Non-macro-based Google searches, uncertainty, and real economic activity ☆

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A B S T R A C T

We propose a set of novel non-macro-based uncertainty indicators that rely on the frequency of Google searches (NM-GSIs) for the following health-, environmental-, security-, and political-related topics: "Symptom", "Pollution", "Terrorism", and "Election". By means of VAR investigations, we document that an intensification of people interest in non-macro-based topics harms the US real economic activity. In particular, NM-GSI shocks generate (*i*) a significant drop in consumer credit and (*ii*) a mild decrease (increase) in production (unemployment) levels. Noteworthy, rising non-macro-based uncertainty is found to have stronger influence on the outstanding level of consumer credit than rising macro-based uncertainty. Our findings suggest that increasing interest in specific non-macro-based topics might be associated with raising people's anxiety. A battery of robustness checks confirms our main findings.

1. Introduction

The role of uncertainty in driving financial and macroeconomic aggregates has received a constantly rising amount of attention in the most recent literature. In his seminal paper, Bloom (2009) highlights the difference between first-moment and second-moment (uncertainty) shocks. In particular, he shows that uncertainty shocks "produce a rapid drop and rebound in aggregate output and employment". Research has focused mainly on the creation of macroeconomic policy-related uncertainty indexes. As highlighted in Bontempi et al. (2017), the most used can be categorized into (*i*) finance-based indexes (Bachmann et al., 2013), (*ii*) forecast-based measures (Bachmann et al., 2013; Jurado et al., 2015) and (*iii*) news-based measures (Baker et al., 2016; Caldara and Iacoviello, 2016; Bontempi et al., 2017).

Since Choi and Varian (2012), the economics academic community has started using data retrieved from Google Trends, i.e., search volume indexes based on specific words/topics of interest. Differently from filtering the perception of sentiment through journalists' feelings, measuring sentiment and uncertainty via rising Google searches on specific finance-related and economics-related keywords has the advantage to intercept the actual behaviour of internet users, which (today) constitute a relevant portion of the population. Recent empirical studies going in this direction are: Da et al. (2011, 2015), Dzielinski (2012), Donadelli (2015), Bijl et al. (2016), Castelnuovo and Tran (2017), Bontempi et al. (2017), Tran (2017) and Kim et al. (2018).

Still, all these (novel) studies have focused on keywords/topics relying exclusively on macroeconomic policy-related issues. For

example, Bontempi et al. (2017) have adopted the very same keywords used by Baker et al. (2016) for the construction of the Economic Policy Uncertainty (EPU) index, while Castelnuovo and Tran (2017) and Tran (2017) make use of the uncertainty-related keywords mentioned in the Federal Reserve's Beige Book for the United States and the Reserve Bank's Monetary Policy Statement for Australia (e.g., "bankruptcy", "stock market", "economic reform", "debt stabilization").

In the present work, we take a different stand by focusing on the search intensity of some terms that may influence (negatively) the mood of individuals, but that do not directly and strictly account for finance- or macroeconomic policy-related uncertainty. In other words, we develop a set of non-macro-related Google search-based uncertainty indicators (NM-GSIs) that rely on the frequency of internet searches for (*i*) "symptom" (i.e., a proxy for uncertainty related to health issues); (*ii*) "pollution" (i.e., a proxy for uncertainty related to environmental issues); (*iii*) "terrorism" (i.e., a proxy for uncertainty related to security issues), and (*iv*) "election" (i.e., a proxy for uncertainty related to political issues). The internet search intensity for the aforementioned non-macro topics is captured at monthly frequency for the period January 2004 - December 2017. In the spirit of recent studies focusing on the macroeconomic and financial implications of rising either news-based macroeconomic policy uncertainty or Google search-based macroeconomic policy uncertainty (see, among others, Dzielinski, 2012; Colombo, 2013; Da et al., 2015; Donadelli, 2015; Caggiano et al., 2017; Castelnuovo and Tran, 2017), our Google searches are limited to the US, where the market share of online search market held by Google is above 60%.[1] Moreover, focusing on the US allows us to compare the effects of Google search-based macroeconomic policy uncertainty shocks with those generated by a shock to our newly developed NM-GSIs.

By means of VAR investigations, we then inspect whether the anxiety and apprehension induced by non-macro-based uncertainty spills over to real economic and financial variables, i.e., stock market prices, long-term rates, consumer credit, industrial production, and unemployment rate. Our main empirical findings suggest that, although the impact is (on average) weaker than the one of macro-related uncertainty shocks (i.e., EPU shocks), there are significant effects of rising non-macro-based uncertainty on the real economic activity. In particular, as population's interest in "symptom", "pollution" or "terrorism" intensifies, consumer credit drops and, as a milder consequence, industrial production (unemployment rate) decreases (increases).

The rest of the paper is organized as follows. Section 2 briefly reviews the literature on uncertainty indicators based on the frequency of Google searches. Section 3 introduces and describes the newly developed NM-GSIs. The employed methodology and the related empirical findings are discussed in Section 4. Section 5 concludes.

2. Related literature: a focus on Google-search-based uncertainty

Our paper fits into a growing literature aimed at developing novel finance-related and macro-related uncertainty indicators based on the volume of internet searches and exploring their implications for financial and macroeconomic dynamics. In this respect, our work is most closely related to Da et al. (2011, 2015), Dzielinski (2012), Donadelli (2015), Bijl et al. (2016), Castelnuovo and Tran (2017), Bontempi et al. (2017) and Kim et al. (2018).

A stream of literature, originating from Da et al. (2011), focuses on the ability of internet search volume indexes based on keywords related to listed companies to predict stock market returns. The existing evidence are mixed. Specifically, Da et al. (2011) focuses on the stock ticker symbol or the main product for companies belonging to Russell 3000, from 2004 to 2008. They find that an increase in the search volume leads to a price increase followed, after one or two weeks, by a price reversal. Bijl et al. (2016) consider search volume indexes based on S&P500 listed company names for the period 2008-2013 and observe that rising internet searches predict low future excess returns. The authors argue that the different result obtained with respect to Da et al. (2011) is likely to be related to the different time period considered. Moreover, they develop a trading strategy based upon search volume indexes: the portfolio based upon this strategy is able to outperform the market portfolio, but not enough to outweigh the associated transaction costs. More recently, Kim et al. (2018) focus on the Norwegian stock market, and build search volume indexes based on the names of listed companies. They find no statistical evidence of any relationship between rising interest in listed companies and associated stock returns, while they find weak but significant evidence of a contemporary relationship and, to a larger extent, also predictive ability of search volume indexes on volatility and trading volume.

Differently from the aforementioned studies, Da et al. (2015) search for words that, more generically, reveal sentiment towards economic conditions like "recession", "bankruptcy" and "depression". These specific searches are then combined in order to construct a Financial and Economic Attitudes Revealed by Search index (FEARS). Da et al. (2015) find that FEARS actually predicts aggregate market returns. Specifically, low returns today and high returns tomorrow. Dzielinski (2012) builds a measure of uncertainty on searches by US users of a single, but widespread, keyword: "economy". Moreover, he transforms the raw series using an year-over-year ratio. His measure is positively correlated with alternative measures of uncertainty and negatively with measures of investor confidence, and the impact on the financial markets is consistent with the drop-and-rebound observed by Bloom (2009).

Google search-based uncertainty indicators have been used to analyse the effects not only on financial markets, but also on the real economic activity. Donadelli (2015) develops three uncertainty indexes based on Google searches (GSIs) for the following keywords: "US stock market", "US politics" and "US Fed". He finds that GSI shocks produce significant adverse effects on main macroeconomic indicators, i.e., (*i*) a rise in unemployment and (*ii*) a drop in share prices, long-term rates, industrial production, consumer credit and consumer confidence.

In a similar fashion, Castelnuovo and Tran (2017) explore the effect of shocks to Google-search-based uncertainty indexes on real

variables for Australia and the US. They document an economically and statistically significant contribution to unemployment dynamics for the US and a milder effect for Australia. Differently from Dzielinski (2012) and Donadelli (2015), the index developed by Castelnuovo and Tran (2017) is based on a wide range of keywords mentioned in the Federal Reserve's Beige Book for the United States and the Reserve Bank's Monetary Policy Statement for Australia.

Finally, in the spirit of Baker et al. (2016), Bontempi et al. (2017) present an uncertainty measure that relies on Google searches for "economy" or "economic" plus "uncertain" or "uncertainty" and one or more policy-relevant terms. They find that for some topics journalists lead the general interest of the public, while for other topics they react to the increased interests of their readers. They also reject the dynamics suggested by Bloom (2009) and conclude that (*i*) "finance-based uncertainty induces overshooting effects", (*ii*) "forecast-based uncertainty induces very persistent effects", and (*iii*) "news-based uncertainty induces transitory effects".

Our newly-developed NM-GSIs complement other existing measures of uncertainty, allowing to measure the genuine interest of the population towards a variety of "anxiety-provoking topics". Actually, as opposed to the existing empirical works, our NM-GSIs do not strictly rely on finance- or macro-related terms, but can be associated to anxiety and apprehension states. Not surprisingly, we observe that the newly-proposed NM-GSIs and the existing macroeconomic policy-related uncertainty indicators are (on average) not correlated or weakly correlated (see Table 2).

3. Data

Non-Macro-Related Google Search-Based Uncertainty Indicators (NM-GSIs). As anticipated in Section 2, our aim is to build uncertainty indexes that are marginally related, or eventually, totally unrelated to topics or events directly affecting current and future financial and real market dynamics. Google trends functions "related topics" and "related queries" allow to understand which topics or (search) terms a given topic/term is related to.[2] We use these functions to select a set of topics that might (*i*) capture a wide range of different "bad" (or uncertain) events and (*ii*) avoid spurious correlations with macro-related or finance-related issues/events. We have thus voted for the following topics: "symptom", "pollution", "terrorism", and "election".[3] Related topics are reported in Table 1. "Symptom" seems to be related with a wide range of health issues, ranging from serious diseases (like cancer or infection) to less problematic ones (like influenza) including pregnancy, which is not a bad event *per se* but implies a substantial amount of uncertainty. Similarly, the topic "pollution" is connected with air, water or land pollution, but even noise or light pollution. Intuitively, "terrorism" is related to some of the most well-known terroristic organizations, like ISIS, dates or locations of tragic terroristic attacks, and war on terror. Finally, "election" tends to be associated with institutions like the President, parties and election candidates, or election outcomes. Surely, among the four selected topics, "election" is the one more likely to be close to macroeconomic issues. On the one hand, it (strictly) represents a non-economic term. On the other, however, it is a policy-related topic. We decide to include this topic in our analysis because not yet considered in previous studies (Donadelli, 2015; Bontempi et al., 2017; Castelnuovo and Tran, 2017).[4] In this respect, our goal is to examine whether attention to future (and uncertain) elections revealed by internet searches could be considered itself as an uncertainty indicator.

Loosely speaking, one could potentially relate the selected topics to higher anxiety and apprehension, which have been found to create negative sentiment that may affect both financial and real aggregates (Kaplanski and Levy, 2010). Moreover, our choice is motivated by the extensive media coverage that can be associated with the aforementioned topics. Widespread media coverage of topics like health, pollution and terrorism – due to the presence of "bad images that can have a potential for psychological damage to viewers" – can be sufficiently emotionally to provoke fear and increase stress, and thus alter economic agents' plans (Kaplanski and Levy, 2010). Similarly, a large number of news related to "election" could represent a signal of increasing uncertainty. As noticed by Kitzinger and Reilly (1997), once a topic gains a certain level of media attention, it attracts more attention, and because it attracts more attention, it becomes more newsworthy. It turns out that, a large number of news and a higher speed of information inflows represent the sources of the observed rise in media attention to selected topics. In the era of internet and social media, this results in rising Google searches on those specific terms/topics. In other words, search frequency intensifies as the level of attention to a specific topic rises. Note that in our VAR analysis the (raw) NM-GSIs will be transformed first as in Da et al. (2011) and then following the procedure of Dzielinski (2012). This implies reducing the full sample (i.e., January 2004-December 2017) to the period January 2005-December 2017.

Moreover, as highlighted in Choi and Varian (2012), Google Trends data are computed using the sampling method. Therefore a drawback of using Google Trends data is related to replicability, since the very same query made in two different moments gives rise to (slightly) different trends. We stress that, for particular queries, these differences might be relevant. One of the novelties of our paper is that, to overcome this issue and be as close as possible to the true population value, we do not rely on a single downloaded series, but we ask the same query for at least ten consecutive days and then use the average of these series. For each single query, the pairwise correlation is never lower than 0.99, meaning that the topics we use are quite robust to the sampling method.[5]

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[2] "[Google trends] topics [...] are groups of terms that share the same concept in any language" (Kim et al., 2018).

[3] Differently from terms such as "economy", "white house", "stock market", "bankruptcy", "US FED", "debt ceiling", "economic reforms" selected by Dzielinski (2012), Donadelli (2015) and Castelnuovo and Tran (2017), the words we search for via Google trends are not directly related to macro-related or finance-related issues/events.

[4] A similar argument holds for the following political-related keywords/topics: "poll" and "voting".

[5] Note that, to the best of our knowledge, most of the existing studies capturing economic policy uncertainty by means of Google Trends are silent on this issue. Two exceptions are Da et al. (2011) ("To increase the response speed, Google currently calculates internet search volume indexes from a random subset of theactual historical search data. This is why Google search volume indexes on the same search term might be slightly different when they are downloaded at different points in time.") and Tran (2017) ("the exact replication of the data is not feasible due to sampling

Table 1

Symptom, pollution, terrorism and election Google Searches – related topics

Symptom		Pollution		Terrorism		Election	
Pregnancy	100	Air pollution	100	War	100	Result	100
Cancer	82	Atmosphere of Earth	98	War on Terror	81	United States presidential election, 2016	41
Pain	72	Water	96	September 11 attacks	65	Voting	26
Disease	66	Water pollution	77	Counter-terrorism	65	President	24
Infection	60	Biophysical environment	26	Threat	47	President of the United States	24
Influenza	57	Ocean	17	Muslim	44	Primary election	22
Blood	36	River	16	Paris	41	Opinion poll	17
Diabetes mellitus	35	Fact	15	Islamic State of Iraq and the Levant	40	Election Day (US)	12
Urinary tract infection	29	China	15	Barack Obama	35	United States presidential election, 2012	12
Allergy	27	Waste	13	Bomb	31	Donald Trump	10
Abdomen	23	Light pollution	12	France	31	Candidate	7
Menstruation	22	Soil	11	Islamic terrorism	31	Barack Obama	7
Anxiety	21	Noise pollution	11	London	29	Democratic Party	6
Virus	20	Soil contamination	11	Domestic terrorism	29	Republican Party	6
Feeling	20	Marine pollution	11	Organization	23	Hillary Clinton	5
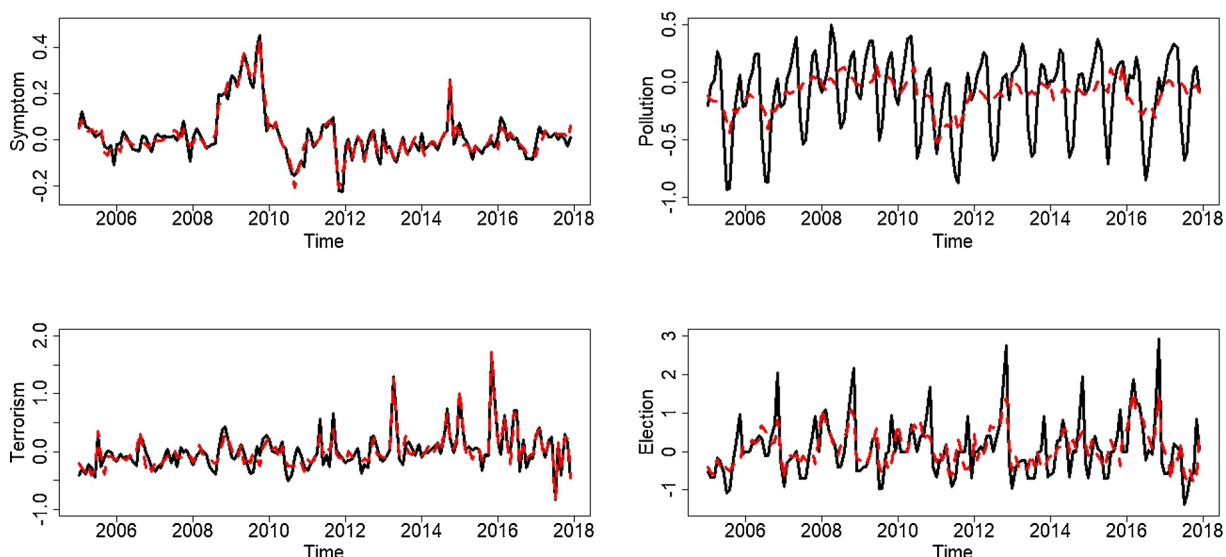
Fig. 1. Evolution of NM-GSIs for the United States. *Notes*: This figure shows the evolution of the NM-GSIs. Black (solid) line: NM-GSIs are transformed according to Da et al. (2011). Red (dashed) line: NM-GSIs are first transformed as in Da et al. (2011) and then seasonally adjusted using the `X-11-ARIMA` procedure.

Fig. 1 shows the evolution of our four NM-GSIs for the US. Outstanding peaks can be easily related to key events: for example, "terrorism" NM-GSI peaks around the Boston Marathon bombing of April 2013 or the November 2015 Paris attacks. Similarly, "election" highest peaks correspond to October and November of presidential-elections and mid-term-elections years; that is, the month preceding the election and the month of the election. It is worth noting that in December (i.e., after the election but still before the freshly elected formally assume the office) the interest has already almost completely vanished.

In Table 2, we show the correlation between our four newly developed NM-GSIs and a variety of existing popular indicators of equity market- and economic policy-related uncertainty. In order to match the frequency of our NM-GSIs, only indicators available at monthly frequency are used. These are: VIX, EPU-US, EPU-GLOBAL, GPR, GSI ("US stock market") and GTU. Notably, "symptom", "pollution" and "terrorism" are uncorrelated or even negatively correlated with the majority of the existing uncertainty measures. Sizable co-movement is found only between "terrorism" and the GPR index of Caldara and Iacoviello (2016). Actually, we observe a statistically significant positive correlation of 0.53. This should not come as a surprise given that the news-based GPR index relies also on terms related to war and terrorist threats (i.e., words groups 3 and 4 of the GPR). A similar argument applies for the observed positive (but milder) and significant correlation between the Global EPU indexes and our "terrorism" NM-GSI. In fact, the construction of the Global EPU involves searches for war-related words in some countries (e.g., "military" or "Guerra" for Mexico). Moreover, we observe a significant (mild) positive correlation between the

Table 2

Correlation: NM-GSIs vs. macroeconomic policy-related indexes

	VIX	EPU US (news)	EPU US	EPU Global	EPU Global (PPP)	GPR	GSI	GTU US
Symptom	0.47***	− 0.01	0.08	− 0.10	− 0.10	− 0.09	0.11	0.51***
Pollution	0.24***	0.06	0.01	0.05	0.07	0.02	0.21***	0.17**
Terrorism	0.03	0.07	0.00	0.21***	0.21***	0.53***	0.18**	− 0.26***
Election	0.18**	0.27***	0.19**	0.25***	0.24***	− 0.04	0.28***	0.02

Notes: This table reports the correlation between a number of different economic policy related uncertainty indicators and NM-GSIs. NM-GSIs are transformed according to Da et al. (2011) and seasonally adjusted using X-11-ARIMA procedure. VIX: = CBOE Volatility Index; EPU US (news): = (Baker et al., 2016) US news-based economic policy uncertainty index; EPU (US): = (Baker et al., 2016) US economic policy uncertainty index; EPU (Global): = (Baker et al., 2016) global economic policy uncertainty index based on current-price GDP; EPU Global (PPP): = (Baker et al., 2016) global economic policy uncertainty index based on PPP-adjusted GDP; GPR: = Caldara and Iacoviello (2016) geopolitical risk index; GSI: = (Donadelli, 2015) Google search-based index for "US Stock Market"; GTU: = (Castelnuovo and Tran, 2017) US Google trend uncertainty index, available until 2016:M12.

"symptom" and "pollution" NM-GSIs and both the VIX and the GTU of Castelnuovo and Tran (2017). In this respect, some studies have shown that shocks to health-(Huberman and Regev, 2001; Donadelli et al., 2017b) and environmental-related (Bansal et al., 2016; Donadelli et al., 2017a) issues might be related to negative equity market outcomes (i.e., high equity market volatility).[6] Then, and not surprisingly, the policy-related topic "election" is significantly correlated with the majority of the considered proxies of fear/uncertainty. Still, the absolute value of these correlations is quite low, ranging from a min of -0.04 (GPR) to a max 0.28 (GSI).

Financial and Macroeconomic Variables. As US macroeconomic indicators, we use the industrial production index (IP), civilian unemployment rate (UR), total consumer credit owned and securitized (CC). All the US macroeconomic aggregates are from the Federal Reserve Bank of St. Louis database. As financial indicators, we use the share price index (SPI), which is measured as the closing value of the S&P500 and is retrieved from yahoo.finance database, and the 10-year treasury constant maturity rate (R), from the FRED database. We also use both the Consumer (CCI) and the Business Confidence Index (BCI), from OECD. All data are monthly and run from January 2004 to December 2017.

4. Empirical analysis

4.1. Methodology

The effects of a NM-GSI shock on main financial and macroeconomic aggregates are identified via standard VAR models (Donadelli, 2015; Bontempi et al., 2017; Castelnuovo and Tran, 2017). Our benchmark VAR model reads as follows:

$$\mathbb{Y}_t = \mathbb{C}_0 + \sum_{j=1}^{p} \mathbb{B}_j \mathbb{Y}_{t-p} + \mathbb{V}_t$$

(1)

where the reduced-form residuals in $\mathbb{V}$ are normal with zero mean and variance covariance matrix $\mathbb{E}(\mathbb{V}\mathbb{V}') = \Omega$, $\mathbb{Y} = [NM - GSI, SPI, R, CCI, BCI, CC, IP, UN]'$ is the vector including all endogenous variables, $\mathbb{C}_0$ is a vector of constants, $\mathbb{B}$ is the VAR's coefficient matrix. VAR coefficients are estimated via OLS. All variables in our VAR analysis are expressed in percentage change form, except for the NM-GSI,[7] the interest rate, R, and the unemployment rate, UR, which are in levels. In the spirit of Donadelli (2015), the ordering in $\mathbb{Y}_t$ is based on the assumptions that NM-GSI shocks contemporaneously affect financial market dynamics (*SPI* and *R*), then consumer and business confidence, and finally the real economic activity (*CC, IP* and *UR*).[8] NM-GSIs are thus ordered first in a Cholesky decomposition.[9] The AIC, SC and HQC are jointly employed to select the optimal number of endogenous lags. Unless specified in the text or in the caption, this number of endogenous lags is equal to two.

4.2. Main results

In this section we report the impulse response functions of main financial, confidence and macroeconomic indicators to different NM-GSI shocks. Specifically, we discuss the implications on the real economic activity of a shock to a (i) "symptom" NM-GSI (Fig. 2); (ii) "pollution" NM-GSI (Fig. 3); (iii) "terrorism" NM-GSI (Fig. 4) and (iv) "election" NM-GSI (Fig. 5).

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[6] Note that controlling for the VIX (or GTU) does not alter the main effects of "symptom" and "pollution" NM-GSI shocks. Unreported results are available upon request.

[7] Please note that our baseline NM-GSI measures the percentage change deviation from the median value of the preceding year.

[8] Note that assuming uncertainty responding not contemporaneously to changes in financial and macroeconomic variables represents a very common restriction (see, among others, Bachmann et al., 2013; Caggiano et al., 2014; Castelnuovo and Tran, 2017).

[9] In Section 4.3 we perform a couple of robustness checks to show that the macroeconomic implications of NM-GSI shocks are not affected by alternative variable orderings.

A: "DA" B: "DA" WITH SEASONAL DUMMIES C: "DZ"
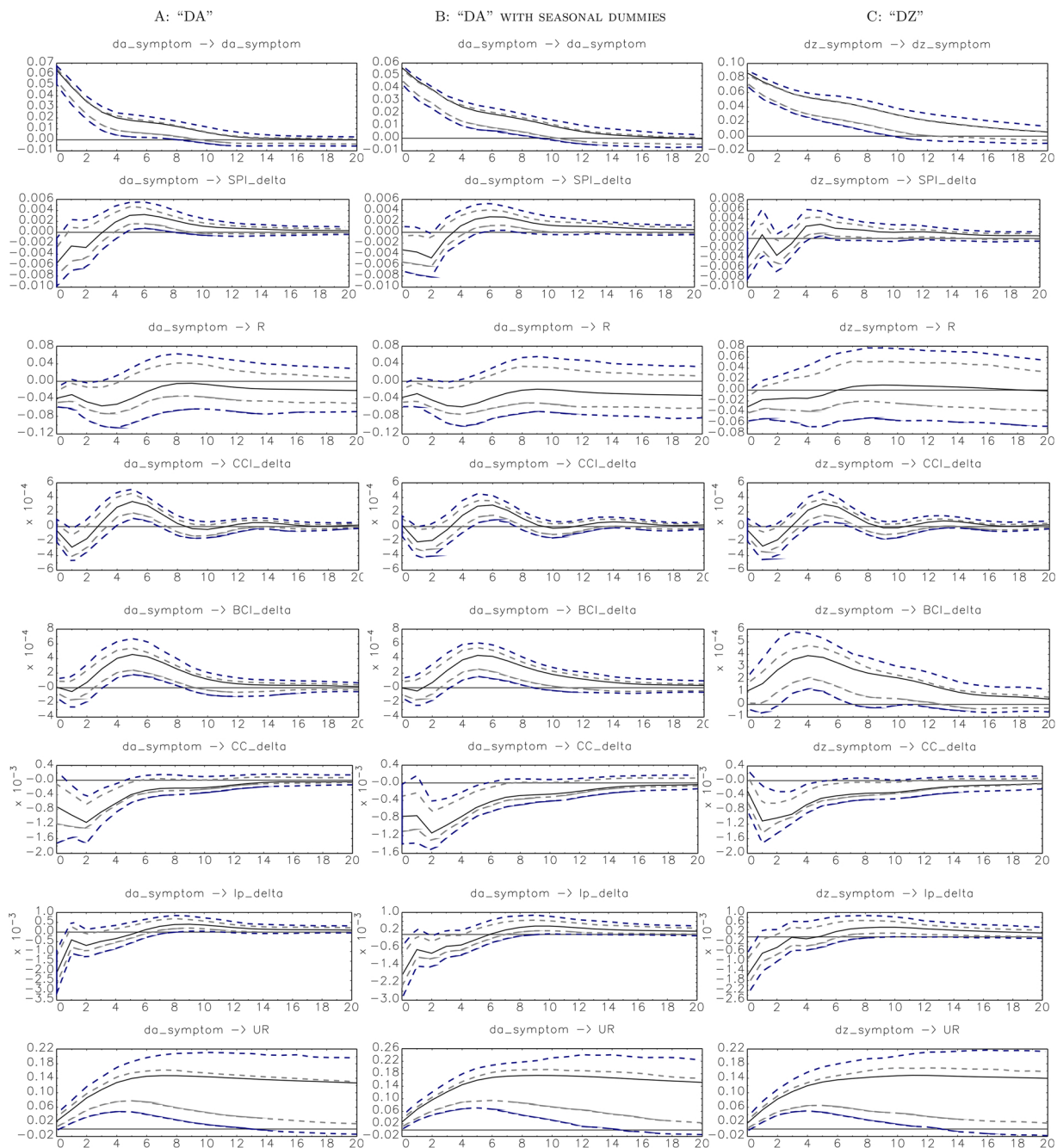
Fig. 2. Impulse Responses to a "Symptom" NM-GSI Shock. *Notes:* This figure reports "Cholesky" orthogonalized impulse responses to a "Symptom" NM-GSI (1sd) shock. Column A: the raw NM-GSI is transformed as in Da et al. (2011). Column B: the raw NM-GSI is transformed as in Da et al. (2011) and the VAR includes seasonal dummies. Column C: the raw NM-GSI is transformed as in Dzielinski (2012). VARs are estimated with a constant. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

For the sake of robustness, impulse responses are estimated using three different VAR specifications. First, impulse responses are obtained from a VAR where the raw Google trends are transformed following the procedure described in Da et al. (2011) (Figs. 2–5, Column A). Since the approach suggested by Da et al. (2011) seems to account only partially for seasonality, in a second check, we compute impulse responses from a VAR including seasonal dummies (Figs. 2–5, Column B). Finally, we transform our raw NM-GSIs by using the transformation suggested by Dzielinski (2012) (Figs. 2–5, Column C). VAR estimated impulse responses are reported jointly with 90% bootstrapped confidence intervals. Following recent empirical works focusing on the macroeconomic effects of
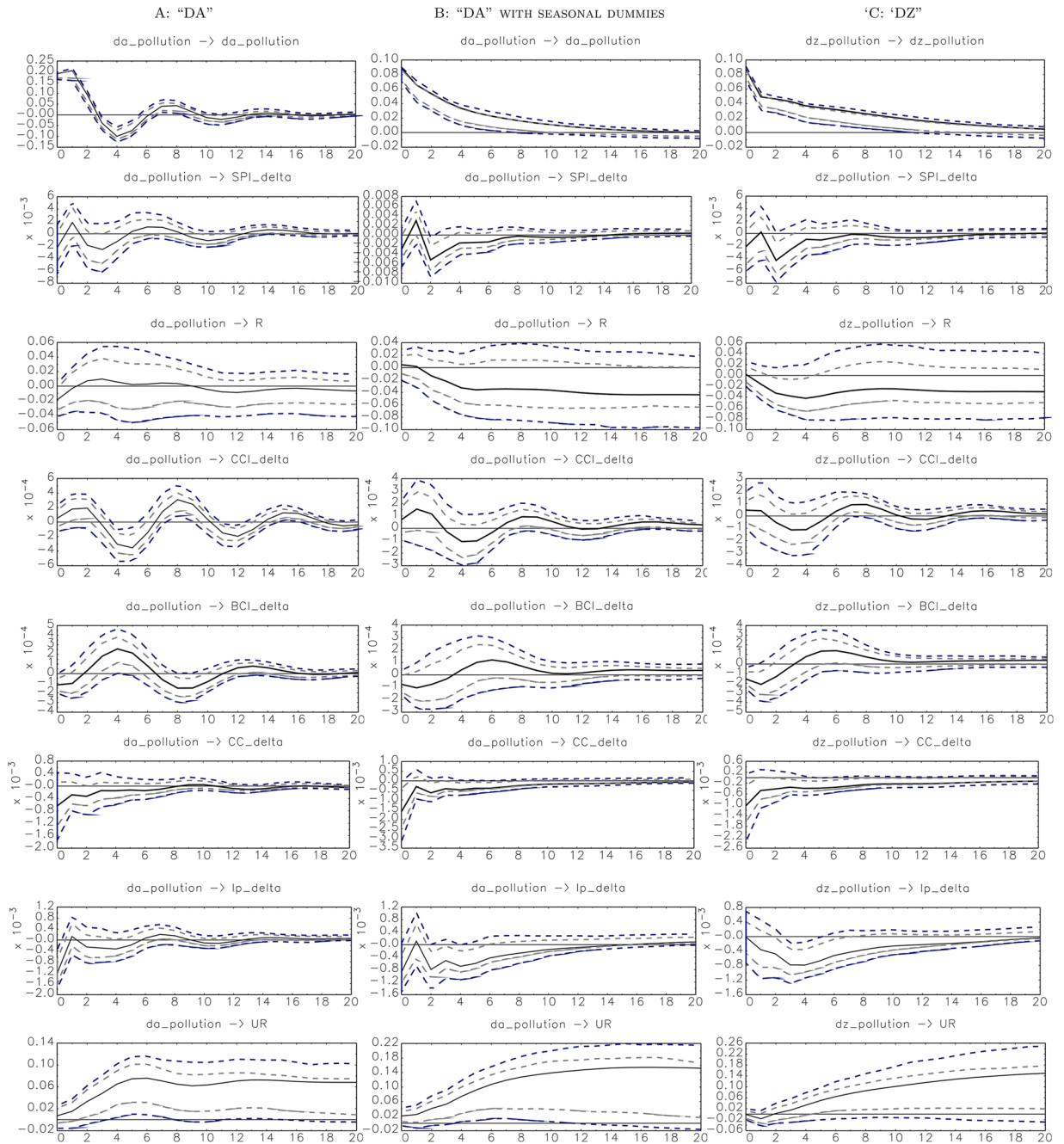
Fig. 3. Impulse Responses to a "Pollution" NM-GSI Shock. *Notes:* This figure reports "Cholesky" orthogonalized impulse responses to a "Pollution" NM-GSI (1sd) shock. Column A: the raw NM-GSI is transformed as in Da et al. (2011). Column B: the raw NM-GSI is transformed as in Da et al. (2011) and the VAR includes seasonal dummies. Column C: the raw NM-GSI is transformed as in Dzielinski (2012). VARs are estimated with a constant. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

uncertainty shocks and rising policy uncertainty, 68% bootstrapped confidence intervals are also reported (Caggiano et al., 2014, 2017; Castelnuovo and Tran, 2017).[10]

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[10] For instance, Castelnuovo and Tran (2017) compute impulse response functions to a GTU shock where only 68% confidence bands are added. Only 68% confidence bands are reported also in Caggiano et al. (2017) who examine the impact of an EPU shock in the US using a non-linear approach. Differently from these studies, for the sake of completeness, we compute both 68% and 90% confidence bands.

A: "DA"   B: "DA" WITH SEASONAL DUMMIES   C: "DZ"
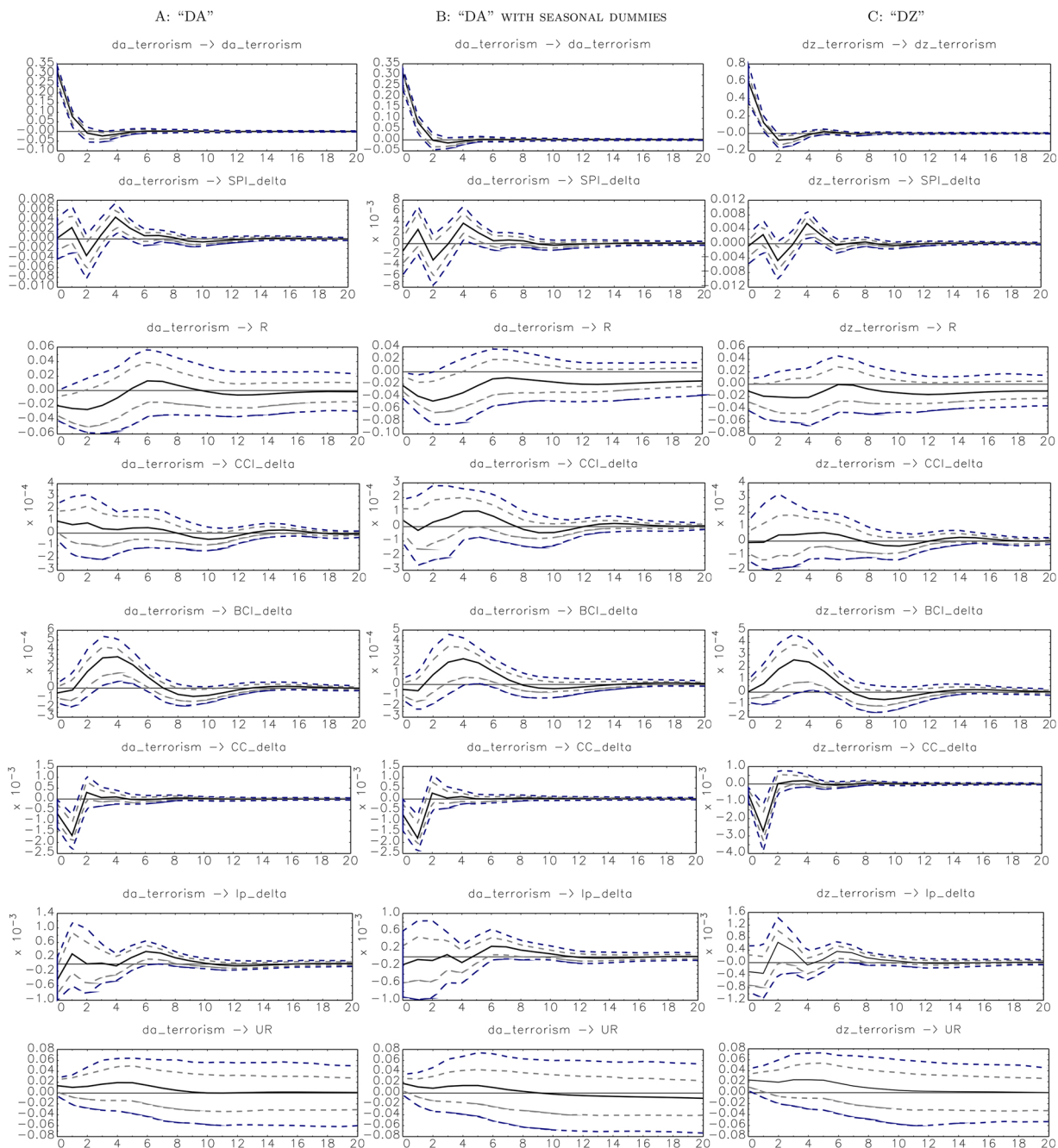
Fig. 4. Impulse Responses to a "Terrorism" NM-GSI Shock. *Notes:* This figure reports "Cholesky" orthogonalized impulse responses to a "Terrorism" NM-GSI (1sd) shock. Column A: the raw NM-GSI is transformed as in Da et al. (2011). Column B: the raw NM-GSI is transformed as in Da et al. (2011) and the VAR includes seasonal dummies. Column C: the raw NM-GSI is transformed as in Dzielinski (2012). VARs are estimated with a constant. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

"**Symptom.**" The most relevant and significant consequences of an unanticipated 10% increase in the frequency of internet searches for the topic "symptom" are observed in the real economy. Precisely, a rising search intensity for the topic "symptom" generates (*i*) a drop in consumer credit of around 0.1 percentage points (pp) lasting for five months and (*ii*) a long-lasting significant increase in the unemployment rate. A significant decrease on impact in the industrial production growth (of around 0.15pp) and in

A: "DA" B: "DA" WITH SEASONAL DUMMIES C: "DZ"
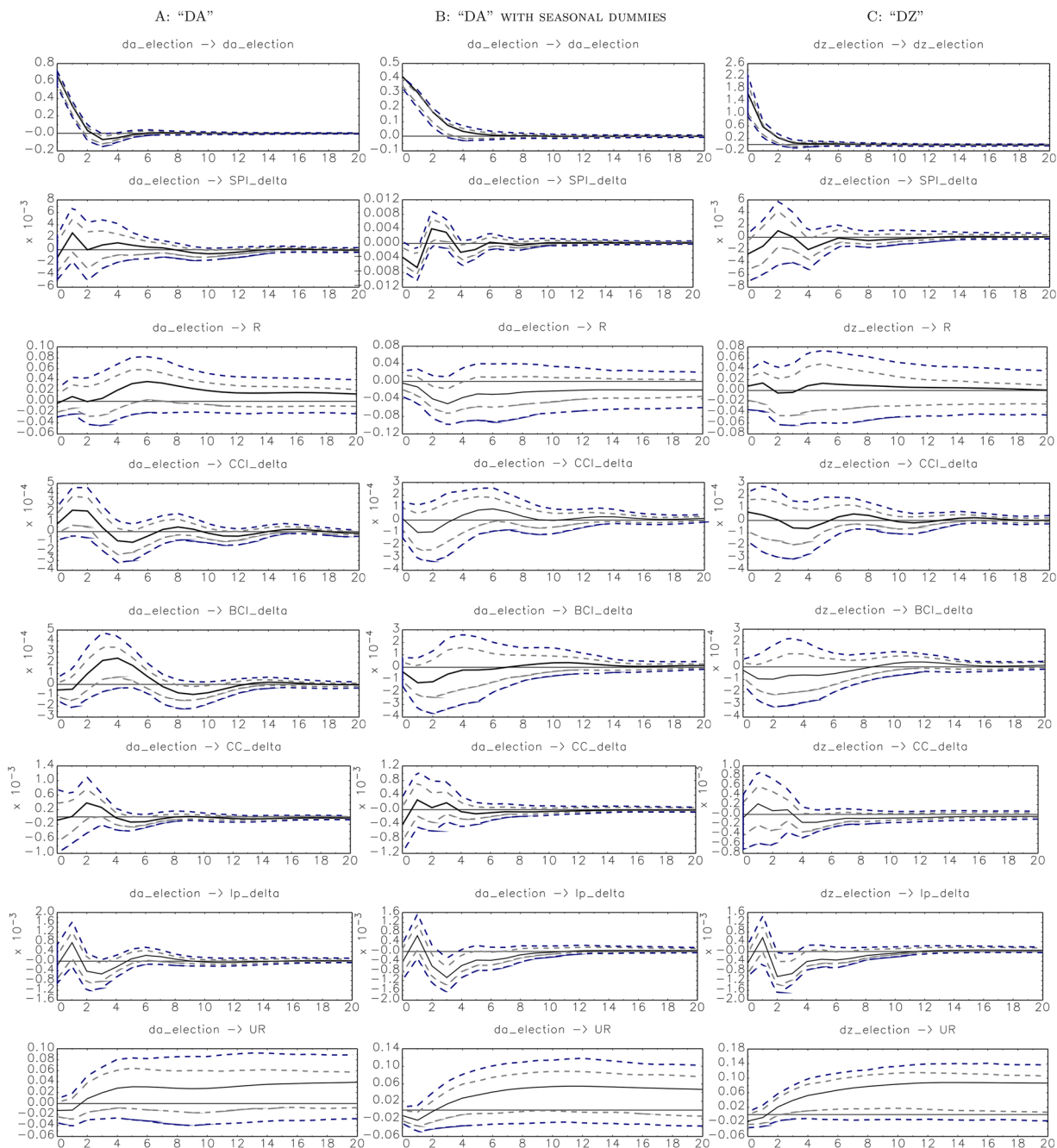
Fig. 5. Impulse Responses to a "Election" NM-GSI Shock. *Notes:* This figure reports "Cholesky" orthogonalized impulse responses to a "Election" NM-GSI (1sd) shock. Column A: the raw NM-GSI is transformed as in Da et al. (2011). Column B: the raw NM-GSI is transformed as in Da et al. (2011) and the VAR includes seasonal dummies. Column C: the raw NM-GSI is transformed as in Dzielinski (2012). VARs are estimated with a constant. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the long-term interest rate is also observed following a "symptom" NM-GSI shock.[11]

"**Pollution.**" An intensification of internet searches for "pollution" gives rise to adverse effects both in the financial markets and in the real economy. For instance, a 10% "pollution" NM-GSI shock produces on impact a drop of around 0.05pp (0.02pp) in the consumer credit (industrial production). Both effects last for several months after the shock. Moreover, from five months after the

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[11] Please note that, unless differently specified, by "significant" we mean "significant at the 10% level".
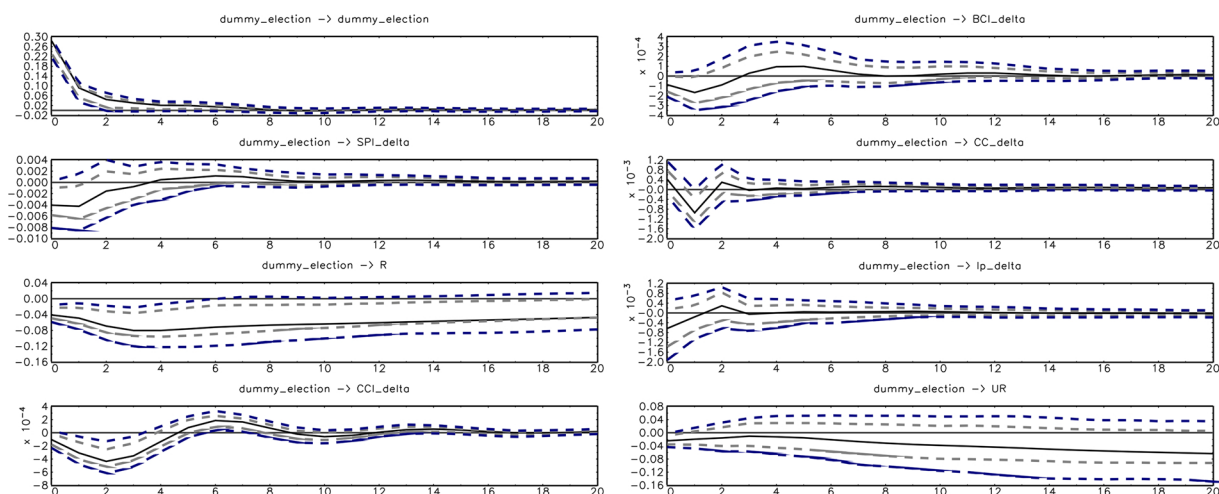
Fig. 6. Impulse Responses to a Shock to the dummy indicator for abnormal interest in the topic "Election". *Notes:* This figure depicts "Cholesky" orthogonalized impulse responses to a (1sd) shock to the dummy indicator for abnormal interest in the topic "Election" (far from an election). This indicator assumes value one when two conditions are satisfied (i) NM-GSI "Election" is in the top quartile and (ii) the month is different from October or November of an even year. VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

shock there is also a significant rise in the unemployment rate. A "pollution" NM-GSI shock affects also the stock market. Precisely, we observe a significant drop in the SPI of around 0.15pp two months after the shock. The fact that the aggregate stock market price falls after the shock (see Fig. 3) with no evidence of a short-time price-reversal seems to be in line with recent empirical evidence suggesting that climate change-related phenomena lower equity valuations (Bansal et al., 2016; Balvers et al., 2017; Donadelli et al., 2017a). As briefly mentioned in Section 3, the idea here is that increasing media attention to environmental-related phenomena is associated to an intensification of Google searches for "pollution".

"**Terrorism.**" The impulse responses depicted in Fig. 4 suggest that the most relevant result related to a "terrorism" NM-GSI shock is the strong and highly significant decrease in consumer credit both on impact (of around 0.02pp following a 10% shock) and after one month (of around 0.06pp). Moreover, on impact, the shock leads to (*i*) a significant drop (of around 0.01pp) in the interest rate and (*ii*) a 0.01pp increase in the unemployment rate. Counterintuitively, a 0.1pp increase in the stock market returns fourth months after the shock is also observed.

"**Election.**" Perhaps surprisingly, a rise in the frequency of internet searches for the topic "election", which could be considered as the least "macro-neutral" of the four selected topics, does not have significant macroeconomic implications. In particular, it does not generate a contraction is consumer credit (as observed following a "symptom" and "terrorism" NM-GSI shock). The only effect detected in the real economy is a decline (of around 0.01pp) in the industrial production growth three months after the shock. Let us remark that this effect is weaker and less long-lasting than the one generated by a "symptom" and "pollution" NM-GSI shock. There is also a significant 0.08pp decrease in the share price after one month.

Probably, uncertainty caused by the imminence of an election is an *expected* source of uncertainty. Households and firms are not surprised by the occurrence of an election at the beginning of November of an even year, and they do not sharply revise their consumption habits or production plans. Therefore, there are macroeconomic effects, but these are milder if compared to sudden and *unexpected* shocks, concerning for example health or environmental issues, that induce households to suddenly change their behaviour. Following this intuition, we construct a dummy indicator for abnormal interest in the topic "election" far from an election. This indicator assumes value one when the following two conditions are satisfied: (*i*) NM-GSI "election" is in the top quartile and (*ii*) the month is different from October or November of an even year. In doing so, we check whether worrying for elections, when there are no immediate reasons to care about elections, has any aggregate real effect. Actually, using this indicator we obtain impulse responses (Fig. 6) more in line with those generated by a shock to the other NM-GSIs. In particular, we observe a significant (at 32% level) drop in the consumer credit after one month. A significant drop in consumer confidence and long-term rates is also observed.

Taken together, our findings suggest that an increase in the search intensity concerning non-macro-based topics, but that are anyway related to fear and uncertainty (i.e., bad mood states or stressed times), has significant implications for real economic variables, i.e., a drop in the outstanding amount of consumer credit (except for "election"), a decrease in industrial production (except for "terrorism") and an increase in the unemployment rate (except for "election"). Among these three observed effects, the one that appears to be more relevant and significant is the one on consumer credit which, most likely, is the macroeconomic aggregate more directly affected by consumers' behaviour (which determine the demand side of consumer credit) among the financial and macroeconomic variables we considered.[12] Actually, the observed drop in consumer credit is likely to be related to the increase in

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[12] Note that this finding is not altered by different VAR specifications, including controlling for credit tightness using the Credit Easing (CE) Index, as suggested by Carroll et al. (2012). All these robustness tests are discussed in Section 4.3.

precautionary saving motives that follows a first-moment or second-moment adverse shock; i.e., rising consumers' anxiety affects their willingness to borrow money for consumption purposes. Within our analysis, stronger credit implications are found to occur upon the realization of shocks to a very frequently searched topic (i.e., "symptom") and unexpected and exceptional fear-provoking events (i.e., "terrorism"). The order of magnitude is a monthly decrease of 0.05pp-0.1pp in the outstanding amount of consumer credit following a 10% increase in the search volume of "symptom" or "terrorism". The consequences of shocks to less frequently searched topics ("pollution") or unfrequent but unsurprising uncertainty-provoking events ("election") are present, but milder.

Let us stress that the downside of anxiety related to a sudden, maybe even irrational, shock of interest for a non-macro-based source of uncertainty is somehow limited and unlikely to be large enough to provoke a new Great Depression. In fact, an exceptional ten-fold increase in the search frequency would imply a drop of around 2-3pp of the outstanding amount of consumer credit. Still, it is worth mentioning that the macroeconomic effects of "non-macro-based anxiety" are tangible and not trivial.

4.3. A battery of robustness checks

In this section we perform a battery of robustness empirical tests regarding the implications of NM-GSI shocks on the US financial, confidence, and macroeconomic indicators.[13]

Alternative topics. As a first set of robustness test, we examine the implications of rising interest in topics close to "symptom" and "pollution". In doing so, one can account for different dimensions of non-macro-based uncertainty/anxiety. First, we focus on the following health-related topics: "health", "disease", and "cancer".[14] An intensification of the interest in each of these topics has a different quantitative economic relevance and statistical significance, but the qualitative interpretation of the adverse macro-economic effects is basically unaffected, i.e., a "health", "disease", or "cancer" NM-GSI shock generates a drop in industrial production and consumer credit (Fig. A1).[15] We then consider a set of environmental-related topics, with a particular focus on climate issues, i.e., "climate change" and "global warming". Impulse responses to "climate change" and "global warming" NM-GSI shocks are rather similar (Fig. A2). For instance, on impact, consumer credit and industrial production drop following a "global warming" NM-GSI shock. Slightly different effects are found among confidence and financial indicators.

Different lag-order (3 lags). In the baseline analysis, the endogenous number of lags is selected according to the AIC, SC and HQC criteria, which for all the considered cases suggest a value of two. Here we fix (for all VARs) the number of lags to three. Impulse responses obtained from a VAR with three lags are reported in Fig. A3. Results are qualitatively similar.[16] Importantly, we still observe consumer credit (unemployment) significantly decreasing (increasing) upon the realization of a "symptom" or "pollution" NM-GSI shock.

Different variables ordering. In the spirit of recent studies examining the impact of macroeconomic policy-related shocks on financial and macro dynamics (Bachmann et al., 2013; Caggiano et al., 2014; Jurado et al., 2015; Castelnuovo and Tran, 2017), in our baseline VAR analysis, uncertainty is ordered first. What about ordering it last? To address this issue, we rely on the following vector, $\Upsilon = [\text{SPI}, R, \text{CCI}, \text{BCI}, \text{CC}, \text{IP}, \text{UN}, \text{NM} - \text{GSI},]'$, where our newly developed NM-GSIs are ordered last in a Cholesky decomposition. Note that this allows us to control for the possible role played by contemporaneous variables in the VAR in affecting non-macro-based uncertainty. Impulse responses from this alternative VAR specification are reported in Fig. A4. The imposed alternative ordering marginally affects the impulse responses to a "symptom" (Fig. A4, Panel A) and a "terrorism" (Fig. A4, Panel C) NM-GSI shock. In particular, rising internet search frequency for symptom and terrorism still generates a significant drop in consumer credit. Differently, under this alternative ordering the response of consumer credit to "pollution" (Fig. A4, Panel B) and "election" (Fig. A4, Panel D) NM-GSI shocks is partially altered. For instance, the impact response of consumer credit following a NM-GSI "pollution" shock becomes statistically insignificant. Specifically, a significant drop on consumer credit is found (at 32% level) only from three to five months after the shock (see Fig. 3 vs. Fig. A4 "Panel B").

Generalized IRFs. As a further robustness check, instead of imposing a given variables ordering, we adopt the generalized impulse response function (GIRF), which "does not require orthogonalization of shocks and is invariant to the ordering of the variables in the VAR" (Pesaran and Shin, 1998). Results are reported in Fig. A5. Following this order-agnostic approach leads to similar macroeconomic implications. Importantly, we still observe a significant drop in consumer credit (at least at 90% confidence interval) following a "symptom" (Fig. A5, Panel A), a "pollution" (Fig. A5, Panel B) and a "terrorism" (Fig. A5, Panel C) NM-GSI shock.[17] A significant drop in production and a rise in the unemployment rate following a "symptom" NM-GSI shock is also found.

Seasonally adjusted indexes. The transformation suggested by Da et al. (2011) is quite robust, since the raw value is divided by the median of the monthly values of the previous year, but does not get rid of the seasonality presented by several queries. For instance, we still have a very strong seasonality for "pollution" (see Fig. 1). As previously mentioned, this motivates our choice of

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[13] We thank two anonymous referee for asking questions and raising issues that elicited the information in this section.

[14] We prefer "symptom" rather than queries concerning specific diseases because (i) it is more frequently searched and (ii) it allows to capture a broader range of health issues. We also prefer "symptom" rather than "health" because the latter is more mood-neutral and, among the related topics, several are administrative ones, like "health care", "health insurance" or "clinic".

[15] This is not surprising given that "disease", and "cancer" are among the most closely related topics searched jointly with "symptom" (see Table 1).

[16] Similar conclusions can be drawn by estimating a VAR with one or four lags. For the sake of brevity results are not reported but available upon request.

[17] Notice that impulse responses in Fig. A5 are accompanied with 95% Montecarlo simulated confidence bands (and not 90% or 68% confidence bands).

Table 3

Correlation: random composite NM-GSIs vs. baseline NM-GSIs

	Random1	Random2	Random3	Random4	Random5	Random6
Symptom	0.21***	0.05	−0.02	−0.08	0.07	0.12
Pollution	−0.14*	−0.05	−0.09	0.05	−0.21***	−0.18**
Terrorism	0.02	0.2**	0.09	0.07	0.08	0.06
Election	−0.21***	−0.29***	0.19**	0.01	−0.15*	0.07

Notes: This table reports the correlation between random composite NM-GSIs and baseline NM-GSIs. NM-GSIs are transformed according to Da et al. (2011) and seasonally adjusted using X-11-ARIMA procedure.

presenting both the VAR including time dummies and the VAR in which raw data are transformed following Dzielinski (2012), which has the drawback of being sensitive to outliers but, at the very same time, accounts (almost fully) for seasonality. For the sake of completeness, in this robustness test the Da et al. (2011) transformed NM-GSIs are also seasonally adjusted by using the X-11-ARIMA procedure. Of course, seasonal dummies are no more included in the VAR. Intuitively, VAR investigations deliver very similar impulse responses (see Fig. A6).

Growth vs. level effects. In the baseline VAR analysis, all the financial and macroeconomic variables (except for long-term rates and unemployment) enter as growth rates. In recent existing similar studies (Donadelli, 2015; Castelnuovo and Tran, 2017), however, these variables have been expressed in log-levels. For robustness and comparison purposes, we also estimate our baseline VAR where stock market prices, confidence indicators, consumer credit and production are expressed in log-levels. Not surprisingly, the effects tend to be more long-lasting. Still, an increase in the Google search intensity for "symptom", "pollution" or "terrorism" turns out to have adverse real economic effects.

Controlling for general uncertainty. Even if correlation coefficients reported in Table 2 suggest that NM-GSIs and standard indicators of macroeconomic policy uncertainty tend to capture different dimensions of uncertainty, we augment our baseline VAR first by controlling for the general level of economic policy uncertainty in the US, and secondly by controlling for the Google search-based index for "US Stock Market" (Donadelli, 2015). Specifically, in the first analysis we add to our baseline vector the US EPU index and order it first, i.e., $\Upsilon = [EPU, NM-GSI, SPI, R, CCI, BCI, CC, IP, UN]'$, while in the second we add the GSI index and order it first, i.e., $\Upsilon = [GSI, NM-GSI, SPI, R, CCI, BCI, CC, IP, UN]'$. By doing so, we purge each NM-GSI from the contemporaneous movements in the general level of uncertainty, or from contemporaneous shifts in the interest for the "US Stock Market". Results – reported in (A8–A11) – suggest that the macroeconomic implications of NM-GSI shocks are not altered by variations in the EPU or the GSI level. Moreover, it is interesting to note that these economics-related uncertainty indexes have, as theoretically expected, a stronger and more significant adverse impact than non-macro uncertainty on all the macroeconomic and financial variables we consider – except for consumer credit. Turning the attention to the effects on consumer credit, the effect of rising EPU is not significant, while the one of a GSI shock is significant but smaller than that one generated by a "symptom" or "terrorism" NM-GSI shock.

Controlling for credit tightness. For three of the four NM-GSIs we consider, we find a relevant and significant effect on consumer credit. Of course, this is not necessarily related to consumers' anxiety states (demand side) but could also be the consequence of credit tightness (supply side). For this reason, we control for credit tightness by including a proxy for the Credit Easing in our VAR analysis. As in Carroll et al. (2012), this is represented by "the change in the banks' willingness to provide consumer instalment loans from the Senior Loan Officer Opinion Survey on Bank Lending Practices" (http://www.federalreserve.gov/boarddocs/snloansurvey/).[18] Unfortunately, these data are available only at quarterly frequency. Monthly figures are obtained using the Chow-Lin interpolation method (Chow and Lin, 1971). CE is added and ordered first, i.e. $\Upsilon = [CE, NM-GSI, SPI, R, CCI, BCI, CC, IP, UN]'$. The impulse response of consumer credit to a shock to "terrorism" and "symptom" maintains the order of magnitude estimated in the baseline analysis and remains statistically significant at the 10% level, while the one to a "pollution" shock has, on impact, an effect which is barely significant at conventional levels, but significant at the 32% level.

Composite NM-GSIs. In this robustness test, we test whether the selected four non-macro-related NM-GSIs pooled together generate similar financial and macroeconomic effects. We build first an aggregate NM-GSI by computing the simple (weighted) average of the four search intensities.[19] We denote this index as "NM-GSI_AVG". Then, for the sake of completeness, we build and additional composite index ("NM-GSI_PCI") by relying on the first principal component extracted from the dataset composed by the four different Google searches (i.e., Google trends for "symptom", "pollution", "terrorism" and "election"). Impulse responses to composite NM-GSI shocks are reported in Fig. A13. Actually, a shock to "NM-GSI_AVG" generates significant adverse effects on the real economy, namely a drop on impact in consumer credit and, after two months, a decline in industrial production and an increase in the unemployment rate. We observe also a decrease on impact in *SPI* followed by a decrease in *R* (*flight-to-quality effect*). Similar conclusions can be drawn by looking at the effects of a "NM-GSI_PCI" shock (Fig. A13, Panel B).

"Random Search" Are our results just driven by luck? Are they influenced by spurious correlations? To exclude the (unfortunate) hypothesis that any Google query is able to explain financial and macroeconomic patterns, we have download six different sets of quartets of random words/topics. The randomly chosen keywords sets are:

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[18] Carroll et al. (2012) use the accumulated change, while we use the change.

[19] Specifically, downloading Google trends for more than one keyword at the same time, all data are scaled with respect to the "highest monthly maximum" among the requested keywords. Therefore, it is possible to compare the distribution of two, or more, keywords using the same measure, and to infer their relative importance in Google users' searches.

i. "Attorney", "Bag", "Boot", "Bread".
ii. "Beach", "Movie", "Song", "Play".
iii. "Flower", "Rain", "Sun", "Team".
iv. "Bed", "Cup", "King", "Star".
v. "Ball", "Boat", "Shoes", "Snow".
vi. "Bike", "Final", "Flight", "Restaurant".

Each quartet is then aggregated as done for the benchmark "NM-GSI_AVG". This leads us to having six different Random Composite NM-GSIs.

First and most importantly, one can observe that the newly developed (by means of random searches) composite NM-GSIs are weakly correlated with our "symptom", "pollution", "terrorism" and "election" NM-GSIs (see Table 3). Only sporadically, we observe a statistically significant correlation. However, this is either negative or really small (i.e., < 0.3).

Figs. A14–A16 present the results against those obtained using the benchmark "NM-GSI_AVG". The effects on macroeconomic and financial variables are rarely statistically significant. There are very few exceptions. For instance, a shock to the NM-GSI built using the first random set of keyword (i.e., "attorney", "bag", "boot" and "bread") seems to have a significant impact on the interest rate, consumer credit and production. We stress that the the drop in consumer credit (industrial production) is significant at 32% only two months (one month) after the shock. One might argue that this random set includes "attorney", which is a term likely to induce anxiety and apprehension. Moreover, it is reasonable to assume that an increased volume of searches for "attorney" is related to an higher demand for attorney services, and the expected high expense induces higher saving and lower borrowing. A short term drop in consumer credit is also induced by a shock to the composite NM-GSI built using the random set (ii) and (vi). However, the effect is less significant, smaller in magnitude and less long-lasting than the one produce by a "symptom" (Fig. 2), "pollution" (Fig. 3) or "terrorism" (Fig. 4) NM-GSI shock. The above examples highlights that, for sure, "symptom", "pollution", "terrorism" and "election" are not the only four topics which induce anxiety and apprehension. We select these words to have proxies of different kind of uncertainties - related to health, environmental, security and political issues, respectively - and to check whether these sources of uncertainty have implications on the real economy, but the set of words affecting the mood of individuals is definitely much larger. An analysis of the macroeconomic implications of raising interest in different topics is left for future research.

Different countries: Evidence from the UK and Australia. In this section, we analyze whether anxiety for health-, environmental-, security- or political-related issues have comparable results also in other countries. Specifically, we select other two English-speaking countries, i.e., UK and Australia. All financial and macroeconomic variables for the UK are from the OECD, except for the consumer credit (monthly amounts outstanding of total sterling consumer credit lending to individuals), which is from the Bank of England. Australian data on stock market prices, long-term rates, consumer and business confidence are from the OECD. Data on industrial production (monthly activity indicators - retail sales - all industries) and consumer credit (credit - total) are instead from the Reserve Bank of Australia.

The impulse responses to NM-GSI shocks for Australia and the UK are depicted in Figs. A17 and A18, respectively. Apparently, in the UK there seems to be a recessionary effect on the consumer credit. However, it appears to be less statistically significant than the one found in the US. Conversely, in Australia significant macroeconomic implications of rising search intensity for "symptom", "pollution", "terrorism" and "election" are not present.[20]

5. Concluding remarks

The empirical analysis carried out in this paper has shed new light on the most recent and growing literature focusing on the macroeconomic effects of internet-search-based uncertainty. By building four indicators of non-macro uncertainty based on the frequency of Google searches for "symptom", "pollution", "terrorism" and "election", we show that not only rising interest in topics (strictly) related to economic and financial issues are associated with negative macroeconomic outcomes. Via standard VAR investigations, we show that a shock to the frequency of internet searches for anxiety-related and fear-related topics, i.e., "symptom", "pollution" and "terrorism", harms the real economic activity. In particular, a significant drop in consumer credit is observed. Noteworthy, shocks in the attention for a policy-related topic (i.e., "election") are less effective than pure non-macro-based anxiety and fear in explaining the movement of consumer credit. Adverse effects on the industrial production and the unemployment rate are also observed. However, for these macroeconomic aggregates non-macro-based uncertainty seems to be less relevant than macroeconomic policy uncertainty. Finally, rising interest in selected non-macro topics (e.g., "symptom") is found to have (mild) effects on financial aggregates.

Overall, our novel empirical findings have shown that increasing attention to specific topics that might be anxiety-inducing are associated with negative macroeconomic outcomes. Not surprisingly, the most relevant is a drop in consumer credit. Google trends data are available almost in real time. Measuring the interest for anxiety/fear-provoking topics affecting directly households' spending decisions could be thus helpful for financial intermediaries in estimating one step ahead liquidity demand.

There are, of course, a number of directions in which our empirical analysis could be fruitfully extended. First, we focus mainly on the U.S. It would be interesting to check whether an intensification of Google searches concerning health issues, the environment, security issues and politics have similar macroeconomic implications in other advanced or emerging economies. Second, we limit our main analysis to the search of four, quite broad, topics. One could potentially build a larger set of NM-GSIs by focusing on alternative anxiety-inducing topics. For

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[20] Mild effects on unemployment, production and prices for Australia following a Google trend based uncertainty indicator (GTU) shock can be found also in Castelnuovo and Tran (2017). However, differently from us, their GTU relies exclusively on macroeconomic policy-related variables.

instance, what about building an index based on Google searches for very particular topics/events such as "Dieselgate" in Germany and "Zika" in South America and Africa, or more general issues such as "hurricane" in the US, or "climate change" (Globally), or "CO2 emission" in the World's most polluted countries (China, India, Pakistan, Egypt)? All these additional empirical tests are left for future research.

## Appendix A. Robustness tests

Alternative health- and environmental-related topics
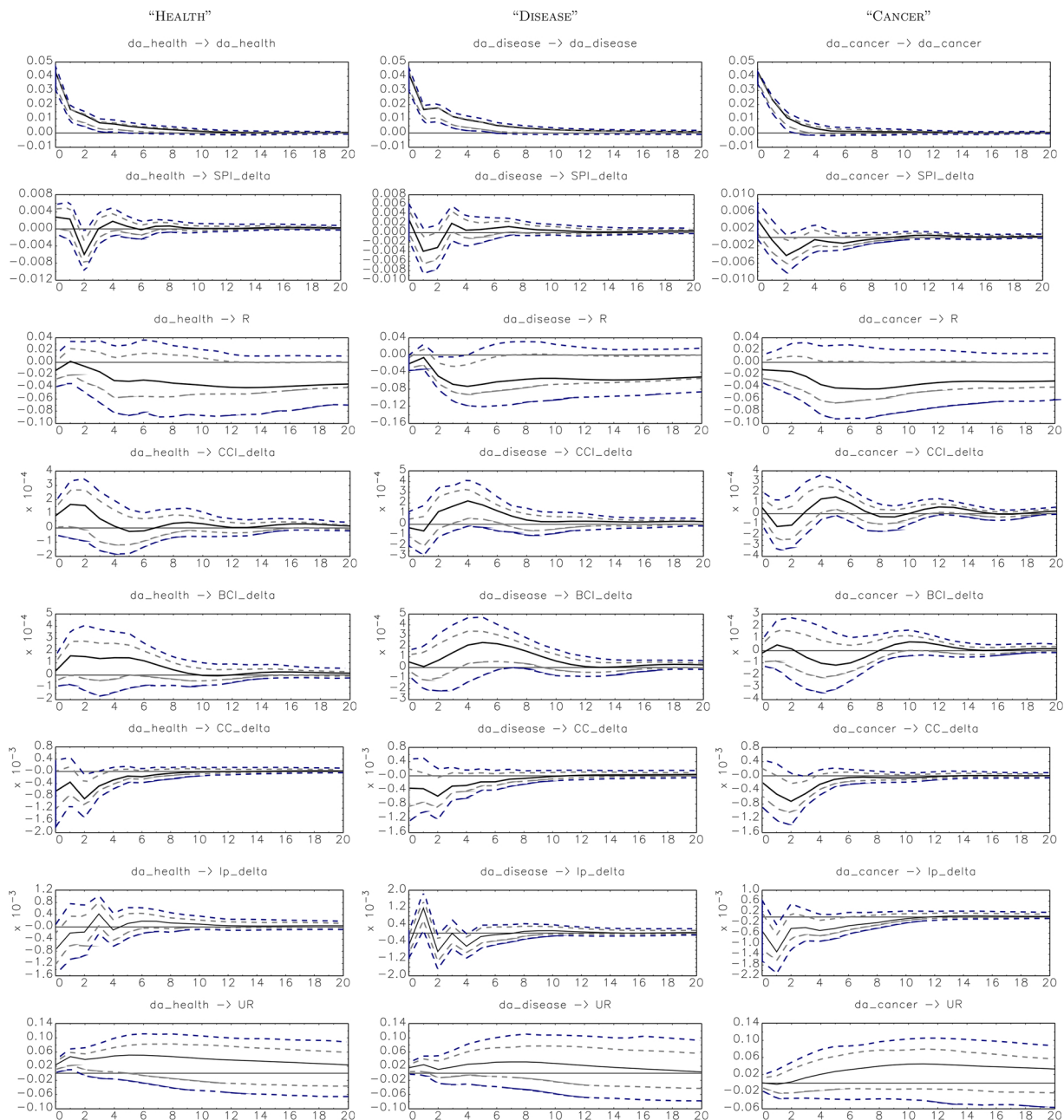
Fig. A1. Impulse Responses to alternative health-related NM-GSIs Shocks. *Notes:* This figure reports "Cholesky" orthogonalized impulse responses to alternative health-related ("Health", "Disease", "Cancer") NM-GSI (1sd) shocks. All "health-related" raw NM-GSIs are transformed as in Da et al. (2011).VARs are estimated with a constant and include seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
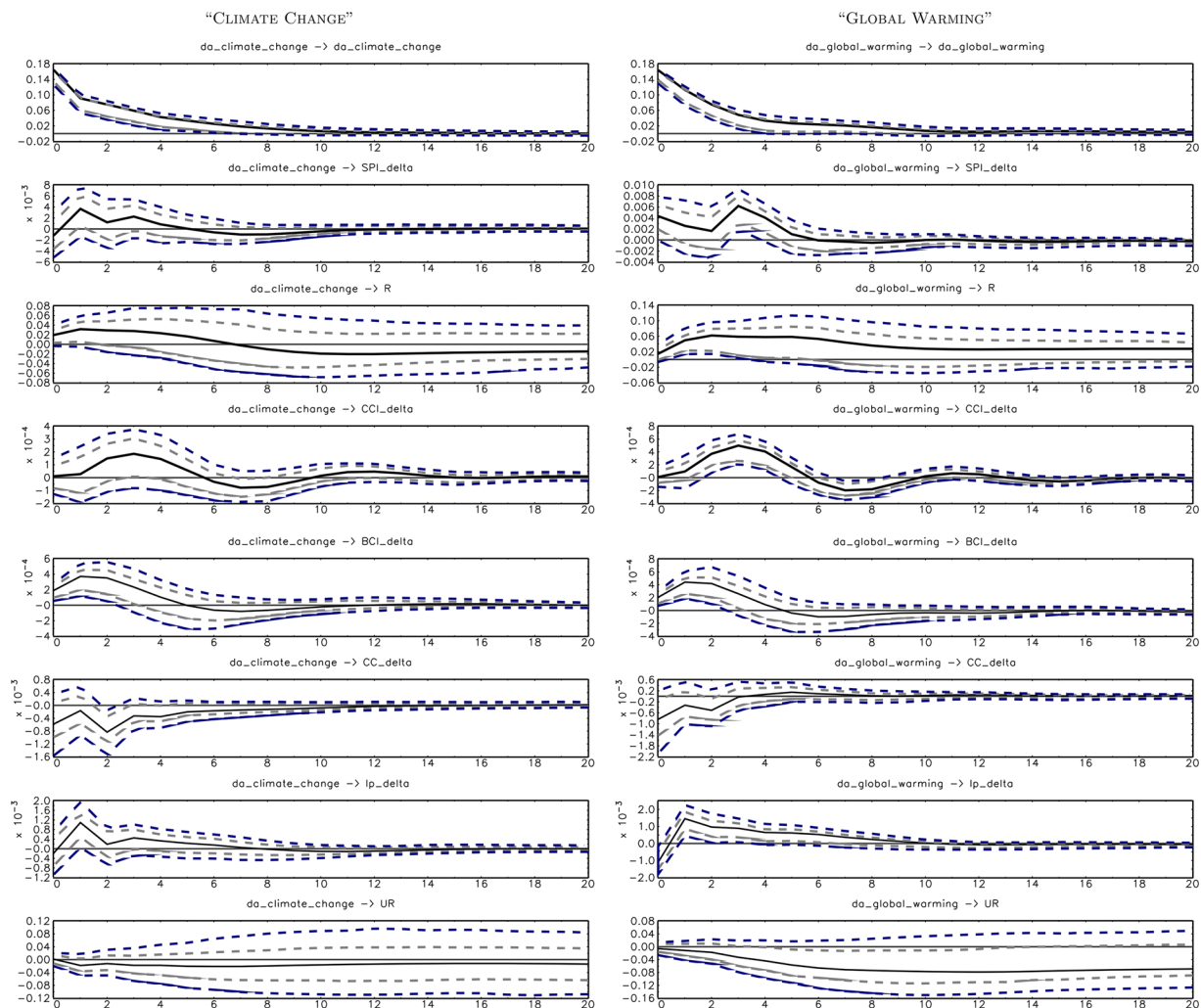
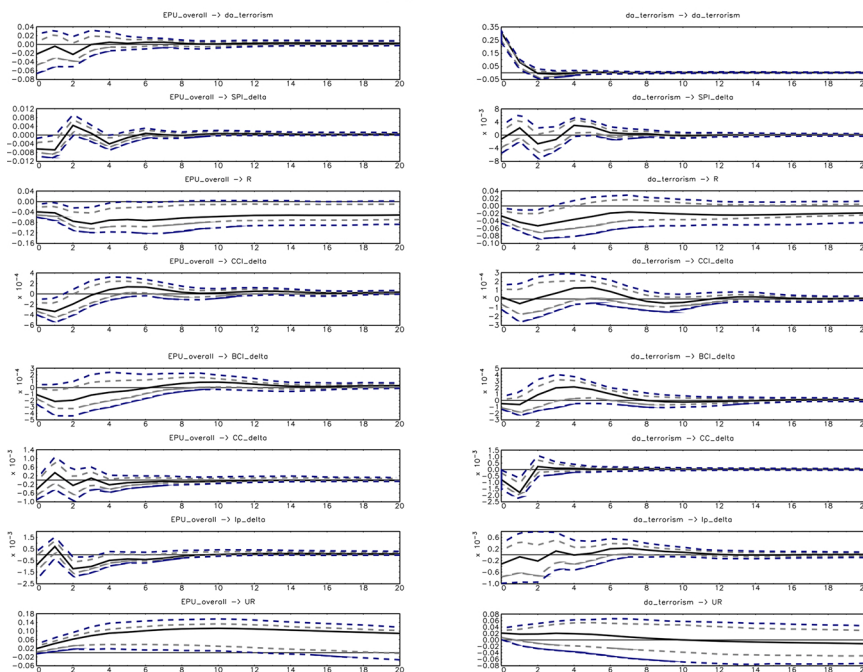**Fig. A2.** Impulse Responses to alternative envinronmental-related NM-GSIs Shocks. *Notes:* This figure reports "Cholesky" orthogonalized impulse responses to alternative climate-related ("Climate Change" and "Global Warming") (1sd) NM-GSI shocks. Both "climate-related" raw NM-GSIs are transformed as in Da et al. (2011). VARs are estimated with a constant and include seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
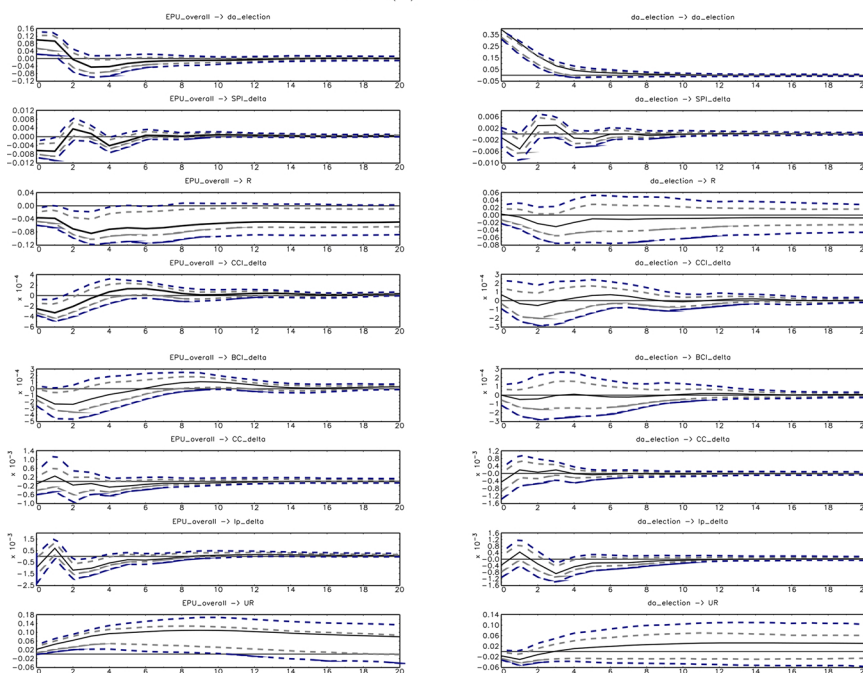
Different lag-order
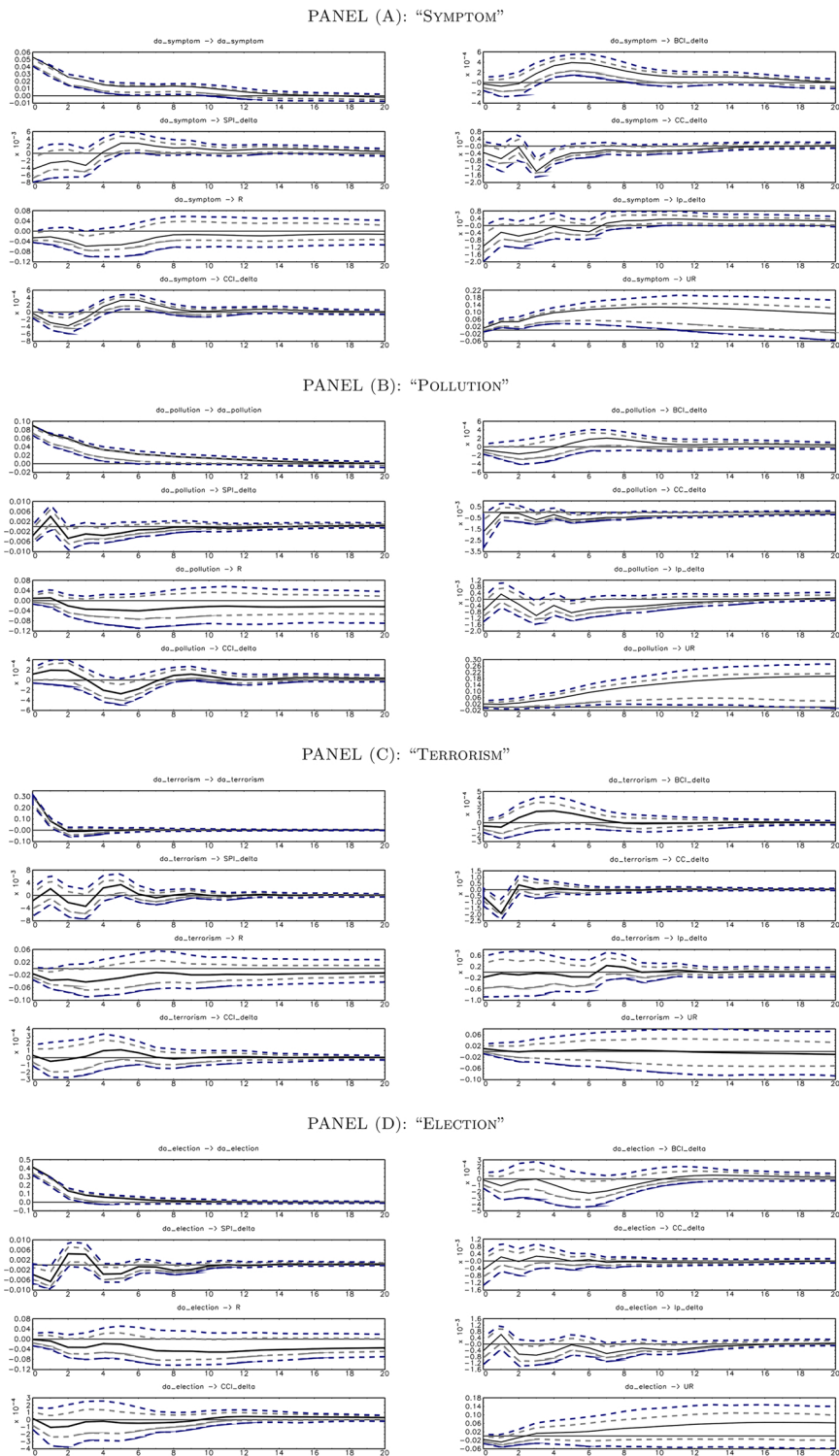
Fig. A3. Impulse Response to NM-GSI Shocks (3-Lags). *Notes:* This figure reports orthogonalized impulse responses to a "Symptom" (Panel A), "Pollution" (Panel B), "Terrorism" (Panel C) and "Election" (Panel D) NM-GSI (1sd) shock. Raw NM-GSIs are transformed as in Da et al. (2011). VARs are estimated with a constant, seasonal dummies and three endogenous lags. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Different variables ordering
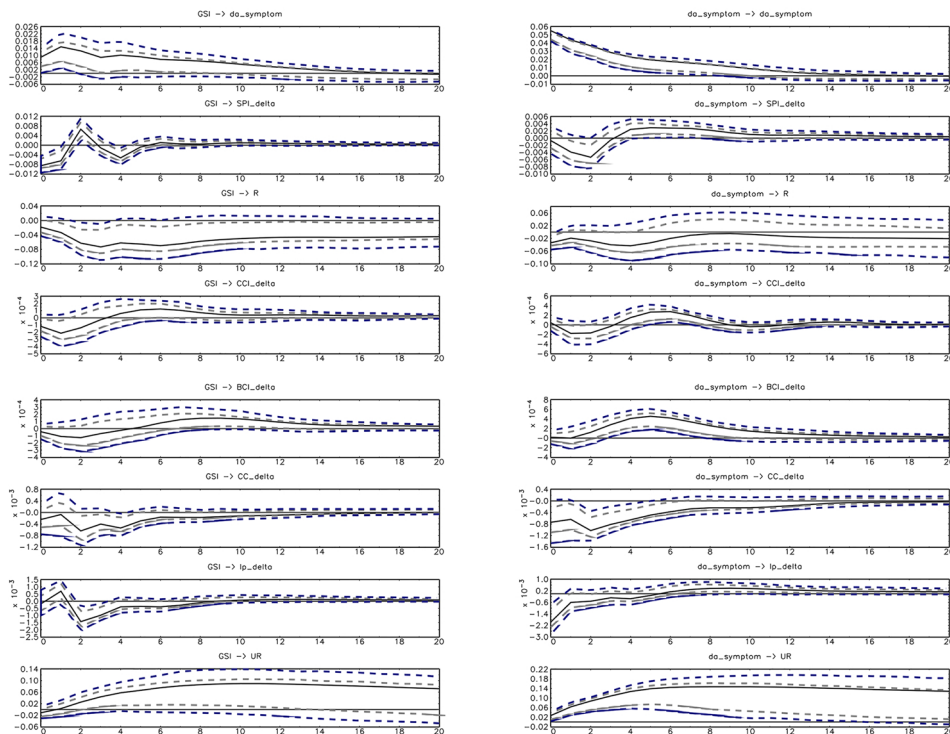
PANEL (A): "Symptom"

PANEL (B): "Pollution"

PANEL (C): "Terrorism"
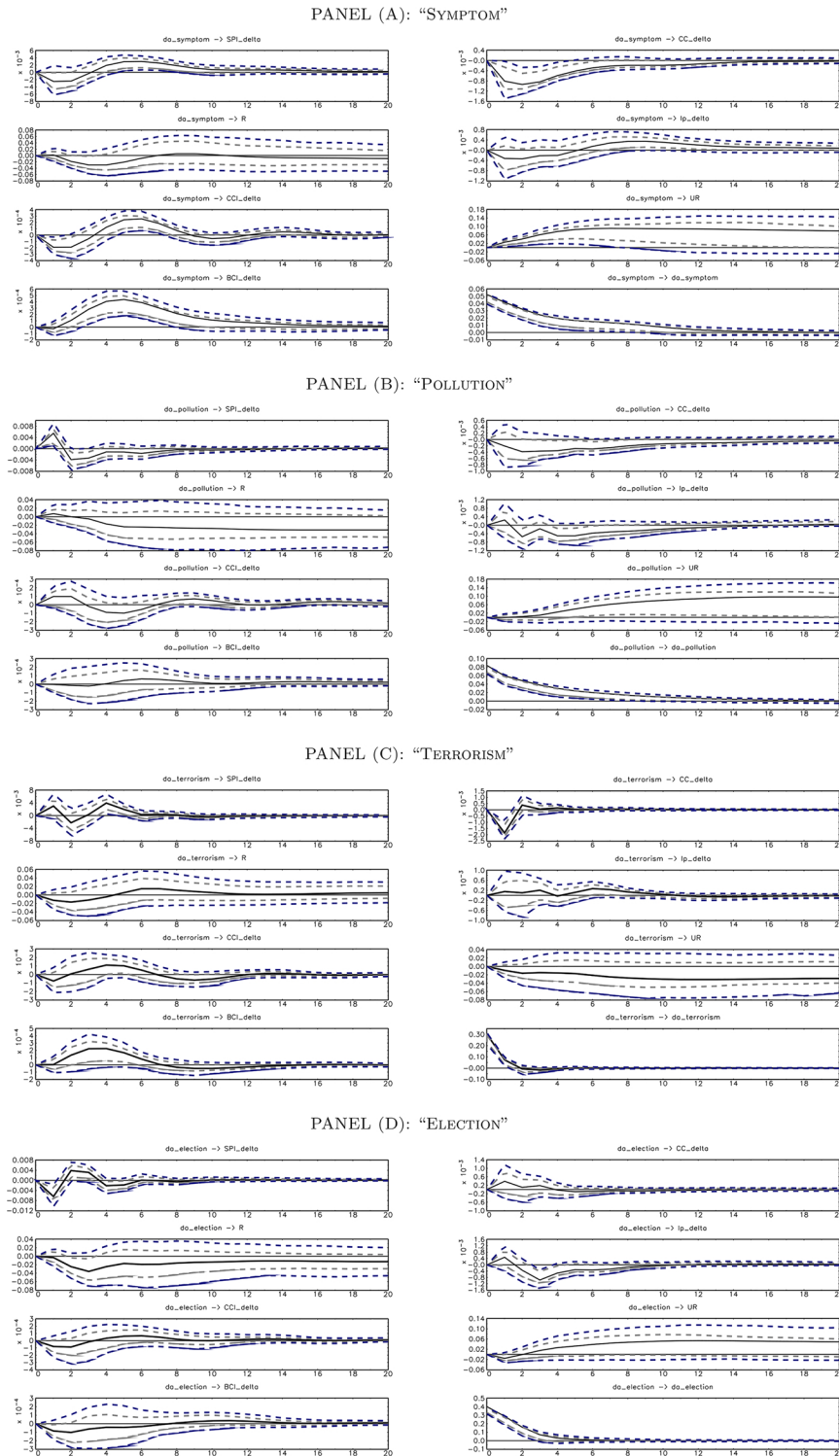
PANEL (D): "Election"

Fig. A4. Impulse Responses to NM-GSI Shocks (NM-GSI LAST). *Notes:* This figure reports orthogonalized impulse responses to a "Symptom" (Panel A), "Pollution" (Panel B), "Terrorism" (Panel C) and "Election" (Panel D) NM-GSI (1sd) shock. NM-GSIs are transformed as in Da et al. (2011). VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. In all VARs, NM-GSI is ordered last in a Cholesky decomposition. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Generalized IRFs
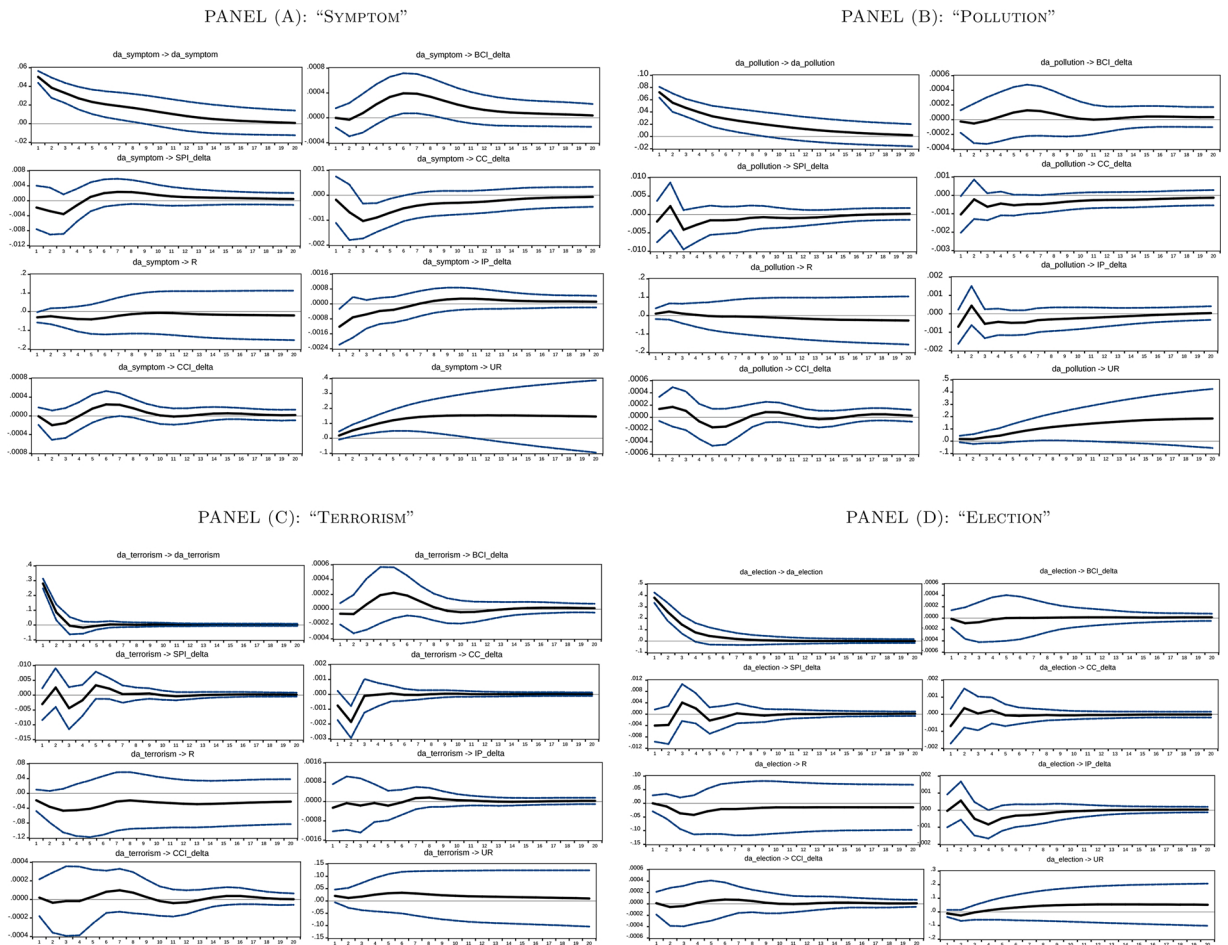
Fig. A5. "Generalized" Impulse Responses to NM-GSI Shocks. *Notes:* This figure reports Generalized impulse responses to a "Symptom" (Panel A), "Pollution" (Panel B), "Terrorism" (Panel C) and "Election" (Panel D) NM-GSI (1sd) shock. Raw NM-GSIs are transformed as in Da et al. (2011) and seasonally adjusted following the X-11-ARIMA procedure. VARs are estimated with a constant. Solid "black" lines: estimated impulse responses. Solid "blue" lines: 95% (Montecarlo simulated) confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
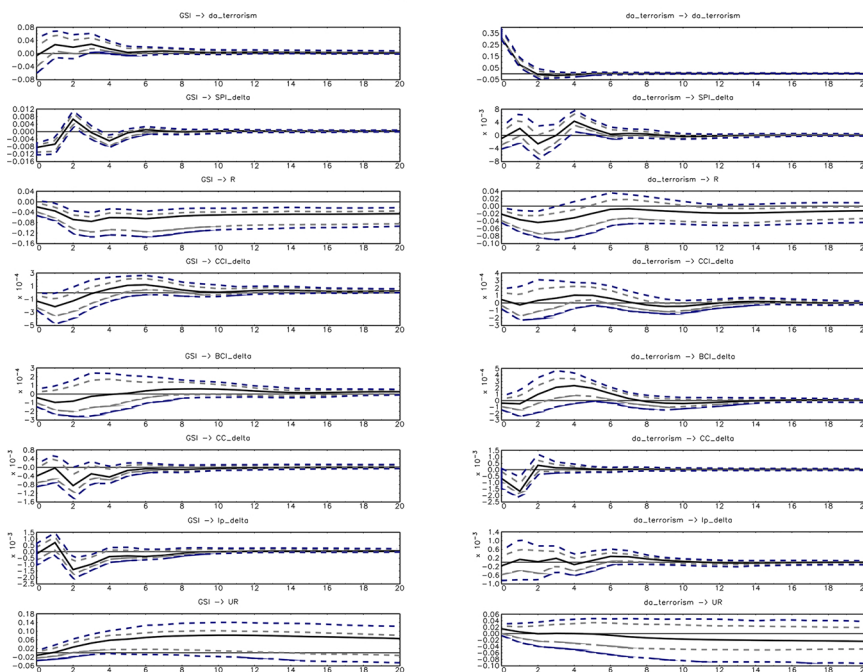
Seasonal-adjusted NM-GSIs
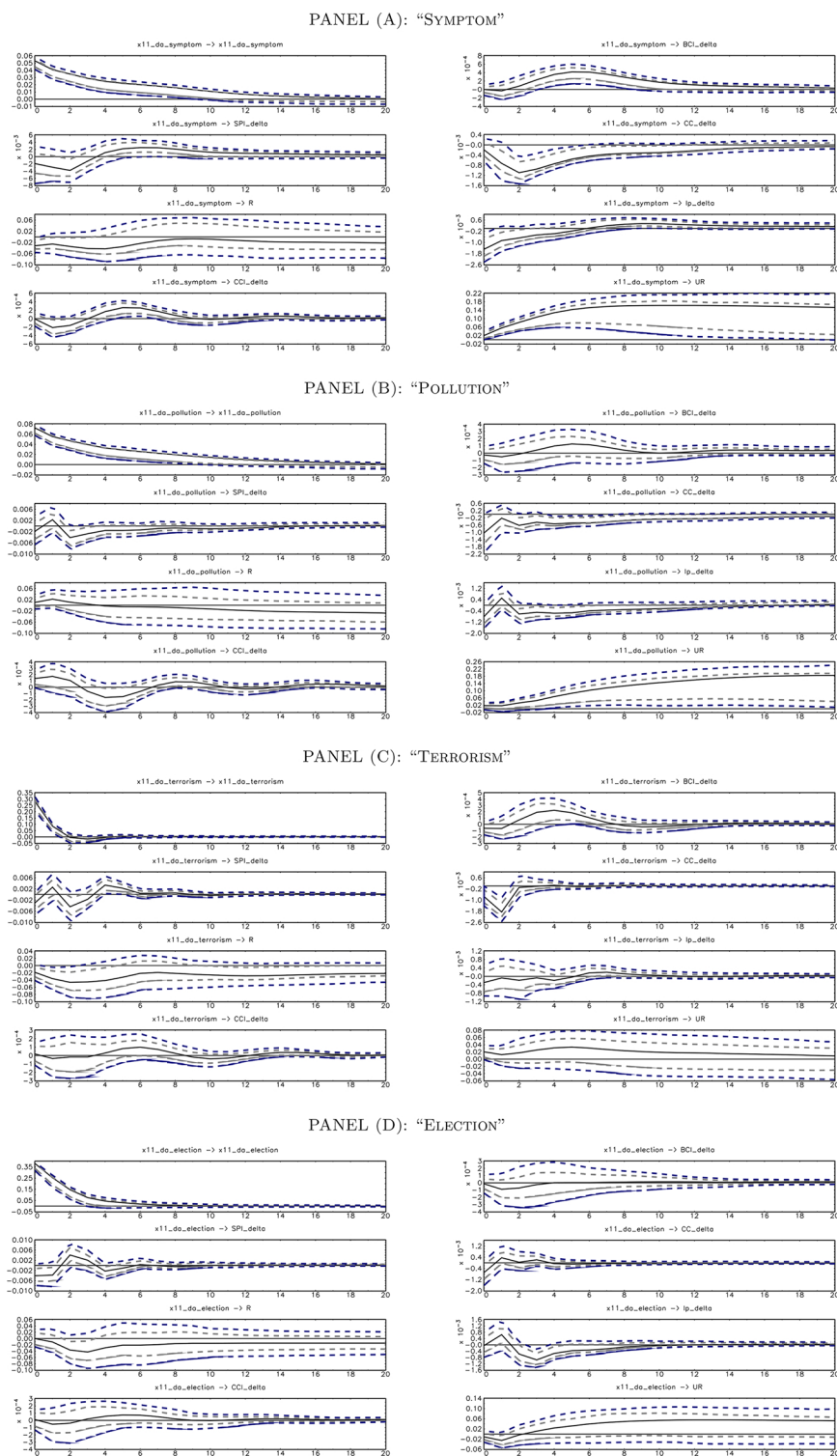
Fig. A6. Impulse Responses to NM-GSI Shocks (X11-SA). *Notes:* This figure reports orthogonalized impulse responses to a "Symptom" (Panel A), "Pollution" (Panel B), "Terrorism" (Panel C) and "Election" (Panel D) NM-GSI (1sd) shock. Raw NM-GSIs are transformed as in Da et al. (2011) and seasonally-adjusted using the X-11-ARIMA procedure. VARs are estimated with a constant. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Growth vs level effects
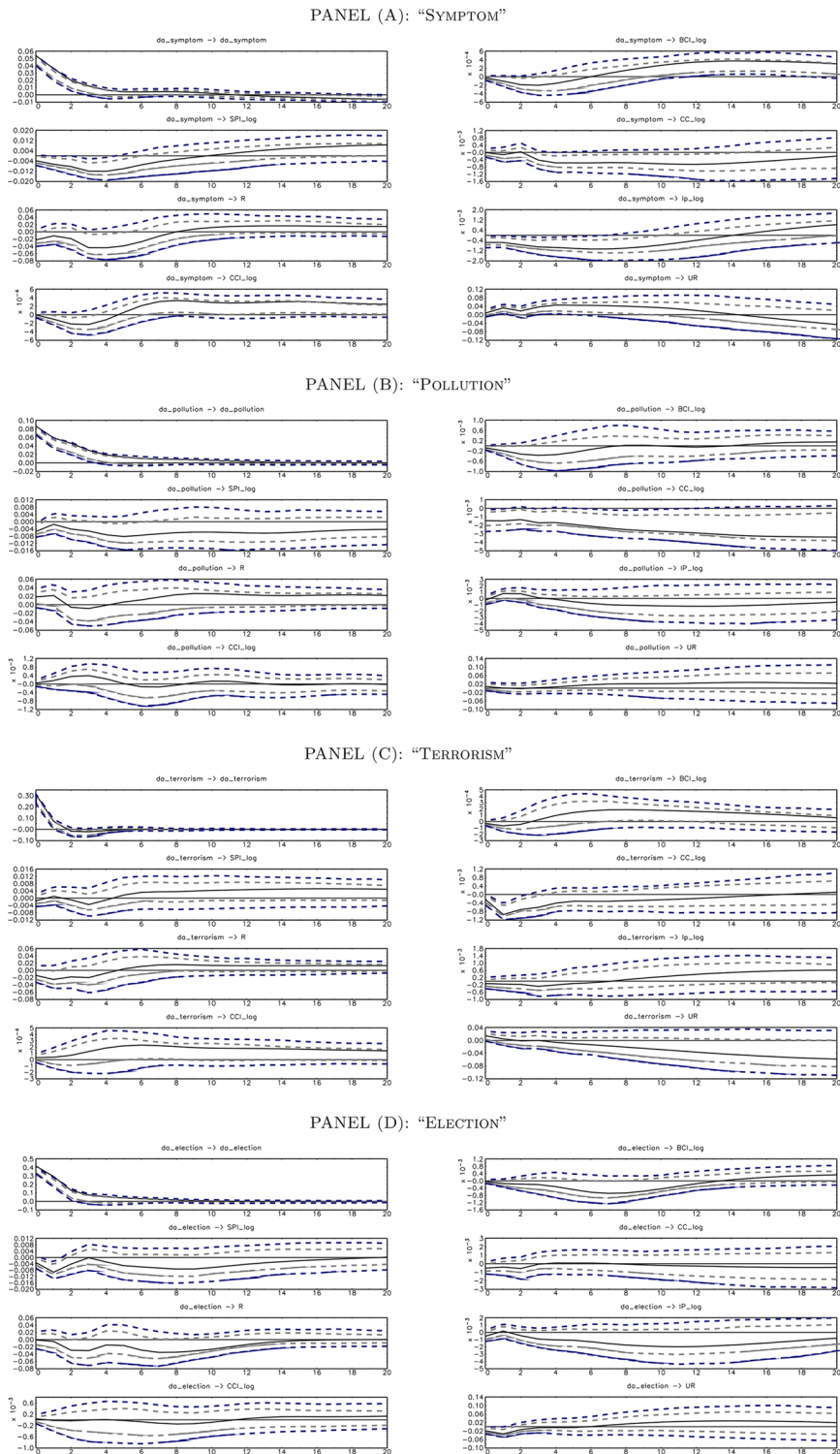
Fig. A7. Impulse Responses to NM-GSI Shocks (Variables in log-levels). *Notes:* This figure reports orthogonalized impulse responses to a "Symptom" (Panel A), "Pollution" (Panel B), "Terrorism" (Panel C) and "Election" (Panel D) NM-GSI (1sd) shock. Raw NM-GSIs are transformed as in Da et al. (2011). VARs are estimated with a constant, seasonal dummies and three endogenous lags. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. The NM-GSIs, the interest rate and the unemployment rate are in levels, while the remaining variables are in log-levels. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

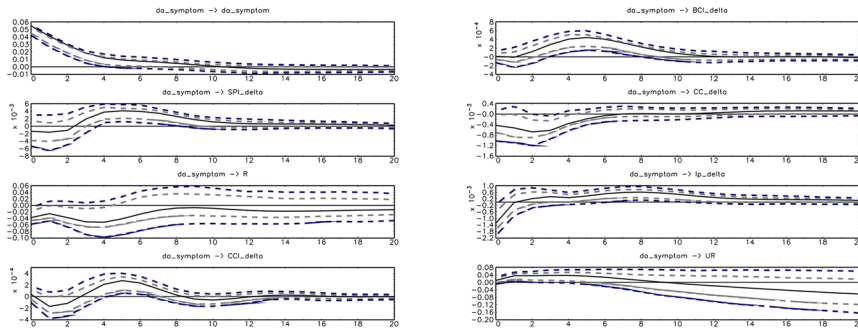*Controlling for general uncertainty*

PANEL (A): "Symptom"
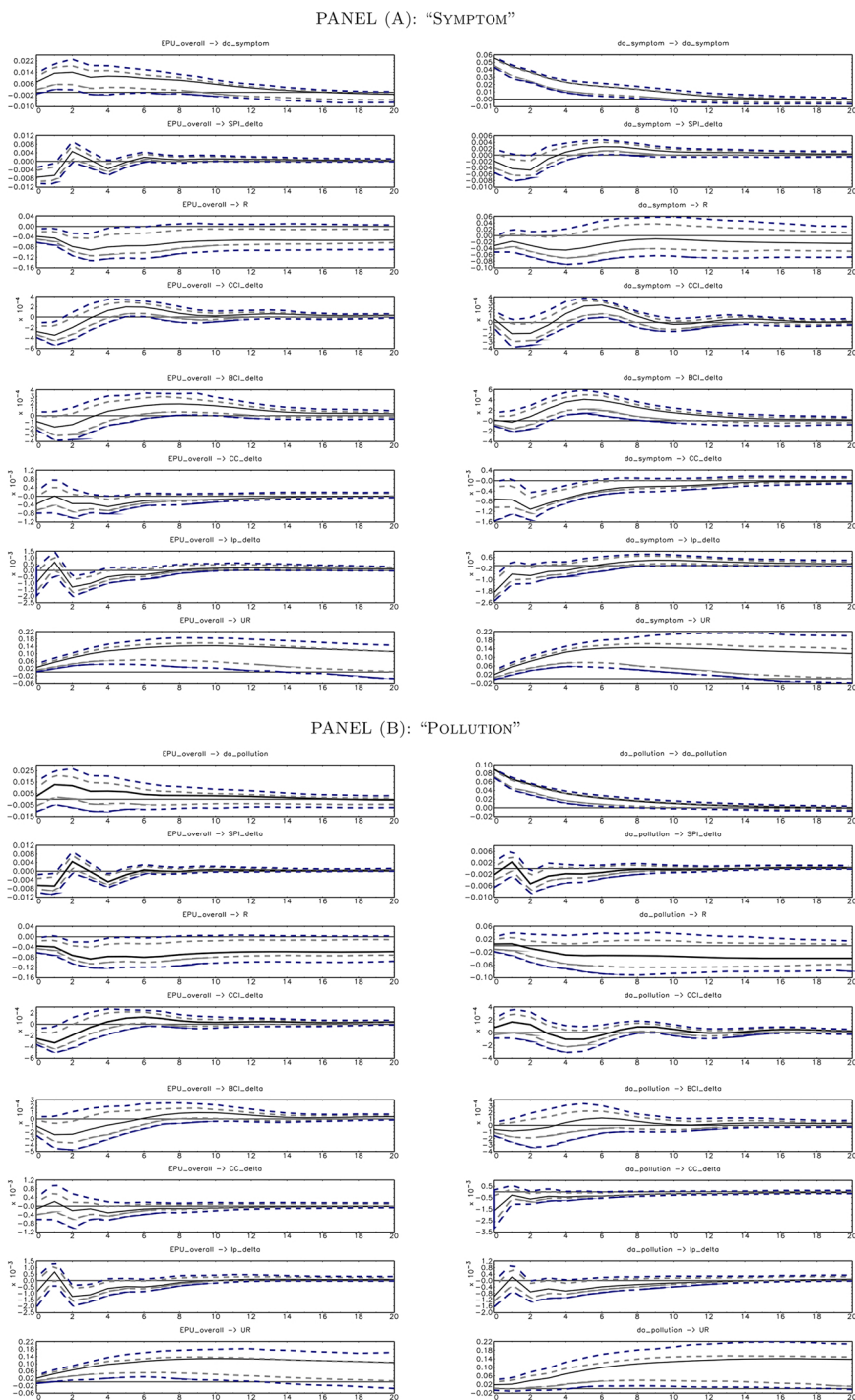
PANEL (B): "Pollution"

Fig. A8. Impulse Responses to EPU and NM-GSI Shocks. *Notes:* This figure reports orthogonalized impulse responses to a EPU (left column) and "Symptom" (Panel "A", right column) and "Pollution" (Panel "B", right column) NM-GSI (1sd) shocks. NM-GSIs are transformed as in Da et al. (2011). The Baker et al. (2016) EPU is added to the original baseline vector and ordered first in a Cholesky decomposition (i.e., Υ = [EPU, NM − GSI, SPI, R, CCI, BCI, CC, IP, UN]′). VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
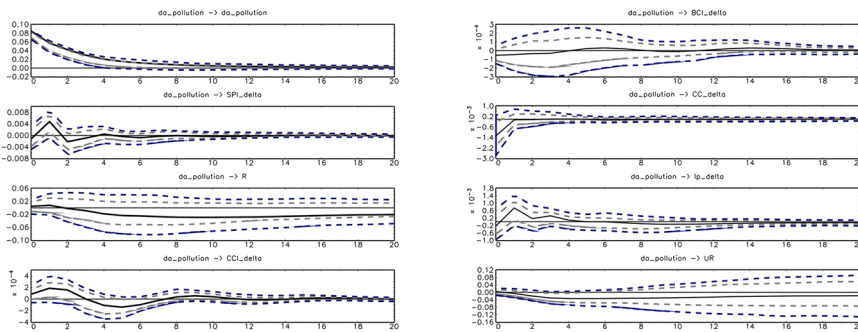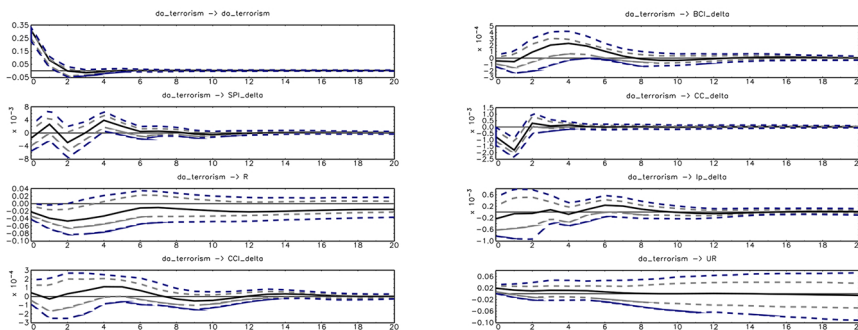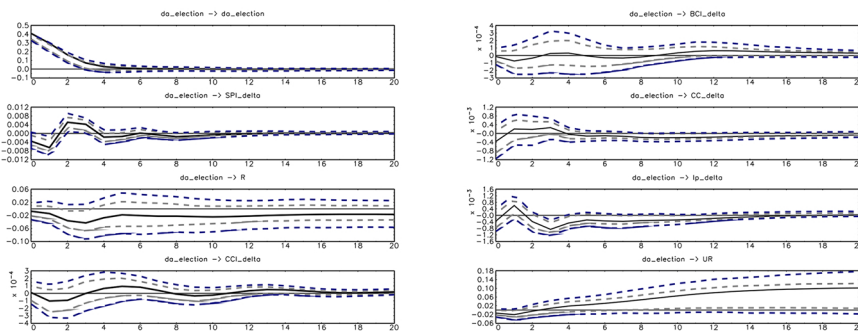
PANEL (A): "Terrorism"

PANEL (B): "Election"
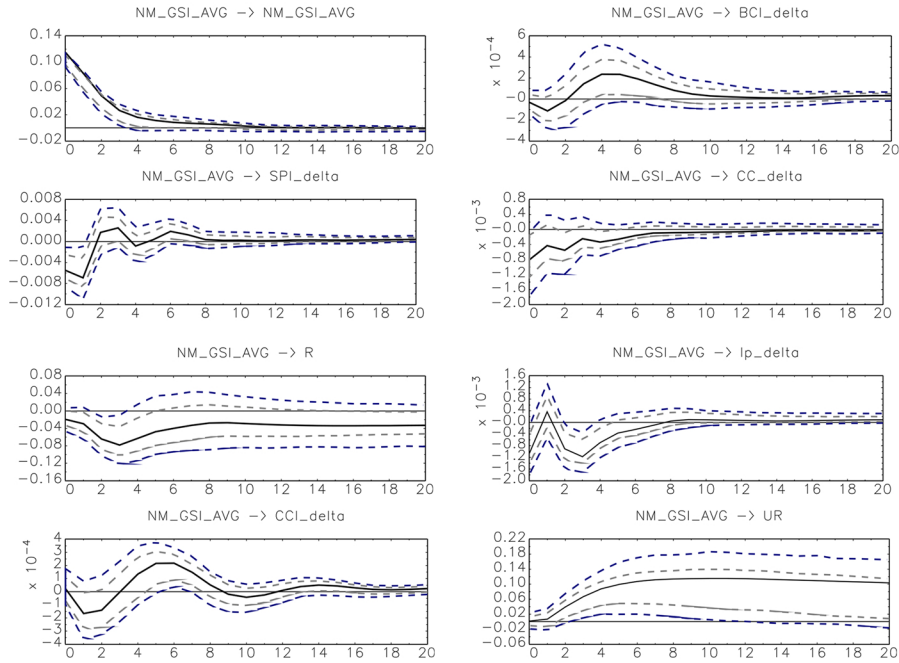

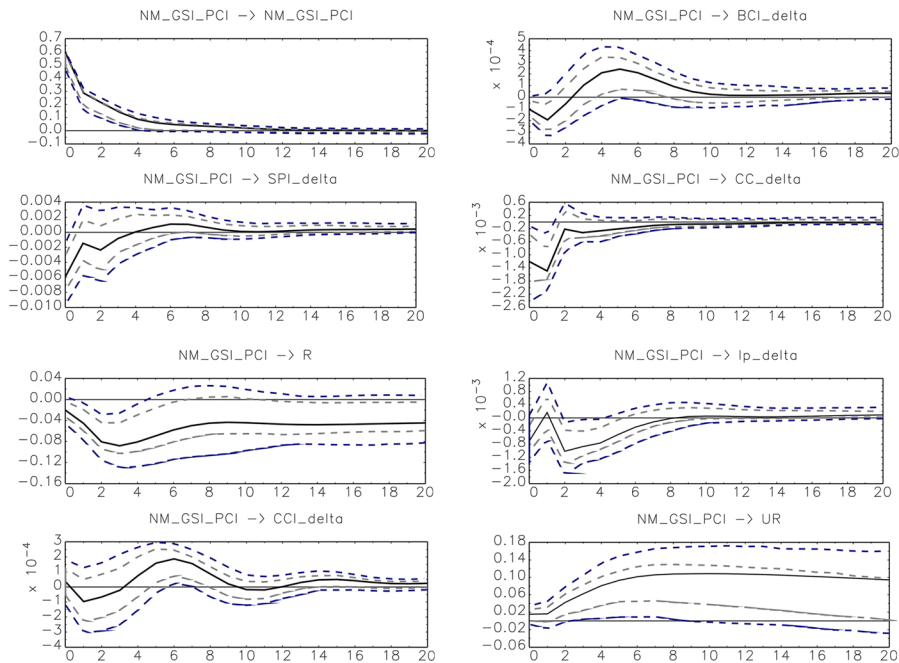**Fig. A9.** Impulse Responses to EPU and NM-GSI Shocks. *Notes:* This figure reports orthogonalized impulse responses to a EPU (left column) and "Terrorism" (Panel "A", right column) and "Election" (Panel "B", right column) NM-GSI (1sd) shocks. NM-GSIs are transformed as in Da et al. (2011). The Baker et al. (2016) EPU is added to the original baseline vector and ordered first in a Cholesky decomposition (i.e., Ƴ = [EPU, NMGSI, SPI, *R*, CCI, BCI, CC, IP, UN]′). VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

PANEL (A): "SYMPTOM"

PANEL (B): "POLLUTION"

Fig. A10. Impulse Responses to "US Stock Market" GSI and NM-GSI Shocks. *Notes:* This figure reports orthogonalized impulse responses to a "US Stock Market" GSI (left column) and Google "Symptom" (Panel "A", right column) and "Pollution" (Panel "B", right column) NM-GSI (1sd) shocks. NM-GSIs are transformed as in Da et al. (2011). The Donadelli (2015) "US Stock Market" GSI is added to the original baseline vector and ordered first in a Cholesky decomposition (i.e., Ƴ = [GSI, NMGSI, SPI, *R*, CCI, BCI, CC, IP, UN]′). VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
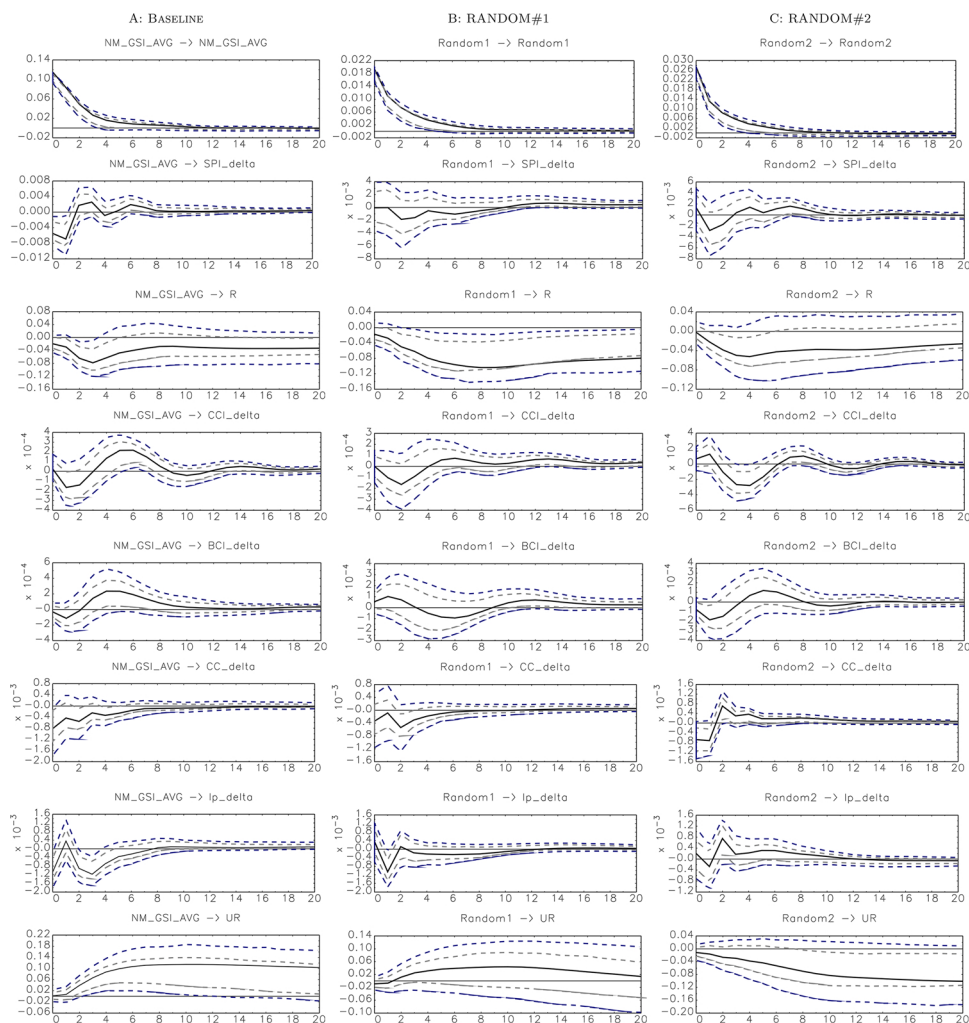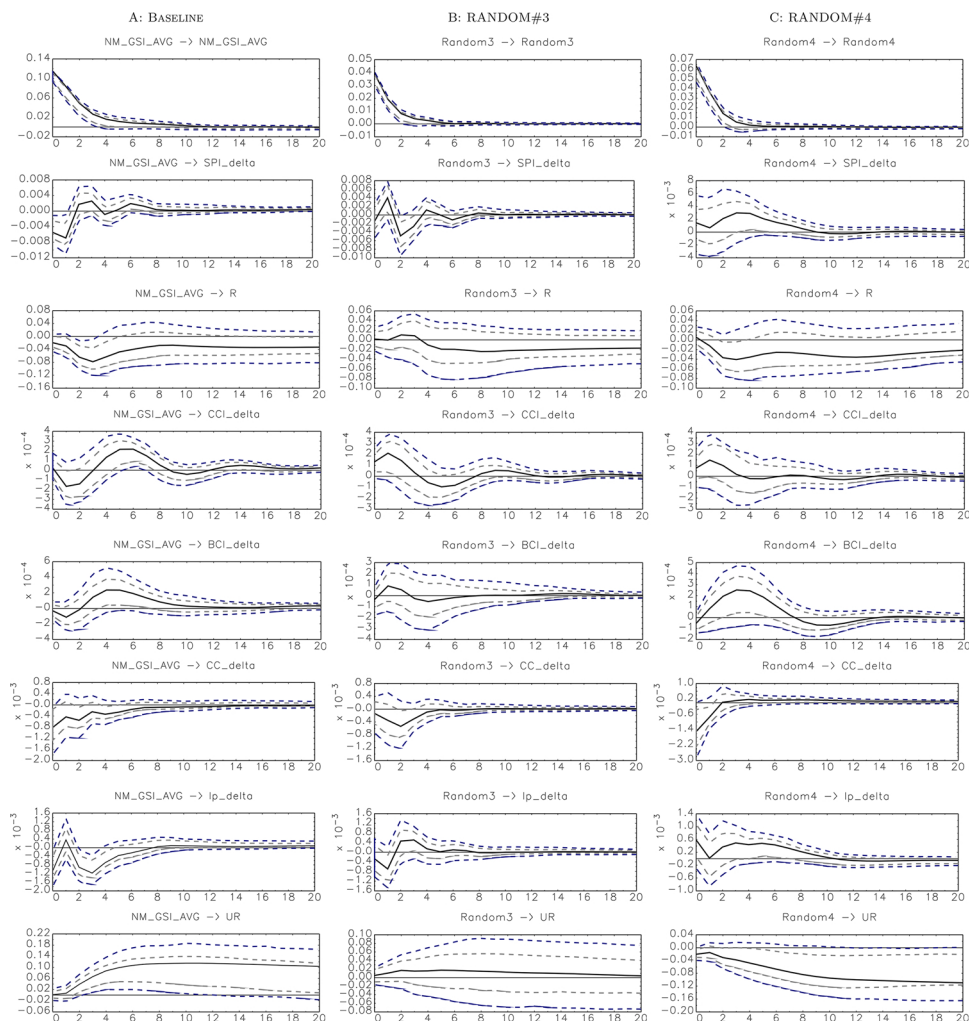
PANEL (A): "TERRORISM"

PANEL (B): "ELECTION"

Fig. A11. Impulse Responses to "US Stock Market" GSI and NM-GSI Shocks. *Notes:* This figure reports orthogonalized impulse responses to a "US Stock Market" GSI (left column) and Google "Terrorism" (Panel "A", right panel) and "Election" (Panel "B", right panel) NM-GSI (1sd) shocks. NM-GSIs are transformed as in Da et al. (2011). The Donadelli (2015) "US Stock Market" GSI is added to the original baseline vector and ordered first in a Cholesky decomposition (i.e., Ɏ = [GSI, NMGSI, SPI, R, CCI, BCI, CC, IP, UN]′). VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Controlling for credit tightness

PANEL (A): "SYMPTOM"

PANEL (B): "POLLUTION"

PANEL (C): "TERRORISM"

PANEL (D): "ELECTION"

(caption on next page)

Fig. A12. Impulse Responses to NM-GSI Shocks. *Notes:* This figure reports orthogonalized impulse responses to a "Symptom" (Panel A), "Pollution" (Panel B), "Terrorism" (Panel C) and "Election" (Panel D) NM-GSI (1sd) shock. NM-GSI s are transformed as in Da et al. (2011). Credit Easing Accumulated (CEA) Index is added to the original baseline vector and ordered first in a Cholesky decomposition (i.e., $\Upsilon = [CEA, NMGSI, SPI, R, CCI, BCI, CC, IP, UN]'$). VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Composite NM-GSIs

PANEL (A): "AVERAGE"

PANEL (B): "PRINCIPAL COMPONENT"

(caption on next page)

Composite "Random NM-GSIs"

Fig. A15. Impulse Responses to Alternative Composite NM-GSI Shocks. *Notes:* This figure reports orthogonalized impulse responses to different "composite NM-GSI" (1sd) shocks. All raw NM-GSIs are transformed following Da et al. (2011). Composite NM-GSIs are defined as the weighted average of four different search volume indexes. Column A: baseline set of words: "Symptom", "Pollution", "Election" and "Terrorism". Column B: first set of random words: "Flower", "Rain", "Sun", "Team". Column C: second set of random words: "Bed", "Cup", "King", "Star". VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
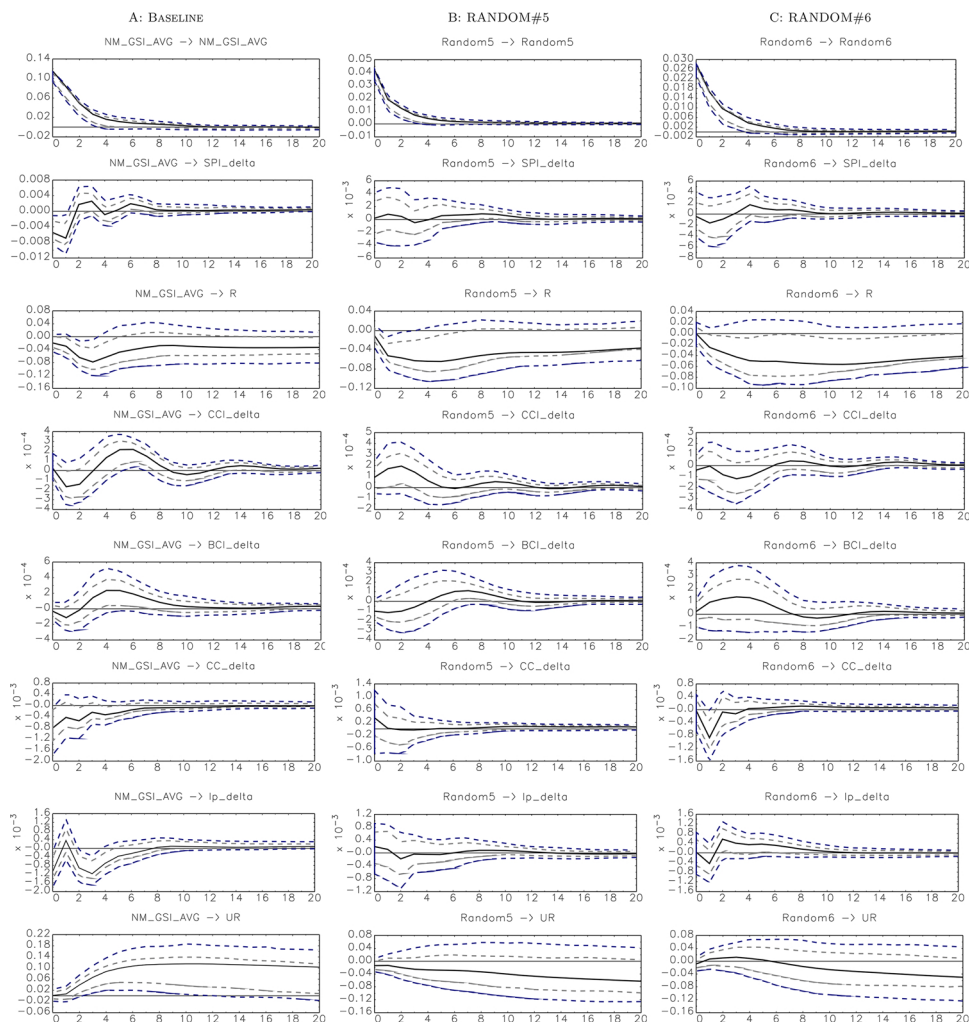
Fig. A16. Impulse Responses to Alternative Aggregate NM-GSI Shocks. *Notes:* This figure reports orthogonalized impulse responses to different "composite NM-GSI" (1sd) shocks. All raw NM-GSIs are transformed following Da et al. (2011). Composite NM-GSIs are defined as the weighted average of four different search volume indexes. Column A: baseline set of words: "Symptom", "Pollution", "Election" and "Terrorism". Column B: first set of random words: "Ball", "Boat", "Shoes", "Snow". Column C: second set of random words: "Bike", "Final", "Flight", "Restaurant". VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2017:M12. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

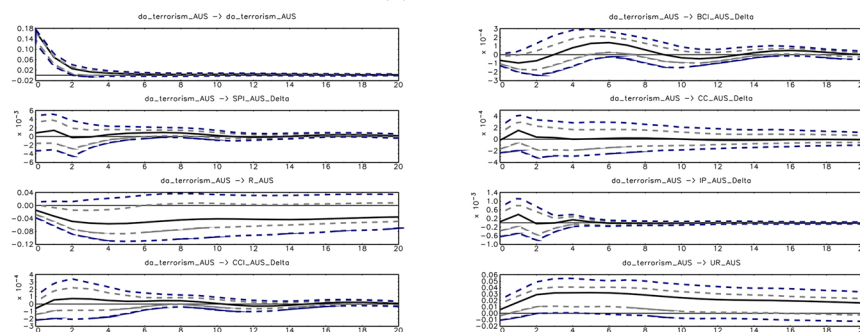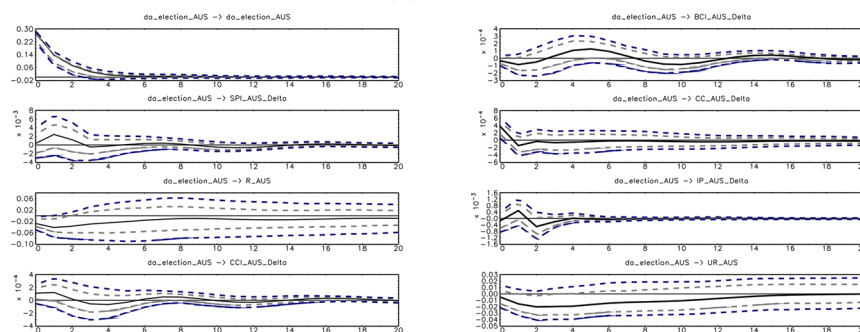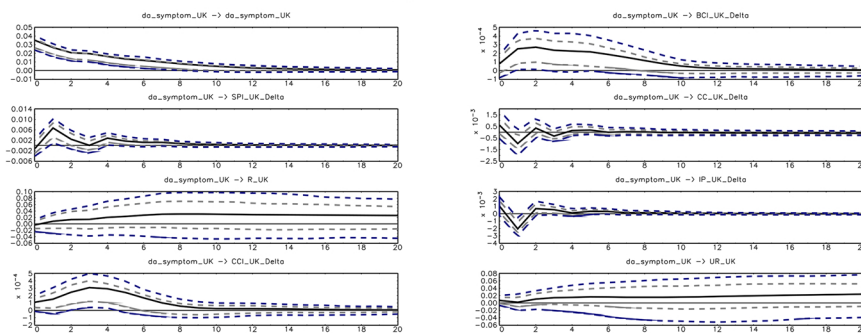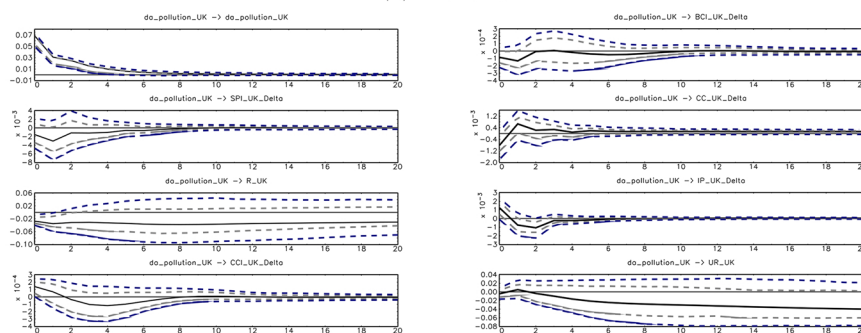*Different countries: Evidence from the UK and Australia*
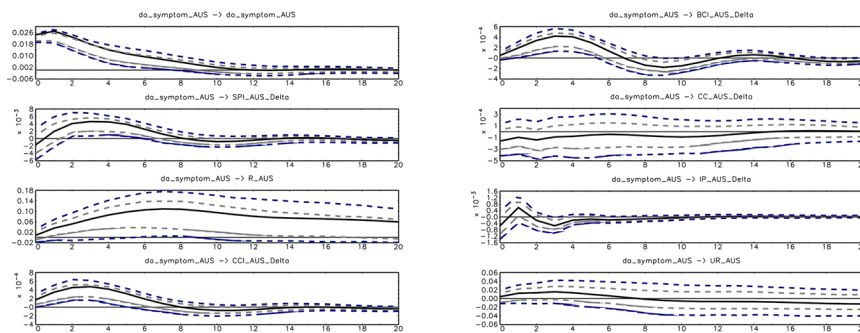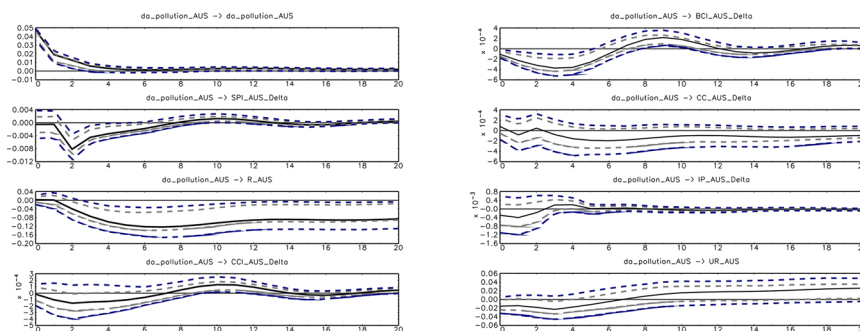
Fig. A17. Evidence from other countries: Australia. *Notes:* This figure reports orthogonalized impulse responses to a "Symptom" (Panel A), "Pollution" (Panel B), "Terrorism" (Panel C) and "Election" (Panel D) NM-GSI (1sd) shock in Australia. NM-GSIs are transformed as in Da et al. (2011). VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2018:M3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

PANEL (A): "Symptom"

PANEL (B): "Pollution"
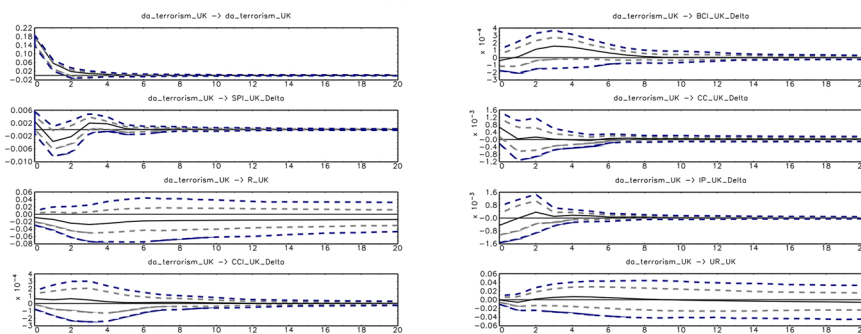
PANEL (C): "Terrorism"
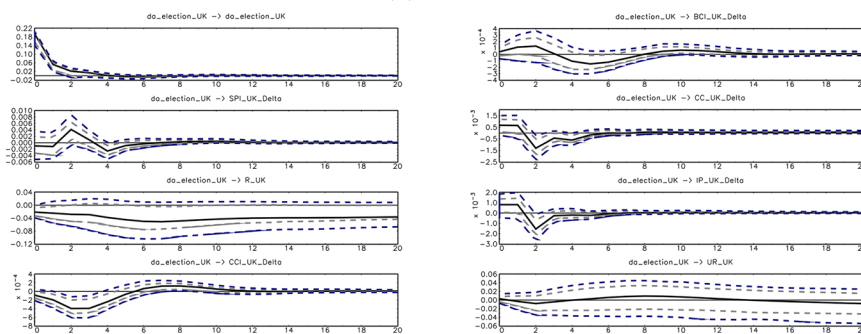
PANEL (D): "Election"

Fig. A18. Evidence from other countries: United Kingdom. *Notes:* This figure reports orthogonalized impulse responses to a "Symptom" (Panel A), "Pollution" (Panel B), "Terrorism" (Panel C) and "Election" (Panel D) NM-GSI (1sd) shock in the UK. NM-GSI s are transformed as in Da et al. (2011). VARs are estimated with a constant and seasonal dummies. Solid "black" lines: estimated impulse responses. Dashed "blue" lines: 90% bootstrapped confidence bands. Dashed "grey" lines: 68% bootstrapped confidence bands. Sample: 2005:M1-2018:M3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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