investors about the outcome and the consequences of an incoming vote, pours into the stock market by determining a -1% loss one month later the shock occurs. Interestingly, the recovery of stock prices appears to be slow if compared to $\text{Dummy Trend SVI}\{Cancer\_Investment\}$ and $\text{Dummy Trend SVI}\{Natural\ Disaster\}$ shocks. This latter finding implies that the "Opinion Poll" information is incorporated in the asset prices at a slower pace. Asymmetry of information and different investors' beliefs (consistent with an increment in volume trading) might be the drivers of such a trend. The average interest of 3-months maturity of Treasury Bill displays a significant negative pattern at 95% level. Thus, under electoral ambiguity, the portfolio composition shifts towards risk free assets such as the 13-week government bond. As expected, the uncertainty shock produce in both the leading confidence indicators[44] a decline that reaches the peak around the fifth month, fully reversed 16 months after the vote upset.

The industrial production appears to respond to the "Opinion Poll" shock only after four months, suggesting a delay in the downward update of production and investment plan. This delay is explained by the initial decline of the short term interest rate, which keep low the cost of debt and therefore feasible the original business plans. On the other hand, once the interest rate stabilizes the drop in the consumer demand (elicited by the decline in confidence) lead enterprises to adjust downward the production.

Figure 11 shows the impulse response function dynamics of economic conditions to a shock

[43] In Figure 10, only Business Confidence IRF dynamics display full significance at 95% confidence intervals.

[44] In Figure 11, Consumer Confidence and Industrial Production Impulse response functions dynamics display little significance at 95% confidence intervals.

in the uncertainty metric based on "Terrorism" Google searches, by users who are willing to invest. As expected, the shock produces a short term decline in the stock prices: market returns reached the bottom peak already after 1 months (-0,6%), followed by a relatively slow rebound starting from the second month. Conversely, the monthly average interest rate of Treasury Bills experience a gradual increase throughout the whole period. This finding implies that under the uncertainty resulting from a terrorist threat, investors display a "blocking fear" both in the stock and bond market. However, the latter dynamic as well as the one described by the consumer confidence IRF (which seems to be positively affected by the uncertainty shock) are blurred by low significance. Business confidence declines up to four months following the occurrence of the search behaviour shock, whereas the industrial production steeply decrease the whole first year without any positive reversal within the considered period of 20 months.

4.2.1 Composite Uncertainty Indicators

Up to this point, in our empirical study we considered the effect of *standalone* uncertainty measures, namely based on single sources of ambiguity such as the Google searches of the term Terrorism. As our final contribution, we test the impact of composite uncertainty indicators, i.e. made up of four different sources of ambiguity[45], on the U.S. business cycle. To construct these indicators we employ the Principal Component Analysis (PCA) on each SVI measure that we previously built (see section 3.2.1). PCA is a useful technique for transforming a large number of variables in a data set into a smaller and more coherent set of uncorrelated (orthogonal) factors, the principal components. The principal components account for much of the variance among the set of original variables. Each component is a linear weighted combination of the initial variables. The weights for each principal component are given by the eigenvectors of the correlation matrix or the covariance matrix, if the data were standardized. The variance for each principal component is represented by the eigenvalue of the corresponding eigenvector. The components are ordered so that the first component accounts for the largest possible amount of variation in the original variables. The second component is completely uncorrelated

[45] Terrorism, Cancer, Natural Disaster and Opinion Poll. We recall that the Google Trends of these terms are downloaded together, i.e. they are indexed to the same SVI peak. This allow us to get comparable series and eventually to construct a composite index by mean of a linear combination of them.

with the first component, and accounts for the maximum variation that is not accounted for the first. The third accounts for the maximum that the first and the second not accounted for and so on. The aim of constructing a composite indicator is to develop an alternative uncertainty measure that encompasses the ambiguity arising from all the four events/ concept. Moreover, the composite measures give us the opportunity to compare our findings based on the uncertainty about external events, against the results obtained by employing the Economic Policy Uncertainty index (Baker et al., 2013). The dynamic of the Principal Component Indicator in Trend form[46] is shown in Figure 17 – Appendix A10.

Table 17: *Predicting Monthly Macroeconomic Conditions Using* ***the Principal Component Analysis*** *as uncertainty metric*

PRINCIPAL COMPONENT ANALYSIS								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	-0.001322	-0.002689	-0.005580	-0.003400	-0.001818	-0.008795	0.001022	-0.007024**
	[-0.38742]	[-0.98552]	[-1.56248]	[-1.14188]	[-0.62238]	[-0.64454]	[0.31113]	[-2.23875]
3TBILL	-0.012974	-0.002743	-0.015872	-0.003112	0.016136	0.059378	-0.019625	-0.022656 *
	[-1.00732]	[-0.26409]	[-1.16394]	[-0.27358]	[1.46325]	[1.14968]	[-1.58424]	[-1.88888]
CCI	0.000215	0.000130	-0.000173	-0.000159	0.000150	0.001441 **	8.80E-05	-0.000215
	[1.13857]	[0.85945]	[-0.85435]	[-0.94487]	[0.92412]	[1.91948]	[0.47546]	[-1.20249]
BCI	-6.20E-05	-0.000366***	-0.000218	-0.000105	-0.000412***	-0.000813	-0.000173	-0.000176
	[-0.36773]	[-2.75963]	[-1.24289]	[-0.71912]	[-2.91917]	[-1.20486]	[-1.08027]	[-1.13089]
IP	-0.000631	2.68E-07	0.000431	0.000552	-0.000183	0.002888	0.000332	0.000875 *
	[-1.16322]	[0.00061]	[0.78523]	[1.21443]	[-0.39169]	[1.32692]	[0.66172]	[1.81331]

The table displays the coefficient estimates of each uncertainty measure lagged 1, derived from the principal component analysis of the Search Volume Index for each of the four terms: Terrorism, Cancer, Opinion Poll and Natural Disaster. Numbers in parenthesis indicate the respective t-statistics of each coefficient estimate. Three stars denote significance at 1% or less; two stars denote significance at 5% or less; one star denotes significance at 10% or less. The regressions are based on 163 observations from January 2004 to July 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to one lag are used. The table data come from Google, Yahoo! Finance, OECD and FRED. The circled uncertainty metric is the one employed in the regression whose Impulse Response Function is plotted in Figure 16.

[46] No category specification

Figure 13: *Response to Cholesky One S.D. Innovations* Dummy Trend SVI $\{Composite\ Index\_Investment\}$

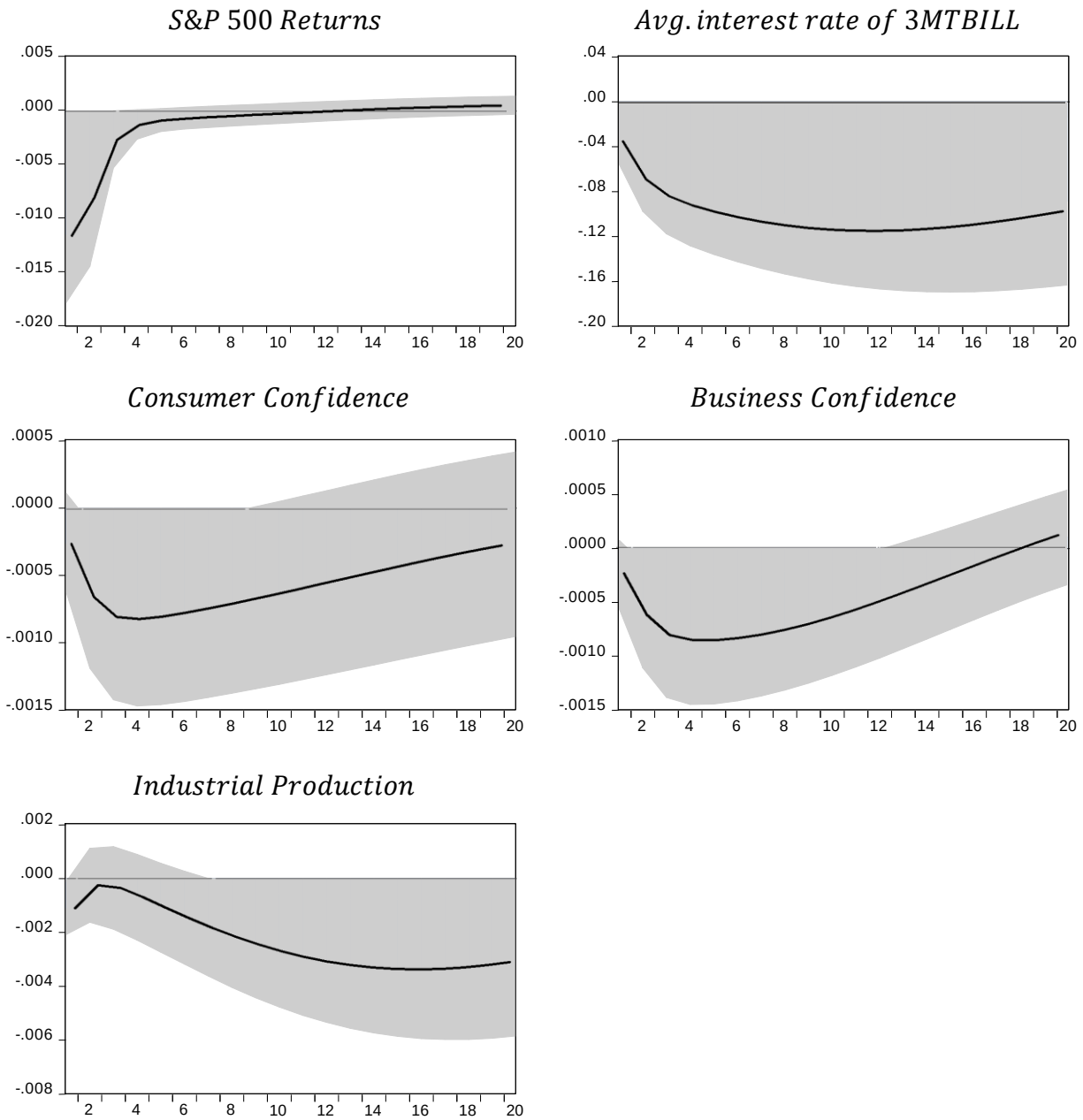


Figure 13 displays the dynamic responses of each endogenous variable to Dummy Trend SVI $\{Composite\ Index\_Investment\}$ shock. The latter metric is based on the Google Search Volume Index for the four terms "Terrorism", "Cancer", "Natural Disaster" and "Opinion Poll" category Investment. The Cholesky decomposition (orthogonalized) is used to compute the responses to one standard deviation innovations. The ordering of the lower triangular matrix is as follows: the uncertainty metric, the stock market returns, the average interest of 3-months Treasury Bill, the consumer confidence index, the business confidence index and the industrial production. All the variables, except for the uncertainty metric and the 3TBILL are entered in the regression estimation in log form. Solid lines identify the estimated impulse response function; shaded areas represent the 95% level bootstrap confidence intervals

Figure 13 plots the impulse responses of the endogenous variables to a one standard deviation shock in the uncertainty metric based on four different Google searches. In particular, Dummy Trend SVI $\{Composite\ Index\_Investment\}$ reflects the arising of an extraordinary level of investors' attention directed to the occurrence of a terrorist attack, an imminent and controversial vote, a severe disease or a natural adverse event. Consistent with previous results, the shock produce a short term decline in the stock prices: market returns reach the bottom peak already the following month (-1,1%), followed by a rapid rebound starting from period 2[47]. The short-term bond market displays an opposite behaviour, indeed the price of the risk free 13-week Treasury Bill appears to increase as the related interest rate subside throughout the whole periods. Hence, our composite uncertainty is associated with the tendency of economic agents to sell their risky assets such as the S&P500 stocks and buy safer short-term bonds. Although less statistically significant[48], the search-behaviour has an adverse shock on the economic activity as well. Both consumer and business confidence are found to diminish until the third month, however the rate of recovery is quite different as BCI experience a positive reversal from the 18th month, whereas CCI does not appear to fully recover within the covered period. This evidence suggests that consumers adjust upward their demand at a gradual pace (strong consumption smoothing), waiting for reassuring signals from the policymaker strategies and the economic activity. Eventually, after an initial adjustment, the industrial production decrease throughout the whole period as result of lower consumer spending and investment plan' delay.

4.2.2 Concluding remarks

A large literature in macroeconomics investigates the relationship between uncertainty and business cycle fluctuations. Nevertheless, the question of whether uncertainty is an exogenous source of business cycle fluctuations or an endogenous response to economic fundamentals is not fully understood. Existing results are based on convenient, but restrictive assumptions and employ uncertainty measures that are strongly correlated with financial market variables (as in the case of the CBOE Volatility Index) or economic policy

[47] The dynamic of the S&P 500' IRF appears to be significant until the fifth month.

[48] In Figure 13, Consumer Confidence, Business Confidence and Industrial Production Impulse response functions dynamics display little significance at 95% confidence intervals, as the band errors include zeros already in the first period.

strategies (as in the case of the EPU Index). This empirical application considers a set of novel uncertainty measures entirely based on external events or concepts, in order to shed light on the role of ambiguity as a cause and not a consequence of economic and financial contraction. Truth be told, theoretical literature did not reach consensus on the sign of an ambiguity shock, as a strand of literature has raised the possibility that uncertainty can actually increase economic activity. “Growth options” theories of uncertainty postulate that a mean-preserving spread in risk generated from an unbounded upside, coupled with a limited downside, can induce firms to invest and hire, since the increase in mean-preserving risk increases expected profits. Such theories were often used to explain the dot-com boom. Examples include Kraft, Schwartz, and Weiss (2013), Segal, Shaliastovich, and Yaron (2015). Similarly, the question of causality and the identification of exogenous variation in uncertainty is a long-standing challenge of the uncertainty literature. The challenge arises in part because there is no theoretical consensus on whether the uncertainty that accompanies deep recessions is primarily a cause or effect (or both) of declines in economic activity. Classic theories assert that uncertainty originates endogenously from economic fundamentals such as productivity, and that such real economic uncertainty, when interacted with market frictions, discourages real activity. On the other hand, some researchers have argued that uncertainty dampens the economy through its influence on financial markets (e.g., Gilchrist, Sim, and Zakrajsek (2010)). Econometric analyses aimed at understanding the role of uncertainty for business cycle fluctuations face their own challenges, especially when the origination of ambiguity is identified within the financial or economic activity. Attempts to identify the effects of uncertainty shocks in existing empirical work are based as well on recursive schemes within the framework of vector-auto regressions (VAR). But results differ according to whether uncertainty is ordered ahead of or after real activity variables in the VAR. While a recursive structure is a reasonable starting point, any presumed ordering of the variables is hard to defend on theoretical grounds given that contemporaneous changes in macroeconomic or financial uncertainty can arise both as a cause of business cycle fluctuations and as a response to other shocks. Recursive structures explicitly rule out this possibility since they presume that some variables respond only with a lag to others. It is with these challenges in mind that we addressed the question on whether uncertainty is primarily a source or a consequence of business cycle fluctuations, by employing several vector auto regression. To confront the challenges just discussed, we propose novel ambiguity metrics based on the web-searches for events and concepts whose

occurrence is unconnected with the economic system. Therefore, the ordering of the uncertainty in the recursive scheme leaves no room for doubt since by definition our indicator are exogenous to the business cycle. Our main results may be stated as follows. First, positive shocks to web-search based uncertainty are found to cause a sharp decline in financial activity that persists for the initial four months, lending support to the hypothesis that investors initially tend to sell risky assets in favour of safer gov. bonds (i.e. *Flight-to-quality*). In the second place, the search behaviour shock is associated with reduced consumer and business confidence, which in turn generate a decline in the economic output. The finding that heightened uncertainty has negative consequences for real activity is qualitatively similar to that of pre-existing empirical work that uses as well recursive identification schemes (e.g., Bloom (2009), Donadelli (2015)), but differs in the way we trace the source of this result specifically to external adverse events uncertainty rather than to macro based uncertainty.

Broadly speaking, we see two ways to interpret our VAR-based evidence. Under the first interpretation, an upward uncertainty innovation corresponds to an unforeseen adverse event shock that causes the worsening of macroeconomic performance through real options effects, cost-of-capital effects or other mechanisms. Second, the search-based uncertainty has no role as either an impulse or a propagation mechanism; instead, it simply acts as a useful summary statistic for information missing from the other variables in our system — market returns, short term interest rate, consumer confidence, business confidence and industrial production. This latter interpretation is hard to reconcile with the kind of information, which web searches can provide. It appears a bit of a stretch to claim that Google queries about “terrorism”, “cancer” etc. include relevant pieces of information about macroeconomic conditions that are not already captured by the covered variables. Rather, it makes more sense to us that an increased need of information expresses a greater degree of uncertainty among economic agents and this produces behavioural biases at the time of investment and consumption decisions.

5. Robustness Check

Empirical findings highlight that the effects of uncertainty shocks are significantly term-dependent as different web searches lead to distinct results. Moreover, we point out that the need of information, rather than on the channel through which the information is conveyed, might as well imply a significant state of ambiguity among economic agents and predict a decline of both financial and real activity. In this section, we check the robustness of our main findings to several changes of the baseline VAR that is set to predict the monthly fluctuations of the US business cycle (equation (7)).

5.1 Alternative Google searches

As first exercise, we test whether by employing different but related Google queries as source of uncertainty we obtain considerable different results. It seems straightforward that separate concept or events shall trigger quite distinct level of ambiguity. In other words, our choice of web search keywords is a long way from being casual, since each of the selected term identifies a well-defined notion whose negative connotation is found, by behavioural evidence, to affect economic agents' decisions. Hence, testing completely different search topics might be less relevant for the purpose of assessing the validity of our models. On the other hand, we expect that by replacing our key terms with words spelled differently but linked to the same underlying topic, the regressions outputs do not change dramatically. We proceed by constructing new uncertainty metrics based on four new terms. The selection of related Google keywords is conducted by taking into account the semantic relationship with the respective original terms, as well as the relevance in terms of users attention (e.g. we excluded any technicality or specific events). As we can see in the following table, terms without category specification display positive correlation (significantly good resemblance only in the case of Poll and Vote); however, Investment category specification essentially deletes the relation. The reason shall be found in the lack of observations, as the category Investment SVIs are described by lower web-traffic, which is filtered in conjunction with a users' trading activity. Recalling that each Google Trends data point is divided by the total searches of the geography and time range it represents, less popular SVI are likely to exhibit series mainly defined by zero values[49], hence the

[49] Google Trends time series are composed by natural numbers.

pattern of search behaviour might be misleading.

Table 18

Google SVI Terms Alternatives				
	Cancer → Carcinoma	Natural Disaster → Natural Catastrophe	Terrorism → Organized Crime	Polls → Vote
No category	*correlation = 56%*	*correlation = 42%*	*correlation = 50%*	*correlation = 90%*
Investment	*correlation = 0,1%*	*correlation = 0,1%*	*correlation = 0,1%*	*correlation = 70%*

The first row reports the correlation between each alternative term without category specification; the second row displays the correlation between each alternative with the Investment category specification. The correlation is computed on the Search Volume Indexes downloaded from Google Trends

In line with section 4.2, we test equation (7) by employing as ambiguity index the uncertainty metrics based on the web searches of "alternative" terms. For the sake of brevity, we summarize here below (Table 19) only the most significant results for each new keyword[50]. As before, we provide the coefficient estimates of the (lagged 1) uncertainty metrics under the business cycle prediction framework.

Table 19: *Predicting Monthly Macroeconomic Conditions Using* ***Alternative Google searches*** *as sources of uncertainty*

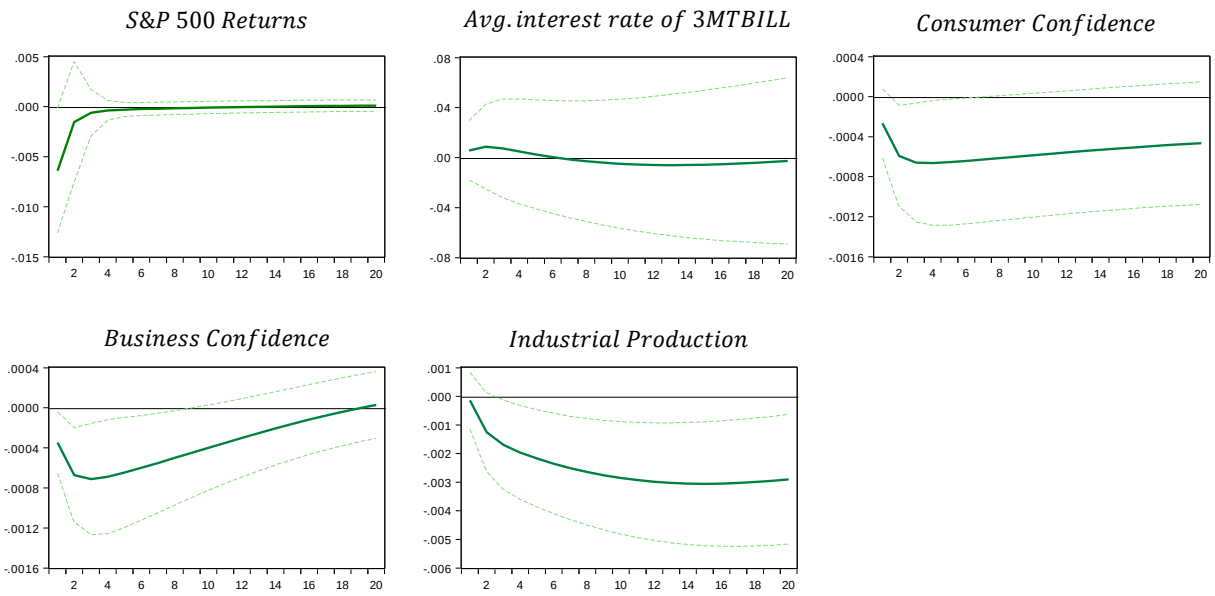
Term	CARCINOMA	NATURAL CATASTROPHE	ORGANIZED CRIME	VOTE
Category	-	*Investment*	-	*Investment*
Metric	Dummy SVI	Dummy SVI	SVI	Trend SVI
SP500	-0.002884 [-0.19825]	-0.022861 * [-1.78167]	-0.000466 * [-1.61046]	-0.003028 [-0.79673]
3TBILL	0.047494 [0.86242]	0.014712 [0.29916]	0.000472 [0.42702]	0.005628 [0.38864]
CCI	-0.001106 [-1.38034]	-7.77E-05 [-0.10811]	-8.42E-06 [-0.52010]	-0.000218 [-1.02117]
BCI	-0.000977 [-1.36656]	-0.001199 * [-1.89277]	-2.95E-05 ** [-2.06589]	-0.000292 [-1.58137]
IP	-0.004775 ** [-2.07743]	-0.003204 [-1.55463]	-0.000122 *** [-2.66819]	-0.001152 ** [-2.00570]

The table displays the coefficient estimates of each uncertainty measure lagged 1, for the respective dependent variables (S&P500, 3TBILL, CCI, BCI, IP) Numbers in parenthesis indicate the respective t-statistics of each coefficient estimate. Three stars denote significance at 1% or less; two stars denote significance at 5% or less; one star denotes significance at 10% or less. The regressions are based on 163 observations from January 2004 to July 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to one lag are used. The table data come from Google, Yahoo! Finance, OECD and FRED.

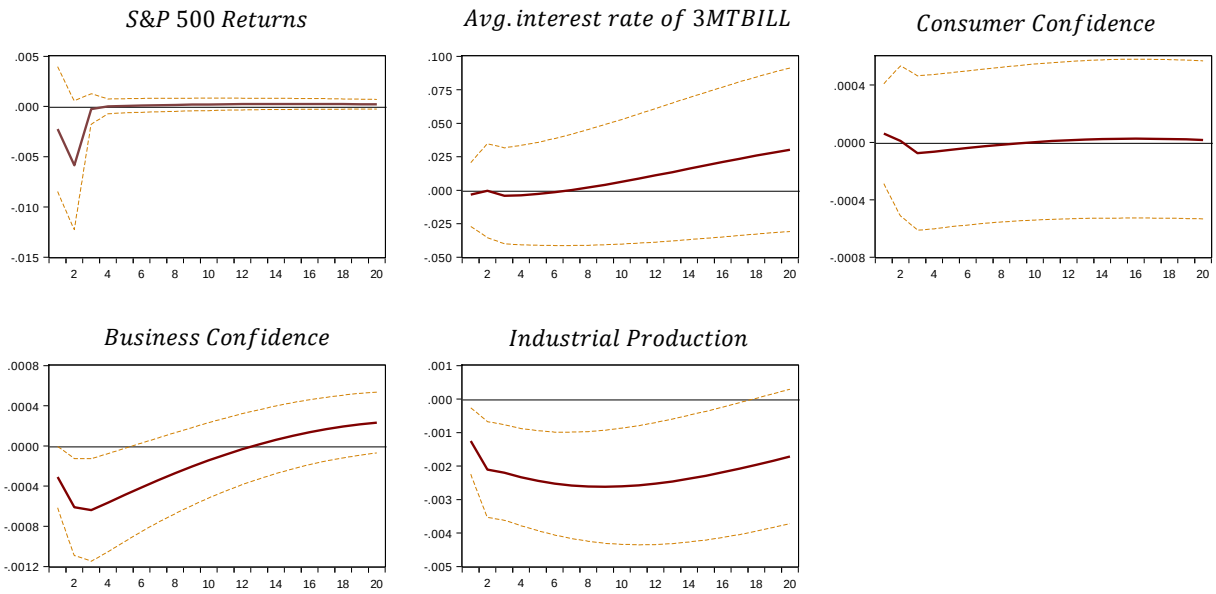
[50] Full estimates results can be found in the Appendix A9.

Figure 15: *Response to Cholesky One S.D. Innovations*[51]

Panel (A): $CARCINOMA$

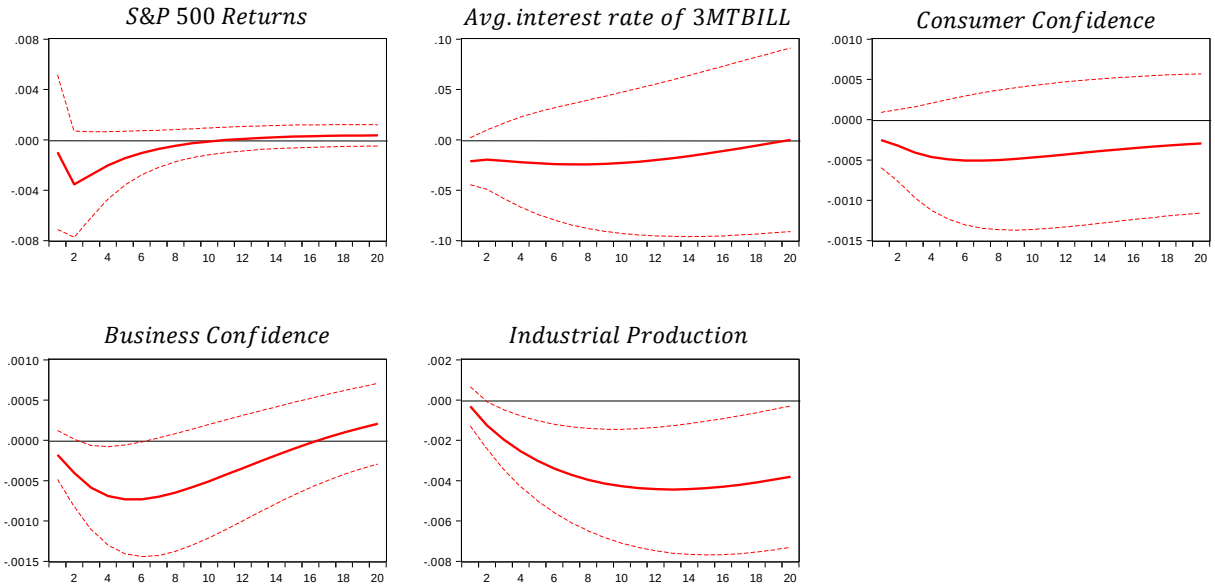


Panel (B): $NATURAL\ CATASTROPHE$



[51] Innovations are built upon the uncertainty metrics entered in the regressions displayed in Table 19.

Panel (C): $ORGANIZED\ CRIME$



Panel (D): $VOTE$

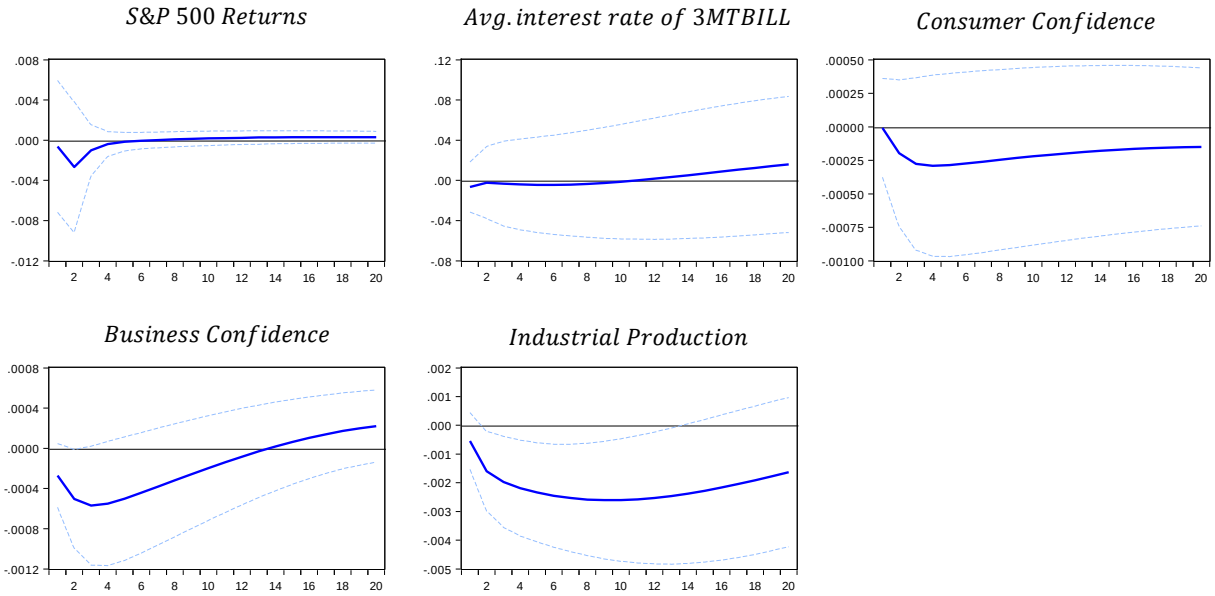


Figure 15 displays the dynamic responses of each endogenous variable to the four alternative SVI $\{Carcinoma, Natural\ Catastrophe, Organized\ Crime, Vote\}$ shocks shown in Table 19. The Cholesky decomposition (orthogonalized) is used to compute the responses to one standard deviation innovations. The ordering of the lower triangular matrix is as follows: the uncertainty metric, the stock market returns, the average interest of 3-months Treasury Bill, the consumer confidence index, the business confidence index and the industrial production. All the variables, except for the uncertainty metric and the 3TBILL are entered in the regression estimation in log form. Solid lines identify the estimated impulse response function; dashed lines represent the 95% level bootstrap confidence intervals

As we can see from the estimation output and the impulse response functions graphs, the uncertainty based on web searches of terms closely related to those employed in section 4, generate effects on the business cycle conditions that are fully consistent with the previous results. In particular, analyzing the coefficient estimates displayed in Table 21, we immediately notice that all the dependent variables, except for the interest rate, are negatively affected by each ambiguity metrics. Indeed, just as in the case of "Cancer" SVI[52], "Carcinoma" uncertainty shock produces a short term drop in the stock market returns (-0,6% within one month). The 3 months T-Bill price remains essentially unchanged; the consumer and business confidence IRFs exhibit a similar negative patterns (with CCI that recovers at a slower pace than BCI). Eventually, the Industrial Production steeply decreases the whole first year without any positive reversal within the considered period of 20 months. In a similar manner, the impact of "Natural Catastrophe", "Organized Crime" and "Vote" uncertainty is in accordance with the results obtained by employing "Natural Disaster", "Terrorism" and "Poll" SVI respectively (Figures 10, 11 and 12). The only exception is represented by the interest rate whose IRF, in the case of "Natural Catastrophe" and "Organized Crime", exhibits an opposite behaviour. Nevertheless, the particularly low statistical significance associated with the respective impulse response functions, does not lead us to place too much weight into this counterevidence. Overall, despite a lower statistical significance[53], we find that estimation outcomes are widely in line with those attained in section 4. Therefore, we can safely assume that our results are robust to the replacement of original keywords with strictly related terms, which might be used as alternative Google queries by economic agents and thereby expressing a similar degree of uncertainty.

[52] Figure 9.

[53] With 95% level bootstrap confidence intervals, we find significant the following IRFs: the stock market returns in Panel A, the business confidence in Panels A-B, the Industrial Production in Panel B.

5.2 Independent Uncertainty vs Policy Uncertainty

Thus far, the effects of uncertainty shocks on the business cycle were based exclusively on the web-search based metrics. This section examines the robustness of our results to different metric and source of ambiguity. In performing this analysis, we compare the uncertainty measure derived from the PCA technique (Dummy Trend SVI, section 4.2.1), with another composite index, that is the Economic Policy Uncertainty (EPU) developed by Baker, Bloom and Davis in 2013. We employ the same VAR framework and impulse response scheme as in the previous specification. Our aim is twofold. On the one hand, we want to gauge the extent of our Google-search-based metrics in shaping the business cycle dynamics. On the other hand, we want to identify the difference of financial and macroeconomic implications in case of independent external uncertainty shocks and economic policy uncertainty shocks.

Figure 16: *Comparison of Responses to Cholesky One S.D. Innovations*

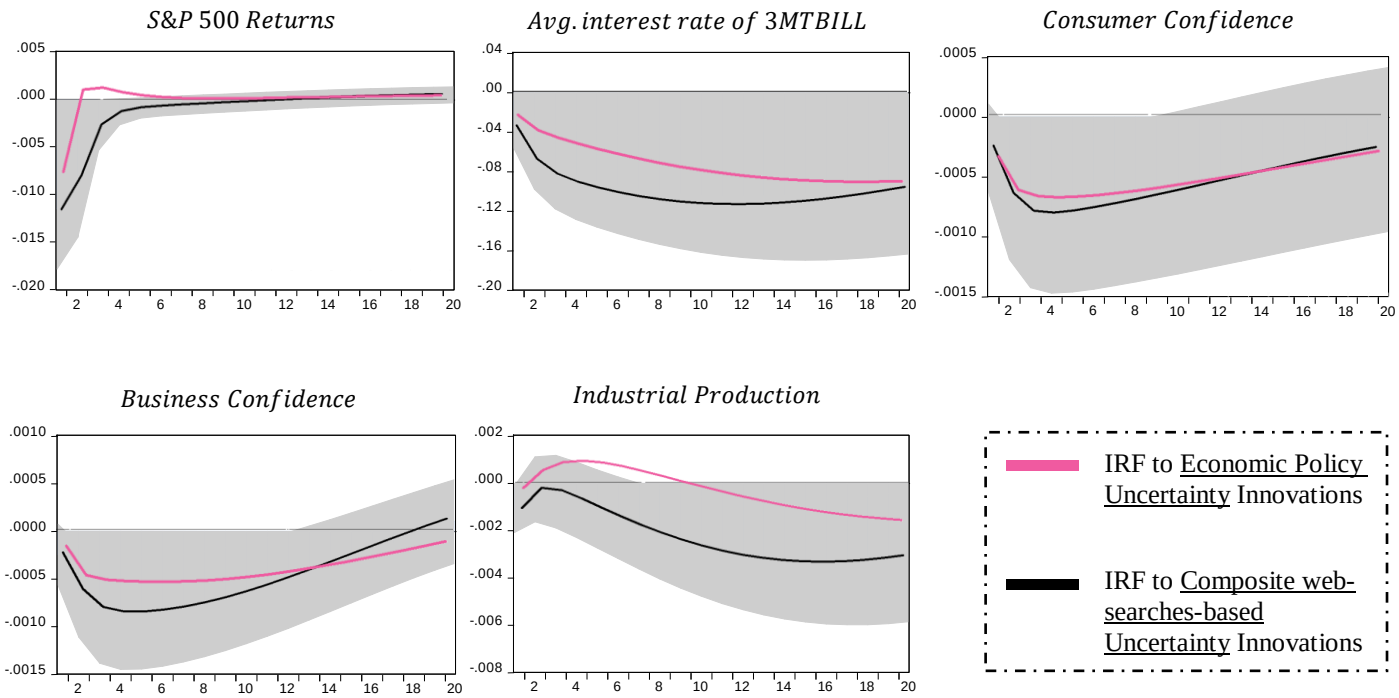


Figure 16 displays the dynamic responses of each endogenous variable to one standard deviation innovation of EPU index and of Dummy Trend SVI $\{Composite\ Index\_Investment\}$ shock. The latter metric is based on the Google Search Volume Index for the four terms "Terrorism", "Cancer", "Natural Disaster" and "Opinion Poll" category Investment. Both indexes consist of 163 monthly observations from January 2004 to July 2017. The Cholesky decomposition (orthogonalized) is used to compute the responses to one standard deviation innovations. The ordering of the lower triangular matrix is as follows: the uncertainty metric, the stock market returns, the average interest of 3-months Treasury Bill, the consumer confidence index, the business confidence index and the industrial production. All the variables, except for the uncertainty metric and the 3TBILL are entered in the regression estimation in log form. Solid lines identify the estimated impulse response function; gray areas represent the 95% level bootstrap confidence intervals for the Dummy Trend SVI $\{Composite\ Index\_Investment\}$ shock.

As we can see in Figure 16, the effects of policy uncertainty on the US Business cycle lead to fairly similar financial and macroeconomic implications to those generated by web-search based uncertainty. In both cases, unanticipated jumps in ambiguity induce a notable tightening of stock market returns, yet within 5 months the adverse influence is completely reversed. In case of a policy uncertainty shock the positive rebound of the S&P 500 index is more pronounced, reflecting the fact that investors seem to require a higher risk premium under a change in macro fundamentals rather than under the occurrence of an adverse external event. In return, the shift towards safer assets appear to be more prominent in case of a web-search uncertainty, as shown by the steeper decline of the average interest of 3-months maturity Treasury Bill. The consumer and business confidence IRFs express a very similar pattern, whether they are elicited by EPU innovations or Search Volume innovations. Predictably, the impact of both shocks generates a decline in the industrial output, however it is worth noting that the responses of the real economy to the occurrence of possible hostile events are somewhat more muted. This remarkable finding suggests that the ambiguity associated with the happening of a terrorist threat, a severe disease, an election or a natural disaster affects the consumption and investment decisions more than the uncertainty involved at monetary or fiscal policy shifts. Alternatively, our novel composite index does capture a degree of ambiguity that, conversely to the EPU, the VIX or other uncertainty measures, are entirely exogenous to the economic activity. In other words, the smaller extent of the results obtained by employing the index developed by Baker et al. (2013) might be due the "endogeneity" issue, which arises as policy uncertainty can, at least partially, be a *response* to anticipated future economic conditions. Hence, part of the information conveyed by this latter index could have been subsumed by the other macro or financial variables.

In short, we found that the magnitude of the impact of Google-search-based uncertainty metrics on the business cycle are not only statistically significant, but also fully comparable to the effects produced by employing the well-known EPU. Moreover, the composite indicator built on the frequency of the web searches about external and independent events seems to capture a state of ambiguity that shapes consumer and business decisions in a greater extent.

6. Conclusions

Beyond the suggestive finding that the frequency of web-searches has significant explanatory power in the prediction of the financial market activity and the business cycle fluctuations, the most valuable contribution of our study lies in the empirical evidence that uncertainty shocks, whose source is neither financial nor economic, do worsen the real economy. A growing body of research establishes uncertainty as a feature of deep recessions but leaves open two key questions: is uncertainty primarily a source of business cycle fluctuations or an endogenous response to them? And where does uncertainty originate from? This study addresses both questions by testing whether the need for information about the occurrence of potentially hostile events, unrelated to economic setups, does affect the consumer demand and the investment allocation in a similar manner to the one expressed by the real option theories (see e.g. Bloom, 2009 and Bernanke 1983). To do so, we constructed novel ambiguity metrics following the works of Dzielienski (2011) and Donadelli (2015) and we investigated their impact on daily S&P 500' activity and monthly US economic conditions within different VAR frameworks. The results from these estimations are remarkable. In first place, we found that an increased level of attention towards certain concept or events whose occurrence might lead to augmented risk aversion, do indeed affects the volume of stocks transactions performed at daily levels, as well as the next days returns. In particular, consistent with prior behavioural finance evidence, increasing uncertainty makes risky assets like stocks less desirable as investors' decisions are affected by a less clear outlook and probabilities definition. Here, the striking finding is that uncertainty does not come from changes in asset's fundamentals, macroeconomic conditions or financial downturns, but from external and independent events that strongly influence people' decisions, such as a terrorist threat or an imminent election.

In the second part of our empirical study, we found out that the same sources of ambiguity, which causes a drop in daily S&P 500 prices, have an adverse effect on the monthly US Business cycle conditions. Both the sign and the extent of uncertainty shocks are consistent with those produced by employing the Economic Policy Uncertainty index, developed by Baker, Bloom and Davis (2013). This result becomes even more relevant as it constitutes a piece of evidence that uncertainty do not only arises (or increases) in *reaction* to a change in the economic setups, but it can actually *originate* a tightening of business cycle conditions.

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8. Appendix

A1 – Uncertainty Measures

VIX: Sample Period 2005:M01-2017M12. The VIX is the square root of the risk-neutral expectation of the S&P 500 variance over the next 30 calendar days, calculated as the square root of the variance swap rate for a 30-day term

EPU (for the United States): Sample Period 2005:M01-2017M12. The index is composed of three sets of measures: monthly news articles containing 'uncertain' or 'uncertainty', 'economic' or 'economy', and policy-relevant terms (scaled by the smoothed number of articles containing 'today'); the number of tax laws expiring in coming years; and a composite of quarterly forecasts of government expenditures and one-year CPI (consumer price index) from the Philadelphia Fed Survey of Forecasters. The data are available at www.policyuncertainty.com.

BOS: Sample Period 2005:M01-2017M12. We reconstruct the Business expectations dispersions following the approach of Bachmann et al. (2013). As first step, we retrieve the information on the current state of firms' business conditions and their expectations of future business conditions contained in the Philadelphia Fed's Business Outlook Survey. As Bachmann et al. (2013), we focus on two questions:

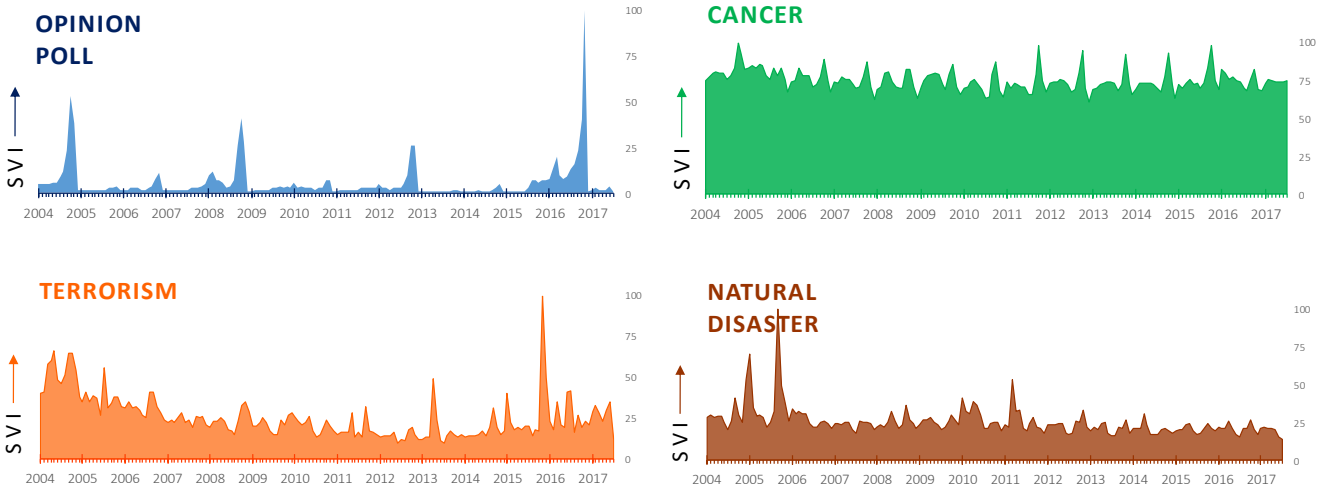
1. *General Business Conditions*: What is your evaluation of the level of general business activity six months from now versus current month? Answers: decrease; no change; increase.
2. *Company Business Indicators*: Shipments six months from now versus current month? Answers: decrease; no change; increase.

The qualitative survey responses to both questions are coded into three discrete numerical categories: -1 = decrease; 0 = no change; and 1 = increase. For each question, the (unweighted) proportion of firms that responded with "increase" at time t is defined "$Frac_t^+$" and "$Frac_t^-$" the (unweighted) proportion of firms that responded with "decrease" at time t. The cross-sectional forecast dispersion for any of the two questions is then computed according to $BOS_t = \sqrt{Frac_t^+ + Frac_t^- - (Frac_t^+ - Frac_t^-)^2}$

GT: Sample Period 2005:M01-2017M12. The index is reconstructed following the approach of Dzielinski (2011), namely we retrieved the Search Volume Index for the term "Economy" (Geographic Restriction: United States; Category Specifications: Investment) provided by the Web Application Google Trends. Thereafter we isolate the trend information by dividing the current value of the obs. *i* by the value of the corresponding month one year ago.

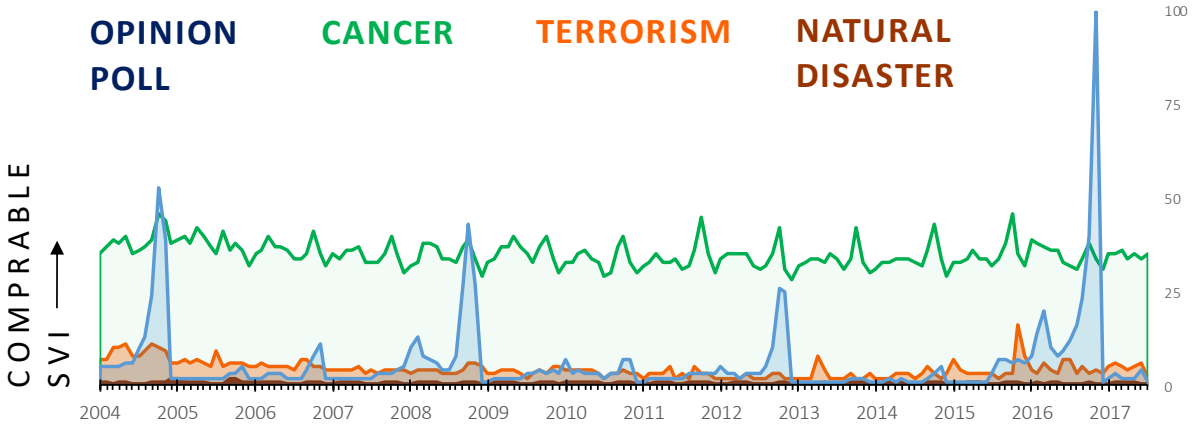
A2 – Google Search Volume Indexes

No Category specification – *Standalone* Indexes



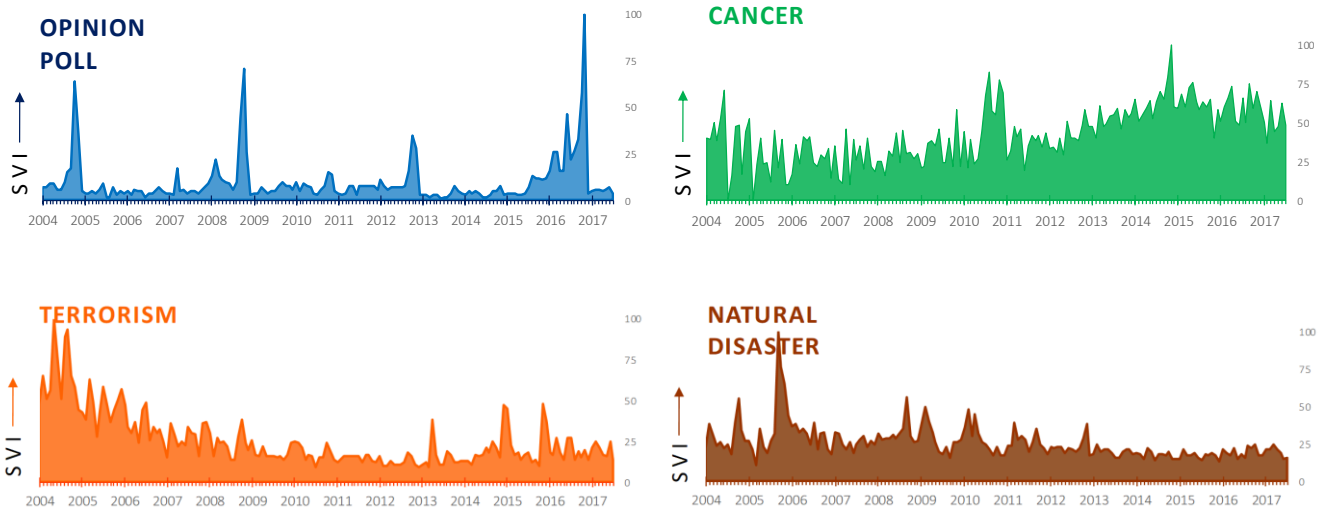
The above figures plots the SVI for "Cancer", "Natural Disaster", "Opinion Poll" and "Terrorism" as downloaded from Google. Monthly data from Jan-04 to Jul-17, T=165 obs. Location: United Sates; Category: All categories (No specification). Vertical axis measures the frequency with which a particular keyword is entered in the Google Search Engine in a month. The horizontal axis of the main graph represents time.

No Category specification – *Comparable* Indexes



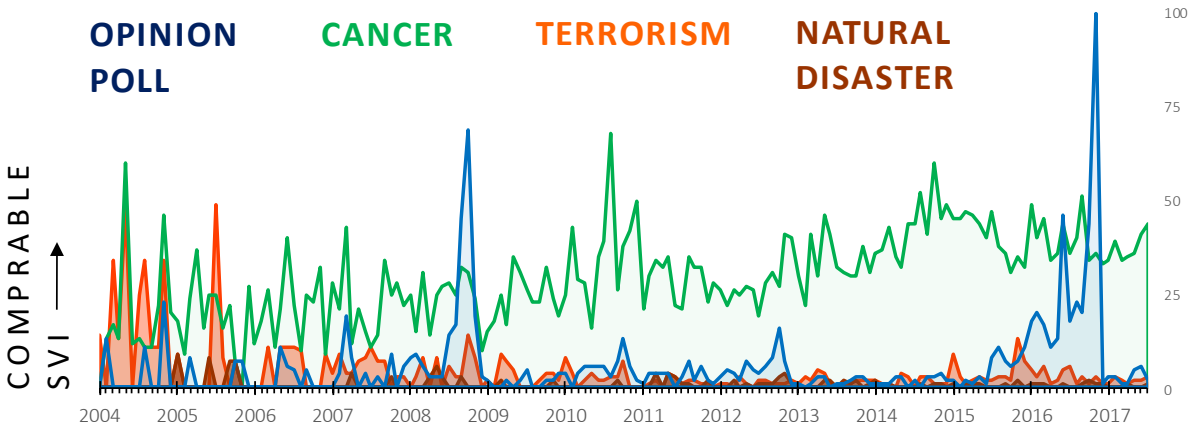
The above figures plots the SVI for "Cancer", "Natural Disaster", "Opinion Poll" and "Terrorism" downloaded **together** from Google. This extraction method allow us to compare the series each other, as the variables are indexed to the same peak (which in our case coincide with the observation of "Opinion Poll", Nov-17). Monthly data from Jan-04 to Jul-17, T=165 obs. Location: United Sates; Category: All categories (No specification). Vertical axis measures the frequency with which a particular keyword is entered in the Google Search Engine in a month. The horizontal axis of the main graph represents time.

Investment Category specification – *Standalone* Indexes



The above figures plots the SVI for "Cancer", "Natural Disaster", "Opinion Poll" and "Terrorism" as downloaded from Google. Monthly data from Jan-04 to Jul-17, T=165 obs. Location: United Sates; Category: Finance>> Investment. Vertical axis measures the frequency with which a particular keyword is entered in the Google Search Engine in a month. The horizontal axis of the main graph represents time.

Investment Category specification – *Comparable* Indexes



The above figures plots the SVI for "Cancer", "Natural Disaster", "Opinion Poll" and "Terrorism" downloaded **together** from Google. This extraction method allow us to compare the series each other, as the variables are indexed to the same peak (which in our case coincide with the observation of "Opinion Poll", Nov-17). Monthly data from Jan-04 to Jul-17, T=165 obs. Location: United Sates; Category: Finance>> Investment. Vertical axis measures the frequency with which a particular keyword is entered in the Google Search Engine in a month. The horizontal axis of the main graph represents time.

A3 - R script to automate Google Trends download

This script[54] automates the downloading of Google Trends. It works best with the R version i386 3.3.0.; Google Trends restricts the number of download to roughly 400 at a time

```
install.packages("drat")
drat:::add("ghrr")
if (!require("devtools")) install.packages("devtools")
devtools::install_github("PMassicotte/gtrendsR")
install.packages(c('devtools','curl'))
library('devtools')
library(gtrendsR)
#Search in GoogleTrend the topic of concern and copy the url
x <- gsub("^.*?%","%","<paste here the GoogleTrend url>")
y <- URLdecode(x)
#Select the time series
start=which(data[,1]==="")[1]+3
stop=which(data[,1]==="")[2]-2
#Geographic restrictions
z=”<insert the country ticker here (e.g. US)>"
#Category restrictions:
w=”<insert the category number here>"
{data_frame_1<-  gtrends(c(y), geo = z, cat = w, time
="start stop")$interest_over_time}
#Saving the GoogleTrend time series in a csv file (if you
want to get time series with different specifications in
the same csv file, just modify the restrictions parameters
and write additional data_frames
write.table(rbind(data_frame_1, data_frame_2, …, ),
"File_Name_here.csv", row.names=FALSE)
```

[54] The script exploit the package ‘gtrendsR’ developed by Massicotte. (https://github.com/PMassicotte/gtrendsR, 2016). An interface for retrieving and displaying the information returned online by Google Trends is provided. Trends (number of hits) over the time as well as geographic representation of the results can be displayed.

A4 – Daily VAR Output: Search-based uncertainty and Stock Market

ASVI Cancer - Category Specification: None; Inclusion of Crisis Dummy: No

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(CANCER)	D(VOLUME)	SP500_Y
D(CANCER(-1))	-0.431231	77870049	-0.000122
	(0.01881)	(2.0E+07)	(0.00022)
	[-22.9251]	[3.98785]	[-0.56437]
D(CANCER(-2))	-0.411218	3093607.	-0.000108
	(0.02011)	(2.1E+07)	(0.00023)
	[-20.4437]	[0.14816]	[-0.46669]
D(CANCER(-3))	-0.283830	4328606.	0.000266
	(0.02090)	(2.2E+07)	(0.00024)
	[-13.5780]	[0.19948]	[1.10452]
D(CANCER(-4))	-0.186380	-30015699	-1.87E-05
	(0.01984)	(2.1E+07)	(0.00023)
	[-9.39479]	[-1.45748]	[-0.08197]
D(CANCER(-5))	-0.038978	-5728498.	0.000378
	(0.01848)	(1.9E+07)	(0.00021)
	[-2.10874]	[-0.29855]	[1.77469]
D(VOLUME(-1))	-3.95E-11	-0.507149	5.05E-14
	(1.9E-11)	(0.02024)	(2.2E-13)
	[-2.02367]	[-25.0591]	[0.22499]
D(VOLUME(-2))	-3.53E-11	-0.290071	-1.74E-13
	(2.2E-11)	(0.02240)	(2.5E-13)
	[-1.63542]	[-12.9471]	[-0.69854]
D(VOLUME(-3))	-2.37E-11	-0.303022	-2.50E-13
	(2.2E-11)	(0.02255)	(2.5E-13)
	[-1.09266]	[-13.4364]	[-1.00006]
D(VOLUME(-4))	3.42E-11	-0.246907	-4.07E-13
	(2.2E-11)	(0.02278)	(2.5E-13)
	[1.55737]	[-10.8410]	[-1.61185]
D(VOLUME(-5))	1.91E-12	-0.059126	-4.37E-13
	(2.0E-11)	(0.02034)	(2.3E-13)
	[0.09726]	[-2.90675]	[-1.93505]
SP500_Y(-1)	0.785371	-5.55E+09	-0.066142
	(1.68755)	(1.8E+09)	(0.01944)
	[0.46539]	[-3.16771]	[-3.40289]
SP500_Y(-2)	-0.811963	3.56E+08	-0.007348
	(1.68827)	(1.8E+09)	(0.01945)
	[-0.48094]	[0.20302]	[-0.37788]
SP500_Y(-3)	-2.351032	2.82E+09	-0.001033
	(1.69016)	(1.8E+09)	(0.01947)
	[-1.39101]	[1.60845]	[-0.05305]
SP500_Y(-4)	-0.634714	2.63E+09	-0.017496
	(1.71532)	(1.8E+09)	(0.01976)
	[-0.37003]	[1.47517]	[-0.88555]
SP500_Y(-5)	0.297169	-3.40E+09	0.009086
	(1.72857)	(1.8E+09)	(0.01991)
	[0.17192]	[-1.89223]	[0.45637]
C	-0.032040	-20871542	0.000363
	(0.01198)	(1.2E+07)	(0.00014)
	[-2.67498]	[-1.67860]	[2.62927]
D(VIX)	-0.000885	71249532	-0.005645
	(0.00628)	(6521184)	(7.2E-05)
	[-0.14095]	[10.9259]	[-78.0156]
D(VIX(-1))	0.002610	12610972	-0.000466
	(0.01163)	(1.2E+07)	(0.00013)
	[0.22433]	[1.04431]	[-3.48056]
D(VIX(-2))	0.003078	27779226	5.30E-05
	(0.01162)	(1.2E+07)	(0.00013)
	[0.26487]	[2.30278]	[0.39587]
D(VIX(-3))	-0.000374	33231274	-0.000282
	(0.01158)	(1.2E+07)	(0.00013)
	[-0.03232]	[2.76422]	[-2.11237]
D(VIX(-4))	-0.006923	47042237	-0.000198
	(0.01178)	(1.2E+07)	(0.00014)
	[-0.58773]	[3.84725]	[-1.46274]
D(VIX(-5))	-0.007070	-19179107	0.000357
	(0.01174)	(1.2E+07)	(0.00014)
	[-0.60244]	[-1.57438]	[2.64462]
ADS	-0.003710	2863437.	0.000544
	(0.01475)	(1.5E+07)	(0.00017)
	[-0.25146]	[0.18696]	[3.20198]
D(ADS(-1))	-0.164307	-1.29E+09	-0.024004
	(0.79696)	(8.3E+08)	(0.00918)
	[-0.20617]	[-1.56476]	[-2.61503]
D(ADS(-1))	-0.164307	-1.29E+09	-0.024004
	(0.79696)	(8.3E+08)	(0.00918)
	[-0.20617]	[-1.56476]	[-2.61503]
D(ADS(-2))	0.775413	6.50E+08	0.013248
	(0.78905)	(8.2E+08)	(0.00909)
	[0.98272]	[0.79376]	[1.45775]
D(ADS(-3))	1.182672	42795361	-0.005097
	(0.79865)	(8.3E+08)	(0.00920)
	[1.48085]	[0.05162]	[-0.55407]
D(ADS(-4))	-1.028632	5.82E+08	0.015284
	(0.80534)	(8.4E+08)	(0.00928)
	[-1.27726]	[0.69561]	[1.64776]
D(ADS(-5))	-0.126396	63295638	0.003198
	(0.81397)	(8.4E+08)	(0.00938)
	[-0.15528]	[0.07491]	[0.34108]

R-squared	0.219668	0.253097	0.703442
Adj. R-squared	0.211789	0.245556	0.700448
Sum sq. resids	862.7281	9.30E+20	0.114450
S.E. equation	0.568010	5.90E+08	0.006542
F-statistic	27.87948	33.55996	234.9180
Log likelihood	-2291.605	-58386.87	9769.741
Akaike AIC	1.716954	43.23824	-7.210763
Schwarz SC	1.778112	43.29940	-7.149605
Mean dependent	-0.029167	-27186318	0.000282
S.D. dependent	0.639786	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	4.71E+12
Determinant resid covariance	4.56E+12
Log likelihood	-50882.70
Akaike information criterion	37.72517
Schwarz criterion	37.90864

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

ASVI Cancer - Category Specification: None; Inclusion of Crisis Dummy: Yes

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(CANCER)	D(VOLUME)	SP500_Y
D(CANCER(-1))	-0.430843	80082255	-6.20E-05
	(0.01882)	(2.0E+07)	(0.00022)
	[-22.8886]	[4.09112]	[-0.28685]
D(CANCER(-2))	-0.411475	3726716.	-8.38E-05
	(0.02008)	(2.1E+07)	(0.00023)
	[-20.4871]	[0.17843]	[-0.36341]
D(CANCER(-3))	-0.284038	5212060.	0.000295
	(0.02087)	(2.2E+07)	(0.00024)
	[-13.6099]	[0.24016]	[1.23051]
D(CANCER(-4))	-0.186361	-29723670	-4.33E-07
	(0.01980)	(2.1E+07)	(0.00023)
	[-9.41307]	[-1.44373]	[-0.00191]
D(CANCER(-5))	-0.038320	-5174350.	0.000395
	(0.01844)	(1.9E+07)	(0.00021)
	[-2.07794]	[-0.26982]	[1.86643]
D(VOLUME(-1))	-3.77E-11	-0.505710	6.34E-14
	(1.9E-11)	(0.02024)	(2.2E-13)
	[-1.93886]	[-24.9839]	[0.28367]
D(VOLUME(-2))	-3.85E-11	-0.289783	-1.63E-13
	(2.2E-11)	(0.02241)	(2.5E-13)
	[-1.78542]	[-12.9316]	[-0.65842]
D(VOLUME(-3))	-2.43E-11	-0.300294	-1.69E-13
	(2.2E-11)	(0.02259)	(2.5E-13)
	[-1.11835]	[-13.2960]	[-0.67831]
D(VOLUME(-4))	3.38E-11	-0.243495	-3.16E-13
	(2.2E-11)	(0.02281)	(2.5E-13)
	[1.53921]	[-10.6768]	[-1.25483]
D(VOLUME(-5))	1.48E-12	-0.057423	-3.85E-13
	(2.0E-11)	(0.02036)	(2.2E-13)
	[0.07577]	[-2.82047]	[-1.71423]
SP500_Y(-1)	0.745334	-5.47E+09	-0.068558
	(1.68999)	(1.8E+09)	(0.01940)
	[0.44103]	[-3.11496]	[-3.53419]
SP500_Y(-2)	-1.438977	2.91E+08	-0.008468
	(1.69105)	(1.8E+09)	(0.01941)
	[-0.85094]	[0.16564]	[-0.43624]
SP500_Y(-3)	-2.498994	3.13E+09	0.007214
	(1.69382)	(1.8E+09)	(0.01944)
	[-1.47536]	[1.77871]	[0.37103]
SP500_Y(-4)	-0.776053	2.84E+09	-0.012364
	(1.71579)	(1.8E+09)	(0.01969)
	[-0.45230]	[1.59287]	[-0.62779]
SP500_Y(-5)	0.476497	-3.57E+09	0.006724
	(1.72830)	(1.8E+09)	(0.01984)
	[0.27570]	[-1.98678]	[0.33892]
C	-0.033434	-22740763	0.000328
	(0.01213)	(1.3E+07)	(0.00014)
	[-2.75635]	[-1.80282]	[2.35710]
DUMMY_CRISIS	0.005340	1.94E+08	-0.007512
	(0.57399)	(6.0E+08)	(0.00659)
	[0.00930]	[0.32553]	[-1.14017]
DUMMY_CRISIS(-1)	-0.159260	-1.68E+09	-0.023736
	(0.80748)	(8.4E+08)	(0.00927)
	[-0.19723]	[-1.99852]	[-2.56084]
DUMMY_CRISIS(-2)	0.069219	2.17E+09	0.032399
	(0.80868)	(8.4E+08)	(0.00928)
	[0.08559]	[2.57941]	[3.49036]
DUMMY_CRISIS(-3)	-2.434750	-7.39E+08	0.000544
	(0.81035)	(8.4E+08)	(0.00930)
	[-3.00455]	[-0.87690]	[0.05853]
DUMMY_CRISIS(-4)	2.867128	1.01E+09	0.022300
	(0.81022)	(8.4E+08)	(0.00930)
	[3.53868]	[1.20328]	[2.39781]
DUMMY_CRISIS(-5)	-0.440553	-1.03E+09	-0.025348
	(0.57601)	(6.0E+08)	(0.00661)
	[-0.76484]	[-1.71799]	[-3.83387]
D(VIX)	-0.001091	71154662	-0.005639
	(0.00627)	(6524619)	(7.2E-05)
	[-0.17388]	[10.9056]	[-78.2999]
D(VIX(-1))	0.003357	13388799	-0.000469
	(0.01162)	(1.2E+07)	(0.00013)
	[0.28878]	[1.10757]	[-3.51459]
D(VIX(-2))	0.000149	27331021	4.07E-05
	(0.01161)	(1.2E+07)	(0.00013)
	[0.01279]	[2.26292]	[0.30537]
D(VIX(-3))	-0.000356	34088357	-0.000255
	(0.01157)	(1.2E+07)	(0.00013)
	[-0.03076]	[2.83300]	[-1.92327]
D(VIX(-4))	-0.007009	48212791	-0.000179
	(0.01175)	(1.2E+07)	(0.00013)
	[-0.59627]	[3.94424]	[-1.32504]
D(VIX(-5))	-0.007118	-19994641	0.000347
	(0.01171)	(1.2E+07)	(0.00013)
	[-0.60768]	[-1.64152]	[2.57787]
ADS	-0.018865	-12332025	0.000274
	(0.02377)	(2.5E+07)	(0.00027)
	[-0.79373]	[-0.49894]	[1.00548]
D(ADS(-1))	-0.091612	-1.21E+09	-0.021550
	(0.79687)	(8.3E+08)	(0.00915)
	[-0.11497]	[-1.46549]	[-2.35603]
D(ADS(-2))	0.804708	6.56E+08	0.012114
	(0.78917)	(8.2E+08)	(0.00906)
	[1.01969]	[0.79889]	[1.33734]
D(ADS(-3))	1.199453	-1.25E+08	-0.008286
	(0.79894)	(8.3E+08)	(0.00917)
	[1.50130]	[-0.15081]	[-0.90352]
D(ADS(-4))	-0.926400	7.16E+08	0.016811
	(0.80717)	(8.4E+08)	(0.00927)
	[-1.14771]	[0.85339]	[1.81443]
D(ADS(-5))	-0.328363	1.22E+08	0.005134
	(0.81738)	(8.5E+08)	(0.00938)
	[-0.40173]	[0.14366]	[0.54715]

R-squared	0.225560	0.256138	0.707689
Adj. R-squared	0.215982	0.246938	0.704074
Sum sq. resids	856.2132	9.26E+20	0.112811
S.E. equation	0.566498	5.89E+08	0.006503
F-statistic	23.54764	27.83905	195.7354
Log likelihood	-2281.365	-58381.36	9789.229
Akaike AIC	1.713816	43.23861	-7.220747
Schwarz SC	1.788079	43.31287	-7.146484
Mean dependent	-0.029167	-27186318	0.000282
S.D. dependent	0.639786	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	4.63E+12
Determinant resid covariance	4.45E+12
Log likelihood	-50849.45
Akaike information criterion	37.71388
Schwarz criterion	37.93667

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ASVI Cancer - Category Specification: Investment; Inclusion of Crisis Dummy: No

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(INV_CAN...	D(VOLUME)	SP500_Y
D(INV_CANCER(-1))	-0.862184	2280278.	1.21E-05
	(0.01916)	(2267712)	(2.5E-05)
	[-44.9951]	[1.00554]	[0.48100]
D(INV_CANCER(-2))	-0.746996	1517865.	4.83E-05
	(0.02468)	(2920787)	(3.2E-05)
	[-30.2672]	[0.51968]	[1.49584]
D(INV_CANCER(-3))	-0.453118	3482073.	1.85E-05
	(0.02717)	(3215537)	(3.6E-05)
	[-16.6768]	[1.08289]	[0.52053]
D(INV_CANCER(-4))	-0.287893	4432304.	-5.14E-06
	(0.02461)	(2912029)	(3.2E-05)
	[-11.7001]	[1.52207]	[-0.15972]
D(INV_CANCER(-5))	-0.120169	2559182.	-1.25E-05
	(0.01885)	(2231087)	(2.5E-05)
	[-6.37427]	[1.14706]	[-0.50833]
D(VOLUME(-1))	-1.33E-10	-0.505337	2.72E-14
	(1.7E-10)	(0.02025)	(2.2E-13)
	[-0.77897]	[-24.9573]	[0.12126]
D(VOLUME(-2))	-2.24E-10	-0.295393	-1.33E-13
	(1.9E-10)	(0.02240)	(2.5E-13)
	[-1.18393]	[-13.1901]	[-0.53663]
D(VOLUME(-3))	-1.95E-10	-0.309593	-2.16E-13
	(1.9E-10)	(0.02252)	(2.5E-13)
	[-1.02694]	[-13.7477]	[-0.86767]
D(VOLUME(-4))	-1.13E-10	-0.249940	-3.67E-13
	(1.9E-10)	(0.02272)	(2.5E-13)
	[-0.58741]	[-11.0020]	[-1.46191]
D(VOLUME(-5))	-1.93E-10	-0.055789	-4.03E-13
	(1.7E-10)	(0.02031)	(2.2E-13)
	[-1.12329]	[-2.74621]	[-1.79309]
SP500_Y(-1)	0.168012	-5.60E+09	-0.066988
	(14.8697)	(1.8E+09)	(0.01946)
	[0.01130]	[-3.18146]	[-3.44195]
SP500_Y(-2)	-20.14798	3.97E+08	-0.007903
	(14.8732)	(1.8E+09)	(0.01947)
	[-1.35465]	[0.22538]	[-0.40595]
SP500_Y(-3)	12.92951	2.76E+09	0.001281
	(14.9020)	(1.8E+09)	(0.01950)
	[0.86764]	[1.56501]	[0.06566]
SP500_Y(-4)	12.41956	2.38E+09	-0.017181
	(15.0959)	(1.8E+09)	(0.01976)
	[0.82271]	[1.33348]	[-0.86958]
SP500_Y(-5)	4.071183	-3.36E+09	0.007699
	(15.2076)	(1.8E+09)	(0.01990)
	[0.26771]	[-1.86619]	[0.38680]
C	-0.067772	-21341308	0.000371
	(0.10541)	(1.2E+07)	(0.00014)
	[-0.64291]	[-1.71067]	[2.69133]
D(VIX)	0.013753	70407487	-0.005641
	(0.05531)	(6545571)	(7.2E-05)
	[0.24866]	[10.7565]	[-77.9178]
D(VIX(-1))	-0.017703	12433076	-0.000468
	(0.10235)	(1.2E+07)	(0.00013)
	[-0.17296]	[1.02643]	[-3.49214]
D(VIX(-2))	-0.065502	28657065	4.11E-05
	(0.10223)	(1.2E+07)	(0.00013)
	[-0.64074]	[2.36867]	[0.30737]
D(VIX(-3))	0.094797	34360478	-0.000274
	(0.10194)	(1.2E+07)	(0.00013)
	[0.92994]	[2.84818]	[-2.05057]
D(VIX(-4))	0.071351	46805764	-0.000208
	(0.10360)	(1.2E+07)	(0.00014)
	[0.68871]	[3.81750]	[-1.53523]
D(VIX(-5))	0.034135	-19714229	0.000349
	(0.10330)	(1.2E+07)	(0.00014)
	[0.33046]	[-1.61264]	[2.58006]
ADS	-0.035626	3126996.	0.000541
	(0.12987)	(1.5E+07)	(0.00017)
	[-0.27432]	[0.20345]	[3.18205]
D(ADS(-1))	-13.38533	-1.31E+09	-0.023400
	(7.00727)	(8.3E+08)	(0.00917)
	[-1.91021]	[-1.58306]	[-2.55135]
D(ADS(-2))	8.920944	5.23E+08	0.013328
	(6.94519)	(8.2E+08)	(0.00909)
	[1.28448]	[0.63686]	[1.46621]
D(ADS(-3))	2.445354	1.23E+08	-0.003894
	(7.02714)	(8.3E+08)	(0.00920)
	[0.34799]	[0.14781]	[-0.42334]
D(ADS(-4))	0.010387	7.60E+08	0.013792
	(7.08961)	(8.4E+08)	(0.00928)
	[0.00147]	[0.90525]	[1.48633]
D(ADS(-5))	-1.090429	-59534481	0.003041
	(7.16343)	(8.5E+08)	(0.00938)
	[-0.15222]	[-0.07023]	[0.32437]
R-squared	0.448185	0.247667	0.703204
Adj. R-squared	0.442613	0.240071	0.700208
Sum sq. resids	66862.08	9.36E+20	0.114542
S.E. equation	5.000452	5.92E+08	0.006545
F-statistic	80.43797	32.60291	234.6507
Log likelihood	-8168.844	-58396.65	9768.659
Akaike AIC	6.067242	43.24549	-7.209962
Schwarz SC	6.128400	43.30665	-7.148804
Mean dependent	-0.018900	-27186318	0.000282
S.D. dependent	6.697779	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	3.70E+14
Determinant resid covariance	3.58E+14
Log likelihood	-56776.66
Akaike information criterion	42.08783
Schwarz criterion	42.27130

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ASVI Cancer - Category Specification: Investment; Inclusion of Crisis Dummy: Yes

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(INV_CAN...	D(VOLUME)	SP500_Y
D(INV CANCER(-1))	-0.862307	2227193.	1.05E-05
	(0.01918)	(2266468)	(2.5E-05)
	[-44.9541]	[0.98267]	[0.41978]
D(INV_CANCER(-2))	-0.746978	1518971.	4.79E-05
	(0.02470)	(2918846)	(3.2E-05)
	[-30.2381]	[0.52040]	[1.49282]
D(INV CANCER(-3))	-0.453038	3476829.	1.81E-05
	(0.02720)	(3213399)	(3.5E-05)
	[-16.6582]	[1.08198]	[0.51343]
D(INV_CANCER(-4))	-0.287881	4445010.	-5.24E-06
	(0.02463)	(2910107)	(3.2E-05)
	[-11.6886]	[1.52744]	[-0.16365]
D(INV CANCER(-5))	-0.120256	2547238.	-1.35E-05
	(0.01887)	(2229786)	(2.5E-05)
	[-6.37238]	[1.14237]	[-0.54838]
D(VOLUME(-1))	-1.37E-10	-0.503865	4.15E-14
	(1.7E-10)	(0.02025)	(2.2E-13)
	[-0.80058]	[-24.8761]	[0.18637]
D(VOLUME(-2))	-2.21E-10	-0.295075	-1.24E-13
	(1.9E-10)	(0.02241)	(2.5E-13)
	[-1.16517]	[-13.1699]	[-0.50334]
D(VOLUME(-3))	-1.85E-10	-0.307187	-1.37E-13
	(1.9E-10)	(0.02256)	(2.5E-13)
	[-0.97134]	[-13.6187]	[-0.55134]
D(VOLUME(-4))	-1.04E-10	-0.246648	-2.76E-13
	(1.9E-10)	(0.02275)	(2.5E-13)
	[-0.53977]	[-10.8396]	[-1.10427]
D(VOLUME(-5))	-1.86E-10	-0.054025	-3.49E-13
	(1.7E-10)	(0.02034)	(2.2E-13)
	[-1.07838]	[-2.65641]	[-1.55874]
SP500 Y(-1)	-0.524714	-5.52E+09	-0.069386
	(14.9440)	(1.8E+09)	(0.01942)
	[-0.03511]	[-3.12816]	[-3.57231]
SP500_Y(-2)	-19.48761	3.32E+08	-0.008918
	(14.9511)	(1.8E+09)	(0.01943)
	[-1.30343]	[0.18780]	[-0.45892]
SP500 Y(-3)	14.05227	3.02E+09	0.009514
	(14.9860)	(1.8E+09)	(0.01948)
	[0.93770]	[1.70722]	[0.48846]
SP500_Y(-4)	13.08200	2.57E+09	-0.012283
	(15.1523)	(1.8E+09)	(0.01969)
	[0.86337]	[1.43572]	[-0.62371]
SP500_Y(-5)	4.031889	-3.55E+09	0.005238
	(15.2587)	(1.8E+09)	(0.01983)
	[0.26424]	[-1.96876]	[0.26412]
C	-0.073899	-23228506	0.000336
	(0.10713)	(1.3E+07)	(0.00014)
	[-0.68979]	[-1.83501]	[2.41579]
DUMMY_CRISIS	-1.301882	1.97E+08	-0.007461
	(5.07080)	(6.0E+08)	(0.00659)
	[-0.25674]	[0.32929]	[-1.13206]
DUMMY CRISIS(-1)	-0.068355	-1.68E+09	-0.023686
	(7.13397)	(8.4E+08)	(0.00927)
	[-0.00958]	[-1.99534]	[-2.55445]
DUMMY_CRISIS(-2)	-0.563825	2.16E+09	0.032278
	(7.14425)	(8.4E+08)	(0.00929)
	[-0.07892]	[2.55836]	[3.47609]
DUMMY CRISIS(-3)	5.464033	-7.37E+08	0.000746
	(7.15904)	(8.5E+08)	(0.00930)
	[0.76324]	[-0.87079]	[0.08020]
DUMMY_CRISIS(-4)	-0.140893	8.25E+08	0.022300
	(7.14895)	(8.4E+08)	(0.00929)
	[-0.01971]	[0.97713]	[2.40001]
DUMMY_CRISIS(-5)	-3.588925	-8.35E+08	-0.025537
	(5.07516)	(6.0E+08)	(0.00660)
	[-0.70716]	[-1.39321]	[-3.87140]
D(VIX)	0.015562	70310588	-0.005636
	(0.05544)	(6550593)	(7.2E-05)
	[0.28069]	[10.7335]	[-78.2091]
D(VIX(-1))	-0.021268	13199571	-0.000471
	(0.10265)	(1.2E+07)	(0.00013)
	[-0.20720]	[1.08834]	[-3.52884]
D(VIX(-2))	-0.063024	28274740	2.90E-05
	(0.10254)	(1.2E+07)	(0.00013)
	[-0.61464]	[2.33376]	[0.21755]
D(VIX(-3))	0.099491	35028511	-0.000247
	(0.10221)	(1.2E+07)	(0.00013)
	[0.97336]	[2.90037]	[-1.85747]
D(VIX(-4))	0.072658	47911206	-0.000189
	(0.10376)	(1.2E+07)	(0.00013)
	[0.70028]	[3.90808]	[-1.40506]
D(VIX(-5))	0.035363	-20576655	0.000337
	(0.10347)	(1.2E+07)	(0.00013)
	[0.34176]	[-1.68303]	[2.50593]
ADS	-0.082539	-12330670	0.000269
	(0.20983)	(2.5E+07)	(0.00027)
	[-0.39336]	[-0.49735]	[0.98461]
D(ADS(-1))	-13.07647	-1.25E+09	-0.020871
	(7.03235)	(8.3E+08)	(0.00914)
	[-1.85947]	[-1.50309]	[-2.28341]
D(ADS(-2))	8.632654	5.32E+08	0.012138
	(6.97059)	(8.2E+08)	(0.00906)
	[1.23844]	[0.64601]	[1.33976]
D(ADS(-3))	2.312177	-37618188	-0.007026
	(7.05461)	(8.3E+08)	(0.00917)
	[0.32775]	[-0.04513]	[-0.76624]
D(ADS(-4))	-0.110028	8.97E+08	0.015382
	(7.13041)	(8.4E+08)	(0.00927)
	[-0.01543]	[1.06508]	[1.65977]
D(ADS(-5))	-0.454947	-2485230.	0.004910
	(7.21856)	(8.5E+08)	(0.00938)
	[-0.06302]	[-0.00291]	[0.52328]
R-squared	0.448454	0.250441	0.707469
Adj. R-squared	0.441632	0.241170	0.703850
Sum sq. resids	66829.50	9.33E+20	0.112896
S.E. equation	5.004851	5.91E+08	0.006505
F-statistic	65.73665	27.01287	195.5270
Log likelihood	-8168.186	-58391.66	9788.211
Akaike AIC	6.071196	43.24624	-7.219993
Schwarz SC	6.145459	43.32050	-7.145730
Mean dependent	-0.018900	-27186318	0.000282
S.D. dependent	6.697779	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	3.66E+14
Determinant resid covariance	3.52E+14
Log likelihood	-56753.25
Akaike information criterion	42.08383
Schwarz criterion	42.30662

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ASVI Opinion Poll - Category Specification: None; Inclusion of Crisis Dummy: No

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(OPINION...	D(VOLUME)	SP500_Y
D(OPINION_POLL(-1))	-0.270622	15419226	-5.37E-05
	(0.01916)	(4031601)	(4.5E-05)
	[-14.1264]	[3.82459]	[-1.20109]
D(OPINION_POLL(-2))	-0.424016	10251446	2.04E-06
	(0.01929)	(4060351)	(4.5E-05)
	[-21.9767]	[2.52477]	[0.04529]
D(OPINION_POLL(-3))	-0.248513	11609825	-1.04E-05
	(0.02040)	(4293596)	(4.8E-05)
	[-12.1807]	[2.70399]	[-0.21815]
D(OPINION_POLL(-4))	-0.186308	6364049.	2.18E-05
	(0.01926)	(4053855)	(4.5E-05)
	[-9.67182]	[1.56988]	[0.48397]
D(OPINION_POLL(-5))	-0.123630	4827876.	2.93E-06
	(0.01882)	(3960952)	(4.4E-05)
	[-6.56856]	[1.21887]	[0.06671]
D(VOLUME(-1))	-2.66E-10	-0.510003	1.53E-14
	(9.6E-11)	(0.02026)	(2.2E-13)
	[-2.76395]	[-25.1681]	[0.06806]
D(VOLUME(-2))	-1.57E-10	-0.296323	-1.79E-13
	(1.1E-10)	(0.02250)	(2.5E-13)
	[-1.46753]	[-13.1727]	[-0.71708]
D(VOLUME(-3))	-1.71E-10	-0.308743	-2.51E-13
	(1.1E-10)	(0.02261)	(2.5E-13)
	[-1.59216]	[-13.6537]	[-0.99975]
D(VOLUME(-4))	-1.19E-10	-0.247650	-3.92E-13
	(1.1E-10)	(0.02278)	(2.5E-13)
	[-1.09785]	[-10.8695]	[-1.55218]
D(VOLUME(-5))	-4.09E-11	-0.053383	-4.06E-13
	(9.7E-11)	(0.02033)	(2.3E-13)
	[-0.42333]	[-2.62615]	[-1.80074]
SP500_Y(-1)	12.06881	-5.40E+09	-0.066504
	(8.33287)	(1.8E+09)	(0.01946)
	[1.44834]	[-3.08187]	[-3.41824]
SP500_Y(-2)	7.649763	3.89E+08	-0.007455
	(8.33677)	(1.8E+09)	(0.01946)
	[0.91759]	[0.22155]	[-0.38298]
SP500_Y(-3)	11.78043	2.58E+09	0.000378
	(8.34914)	(1.8E+09)	(0.01949)
	[1.41098]	[1.46870]	[0.01937]
SP500_Y(-4)	21.76391	2.08E+09	-0.017051
	(8.46674)	(1.8E+09)	(0.01977)
	[2.57052]	[1.16569]	[-0.86253]
SP500_Y(-5)	11.76696	-3.86E+09	0.009355
	(8.53879)	(1.8E+09)	(0.01994)
	[1.37806]	[-2.14538]	[0.46922]
C	-0.047480	-20613457	0.000367
	(0.05912)	(1.2E+07)	(0.00014)
	[-0.80310]	[-1.65678]	[2.65774]
D(VIX)	-0.064255	70892536	-0.005645
	(0.03101)	(6526402)	(7.2E-05)
	[-2.07193]	[10.8624]	[-77.9604]
D(VIX(-1))	0.086663	14817482	-0.000468
	(0.05744)	(1.2E+07)	(0.00013)
	[1.50864]	[1.22568]	[-3.49116]
D(VIX(-2))	0.039036	28887997	5.00E-05
	(0.05742)	(1.2E+07)	(0.00013)
	[0.67984]	[2.39065]	[0.37298]
D(VIX(-3))	0.105615	33852573	-0.000276
	(0.05722)	(1.2E+07)	(0.00013)
	[1.84565]	[2.81106]	[-2.06256]
D(VIX(-4))	0.179534	44685215	-0.000200
	(0.05821)	(1.2E+07)	(0.00014)
	[3.08443]	[3.64794]	[-1.46936]
D(VIX(-5))	0.059342	-23476268	0.000362
	(0.05808)	(1.2E+07)	(0.00014)
	[1.02167]	[-1.92057]	[2.66739]
ADS	-0.043843	3901433.	0.000539
	(0.07284)	(1.5E+07)	(0.00017)
	[-0.60190]	[0.25451]	[3.16681]
D(ADS(-1))	-11.29393	-1.22E+09	-0.023882
	(3.92958)	(8.3E+08)	(0.00917)
	[-2.87408]	[-1.47522]	[-2.60296]
D(ADS(-2))	6.926560	6.67E+08	0.012752
	(3.89554)	(8.2E+08)	(0.00910)
	[1.77808]	[0.81379]	[1.40200]
D(ADS(-3))	-0.206153	1.02E+08	-0.004015
	(3.94268)	(8.3E+08)	(0.00921)
	[-0.05229]	[0.12240]	[-0.43617]
D(ADS(-4))	4.045103	6.93E+08	0.014331
	(3.97559)	(8.4E+08)	(0.00928)
	[1.01748]	[0.82805]	[1.54389]
D(ADS(-5))	-0.006962	-2.13E+08	0.003739
	(4.02008)	(8.5E+08)	(0.00939)
	[-0.00173]	[-0.25190]	[0.39830]

R-squared	0.189318	0.251773	0.702961
Adj. R-squared	0.181132	0.244218	0.699961
Sum sq. resids	21029.05	9.31E+20	0.114636
S.E. equation	2.804330	5.90E+08	0.006548
F-statistic	23.12800	33.32525	234.3769
Log likelihood	-6606.106	-58389.26	9767.550
Akaike AIC	4.910515	43.24002	-7.209142
Schwarz SC	4.971673	43.30117	-7.147984
Mean dependent	-0.011712	-27186318	0.000282
S.D. dependent	3.099004	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	1.16E+14
Determinant resid covariance	1.12E+14
Log likelihood	-55207.73
Akaike information criterion	40.92652
Schwarz criterion	41.11000

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ASVI Opinion Poll - Category Specification: None; Inclusion of Crisis Dummy: Yes

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(OPINION...	VOL_PER	SP500_Y
D(OPINION POLL(-1))	-0.269455	0.006582	-5.63E-05
	(0.01917)	(0.00192)	(4.4E-05)
	[-14.0530]	[3.42413]	[-1.26490]
D(OPINION POLL(-2))	-0.425392	0.002931	4.60E-06
	(0.01928)	(0.00193)	(4.5E-05)
	[-22.0584]	[1.51619]	[0.10280]
D(OPINION POLL(-3))	-0.250790	0.005153	-9.58E-06
	(0.02037)	(0.00204)	(4.7E-05)
	[-12.3111]	[2.52324]	[-0.20277]
D(OPINION POLL(-4))	-0.185909	0.001229	1.73E-05
	(0.01923)	(0.00193)	(4.5E-05)
	[-9.66678]	[0.63718]	[0.38852]
D(OPINION_POLL(-5))	-0.124902	0.002200	1.85E-06
	(0.01877)	(0.00188)	(4.4E-05)
	[-6.65460]	[1.16904]	[0.04247]
VOL_PER(-1)	-0.664428	-0.402757	-0.000226
	(0.19481)	(0.01953)	(0.00045)
	[-3.41058]	[-20.6215]	[-0.50108]
VOL_PER(-2)	-0.164711	-0.187632	-0.000666
	(0.20914)	(0.02097)	(0.00049)
	[-0.78757]	[-8.94890]	[-1.37239]
VOL_PER(-3)	-0.497027	-0.147717	-2.69E-05
	(0.21060)	(0.02111)	(0.00049)
	[-2.36010]	[-6.99646]	[-0.05501]
VOL PER(-4)	-0.291538	-0.135649	-0.000587
	(0.20953)	(0.02101)	(0.00049)
	[-1.39137]	[-6.45742]	[-1.20757]
VOL PER(-5)	-0.066010	-0.036518	-0.000978
	(0.18810)	(0.01886)	(0.00044)
	[-0.35093]	[-1.93647]	[-2.24078]
SP500_Y(-1)	9.949291	-1.950249	-0.068207
	(8.30557)	(0.83267)	(0.01927)
	[1.19791]	[-2.34216]	[-3.53991]
SP500_Y(-2)	6.757848	-0.362706	-0.010282
	(8.30272)	(0.83238)	(0.01926)
	[0.81393]	[-0.43574]	[-0.53380]
SP500_Y(-3)	11.39286	0.782956	0.005913
	(8.31280)	(0.83339)	(0.01928)
	[1.37052]	[0.93948]	[0.30662]
SP500_Y(-4)	21.53125	0.585937	-0.013406
	(8.39582)	(0.84172)	(0.01948)
	[2.56452]	[0.69612]	[-0.68829]
SP500 Y(-5)	11.73467	-0.705181	0.006961
	(8.46978)	(0.84913)	(0.01965)
	[1.38548]	[-0.83047]	[0.35425]
C	0.015691	0.066275	0.000427
	(0.06500)	(0.00652)	(0.00015)
	[0.24141]	[10.1708]	[2.83263]
DUMMY CRISIS	0.616748	0.208150	-0.007388
	(2.83577)	(0.28430)	(0.00658)
	[0.21749]	[0.73215]	[-1.12301]
DUMMY CRISIS(-1)	-0.296344	-0.501674	-0.023930
	(3.99133)	(0.40015)	(0.00926)
	[-0.07425]	[-1.25372]	[-2.58435]
DUMMY CRISIS(-2)	0.037092	0.386110	0.032133
	(3.99802)	(0.40082)	(0.00928)
	[0.00928]	[0.96330]	[3.46450]
DUMMY_CRISIS(-3)	-0.253739	0.286340	0.001262
	(4.00199)	(0.40122)	(0.00928)
	[-0.06340]	[0.71368]	[0.13594]
DUMMY CRISIS(-4)	-0.034391	-0.315942	0.022501
	(3.99839)	(0.40086)	(0.00928)
	[-0.00860]	[-0.78817]	[2.42574]
DUMMY CRISIS(-5)	-0.081486	-0.038656	-0.025884
	(2.84003)	(0.28472)	(0.00659)
	[-0.02869]	[-0.13577]	[-3.92868]
D(VIX)	-0.066465	0.023602	-0.005641
	(0.03103)	(0.00311)	(7.2E-05)
	[-2.14173]	[7.58616]	[-78.3554]
D(VIX(-1))	0.071594	0.002919	-0.000462
	(0.05648)	(0.00566)	(0.00013)
	[1.26764]	[0.51549]	[-3.52489]
D(VIX(-2))	0.028567	0.001029	2.99E-05
	(0.05649)	(0.00566)	(0.00013)
	[0.50573]	[0.18171]	[0.22788]
D(VIX(-3))	0.101701	0.008215	-0.000274
	(0.05629)	(0.00564)	(0.00013)
	[1.80689]	[1.45582]	[-2.09704]
D(VIX(-4))	0.179198	0.006262	-0.000197
	(0.05710)	(0.00572)	(0.00013)
	[3.13822]	[1.09387]	[-1.48882]
D(VIX(-5))	0.052746	-0.006118	0.000356
	(0.05722)	(0.00574)	(0.00013)
	[0.92178]	[-1.06641]	[2.68080]
ADS	-0.044781	0.005984	0.000287
	(0.11764)	(0.01179)	(0.00027)
	[-0.38065]	[0.50740]	[1.05033]
D(ADS(-1))	-11.45460	0.005222	-0.021234
	(3.94057)	(0.39506)	(0.00914)
	[-2.90684]	[0.01322]	[-2.32274]
D(ADS(-2))	7.381151	0.310396	0.011359
	(3.90692)	(0.39169)	(0.00906)
	[1.88925]	[0.79246]	[1.25322]
D(ADS(-3))	-0.335933	0.107138	-0.006801
	(3.95174)	(0.39618)	(0.00917)
	[-0.08501]	[0.27043]	[-0.74187]
D(ADS(-4))	4.065540	-0.014937	0.015613
	(3.99316)	(0.40033)	(0.00926)
	[1.01813]	[-0.03731]	[1.68540]
D(ADS(-5))	-0.110495	-0.511199	0.005767
	(4.04163)	(0.40519)	(0.00938)
	[-0.02734]	[-1.26162]	[0.61506]

R-squared	0.191819	0.168292	0.707644
Adj. R-squared	0.181823	0.158005	0.704028
Sum sq. resids	20964.17	210.7094	0.112828
S.E. equation	2.803147	0.281028	0.006503
F-statistic	19.18911	16.35929	195.6926
Log likelihood	-6601.931	-387.2091	9789.020
Akaike AIC	4.911866	0.311776	-7.220592
Schwarz SC	4.986129	0.386039	-7.146329
Mean dependent	-0.011712	0.029959	0.000282
S.D. dependent	3.099004	0.306263	0.011953

Determinant resid covariance (dof adj.)	2.62E-05
Determinant resid covariance	2.52E-05
Log likelihood	2801.194
Akaike information criterion	-1.997923
Schwarz criterion	-1.775133

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ASVI Opinion Poll - Category Specification: Investment; Inclusion of Crisis Dummy: No

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(INV_OPIN...	D(VOLUME)	SP500_Y
D(INV_OPINION_POLL(...	-0.372150	16831419	-6.67E-05
	(0.01926)	(5352004)	(5.9E-05)
	[-19.3233]	[3.14488]	[-1.12289]
D(INV_OPINION_POLL(...	-0.419847	17487266	-4.86E-05
	(0.02001)	(5561112)	(6.2E-05)
	[-20.9802]	[3.14456]	[-0.78722]
D(INV_OPINION_POLL(...	-0.257754	16406961	-3.15E-05
	(0.02109)	(5859893)	(6.5E-05)
	[-12.2235]	[2.79987]	[-0.48512]
D(INV_OPINION_POLL(...	-0.204332	17782382	5.03E-05
	(0.01999)	(5555347)	(6.2E-05)
	[-10.2213]	[3.20095]	[0.81592]
D(INV_OPINION_POLL(...	-0.096740	12006848	2.93E-05
	(0.01933)	(5371002)	(6.0E-05)
	[-5.00527]	[2.23549]	[0.49138]
D(VOLUME(-1))	-2.23E-10	-0.512965	3.12E-14
	(7.3E-11)	(0.02026)	(2.2E-13)
	[-3.06022]	[-25.3161]	[0.13859]
D(VOLUME(-2))	-1.64E-10	-0.300935	-1.73E-13
	(8.1E-11)	(0.02249)	(2.5E-13)
	[-2.02051]	[-13.3803]	[-0.69449]
D(VOLUME(-3))	-2.35E-10	-0.313041	-2.73E-13
	(8.1E-11)	(0.02263)	(2.5E-13)
	[-2.88670]	[-13.8335]	[-1.08743]
D(VOLUME(-4))	-1.29E-10	-0.249964	-4.24E-13
	(8.2E-11)	(0.02278)	(2.5E-13)
	[-1.57646]	[-10.9715]	[-1.67741]
D(VOLUME(-5))	-3.59E-12	-0.052185	-4.14E-13
	(7.3E-11)	(0.02034)	(2.3E-13)
	[-0.04908]	[-2.56532]	[-1.83559]
SP500_Y(-1)	12.35124	-5.52E+09	-0.066471
	(6.31214)	(1.8E+09)	(0.01946)
	[1.95674]	[-3.14574]	[-3.41589]
SP500_Y(-2)	7.649540	2.95E+08	-0.006471
	(6.31852)	(1.8E+09)	(0.01948)
	[1.21065]	[0.16805]	[-0.33221]
SP500_Y(-3)	6.565519	2.56E+09	0.001447
	(6.32788)	(1.8E+09)	(0.01951)
	[1.03755]	[1.45477]	[0.07420]
SP500_Y(-4)	9.934466	2.05E+09	-0.017456
	(6.41572)	(1.8E+09)	(0.01978)
	[1.54846]	[1.15107]	[-0.88255]
SP500_Y(-5)	2.278254	-3.81E+09	0.008158
	(6.46231)	(1.8E+09)	(0.01992)
	[0.35254]	[-2.12270]	[0.40949]
C	-0.025604	-20566172	0.000366
	(0.04477)	(1.2E+07)	(0.00014)
	[-0.57196]	[-1.65323]	[2.65466]
D(VIX)	0.004081	70808098	-0.005642
	(0.02349)	(6528739)	(7.2E-05)
	[0.17369]	[10.8456]	[-77.8961]
D(VIX(-1))	0.070953	13561267	-0.000464
	(0.04348)	(1.2E+07)	(0.00013)
	[1.63198]	[1.12244]	[-3.46099]
D(VIX(-2))	0.118685	28291656	5.16E-05
	(0.04346)	(1.2E+07)	(0.00013)
	[2.73114]	[2.34276]	[0.38518]
D(VIX(-3))	0.087387	32661272	-0.000264
	(0.04336)	(1.2E+07)	(0.00013)
	[2.01555]	[2.71081]	[-1.97454]
D(VIX(-4))	0.095974	44243439	-0.000198
	(0.04409)	(1.2E+07)	(0.00014)
	[2.17668]	[3.61086]	[-1.45443]
D(VIX(-5))	0.013743	-23412223	0.000358
	(0.04393)	(1.2E+07)	(0.00014)
	[0.31283]	[-1.91775]	[2.64148]
ADS	-0.034614	3853543.	0.000538
	(0.05515)	(1.5E+07)	(0.00017)
	[-0.62760]	[0.25143]	[3.16128]
D(ADS(-1))	-5.843741	-1.26E+09	-0.023634
	(2.97466)	(8.3E+08)	(0.00917)
	[-1.96451]	[-1.52568]	[-2.57722]
D(ADS(-2))	3.289889	5.95E+08	0.012952
	(2.94721)	(8.2E+08)	(0.00909)
	[1.11627]	[0.72697]	[1.42557]
D(ADS(-3))	-1.121985	1.34E+08	-0.004422
	(2.98257)	(8.3E+08)	(0.00919)
	[-0.37618]	[0.16158]	[-0.48089]
D(ADS(-4))	2.708459	6.95E+08	0.014142
	(3.00832)	(8.4E+08)	(0.00927)
	[0.90032]	[0.83122]	[1.52484]
D(ADS(-5))	0.094003	-1.45E+08	0.003909
	(3.04185)	(8.5E+08)	(0.00938)
	[0.03090]	[-0.17128]	[0.41682]
R-squared	0.197289	0.252067	0.703125
Adj. R-squared	0.189184	0.244515	0.700127
Sum sq. resids	12055.39	9.31E+20	0.114572
S.E. equation	2.123293	5.90E+08	0.006546
F-statistic	24.34113	33.37724	234.5608
Log likelihood	-5854.419	-58388.73	9768.295
Akaike AIC	4.354122	43.23962	-7.209693
Schwarz SC	4.415280	43.30078	-7.148535
Mean dependent	0.000346	-27186318	0.000282
S.D. dependent	2.358026	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	6.61E+13
Determinant resid covariance	6.40E+13
Log likelihood	-54451.07
Akaike information criterion	40.36645
Schwarz criterion	40.54992

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

ASVI Opinion Poll - Category Specification: Investment; Inclusion of Crisis Dummy: Yes

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(INV_OPIN...	VOL_PER	SP500_Y
D(INV_OPINION_POLL(...	-0.373681	0.006835	-6.79E-05
	(0.01926)	(0.00255)	(5.9E-05)
	[-19.4027]	[2.67922]	[-1.15192]
D(INV_OPINION_POLL(...	-0.421696	0.005896	-4.73E-05
	(0.01999)	(0.00265)	(6.1E-05)
	[-21.0953]	[2.22673]	[-0.77267]
D(INV_OPINION_POLL(...	-0.261034	0.005104	-3.14E-05
	(0.02103)	(0.00279)	(6.4E-05)
	[-12.4102]	[1.83186]	[-0.48690]
D(INV_OPINION_POLL(...	-0.205690	0.006408	4.47E-05
	(0.01994)	(0.00264)	(6.1E-05)
	[-10.3147]	[2.42591]	[0.73247]
D(INV_OPINION_POLL(...	-0.097799	0.003335	2.87E-05
	(0.01927)	(0.00255)	(5.9E-05)
	[-5.07407]	[1.30646]	[0.48567]
VOL_PER(-1)	-0.519581	-0.403931	-0.000203
	(0.14744)	(0.01953)	(0.00045)
	[-3.52397]	[-20.6834]	[-0.44947]
VOL_PER(-2)	-0.316611	-0.188655	-0.000653
	(0.15824)	(0.02096)	(0.00048)
	[-2.00079]	[-9.00075]	[-1.34643]
VOL_PER(-3)	-0.545233	-0.147992	-8.06E-05
	(0.15950)	(0.02113)	(0.00049)
	[-3.41846]	[-7.00523]	[-0.16495]
VOL_PER(-4)	-0.243448	-0.136575	-0.000635
	(0.15884)	(0.02104)	(0.00049)
	[-1.53266]	[-6.49155]	[-1.30522]
VOL_PER(-5)	0.055650	-0.033053	-0.000985
	(0.14262)	(0.01889)	(0.00044)
	[0.39019]	[-1.74966]	[-2.25569]
SP500_Y(-1)	10.19616	-1.994966	-0.068088
	(6.29288)	(0.83351)	(0.01927)
	[1.62027]	[-2.39344]	[-3.53262]
SP500_Y(-2)	6.717410	-0.417959	-0.009534
	(6.29227)	(0.83343)	(0.01927)
	[1.06757]	[-0.50149]	[-0.49472]
SP500_Y(-3)	5.506661	0.798297	0.006789
	(6.30002)	(0.83446)	(0.01930)
	[0.87407]	[0.95666]	[0.35186]
SP500_Y(-4)	10.29846	0.590622	-0.013896
	(6.36257)	(0.84274)	(0.01949)
	[1.61860]	[0.70083]	[-0.71307]
SP500_Y(-5)	2.781529	-0.677736	0.005901
	(6.41091)	(0.84915)	(0.01964)
	[0.43387]	[-0.79814]	[0.30054]
C	0.030595	0.066249	0.000429
	(0.04922)	(0.00652)	(0.00015)
	[0.62163]	[10.1624]	[2.84547]
DUMMY_CRISIS	0.408896	0.208653	-0.007462
	(2.14756)	(0.28445)	(0.00658)
	[0.19040]	[0.73353]	[-1.13443]
DUMMY_CRISIS(-1)	-0.539144	-0.503683	-0.023962
	(3.02267)	(0.40036)	(0.00926)
	[-0.17837]	[-1.25806]	[-2.58827]
DUMMY_CRISIS(-2)	0.060538	0.388261	0.032214
	(3.02774)	(0.40104)	(0.00927)
	[0.01999]	[0.96815]	[3.47382]
DUMMY_CRISIS(-3)	0.108061	0.294371	0.001365
	(3.03075)	(0.40143)	(0.00928)
	[0.03565]	[0.73330]	[0.14707]
DUMMY_CRISIS(-4)	0.613434	-0.321098	0.022465
	(3.02794)	(0.40106)	(0.00927)
	[0.20259]	[-0.80062]	[2.42231]
DUMMY_CRISIS(-5)	-0.753517	-0.042070	-0.025936
	(2.15075)	(0.28487)	(0.00659)
	[-0.35035]	[-0.14768]	[-3.93722]
D(VIX)	0.002402	0.023555	-0.005638
	(0.02351)	(0.00311)	(7.2E-05)
	[0.10217]	[7.56347]	[-78.2907]
D(VIX(-1))	0.057234	0.002412	-0.000456
	(0.04276)	(0.00566)	(0.00013)
	[1.33858]	[0.42591]	[-3.48433]
D(VIX(-2))	0.111248	0.000585	3.03E-05
	(0.04276)	(0.00566)	(0.00013)
	[2.60160]	[0.10330]	[0.23132]
D(VIX(-3))	0.077756	0.007735	-0.000263
	(0.04266)	(0.00565)	(0.00013)
	[1.82274]	[1.36893]	[-2.01599]
D(VIX(-4))	0.096413	0.006243	-0.000196
	(0.04327)	(0.00573)	(0.00013)
	[2.22836]	[1.08930]	[-1.48112]
D(VIX(-5))	0.010608	-0.006087	0.000352
	(0.04329)	(0.00573)	(0.00013)
	[0.24505]	[-1.06161]	[2.65695]
ADS	-0.054841	0.005921	0.000284
	(0.08909)	(0.01180)	(0.00027)
	[-0.61556]	[0.50175]	[1.04025]
D(ADS(-1))	-5.896787	-0.028845	-0.020937
	(2.98337)	(0.39516)	(0.00914)
	[-1.97655]	[-0.07300]	[-2.29126]
D(ADS(-2))	3.386674	0.291390	0.011517
	(2.95609)	(0.39155)	(0.00905)
	[1.14566]	[0.74421]	[1.27197]
D(ADS(-3))	-1.231999	0.122119	-0.007315
	(2.98946)	(0.39597)	(0.00916)
	[-0.41211]	[0.30841]	[-0.79893]
D(ADS(-4))	2.943072	-0.021208	0.015456
	(3.02186)	(0.40026)	(0.00926)
	[0.97393]	[-0.05299]	[1.66996]
D(ADS(-5))	0.090730	-0.469551	0.006033
	(3.05855)	(0.40512)	(0.00937)
	[0.02966]	[-1.15905]	[0.64398]
R-squared	0.199518	0.167494	0.707776
Adj. R-squared	0.189617	0.157197	0.704162
Sum sq. resids	12021.91	210.9116	0.112777
S.E. equation	2.122725	0.281162	0.006502
F-statistic	20.15130	16.26607	195.8176
Log likelihood	-5850.661	-388.5053	9789.631
Akaike AIC	4.355782	0.312735	-7.221044
Schwarz SC	4.430045	0.386999	-7.146781
Mean dependent	0.000346	0.029959	0.000282
S.D. dependent	2.358026	0.306263	0.011953

Determinant resid covariance (dof adj.)	1.50E-05
Determinant resid covariance	1.45E-05
Log likelihood	3553.433
Akaike information criterion	-2.554724
Schwarz criterion	-2.331934

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

ASVI Natural Disaster - Category Specification: None; Inclusion of Crisis Dummy: No

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(NATURAL...	D(VOLUME)	SP500_Y
D(NATURAL_DISASTER...	-0.080696	78099103	0.000401
	(0.01911)	(2.4E+07)	(0.00027)
	[-4.22301]	[3.19941]	[1.48477]
D(NATURAL_DISASTER...	-0.010299	23463511	0.000327
	(0.01946)	(2.5E+07)	(0.00028)
	[-0.52912]	[0.94365]	[1.18805]
D(NATURAL_DISASTER...	0.008238	-4904254.	0.000408
	(0.02094)	(2.7E+07)	(0.00030)
	[0.39350]	[-0.18338]	[1.37844]
D(NATURAL_DISASTER...	0.023088	-11418020	0.000162
	(0.02042)	(2.6E+07)	(0.00029)
	[1.13084]	[-0.43778]	[0.56111]
D(NATURAL_DISASTER...	-0.011387	-11522267	0.000178
	(0.01902)	(2.4E+07)	(0.00027)
	[-0.59875]	[-0.47428]	[0.66091]
D(VOLUME(-1))	-2.12E-11	-0.505848	8.56E-15
	(1.6E-11)	(0.02023)	(2.2E-13)
	[-1.33720]	[-25.0024]	[0.03821]
D(VOLUME(-2))	-3.62E-11	-0.293345	-1.66E-13
	(1.8E-11)	(0.02240)	(2.5E-13)
	[-2.06454]	[-13.0938]	[-0.67100]
D(VOLUME(-3))	-1.76E-11	-0.305814	-2.22E-13
	(1.8E-11)	(0.02254)	(2.5E-13)
	[-0.99567]	[-13.5679]	[-0.89071]

D(VOLUME(-4))	3.33E-11	-0.248011	-3.65E-13
	(1.8E-11)	(0.02273)	(2.5E-13)
	[1.86960]	[-10.9106]	[-1.45134]
D(VOLUME(-5))	1.23E-11	-0.057119	-4.10E-13
	(1.6E-11)	(0.02032)	(2.3E-13)
	[0.77025]	[-2.81068]	[-1.82161]
SP500_Y(-1)	-0.500120	-5.72E+09	-0.069331
	(1.37595)	(1.8E+09)	(0.01947)
	[-0.36347]	[-3.25423]	[-3.56146]
SP500_Y(-2)	-0.570031	5.53E+08	-0.009860
	(1.37682)	(1.8E+09)	(0.01948)
	[-0.41402]	[0.31417]	[-0.50616]
SP500_Y(-3)	-0.975717	2.92E+09	-0.001358
	(1.37863)	(1.8E+09)	(0.01950)
	[-0.70774]	[1.66026]	[-0.06962]
SP500_Y(-4)	-0.459047	2.49E+09	-0.017047
	(1.39557)	(1.8E+09)	(0.01974)
	[-0.32893]	[1.39838]	[-0.86336]
SP500_Y(-5)	2.771068	-3.26E+09	0.009747
	(1.40664)	(1.8E+09)	(0.01990)
	[1.96999]	[-1.81617]	[0.48975]
C	-0.014647	-21271222	0.000383
	(0.00977)	(1.2E+07)	(0.00014)
	[-1.49957]	[-1.70476]	[2.76904]

D(VIX)	0.005766	69808265	-0.005650
	(0.00512)	(6536104)	(7.2E-05)
	[1.12702]	[10.6804]	[-78.0496]
D(VIX(-1))	-6.56E-05	11422467	-0.000487
	(0.00948)	(1.2E+07)	(0.00013)
	[-0.00692]	[0.94299]	[-3.62789]
D(VIX(-2))	-0.003209	29264433	2.94E-05
	(0.00948)	(1.2E+07)	(0.00013)
	[-0.33867]	[2.41761]	[0.21958]
D(VIX(-3))	0.001404	35602907	-0.000289
	(0.00944)	(1.2E+07)	(0.00013)
	[0.14873]	[2.95244]	[-2.16362]
D(VIX(-4))	-0.010195	46922371	-0.000209
	(0.00958)	(1.2E+07)	(0.00014)
	[-1.06428]	[3.83435]	[-1.53963]
D(VIX(-5))	0.012628	-18868548	0.000362
	(0.00956)	(1.2E+07)	(0.00014)
	[1.32142]	[-1.54556]	[2.67574]
ADS	-0.012914	3669442.	0.000557
	(0.01203)	(1.5E+07)	(0.00017)
	[-1.07385]	[0.23886]	[3.27119]
D(ADS(-1))	-0.288020	-1.42E+09	-0.023387
	(0.65004)	(8.3E+08)	(0.00920)
	[-0.44308]	[-1.71164]	[-2.54299]

D(ADS(-2))	-1.745897	4.96E+08	0.013154
	(0.64273)	(8.2E+08)	(0.00909)
	[-2.71636]	[0.60354]	[1.44653]
D(ADS(-3))	-0.325417	3.04E+08	-0.004190
	(0.65082)	(8.3E+08)	(0.00921)
	[-0.50001]	[0.36557]	[-0.45499]
D(ADS(-4))	-0.173771	8.11E+08	0.014918
	(0.65612)	(8.4E+08)	(0.00928)
	[-0.26485]	[0.96806]	[1.60701]
D(ADS(-5))	1.762805	-1.22E+08	0.002786
	(0.66324)	(8.5E+08)	(0.00938)
	[2.65788]	[-0.14378]	[0.29688]
R-squared	0.020510	0.250014	0.703296
Adj. R-squared	0.010620	0.242441	0.700300
Sum sq. resids	572.0544	9.34E+20	0.114506
S.E. equation	0.462528	5.91E+08	0.006544
F-statistic	2.073766	33.01474	234.7540
Log likelihood	-1736.526	-58392.43	9769.077
Akaike AIC	1.306089	43.24236	-7.210272
Schwarz SC	1.367247	43.30352	-7.149114
Mean dependent	-0.010987	-27186318	0.000282
S.D. dependent	0.465004	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	3.15E+12
Determinant resid covariance	3.05E+12
Log likelihood	-50338.52
Akaike information criterion	37.32237
Schwarz criterion	37.50585

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

ASVI Natural Disaster - Category Specification: None; Inclusion of Crisis Dummy: Yes

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(NATURAL...	VOL_PER	SP500_Y
D(NATURAL DISASTER...	-0.079966	0.036581	0.000403
	(0.01914)	(0.01162)	(0.00027)
	[-4.17857]	[3.14917]	[1.50191]
D(NATURAL DISASTER...	-0.014240	0.007314	0.000322
	(0.01950)	(0.01184)	(0.00027)
	[-0.73031]	[0.61794]	[1.17736]
D(NATURAL DISASTER...	0.004727	0.009298	0.000423
	(0.02096)	(0.01272)	(0.00029)
	[0.22549]	[0.73068]	[1.43857]
D(NATURAL DISASTER...	0.023403	0.014070	0.000148
	(0.02044)	(0.01241)	(0.00029)
	[1.14500]	[1.13404]	[0.51654]
D(NATURAL DISASTER...	-0.008093	-0.012344	0.000163
	(0.01905)	(0.01156)	(0.00027)
	[-0.42490]	[-1.06776]	[0.61054]
VOL PER(-1)	-0.035479	-0.397852	-0.000217
	(0.03220)	(0.01955)	(0.00045)
	[-1.10167]	[-20.3526]	[-0.48084]
VOL PER(-2)	-0.061595	-0.186486	-0.000614
	(0.03446)	(0.02092)	(0.00048)
	[-1.78751]	[-8.91598]	[-1.27042]
VOL PER(-3)	-0.030992	-0.147387	4.19E-05
	(0.03469)	(0.02106)	(0.00049)
	[-0.89333]	[-6.99916]	[0.08601]
VOL_PER(-4)	0.035290	-0.137115	-0.000522
	(0.03450)	(0.02094)	(0.00048)
	[1.02280]	[-6.54704]	[-1.07865]
VOL_PER(-5)	-0.055787	-0.038415	-0.000983
	(0.03096)	(0.01879)	(0.00043)
	[-1.80205]	[-2.04435]	[-2.26114]

SP500 Y(-1)	-0.782308	-2.103654	-0.071170
	(1.37419)	(0.83412)	(0.01929)
	[-0.56929]	[-2.52200]	[-3.68975]
SP500 Y(-2)	-0.651914	-0.338666	-0.012477
	(1.37440)	(0.83425)	(0.01929)
	[-0.47432]	[-0.40595]	[-0.64676]
SP500 Y(-3)	-1.007197	0.893042	0.004506
	(1.37580)	(0.83510)	(0.01931)
	[-0.73208]	[1.06939]	[0.23332]
SP500 Y(-4)	-0.155545	0.729795	-0.013219
	(1.38660)	(0.84166)	(0.01946)
	[-0.11218]	[0.86709]	[-0.67922]
SP500 Y(-5)	2.618207	-0.446665	0.007151
	(1.39771)	(0.84840)	(0.01962)
	[1.87321]	[-0.52648]	[0.36449]
C	-0.009960	0.066396	0.000438
	(0.01076)	(0.00653)	(0.00015)
	[-0.92582]	[10.1679]	[2.89943]
DUMMY CRISIS	0.034493	0.200776	-0.007484
	(0.46849)	(0.28437)	(0.00658)
	[0.07363]	[0.70604]	[-1.13805]
DUMMY CRISIS(-1)	-0.169557	-0.501587	-0.023903
	(0.65945)	(0.40028)	(0.00926)
	[-0.25712]	[-1.25310]	[-2.58240]
DUMMY CRISIS(-2)	0.287538	0.401822	0.032034
	(0.66057)	(0.40096)	(0.00927)
	[0.43529]	[1.00215]	[3.45494]
DUMMY CRISIS(-3)	-0.193910	0.268881	0.001232
	(0.66118)	(0.40133)	(0.00928)
	[-0.29328]	[0.66998]	[0.13275]

DUMMY CRISIS(-4)	-0.587070	-0.305252	0.022684
	(0.66054)	(0.40094)	(0.00927)
	[-0.88877]	[-0.76133]	[2.44658]
DUMMY CRISIS(-5)	0.550563	-0.036622	-0.025785
	(0.46917)	(0.28478)	(0.00659)
	[1.17348]	[-0.12860]	[-3.91545]
D(VIX)	0.005486	0.023061	-0.005646
	(0.00513)	(0.00311)	(7.2E-05)
	[1.06988]	[7.40888]	[-78.4432]
D(VIX(-1))	-0.002081	0.001239	-0.000481
	(0.00935)	(0.00567)	(0.00013)
	[-0.22264]	[0.21849]	[-3.67062]
D(VIX(-2))	-0.004894	0.000928	9.32E-06
	(0.00935)	(0.00568)	(0.00013)
	[-0.52334]	[0.16357]	[0.07098]
D(VIX(-3))	0.000950	0.008771	-0.000285
	(0.00931)	(0.00565)	(0.00013)
	[0.10198]	[1.55160]	[-2.18189]
D(VIX(-4))	-0.006505	0.007102	-0.000205
	(0.00942)	(0.00572)	(0.00013)
	[-0.69053]	[1.24211]	[-1.55084]
D(VIX(-5))	0.014173	-0.004152	0.000354
	(0.00943)	(0.00572)	(0.00013)
	[1.50308]	[-0.72539]	[2.67608]
ADS	-0.028025	0.006984	0.000323
	(0.01947)	(0.01182)	(0.00027)
	[-1.43972]	[0.59108]	[1.18210]
D(ADS(-1))	-0.433389	-0.065609	-0.020816
	(0.65271)	(0.39619)	(0.00916)
	[-0.66399]	[-0.16560]	[-2.27209]

D(ADS(-2))	-1.667217	0.236815	0.011836
	(0.64528)	(0.39168)	(0.00906)
	[-2.58373]	[0.60462]	[1.30678]
D(ADS(-3))	-0.208226	0.194467	-0.007043
	(0.65295)	(0.39633)	(0.00916)
	[-0.31890]	[0.49067]	[-0.76845]
D(ADS(-4))	-0.075922	-0.001718	0.016172
	(0.65973)	(0.40045)	(0.00926)
	[-0.11508]	[-0.00429]	[1.74644]
D(ADS(-5))	1.692092	-0.456406	0.004781
	(0.66764)	(0.40525)	(0.00937)
	[2.53443]	[-1.12623]	[0.51014]
R-squared	0.020553	0.168102	0.707979
Adj. R-squared	0.008438	0.157813	0.704367
Sum sq. resids	572.0293	210.7574	0.112699
S.E. equation	0.463038	0.281060	0.006499
F-statistic	1.696535	16.33711	196.0101
Log likelihood	-1736.467	-387.5174	9790.570
Akaike AIC	1.310486	0.312004	-7.221739
Schwarz SC	1.384750	0.386267	-7.147476
Mean dependent	-0.010987	0.029959	0.000282
S.D. dependent	0.465004	0.306263	0.011953

Determinant resid covariance (dof adj.)	7.14E-07
Determinant resid covariance	6.87E-07
Log likelihood	7669.940
Akaike information criterion	-5.601732
Schwarz criterion	-5.378942

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

ASVI Natural Disaster - Category Specification: Investment; Inclusion of Crisis Dummy: No

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(INV_NAT...	D(VOLUME)	SP500_Y
D(INV_NATURAL_DISA...	-0.782991	4039454.	4.47E-05
	(0.01921)	(5179456)	(5.7E-05)
	[-40.7571]	[0.77990]	[0.78054]
D(INV_NATURAL_DISA...	-0.621628	2573145.	0.000101
	(0.02401)	(6473002)	(7.2E-05)
	[-25.8914]	[0.39752]	[1.40631]
D(INV_NATURAL_DISA...	-0.410709	-315346.5	0.000100
	(0.02581)	(6957290)	(7.7E-05)
	[-15.9157]	[-0.04533]	[1.30267]
D(INV_NATURAL_DISA...	-0.261195	-591760.7	9.90E-05
	(0.02433)	(6560434)	(7.3E-05)
	[-10.7341]	[-0.09020]	[1.36511]
D(INV_NATURAL_DISA...	-0.155544	-2629807.	4.99E-05
	(0.01966)	(5300595)	(5.9E-05)
	[-7.91149]	[-0.49613]	[0.85176]
D(VOLUME(-1))	-3.79E-11	-0.505511	1.62E-14
	(7.5E-11)	(0.02025)	(2.2E-13)
	[-0.50406]	[-24.9661]	[0.07225]
D(VOLUME(-2))	-3.80E-11	-0.295549	-1.56E-13
	(8.3E-11)	(0.02239)	(2.5E-13)
	[-0.45745]	[-13.1994]	[-0.62880]
D(VOLUME(-3))	-4.77E-11	-0.309998	-2.31E-13
	(8.3E-11)	(0.02251)	(2.5E-13)
	[-0.57109]	[-13.7705]	[-0.92816]
D(VOLUME(-4))	-3.40E-11	-0.250826	-3.75E-13
	(8.4E-11)	(0.02271)	(2.5E-13)
	[-0.40343]	[-11.0446]	[-1.49153]
D(VOLUME(-5))	1.04E-11	-0.056279	-4.06E-13
	(7.5E-11)	(0.02032)	(2.2E-13)
	[0.13783]	[-2.76922]	[-1.80742]
SP500_Y(-1)	-1.468544	-5.49E+09	-0.067343
	(6.52208)	(1.8E+09)	(0.01944)
	[-0.22516]	[-3.12478]	[-3.46343]
SP500_Y(-2)	-3.085060	5.29E+08	-0.008437
	(6.52294)	(1.8E+09)	(0.01945)
	[-0.47296]	[0.30077]	[-0.43384]
SP500_Y(-3)	-4.522926	2.80E+09	-9.99E-05
	(6.53162)	(1.8E+09)	(0.01947)
	[-0.69247]	[1.59070]	[-0.00513]
SP500_Y(-4)	0.470763	2.37E+09	-0.017035
	(6.62274)	(1.8E+09)	(0.01974)
	[0.07108]	[1.32530]	[-0.86279]
SP500_Y(-5)	-5.766610	-3.43E+09	0.009419
	(6.67385)	(1.8E+09)	(0.01990)
	[-0.86406]	[-1.90644]	[0.47342]
C	0.000556	-21443817	0.000367
	(0.04630)	(1.2E+07)	(0.00014)
	[0.01200]	[-1.71805]	[2.66067]
D(VIX)	0.017709	70501862	-0.005646
	(0.02429)	(6548695)	(7.2E-05)
	[0.72908]	[10.7658]	[-77.9643]
D(VIX(-1))	0.009631	12913999	-0.000471
	(0.04494)	(1.2E+07)	(0.00013)
	[0.21431]	[1.06589]	[-3.51541]
D(VIX(-2))	0.011346	28979171	4.09E-05
	(0.04487)	(1.2E+07)	(0.00013)
	[0.25287]	[2.39554]	[0.30545]
D(VIX(-3))	-0.048825	34687165	-0.000280
	(0.04473)	(1.2E+07)	(0.00013)
	[-1.09166]	[2.87664]	[-2.10249]
D(VIX(-4))	0.023975	46820068	-0.000204
	(0.04548)	(1.2E+07)	(0.00014)
	[0.52711]	[3.81809]	[-1.50765]
D(VIX(-5))	-0.020325	-20087132	0.000359
	(0.04535)	(1.2E+07)	(0.00014)
	[-0.44818]	[-1.64286]	[2.65765]
ADS	0.002367	3109338.	0.000535
	(0.05705)	(1.5E+07)	(0.00017)
	[0.04148]	[0.20215]	[3.14533]
D(ADS(-1))	-1.160229	-1.29E+09	-0.023128
	(3.07730)	(8.3E+08)	(0.00917)
	[-0.37703]	[-1.55297]	[-2.52095]
D(ADS(-2))	0.427239	5.05E+08	0.013206
	(3.04794)	(8.2E+08)	(0.00909)
	[0.14017]	[0.61460]	[1.45329]
D(ADS(-3))	-1.863392	1.47E+08	-0.004417
	(3.08586)	(8.3E+08)	(0.00920)
	[-0.60385]	[0.17637]	[-0.48014]
D(ADS(-4))	-4.898157	7.28E+08	0.014230
	(3.11240)	(8.4E+08)	(0.00928)
	[-1.57376]	[0.86730]	[1.53353]
D(ADS(-5))	4.503474	-56679277	0.003215
	(3.14696)	(8.5E+08)	(0.00938)
	[1.43106]	[-0.06680]	[0.34265]
R-squared	0.388405	0.246985	0.703028
Adj. R-squared	0.382229	0.239382	0.700030
Sum sq. resids	12894.91	9.37E+20	0.114610
S.E. equation	2.195980	5.92E+08	0.006547
F-statistic	62.89531	32.48362	234.4526
Log likelihood	-5945.369	-58397.88	9767.857
Akaike AIC	4.421443	43.24639	-7.209369
Schwarz SC	4.482601	43.30755	-7.148211
Mean dependent	-0.015114	-27186318	0.000282
S.D. dependent	2.793926	6.79E+08	0.011953
Determinant resid covariance (dof adj.)		7.14E+13	
Determinant resid covariance		6.92E+13	
Log likelihood		-54555.86	
Akaike information criterion		40.44401	
Schwarz criterion		40.62749	

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

ASVI Natural Disaster - Category Specification: Investment; Inclusion of Crisis Dummy: Yes

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(INV_NAT...	D(VOLUME)	SP500_Y
D(INV_NATURAL_DISA...	-0.783140	3873574.	4.02E-05
	(0.01922)	(5178122)	(5.7E-05)
	[-40.7434]	[0.74807]	[0.70514]
D(INV_NATURAL_DISA...	-0.621828	2377423.	9.60E-05
	(0.02402)	(6470887)	(7.1E-05)
	[-25.8879]	[0.36740]	[1.34940]
D(INV_NATURAL_DISA...	-0.411306	-495948.2	9.62E-05
	(0.02582)	(6954874)	(7.6E-05)
	[-15.9319]	[-0.07131]	[1.25742]
D(INV_NATURAL_DISA...	-0.261937	-839394.0	9.33E-05
	(0.02434)	(6558390)	(7.2E-05)
	[-10.7595]	[-0.12799]	[1.29328]
D(INV_NATURAL_DISA...	-0.156016	-2834837.	4.52E-05
	(0.01967)	(5297885)	(5.8E-05)
	[-7.93337]	[-0.53509]	[0.77586]
D(VOLUME(-1))	-3.78E-11	-0.504008	3.07E-14
	(7.5E-11)	(0.02025)	(2.2E-13)
	[-0.50337]	[-24.8835]	[0.13768]
D(VOLUME(-2))	-3.14E-11	-0.295214	-1.47E-13
	(8.3E-11)	(0.02240)	(2.5E-13)
	[-0.37766]	[-13.1787]	[-0.59654]
D(VOLUME(-3))	-4.77E-11	-0.307560	-1.52E-13
	(8.4E-11)	(0.02255)	(2.5E-13)
	[-0.56942]	[-13.6396]	[-0.61373]
D(VOLUME(-4))	-3.27E-11	-0.247503	-2.84E-13
	(8.4E-11)	(0.02275)	(2.5E-13)
	[-0.38771]	[-10.8805]	[-1.13457]
D(VOLUME(-5))	1.08E-11	-0.054502	-3.52E-13
	(7.6E-11)	(0.02035)	(2.2E-13)
	[0.14255]	[-2.67881]	[-1.57167]
SP500_Y(-1)	-1.147995	-5.42E+09	-0.069740
	(6.54935)	(1.8E+09)	(0.01941)
	[-0.17528]	[-3.07129]	[-3.59360]
SP500_Y(-2)	-2.286855	4.66E+08	-0.009470
	(6.55160)	(1.8E+09)	(0.01941)
	[-0.34905]	[0.26378]	[-0.48779]
SP500_Y(-3)	-4.999178	3.07E+09	0.008050
	(6.56290)	(1.8E+09)	(0.01945)
	[-0.76173]	[1.73366]	[0.41395]
SP500_Y(-4)	0.156198	2.55E+09	-0.012182
	(6.64171)	(1.8E+09)	(0.01968)
	[0.02352]	[1.42566]	[-0.61897]
SP500_Y(-5)	-6.543243	-3.62E+09	0.006935
	(6.69070)	(1.8E+09)	(0.01983)
	[-0.97796]	[-2.01099]	[0.34982]
C	-0.010384	-23322885	0.000333
	(0.04701)	(1.3E+07)	(0.00014)
	[-0.22090]	[-1.84164]	[2.39269]
DUMMY_CRISIS	0.358324	1.85E+08	-0.007377
	(2.22494)	(6.0E+08)	(0.00659)
	[0.16105]	[0.30826]	[-1.11888]
DUMMY_CRISIS(-1)	-0.668207	-1.68E+09	-0.023762
	(3.13027)	(8.4E+08)	(0.00928)
	[-0.21347]	[-1.98706]	[-2.56178]
DUMMY_CRISIS(-2)	1.612796	2.17E+09	0.032135
	(3.13497)	(8.4E+08)	(0.00929)
	[0.51445]	[2.56806]	[3.45931]
DUMMY_CRISIS(-3)	1.666421	-7.44E+08	0.000732
	(3.14134)	(8.5E+08)	(0.00931)
	[0.53048]	[-0.87929]	[0.07865]
DUMMY_CRISIS(-4)	-5.989627	8.27E+08	0.022261
	(3.13651)	(8.4E+08)	(0.00929)
	[-1.90964]	[0.97905]	[2.39526]
DUMMY_CRISIS(-5)	2.587482	-8.33E+08	-0.025318
	(2.22732)	(6.0E+08)	(0.00660)
	[1.16170]	[-1.38804]	[-3.83619]
D(VIX)	0.018783	70409329	-0.005641
	(0.02433)	(6553601)	(7.2E-05)
	[0.77210]	[10.7436]	[-78.2520]
D(VIX(-1))	0.010868	13686078	-0.000474
	(0.04503)	(1.2E+07)	(0.00013)
	[0.24134]	[1.12820]	[-3.55208]
D(VIX(-2))	0.017239	28605704	2.89E-05
	(0.04497)	(1.2E+07)	(0.00013)
	[0.38336]	[2.36137]	[0.21692]
D(VIX(-3))	-0.050704	35354518	-0.000254
	(0.04481)	(1.2E+07)	(0.00013)
	[-1.13156]	[2.92883]	[-1.91309]
D(VIX(-4))	0.024760	47903807	-0.000186
	(0.04551)	(1.2E+07)	(0.00013)
	[0.54402]	[3.90701]	[-1.38098]
D(VIX(-5))	-0.020500	-20962963	0.000347
	(0.04539)	(1.2E+07)	(0.00013)
	[-0.45165]	[-1.71435]	[2.58272]
ADS	-0.092539	-12312375	0.000270
	(0.09207)	(2.5E+07)	(0.00027)
	[-1.00506]	[-0.49638]	[0.99056]
D(ADS(-1))	-1.578545	-1.22E+09	-0.020607
	(3.08577)	(8.3E+08)	(0.00914)
	[-0.51156]	[-1.47342]	[-2.25372]
D(ADS(-2))	0.452837	5.13E+08	0.012045
	(3.05675)	(8.2E+08)	(0.00906)
	[0.14814]	[0.62335]	[1.32985]
D(ADS(-3))	-1.794918	-15740745	-0.007591
	(3.09547)	(8.3E+08)	(0.00917)
	[-0.57985]	[-0.01888]	[-0.82763]
D(ADS(-4))	-4.591427	8.66E+08	0.015790
	(3.12792)	(8.4E+08)	(0.00927)
	[-1.46789]	[1.02830]	[1.70361]
D(ADS(-5))	5.145336	1160670.	0.005074
	(3.16885)	(8.5E+08)	(0.00939)
	[1.62372]	[0.00136]	[0.54033]
R-squared	0.389710	0.249768	0.707253
Adj. R-squared	0.382161	0.240489	0.703632
Sum sq. resids	12867.40	9.34E+20	0.112979
S.E. equation	2.196102	5.92E+08	0.006507
F-statistic	51.62700	26.91620	195.3232
Log likelihood	-5942.484	-58392.88	9787.214
Akaike AIC	4.423748	43.24713	-7.219255
Schwarz SC	4.498011	43.32140	-7.144992
Mean dependent	-0.015114	-27186318	0.000282
S.D. dependent	2.793926	6.79E+08	0.011953
Determinant resid covariance (dof adj.)		7.05E+13	
Determinant resid covariance		6.79E+13	
Log likelihood		-54530.27	
Akaike information criterion		40.43840	
Schwarz criterion		40.66119	

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

ASVI Terrorism - Category Specification: None; Inclusion of Crisis Dummy: No

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(TERRORI...	D(VOLUME)	SP500_Y
D(TERRORISM(-1))	-0.349280	-205346.9	-2.13E-07
	(0.01902)	(7582210)	(8.4E-05)
	[-18.3682]	[-0.02708]	[-0.00254]
D(TERRORISM(-2))	-0.339203	-3103831.	-9.32E-05
	(0.01945)	(7754643)	(8.6E-05)
	[-17.4416]	[-0.40025]	[-1.08667]
D(TERRORISM(-3))	-0.215930	-2727083.	-3.96E-05
	(0.02007)	(8004082)	(8.9E-05)
	[-10.7570]	[-0.34071]	[-0.44753]
D(TERRORISM(-4))	-0.138784	2434396.	-1.71E-05
	(0.01905)	(7594339)	(8.4E-05)
	[-7.28683]	[0.32055]	[-0.20412]
D(TERRORISM(-5))	-0.082798	4466989.	-2.31E-05
	(0.01815)	(7235363)	(8.0E-05)
	[-4.56299]	[0.61738]	[-0.28832]
D(VOLUME(-1))	-3.20E-11	-0.505621	2.20E-14
	(5.1E-11)	(0.02025)	(2.2E-13)
	[-0.63106]	[-24.9730]	[0.09803]
D(VOLUME(-2))	3.12E-11	-0.295966	-1.53E-13
	(5.6E-11)	(0.02239)	(2.5E-13)
	[0.55510]	[-13.2185]	[-0.61789]
D(VOLUME(-3))	7.34E-11	-0.310732	-2.35E-13
	(5.6E-11)	(0.02252)	(2.5E-13)
	[1.30066]	[-13.8008]	[-0.94568]
D(VOLUME(-4))	6.18E-11	-0.251296	-3.75E-13
	(5.7E-11)	(0.02271)	(2.5E-13)
	[1.08484]	[-11.0652]	[-1.49188]
D(VOLUME(-5))	1.74E-11	-0.056565	-4.00E-13
	(5.1E-11)	(0.02034)	(2.2E-13)
	[0.34201]	[-2.78128]	[-1.77627]
SP500_Y(-1)	-4.018342	-5.51E+09	-0.066806
	(4.41022)	(1.8E+09)	(0.01945)
	[-0.91114]	[-3.13475]	[-3.43481]
SP500_Y(-2)	-2.622721	5.27E+08	-0.007809
	(4.41091)	(1.8E+09)	(0.01945)
	[-0.59460]	[0.29966]	[-0.40145]
SP500_Y(-3)	6.639065	2.78E+09	-0.000622
	(4.41794)	(1.8E+09)	(0.01948)
	[1.50275]	[1.57948]	[-0.03191]
SP500_Y(-4)	1.293391	2.30E+09	-0.017968
	(4.48029)	(1.8E+09)	(0.01976)
	[0.28868]	[1.28714]	[-0.90937]
SP500_Y(-5)	-0.505260	-3.41E+09	0.009297
	(4.51526)	(1.8E+09)	(0.01991)
	[-0.11190]	[-1.89323]	[0.46689]
C	-0.031001	-21525719	0.000368
	(0.03130)	(1.2E+07)	(0.00014)
	[-0.99030]	[-1.72449]	[2.66843]
D(VIX)	0.017348	70537700	-0.005642
	(0.01643)	(6549810)	(7.2E-05)
	[1.05612]	[10.7694]	[-77.8865]
D(VIX(-1))	0.000160	12775593	-0.000466
	(0.03039)	(1.2E+07)	(0.00013)
	[0.00527]	[1.05444]	[-3.47740]
D(VIX(-2))	-0.005695	29112772	4.74E-05
	(0.03035)	(1.2E+07)	(0.00013)
	[-0.18766]	[2.40595]	[0.35419]
D(VIX(-3))	0.036980	34584059	-0.000280
	(0.03026)	(1.2E+07)	(0.00013)
	[1.22226]	[2.86674]	[-2.10135]
D(VIX(-4))	0.033666	46362308	-0.000209
	(0.03076)	(1.2E+07)	(0.00014)
	[1.09446]	[3.77991]	[-1.54240]
D(VIX(-5))	-0.009049	-20158546	0.000359
	(0.03068)	(1.2E+07)	(0.00014)
	[-0.29492]	[-1.64765]	[2.65234]
ADS	0.006092	3043143.	0.000543
	(0.03857)	(1.5E+07)	(0.00017)
	[0.15795]	[0.19788]	[3.19019]
D(ADS(-1))	0.189727	-1.29E+09	-0.023666
	(2.08014)	(8.3E+08)	(0.00917)
	[0.09121]	[-1.55831]	[-2.57976]
D(ADS(-2))	-0.906059	5.23E+08	0.013355
	(2.06038)	(8.2E+08)	(0.00909)
	[-0.43975]	[0.63600]	[1.46980]
D(ADS(-3))	1.140736	1.61E+08	-0.004405
	(2.08564)	(8.3E+08)	(0.00920)
	[0.54695]	[0.19357]	[-0.47888]
D(ADS(-4))	-1.057511	7.36E+08	0.014149
	(2.10372)	(8.4E+08)	(0.00928)
	[-0.50269]	[0.87715]	[1.52508]
D(ADS(-5))	1.265001	-1.02E+08	0.003585
	(2.12626)	(8.5E+08)	(0.00938)
	[0.59494]	[-0.11982]	[0.38233]
R-squared	0.158855	0.246956	0.702890
Adj. R-squared	0.150362	0.239352	0.699890
Sum sq. resids	5895.484	9.37E+20	0.114663
S.E. equation	1.484838	5.92E+08	0.006548
F-statistic	18.70376	32.47849	234.2973
Log likelihood	-4888.015	-58397.93	9767.228
Akaike AIC	3.638797	43.24643	-7.208903
Schwarz SC	3.699955	43.30759	-7.147745
Mean dependent	-0.022569	-27186318	0.000282
S.D. dependent	1.610876	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	3.27E+13
Determinant resid covariance	3.17E+13
Log likelihood	-53499.30
Akaike information criterion	39.66196
Schwarz criterion	39.84543

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

ASVI Terrorism - Category Specification: None; Inclusion of Crisis Dummy: Yes

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(TERRORI...	D(VOLUME)	SP500_Y
D(TERRORISM(-1))	-0.349299	-417911.1	-4.32E-06
	(0.01904)	(7577353)	(8.3E-05)
	[-18.3490]	[-0.05515]	[-0.05180]
D(TERRORISM(-2))	-0.339221	-3219497.	-9.67E-05
	(0.01947)	(7750365)	8.52616297...
	[-17.4218]	[-0.41540]	[-1.13399]
D(TERRORISM(-3))	-0.216021	-2866246.	-4.31E-05
	(0.02010)	(7999559)	(8.8E-05)
	[-10.7489]	[-0.35830]	[-0.48996]
D(TERRORISM(-4))	-0.138835	2329567.	-1.94E-05
	(0.01907)	(7590008)	(8.3E-05)
	[-7.28095]	[0.30693]	[-0.23202]
D(TERRORISM(-5))	-0.082815	4362436.	-2.45E-05
	(0.01817)	(7230770)	(8.0E-05)
	[-4.55887]	[0.60332]	[-0.30844]
D(VOLUME(-1))	-3.14E-11	-0.504148	3.60E-14
	(5.1E-11)	(0.02025)	(2.2E-13)
	[-0.61637]	[-24.8919]	[0.16174]
D(VOLUME(-2))	3.13E-11	-0.295667	-1.45E-13
	(5.6E-11)	(0.02240)	(2.5E-13)
	[0.55626]	[-13.1994]	[-0.58699]
D(VOLUME(-3))	7.58E-11	-0.308300	-1.56E-13
	(5.7E-11)	(0.02255)	(2.5E-13)
	[1.33773]	[-13.6705]	[-0.63043]
D(VOLUME(-4))	6.29E-11	-0.247975	-2.84E-13
	(5.7E-11)	(0.02275)	(2.5E-13)
	[1.10115]	[-10.9013]	[-1.13392]
D(VOLUME(-5))	1.71E-11	-0.054779	-3.45E-13
	(5.1E-11)	(0.02036)	(2.2E-13)
	[0.33454]	[-2.69044]	[-1.53955]
SP500_Y(-1)	-3.991993	-5.44E+09	-0.069230
	(4.43285)	(1.8E+09)	(0.01941)
	[-0.90055]	[-3.08226]	[-3.56657]
SP500_Y(-2)	-2.575819	4.63E+08	-0.008825
	(4.43449)	(1.8E+09)	(0.01942)
	[-0.58086]	[0.26220]	[-0.45449]
SP500_Y(-3)	6.880914	3.05E+09	0.007552
	(4.44337)	(1.8E+09)	(0.01946)
	[1.54858]	[1.72294]	[0.38815]
SP500_Y(-4)	1.219949	2.49E+09	-0.013077
	(4.49740)	(1.8E+09)	(0.01969)
	[0.27126]	[1.38962]	[-0.66402]
SP500_Y(-5)	-0.537670	-3.60E+09	0.006845
	(4.53088)	(1.8E+09)	(0.01984)
	[-0.11867]	[-1.99559]	[0.34501]
C	-0.032368	-23425080	0.000333
	(0.03182)	(1.3E+07)	(0.00014)
	[-1.01722]	[-1.84950]	[2.39012]
DUMMY CRISIS	-0.753387	1.89E+08	-0.007400
	(1.50574)	(6.0E+08)	(0.00659)
	[-0.50034]	[0.31573]	[-1.12237]
DUMMY CRISIS(-1)	0.840461	-1.68E+09	-0.023721
	(2.11855)	(8.4E+08)	(0.00928)
	[0.39671]	[-1.98680]	[-2.55695]
DUMMY CRISIS(-2)	0.215604	2.16E+09	0.032130
	(2.12176)	(8.4E+08)	(0.00929)
	[0.10162]	[2.55626]	[3.45819]
DUMMY CRISIS(-3)	-0.433587	-7.36E+08	0.000819
	(2.12612)	(8.5E+08)	(0.00931)
	[-0.20393]	[-0.87001]	[0.08794]
DUMMY CRISIS(-4)	0.855042	8.37E+08	0.022338
	(2.12277)	(8.4E+08)	(0.00930)
	[0.40280]	[0.99064]	[2.40318]
DUMMY CRISIS(-5)	-0.776625	-8.46E+08	-0.025544
	(1.50699)	(6.0E+08)	(0.00660)
	[-0.51535]	[-1.40977]	[-3.87092]
D(VIX)	0.017435	70448414	-0.005637
	(0.01647)	(6554844)	(7.2E-05)
	[1.05874]	[10.7475]	[-78.1735]
D(VIX(-1))	0.000496	13542601	-0.000469
	(0.03048)	(1.2E+07)	(0.00013)
	[0.01629]	[1.11636]	[-3.51419]
D(VIX(-2))	-0.006010	28740226	3.57E-05
	(0.03044)	(1.2E+07)	(0.00013)
	[-0.19742]	[2.37185]	[0.26779]
D(VIX(-3))	0.038246	35264159	-0.000254
	(0.03034)	(1.2E+07)	(0.00013)
	[1.26054]	[2.91995]	[-1.90951]
D(VIX(-4))	0.033518	47472439	-0.000190
	(0.03081)	(1.2E+07)	(0.00013)
	[1.08787]	[3.87089]	[-1.41157]
D(VIX(-5))	-0.009185	-21010839	0.000347
	(0.03074)	(1.2E+07)	(0.00013)
	[-0.29880]	[-1.71717]	[2.58046]
ADS	-0.005428	-12502488	0.000267
	(0.06232)	(2.5E+07)	(0.00027)
	[-0.08711]	[-0.50404]	[0.97750]
D(ADS(-1))	0.258501	-1.23E+09	-0.021125
	(2.08787)	(8.3E+08)	(0.00914)
	[0.12381]	[-1.47651]	[-2.31061]
D(ADS(-2))	-1.002605	5.31E+08	0.012186
	(2.06828)	(8.2E+08)	(0.00906)
	[-0.48475]	[0.64487]	[1.34550]
D(ADS(-3))	1.158488	-843882.0	-0.007558
	(2.09413)	(8.3E+08)	(0.00917)
	[0.55321]	[-0.00101]	[-0.82417]
D(ADS(-4))	-0.980387	8.74E+08	0.015746
	(2.11618)	(8.4E+08)	(0.00927)
	[-0.46328]	[1.03795]	[1.69924]
D(ADS(-5))	1.283627	-44394044	0.005464
	(2.14303)	(8.5E+08)	(0.00938)
	[0.59898]	[-0.05204]	[0.58230]
R-squared	0.159042	0.249742	0.707150
Adj. R-squared	0.148640	0.240462	0.703528
Sum sq. resids	5894.176	9.34E+20	0.113019
S.E. equation	1.486342	5.92E+08	0.006509
F-statistic	15.29008	26.91239	195.2266
Log likelihood	-4887.715	-58392.92	9786.742
Akaike AIC	3.643016	43.24717	-7.218906
Schwarz SC	3.717279	43.32143	-7.144642
Mean dependent	-0.022569	-27186318	0.000282
S.D. dependent	1.610876	6.79E+08	0.011953

Determinant resid covariance (dof adj.)	3.23E+13
Determinant resid covariance	3.11E+13
Log likelihood	-53476.23
Akaike information criterion	39.65820
Schwarz criterion	39.88099

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ASVI Terrorism - Category Specification: Investment; Inclusion of Crisis Dummy: No

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(INV_TER...	D(VOLUME)	SP500_Y
D(INV_TERRORISM(-1))	-0.847659	-801822.7	3.51E-05
	(0.01865)	(1998704)	(2.2E-05)
	[-45.4417]	[-0.40117]	[1.58793]
D(INV_TERRORISM(-2))	-0.702475	-1377770.	6.82E-06
	(0.02333)	(2499942)	(2.8E-05)
	[-30.1081]	[-0.55112]	[0.24665]
D(INV_TERRORISM(-3))	-0.562863	-2269824.	5.97E-06
	(0.02453)	(2628856)	(2.9E-05)
	[-22.9413]	[-0.86343]	[0.20529]
D(INV_TERRORISM(-4))	-0.396805	-406887.2	-5.09E-06
	(0.02301)	(2465993)	(2.7E-05)
	[-17.2412]	[-0.16500]	[-0.18654]
D(INV_TERRORISM(-5))	-0.286260	-414182.4	8.67E-06
	(0.01860)	(1992681)	(2.2E-05)
	[-15.3923]	[-0.20785]	[0.39353]
D(VOLUME(-1))	-4.93E-11	-0.505426	1.62E-14
	(1.9E-10)	(0.02025)	(2.2E-13)
	[-0.26098]	[-24.9595]	[0.07257]
D(VOLUME(-2))	4.92E-11	-0.296025	-1.51E-13
	(2.1E-10)	(0.02239)	(2.5E-13)
	[0.23548]	[-13.2219]	[-0.61119]
D(VOLUME(-3))	3.00E-10	-0.310304	-2.32E-13
	(2.1E-10)	(0.02251)	(2.5E-13)
	[1.42940]	[-13.7878]	[-0.93171]

D(VOLUME(-4))	1.92E-10	-0.250812	-3.84E-13
	(2.1E-10)	(0.02271)	(2.5E-13)
	[0.90411]	[-11.0428]	[-1.52755]
D(VOLUME(-5))	1.90E-11	-0.056120	-4.05E-13
	(1.9E-10)	(0.02033)	(2.2E-13)
	[0.10039]	[-2.76017]	[-1.80184]
SP500_Y(-1)	4.097861	-5.50E+09	-0.066401
	(16.4145)	(1.8E+09)	(0.01944)
	[0.24965]	[-3.12873]	[-3.41520]
SP500_Y(-2)	1.292763	5.61E+08	-0.008404
	(16.4191)	(1.8E+09)	(0.01945)
	[0.07874]	[0.31905]	[-0.43210]
SP500_Y(-3)	-27.28271	2.75E+09	0.000193
	(16.4399)	(1.8E+09)	(0.01947)
	[-1.65955]	[1.56122]	[0.00991]
SP500_Y(-4)	-1.032485	2.30E+09	-0.016857
	(16.6773)	(1.8E+09)	(0.01975)
	[-0.06191]	[1.28821]	[-0.85333]
SP500_Y(-5)	11.80236	-3.46E+09	0.008178
	(16.8101)	(1.8E+09)	(0.01991)
	[0.70210]	[-1.92286]	[0.41070]
C	-0.022452	-21437824	0.000368
	(0.11648)	(1.2E+07)	(0.00014)
	[-0.19274]	[-1.71764]	[2.66844]

D(VIX)	0.007022	70330750	-0.005645
	(0.06108)	(6544702)	(7.2E-05)
	[0.11496]	[10.7462]	[-78.0246]
D(VIX(-1))	0.072562	12780122	-0.000466
	(0.11306)	(1.2E+07)	(0.00013)
	[0.64182]	[1.05501]	[-3.47821]
D(VIX(-2))	0.045070	29322821	4.09E-05
	(0.11293)	(1.2E+07)	(0.00013)
	[0.39909]	[2.42329]	[0.30600]
D(VIX(-3))	-0.082964	34429293	-0.000278
	(0.11257)	(1.2E+07)	(0.00013)
	[-0.73700]	[2.85443]	[-2.08408]
D(VIX(-4))	0.001973	46484006	-0.000205
	(0.11444)	(1.2E+07)	(0.00014)
	[0.01724]	[3.79088]	[-1.51435]
D(VIX(-5))	0.149434	-20249360	0.000355
	(0.11412)	(1.2E+07)	(0.00014)
	[1.30942]	[-1.65600]	[2.62263]
ADS	0.084735	3271050.	0.000540
	(0.14352)	(1.5E+07)	(0.00017)
	[0.59040]	[0.21271]	[3.17377]
D(ADS(-1))	10.74730	-1.29E+09	-0.023862
	(7.73991)	(8.3E+08)	(0.00917)
	[1.38856]	[-1.55609]	[-2.60278]

D(ADS(-2))	-7.379215	5.34E+08	0.012967
	(7.67120)	(8.2E+08)	(0.00909)
	[-0.96194]	[0.64934]	[1.42712]
D(ADS(-3))	2.638863	1.72E+08	-0.004082
	(7.76551)	(8.3E+08)	(0.00920)
	[0.33982]	[0.20678]	[-0.44384]
D(ADS(-4))	-7.038402	7.33E+08	0.014349
	(7.82609)	(8.4E+08)	(0.00927)
	[-0.89935]	[0.87430]	[1.54789]
D(ADS(-5))	-2.214799	-1.25E+08	0.003618
	(7.91845)	(8.5E+08)	(0.00938)
	[-0.27970]	[-0.14764]	[0.38575]
R-squared	0.444793	0.246992	0.703198
Adj. R-squared	0.439187	0.239389	0.700201
Sum sq. resids	81641.68	9.37E+20	0.114544
S.E. equation	5.525547	5.92E+08	0.006545
F-statistic	79.34161	32.48488	234.6434
Log likelihood	-8438.650	-58397.87	9768.630
Akaike AIC	6.266950	43.24638	-7.209940
Schwarz SC	6.328108	43.30754	-7.148782
Mean dependent	-0.023478	-27186318	0.000282
S.D. dependent	7.378470	6.79E+08	0.011953
Determinant resid covariance (dof adj.)		4.52E+14	
Determinant resid covariance		4.38E+14	
Log likelihood		-57048.44	
Akaike information criterion		42.28900	
Schwarz criterion		42.47248	

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ASVI Terrorism - Category Specification: Investment; Inclusion of Crisis Dummy: Yes

Vector Autoregression Estimates
Sample (adjusted): 1/12/2004 7/31/2017
Included observations: 2702 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	D(INV_TER...	D(VOLUME)	SP500_Y
D(INV_TERRORISM(-1))	-0.847698	-731597.1	3.69E-05
	(0.01867)	(1997650)	(2.2E-05)
	[-45.3944]	[-0.36623]	[1.68025]
D(INV_TERRORISM(-2))	-0.702223	-1267065.	1.02E-05
	(0.02336)	(2498855)	(2.7E-05)
	[-30.0618]	[-0.50706]	[0.37038]
D(INV_TERRORISM(-3))	-0.562323	-2155286.	8.92E-06
	(0.02457)	(2627980)	(2.9E-05)
	[-22.8899]	[-0.82013]	[0.30877]
D(INV_TERRORISM(-4))	-0.396615	-440943.1	-5.62E-06
	(0.02304)	(2464709)	(2.7E-05)
	[-17.2141]	[-0.17890]	[-0.20741]
D(INV_TERRORISM(-5))	-0.286379	-391373.2	7.95E-06
	(0.01862)	(1991903)	(2.2E-05)
	[-15.3799]	[-0.19648]	[0.36321]
D(VOLUME(-1))	-5.30E-11	-0.503951	3.08E-14
	(1.9E-10)	(0.02026)	(2.2E-13)
	[-0.28001]	[-24.8781]	[0.13833]
D(VOLUME(-2))	4.42E-11	-0.295700	-1.42E-13
	(2.1E-10)	(0.02240)	(2.5E-13)
	[0.21130]	[-13.2017]	[-0.57849]
D(VOLUME(-3))	3.03E-10	-0.307899	-1.53E-13
	(2.1E-10)	(0.02254)	(2.5E-13)
	[1.43702]	[-13.6585]	[-0.61636]
D(VOLUME(-4))	1.98E-10	-0.247555	-2.93E-13
	(2.1E-10)	(0.02275)	(2.5E-13)
	[0.92963]	[-10.8819]	[-1.17297]
D(VOLUME(-5))	2.88E-11	-0.054410	-3.52E-13
	(1.9E-10)	(0.02035)	(2.2E-13)
	[0.15126]	[-2.67308]	[-1.57112]

SP500_Y(-1)	2.949222	-5.43E+09	-0.068822
	(16.4977)	(1.8E+09)	(0.01940)
	[0.17877]	[-3.07568]	[-3.54676]
SP500_Y(-2)	0.351372	4.95E+08	-0.009447
	(16.5058)	(1.8E+09)	(0.01941)
	[0.02129]	[0.28020]	[-0.48664]
SP500_Y(-3)	-27.15063	3.02E+09	0.008504
	(16.5336)	(1.8E+09)	(0.01945)
	[-1.64215]	[1.70563]	[0.43730]
SP500_Y(-4)	-0.293948	2.49E+09	-0.011858
	(16.7404)	(1.8E+09)	(0.01969)
	[-0.01756]	[1.38915]	[-0.60224]
SP500_Y(-5)	12.37818	-3.65E+09	0.005731
	(16.8669)	(1.8E+09)	(0.01984)
	[0.73387]	[-2.02462]	[0.28888]
C	-0.029588	-23325697	0.000333
	(0.11839)	(1.3E+07)	(0.00014)
	[-0.24993]	[-1.84185]	[2.39469]
DUMMY_CRISIS	1.094206	1.80E+08	-0.007464
	(5.60459)	(6.0E+08)	(0.00659)
	[0.19523]	[0.30018]	[-1.13225]
DUMMY_CRISIS(-1)	-3.383204	-1.66E+09	-0.023768
	(7.88575)	(8.4E+08)	(0.00928)
	[-0.42903]	[-1.96270]	[-2.56254]
DUMMY_CRISIS(-2)	-1.798710	2.16E+09	0.032545
	(7.89735)	(8.4E+08)	(0.00929)
	[-0.22776]	[2.55086]	[3.50375]
DUMMY_CRISIS(-3)	2.678633	-7.48E+08	0.000581
	(7.91397)	(8.5E+08)	(0.00931)
	[0.33847]	[-0.88355]	[0.06239]

DUMMY_CRISIS(-4)	3.969813	8.28E+08	0.022275
	(7.89975)	(8.5E+08)	(0.00929)
	[0.50252]	[0.97934]	[2.39732]
DUMMY_CRISIS(-5)	-2.896231	-8.31E+08	-0.025529
	(5.60885)	(6.0E+08)	(0.00660)
	[-0.51637]	[-1.38507]	[-3.86981]
D(VIX)	0.008670	70242904	-0.005640
	(0.06123)	(6549852)	(7.2E-05)
	[0.14160]	[10.7243]	[-78.3164]
D(VIX(-1))	0.068395	13537824	-0.000469
	(0.11339)	(1.2E+07)	(0.00013)
	[0.60320]	[1.11611]	[-3.51725]
D(VIX(-2))	0.042005	28920253	2.85E-05
	(0.11328)	(1.2E+07)	(0.00013)
	[0.37082]	[2.38662]	[0.21395]
D(VIX(-3))	-0.081526	35118280	-0.000251
	(0.11288)	(1.2E+07)	(0.00013)
	[-0.72225]	[2.90835]	[-1.88986]
D(VIX(-4))	0.003860	47585905	-0.000186
	(0.11462)	(1.2E+07)	(0.00013)
	[0.03368]	[3.88109]	[-1.37962]
D(VIX(-5))	0.151694	-21106098	0.000343
	(0.11432)	(1.2E+07)	(0.00013)
	[1.32694]	[-1.72588]	[2.54911]
ADS	0.020991	-12267368	0.000267
	(0.23188)	(2.5E+07)	(0.00027)
	[0.09052]	[-0.49454]	[0.97737]
D(ADS(-1))	11.08070	-1.23E+09	-0.021320
	(7.76817)	(8.3E+08)	(0.00914)
	[1.42642]	[-1.47657]	[-2.33339]

D(ADS(-2))	-7.325472	5.40E+08	0.011740
	(7.70027)	(8.2E+08)	(0.00906)
	[-0.95133]	[0.65547]	[1.29630]
D(ADS(-3))	2.467011	10539270	-0.007299
	(7.79667)	(8.3E+08)	(0.00917)
	[0.31642]	[0.01264]	[-0.79596]
D(ADS(-4))	-7.232267	8.73E+08	0.015977
	(7.87191)	(8.4E+08)	(0.00926)
	[-0.91874]	[1.03672]	[1.72565]
D(ADS(-5))	-1.942765	-66360123	0.005567
	(7.98076)	(8.5E+08)	(0.00939)
	[-0.24343]	[-0.07773]	[0.59307]
R-squared	0.445028	0.249739	0.707474
Adj. R-squared	0.438163	0.240459	0.703855
Sum sq. resids	81607.19	9.34E+20	0.112894
S.E. equation	5.530588	5.92E+08	0.006505
F-statistic	64.83175	26.91194	195.5316
Log likelihood	-8438.079	-58392.93	9788.233
Akaike AIC	6.270969	43.24717	-7.220010
Schwarz SC	6.345232	43.32143	-7.145747
Mean dependent	-0.023478	-27186318	0.000282
S.D. dependent	7.378470	6.79E+08	0.011953
Determinant resid covariance (dof adj.)		4.47E+14	
Determinant resid covariance		4.30E+14	
Log likelihood		-57025.09	
Akaike information criterion		42.28504	
Schwarz criterion		42.50783	

The first difference of S&P 500 Volume Trading and the daily returns of S&P 500 enter in the Vector autoregressive models as endogenous variables. The first difference in VIX and ADS enter in the models as exogenous variables up to five lags. The regressions are based on 3.418 daily observations from January 2nd, 2004 to July, 31 2017. Newey and West standard errors that are robust to heteroskedasticity and autocorrelation for up to five lags are used. The table data come from Google, Yahoo! Finance, FED Philadelphia and FRED

A5 – Stability of Daily VARs: AR Roots Tables

VAR specification:
Cancer

Root	Modulus
0.294740 - 0.660160i	0.722968
0.294740 + 0.660160i	0.722968
0.324443 - 0.598589i	0.680861
0.324443 + 0.598589i	0.680861
-0.501129 - 0.371066i	0.623554
-0.501129 + 0.371066i	0.623554
-0.314453 - 0.471181i	0.566474
-0.314453 + 0.471181i	0.566474
0.236356 - 0.404282i	0.468303
0.236356 + 0.404282i	0.468303
-0.303939 - 0.309947i	0.434104
-0.303939 + 0.309947i	0.434104
-0.420079 - 0.089119i	0.429429
-0.420079 + 0.089119i	0.429429
0.363601	0.363601

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Cancer
Inclusion of Crisis Dummy

Root	Modulus
0.294057 - 0.660339i	0.722854
0.294057 + 0.660339i	0.722854
0.322686 - 0.598374i	0.679836
0.322686 + 0.598374i	0.679836
-0.501628 - 0.371291i	0.624090
-0.501628 + 0.371291i	0.624090
-0.309811 - 0.471467i	0.564149
-0.309811 + 0.471467i	0.564149
0.227889 - 0.385140i	0.447511
0.227889 + 0.385140i	0.447511
-0.426680 - 0.089011i	0.435865
-0.426680 + 0.089011i	0.435865
-0.290648 - 0.319736i	0.432097
-0.290648 + 0.319736i	0.432097
0.363161	0.363161

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Cancer - Investment

Root	Modulus
0.339254 - 0.628276i	0.714020
0.339254 + 0.628276i	0.714020
-0.378584 - 0.569860i	0.684154
-0.378584 + 0.569860i	0.684154
0.234857 - 0.640792i	0.682475
0.234857 + 0.640792i	0.682475
-0.487023 - 0.355524i	0.602983
-0.487023 + 0.355524i	0.602983
-0.553819	0.553819
-0.290008 - 0.417889i	0.508661
-0.290008 + 0.417889i	0.508661
-0.484902	0.484902
0.208024 - 0.360037i	0.415813
0.208024 + 0.360037i	0.415813
0.350123	0.350123

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Cancer - Investment
Inclusion of Crisis Dummy

Root	Modulus
0.340156 - 0.628210i	0.714390
0.340156 + 0.628210i	0.714390
-0.378586 - 0.569520i	0.683872
-0.378586 + 0.569520i	0.683872
0.235224 - 0.641322i	0.683099
0.235224 + 0.641322i	0.683099
-0.488335 - 0.356373i	0.604543
-0.488335 + 0.356373i	0.604543
-0.550666	0.550666
-0.302529 - 0.415211i	0.513735
-0.302529 + 0.415211i	0.513735
-0.491810	0.491810
0.220834 - 0.384625i	0.443514
0.220834 + 0.384625i	0.443514
0.354438	0.354438

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Opinion Poll

Root	Modulus
0.391546 - 0.614554i	0.728687
0.391546 + 0.614554i	0.728687
-0.243473 - 0.608308i	0.655223
-0.243473 + 0.608308i	0.655223
0.313825 - 0.520865i	0.608101
0.313825 + 0.520865i	0.608101
-0.433121 - 0.332297i	0.545908
-0.433121 + 0.332297i	0.545908
-0.541734	0.541734
-0.279167 - 0.424244i	0.507856
-0.279167 + 0.424244i	0.507856
-0.460039	0.460039
0.214029 - 0.359737i	0.418592
0.214029 + 0.359737i	0.418592
0.334074	0.334074

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Opinion Poll
Inclusion of Crisis Dummy

Root	Modulus
0.367792 - 0.598783i	0.702718
0.367792 + 0.598783i	0.702718
-0.305803 - 0.561134i	0.639052
-0.305803 + 0.561134i	0.639052
0.298019 - 0.546648i	0.622606
0.298019 + 0.546648i	0.622606
-0.444751 - 0.334066i	0.556241
-0.444751 + 0.334066i	0.556241
-0.503918	0.503918
-0.255543 - 0.412334i	0.485099
-0.255543 + 0.412334i	0.485099
-0.442280	0.442280
0.221948 - 0.357400i	0.420709
0.221948 + 0.357400i	0.420709
0.337175	0.337175

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Opinion Poll- Investment

Root	Modulus
0.387774 - 0.621612i	0.732646
0.387774 + 0.621612i	0.732646
0.302290 - 0.635410i	0.703651
0.302290 + 0.635410i	0.703651
-0.299352 - 0.558379i	0.633560
-0.299352 + 0.558379i	0.633560
-0.505336 - 0.358492i	0.619581
-0.505336 + 0.358492i	0.619581
-0.500870	0.500870
-0.282139 - 0.401746i	0.490920
-0.282139 + 0.401746i	0.490920
-0.477259	0.477259
0.223491 - 0.402897i	0.460732
0.223491 + 0.402897i	0.460732
0.373086	0.373086

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Opinion Poll - Investment
Inclusion of Crisis Dummy

Root	Modulus
0.394123 - 0.624841i	0.738755
0.394123 + 0.624841i	0.738755
0.326963 - 0.624551i	0.704960
0.326963 + 0.624551i	0.704960
-0.244733 - 0.605267i	0.652873
-0.244733 + 0.605267i	0.652873
-0.498971 - 0.357892i	0.614051
-0.498971 + 0.357892i	0.614051
-0.545695	0.545695
-0.293114 - 0.411539i	0.505253
-0.293114 + 0.411539i	0.505253
-0.488174	0.488174
0.222020 - 0.404744i	0.461639
0.222020 + 0.404744i	0.461639
0.374163	0.374163

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Disaster

Root	Modulus
0.338340 - 0.634112i	0.718729
0.338340 + 0.634112i	0.718729
-0.352480 - 0.602692i	0.698198
-0.352480 + 0.602692i	0.698198
0.297541 - 0.620149i	0.687834
0.297541 + 0.620149i	0.687834
-0.670370	0.670370
-0.490032 - 0.357780i	0.606743
-0.490032 + 0.357780i	0.606743
-0.296719 - 0.412537i	0.508163
-0.296719 + 0.412537i	0.508163
-0.488553	0.488553
0.225393 - 0.394882i	0.454680
0.225393 + 0.394882i	0.454680
0.358992	0.358992

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Disaster
Inclusion of Crisis Dummy

Root	Modulus
0.339730 - 0.637152i	0.722066
0.339730 + 0.637152i	0.722066
-0.496409 - 0.362521i	0.614690
-0.496409 + 0.362521i	0.614690
-0.526729	0.526729
-0.302105 - 0.402178i	0.503005
-0.302105 + 0.402178i	0.503005
0.488562	0.488562
-0.141504 - 0.451122i	0.472794
-0.141504 + 0.451122i	0.472794
0.356582 - 0.298088i	0.464766
0.356582 + 0.298088i	0.464766
-0.453089	0.453089
0.161398 - 0.421130i	0.450998
0.161398 + 0.421130i	0.450998

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Disaster-Investment

Root	Modulus
0.324699 - 0.508157i	0.603037
0.324699 + 0.508157i	0.603037
-0.483309 - 0.355277i	0.599841
-0.483309 + 0.355277i	0.599841
-0.557249	0.557249
-0.280696 - 0.440404i	0.522251
-0.280696 + 0.440404i	0.522251
-0.132491 - 0.495451i	0.512860
-0.132491 + 0.495451i	0.512860
0.485865	0.485865
0.193654 - 0.440646i	0.481322
0.193654 + 0.440646i	0.481322
0.356962 - 0.282387i	0.455153
0.356962 + 0.282387i	0.455153
-0.435242	0.435242

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Disaster-Investment
Inclusion of Crisis Dummy

Root	Modulus
0.337682 - 0.633761i	0.718110
0.337682 + 0.633761i	0.718110
-0.352759 - 0.602862i	0.698485
-0.352759 + 0.602862i	0.698485
0.297610 - 0.620857i	0.688502
0.297610 + 0.620857i	0.688502
-0.670924	0.670924
-0.488699 - 0.357084i	0.605257
-0.488699 + 0.357084i	0.605257
-0.283664 - 0.416398i	0.503838
-0.283664 + 0.416398i	0.503838
-0.486395	0.486395
0.213119 - 0.370184i	0.427148
0.213119 + 0.370184i	0.427148
0.353854	0.353854

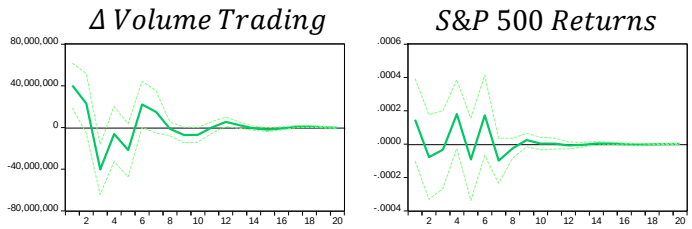
No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification: *Terrorism*		VAR specification: *Terrorism* *Inclusion of Crisis Dummy*		VAR specification: *Terrorism - Investment*		VAR specification: *Terrorism - Investment* *Inclusion of Crisis Dummy*	
Root	Modulus	Root	Modulus	Root	Modulus	Root	Modulus
0.345967 - 0.626446i	0.715630	0.345306 - 0.626511i	0.715369	-0.789914	0.789914	-0.789861	0.789861
0.345967 + 0.626446i	0.715630	0.345306 + 0.626511i	0.715369	0.357181 - 0.692937i	0.779576	0.356994 - 0.693244i	0.779764
0.336159 - 0.568390i	0.660356	0.336459 - 0.567815i	0.660014	0.357181 + 0.692937i	0.779576	0.356994 + 0.693244i	0.779764
0.336159 + 0.568390i	0.660356	0.336459 + 0.567815i	0.660014	-0.384454 - 0.670051i	0.772511	-0.384383 - 0.669898i	0.772343
-0.492071 - 0.357007i	0.607937	-0.490752 - 0.356235i	0.606417	-0.384454 + 0.670051i	0.772511	-0.384383 + 0.669898i	0.772343
-0.492071 + 0.357007i	0.607937	-0.490752 + 0.356235i	0.606417	0.338256 - 0.633234i	0.717915	0.338867 - 0.633298i	0.718260
-0.246029 - 0.539524i	0.592972	-0.245909 - 0.539847i	0.593216	0.338256 + 0.633234i	0.717915	0.338867 + 0.633298i	0.718260
-0.246029 + 0.539524i	0.592972	-0.245909 + 0.539847i	0.593216	-0.491935 - 0.357492i	0.608112	-0.493234 - 0.358359i	0.609673
-0.542778	0.542778	-0.542650	0.542650	-0.491935 + 0.357492i	0.608112	-0.493234 + 0.358359i	0.609673
-0.303316 - 0.410412i	0.510331	-0.291019 - 0.413103i	0.505318	-0.284769 - 0.416650i	0.504669	-0.297528 - 0.412713i	0.508777
-0.303316 + 0.410412i	0.510331	-0.291019 + 0.413103i	0.505318	-0.284769 + 0.416650i	0.504669	-0.297528 + 0.412713i	0.508777
-0.486760	0.486760	-0.484789	0.484789	-0.487721	0.487721	-0.489577	0.489577
0.228970 - 0.403735i	0.464144	0.215383 - 0.382051i	0.438580	0.212004 - 0.377430i	0.432896	0.225706 - 0.400480i	0.459703
0.228970 + 0.403735i	0.464144	0.215383 + 0.382051i	0.438580	0.212004 + 0.377430i	0.432896	0.225706 + 0.400480i	0.459703
0.368471	0.368471	0.365824	0.365824	0.364598	0.364598	0.367109	0.367109
No root lies outside the unit circle. VAR satisfies the stability condition.		No root lies outside the unit circle. VAR satisfies the stability condition.		No root lies outside the unit circle. VAR satisfies the stability condition.		No root lies outside the unit circle. VAR satisfies the stability condition.	

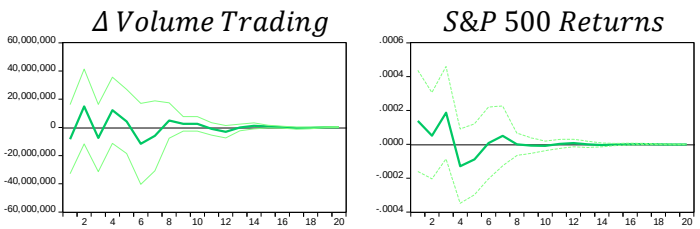
A6 – Impulse Response Functions dynamics without the inclusion of Crisis Dummy (Regressions (i) and (iii) - Daily VARs)

Response to Cholesky One S.D. Innovations:

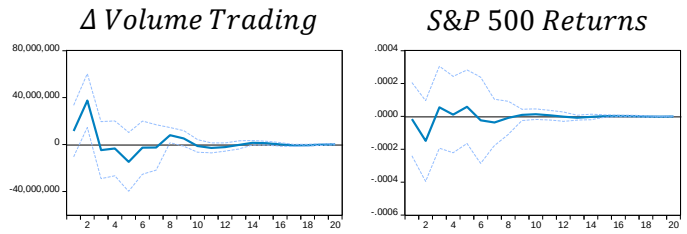
Δ ASVI{Cancer}



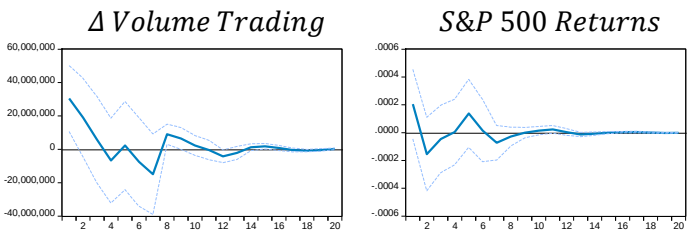
Δ ASVI{*Investment* Cancer}



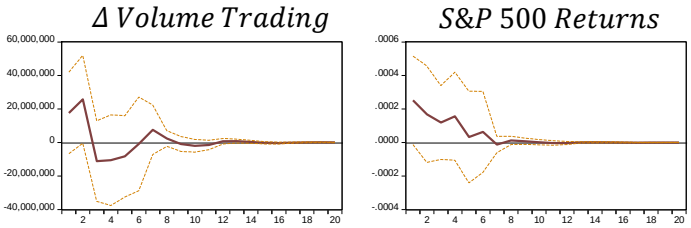
Δ ASVI{Opinion Poll}



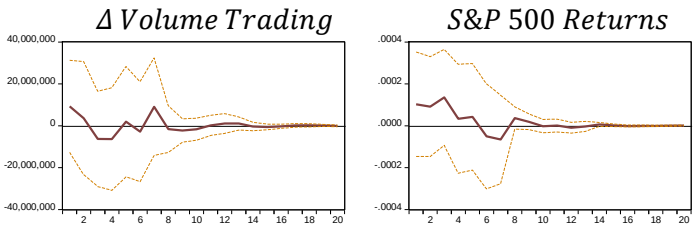
Δ ASVI{*Investment* Opinion Poll}



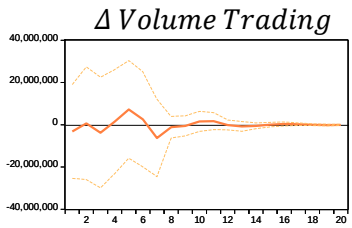
Δ ASVI{Natural Disaster}

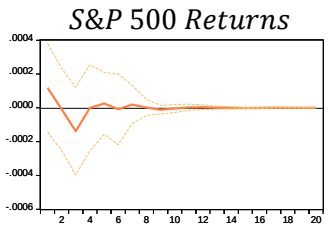


Δ ASVI{*Investment* Natural Disaster}

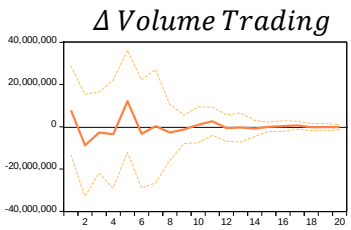


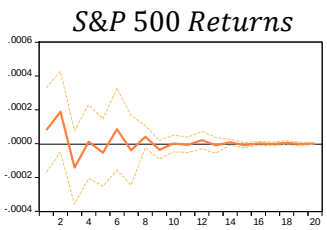
Δ ASVI{Terrorism}





Δ ASVI{*Investment* Terrorism}





A7 – Stability of <u>Monthly</u> VARs: AR Roots Tables

VAR specification:
Cancer – Investment
Dummy Trend SVI

Root	Modulus
0.988837 - 0.016050i	0.988967
0.988837 + 0.016050i	0.988967
0.959867 - 0.083789i	0.963517
0.959867 + 0.083789i	0.963517
0.097477	0.097477
-0.000699	0.000699

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Disaster
Dummy Trend SVI

Root	Modulus
0.989093 - 0.016031i	0.989223
0.989093 + 0.016031i	0.989223
0.960107 - 0.108468i	0.966214
0.960107 + 0.108468i	0.966214
0.154913	0.154913
0.024666	0.024666

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Opinion Poll-Investment
Trend SVI

Root	Modulus
0.988975 - 0.017215i	0.989125
0.988975 + 0.017215i	0.989125
0.957302 - 0.108952i	0.963482
0.957302 + 0.108952i	0.963482
0.503694	0.503694
0.020703	0.020703

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Terrorism - Investment
SVI

Root	Modulus
0.988485 - 0.016031i	0.988615
0.988485 + 0.016031i	0.988615
0.959919 - 0.106663i	0.965827
0.959919 + 0.106663i	0.965827
0.233697	0.233697
0.092266	0.092266

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Cancer
SVI

Root	Modulus
0.988929 - 0.016590i	0.989068
0.988929 + 0.016590i	0.989068
0.959661 - 0.083371i	0.963276
0.959661 + 0.083371i	0.963276
0.307961	0.307961
0.128813	0.128813

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Disaster
SVI

Root	Modulus
0.988792 - 0.016790i	0.988934
0.988792 + 0.016790i	0.988934
0.960677 - 0.083977i	0.964340
0.960677 + 0.083977i	0.964340
0.364540	0.364540
0.070160	0.070160

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Opinion Poll
SVI

Root	Modulus
0.988487 - 0.016362i	0.988623
0.988487 + 0.016362i	0.988623
0.959199 - 0.083157i	0.962796
0.959199 + 0.083157i	0.962796
0.412788	0.412788
0.110372	0.110372

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Terrorism
SVI

Root	Modulus
0.987927 - 0.015739i	0.988052
0.987927 + 0.015739i	0.988052
0.956439 - 0.082438i	0.959985
0.956439 + 0.082438i	0.959985
0.455322	0.455322
0.069501	0.069501

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Cancer
Dummy SVI

Root	Modulus
0.988751 - 0.016447i	0.988888
0.988751 + 0.016447i	0.988888
0.959497 - 0.083572i	0.963130
0.959497 + 0.083572i	0.963130
0.108012	0.108012
0.032735	0.032735

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Disaster
Dummy SVI

Root	Modulus
0.989086 - 0.016510i	0.989224
0.989086 + 0.016510i	0.989224
0.959788 - 0.084325i	0.963486
0.959788 + 0.084325i	0.963486
0.236129	0.236129
0.044355	0.044355

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Opinion Poll
Dummy SVI

Root	Modulus
0.989795 - 0.017167i	0.989943
0.989795 + 0.017167i	0.989943
0.959504 - 0.082926i	0.963081
0.959504 + 0.082926i	0.963081
0.406708	0.406708
0.139892	0.139892

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Terrorism
Dummy SVI

Root	Modulus
0.988600 - 0.016416i	0.988736
0.988600 + 0.016416i	0.988736
0.958007 - 0.083153i	0.961609
0.958007 + 0.083153i	0.961609
0.479850	0.479850
0.078644	0.078644

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Cancer
Trend SVI

Root	Modulus
0.988837 - 0.016050i	0.988967
0.988837 + 0.016050i	0.988967
0.959867 - 0.083789i	0.963517
0.959867 + 0.083789i	0.963517
0.097477	0.097477
-0.000699	0.000699

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Disaster
Trend SVI

Root	Modulus
0.989093 - 0.016031i	0.989223
0.989093 + 0.016031i	0.989223
0.960107 - 0.108468i	0.966214
0.960107 + 0.108468i	0.966214
0.154913	0.154913
0.024666	0.024666

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Opinion Poll
Trend SVI

Root	Modulus
0.988975 - 0.017215i	0.989125
0.988975 + 0.017215i	0.989125
0.957302 - 0.108952i	0.963482
0.957302 + 0.108952i	0.963482
0.503694	0.503694
0.020703	0.020703

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Terrorism
Trend SVI

Root	Modulus
0.988485 - 0.016031i	0.988615
0.988485 + 0.016031i	0.988615
0.959919 - 0.106663i	0.965827
0.959919 + 0.106663i	0.965827
0.233697	0.233697
0.092266	0.092266

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Carcinoma
Dummy SVI

Root	Modulus
0.988751 - 0.016447i	0.988888
0.988751 + 0.016447i	0.988888
0.959497 - 0.083572i	0.963130
0.959497 + 0.083572i	0.963130
0.108012	0.108012
0.032735	0.032735

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Natural Catastrophe-Inv.
Dummy SVI

Root	Modulus
0.989086 - 0.016510i	0.989224
0.989086 + 0.016510i	0.989224
0.959788 - 0.084325i	0.963486
0.959788 + 0.084325i	0.963486
0.236129	0.236129
0.044355	0.044355

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Vote-Investment
Trend SVI

Root	Modulus
0.989795 - 0.017167i	0.989943
0.989795 + 0.017167i	0.989943
0.959504 - 0.082926i	0.963081
0.959504 + 0.082926i	0.963081
0.406708	0.406708
0.139892	0.139892

No root lies outside the unit circle.
VAR satisfies the stability condition.

VAR specification:
Organized Crime
SVI

Root	Modulus
0.988600 - 0.016416i	0.988736
0.988600 + 0.016416i	0.988736
0.958007 - 0.083153i	0.961609
0.958007 + 0.083153i	0.961609
0.479850	0.479850
0.078644	0.078644

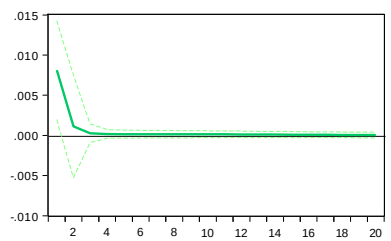
No root lies outside the unit circle.
VAR satisfies the stability condition.

A8 – Monthly VARs-Impulse Response Functions dynamics

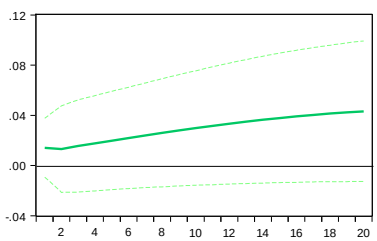
*Response to Cholesky One S.D. Innovations - **SVI** Uncertainty Metrics*

CANCER

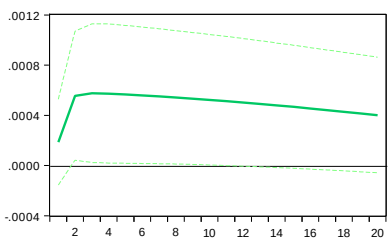
S&P 500 Returns



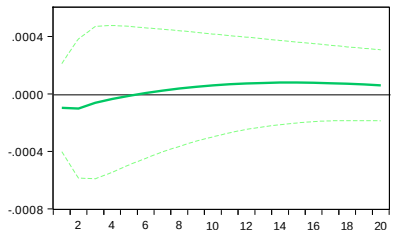
Avg. interest rate of 3MTBILL



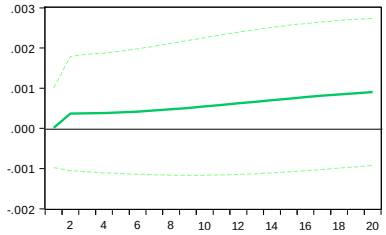
Consumer Confidence



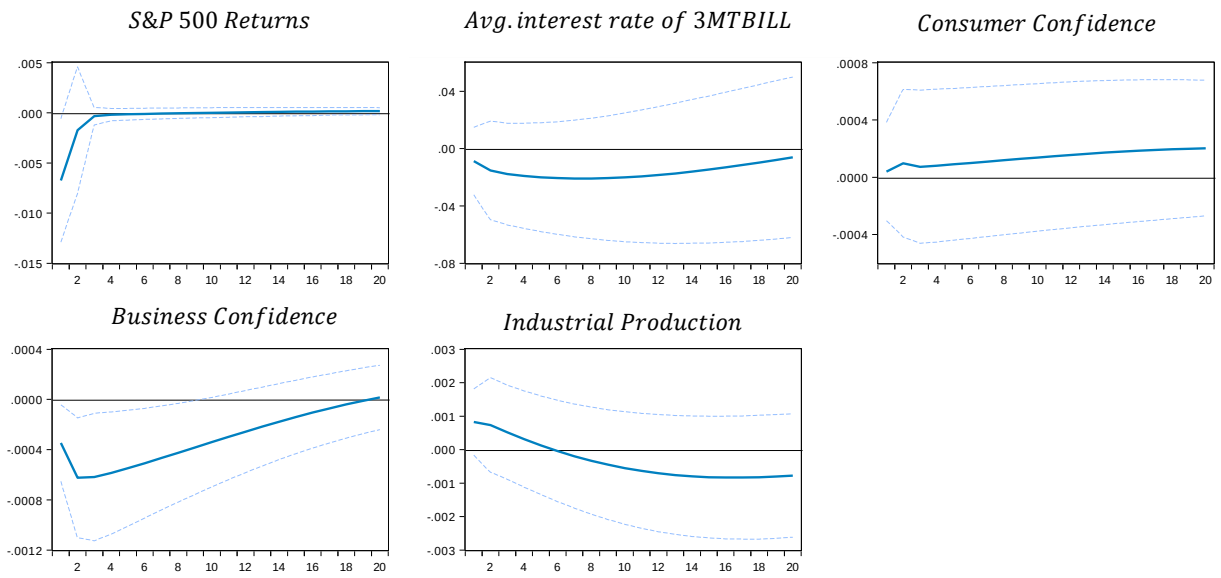
Business Confidence



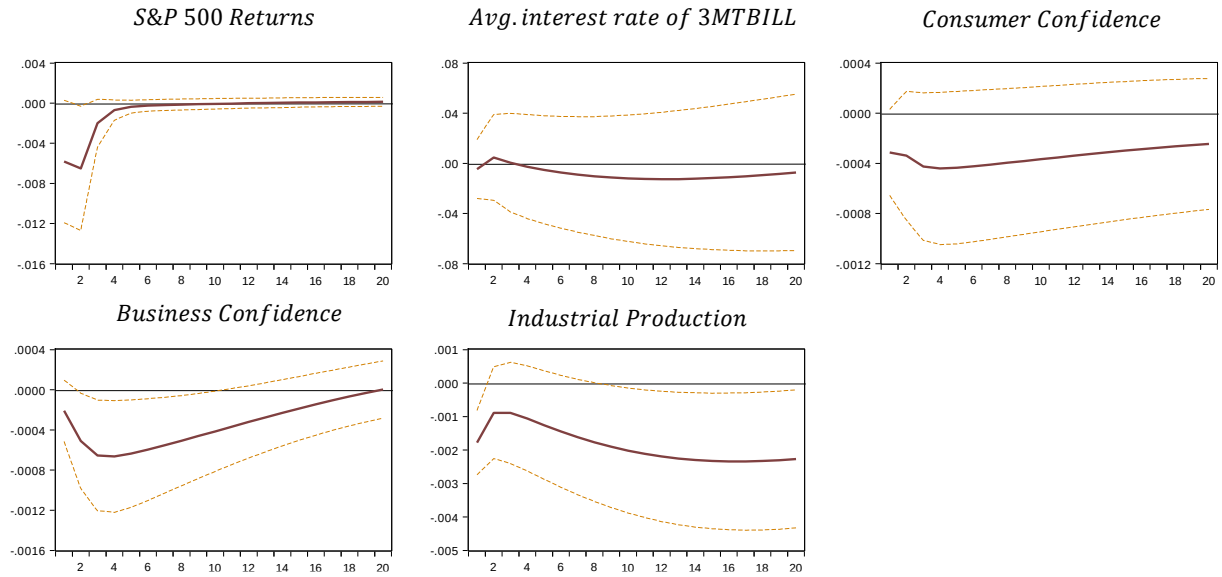
Industrial Production



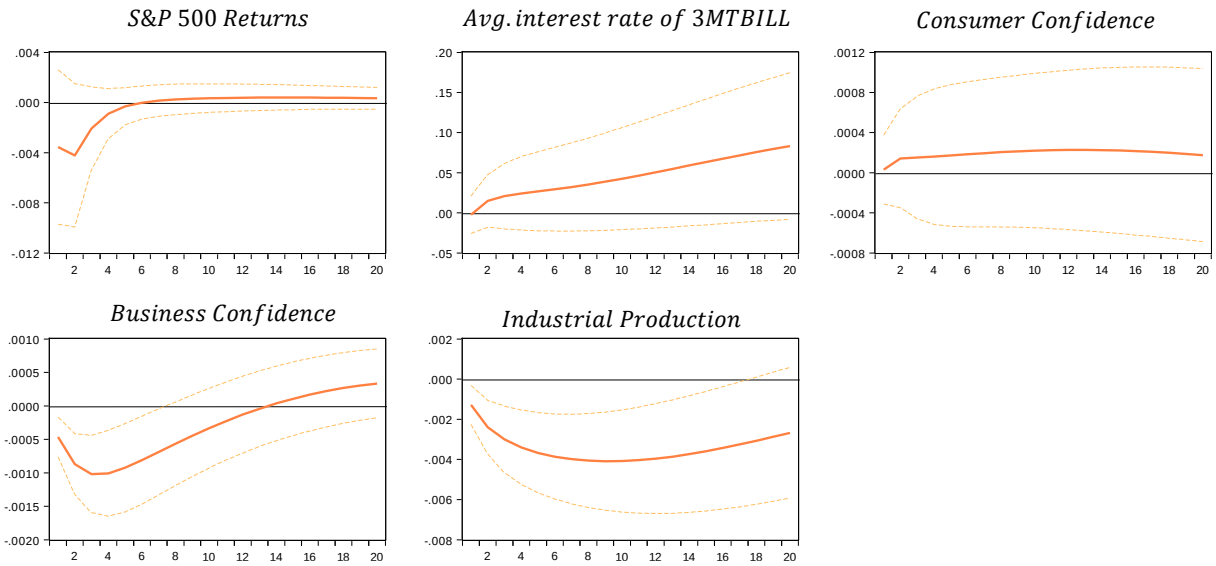
OPINION POLL



NATURAL DISASTER

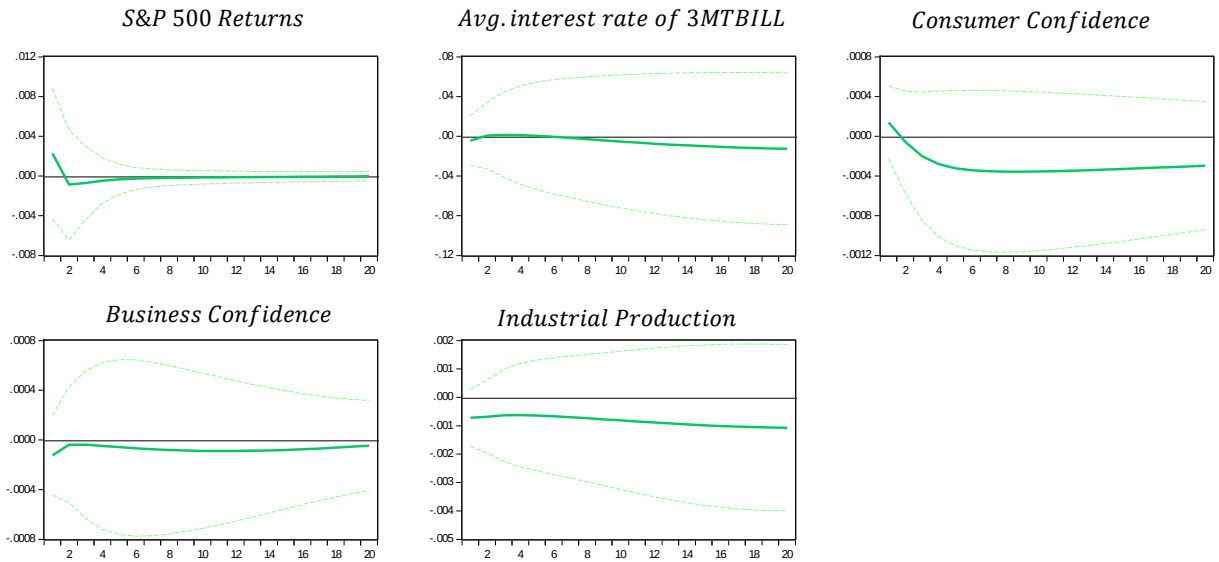


TERRORISM

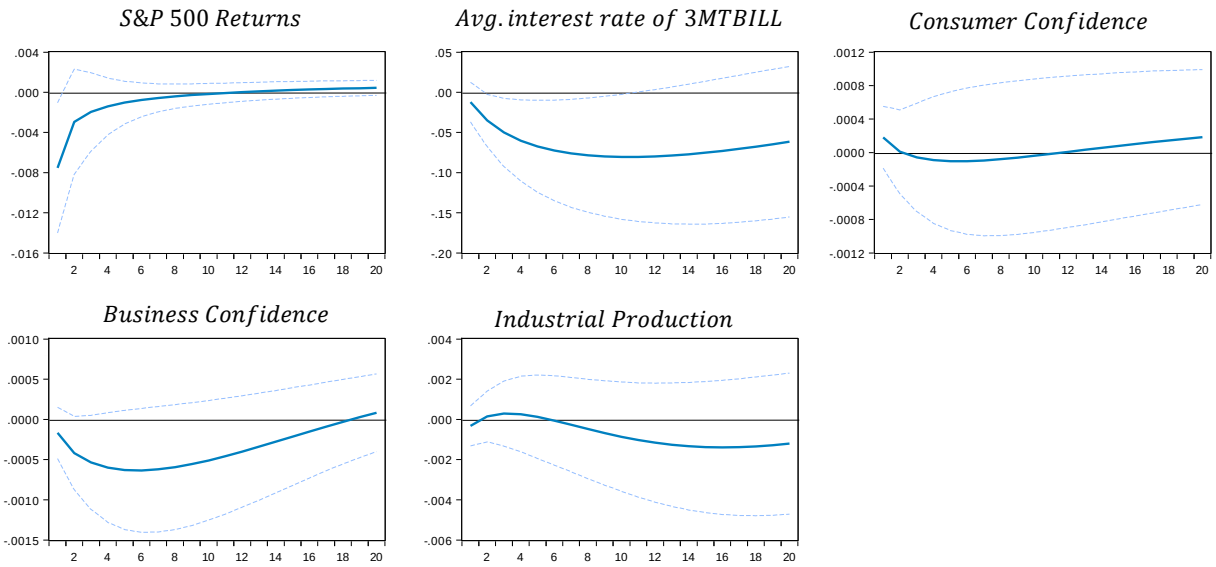


*Response to Cholesky One S.D. Innovations - **Trend** **SVI** Uncertainty Metrics*

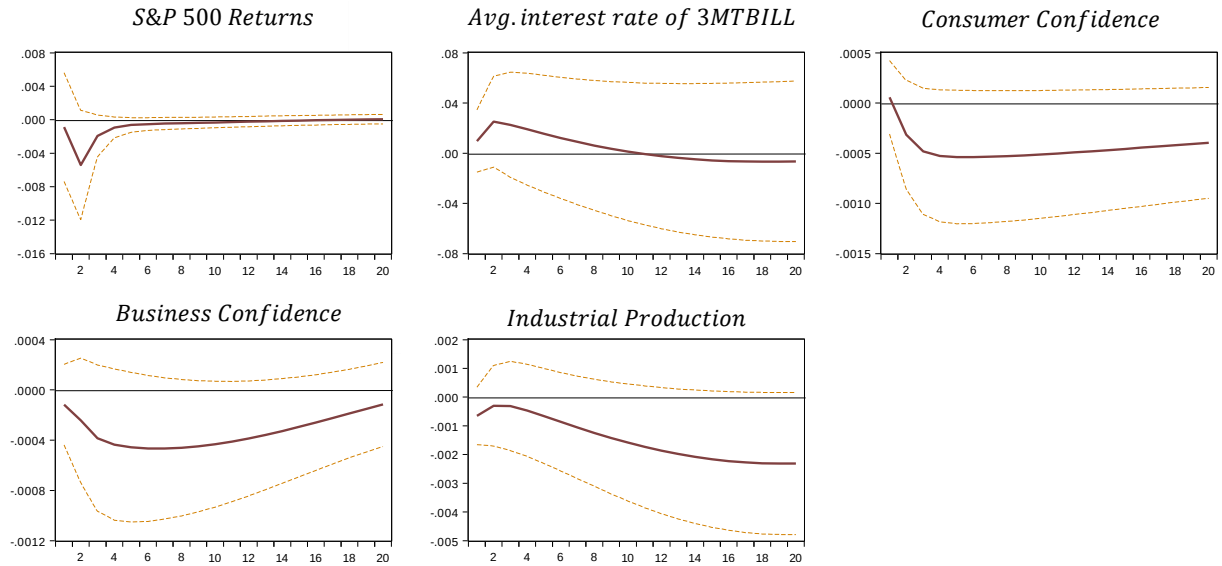
CANCER



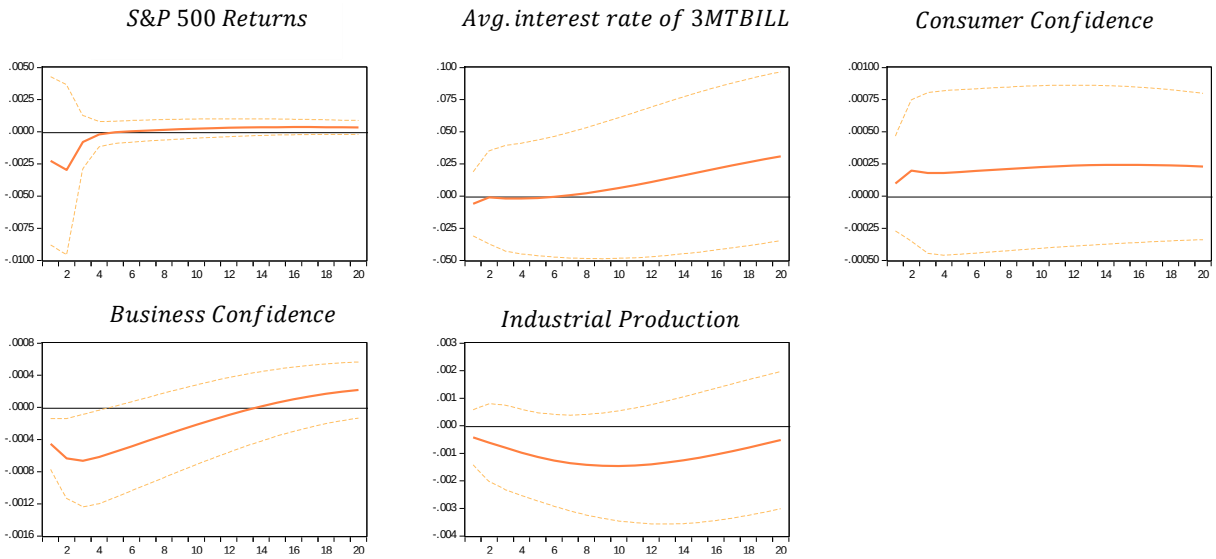
OPINION POLL



NATURAL DISASTER

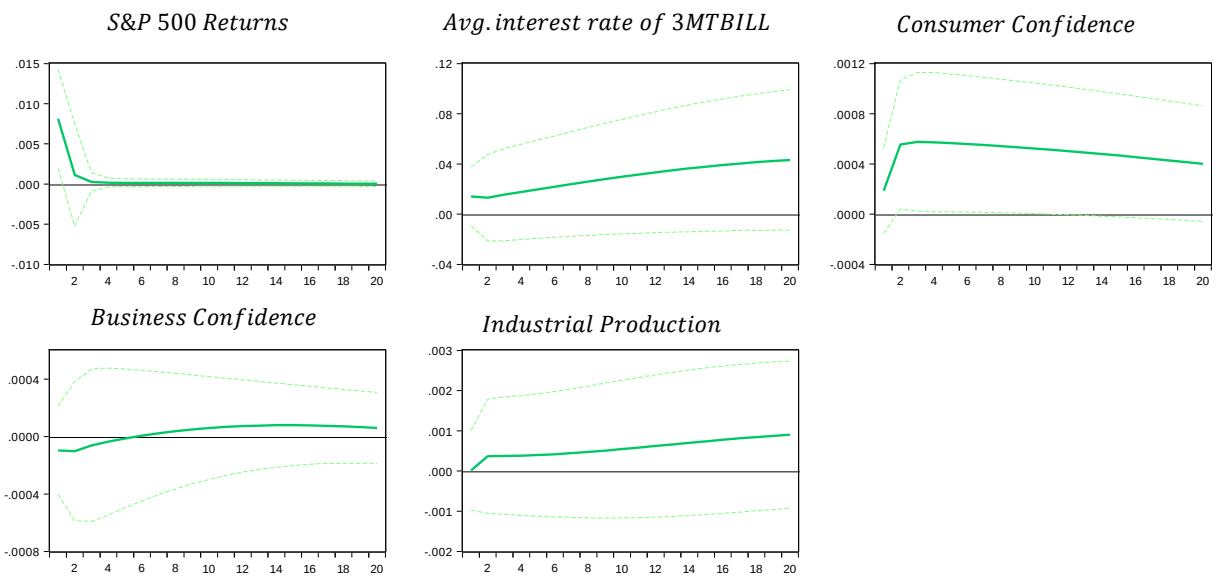


TERRORISM

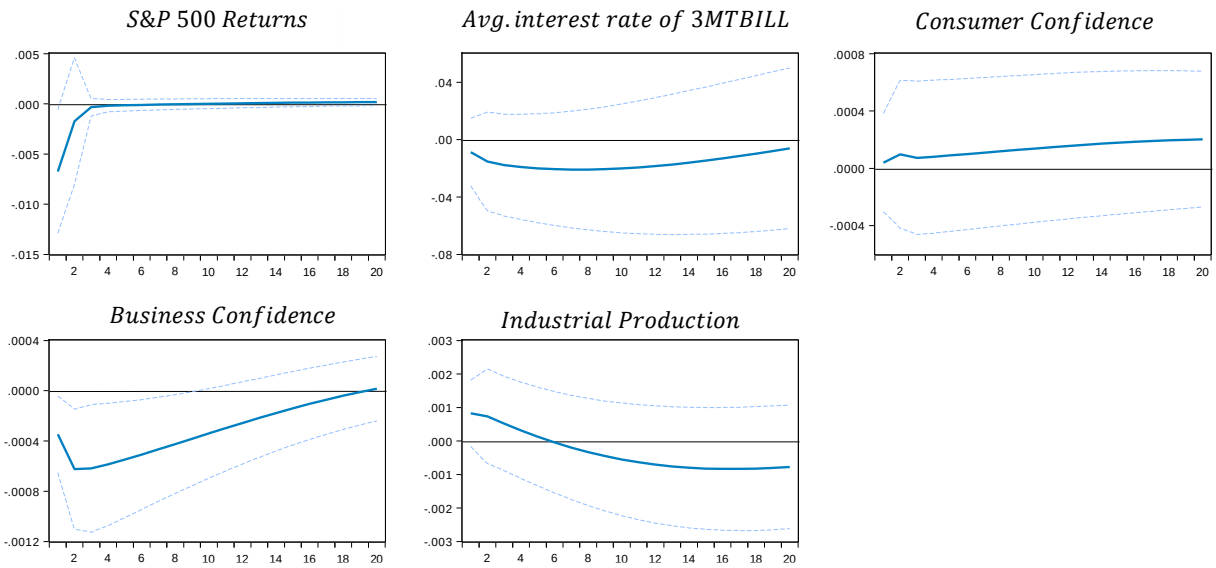


*Response to Cholesky One S.D. Innovations - **Dummy** **SVI** Uncertainty Metrics*

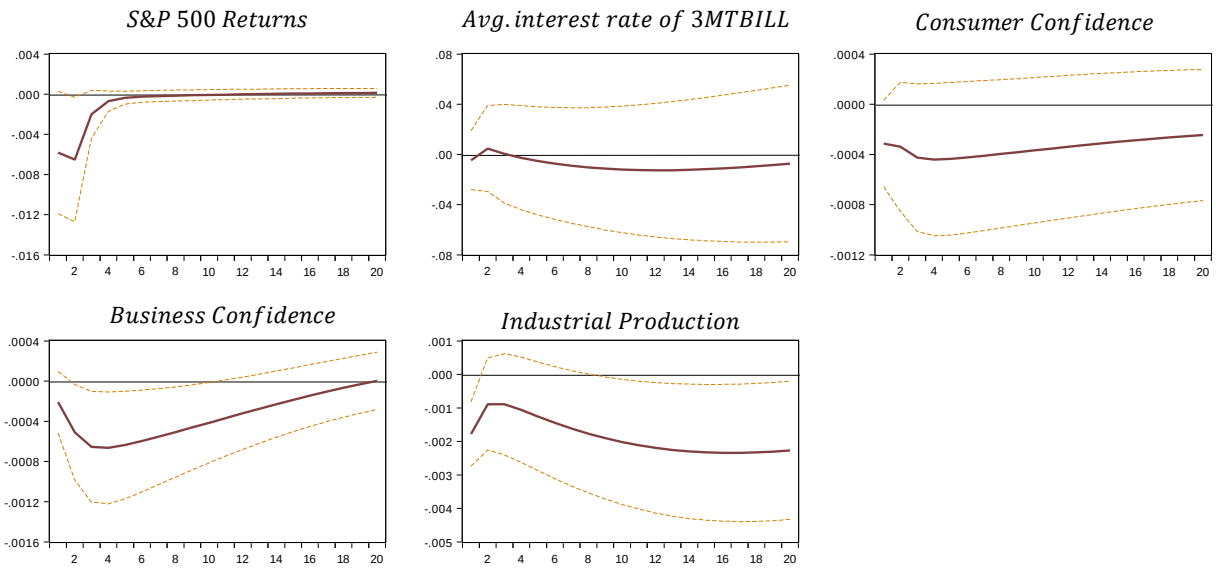
CANCER



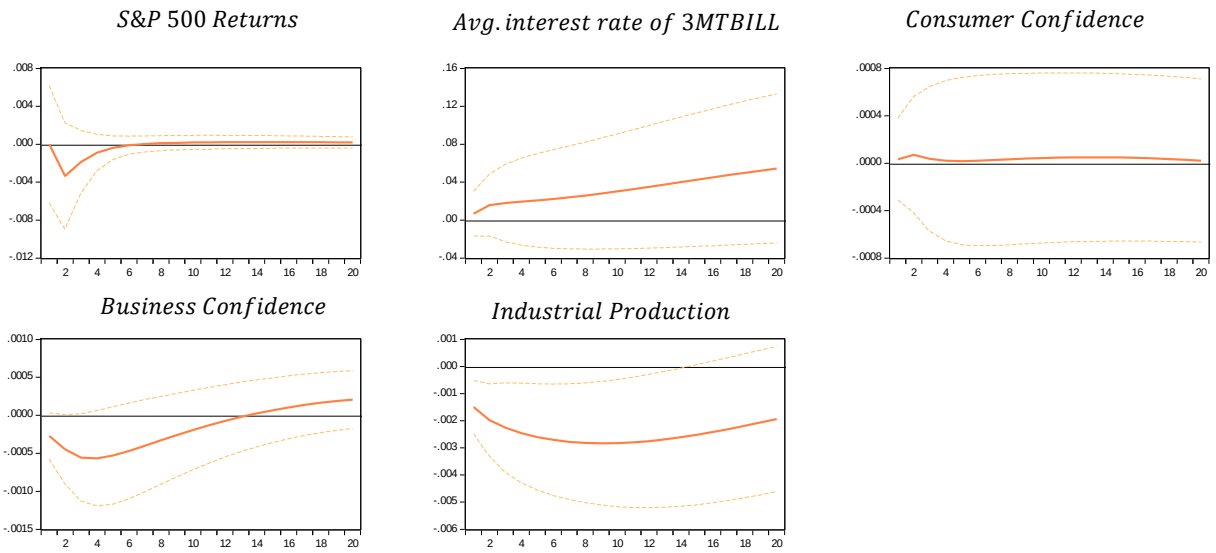
OPINION POLL



NATURAL DISASTER



TERRORISM



A9 – Monthly VAR Coefficient Estimates: Alternative Search-based uncertainty and Macroeconomic conditions

The circled uncertainty metric are those displayed and analysed in section 5.1

Predicting Monthly Macroeconomic Conditions Using ***Carcinoma Google searches*** *as sources of uncertainty*

Term: CARCINOMA								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	-0.000254	-0.002884	0.001236	-0.033548	0.000188	0.006378	-0.006169	-0.009631
	[-0.52775]	[-0.19825]	[0.05307]	[-0.82305]	[0.70587]	[0.43769]	[-0.23961]	[-0.40276]
3TBILL	0.002262	0.047494	-0.246790 ***	-0.003906	0.000383	0.011070	-0.023182	0.002728
	[1.24178]	[0.86242]	[-2.86467]	[-0.02513]	[0.37851]	[0.20008]	[-0.23670]	[0.03013]
CCI	-2.40E-05	-0.001106	-0.001367	-0.000953	1.69E-05	0.000569	-0.001164	0.000534
	[-0.89898]	[-1.38034]	[-1.04521]	[-0.41383]	[1.14748]	[0.70551]	[-0.80348]	[0.39923]
BCI	-5.61E-05 **	-0.000977	7.22E-05	-0.002234	1.56E-05	0.000937	-0.000869	-0.000910
	[-2.38996]	[-1.36656]	[0.06333]	[-1.12190]	[1.18705]	[1.30631]	[-0.69037]	[-0.77922]
IP	-9.14E-05	-0.004775 **	-0.004133	-0.003471	9.94E-05 **	0.005805 ***	0.000711	-0.002286
	[-1.18849]	[-2.07743]	[-1.16674]	[-0.55641]	[2.37138]	[2.53631]	[0.18058]	[-0.62889]

Predicting Monthly Macroeconomic Conditions Using ***Natural Catastrophe Google searches*** *as sources of uncertainty*

Term: NATURAL CATASTROPHE								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	0.000229	0.010776	0.006618	0.011907	0.000101	-0.022861*	-0.000376	0.002118
	[1.16627]	[0.79020]	[1.56059]	[0.82459]	[0.62853]	[-1.78167]	[-0.04894]	[0.15708]
3TBILL	0.000399	0.031048	-0.021244	-0.028283	0.000285	0.014712	0.004820	-0.027505
	[0.53440]	[0.59945]	[-1.31361]	[-0.51687]	[0.46760]	[0.29916]	[0.16509]	[-0.53955]
CCI	2.82E-06	0.001359*	0.000176	0.000537	6.03E-06	-7.77E-05	-0.000194	0.000102
	[0.25770]	[1.81339]	[0.73137]	[0.66435]	[0.67563]	[-0.10811]	[-0.44823]	[0.13462]
BCI	-5.67E-06	-0.000660	-9.33E-06	0.001204*	-2.78E-06	-0.001199**	0.000497	-0.000316
	[-0.58132]	[-0.97945]	[-0.04458]	[1.71833]	[-0.34881]	[-1.89277]	[1.33149]	[-0.47926]
IP	6.08E-06	0.000126	-9.16E-05	0.000768	3.91E-06	-0.003204	3.04E-05	0.000590
	[0.19291]	[0.05747]	[-0.14018]	[0.34894]	[0.15196]	[-1.55463]	[0.02590]	[0.28757]

Predicting Monthly Macroeconomic Conditions Using ***Vote Google searches*** *as sources of uncertainty*

Term: VOTE								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	1.93E-05	0.008727	-0.000636	-0.005365	0.000116	0.012157	-0.003028	-0.017995
	[0.06872]	[0.58402]	[-0.34643]	[-0.38815]	[0.38220]	[0.80374]	[-0.79673]	[-1.14026]
3TBILL	-0.000874	0.024307	0.013118*	0.141465***	-0.000492	0.022920	0.005628	0.033610
	[-0.82199]	[0.42844]	[1.90085]	[2.75987]	[-0.42569]	[0.39868]	[0.38864]	[0.55794]
CCI	2.07E-05	0.000588	-0.000125	-0.000829	1.45E-05	0.000842	-0.000218	-0.000886
	[1.33651]	[0.71022]	[-1.21168]	[-1.06745]	[0.86094]	[1.00511]	[-1.02117]	[-0.99490]
BCI	-1.28E-05	-0.000596	1.08E-06	0.000325	-5.41E-06	-0.000206	-0.000292	-0.000428
	[-0.92033]	[-0.80710]	[0.01201]	[0.48044]	[-0.35835]	[-0.27429]	[-1.58137]	[-0.55266]
IP	2.32E-05	-0.000735	-0.000319	-0.001693	-8.09E-06	-0.002073	-0.001152**	-0.002136
	[0.51603]	[-0.30667]	[-1.14079]	[-0.80287]	[-0.16601]	[-0.85551]	[-2.00570]	[-0.88403]

Predicting Monthly Macroeconomic Conditions Using ***Organized Crime Google searches*** *as sources of uncertainty*

Term: ORGANIZED CRIME								
	No category specification				*Investment*			
	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI	SVI	Dummy SVI	Trend SVI	Dummy Trend SVI
SP500	-0.000466*	-0.009096	0.008850	0.001474	0.000142	-0.003593	-0.000678	-0.003391
	[-1.61046]	[-0.64661]	[0.52100]	[0.09131]	[0.44761]	[-0.25953]	[-0.02150]	[-0.11496]
3TBILL	0.000472	0.013892	-0.193467***	-0.132674**	-0.001196	-0.032640	0.044478	0.013027
	[0.42702]	[0.25995]	[-3.08925]	[-2.20924]	[-0.99259]	[-0.62191]	[0.37100]	[0.11671]
CCI	-8.42E-06	0.000957	-0.002001	-0.000375	2.06E-05	0.000155	-0.001640	-0.000252
	[-0.52010]	[1.23135]	[-2.12008]	[-0.41543]	[1.16788]	[0.20116]	[-0.92560]	[-0.15291]
BCI	-2.95E-05**	-0.000793	0.000126	-0.000517	-1.97E-05	-0.001005	0.001206	-0.000616
	[-2.06589]	[-1.14280]	[0.15118]	[-0.65539]	[-1.25569]	[-1.47562]	[0.78266]	[-0.42738]
IP	-0.000122***	-0.004590**	-0.001293	0.002320	-1.66E-06	0.000195	-0.000691	0.000844
	[-2.66819]	[-2.06158]	[-0.49782]	[0.94754]	[-0.03256]	[0.08769]	[-0.14343]	[0.18799]

A10 - Figure 17

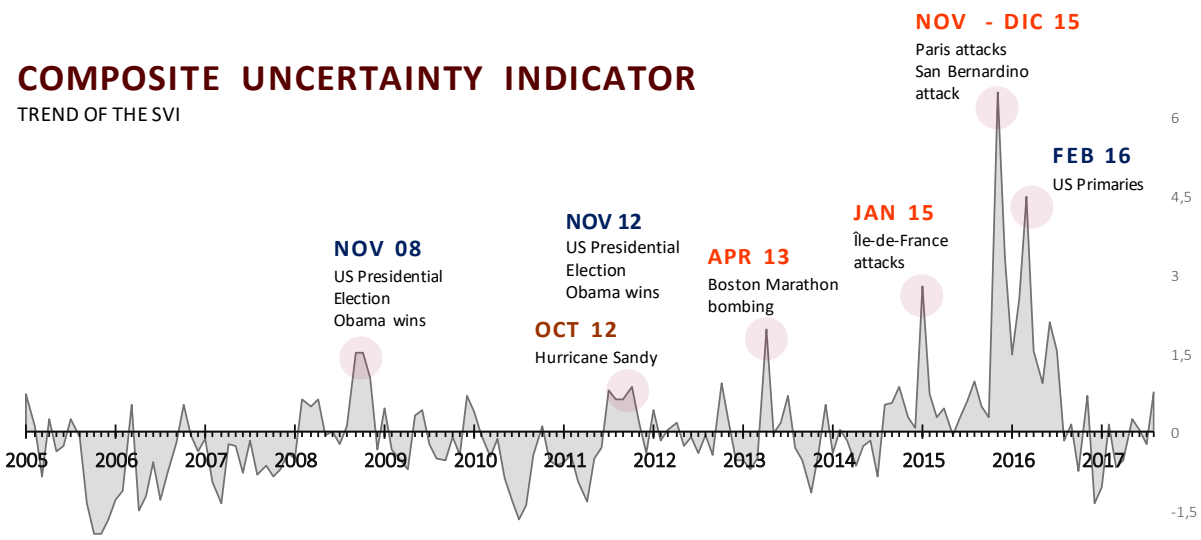


Figure 17 displays the dynamics of the composite uncertainty indicator built, via PCA, on the trends (each observation is divided by the value of the corresponding month one year ago) of the search volume for the terms "Terrorism", "Cancer", "Opinion Poll" and "Natural Disaster". The goal of the PCA is to come up with optimal weights, which can capture as much information in the original variables as possible, based on the correlations among those variables. The new variable is described by the component scores series, based on the observation's component loading and the standardized value of the original variable, summed over all variables ($Score_{ik} = \sum D_{ij} L_{jk}$ where $D_{ij}$is the standardized value for observation i on variable j and L_{jk} is the loading of variable j on component k). Vertical axis measures the magnitude (eigenvalues) of the relationship between factor loadings and original variables. Positive scores values implies positive relation between variables and factors, negative loadings express inverse direction.